Pontifícia Universidade Católica
do Rio de Janeiro

Pedro Henrique Rosado de Castro

Essays on Empirical Finance

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor: Prof. Ruy Monteiro Ribeiro

Rio de Janeiro
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Prof. Ruy Monteiro Ribeiro
Advisor
Instituto de Ensino e Pesquisa – Insper

Prof. Marcelo Cunha Medeiros
President
Departamento de Economia – PUC-Rio

Prof. Carlos Viana de Carvalho
Departamento de Economia – PUC-Rio

Prof. Marco Antonio Cesar Bonomo
Instituto de Ensino e Pesquisa – Insper

Prof. Axel Andre Simonsen
Itaú – BBA

Rio de Janeiro, May 22nd, 2020

Pedro Henrique Rosado de Castro

Completed his Bachelor of Arts degree in Economics from University of Campinas (UNICAMP) in 2004 and obtained his Master of Science degree in Economics from Pontifical Catholic University of Rio de Janeiro (PUC-Rio) in 2008. During his Ph.D. studies he was an associate visiting researcher of the Stanford Graduate School of Business Finance Program.

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Abstract

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The thesis is composed of two essays on empirical finance. The first focuses on FX markets and presents measures of interest rates short-term structure slope changes for the US and other G10 countries using 3- and 6-month futures contracts. These changes in *slopes* have immediate impact on currency returns but also a strong delayed effect over the following weeks, implying that currencies are predictable both in and out-of-sample. Investors that condition on *slope* to tactically trade a long G10 portfolio improve Sharpe ratios to 0.4-0.9, relative to 0.15 for a buy-and-hold strategy. A dollar-neutral currency portfolio that sorts G10 country currencies on the cross-section *slope* also deliver higher Sharpe ratios than other currency strategies, such as the carry trade. These findings are compatible with delayed currency market reaction to information in interest rates. The second essay proposes a novel measure that solely use cross-sectional dispersion information on CAPM betas to forecast aggregate market returns for the US. This choice of predictors is based on simple theoretical arguments that measures associated with the dispersion of CAPM betas, in some settings, should be related with expected future market returns. We find that these dispersion measures do indeed forecast market risk premium over multiple horizons and deliver high in-sample and out-of-sample predictive power: out-of-sample R^2 reaches up to 10% at the annual frequency (0.7% monthly) and are robust to different estimation windows. Unlike most measures in the literature, ours is not a price- or valuation-based ratio. Our approach is also an alternative to models that use the cross-section of valuation ratios to infer the conditional market risk premium. Our measures vary with the business cycle and correlate with other commonly used forecasting variable such as dividend-price or consumption-wealth ratios, but they provide explanatory power above and beyond the standard predictors. Our findings provide additional evidence that the betas dispersion across time is a function of time varying risk premium.

Keywords

Currency Return Predictability Monetary Policy Term Structure of Interest Rates Equity Risk premium Conditional Asset Pricing Models (CAPM)

Resumo

Castro, Pedro Henrique Rosado de; Monteiro Ribeiro, Ruy. **Ensaios em Finanças Empíricas**. Rio de Janeiro, 2020. 148p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta tese é composta por dois ensaios sobre finanças empíricas. O primeiro se concentra nos mercados de câmbio e apresenta medidas de mudanças na inclinação da estrutura de curto prazo das taxas de juros para os EUA e outros países de G10, usando contratos de futuros de 3 e 6 meses. Essas mudanças na inclinação têm impacto imediato nos retornos da moeda e também forte efeito retardado nas semanas seguintes, o que implica que as moedas são previsíveis tanto dentro quanto fora da amostra. Os investidores que condicionam na inclinação para negociar taticamente uma carteira comprada em moedas G10 contra o Dólar americano melhoram os índices de Sharpe para 0,4-0,9, em relação a 0,15 de uma estratégia de *buy and hold*. Uma carteira de moeda neutra em dólares que classifica as moedas dos países do G10 de acordo com a inclinação no *cross-section* também oferece índices de Sharpe mais altos do que outras estratégias de moeda como o *carry trade*. Essas descobertas são compatíveis com uma reação defasada do mercado de câmbio às informações sobre taxas de juros. O segundo ensaio propõe uma nova medida que usa apenas informações de dispersão *cross-section* de betas do modelo CAPM para prever retornos agregados de mercado para os EUA. Esta escolha de preditores é baseada em argumentos teóricos simples de que as medidas associadas à dispersão dos betas do CAPM, em alguns cenários, devem ser relacionadas aos retornos futuros de mercado esperados. Essas medidas de dispersão de fato prevêem o prêmio de risco de mercado em vários horizontes e fornecem alto poder preditivo dentro e fora da amostra. O R^2 fora da amostra atinge até 10% na frequência anual (0,7% mensal) e são robustos a diferentes janelas de estimação. Ao contrário da maioria das medidas encontradas na literatura, a nossa não é baseado em preço ou *valuation ratios*. Nossas medidas variam com o ciclo econômico e se correlacionam com outras variáveis de previsão comumente usadas, como razões de dividendo-preço e consumo-riqueza, mas fornecem poder explicativo acima e além dos preditores padrão. Nossos resultados fornecem evidências adicionais de que a dispersão dos betas ao longo do tempo é função da variação temporal do prêmio de risco de mercado.

Palavras-chave

Previsibilidade do Retorno de Moedas   Política Monetária   Estrutura a Termo de Taxas de Juros   Prêmio de Risco de Mercado   Modelos CAPM Condicionais

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List of Abreviations

AUD	Australia
BAB	betting against beta
CAPM	Capital Asset Pricing Model
CBOE	Chicago Board Options Exchange
CIP	interest rate parity
CRSP	Center for Research in Security Prices
CSBD	cross-section beta dispersion
ENC-New	statistic test proposed by Clark & McCracken (2001)
ENC-T	statiscit test proposed by Diebold & Mariano (2002)
ERP	Equity Risk Premium
EUA	Estados Unidos da América
EUR	Eurozone
FED	Federal Reserve
FOMC	Federal Open Market Committee
FX	foreign exchange
G10	Group of Tem
GBP	Great-Britain
MSE	mean squared error
NASDAQ	National Association of Securities Dealers Automated Quotations
NBER	National Bureau of Economic Research
NOK	Norway
NYSE	New York Stock Exchange
NYSE MKT	New York Stock Exchange (Market)
NZD	New Zealand
OLS	ordinary least squares
OOS	out-of-sample
QE	Quantitative Easing
R^2	R-squared
S&P500	Standard & Poor's 500
SDF	stochastic discount factor
SEK	Sweden
TED	Treasury-Eurodollar rate
UIP	uncovered interest rate parity condition
US	United States
VIX	CBOE Volatility Index
ZLB	zero lower bound

1
Currency Returns and Short-Term Interest Rate Slopes

1.1
Introduction

In no-arbitrage affine term structure models with complete markets, any variable that prices the domestic yield curve potentially predicts exchange rate risk premium. The foreign exchange risk premium is a function of differences in the conditional volatility of the domestic and foreign stochastic discount factor (Backus *et al.*, 2001). Therefore, factors that drive the relative dynamics of the yield curve of two different countries also drive the relative currency risk premium. Moreover, the difference between two countries short-term interest rates, i.e. carry, is the most widely known currency factor, that relies on interest rates to forecast currency returns (Verdelhan *et al.*, 2007): countries with higher interest rates, contrary to what the uncovered interest parity condition predicts (UIP), typically deliver higher currency returns. In addition, Ang & Chen (2010) show that variables that predict yield curve movements, besides carry, like term spreads, short-term interest rate changes and interest rate volatility, also significantly predict excess foreign exchange.

Currency realized returns, when considering a simple present value relation as in Engel & West (2016), are a function of: (i) interest rates differential today, the carry (ii) expected futures rates differential and (iii) currency risk premium. Similar to Campbell & Shiller (1988), we can interpret current and future interest rates differentials – current and future carry – as the cash flow component of a currency investment strategy. However, information extracted from the term structure of long-term bonds, like the term spread, contain both an expected future rates differential component and exchange rate risk. In contrast, one may argue that short-term interest rates futures markets could be more closely related to the future short-term path of monetary policy and present minor changes in risk premium. Neuhierl & Weber (2019) show that, for the US, this short-term slope of futures interest rates contracts, or *monetary slope*, contains information about the speed of future monetary policy tightening and loosening, predicts future changes in the FED funds rate and also revisions of professional forecasters[1.1].

In this paper, we test the relation between currency returns and the short-term interest rate futures curves of G10 countries[1.2]. Our findings suggest that changes in 3- and 6-month interest futures *slope*, the *monetary policy slope*, predict individual currency returns in a panel setting and also a portfolio that is long G10 currencies and short the US dollar, also known in the literature as the Dollar Portfolio. Changes in short-term structure *slope* have immediate impact on currency returns, but also a delayed effect over the following weeks. Contrary to the prevailing literature that struggles to demonstrate empirically currency predictability (Rossi, 2013; Ma & Zhang, 2019), we find strong evidence of out-of-sample weekly currency predictability: investors that condition on international term structure slope to tactically trade the long G10 portfolio improve annualized Sharpe ratios to 0.5, relative to 0.12 of a buy-and-hold strategy. We also construct a dollar-neutral currency portfolio by sorting G10 country currencies based on the cross-section of term structure slope measures, that delivers Sharpe ratios above and beyond other currency strategies, like the carry trade. Currency predictability is robust to several short-term structure slope measures and survives the inclusion of slope constructed from longer bond yields, like a 10-year minus 3-month bond yield spread. Predictability is present in alternative sub-samples and it is not restricted to FOMC weeks, improving substantially when focusing on weeks with large shifts in G10 interest futures term structures.

So what drives this particular currency return predictability? As previously noted, currency realized returns are related to (i) risk premium and (ii) expectations of future interest rate changes. Our empirical findings suggest that a higher *monetary slope* for a given currency predict positive currency returns both in the current and subsequent weeks. In a single country setting, like Neuhierl & Weber (2019), *slope* measure seems to be capturing mostly information about the expected path of monetary policy. In this paper we show that this result also holds in a cross-section of G10 countries: we find supporting evidence that relative changes in *slope* are capturing more information about changes in the expected future path of relative monetary policy between

[1.1] Neuhierl & Weber (2019) also show that this short-term *slope* extracted from US interest rates futures contracts also forecasts one-week ahead returns for the S&P500 stock index. *slope* not only predicts future changes in the FED funds rate and revisions of professional forecasters but is correlated with a linguistic analysis of speeches by Federal Reserve Board members: a hawkish speech, as defined in their linguistic approach, is correlated with increases in *slope*, that is, an increase in the short-term *slope* is compatible with a communication of a faster monetary policy tightening in the future

[1.2] In our setting instead of using long-term bond prices and yields, as in the case of Ang & Chen (2010), we follow the idea of Neuhierl & Weber (2019) and construct a similar measure of slope from short-term interest rates futures contracts for all available G10 countries

G10 countries, or the future cash flow component of the currency investment strategy. If it were the case that they were capturing only expected future changes in relative risk premium, a higher short-term *slope* should forecast lower currency realized returns because of an increase in the expected risk or discount factor component of the currency investment.

We construct several measures of the *monetary slope*, or simply *slope*, using international interest rates futures contracts at different short-run horizons for all G10 countries. One such simple measure considers the difference of k-month minus 1-month futures implied rates changes[1.3]. Alternative modified measures perform regressions of changes in k-month interest futures on changes in 1-month futures implied rates. These measures control for the correlation between changes in the slope and the level of each individual country short-run term structure. This methodology follows Neuhierl & Weber (2018), extending their measure to a cross-country setting[1.4].

Our evidence that *slope* explains current and predicts future individual currency returns against the US dollar arises both in panel regressions, that exploit the whole cross-section information of G10 currency returns across time, and in the context of currency portfolios, like a portfolio of equally-weighted long G10 currencies against the US dollar, typically referred in the literature as the Dollar portfolio. We also find supporting evidence of a delayed reaction in currencies to a *slope* change: an increase in the *slope* difference between country i and the US leads to a positive impact both on current week and up to 4-week ahead currency i returns against the US dollar.

We use this delayed reaction evidence to construct two novel currency portfolios. The first strategy conditions on international *slope* to tactically trade the Dollar portfolio: depending on relative *slope* differences between the US and a synthetic G10 average on a given week, it goes either long or short the US Dollar on the subsequent week. The predictability of this strategy is economically significant, delivering an annualized Sharpe ratio, when implemented on all weeks, of 0.4 adjusting for transaction costs. As a comparison, in our sample, Sharpe ratios reach 0.3 for the carry-trade and for 0.15 the Dollar portfolio buy-and-hold strategy. Other papers with a more

[1.3]One natural candidate for changes in the slope of the term structure is the simple difference between a k-month and 1-month futures implied rates ($\Delta ff_t^k - ff_t^1$). One of the problems with this measure is that it is correlated to changes in the level of the interest rate

[1.4]We consider several versions of this modified slope measure. One example is a simple extension of Neuhierl & Weber (2019) to an international setting: we define *slope* for country i as the residual of the following regression: $\Delta ff_{i,t}^3 = \alpha^i + \beta_1^i \cdot \Delta ff_{i,t}^1 + \text{slope}_t^i$. Another example is a version for country i slope that is completely orthogonal to US futures rates: $\Delta ff_{i,t}^3 = \alpha^n + \beta_1^i \cdot \Delta ff_{i,t}^1 + \beta_2^n \cdot \Delta ff_{us,t}^1 + \beta_3^n \cdot \Delta ff_{us,t}^1 + \text{slope}_t^{n \perp us}$. We use both 3-month and 6-month horizon interest rates futures contracts in our setting. In our paper we refer to *slope* or *monetary slope* generically since we are considering a wide range of measures complete data set of countries, not restricted to G10 currencies, like Hassan & Mano (2019), present gross Sharpe ratios (not adjusted for transaction costs) of 0.5 and 0.16 for the carry and Dollar trade portfolios, respectively. Out-of-sample weekly predictability of the US Dollar portfolio using *slope* measured by R-squared statistics is also high, specially when considering the literature on currency predictability and the general difficulty in forecasting currency returns using macroeconomic variables[1.5].

The second strategy constructs a US dollar-neutral currency portfolio by sorting G10 country currencies based on each country's *slope* measure. With individual country panel regressions, we find evidence that a country with a positive (negative) *slope* has on average a positive (negative) currency return against the US dollar up to four weeks ahead. Following this result, we construct a long-short dollar neutral strategy that sorts currencies into High *slope* and Low *slope* bins, based on each country's *slope* measure. While a carry-trade strategy sorts countries based on interest rate differentials, our proposed strategy sorts on *slope*. This long-short individual country slope portfolio, or simply long-short *slope*, delivers Sharpe ratios that are above and beyond other currency strategies. We find that this strategy has a statistically significant alpha that is not explained by the exposures to both carry and dollar risk factors.

Predictability of future currency returns by *slope* is robust to a series of changes. It remains significant after the inclusion of lagged currency returns, of slope extracted from long-run interest rates, like the term spread between a 10-year and a 3-month bond yield, and other controls. Predictability is present for several *slope* definitions, like using 6-month maturities instead of 3-month, individual G10 *slope* measures orthogonal to US *slope* or even using US *slope* only. Results are robust to different sub-samples, like weeks with no FOMC meetings or a pre-2008 sample to evaluate the impact of Quantitative Easing on our results. Sharpe ratios increase even further if we focus on specific weeks, like sub-samples of large slope movements, FOMC Weeks or No-FOMC weeks with large moves. Table B.1 on the Appendix B below summarizes some of our

[1.5]For the large-slope sub-sample weeks, out-of-sample R^2 range from 0.1% to 0.3%. Using insights from Cochrane (2009) these out-of-sample statistics suggest that an active investor who condition on *slope* can increase annualized weekly Sharpe ratios from 0.27 (the Sharpe ratio for a buy-and-hold long US Dollar strategy implemented only on the these weeks, see Table B.1) on the Appendix B up to 0.48, a 70% increase. Just as a comparison, in their paper Neuhierl & Weber (2019), find a weekly out-of-sample R-squared of 0.27% when forecasting equity returns in the US, which delivers a 23.3% increase in annualized Sharpe ratio considering the same methodology. Out-of-sample currency return predictability using international *slope* from short-term is an order of magnitude higher, which is even more striking considering the difficulty in forecasting currency returns findings[1.6].

Our work contributes to the existing literature in four ways. Our first contribution is related to the large literature on currency predictability. Exchange rates are stubbornly disconnected from macroeconomic fundamentals. Since Meese & Rogoff (1983), empirical attempts to forecast currency returns using macroeconomics prices and quantities usually fall-short of a simple random walk, suggesting that macro related variables are not relevant to forecasting currencies. In a recent paper, Ma & Zhang (2019) document that the ratio of residential-to-nonresidential investment, a macro variable, is a strong in-sample and out-of-sample predictor for for US Dollar returns[1.7]. Currencies returns are also hard to predict. Rossi (2013) show, in a survey of empirical papers that have tried to forecast exchange rates, that even for macro predictors or models that seem to exhibit forecastability in-sample, it is usually present for only a sub-set of countries and samples, is unstable out-of-sample and does not beat the random-walk *benchmark*. Therefore, Meese & Rogoff (1983) puzzle does not seem to be convincingly overturned. Our paper contributes directly to this literature since we find a variable strongly related to expectations about future monetary path of G10 countries relative to the US with strong out-of-sample predictive power. *Slope* information is relevant in the time-series dimension: conditioning on *slope* to tactically go long or short all G10 currencies against the US dollar significantly increase returns adjusted for risk. Moreover, *slope* is also relevant in the cross-section dimension: our long-short portfolio based on individual country *slope* information exploits this predictability and delivers Sharpe ratios above and beyond other currency strategies, like the carry-trade. In that sense, our empirical findings help to add another layer of evidence into this long standing debate in international finance and macroeconomics.

Second, we document that currency return predictability using *slope* measures is not restricted to weeks with regular policy decisions. A large literature, starting with Bernanke & Kuttner (2005), documents that asset prices respond directly and immediately to monetary policy actions. More recent papers have shown that stock market returns and Sharpe ratios are significantly higher on macroeconomic announcement days (Savor & Wilson, 2013). While this evidence is mostly studied for equity returns, a few papers

[1.6]We use as benchmark for large slope weeks ones in which the absolute modified term structure slope is higher than 0.5, it's unconditional standard deviation. Formally, when looking at Long G10 portfolio we include weeks for which $|\text{slope difference}_{G10,t}| > \mu_{\text{diff}} + 0.5 \cdot \sigma_{\text{diff}}$

[1.7]Their measure is different from most existing predictors based on prices, flows, and sentiments, as reviewed by Rossi (2013) and links directly exchange rates and macroeconomic quantities. Out-of-sample predictability of their proposed measure is significant: for the broad nominal Dollar index out-of-sample R^2 reaches up to 2.75% for the 1-quarter ahead horizon focus on currencies. Karnaukh (2020) document that the US dollar appreciates (depreciates) over the two day before FOMC tightening (easing) decisions, with FED funds futures anticipating these returns. Salehi *et al.* (2017) document larger excess returns and a pre-announcement drift for individual and portfolios of currencies on days with scheduled FOMC meetings, relating these findings to a compensation that investors demand for monetary policy uncertainty risk.

The evidence above suggest not only a reaction to monetary and other macro news shocks, but also that this response is concentrated. But uncertainty about future policy is present not only during meeting weeks. Policy makers often highlight that deliberations happen on a continuous basis. Speeches by governors, increased transparency and communication and forward guidance are all examples of efforts pursued by monetary authorities to shape expectations of future actions. Consistent with this view, Neuhierl & Weber (2019) show evidence that shifts in the short-end of term structure of US interest rates future forecast equity returns one-week ahead. They argue that, since the whole future path of interest rates is relevant for future equity returns, the FOMC releases information also outside scheduled FOMC meetings. In a currency setting, this also seems to be the case, since currency returns react both to changes in the US and G10 *monetary slope* independently of the considered sub-sample.

Our third contribution is to connect the vast literature that documents the impact of macroeconomic variables and news, monetary policy shocks and interest rates changes on the term structure of interest rates, with the currency return predictability literature. We provide additional empirical evidence that relative shifts in international interest rates futures term structure help predict currency movements. Our paper is not the first to relate currency returns to interest rates. There is a large literature on the empirical failure of covered interest rate parity hypothesis and the ability of the carry component of a currency to forecast future returns, like in Verdelhan *et al.* (2007), Verdelhan *et al.* (2011) and Menkhoff *et al.* (2017).

Our paper is not the first to use relative information embedded in the term structure of interest rates of different countries, other that the level of short-term rates differential, to predict currency returns. Our results are, however, quite different. Ang & Chen (2010) derive several term structures models and use them to implement different currency strategies that sort on different variables constructed from the term structure of interest rates. They show empirically that, besides the level of short-term rates differential (the carry), changes in short-term rates, the term spread of long-term bond yields and also changes in the long-term spread all have predictive power for one month-ahead and up to 12-month ahead currency returns: as an example, sorting currencies into a long-short portfolio that conditions on the long-term slope of the yield bond curve leads to negative realized returns and Sharpe ratios in their paper.

Our paper contributes to their finding by showing that the changes in the short-term *slope* of interest rates futures, in theory more related to the expected monetary policy path, also predict currency returns over shorter horizons. Our empirical findings complement theirs in the sense that a higher short-term *slope* or *monetary slope* for a given currency predict positive, not negative, future currency returns. It seems to be the case that, in a cross-section of G10 countries, relative changes in short-term *slope* are capturing more information about the relative expected path of future monetary policy rather than changes in risk premium. Since Ang & Chen (2010) constructs slope from 10-year bonds, their measure potentially captures more information about relative currency risk premia. Is is worth mentioning that our forecastability results survive in-sample the inclusion of the term spread of longer horizon bond yields, the sorting variable used in their paper. Additionally, our proposed novel tactical Dollar portfolio, that goes either long or short the US Dollar, using relative information from US *slope* and a synthetic G10 average *slope*, delivers high Sharpe ratios. This finding, not present in their paper, suggest that, for the US Dollar risk premium, it is relevant to condition not only on US term structure information, but also on other G10 countries short-term structure information. Even though short-term structure *slopes* have a common component, relative shifts are important to explain the US Dollar exchange rate returns against other G10 countries.

Finally, our findings of a strong delayed or lagged effect of changes in the *slope* of the short-term structure of interest rates futures are compatible with behavioral interpretations such as under-reaction to news. Our empirical evidence supports that currency markets tend to react with a delay to information embedded in the interest rate futures market. An increase in *slope* difference between country i and the US leads to a positive impact currency n returns against the US dollar both on current week and up to 4-week ahead. This lagged and persistent effect survives the inclusion of lagged returns as a control variable and it is not restricted to weeks with scheduled FOMC meetings. Quiet the opposite: conditioning on No-FOMC weeks with large slope changes tend to increase the persistence of *slope* on currency return predictability up to 4-weeks ahead. This evidence for currency markets provide additional anecdotal evidence in line with models of market segmentation such as in Greenwood *et al.* (2018) and extends the findings of delayed response of equity returns to *slope* shocks in the US (Neuhierl & Weber, 2019). That this under reaction arise in the interaction of foreign exchange rates markets for G10 countries, the worlds largest and most liquid financial market with a daily trading over 5 trillion US dollars, and G10 interest rate futures, also a very liquid and active market, is an interesting phenomenon.

1.2 Term Structure of Interest Rates and FX Returns

In this section, we present basic definitions of currency returns. We also derive the relation between currency returns and the stochastic discount factor of different countries in a complete markets setting. Following Ang & Chen (2010), we present a simple term structure model of interest rates to show the link between currency returns and the term structure of interest rates, besides the level of interest rate differential (the carry). We then present our proposed measure of short-term *slope* derived from interest rates futures contracts showing why this measure is, according to Neuhierl & Weber (2019), more correlated to the expected path of monetary policy rather than risk. Finally, we present all the empirical measures used in this paper for the international interest rate short-term structure slope derived from interest rates futures contracts, simply *slope* or *monetary policy slope*.

1.2.1 Currency Returns: Basic Definitions

We must first define the return of a currency: the log excess return of purchasing a foreign currency i in the forward market and then selling it in the spot market after one month, following Verdelhan *et al.* (2011) and Verdelhan *et al.* (2014), is:

$$rx^i_{t+1} = f^i_t - s^i_{t+1},$$

where s^i_t is the (log) spot exchange rate of country i against the US dollar, f^i_t denote the one month (log) forward rate. Currency is defined as one unit of foreign currency against one US dollar so that, an increase in s^i_t, means a depreciation of country i currency and an appreciation of the US dollar.

This excess return can also be stated as the log forward discount minus the change in the spot rate: $rx^i_{t+1} = f^i_t - s^i_t - \Delta s^i_{t+1}\cdot$ If we assume that covered interest rate parity (CIP) holds, then the interest rate differential between country i and the US can be measured by the forward discount: $r^i_t - r^{us}_t \approx f^i_t - s^i_t$. Here r^i and r^{us} are, respectively, the foreign nominal risk-free rate and domestic (US) nominal risk-free rate over the maturity of the contract.

$$rx^i_{t+1} = f^i_t - s^i_t - \Delta s^i_{t+1} \approx r^i_t - r^{us}_t - \Delta s^i_{t+1} \tag{1.1}$$

1.2.2 Currency Returns in a Complete Markets Setting

Under no-arbitrage conditions, there exists a stochastic discount factor, or pricing kernel (M_{t+1}), which prices any payoff P_{t+1} at time $t+1$ so that the price of any security at time t satisfies the basic asset pricing Euler equation[1.8]:

$$P_t = E_t[M_{t+1}\, P_{t+1}]$$

In particular, the price of a n-period zero coupon bond $P^{(n)}_t$ is given by:

$$P^{(n)}_t = E_t\Big[M_{t+1}\, P^{(n-1)}_{t+1}\Big]$$

The price of a one-period zero coupon bond is the risk free rate: $P^{(1)}_t = E_t[M_{t+1} \cdot 1] = exp(-r_t)$, since $R^f_t = 1/P^{(1)}_t$. We defined r_t as the (log) risk free-rate (R^f_t).

The stochastic discount factor embodies risk premium that is potentially time-varying. Several theoretical representative agent models in asset pricing take structural approaches to model this time variation in risk and, more specifically, time-varying exchange rate risk premium. One such example is Verdelhan (2010). We follow a reduced form approach as in Backus *et al.* (2001), Verdelhan *et al.* (2014) and Ang & Chen (2010) to incorporate multiple factors.

Suppose the stochastic discount factor takes the form below. We assume that the same pricing kernel functional form hold both for the home country, in our example the US and the US dollar, and for the foreign country i.

$$M^i_{t+1} = exp\Big(-r^i_t - 1/2(\lambda^i)^2_t - \lambda^i_t\, \epsilon^i_{t+1}\Big) \tag{1.2}$$

where λ^i_t is a time varying parameter that prices the shock to the short rate (ϵ^i_{t+1}). We assume that all shocks are $N(0,1)$. The price of risk λ is potentially driven by multiple factors and is related to time-varying risk premia.

The spot exchange rate S^i_t is expressed as the amount of foreign currency per one unit of the US dollar. An increase in S represents a depreciation of the foreign currency and an appreciation of the US Dollar. Consider an US

[1.8] More generally, the SDF is a positive random variable that satisfies this pricing relation for any return R on all traded assets, and whose existence is both necessary and sufficient for an economy that does not admit risk-less arbitrage opportunities. Additionally, if such an economy has complete markets for state-contingent claims, M is the unique solution to the above equation. Otherwise, there exist a large number of random variables M that satisfy the pricing relation for returns on all traded assets (Backus *et al.*, 2001) investor that is willing to invest one US dollar in any asset n, for which the return in US dollars is R^n_{t+1}. The fundamental asset pricing equation states that:

$$E_t[M^{us}_{t+1} R^n_{t+1}] = 1 \tag{1.3}$$

Alternatively, a foreign investor can convert his currency to US dollars at a rate $1/S^i_t$, invest in the same asset n and convert back the dollar amount to his home currency after one period for the spot exchange rate S^i_{t+1}, satisfying the Euler equation below:

$$E_t\Big[M^i_{t+1} \frac{S^i_{t+1}}{S^i_t} \cdot R^n_{t+1}\Big] = 1 \tag{1.4}$$

Under the assumption that the economy has complete markets for state-contingent claims, the stochastic discount factor is unique. For equations (1.3) and (1.4) to hold simultaneously, it must be the case that $M^{us}_{t+1} = S^i_{t+1}/S^i_t \cdot M^i_{t+1}$ (Backus *et al.*, 2001). Therefore, the exchange rate between the US Dollar and country i is the ratio of the stochastic discount factors:

$$\frac{M^{us}_{t+1}}{M^i_{t+1}} = \frac{S^i_{t+1}}{S^i_t}$$

Taking logs and denoting with lower case letter $log(M^i_t) = m^i_t$, substitute for the price kernel of the US and the foreign country i in equation (1.2):

$$\begin{aligned} \Delta s^i_{t+1} &= m^{us}_{t+1} - m^i_{t+1} \\ &= \Big(r^i_t - r^{us}_t\Big) + 1/2\Big[(\lambda^i)^2_t - (\lambda^{us})^2_t\Big] + \Big[\lambda^i_t \epsilon^i_{t+1} - \lambda^{us}_t \epsilon^{us}_{t+1}\Big] \end{aligned} \tag{1.5}$$

If we substitute in equation (1.1), currency i expected excess returns against the US dollar can be approximated, if the covered interest rate (CIP) parity holds and $E_t(\epsilon^{us}_{t+1}) = E_t(\epsilon^i_{t+1}) = 0$, by:

$$E_t\Big[rx^i_{t+1}\Big] = r^i_t - r^{us}_t - E_t \Delta s^i_{t+1} = 1/2\Big[(\lambda^{us})^2_t - (\lambda^i)^2_t\Big] \tag{1.6}$$

The exchange risk premium is defined as the expected currency return. The uncovered interest rate parity condition (UIP) assumes that the right hand side of equation (1.6) is zero. If the expected excess return is zero, then the expected change in the exchange rate is exactly equal to the interest rate differential between country i and the US. Investing in a foreign currency has a high expected excess return when the difference between the variance of us price kernel and the foreign price kernel is large. When domestic risk premium is large relative to foreign risk premium a US investor holding foreign assets must be compensated for this excessive risk, therefore, the US dollar (foreign currency) should appreciate (depreciate) in expectation, leading to higher returns in equation (1.6).

Any variable that affects the time varying price of risk in both countries is a potential candidate to forecast the expected exchange rate risk premium by equation (1.6). We now turn to models of the term structure of interest rates to shed some light into what information they potentially carry about λ and, therefore, the currency risk premium.

1.2.3 Currency Returns and the Term Structure of Interest Rates

In this section, we follow Ang & Chen (2010) and motivate under which conditions information contained in the yield curve of two different countries, like the short-term interest rate differentials (difference in levels) or differences in the term spread (slope), have explanatory power for currency expected risk premium.

We start with a simple one factor model for the price of the stochastic discount factor, in which the price of risk of a given country is as a function only of the short-term rate. In this simple model, it can be shown that the expected return of a currency is only a function of short-term interest rates differentials, the carry. Assume that the short rate in country i (and the US) follows the process given by equation (1.7) below:

$$r^i_{t+1} = \theta^i + \rho r^i_t + \sigma_r \epsilon^i_{t+1} \tag{1.7}$$

We consider, for simplicity, that the parameters ρ and σ_r are equal for all countries, while only the constant term θ^i and the zero mean and unit variance shock ϵ^i are country-specific. The price of a two-period zero coupon bond is:

$$\begin{aligned} P^{i,(2)}_t &= E_t\Big[M^i_{t+1}P^{i,(1)}_{t+1}\Big] \\ &= E_t\Big[M^i_{t+1}E_{t+1}[M_{t+2}]\Big] \\ &= E_t\Big[exp\Big(-r^i_t - 1/2(\lambda^i)^2_t\lambda^i_t\epsilon_{t+1} - r^i_{t+1}\Big)\Big] \end{aligned} \tag{1.8}$$

where we used the fact that $E_t[M^i_{t+2}] = 1/R^i_{t+1} = exp(-r^i_{t+1})$. We also assume log-normality of the SDF process. Under this assumption we can use the property that $P^{i,(2)}_t = E_t\Big[exp(Z_t)\Big] = exp\Big[E_t(Z_t) + 1/2Var_t(Z_t)\Big]$, where Z is simply the information inside the parenthesis in equation (1.8) above. We use (1.7) to substitute for the short-term interest rate process and take conditional expectations at time t ($E_t(r^i_{t+1})$) to get:

$$
\begin{aligned}
E_t(Z_t) &= E_t\Big[-r^i_t - 1/2(\lambda^i)^2_t\lambda^i_t\epsilon_{t+1} - r^i_{t+1}\Big] \\
&= -r^i_t - 1/2(\lambda^i)^2_t - \theta^i - \rho r^i_t \\
Var_t(Z_t) &= Var_t(-\lambda^i_t\epsilon_{t+1} - r^i_{t+1}) \\
&= (\lambda^i)^2_t + Var_t(r^i_{t+1}) + 2\lambda^i Cov_t(\epsilon_{t+1}, r^i_{t+1}) \\
&= (\lambda^i)^2_t + \sigma^2_r - 2\lambda^i\sigma_r
\end{aligned}
$$

Using the log-normality assumption and taking logs, we arrive at a the log-price of the 2-period zero coupon bond:

$$p^{i,(2)}_t = 1/2\sigma^2_r - \ (1+\rho)r^i_t - \theta^i - \lambda^i \cdot \sigma_r$$

By definition, the yield of n-period zero coupon bond is $Y^n_t = 1/(P^n_t)^n$. Taking logs, $y^n_t = \frac{1}{n}p^n_t$. Therefore, the yield of a two-period bond:

$$y^{i,(2)}_t = -\frac{1}{2}p^{(2)}_t = \underbrace{-1/4\sigma^2_r}_{\text{jensen's term}} + \underbrace{1/2\Big((1+\rho)r^i_t + \theta^i\Big)}_{\text{Expectation Hypotheses}} + \underbrace{1/2\lambda^i \cdot \sigma_r}_{\text{risk premium}} \tag{1.9}$$

The Expectation Hypothesis states that for the two-period bond $y^{(2)}_t = 1/2[r_t + E_t(r_{t+1})]$. The risk premium is captured by the term $\lambda^i \cdot \sigma_r$. Ignoring the Jensen's term, subtract the short-term rate r^i_t from both sides to get the term spread or the *slope* of the yield curve:

$$y^{i,(2)}_t - r^i_t = 1/2\Big((\rho-1)r^i_t + \theta^i\Big) + 1/2\lambda^i \cdot \sigma_r$$

A positive risk premium ($\lambda^i > 0$) is compatible with an upward sloping yield curve, all else equal. We have shown that both the level of longer term yields and longer term *slopes* carry information about the price of risk for country i for any particular time t, λ^i_t. In section 1.2.2 we also show that, in a complete markets setting, a currency return n against the US Dollar is proportional to the differences in relative variance of the SDFs. Given our hypothesis for SDF process in equation (1.2), this relative variance difference is just the difference in the relative prices of risk (see equation (1.6)). Any variable that contains λ^i_t information is a candidate to forecast currency returns.

For some specific models and conditions, the short-term rate differential (carry) is the only relevant part of the term structure of interest rates to forecast currency returns. One such example is the following simple model similar to Backus *et al.* (2001). Assume that the price of risk in each country is driven by a global factor z_t and by the local short interest rate multiplied by a constant, common to all countries, λ:

$$(\lambda_t^i)^2 = z_t - \lambda r_t^i$$

In this setting, domestic yields reflect both a global common component and a local price of risk that is proportional to the short-term interest rate. The foreign exchange risk premium is than given by a linear difference in short rates, the usual carry-trade predictor. By substituting in equation (1.6) we get that:

$$E_t\Big[rx_{t+1}^i\Big] = 1/2\Big[(\lambda_t^{us})^2 - (\lambda_t^i)^2\Big] = 1/2\lambda\Big[r_t^i - r_t^{us}\Big] \tag{1.10}$$

Therefore, if this simple model holds, long-term bonds yields carry information about risk premium but they do not have any explanatory power for currency risk above and beyond the short rate level. The currency risk premium is a function of the carry: countries with higher interest rate differentials relative to the US have higher currency expected returns. Several papers explore this to construct portfolios of currencies sorted on interest rates differentials, the carry-trade currency strategy (see Verdelhan *et al.* (2007) and Menkhoff *et al.* (2017)).

Now let us consider a more detailed model for the term structure. We follow Ang & Chen (2010) and assume that the price of risk is itself a latent process:

$$\lambda_{t+1}^i = \lambda_0 + \delta\lambda_t^i + \sigma_\lambda + u_{t+1}^i \tag{1.11}$$

Let us take a Taylor expansion of the price of risk λ quadratic term and evaluate it around the unconditional expectation, $E(\lambda_t^i)$:

$$(\lambda_t^i)^2 \approx \Big(E(\lambda_t^i)]\Big)^2 + 2E(\lambda_t^i)\cdot\Big[\lambda_t^i - E(\lambda_t^i)\Big]$$

Taking unconditional expectations of the equation (1.11) above we get that $E(\lambda_t^i) = (1-\delta)^{-1}\lambda_0$. Therefore, $(\lambda_t^i)^2 \approx \text{constant} + \frac{2\lambda_0}{1-\delta}\cdot\lambda_t^i$. Substituting this first order approximation into equation (1.6) for the expected currency returns we arrive at:

$$E_t\Big[rx_{t+1}^i\Big] = \frac{1-\delta}{\lambda_0}\cdot\Big(\lambda_t^{us} - \lambda_t^i\Big)$$

From equation (1.9), ignoring quadratic terms, subtract the short rate from both sides to get the relation between term-spreads or the slope of the yield curve $(y_t^{i,2} - r_t^i)$ and λ:

$$y_t^{i,(2)} - r_t^i = 1/2\Big((\rho-1)r_t^i + \theta\Big) + 1/2\lambda^i\cdot\sigma_r$$

Since interest rate processes have typically a high auto-correlation ($\rho \approx 1$), the equation above can be simplified to, isolating the λ term[1.9]:

$$\lambda_t^i \approx \frac{2 \cdot (y_t^{i,(2)} - r_t^i)}{\sigma_r}$$

Substitute again into the currency risk premium equation to get:

$$E_t\Big[rx_{t+1}^i\Big] = 2\frac{1-\delta}{\lambda_0 \sigma_r} \cdot \Big[(y_t^{us,(2)} - r_t^{us}) - (y_t^{i,(2)} - r_t^i)\Big] \tag{1.12}$$

What is the economic interpretation of equation (1.12)? An increase in the US term structure slope ($\uparrow slope_t^{us} = y_t^{us,(2)} - r_t^{us}$)) is an increase in λ^{us}. From the stochastic discount factor equation (1.2), it follows that an increase in the US price of risk leads to a decrease in the US consumer SDF, that is, $\uparrow \lambda^{us} \implies \downarrow m_{t+1}^{us}$. Currency adjustments under our complete markets assumption are related to relative SDFs by the relation $\Delta s_{t+1}^i = m_{t+1}^{us} - m_{t+1}^i$. So a decrease in the US SDF ($\downarrow m_{t+1}^{us}$) leads to a decrease in s_{t+1}^i, an appreciation against the US dollar and, consequently, a positive currency return for that currency against the US dollar, given the short-term interest rate differential. Conversely, an increase in country i term-structure slope leads to a negative currency return against the US dollar.

Ang & Chen (2010) also show empirically that sorting currencies into a long-short portfolio that conditions on their slope of the long term yield curve leads to a portfolio with negative realized returns. That is exactly what one would expect given the above relation: a higher *slope* in country i relative to the US is consistent with negative expected currency returns for that country. Sorting countries into high-minus-low portfolios would lead to negative returns.

Our paper takes a different approach: we focus on changes in the short-term structure *slope* of interest rates futures contracts. According to Neuhierl & Weber (2019) they have a high correlation to the expected path of monetary policy in the US: they forecast future changes both in FOMC rate and and for a survey of professional forecasters. In the next section we define this short-term *slope*.

[1.9] Note that if we do not make this simplification, the currency risk premium would depend both on interest short-rate differentials, adjusted for the persistence of interest rates, and also on term structure slope. We take these two limiting cases, when only short rates matter as in equation (1.10), and only term spread matters, as in equation (1.12) to simplify the analysis

1.2.4 Interest Rates Futures and Monetary Policy

The term-structure of long-term yields, like the 10-year minus the 3-month bill term spread, carry information about the domestic stochastic discount factor. Relative shifts between two countries term-structures are, as we show in the previous section, natural candidates to forecast the exchange rate risk premium. However, long-term yields are not adequate to measure how shifts in the relative expected future path of monetary policy between two countries affect currency returns, precisely because they also carry information about the domestic price of risk.

So why not focus on short-term interest rates futures markets as shorter maturities could be more likely related to the future path of monetary policy? In a related paper, Neuhierl & Weber (2019) show that shifts in the short-end of the term structure of US interest rates futures are mainly driven by expectations about future monetary policy. Their US *slope* measure predict changes in FED fund's target interest rates in the future, predict revisions of professional forecasters for the US economy short-term rate and is also positively correlated to a linguistic analysis of speeches by FOMC board members[1.10]. This paper tests the relation between currency returns and the short end of the yield curve using, instead of bond prices and yields, the short-term interest rate futures contracts of 3- and 6-month horizons for G10 countries. Therefore, we argue, we are potentially capturing more information about future monetary policy decisions.

We present the idea using as an example the US federal funds futures contracts, but the intuition holds for other G10 contracts[1.11]. Let ff_t^1 denote the rate implied by one-month federal funds futures on date t and let us assume that on that given month there is a scheduled FOMC meeting. If d_1 is the day of the meeting and m_1 is the number of days of that particular month, the federal fund's future contract with maturity for that given month is a weighted

[1.10] They present a linguistic analysis of FED board members speeches, classifying each speech as hawkish or dovish using simple linguistic word count of predetermined phrases, sentences and terms associated with a more prudent or hawkish stance by the FED. They shown that their measure of short-term *slope* increases (decreases) with hawkish (dovish) speeches which suggest that the measure is capturing relative shifts in the expected future path or short-term rates by market participants

[1.11] The FED funds future CME contract is simply stated as 100 minus the simple average of the effective federal fund rate in a given month. Therefore, in months when there is a scheduled FOMC meeting, the contract contains information about the prior effective FED fund rate and also the new effective rate decided at that particular meeting. For other G10 countries, like EONIA futures for the Eurozone, we can have different pricing conventions, like exponential averages rather than simple daily averages. We focus, rather, on changes in futures contracts prices and are not interested in extracting the precise information about next monetary policy decision implicit in a given contract in a given date average of the prior Fed Fund target r_0 and the expected new target after the meeting r_1:

$$ff_t^1 = \frac{d_1}{m_1} r_0 + \frac{m_1 - d_1}{m_1} E_t(r_1) + \mu_t^1,$$

where μ_t^1 is a risk premium. Piazzesi & Swanson (2008) show that this risk premium varies only at business cycle frequencies. Neuhierl & Weber (2019) assume that $\mu_t^k = 0\ , \forall k$. Since we also focus on weekly changes, it is a reasonable assumption that the risk premium embedded in futures contracts is, at least approximately, constant between two given weeks. We make this assumption explicitly for the 1-month contract. The one week change in the one-month futures implied rate in months with FOMC meetings is:

$$\Delta ff_{t,t+1}^1 = \frac{m_1 - d_1}{m_1}\Big[E_{t+1}(r_1) - E_t(r_1)\Big]$$

We can write the one-week change in a three-month forward implied rates in months with FOMC meetings in the same way. We make one minor tilt and assume that for longer futures the risk component is not constant between weeks so $\Delta\mu_t^k \neq 0$, if $k > 1$:

$$\Delta ff_{t,t+1}^3 = \frac{d_3}{m_3} \cdot \Big[E_{t+1}(r_3^-) - E_t(r_3^-)\Big] + \frac{m_3 - d_3}{m_3}\Big[E_{t+1}(r_3) - E_t(r_3)\Big] + \Delta\mu_t^3$$

where r_3^- denotes the federal funds target prevailing right before the FOMC meeting in month $t+3$, which in most cases coincides with r_1. If $r_3^- = r_1$, then $E_{t+1}(r_3^-) - E_t(r_3^-) = E_{t+1}(r_1) - E_t(r_1)$ and we can substitute and write changes in 3-month forward as a function of 1-month forwards:

$$\begin{aligned}\Delta ff_{t,t+1}^3 &= \frac{d_3}{m_3}\frac{m_1}{(m_1 - d_1)} \cdot \Delta ff_{t,t+1}^1 + \frac{m_3 - d_3}{m_3}\Big[E_{t+1}(r_3) - E_t(r_3)\Big] + \Delta\mu_t^3 \\ \Delta ff_{t,t+1}^3 &= \beta \cdot \Delta ff_{t,t+1}^1 + \epsilon_{t,t+1}^3 \qquad (1.13)\end{aligned}$$

In equation (1.13), if we perform an OLS regression, we can recover the residual. We define $\epsilon_{t,t+1}^3$ as the *slope*, or *monetary slope*, recovered from interest rate futures contract changes, following Neuhierl & Weber (2019). Note that, if $\Delta\mu_t^3 \neq 0$, *monetary slope* contains information about changes in the expected future path of monetary policy and also changes in risk premium:

$$\epsilon_{t,t+1}^3 = \text{slope}_{t,t+1}^3 \approx \gamma \cdot \Big[E_{t+1}(r_3) - E_t(r_3)\Big] + \Delta\mu_t^3$$

In the next section we extend the previous framework to an international setting, and present alternative empirical specifications to estimate *slope* or *monetary slope*.

1.2.5
Measures of Term Structure of Interest Rates Futures slope

In this paper we use information embedded in interest rates futures contracts of G10 countries and the US to forecast currency returns. The main empirical question is as follows: do changes in relative term structure of interest rate futures contracts between a country i and the US, measured by short-term contracts of up to 6-months, forecast currency n returns against the dollar? Do they explain contemporaneous changes? Can we use the US and other country's term structure slope of interest rates futures to forecast returns of currency portfolios?

One simple way to measure country i *slope* is to use changes in k-month future interest contract rates minus changes in the 1-month future (the level), where $ff_t^{k,i}$ is the futures contract rate for country i of maturity k at time t, which is equal to assuming $\beta = 1$ in equation (1.13):

$$\text{slope}_t^{k,i} = \Delta[ff_t^{k,i} - ff_t^{1,i}] \tag{1.14}$$

The main concern with this measure is that, typically, changes in 1-month futures are correlated with changes in longer horizon futures, therefore, changes in slope would be correlated to the level of the term structure. Consider, as an example, a decrease in the 1-month future that coincides with a smaller decrease in k-month ahead futures. In this scenario, agents could be postponing and decreasing a previously fixed budget of short-term rate changes to the future, leading to lower expected rates tightening in the future. However, change in this simple slope in equation (1.14) would be positive. Practitioners usually refer to this situations as bear or bull steepening depending on the direction of the movement.

One way to address this concern is by using a first-stage OLS regression, controlling changes in k-month futures by 1-month future rates, as suggested by equation (1.13)[1.12]. To simplify notation we omit the $t-1, t$ term so that $\Delta[ff_{i,t}^k] = \Delta[ff_{n,(t-1\to t)}^k]$, that is, weekly changes in futures contracts implicit rates:

$$\Delta[ff_t^{k,i}] = \alpha^i + \beta^i \cdot \Delta[ff_t^{1,i}] + \epsilon_t^{k,i} \tag{1.15}$$

Our *slope* or *monetary slope* measure is defined as the residual in the above first stage regression. Through-out the paper we use *slope* or *monetary slope* as a short for the adjusted slope as defined in equation (1.15). Note that

[1.12] Alternatively, we could regress the simple slope measure defined in equation (1.14) on 1-month futures changes as in $\Delta[ff_{i,t}^k - ff_{i,t}^1] = \alpha^{*,n} + \beta^{*,n} \cdot \Delta[ff_t^{1,n}] + \epsilon_{i,t}^{*,k}$. The point estimate of β^* would be equal to $1 + \beta^n$. We prefer to estimate equation (1.14) because it measures directly the sensibility of longer futures changes to 1-month changes our adjusted slope for changes in k-maturity future interest contract is defined for each individual G10 country i as $\text{slope}_t^{k,i} = \epsilon_t^{k,i}$.

This definition follows Neuhierl & Weber (2019), extending their work into a cross-country environment. Differently from their setting, which is concerned with forecasting equity returns in the US, here not only the future path of the federal funds rates matters, but also the term structure of interest rates futures of all other countries. However, changes in longer-term futures contracts contain information about the path of future short-term rate changes, but may also capture risk premium in rates, as we have shown in equation (1.13). This key different aspect of our paper is discussed in more detail in the present value equations for currency returns in section 1.6.

We focus on short-run interest rate futures like a 3 or 6-month contracts. Formally for a 3-month contract:

$$\Delta ff_t^{3,i} = \alpha^i + \beta_1^i \cdot \Delta ff_t^{1,i} + \text{slope}_t^i \tag{1.16}$$

We consider several alternative versions of slope thorough the paper. For conciseness we report most results using 3-month futures implied rates, and present 6-month as robustness results for some specifications. As an additional robustness test we consider an extended version of *slope* for G10 countries other than the US that is orthogonal to all information used to construct the US *slope* measure, that is, we control in the first stage regression we also control for changes in US interest rate futures[1.13]:

$$\Delta ff_t^{3,i} = \alpha^i + \beta_1^i \cdot \Delta ff_t^{1.i} + \beta_2^n \cdot \Delta ff_t^{1,us} + \beta_3^n \cdot \Delta ff_t^{3,us} + \text{slope}_t^{n\perp us}$$

For in sample predictability results we focus on versions of *slope* estimated using all available sample information. One main concern with this measure is a look-ahead bias since we estimate a first stage regression for slope in equation (1.16). Therefore, we also construct recursive versions of *slope*. We use them to implement the currency strategies and portfolios that condition real time on *slope*. We discuss them in more detail on subsequent sections.

For the US, we construct futures from original monthly contracts, rolling each week recursively using simple linear interpolations[1.14]. For other G10

[1.13]We omit results using simple changes in slope as defined in equation (1.14) since they perform worse empirically. Results are available upon request

[1.14]By construction, FED funds futures contracts are quoted as the effective average FED funds rate in a given month. If our main concern was using futures to estimate monetary shocks around FOMC meetings, it would be necessary to adjust, as in Neuhierl & Weber (2018), for the day in which the FOMC meeting takes place in a given month. In our setting, we control for 1-month futures to isolate changes in longer maturity futures from changes in the level. We are not concerned about capturing precisely weekly changes in expected movements in FED funds in months with a meeting countries we use the automatic rolled futures contracts available from Reuters (Data Stream)[1.15].

Neuhierl & Weber (2019) end their sample in 2008 because of Quantitative Easing (QE) and the zero lower bound (ZLB) in the US. In our international setting, since several G10 countries did not experience near zero interest rates, we can expand the sample. However, we test our results in their sub-sample as a robustness check as well.

Table B.2 on the Appendix B reports results for regression (1.16), used to compute the full sample *slope* or *monetary slope* for all G10 countries. The point estimate for α^i (constant) is indistinguishable from zero for all countries. For the US, the point estimate for β^{us} is 0.63 and the R^2 reaches 0.44%, indicating that the US *slope* (the residual) explains roughly 56% of the variation in 3-month forward changes that is not captured by 1-month forward changes. These figures are slightly different from results obtained by Neuhierl & Weber (2019). While their sample ends in 2008, ours spans until 2017. For other G10 countries, the point estimate for β_1 range from 0.7 for Great Britain to 1.1 for Japan. In-sample R^2 are also high, ranging from 51.6% in Australia to 66% in Canada. These results point to a strong correlation between movements in 1-month and longer horizon futures, as previously noted, one of the main potential advantages of our measure. Results are very similar when estimating the same equations above using 6-month instead of 3-month interest rates futures contracts and we omit them for conciseness.

In Figure A.1 on the Appendix A, we plot *slope* (changes in 3-month orthogonal to changes in 1-month interest rates futures) for each individual country in our sample against a synthetic *slope* average of G10 countries (ex US). One visually striking feature for all countries is that periods with high volatility, when changes in the slope of the interest rate futures curve are frequent, are followed by periods with almost no activity in the term structure.

Also of interest if the cross-section correlation between *slope*. Table B.3 presents full-sample correlation between the *monetary slope* across G10 countries. Typically pair-wise correlations are below 0.5 suggesting that there is a high idiosyncratic component for weekly changes in interest rate futures of shorter horizons. One interesting exception is the 0.6 correlation between Australia and New Zealand *slope* and also the higher correlation between the G10 average and Australia and New Zealand.

The auto-correlation of *slope* measure using the 3-month interest rates futures range from 0.02 for the US, -0.08 for the Eurozone and 0.05 for

[1.15] Original monthly contracts for other G10 countries were available in Datastream for a smaller sub-sample than the data set used in the present paper. Therefore, we opted to use the automatic rolled contracts provided by Reuters

New Zealand (all not statistically significant). Therefore, issues of spurious predictability arising from persistent regressors is of minor concern in our paper. See for instance Stambaugh (1999)[1.16].

1.3 Data

We now describe the data sources for currency returns and interest rate futures.

1.3.1 Currency Weekly Returns

Define the log excess return of purchasing a foreign currency from country i in the forward market and then selling it in the spot market after one month is $rx^i_{t+1} = f^i_t - s^i_t - \Delta s^i_{t+1}$ (Verdelhan *et al.*, 2007, 2011).

To compute currency weekly excess returns we combine the forward one month discount with weekly (log) exchange rates changes, assuming that interest rates are earned linearly over the length of the one month forward contract (see Salehi *et al.* (2017)). All data are from Reuters Datastream[1.17]. We define currency i return against the US dollar between week t and $t+k$ as:

$$rx^i_{t \to t+k} = (f^i_t - s^i_t) \cdot \frac{k}{4} - \Delta s^i_{t+k} \tag{1.17}$$

To construct currency portfolios, we follow Verdelhan *et al.* (2011) and Verdelhan *et al.* (2007). In the international finance literature, the *Dollar portfolio* is typically defined as the return of going short the US dollar and long an equally weighted average of other currencies (denominated against the US dollar). It is also a risk factor considered in cross-sectional empirical work in currencies. In our G10 countries setting, we define it simply as the Long G10 portfolio: that is, we go long all available G10 currencies and short the US dollar. Throughout the paper we refer to this strategy both as the *Dollar* or the long G10 portfolio.

We construct the long G10 or *Dollar portfolio* (log) currency return by averaging out (equal weights) all available G10 (log) currency returns against

[1.16] We present in-sample regression bootstrapped standard errors in all model specifications presented in the paper to correct for potential generated regressor bias, since *slope* is a first stage residual. We do not perform block bootstrap since persistence of regressors does not seem to be an issue in our setting. As a robustness, we performed statistical inference for our in-sample regressions using corrected Newey-West standard errors. The results are roughly the same both quantitatively and qualitatively and are available upon request

[1.17] For longer horizon currency returns, like 1-year ahead, we used the appropriate currency forward discount rate to correctly approximate the interest rate differential for that time span the US dollar for that week:

$$rx^{\text{G10}}_{t\rightarrow t+k} = N^{-1} \cdot \sum_{i=1}^{N} \left[(f^i_t - s^i_t)\frac{k}{4} - \Delta s^i_{t+k} \right],$$

where the term $k/4$ is the simple linear interpolation term to correct the interest rate differential, obtained by the forward discount, on a monthly basis.

We also follow the usual definition for the carry-trade portfolio. We measure G10 countries interest rates differential for each time period and go long high interest rate countries and short low interest rate countries. As with the dollar in each bin, returns are averaged out with the same weights. Since we have few currency pairs, we sort all available currencies in two bins (when left with odd numbers we put more currencies in the high interest rate bin).

We collect spot currency exchange rates and future currency forward rates against the US Dollar for 1-, 3-, 6- and 12-month contracts from Reuters DataStream. The sample period starts in 1994 and spans until December 2017. G10 currency countries are typically defined as the Eurozone[1.18], Japan, Great Britain, Canada, Australia, New Zealand, Switzerland, Norway and Sweden. We construct weekly currency returns by using end-of-day data from Wednesday of week t to Wednesday of week $t+1$. The Wednesday convention is standard since it minimizes the number of missing observations. For currencies, we use as a convention the London time zone fixing in order to compare currency weekly returns using the same information set.

1.3.2
Interest Rate Futures

In this paper, we use interest rate futures for the United States and G10 countries. We collect data for the US, Eurozone, Japan, Great Britain, Canada, Australia, New Zealand and Switzerland. For interest rate futures contracts longer than one month, Sweden (SEK) and Norway (NOK) have severe data limitations in Datastream, so we drop theses countries and use a smaller G10 subset. We use end-of-day data of all futures with maturities of up to one year, when available. It is worth noting that all these futures contracts for G10 countries face limited counter-party risk due to daily marking to market and collateral requirements

For the United States, we use Federal funds futures data from Reuters Datastream. Federal fund futures started trading on the Chicago Board of Trade in October 1988. These contracts have a face value of USD 5,000,000.

[1.18]We use the Deutsche Mark before January 1999 introduction of the Euro, as is usual in the international finance literature

Prices are quoted as 100 minus the daily average effective federal funds rate as reported by the Federal Reserve Bank of New York. We construct one-month to one-year futures using original contracts with end-of-month maturities. We roll the contracts at the end of each month, so the 3-month forward ff_t^3 is a future that reflects, partly, the expectation of the prevailing effective fed funds rate 3-month ahead from t. For other G10 countries, data is also from Reuters DataStream. However, for G10 ex-US, we use the constructed series from Reuters that roll automatically the contracts forward after expiration.

Our interest rate futures sample period starts in 1994 and spans until December 2017. For the Fed Funds Futures data we could start the sample in 1990 but for other G10 countries the start date for futures contracts from Reuters database varies substantially: as an example, sample starts at 1994 for the Eurozone, 1991 for Switzerland and 1999 for Great Britain.

We construct weekly *slope* by using end-of-day data from Wednesday of week t to Wednesday of week $t+1$ following Neuhierl & Weber (2019). The Wednesday convention is standard since it minimizes the number of missing observations. Since we are using end-of-day information and also the currency London time-zone fixing, 1-month, 3-month and 6-month interest rates futures changes in the US and Canada on a Wednesday-Wednesday may contain information that was released after the closing of the FX London market. One obvious example are FOMC decisions in weeks with meetings, since they fall usually on Wednesdays in our sample. Bank of Canada monetary policy decisions would also fall into this category. In order to control for that and to be sure that we are using only available information up to time t when forming currency portfolios based on *slope* information, we consider changes for the US and Canada in forwards interest rates from Tuesday-to-Tuesday when constructing *slope*. For other G10 countries, we maintain the Wed-Wed convention[1.19].

1.3.3 Descriptive Statistics

We report descriptive statistics for variables like interest rate futures levels, weekly changes and *slope* or *monetary slope* by country. We also report descriptive statistics for individual currency and portfolio returns against the US dollar.

[1.19] Note that Neuhierl & Weber (2019) considers for the US the Wed-Wed convention when constructing *slope* for the US. Since they are interested in local US Equity market returns, in their setting they are not concerned, as usual in the FX literature, with time zone and fixings. Dropping Wednesday was the only robustness available since we are not using intraday information for both currency and interest rates futures contracts

We report in Table B.4 on the Appendix B, to be concise, only results for *slope* estimated using the first stage regression in equation (1.15) for the whole sample. Recursive slope estimates present very similar unconditional moments. Figures are in basis points, that is, 25 bps equals 0.25%. As expected, since the slope measure is constructed as a residual in a first stage regression, the average is zero for all countries in the sample. For the US the 10% and 90% percentiles *slope* reach is -4.1 and 4.9, respectively. This is roughly 20% of a typical federal funds target change of 25 bps: weekly *slope* large conditional shifts are of an order of magnitude of actual interest rate changes. When looking at changes in 1-month and 3-month interest rates futures ($\Delta ff^3_{i,t}$), the same pattern arises: average weekly changes are small, very close to zero.

In Table B.5 we present descriptive statistics for currency returns. All data are in percentage points and returns are annualized[1.20]. Average interest rate differential, as measured by forward discount ($f^i_t - s^i_t$), is reported in the first line of the table. As expected, Australia and New Zealand have the highest average interest rate differential against the US, 2.0 and 2.61, respectively. These are typical G10 high yielding currencies. Japan and Switzerland have the lowest, -2.65 and -1.89, usually referred as funding currencies. We also consider individual currency returns in our sample. Canada, Great Britain and Switzerland have unconditional Sharpe ratios close to zero. Typical low interest rate currencies like the Yen (Japan) experience negative currency returns: unconditional Sharpe ratio reach -0.23 on average for one-week ahead returns. As expected from previous papers that document Uncovered Interest Parity (UIP) failures in the context of the carry trade anomaly (Verdelhan *et al.*, 2007, 2011, 2014) these currencies express negative average returns and negative Sharpe ratios. High yielding currencies, on the other hand, like the AUD (Australia) or the NZD (New Zealand) have Sharpe ratios of 0.27 and 0.20, respectively for one-weej ahead unconditional returns.

Table B.6 presents descriptive statistics for two currency portfolios for different sub-samples, like FOMC weeks and Large slope weeks. The first is the long G10 short US dollar portfolio, or the *Dollar portfolio*. Unconditional Sharpe ratio reaches 0.15, while conditioning on weeks with large slope movements deliver a 0.21 Sharpe ratio[1.21]. The second usual currency strategy is the Carry Trade portfolio, that goes long countries with high interest rate differentials (in the cross-section) and shorts low interest rate differential countries

[1.20] Annualized returns consider 52 weeks-year to compute compounded returns

[1.21] Large *slope* Weeks sub-sample consider weeks where $|\text{slope difference}_{G10,t}| > \mu^{G10} + 0.5 \cdot \sigma^{G10}$, where slope difference$_{G10,t}$ is the difference between the average *slope* of G10 (ex US) and the US *slope*, μ^{G10} and σ^{G10} are unconditional mean and standard-deviations, here computed for the whole sample (against the US). It is a dollar neutral strategy. In our G10 sample this simple carry strategy delivers unconditional Sharpe ratio of 0.31. Conditioning on FOMC weeks increase Sharpe ratio to 0.39, while conditioning on large slope weeks decrease Sharpe to -0.14.

Our sample consists of G10 currencies countries only. As a further comparison, other papers with a more complete data set of countries, like Hassan & Mano (2019), present Sharpe ratios of 0.5 and 0.16 for the carry and the Dollar (long G10-short US Dollar) portfolios, respectively. A higher carry return in these other papers is expected since they include emerging economies that tend to exhibit higher interest rate differentials than G10 countries relative to the US.

1.4
Impact and Predictability with Individual Currencies

The return of going long a currency of country i against the US dollar today is a function of expected future interest rate differentials between country i and the US and also expected currency risk (relative to the US) in the future (Engel & West, 2005). Our *slope* or *monetary slope* measure extracted from term structure of short-term future interest rates markers captures both dimensions: it contains information regarding the whole expected future path of monetary policy (Neuhierl & Weber, 2019) but also carries, potentially, information about risk premia in a particular country. Even short-term maturities may contain inflation risk premium or other compensations for risk embedded in interest rate futures, as discussed in section 1.2.4[1.22].

Our main interest is both the impact of *slope* on currencies and the predictability of currency returns following those changes. By impact we refer to the correlation between current week returns and slope, that is, regressing $rx^i_{t-1\to t} = (f^n_{t-1} - s^n_{t-1}) \cdot 1/4 - \Delta s^i_t$ on current week slope. Data are from end of day on Wednesdays and interest rate differential is fixed one-week before-hand so all the impact is coming from currency movements.

Predictability refers to future currency returns following changes in *slope*. We focus on short-run predictability, of up to 4-week ahead returns (between t and $t+4$ weeks ahead). Predictability comes from currency future movements: given the definition of weekly currency returns in equation (1.17) at the end of time t a currency forward discounts (and by approximation) interest

[1.22]We elaborate more on this topic in 1.6 of the present paper. In that section we start from a standard present value representation for currency returns (Engel & West, 2005, 2016; Menkhoff *et al.*, 2017) and link it to interest rate futures and to our adjusted term structure measure differentials against the US is fixed[1.23].

To make our notation flexible to both impact and predictability we define currency i return as $rx^i_{t-j \to t+k}$, where $j = \{1, 0\}$ and $k \in [0, 4]$. When measuring impact $j = 1$ and $k = 0$ and when measuring forecastability $j = 0$ and k is the relevant weekly horizon we are interested. We consider first a panel-based based approach with all individual G10 currency returns against the US dollar. We then turn our attention in the next section to portfolio-based forecasting regressions, as usual in the international asset pricing literature, using a long G10-short US dollar portfolio.

1.4.1
Empirical Strategy: Panel Regressions

We estimate panel regressions using individual currency returns for the same G10 (ex US) countries. We run standard OLS regressions with country fixed effects in a panel with unbalanced country-week observations. We consider two alternative specifications for the impact and predictability of *slope* or *monetary slope* measure on currency returns. In the first specification, we use the slope difference between country i against the US a forecasting variable. Since currency returns are a theoretical function of expected future interest rates differential and relative currency risk, using slope difference is a straightforward baseline estimation:

$$rx^i_{t-j,t+k} = \phi_1 \cdot \text{slope difference}^i_t + \Omega \cdot \text{controls}^i_t + \mu^i + \epsilon^i_{t+k}, \qquad (1.18)$$

where slope $\text{difference}^i_t = \text{slope}^i_t - \text{slope}^{us}_t$, μ^i are country fixed-effects and X^i_t is a vector of controls known at time t that can potentially also vary at the country level[1.24].

In the second specification we use both the US *slope* and country i individual *slope* independently as forecasting regressors:

$$rx^i_{t-j,t+k} = \phi_1 \cdot \text{slope}^{US}_t + \phi_2 \cdot \text{slope}^i_t + \Omega \cdot \text{controls}^i_t + \mu^i + \epsilon^i_{t+k}, \qquad (1.19)$$

where slope^{US}_t and slope^i_t are, respectively, US and individual G10 (ex US) country i *slope* or *monetary slope* at time t.

[1.23]We adjust approximate monthly interest rate differentials to weekly averages using linear interpolation, we are testing the slope forecasting power on return as defined by $rx^i_{t \to t+k} = (f^i_t - s^i_t) \cdot k/4 - \Delta s^i_{t+k}$. It is clear that, conditional on information at time t, interest rates are fixed and interest rate futures changes have already been incorporated into interest rate differential extracted from forward discounts

[1.24]As previously noted we are using London time fixing to compute currency weekly Wed-to-Wed end of day returns. For the *slope* measures we consider both for the US and Canada, which are countries with time zone market closing information after London closing time, the Tue-to-Tue weekly *slope* changes to be sure that we are using only available information up to time t to forecast currency returns

We include as controls changes in the level of the term structure of interest rates futures contracts measured by changes in 1-month interest rate futures: $\Delta ff1_t^{US}$, which is the weekly change in US 1-month forward interest rate futures, and $\Delta ff1_t^{i}$, which is the change in country i 1-month forward interest future. Other controls include variables like lagged currency returns, the VIX (implied equity volatility measure by CBOE), the US and country i 10-year term spread (the spread between short-run interest rates and interest rate on Government 10-year bonds), the dividend yield for US equities using CRSP data and the level of the Fed funds target.

The main explanatory variables in these regressions, *slope*, are estimated regressors. To address concerns related to constructed variables bias we perform inference using boot-strapped standard errors, with a cluster structure in both time and cross-sectional dimensions[1.25]. Even though persistence of regressors is not a major concern in our setting due to low auto-correlation of *slope*, as discussed in section 1.2.5, we also performed inference using Newey-West corrected standard errors and results are robust to that specification.

Baseline in-sample results presented below consider full sample *slope* measures estimated using equation (1.16). In order to address potential look ahead biases, when presenting Portfolio results sorted on slope and out-of-sample statistics, we consider recursive *slope* estimates.

1.4.2 Main Results

Table B.7 on the Appendix B reports results that use as *slope* difference between country i and the US as the forecasting variable: we define the model that uses equation (1.18) throughout the paper as Model I. First focus on current week returns ($rx^i_{t-1\to t}$). Point estimates for slope difference are always positive (ϕ_1[slope difference^i] > 0): a higher *slope* difference against the US leads to a positive currency return in the current week. Point estimates survive the inclusion of all controls: lagged returns, 1-month futures changes and 10-year term spreads. In-sample weekly regression R^2 range from 1.2% to 1.8% (1.1% to 1.6% for adjusted R^2 measures).

What about forecastability? We present results in Table B.8 for one-week ahead forecasts using *slope* difference ($rx^i_{t\to t+1}$). We can see that that point estimates remain positive (ϕ_1[slope difference^i] > 0) and are roughly 45% of

[1.25] For each sample we estimate the predictive regression using the *slope* obtained in the first stage regression, repeating this process 1000 times to obtain standard errors of the forecasting variables coefficients. In each iteration, we compute standard errors using cluster-robust errors both in the time and cross-sectional dimensions to account both for within individual currency errors correlation and across time country specific error serial correlation the impact of *slope* on current week returns. They also survive the inclusion of all controls with almost unchanged coefficients. In-sample R^2 range from 0.2% to 0.6% depending on the number of control variables included. This is strong evidence of in-sample predictability, specially in the context of weekly currency returns (Rossi, 2013).

Table B.9 presents results for alternative sub-samples. Point estimates remain positive in all sub-samples. For current week returns the impact of *slope* difference range from 0.022 for the full sample to 0.028 for FOMC sub-sample weeks and 0.018 for no FOMC weeks with large *slope*. In terms of forecastability, coefficients for one-week ahead returns range from 55% of the same week impact coefficient for FOMC weeks, to 40% for No-FOMC with large slope weeks, which suggests a strong delayed effect robust to all sub-samples. In-sample R^2 for 1-week ahead returns range from 0.3% for the full sample to 1.1% in FOMC Weeks.

Point estimates are not only statistical but economically relevant: a slope difference coefficient of 0.1 for 1-week ahead returns mean that a decrease of one standard deviation of slope difference (considering all country-week observations) of 8.0 bps is equivalent to a 0.1% increase in weekly returns or 4.5% in annualized terms. That is a high number when compared with the unconditional average annual return of a Long-G10 portfolio of 2.2% (see Table B.6). *slope* difference 75th percentile is of 3.3 bps and the 25th percentile is -2.8, suggesting that on specific weeks *slope* relative changes can have substantial economic impact on currency returns.

These findings suggest that the initial impact of *slope* on current currency week returns is persistent. There is evidence of a strong delayed reaction of currency returns to *slope* or *monetary slope*: current and future individual currency returns are positive (negative) following a positive (negative) *slope* shock. This evidence suggests that 1-week and 4-week ahead predictability do not arise from reversals of initial currency movements. On the contrary, the constantly positive point estimates are compatible with persistence and a delayed response.

We can also see from Table B.9 that this delayed reaction is even more present in some sub-samples: when conditioning on weeks with large slope moves without scheduled FOMC meetings, 4-week ahead returns ($rx_{t \to t+4}$) remain significant, with point estimates that are of the same magnitude or even higher than the impact of slope on current week currency returns. On FOMC weeks this delayed effect is initially more pronounced: point estimates are 55% of the initial impact for 1-week ahead returns. However, it is less persistent, fading out after week one.

1.4.3
Robustness: Alternative Models and *slope* Specifications

In this section we explore the sensitivity of our empirical findings to different models and specification of interest rate futures contracts term structure *slope* measures.

We consider the alternative model in equation (1.19), that is, regressing currency returns on each individual *slope* measure of both the US and individual countries. As one can see from Table B.10, point estimates are consistent with previous results given our definition of slope difference (slope difference$_t^i$ = slope$_t^i$ − slope$_t^{us}$): the coefficient for the US *slope* is negative, while for the individual G10 country is positive under all specifications. The sum of both point estimates is larger than *slope difference* coefficient: for the full sample the combined coefficient adds up to 0.04, almost doubling from the slope difference$_t^i$ coefficient of 0.021 (see Table B.7).

Impact of the US *slope* measure on current week currency returns is negative and significant for almost all sub-sample, with exception of FOMC weeks. This evidence is compatible with US slope information becoming more important in weeks with No-FOMC decisions that, typically, convey less specific information and news about future US monetary policy by policy makers. Karnaukh (2020) shows that the interest rate futures market in the US typically anticipates well both what happens with rates at the meeting decision and with the dollar returns 2-day before the decision. That could be related to the absence of impact of US *slope* on currency returns on these weeks in our setting. Current week impact is also driven by information on other countries *slopes*, even during FOMC weeks: the G10 *slope* coefficient is positive and statistically significant. In-sample R^2 do not increase when considering both *slopes* individually. For current week impact both US and G10 individual *slope* survive the inclusion of all controls when considering the full available sample (see Table B.11), with in-sample R^2 increasing to 1.9% from 1.2%.

US *slope* looses significance for one-week ahead return forecastability in all sub-samples with the exception of FOMC weeks. Delayed currency reaction is more present for other G10 countries *slopes*: in all sub-samples the point estimate is significant suggesting that, at least in terms of statistical significance, it is information on other G10 countries that is driving the delayed reaction of currency returns. In-sample R^2 remain roughly the same and there is no predictability gain of allowing different coefficients for the US and other G10 countries. If we control for all other variables considered previously, the US *slope* becomes statistically significant for forecasting one-week ahead returns. That is true for the full sample (see Table B.12) where point estimate for the US *slope* reaches −0.014, significant at 10% level. For the large-slope week sub-samples the US *slope* coefficient is significant at 5% level (see Table B.14). The G10 individual country *slope* remain statistically significant even after controlling sequentially for variables like 1-month futures changes, past week returns, VIX and even longer maturity government bonds, like 10 Year term spreads, with point estimates almost unchanged from the no control regressions.

As an additional robustness exercise we present results in Table B.15 that use 6-month contracts interest futures to construct the *slope* or *monetary slope* measure. Formally we run the 1-st stage regressions to measure *slope* using 6-month instead of 3-month contracts as the dependent variable: $\Delta ff^6_{i,t} = \alpha^i + \beta^i \cdot \Delta ff^1_{i,t} + \text{slope}^6_{i,t}$. The current week Impact, and one-week ahead forecastability described above are all robust to specifying both US and individual country G10 *slope* with longer horizon futures contracts: *slope* remains statistically significant and economically relevant in all sub-samples.

We can also define in a multi currency setting the individual G10 country *slope* or *monetary slope* as the residual from a regressions that controls for local and also US short interest rates futures changes. Formally, the first stage regression to measure slope orthogonal to US by controlling not only by Δff^1_n, but also to the US 1-month and 3-month futures changes: $\Delta ff^3_{i,t} = \alpha^n + \beta^n_1 \cdot \Delta ff^1_{i,t} + \beta^n_2 \cdot \Delta ff^1_{us,t} + \beta^n_3 \cdot \Delta ff^3_{us,t} + +\text{slope}^3_{n\perp us,t}$. These results can be seen in Table B.16. In terms of impact on current week returns results are roughly in line, with both US and G10 individual *slope* statistically and economically significant. For one-week ahead return forecastability, in-sample results are no longer statistically significant for all sub-samples, since point estimates are a bit lower and standard deviations higher.

1.4.4
Long - Short Individual Country *slope* Portfolio

In this section we implement a currency strategy that explore results presented in the previous section. From panel regressions it follows that *slope* measured by slope difference^i point estimate is positive and extremely robust to different specifications. In the models where we add both US and individual G10 country *slope*, the point estimate for slope^i is positive while the slope^{us} is negative. We can, therefore, construct a dollar neutral strategy that relies on the simple intuition given by the point estimates coefficients: conditional on US *slope* shocks, a country with a positive (negative) idiosyncratic *slope* measure has on average a positive (negative) currency return 1-week to 4-weeks ahead. We exploit this information to to long-short currencies sorting on their *slope* or *monetary slope*.

This long-short portfolio is similar, in spirit, to implementing carry-trade strategies that sort countries conditional on cross-section information on current interest rate differential, the carry. Our sorting is, alternatively, based on cross-section information of a country *slope* relative to it's peers. For each week we sort G10 currencies based on their *slope* measure for that week into two bins. The high slope (slope^H) bin and the low slope bin (slope^L). We consider only weeks with at least four pairs of currency returns and slope observations (2 currencies on each bin). We then go long the high slope currencies (slope^H) and short the low slope currencies (slope^L) from week $t \to t+1$. We re-balance this portfolio weekly after computing recursively the *slope* measure.

Table B.17 presents results for implementing this strategy. Sharpe ratios are high independently of the sub-sample, reaching levels above and beyond other currency strategies like the (unconditional) carry-trade. The columns in the table are fixed yearly cut-offs for both the estimation of first stage *slope* regression and for the computation of out-of-sample Sharpe ratios of the conditional long-short *slope* strategy[1.26]. The column Average is the simple average of all yearly cut-off statistics. Sharpe ratios reach on average 0.40 for the full sample, 0.7 when considering only FOMC weeks, 0.52 on large *slope* weeks, and finally, when considering individual country *slopes* to compute the large cut-off criteria (instead of a synthetic G10 average), Sharpe reach 0.5. All Sharpe ratio figures are annualized and control for transaction-costs of re-balancing weekly the portfolio[1.27].

Figure A.3 on the Appendix A presents the Long-Short *slope* strategy total cumulative return in panel (a), as well as it's draw-down in panel (b). We present results for two training windows for *slope* computation in the 1-st stage regression (5 years and 10 years) in order to tackle potential look ahead bias concerns[1.28]. Total log-returns from this strategy reach 50% between 2000 and

[1.26]For each training sample (Ts) we estimate the model in equation (1.15) using data up to Ts, save for each country i the coefficients of the first stage regression α^n_{Ts} and β^n_{Ts} estimates up to $t = Ts$. We then use them to compute $\text{slope}^n_{\{Ts+1,\dots,T\}}$ and use this conditional *slope* measure to form portfolios of long-short country *slope* for each week until the end of our sample. We re-balance each week and calculate Sharpe ratios of this strategy from year Ts until 2017 (the end of our sample), adjusting for transaction costs of each re-balancing. This test is therefore implicitly controlling for both a potential instability in the first stage regression and also of the strategy conditional return and volatility

[1.27]Sub-samples are formally defined as: (i) all sample weeks, (ii) on FOMC Weeks only; (iii) on weeks with large G10 average slope ($\bar{\text{G10}}^a$): weeks with $|\text{slope}^{G10}_t| > \mu_T + 0.5 \cdot \sigma_T$, where slope^{G10} is a synthetic G10 *slope* average; (iv) in No-FOMC weeks with large G10 slope; (v) weeks with large individual country slopes in each bin (long and short): $|\text{slope}^n_t| > \mu^n_T + 0.5 \cdot \sigma^n_T$), that is we include all weeks when at least the *slope* in the long and short bins are higher than this threshold and (vi) no-FOMC weeks with large individual *slopes*

[1.28]For several training samples $T0 = \{2y, 5y, 10y\}$ we run the first stage slope model, 2017 (the end of our sample) in US dollars. These returns, since are derived from currency strategies, are already excess returns relative to the risk-free rate. Draw-downs reach at most 25%, specially in the beginning of the sample, and are lower for the 10-year sample training estimation.

In Figure A.4 we report Sharpe ratios (annualized) from implementing this strategy, adjusting for transaction costs, for several different training samples for 1-st stage *slope* computation. In the X-axis we fix the training sample and in the Y-axis report the respective Sharpe ratio for the remainder of the sample. The same information in a more detailed fashion can be seen in Table B.14. Implementing this strategy in all weeks using this recursive adjusted slope measure yields Sharpe ratios ranging from 0.32, if we fix 2000 as the start date, to 0.4 (2003 training sample) and numbers as high as 0.075 for 2008 cut off and beyond. It can also be seen both from the figure and the table that conditioning on specific weeks, like FOMC weeks, weeks with large average G10 slope moves and so on, can deliver even higher Sharpe ratios (net of transaction costs).

These Sharpe ratios are significantly higher than other usual currency strategies: in our sample gross Sharpe ratios (not accounting for transaction costs) reach 0.30 for the carry-trade and 0.15 the long G10-short US dollar portfolio (unconditional). Even other papers with a more complete data set of countries that also include Emerging Markets economies, like Hassan & Mano (2019), present gross Sharpe ratios of 0.5 and 0.16 for the carry and dollar trade portfolios, respectively.

Ang & Chen (2010) also construct a long-short currency portfolio sorting, instead of on the short-term *slope*, on countries term-spreads measured by 10 year bond yields minus 1-year or 3-month bill yields. They find full sample annualized Sharpe ratios close to 0.6, using monthly currency returns and not adjusting for transaction costs, in the sub-sample of G10 countries. Our results complement their findings in two ways: (i) we are sorting using short-term interest rates futures in a way that higher *slope* leads consistently to higher currency returns. That can be the case only if conditional *slope* is capturing more information of future expected monetary policy. Ang & Chen (2010) sort currencies going long the low long-term slope bin and achieve positive Sharpe ratios. Therefore, their metric, must be capturing more information about future relative risk premium. We will revisit this more formally in section 1.6 of the paper; (ii) they are more robust in the sense that we are computing

save coefficients and use them to compute *slope* measures from $(T0 : T)$. We then apply the strategy conditioning on each slope country-week measure obtained using this recursive method

Sharpe ratios for several yearly windows to test the stability both of the first-stage *slope* estimate regression and of the strategy. [1.29].

The profitability of this Long-Short *slope* currency strategy across different training samples is another evidence of the strong predictive power of changes in relative short-term structure of interest rates futures contracts for individual currency returns. This currency strategy profitability can not be spanned by traditional currency risk factors like the dollar factor and the carry trade factor (Verdelhan *et al.*, 2011). We perform formal tests in section 1.4.5 to recover the Alpha of all our new currency strategies that condition on slope information.

1.4.5
Loadings on Currency Risk Factors

Can the Long-Short short-term *slope* currency strategy in the previous section be spanned by usual currency risk factors? Verdelhan *et al.* (2011) have identified a common risk factor structure in currency returns. Two factors or mimicking currency portfolio returns, the carry trade portfolio and Dollar portfolio, account for most of the cross-sectional variation in average currency excess returns. High interest rate currencies load more on these risk factors than low interest rate currencies and, therefore, this factor structure help explain the carry trade and the associated failure of uncovered interest parity.

We implement a time-series regression of returns of the long-short *slope* portfolio on the returns of these mimicking portfolios to test if this novel portfolio deliver a significant alpha relative to these risk factors[1.30]. The currency portfolio return factors based on Verdelhan *et al.* (2011) are available on a monthly basis. Our empirical results focus on weekly currency returns. In order to test the spanning, we must combine both data-sets by summing up our weekly currency returns in a given month. Naturally, this may lead to significant measurement errors.

[1.29]Transaction costs for trading highly liquid G10 currencies have reduced dramatically over the last 15 years. However, to tackle potential transaction costs we rely on estimates from Karnaukh (2020): from 1994-2002 average cost of buying/selling the dollar against a basket of the most liquid G10 currencies ranged from 5-10 bps. With improvements in FX liquidity these costs decreased to a range of 1-3 bps in early 2000. We consider an average of 7.5 bps before 2000 and 2 bps after when adjusting annualized Sharpe ratios. We use this estimates both in the Long-Short *slope* Currency Portfolio and in the dollar conditioning on *slope* portfolio presented in the next section. We acknowledge the fact that transactions costs maybe higher when implementing less liquid currency pairs. These figures are higher than our own measure of transaction costs that use bid-ask spreads of individual currency pairs. We opted to use them instead to have an upper bound o Sharpe ratios net of transaction costs, since average bid-ask spreads on a daily frequency could be biased downward

[1.30]See Verdelhan *et al.* (2011). Authors make available data up to 2018 for these currency portfolios on their website on a monthly basis

Table B.15 reports results for both risk factors. We consider portfolio returns based on three different *slope* rolling recursive computations: 2-,5- and 10-year training samples (for both the first-stage regression and Sharpe computation, as previously describe). As we can see from the table, when considering currency risk factors from Verdelhan *et al.* (2011), the estimated alphas for the Long-Short individual country *slope* strategy are all positive and statistically significant delivering annualized alphas of around 5%. The strategy that conditions on cross-section *slope* information to sort countries does not seem to have any exposure to the the carry-trade factor or the dollar factor, since neither coefficient is significant. Also in-sample R^2 are very low, suggesting low correlation.

Alternatively, we construct the same mimicking portfolio but restricted to our sample of G10 currencies. We use the unconditional returns of our G10 sample analogues for Dollar and carry portfolios. The advantage with this approach is that we compare precisely the same horizon returns. The disadvantage is that our sample is restricted to G10 countries and can be less informative of the actual price of risk for each mimicking portfolio, since Verdelhan *et al.* (2011) risk factors encompass a sample of over 80 countries, including emerging markets. Results are roughly the same: alphas are always statistically significant and range from 4.0% to 5.0% on annualized terms (note that these α_s are computed on weekly returns). Loadings on carry and Dollar risk factors are also not significant. In-sample R^2 are higher that in the previous exercise with monthly risk factors, but reach at most 5.0%, suggesting that a significant portion of the time series variation in long-short *slope* portfolio returns is not spanned by these factors.

These results suggest that our novel currency strategy that use short-term *slope* information in the cross-section to sort countries in a given week is not spanned by traditional currency risk factors, like carry or Dollar portfolios.

1.5
Impact and Predictability with Dollar Portfolio

1.5.1
Empirical Strategy

In this section, we test the impact and predictability of changes in short-term structure of interest rates futures contracts slopes, *monetary slope* or simply *slope*, on a currency portfolio that goes long all G10 currencies against the US dollar: we call this portfolio long-G10 (short US Dollar) or, as is usually referred in the literature, the Dollar portfolio. The (log) currency return is the equally weighted average of all available G10 (log) currency returns against the US dollar in a given week:

$$rx^{\text{G10}}_{t\to t+k} = N^{-1} \cdot \sum_{i=1}^{N} \left[rx^{i}_{t\to t+k} \right],$$

where the term rx^i is the log-return of going long currency n against the US Dollar.

We must also define how to measure a proxy of G10 *slope* in a portfolio context. We consider two alternative specifications: (i) the first is the simple cross-sectional average of the individual country *slope* estimated using equation (1.16); (ii) the second first compute cross-section averages of G10 k-month interest rate forwards changes $(N^{-1} \cdot \sum_i^N [\Delta f f_i^k])$ before running the first-stage regression to compute *slope*. Here we focus on the case where we average the slope estimates that result from separate country-level regressions, but our findings are robust to either specification.

We also consider two alternative specifications for the impact (current) and predictability (future) of short-term structure *slope* on the Dollar portfolio returns, as in the panel regression case. In the first specification, we use the slope difference as a forecasting variable. In the second specification, we use both the US *slope* and the *synthetic* G10 (ex US) separately as explanatory variables.

Similar to equation (1.18), the first model (Model I) considers the difference:

$$rx^{G10}_{t-j,t+k} = \phi_1 \cdot \text{slope difference}^{G10}_t + \Omega \cdot \text{controls}_t + \epsilon_{t+k}, \tag{1.20}$$

where rx^{G10}_{t+k} is the *Dollar portfolio* (long G10 - short dollar) log-return between period $t-j$ and $t+k$, slope $\text{difference}^{G10}_t = \text{slope}^{G10}_t - \text{slope}^{us}_t$ is the *slope* difference. Model II is analogous to the panel specification in equation (1.19). As in our panel setting, the main explanatory variables in these regressions, *slope*, are estimated regressors and we perform in-sample inference using bootstrapped standard errors to tackle this potential constructed regressor bias[1.31].

1.5.2 Main Results

Table B.19 presents results for the baseline model that uses the *slope* difference – Model I, following equation (1.20). Point estimates for *slope*

[1.31] We also performed inference using Newey-West corrected standard errors and results are robust. Baseline results consider full sample slope estimation. In order to address potential look ahead biases, when presenting Portfolio results sorted on *slope*, we focus on recursive time-fixed slope estimates difference are always positive, suggesting that higher *slope* differential of the synthetic G10 average against the US leads to a positive return for the long-G10 portfolio, that is, a depreciation (appreciation) of the US dollar (average of G10 currencies) both in the current and up to 4-weeks ahead[1.32].

Let us consider first the impact of *slope* on current week Dollar portfolio returns ($rx^i_{t-1\to t}$). Coefficients are positive and highly significant for all sub-samples, except for FOMC meeting weeks. In-sample R^2 for current week impact range from 1.9% for the full sample, to 2.1% for No-FOMC weeks with large *slope* and 4.2% for FOMC weeks[1.33]. If we control for lagged returns, the VIX and the term-spread using long-maturity bonds yields results also remain unchanged (see Table B.20).

The *Slope difference* between a synthetic G10 and the US also forecasts the returns of the Dollar portfolio up to 4-weeks ahead in sample. Point estimates remain positive and are roughly 34% of the current week impact coefficient. However, results are not statistically significant in some sub-samples and in sample R^2 are lower than in the panel regressions.

1.5.3 Robustness Analysis

We present results for the alternative model that includes separately both slope measures (Model II) in Table B.22. Let us consider first the current week return case. Both *slope* measures are statistically significant and retain the same coefficient signal as in the panel specification. Forecastability results are worse in this specification: letting US *slope* and G10 *slope* load on future returns individually does not increase in-sample R^2, while point estimates loose significance in some sub-samples for one-week ahead returns. Contrary to the panel case, the delayed reaction is driven mainly by the US *slope* coefficiente, at least in statistical significance terms.

[1.32] As previously discussed, to compute currency returns we are using the London fixing. In order to assure that we are not using information unavailable to market participants from interest rates futures contracts, for both the US and Canada, which are in a timezone of GMT minus K hours, we consider Tuesday-Tuesday weekly changes of futures rates contracts to compute *slope*. For all other G10 countries and currency returns, we consider the Wednesday-Wednesday convention as in Neuhierl & Weber (2019). In the case of the tactical Dollar portfolio, this becomes even more important for the strategy sorting since we are using explicitly the US *slope*. For the long-short *slope* portfolio, since it as dollar neutral strategy, we sorted only using individual currency data

[1.33] We include two new sub-samples in Table B.17. First a pre-2008 sample, to control for the Quantitative Easing period in both the US and other Developed economies. Both point estimates and in-sample R^2 remain the same for current week and future returns. Second sample is a No-FOMC week with large *slope* movements that uses a smaller cutoff (1/4 of *slope* standard deviation). Results remain roughly unchanged. Considering only No-FOMC weeks without any cut-off leads to very weak predictability

We also define the synthetic G10 *slope* in other ways, similar to the panel regression section. First we consider a version that is completely orthogonal to information used to construct the US slope. This G10 synthetic orthogonal *slope* remains positive for all horizons, but looses statistical significance for over one-week returns. Alternatively, we define as the synthetic G10 proxy only the a simple average of measures for the Eurozone (EUR) and Great-Britain (GBP), markets that are the most liquid for G10 countries. The *slope* coefficients remain positive and become statistically significant at 10% for 1-week ahead and 5% for 4-week ahead horizons under this alternative specification. Point estimates also increase for the 4-week horizon, suggesting a stronger delayed reaction. We can also ignore the synthetic G10 average at all. This is equivalent to forecast the Dollar portfolio return using only information for the US *slope*. However, when US *slope* has an impact on currency returns in all sub-samples but has no statistical significant predictive power for Dollar portfolio returns is present only on FOMC weeks and we find no delayed reaction whatsoever.

In the next section we explore this predictability and delayed reaction to construct portfolios that trade the US dollar dynamically conditioning on both US and synthetic G10 *slope* information.

1.5.4
Tactical Long G10 - Short US Dollar Portfolio Using *slope*

We develop in this section a novel currency strategy that explores the delayed reaction of G10 currency returns to *slope*, using *slope* difference in the time-series to tactically go long or short the US Dollar portfolio. The sign of the conditional *slope* shock has information about average G10 currency returns 1-week ahead, since point estimate for *slope difference* is positive ($\phi_1 > 0$). Consider the following illustrative example. Form a portfolio long G10 currency returns with equal weights (the Dollar portfolio). Go long or short this portfolio from week $t \to t+1$ depending on the signal of slope difference in week t. A positive *slope* difference measure at time t forecasts a positive long G10 return 1-week ahead. Therefore we form the following portfolio p.

$$R^p_{t+1} = I\Big[\Delta\text{slope difference}^{G10}_t > 0\Big]\cdot rx^{G10}_{t+1} - \Big(1 - I[\Delta\text{slope difference}^{G10}_t > 0]\Big)\cdot rx^{G10}_{t+1} \tag{1.21}$$

where $I[\Delta\text{slope difference}^{G10}_t > 0]$ is a indicator variable that is one when *slope* difference is positive: if slope difference is positive we go long G10 currencies and if it is negative we go short G10 currencies and long the US dollar. We define this portfolio as the Tactical Dollar portfolio (conditional on *slope*).

Full sample *slope* measures suffer from look ahead bias. To tackle this issue, we use out-of-sample slope estimates, just as in the long-short *slope* strategy, proceeding in two-steps. First we perform the first stage slope regression using several training samples ranging from 1998 to 2007. As an example, for the first training sample we estimate equation (1.16) from 1995-1998 and save $\hat{\alpha_{98}}$ and $\hat{\beta_{98}}$. We then compute *slope* forward from 1998 to the end of the sample using these fixed coefficients. [1.34].

Table B.1 in the section 1.1 shows that implementing this strategy has an average annualized Sharpe ratio of 0.4 for the full sample, even after controlling for approximate transaction costs[1.35]. Annualized Sharpe ratio reach, respectively, 0.6 and 0.9 when we implement the strategy only in weeks with large-slope and No-FOMC with large slope movements. On the other hand, FOMC weeks present a 0.3 Sharpe ratio. This is consistent with the evidence in Karnaukh (2020) and Salehi *et al.* (2017) that document a pre-FOMC meeting positive return drift for the Dollar Portfolio. Therefore, conditioning on meeting weeks is potentially less informative because of this pre-FOMC meeting drift.

We present annualized Sharpe ratios for the tactical Dollar portfolio in Table B.23, considering several starting sample cut-offs, while adjusting for transaction costs. In each line we present results for the respective yearly cut-offs for rolling *slope* estimates. In each column we present results for different sub-samples and model specifications we are using to decide either to go long or short the Dollar portfolio[1.36]. We focus the analysis on Model I that uses *slope* difference and has the best out-of-sample predictability. Annualized Sharpe ratios range from 0.35 in the 1998 cut-off to around 0.6 on the final sample cut-offs. Sharpe ratios start at 0.35 for the large-slope week sub-sample, hover around 0.5 and increase to 0.7 in the last years. Finally the highest Sharpe ratios attained by the tactical Dollar portfolio are on no-FOMC weeks with large *slope* movements: they start at 1.2, decrease to -0.8 the final cut-offs.

[1.34]For each training sample $T_k =$ we run the first stage slope model, save coefficients and use them to compute *slope* measure from $(T_k : T)$. We then apply the strategy conditioning on each slope country-week measure obtained using this recursively method

[1.35]Transaction costs for this simple G10 portfolio have reduced dramatically over the last 15 years. However, to tackle potential transaction costs we rely on estimates from Karnaukh (2020): from 1994-2002 average cost of buying/selling the dollar against the most liquid basket of G10 currencies ranged from 5-10 bps. With improvements in FX liquidity these costs decreased to a range of 1-3 bps in early 2000. We consider an average of 7.5 bps before 2000 and 2 bps after when adjusting annualized Sharpe ratios

[1.36]Briefly, Model I refers to equation (1.20), that uses *slope* difference. Model II refers to equation (1.19) in which we include separately as regressors the synthetic G10 and US *slope*. Model III considers only US *slope* as a conditioning variable. Models I and III cases are simple to condition down using equation (1.21): just use the *slope difference* or the US *slope* as the variables to go tactically either long or short the Dollar portfolio. Model II has two variables so we consider only weeks which the direction signaled by both *slopes* is the same. That is if $\text{slope}^{us} < 0$ AND $\text{slope}^{G10} >< 0$ we go long the G10 portfolio and short de US Dollar. We end up, therefore, with fewer weeks than the other two strategies

Figure A.5 presents the strategy total returns, that reach almost 80% both for the 5-year and 10-year cut-off training samples. There are two series in each panel: (i) the first uses Model I and *slope difference* to go either long or short the Dollar portfolio; (ii) the second one uses only US *slope* as conditioning variable. It is clear from the figure that using even a synthetic raw measure of other G10 countries *slope* to decide whether to go long or short the US dollar greatly improves returns across time. The cumulative return is, however, uneven: after 2010 the tactical-Dollar strategy performed poorly up to 2015, when it returned to a positive trend. It is also prone to periods of jumps followed by periods of stability or negative returns. This is even more clear for the 10-year training sample. Figure A.6 presents the strategy draw-downs. In the left-panel we present results for the 5-year training window. When conditioning on *slope difference*, that uses G10 synthetic *slope*, maximum drawn-down reach 15% in the beginning of the sample and almost 20% after 2010, the period when the strategy performed poorly. When conditioning only on US *slope* information the strategy never recovered from it's post 2010 maximum loss, another evidence of the relevance of the information contained in short-term *slope* of G10 interest rates contracts in terms of Dollar forecastability.

Table B.25 show that the returns of the tactical Dollar traded portfolio are not spanned by usual currency risk factors. They also present high and statistically significant alphas. We present results for two alternative measurements of mimicking portfolio returns for the carry trade and the dollar risk factors, as previously showed for the long-short slope portfolio. In panel (a) we use monthly data from Verdelhan *et al.* (2011) and in panel (b) we use our weekly return sample to construct returns for the risk factors. The tactical-dollar strategy conditional on *slope* has no exposure to either the carry factor or the Dollar factors. Annualized alphas range from 3.6% to 5% depending on the training-sample considered. In-sample R^2 are also low. Weekly alphas from G10 risk factors constructed from our data-set are also high and statistically significant, except for the 2-year training sample. They range from 2.6% (annualized weekly alphas) to 5.0%, a bit lower than for Verdelhan *et al.* (2011) data set of risk factors. In-sample R^2 are also low, suggesting there is still a lot of time series variation in the tactical-Dollar strategy not explained by time-variation in these risk factors or mimicking portfolios. Overall, the tactical Dollar portfolio returns seem not to be spanned by traditional currency risk factors like carry or unconditional Dollar portfolio returns.

The tactical Dollar portfolio high returns adjusted for risk and it's robustness to several different sample cut-offs is another evidence supporting the out-of-sample predictability of currency returns using *slope*. It also stresses the importance of considering, in a currency setting, other countries term structure of interest rates when considering the US dollar risk premium: even a synthetic average G10 *slope* increases profitability of this strategy when compared to using only the US *slope* as a conditioning variable to go long-short the Dollar portfolio.

1.5.5
Out-of-Sample Predictability

Our findings suggest that we can create strategies conditioning on *slope* information to tactically trade a long-short Dollar portfolio. These strategies have much larger profitability than the unconditional Sharpe ratio of 0.12. In this section we present out-of-sample R^2 statistics for 1-week ahead Dollar portfolio return forecasting equation using *slope*. This statistic is a complementary metric to reinforce the predictability of currency returns using conditional term structure slope of G10 interest rates futures. The Sharpe ratios from actually implementing these strategies on a real-time basis presented in the previous section are a more robust empirical evidence of *slope* out-of-sample predictability for the Dollar portfolio returns.

We must proceed in 2-steps to generate out-of-sample forecasts, since we are using a 1-st stage constructed regressor. First, we perform the first stage slope regression using several training samples ranging from 1998 to 2007. As an example, for the first 1998 sample cut-off, we estimate equation (1.16) from 1995-1998 and save $\hat{\alpha_{98}}$ and $\hat{\beta_{98}}$. We then calculate *slope* forward from 1999 to the end of the sample using these fixed coefficients. Finally, we compute in the second stage usual out-of-sample R^2 statistics as proposed, for instance, by Campbell & Thompson (2008b). We estimate the forecasting model using the *slope* measure computed above recursively, compute for each iteration the out-of-sample residual and calculate the out-of-sample (OOS) R^2. We compute for the training sample from $t = [1 : T_0]$ the following statistic:

$$R^2_{\mathrm{OOS}} = 1 - \frac{\sum_{s=T_0}^{T}\left(rx^{G10}_{s\to s+1} - \widehat{rx^{G10}_{s\to s+1}}\right)^2}{\sum_{t=T_0}^{T}\left(rx^{G10}_{s\to s+1} - \bar{rx}^{G10}_{s\to s+1}\right)^2}$$

which is the ratio of the sum of squared residuals from model-based forecasts (numerator) compared to the sum of squared residuals of using the simple conditional mean up to $t = T_0$ as the forecasting model. A positive number is compatible with a superior performance of the model relative to the unconditional mean benchmark. We use as the *benchmark* the conditional mean model, instead of the random walk hypothesis as usual in the currency forecastability literature (see Rossi (2013)), following the empirical finance predictability literature. Our results always beat the random-walk benchmark out-of-sample and are available upon request.

Table B.24 presents out-of-sample R^2 statistic for the full sample as well as for the large-slope week sub-sample. If we consider all available weeks statistic are usually negative. We focus on the large *slope* week sub-sample for which results are more robust. Out-of-sample R^2 statistic range from 0.1% to 0.3% for weekly returns when using model I to forecast US dollar against a basket of equally weighted G10 currencies. Model I (M1) refers to the dollar currency portfolio forecast model estimated with slope difference measure. Model II (M2) considers both the US and G10 (average) *slope* separately. This model has the worst out-of-sample performance. Model III (M3) uses only the US *slope* as the variables to go tactically long or short the Dollar portfolio. It presents an out-of-sample R^2 statistic that is usually smaller and sometimes negative. Finally, Model IV uses as a proxy for the G10 synthetic *slope* the simple average *slope* computed for only the Eurozone (EUR) and the United-Kingdom (GBP). In the first sample cut-offs out-of-sample R^2 are negative but, starting in year 2002, results are even better than when considering the synthetic G10 average *slope*.

We use the methodology proposed by Cochrane (2009) to evaluate the economic significance of out-of-sample return predictability. It can be shown that Sharpe ratios of a buy and hold investor S and an alternative investor that conditions of *slope* predictability are related by S^*:

$$S^* = \sqrt{\frac{S^2 + R^2_{\text{OOS}}}{1 - R^2_{\text{OOS}}}}$$

In our setting the unconditional annualized Sharpe ratio of going long in a basket of G10 currencies against the USD is 0.12. Since OOS statistic is positive only for the large-slope week sub-sample, let us consider the unconditional Sharpe ratio on only these weeks of 0.27 (see table (B.1)). The out-of-sample statistics above come from weekly predictive regressions, so numbers close to 0.3% are extremely high. Out-of-sample R^2 statistic range from 0.1% to 0.3% so the proposed method above would increase Sharpe ratio to 0.36 and 0.48, respectively, in annualized terms for this sub-sample. This is a 30% to 70% increase in Sharpe ratio and is, partly, related to the low weekly Sharpe ratio of the unconditional strategy[1.37].

[1.37] Just as a comparison, Neuhierl & Weber (2019) forecast weekly US equity returns using

Out-of-sample R^2 statistics for 1-week ahead Dollar portfolio return forecasting equation using *slope* is a complementary metric to reinforce the predictability of currency returns. The Sharpe ratios from actually implementing these strategies on a real-time basis are a more robust empirical evidence of *slope* out-of-sample predictability for the Dollar portfolio returns.

1.5.6 Long-Term Slope Measures

As previously noted, our paper is not the first to use relative information embedded in the term structure of interest rates of different countries, more specifically *slope*, to predict currency returns. Ang & Chen (2010) is one such example. They show that the term spread of long-term bond yields, or *slope*, have predictive power for one month-ahead and up to 12-month ahead currency returns. Sorting currencies into a long-short portfolio that conditions on the long-term slope of the yield bond curve leads to negative realized returns and Sharpe ratios in their paper: countries with a higher 10-year minus 3-month *slope* today tend to exhibit negative currency returns going forward.

Our paper focus on changes in the short-term *slope* of interest rates futures, in theory more related to the expected monetary policy path. Our empirical findings suggest the opposite: when focusing on short-term *slope*, a higher short-term *slope* or *monetary slope* for a given currency predict positive, not negative, future currency returns. It seems to be the case that, in a cross-section of G10 countries, relative changes in short-term *slope* are capturing more information about the relative expected path of future monetary policy rather than changes in risk premium.

For robustness, we also construct both the long-short *slope* and the tactical-Dollar currency portfolios using, instead of our measures derived from short-term interest rates futures contracts, the 10-year bond Yield minus a 3-month Bond Yield term spread or *slope*. Following Ang & Chen (2010) empirical results, a positive 10-year *slope* for country i leads to negative currency return against the US dollar over the medium term. We build this robustness portfolio going long the Low *slope* bin and go short the High *slope* bin. Results are presented in Figure A.7. We see that the long-short *slope* portfolio still delivers positive excess-returns over the sample horizon, albeit much smaller than the portfolio conditioning on our short-term *slope* measure.

US *slope* and find a weekly out-of-sample R-squared of 0.27%. Relative to the weekly Sharpe ratio of the US stock market of 0.073 (0.52 in annualized terms) an improvement in weekly Sharpe ratio to 0.09 is roughly a 23.3% increase. Therefore, out-of-sample predictability using international *slope* from short-term interest rates futures contracts for currencies are an order of magnitude higher, which is even more striking considering the difficulty in forecasting currency returns

For the tactical-Dollar, on the other hand, conditioning on long-term *slope* does not deliver any excess returns, quite the opposite.

Overall our short-term *slope* measure not only delivers better empirical results but also seems more related to the expected future relative path of monetary policy between G10 countries and the US. Also, even though US monetary policy is a major driver of currency returns, our results support that it is important to condition down on information regarding expected G10 future interest rates to improve predictability and excess returns of both currency strategies presented in this paper.

1.6 Linking *slope* and Currency Returns

We showed in previous sections evidence that currency returns are predicted by our short-term *slope* extracted from interest rates futures contracts of 3- and 6-month maturities. In a single country setting, like Neuhierl & Weber (2019), *slope* measure seems to be capturing mostly information about the expected path of monetary policy. Also, Piazzesi & Swanson (2008) show that risk premium extracted from bond prices tends to vary only at business cycle frequencies. However, in a cross-country setting it can bot be ruled out that even short-term slope differences are not capturing also relative shifts in risk premium across countries.

Our empirical findings suggest that a higher *monetary slope* for a given currency predict positive currency returns both in the current and subsequent weeks. This is suggestive evidence that relative changes in *slope* or *monetary slope* are capturing more information about changes in the expected future path of relative monetary policy between G10 countries, or the future cash flow component of the currency investment strategy. If it were the case that they were capturing mostly expected future changes in relative risk premium, a higher short-term *slope* should forecast lower currency realized returns because of an increase in the expected risk or discount factor component of the currency investment. In this section we formalize this argument using a simple present value relation for exchange rates.

1.6.1 Exchange Rates Present-Value Formulation

To motivate our discussion, we start from the standard present-value formulation of exchange rates as in Engel & West (2005) and Engel & West (2016). From the currency excess return definition in equation (1.1) at $t-1$, iterate forward and take conditional expectations at time t:

$$rx_t^i = [r_{t-1}^n - r_{t-1}^{US}] + \underbrace{\sum_{s=0}^{\infty} E_t\left[(i_{t+s}^n - i_{t+s}^{us})\right]}_{\text{future interest rate differential}} - \underbrace{\sum_{s=1}^{\infty} E_t\left[rx_{t+s}^i\right]}_{\text{FX risk premium}} + \underbrace{s_{t-1}^n - [s_{t\to\infty}^n]}_{\text{FX long run deviation}} , \tag{1.22}$$

where rx_t^i is currency n excess return against the US dollar, i_t^n and i_t^{us} are the nominal interest rate for country i and US, s^n is the (log) exchange rate for country i in terms of foreign currency per 1 US dollar, so a higher s_t means a depreciation).

We can decompose the expected currency return at t in three components: (1) the expected currency risk premium; (2) the expected path of interest rate differential between country i and the US and (3) potential long run equilibrium deviations of the exchange rate (Menkhoff *et al.*, 2017)[1.38]. We relate expected currency returns innovations to innovations in both the expected path of future interest rate differential and to the expected currency risk premium. Consider a simple expectation news version of equation (1.22), in the spirit of Campbell & Shiller (1988):

$$rx_t^i - E_{t-1}rx_t^i = (E_t - E_{t-1})\left[(i_t^n - i_t^{us}) + \sum_{s=1}^{\infty}\left(\underbrace{\left(i_{t+s}^n - i_{t+s}^{us}\right)}_{\text{rates differential}} - \underbrace{rx_{t+s}^i}_{\text{FX risk}}\right)\right]$$

So a higher (lower) unanticipated return today is a function of higher (lower) interest rate differential or lower (higher) FX risk premium. Ex-post currency returns can be decomposed in:

$$rx_t^i = E_t - E_{t-1}(i_t^n - i_t^{us}) + \mathbf{IDN}_t^{n,us} - \mathbf{CRN}_t^{n,us} + \epsilon_t^n, \tag{1.23}$$

where:

1. **IDN**: Innovations in expected future interest rate differential
2. **CRN**: Innovations in expected excess returns (currency risk premium)
3. **Expectational error** $\epsilon_t = E_{t-1}rx_t^i$

We can see both from equations (1.22) and (1.23) that currency returns today are a function of both expected future interest rate differentials and future currency risk. However, the expected impact of these variables is different: positive innovations in relative expected future interest rate differential, or IDN_t, lead to positive currency returns. Positive innovations in currency risk, measured by CRN_t, lead to negative currency returns today against the US dollar.

[1.38] Engel & West (2005) work with real exchange rates and real interest rates so they define the last term as long run deviation from PPP currency. In our setting all we need is that the stochastic process governing nominal currencies, and thus inflation, is long run stationary

In the context of our paper, can we say something about which effect dominates when using *slope* to predict currency returns? Is it relative currency risk premium, using the terminology in equation (1.23), **CRN** (Innovations in expected currency excess returns)? Or is it relative to **IDN**, or Innovations in expected future interest rate differential?

We present a preliminary take to link our empirical findings coefficients to the innovation version of the present value equation for currencies. We run regressions of the form:

$$rx^i_{t-1\to t} = \phi_0 + \phi_1 \cdot \text{slope difference}^i_t + \Omega \cdot \text{controls}^n_t + e^n_{t+k}$$

We consider the schematics below to help interpret the effect of an increase in *slope* difference between country i and the US on currency return, separating both the expected future rates differential and risk channel:

$$\uparrow \text{slope difference}^i_t \to \begin{cases} \uparrow \mathbf{IDN}^{n,us}_t \Rightarrow \quad \uparrow rx^i_t \\ \uparrow \text{risk}^i \quad \Rightarrow \uparrow \mathbf{CRN}^{n,us}_t \Rightarrow \quad \downarrow rx^i_t \end{cases}$$

In our setting ϕ_1 captures what effect dominates: interest rate differential news, or cash flow news in a currency setting, or relative risk news. If an increase in *slope* difference is capturing higher perceived interest rates differential for country i against the US in the future, this should lead to a positive current week currency return through a currency appreciation against the US dollar. Conversely, if it is capturing solely an increase in country i perceived risk, it should lead to an expected currency depreciation and hence negative currency return news today.

But what does equation (1.23) tells us about currency predictability?

$$rx^i_{t+1} = E_{t+1} - E_t(i^n_{t+1} - i^{us}_{t+1}) + \mathbf{IDN}^{n,us}_{t+1} - \mathbf{CRN}^{n,us}_{t+1} + \epsilon^n_{t+1},$$

If short-term *slope* is capturing, as we have seen, increased expected interest rate differentials, or relative carry, it should lead to positive currency returns on the same week. That is exactly the case of our empirical findings. In a single country setting, like Neuhierl & Weber (2019), *slope* measure seems to be capturing mostly information about the expected path of monetary policy. Complementary to their finding, we present supporting empirical evidence that this also holds in a cross-section of G10 countries, since relative changes in *slope* or *monetary slope* are capturing more information about expected future carry or expected relative shifts in the monetary policy stance between countries. Additionally this predictability is persistent: agents incorporate only gradually this information from future monetary policy shifts between G10 countries extracted from interest rates futures contracts into currency markets.

1.6.2 Does *slope* predicts Future Interest Rate Changes?

If the theoretical results derived in the previous section are correct, then *slope* measured from short-term interest rates futures contracts should also forecast future changes in interest rates for a given country. Also *slope difference* should forecast future interest rates differences between G10 countries and the US.

In order to test this empirically we run forecast regressions of future interest rates changes on current *slope*. Table B.26 presents results for the US. We run regressions of future rates changes using several different measures and 4,8,12 and 24-month ahead horizons. We compute future changes using interest rates on deposits, using future changes in 1-month implied rates from FED Funds futures contracts and also from future changes in the FED fund effective rate. For all specifications *slope* coefficient is positive, that is a higher short-term *slope* for the US predicts future higher rates. For future FED funds the point estimate is 0.66 for a 4-week horizon, similar to the magnitudes found in Neuhierl & Weber (2019). In-sample R^2 range from 2.1% to 10.8%, suggesting a high forecastability. A positive coefficient is also what one should expect if *slope* forecasting power for future currency returns is coming from information about future expected monetary policy shifts, rather than expected shifts in risk premium.

Another empirical test is to run regressions of future interest rate differentials between G10 countries and the US on current *slope difference* information. Table B.27 presents results from future interest rates differentials changes extracted from currency forward discounts. As in the case of the US regressions a positive future *slope difference* today forecast a higher interest rate difference between all G10 countries and the US up to 12-weeks ahead. For a 4-week horizon coefficients range from .58 for the EUR to .77 for the JPY. Point estimates are positive and significant for all horizons and all countries, thus corroborating our empirical findings that short-term *slope* predicts with a positive coefficient future currency returns. The channel trough which this forecastability emerges seems to be related to future shifts in the effective interest rate differentials. As agents form expectations about these future rates changes, even without perfect foresight as assumed in these exercises, currency future returns are predictable by current shifts in short-term *slope* or *monetary slope*.

1.7 Concluding Remarks

Currency returns today are a function of both expected future interest rate differentials and future currency risk. The term structure of G10 countries interest rates futures, on the other hand, contain information about both expected interest changes going forward and country risk. We construct an adjusted term structure *slope* for all G10 countries and use if to forecast currency returns. Increases in *slope* difference between country i and the US predict, in a panel regression setting, positive currency returns ahead. This pattern also arises when looking at currency portfolios: a synthetic G10 average *slope* difference measure also predicts a positive Long G10-short US dollar return ahead, anticipating a weak US dollar.

Contrary to the literature, we find strong evidence of short-run predictability both in and out-of-sample. This predictability is robust to several different *slope* specifications, the inclusion of other controls. Currency predictability by *slope* is not restricted to special moments like FOMC weeks, and weeks with no meetings but relevant price shifts are even more important.

This predictive power is relevant in economic terms: Sharpe ratios of currency strategies that use conditional *slope* information to build portfolios are above and beyond other currency strategies, like the Carry-trade and a long G10 (ex US) portfolio. We construct a currency portfolio that goes long-short currencies by conditioning on individual *slope* measures in the cross-section, delivering higher returns adjusted for risk in several time periods and subsamples. Also, using *slope* difference measures between the US and a synthetic G10 average *slope* to tactically trade the US dollar against a basket of G10 currencies significantly improves Sharpe ratios. These portfolio returns are not spanned by traditional currency returns risk factors like the *dollar* and the *carry-trade* factor, delivering statistically and economically significant alphas.

Finally, we document a strong a delayed reaction of currency returns to *slope*: the impact of a slope shock on a currency is of the same order of magnitude and direction both in current and future weeks, which can be interpreted by behavioral stories of under-reaction to news. That this under- and delayed-reaction arise in the interaction of G10 foreign exchange markets, the world's largest and most liquid financial market with a daily trading over 5 trillion US dollar, and G10 interest rate futures market, also a very liquid and active market, is an interesting phenomenon.

2
Beta Dispersion and Market Predictability

2.1
Introduction

Discount rates, risk premium or, equivalently, expected returns vary over time (Cochrane, 2011). Return predictability, or the absence of it, is one of the main research topics in empirical finance. Of particular interest is the predictability of the equity risk premium (ERP) or expected stock market returns. The challenges faced by the research on market predictability are not too dissimilar to the ones identified in the cross-sectional literature. There are hundreds of papers and factors that, potentially, explain the cross section of expected returns. Cochrane (2011), Harvey *et al.* (2016) and others refer to a zoo of factors. Similarly, a zoo of predictors has already been explored in the time series market predictability literature (Koijen & Nieuwerburgh, 2011): (i) financial ratios and valuation-based metrics, like the dividend-to-price ratio, the earnings-to-price ratio (Campbell & Shiller, 1988); (ii) interest rate term spread and credit risk spread measures (Ang & Beakaert, 2007); (iii) macroeconomic variables like the consumption-to-wealth ratio (Lettau & Ludvigson, 2001a) or investment and capital expenditure ratios (Cochrane, 1991). Alternatively, Polk *et al.* (2006) and Kelly & Pruitt (2013) take a different approach: these papers try to infer the conditional market risk premium by using cross-sectional information on individual stocks or portfolios valuation ratios, instead of aggregate variables.

In this paper we take yet another direction: we propose novel forecasting measures that solely use cross-sectional information on conditional CAPM betas to forecast aggregate market returns. This choice of predictors is based on simple theoretical arguments that moments of betas, in some settings, should be associated with expected future market returns. We find that these cross-section dispersion measures do indeed forecast market risk premium over multiple horizons, delivering high in-sample and out-of-sample predictive power: out-of-sample R^2 reaches up to 10% at the annual frequency (0.7% monthly). This out-of-sample predictability is economically relevant: an investor that uses cross-sectional beta dispersion to dynamically trade the market increases her annualized Sharpe ratio up to 38%, in comparison to unconditional buy-and-hold strategies. Additionally, these measures are only mildly correlated with other standard predictors of market returns, like those in Goyal & Welch (2008). Dispersion of betas appears to correlated with the US business cycle and NBER recessions: they tend to increase (decrease) when dividend-price ratios are low (high). These empirical findings provide additional evidence that betas dispersion across time is a function of time varying risk premium.

The standard approach in the predictability literature was to search for variables that were associated with macroeconomic conditions or stocks market valuations (price ratios), following present value equations that relate future returns and cash flows (Campbell & Shiller, 1988). We follow an alternative direction: we start with a simple theoretical argument that measures associated with moments of conditional CAPM betas are likely to be good candidates for conditional variables in the cross-section, in specific settings. We then test whether they are good predictors of future market returns. Hence, variables that jointly explain the variation in betas for individual stocks and portfolios are potential candidates for market predictors. We show that one of these simple variables is the time series of the cross-sectional dispersion in individual stocks and portfolio conditional betas.

The standard approach chooses a z_t based on economic arguments and tests whether it has forecasting power for future realized market returns, running regressions of the form $R_{m,t+k} = a + b \cdot z_t + \epsilon_{t+k}$. Some papers also test if z_t works as a conditioning variable in the cross-section of expected returns. In order to do so, one of the requirements is to explain the time variation in betas for a wide range of individual stocks or portfolios.

Our proposed alternative measures try to identify z_t from the empirical distribution of conditional CAPM betas. Schematically, we compute our measure of z_t using the variation over time of cross-sectional information on CAPM betas, that is, their empirical distribution g: $g_t(\{\beta_t^i\}) \implies z_t \implies E_t[R_{m,t+1}]$. But why should time varying CAPM betas contain information about future expected returns? We show in this paper that, if the conditional CAPM holds, than both equations below should also hold for a conditioning variable z. That is, there should be a common element affecting both betas and the risk premium:

$$\begin{aligned} E_t[R_{m,t+1}] &= \phi_0 + \phi_1 \cdot z_t \\ \beta_t^i &= \theta_0^i + \theta_1^i \cdot z_t \end{aligned}$$

We start from this strong assumption that the conditional CAPM model holds to show the potential theoretical link between time varying conditional betas cross-section moments and market returns. But we know from Lewellen & Nagel (2006) and others that conditional models typically do not work well. The empirical challenge for any such model is that there is not sufficient time series variation in betas to explain the differences in the cross-section of returns. The case we try to make in this paper is that even limited time series variability in the betas of individual stocks and portfolios may still be informative about the variation in equity market risk premium.

Among other empirical moments, we consider measures of cross-sectional dispersion of betas relative to their unconditional time-series mean $(\beta_t^i - \bar{\beta_t^i})$. We find that cross-sectional beta dispersion (CSBD) forecast market returns in-sample, both for one-month and one-year ahead horizons. In-sample R^2 are significant using a bootstrap procedure to tackle the bias due to persistent regressors. CSBD also forecasts market returns out-of-sample, delivering out-of-sample R^2 statistics that range between 5-10% for one-year ahead (0.4-0.7% for one-month ahead) returns. Additionally, the out-of-sample CSBD forecasting power is robust to several different training samples and tend to increase over time (see Figure C.2 on the Appendix C). These levels of predictability match other recent work, like Kelly & Pruitt (2013), with a much simpler empirical methodology.

CSBD works independently of measurement, as results are robust to alternative definitions of cross-section dispersion, like standard deviation, interquartile ranges and winsorized versions that control for potential outliers. CSBD is also robust to different rolling window estimation sizes: we consider time varying betas estimated from rolling CAPM regressions of 24, 36 and 48 months windows. Finally, we also find both in- and out-of-sample predictive power if we compute cross-section dispersion measures from Fama-French univariate portfolio sorts on 15 characteristics betas, instead of individual stock's betas.

Cross-section dispersion (CSBD) predictability is economically relevant: a investor that trades dynamically conditioning on CSBD can increase her annualized Sharpe ratio up to 38% relative to a buy and hold strategy. Additionally, these measures vary along the business cycle: they tend to increase before US recessions as indicated by NBER dating, when prices tend to be high relative to fundamentals, firms, agents and governments are leveraged, equity risk premium is low and future market returns tend to be negative. During NBER recessions, CSBD measures tend to fall sharply, exactly when prices are low relative to fundamentals, risk premia is high. That is, moments of future higher expected returns.

Our article has a clear relation to the literature on stock return predictability, probably one of the most studied topics in empirical asset pricing. As suggested by the present value relationship between prices, discount rates and future cash flows, several papers document that valuation ratios, like the dividend-to-price, book-to-market, earnings-to-price and others, are informative predictive variables (Campbell, 2018; Koijen & Nieuwerburgh, 2011). However, findings of return predictability face several empirical challenges. One is that, if returns are regressed on lagged persistent variables, such as the dividend-to-price ratio, the disturbances in the forecasting equation are correlated with the regressor's innovations. This creates an upward bias in OLS estimates of the forecasting coefficient, which is increasing in the persistence of the regressor (Stambaugh, 1999). This persistence is also a major concern in our setting, since we use to forecast market returns a constructed variable from rolling regression coefficients (CAPM betas). We try to tackle this issue in-sample with a bootstrap procedure. We simulate a distribution of in-sample R-squares generated with the same moments and first-order auto-correlations as the candidate CSBD regressor. We then check if the in-sample R^2 of our proposed regressor is higher than this boot-strapped simulated placebo regressor, under the null hypothesis of no-predictability[2.1].

The instability of the forecasting relationship is another major empirical challenge in the ERP predictability literature. Even variables that have in-sample explanatory power, like the dividend-to-price ratio, tend to fail out-of-sample, partly because of this time instability of parameters. Goyal & Welch (2008) document both the instability of in-sample regressor coefficients and the poor out-of-sample performance for several of these aggregate variables in the literature. In addition, even when out-of-sample predictability survives, it can be also extremely sample dependent: in other words, any out-of-sample statistic result can vary substantially as a function of the training and testing window cut-off. More recently Kelly & Pruitt (2013) update these tests and continue to find lack of out-of-sample predictability for several of these candidates. Our measures have robust out-of-sample predictability when considering the tests proposed in these papers, which are not subject to specific training and estimating sample cut-offs.

Our article is not the first to explore information in the *cross-section*

[2.1]To compute the bootstrapped simulated series we use first and second sample moments for each regressor (mean and variance) and also perform a full sample AR1 estimation model to compute the 1st order auto-correlation coefficient for our forecast candidate. We then compute in-sample R^2 for each of these simulated data and construct an empirical distribution of simulated R^2 with these 1000 bootstrap exercises. We present confidence intervals of 10, 5 and 1% levels. By construction this generated regressors are placebo regressors and should have no predictive power for market returns of individual stocks and portfolios to forecast expected market returns. Polk *et al.* (2006) use cross-sectional data of several financial and valuation ratios and fixed full-sample Betas estimation to construct a variable that captures the price of risk at each point in time. They then use it to forecast market returns in the time series. Another example is Kelly & Pruitt (2013), that propose and implement a new three step econometric estimator to recover a latent common variable from dividend-to-price and book-to-market data of individual stocks and portfolios. Their methodology predicts robustly aggregate market returns both in- and out-of-sample.

The contribution relative to this literature of our novel approach is three-fold in our view: (i) it is an alternative to models that use the cross-section of valuation ratios to infer the conditional market risk premium; (ii) because it is not a price or valuation based ratio it can also be applied to different asset classes in future work, like currencies, commodities or even housing, for which there is a higher controversy as to which could be a correct valuation metric. (iii) It is also a very simple metric with clear relation to the economic cycle, that does not rely on any statistical filtering or less intuitive methods like shrinkage or machine learning.

Another related literature explores time series variability and dispersion in betas across the business cycle. Frazzini & Pedersen (2014) relates the betas dispersion across time to funding liquidity constraints that arise with limited leverage by investors. They derive equilibrium relations in a dynamic economy for which funding liquidity conditions vary over time. This produces variation in the cross-sectional distribution of betas: an increase (decrease) in the mutual exposure of all firms to these funding shocks produces a more compressed (diffuse) distribution of betas. From this model, the dispersion of betas should be negatively related to aggregate measures of funding conditions, which tend to be pro-cyclical relative to the business cycle. In their paper the author's shown that there is a negative relation between the TED spread, a proxy of aggregate funding conditions, and the spread between market betas of the high- and low-betas sorted portfolios. These findings give rise to *betting-against beta* portfolio strategies (BAB), that buy high-beta stocks and sell low-beta stocks. In a related paper, Cederburg & O'Doherty (2016) show, however, that these BAB strategies hold only unconditionally: the conditional beta for the high-minus-low beta portfolio covaries negatively with the equity premium. As a result, the unconditional alpha is a downward-biased estimate of the true alpha.

2.2
Related Literature

This paper's main hypothesis is that we can use time variation in betas to say something about future market returns. We start from a strong assumption that the conditional CAPM model holds to show the theoretical link between time varying conditional CAPM betas moments and market returns. This section presents related literature that also justifies the use of beta dispersion as a forecasting variable.

We know from Lewellen & Nagel (2006) and others that conditional models typically do not work well, because there is simply not sufficient time series variation in betas to explain the differences in the cross-section of returns. Our paper is not about the cross-section of stock returns. The case we try to make is that, even limited time series variability in the betas of individual stocks and portfolios, has enough informative power to forecast the Equity Risk Premium.

There is an extensive theoretical and empirical work relating the dispersion in betas to the equity risk premium. In this section we explore some of these papers, linking their findings to our proposed measures, as an additional motivation to our empirical findings besides the conditional-CAPM relations derive in the previous sub-sections of the paper.

Different sets of investment opportunities along the economic cycle is one potential source for dispersion of firm-level log book-to-market ratios ($\sigma_t[BM_i]$). This cross-section and time variation in book-market (and other financial ratios) can also be related to time variation in betas dispersion. As documented in Cederburg & O'Doherty (2016), high book-to-market can be a summary indicator of firm exposure to systematic risk. One important theoretical link is the presence of frictions, such as costly adjustment to investments. Zhang (2005) develop a model in which high book-to-market firms can have higher exposure to systematic risk because they cannot easily scale back on operations in bad economic times. Alternatively, Carlson *et al.* (2004) show that high book-to-market may be related to high operating leverage and a higher exposure to negative economic shocks that curb access to external financing.

Firm leverage may also impact equity betas through several mechanisms. In a Modigliani-Miller setting, in the sense that the capital structure does not affect investment decisions of a firm, it can be shown that equity beta is increasing in leverage (Rubinstein, 1973). Making the capital structure an endogenous firm decision may also impact the observed relation between beta and leverage. George & Hwang (2010) develop a model in which firms with high systematic risk exposure may optimally choose lower leverage in the presence of distress costs. Other papers that consider joint financing and investment decisions also point to a positive beta-leverage relation. In Livdan *et al.* (2009) leverage reduces the flexibility of financially constrained firms to react to negative shocks. Alternatively, a negative relation between beta and leverage can arise if debt is used to finance investments that lower a firm ROE and it's average asset beta, as in Choi (2013). To the extent that firm leverage affects beta, the cross-sectional distribution of betas may be more disperse when $\sigma_t[\text{leverage}_i]$ is large. Aggregate and individual leverage correlate with the business cycles: there is ample empirical evidence that the balance of firms, families and government tend to deteriorate prior to recessions (Reinhart & Rogoff, 2009).

Several studies show that a stock's beta can be influenced by firm-specific shocks. Babenko *et al.* (2015) develop a model in which past idiosyncratic cash flow shocks affect a firm's current exposure to systematic risk. A firm cash flow can have different sub-components that are more exposed to firm-specific or to aggregate systematic risks. A positive (negative) idiosyncratic shock increases the importance of the idiosyncratic (systematic) component of firm value, leading to a decrease (increase) in firm beta. In those models beta dispersion can be negatively related to measures of aggregate volatility, given that larger firm-specific shocks have lesser impact on beta in times of high volatility.

Another related literature explores time series variability and dispersion in betas across the business cycle. Frazzini & Pedersen (2014) relates the betas dispersion across time to funding liquidity constraints that arise with limited leverage by investors. They derive equilibrium relations in a dynamic economy for which funding liquidity conditions vary over time. This produces variation in the cross-sectional distribution of betas: an increase (decrease) in the mutual exposure of all firms to these funding shocks produces a more compressed (diffuse) distribution of betas. From this model, the dispersion of betas should be negatively related to aggregate measures of funding conditions, which tend to be pro-cyclical relative to the business cycle. In their paper the author's shown that there is a negative relation between the TED spread, a proxy of aggregate funding conditions, and the spread between market betas of the high- and low-betas sorted portfolios. These findings give rise to *betting-against beta* portfolio strategies (BAB), that buy high-beta stocks and sell low-beta stocks. In a related paper, Cederburg & O'Doherty (2016) show, however, that these BAB strategies hold only unconditionally: the conditional beta for the high-minus-low beta portfolio covaries negatively with the equity premium.

As a result, the unconditional alpha is a downward-biased estimate of the true alpha.

There are, additionally, theoretical models under which the time variation and dispersion in betas are related to investor uncertainty about the state of the economy. One such example is Chague (2013): in this paper the dynamics of betas in times of high /low uncertainty about the state of the economy vary across assets, that is, in the cross-section. This pattern is related to the asset's cash flow structure and it's sensitivity to aggregate economic uncertainty. In an related paper Ribeiro & Veronesi (2002) present a rational expectations dynamic equilibrium model where the cross-sectional covariances and correlations of international market returns increase during bad times, as a consequence of an endogenous increase in the uncertainty about the state of global economy. In other words, time variation in aggregate uncertainty leads to time variation in cross-covariances and correlations. Even though this paper is built for an international setting, we can think of a limiting case where all covariances converge to the market beta ($\beta_i = \beta_m = 1 \forall i$): increases in aggregate economic uncertainty lead qualitatively to the same result as in Frazzini & Pedersen (2014), but with a different theoretical motivation.

2.3
Betas Dispersion and Return Predictability

Our empirical analysis starts from the cross-section distribution of conditional betas to forecast the equity risk premium (ERP). The previous section explored the likely link between our cross-section betas dispersion measures (CSBD) and the ERP. We present in this section the empirical approach of this paper: (i) the data and methodology used to construct the empirical CAPM betas; (ii) then we give an overview of in-sample predictability results using CSBD; (iii) we also present out-of-sample results and, (iv) finally, we discuss the economical interpretation and relevance of our findings.

2.3.1
Data and Empirical Approach

We construct a panel set of all individual firm level data using the CRSP U.S. Stock database. It contains end-of-month prices on primary listings for the NYSE, NYSE MKT, NASDAQ, and Arca exchanges, along with basic market indices. We compute individual monthly stock returns cum dividends starting in 1925. Additionally, we restrict our analysis to the S&P500[2.2] constituent

[2.2]The Standard and Poor's 500 is a index of the 500 largest US companies (by market capitalization). This list can change from month-to-month as market cap varies. For each month t we estimate for the constituent list the rolling betas for 24, 36 and 48-month stocks in order to avoid putting excessive weight on small stocks or other outliers.

For each month in our sample we select the constituent list for the S&P500. We estimate rolling CAPM betas using the market model in equation (2.1) below. We perform rolling regressions, as usual in the literature, by defining a sample size, fixing it and estimating rolling windows Betas. We perform 3 fixed month sample sizes estimation with $T = 24$, $T = 36$ and $T = 48$ months. For each iteration we discard one month and roll forward the sample:

$$R_{t+1}^{e,i} = \alpha_t^i + \beta_t^i \cdot R_{t+1}^{e,m} \tag{2.1}$$

We end up with a monthly panel data set of individual stocks rolling CAPM Betas, from 1925 up to 2018. Since the S&P500 index constituents change on a regular basis by the market cap, the panel is unbalanced, by construction. However we are not interested in specific firm's characteristics, rather we focus on cross-sectional moments. Thus, the fact that index membership is a function of a company's market cap leaves us with a sample that is "balanced" in the size dimension, in the sense that we measure the dispersion in a representative sample of the largest US companies, regardless of the time period.

We compute for each t cross-section betas dispersion measures (CSBD) for the conditional stock beta relative to it's unconditional mean: for each t in our sample we compute, for instance, for $t = T$, CSBD measures for $\tilde{\beta_{i,T}} = \beta_T^i - \overline{\beta_T^i}$, where $\overline{\beta_T^i} = T^{-1}\sum_{s=1}^{T}(\beta_s^i)$ is the time series average of conditional betas for stock i up to time $t = T$. Using the cross-sectional sample standard deviation as an example for CSBD, fixing $t = T$ and k stocks in the sample we get:

$$\sigma_T^{\beta} = \sqrt{\frac{\sum_{i=1}^{K}\left[\tilde{\beta}_{i,T} - \overline{\tilde{\beta}_T^i}\right]^2}{K}}$$

where $\overline{\tilde{\beta}_T^i}$ is the cross-section average of $\tilde{\beta}_T^i$ at time $t = T$.

We compute several dispersion measures for demeaned CAPM Betas ($\tilde{\beta}_T$): examples are interquartile ranges for 90-10%, 80-20% and 70-30% percentiles, log-dispersion and winsorized versions of dispersion to further control for potential outliers[2.3]. We also compute higher moments of $\tilde{\beta}_T$, like cross-

horizons. We estimate betas for all constituents but discard stocks that don't have at least 12 months of available information when constructing the time series of cross-section dispersion measures

[2.3] Winsorization is the transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers. We set all data above a specific percentile threshold to outliers to a specified percentile of the data; for example, a 90% winsorization would see all data below the 90th (10th) percentile set to the value of the 90th (10th) percentile sectional skewness and kurtosis.

We sample monthly market returns from the CRSP value-weighted index including dividends directly from CRSP. The index is an average of all common stocks trading on NYSE, Amex, or Nasdaq. We then subtract the risk-free rate to obtain excess returns ($R^{e,m}_{t+1}$). We use standard aggregate market predictors in the literature as controls in our in-sample regressions. We do this, first, to study the correlation of our CSDB measures to these variables and, second, to check whether CSDB has explanatory power above-and-beyond those predictors. Examples are the dividend-price ratio, book-to-market ratio and the consumption-to-wealth ratio. All data were obtained from author's websites on a monthly basis (see Goyal & Welch (2008) and Lettau & Ludvigson (2001b)).

We also test our CSBD measures using portfolio data to estimate betas, instead of individual stocks information from the S&P 500, as an additional robustness check. We use, as common in the empirical finance literature, Fama and French's portfolios data-set, available on the author's website. We perform the computation of monthly rolling CAPM betas for the fifteen available uni-variate portfolio sorts based on characteristics, namely: size, book-to-market, operating profitability, Investment, Earnings-price, cash-flow-price, dividend-yield, accruals, market betas, net share issuance, variance and residual variance and, finally, all sorts based on prior returns (momentum, short term and long term reversal). We end up with a panel data set of 150 portfolios rolling betas. We then compute all CSDB metrics discussed above for the cross-section of FF150 uni-variate portfolios betas. We end um with a sample shorter for this robustness analysis, starting in 1968, because there is no data prior to 1968 for several uni-variate sorts on characteristics.

We plot the time series of three of our CSBD measures in Figure C.1 on the Appendix C, namely the betas standard deviation in the cross-section, the 70-th interquartile range and the second method used for winsorizing the data[2.4]. We can see from visual inspection that unconditional averages are very close and that these measures are very correlated across both time and the business cycle. Table D.1 on the Appendix D presents descriptive statistics for our proposed CSDB in panel (a) ($\tilde{\beta_{i,}} = \beta_{i,t} - \overline{\beta^i}$). The standard-deviation averages 0.46 and range from 0.26 to 0.84, which is a high variation given that we are controlling for betas unconditional means.

Alternatively, we can compute, following Frazzini & Pedersen (2014), dispersion of betas around the market beta of one ($\beta^* = \beta^i_t - 1$). In their

[2.4] *sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark paper the author's show that funding shocks have further implications for the cross-section of asset returns. Specifically, a funding shock makes all security prices drop together, compressing betas toward one[2.5]. Table D.1 shows that this measure has higher dispersion, measured in the cross-section, than our proposed metric: the standard-deviation is 0.58 with interquartile ranges 0.3-0.4 higher. Skewness is also higher for this metric.

Table D.2 presents simple correlation (in-sample) for both our proposed measure and this alternative metric. As expected, correlations between alternative measures of CSBD are very high, ranging from 0.89 to 0.96. Correlation between these alternative metrics, albeit lower, range from 0.65 to 0.83, still a high figure. This suggests that, at least unconditionally, both dispersion measures have a strong correlation in-sample. We return to this topic in the robustness section 2.4, where we present strong evidence of the superior out-of-sample performance of our metric when forecasting market returns.

2.3.2 In-Sample Regressions

We test the predictability of CSBD measures for the equity risk premium for 1-month and 12-month ahead returns. We compute aggregate market cumulative log-returns over 1 month and 12 months horizons over the risk free rate ($r^m_{t+1,t+k}$) as follows:

$$r^m_{t+1,t+k} = \sum_{s=t+1}^{t+k} r^m_s$$

where r^m_s is the (log) excess-return for the market.

We perform linear forecast regressions using equation (2.2). X_t is a vector of observable variables at time t used to forecast realized market returns.

$$r^m_{t+1,t+k} = a + b \cdot X_t + \epsilon_{t+1} \tag{2.2}$$

Table D.3 on the Appendix D presents in-sample results for the rolling 24-month betas of individual S&P stocks for the whole sample. In each row it presents regression results for each of the betas cross-section dispersion measures (CSBD) considered. For example, the cross-section beta standard deviation has a in-sample R^2 of 0.4% (0.3% for the adjusted R^2) for 1-month ahead and 3.6% (3.5%) for 1-year ahead horizon forecasts. interquartile ranges and Winsorized versions of the beta cross-section standard deviation

[2.5] Proposition 4 of Frazzini & Pedersen (2014) show that when the conditional variance of the stochastic discount factor rises (falls) the conditional return betas of all securities are compressed toward one (become more dispersed) present typically higher in-sample R^2: for instance, the 70th interquartile range percentile presents 0.65% and 5.8% for the 1-month and 1-year ahead forecasts, respectively.

These figures compare well to other usual variables in the predictability zoo. In a recent paper Kelly & Pruitt (2013) document the performance of traditional forecasting variables between 1930 and 2010. in-sample R^2 for 1-year ahead returns (1-month) range from 0.49% (0.05%) for default yield spread, to 3.16% (0.18%) for the dividend-price ratio and 8.8% (0.7%) to the book-to-market ratio, among others. Their methodology, a 3-step statistical approach to forecast market returns, deliver an in-sample R^2 of 1.1% on a monthly basis and 13% on a yearly basis.

Findings of return predictability face several empirical challenges, as we have previously argued. One is that the correct inference of the coefficient of interest b in equation (2.2) is problematic, because financial ratios and other predictors considered in the literature are typically extremely persistent (Koijen & Nieuwerburgh, 2011). The persistence of regressors is a major concern in our setting, since we are using to forecast market returns a constructed variable from rolling regression coefficients. We tackle this issue in-sample in the following way. For each regressor (betas standard deviation, interquartile ranges etc), we compute a bootstrap simulation generating 1000 series with the same number of observations, moments (mean and variance) and 1st order auto-correlations as the candidate dispersion measure regressor[2.6]. We then present the in-sample R^2 empirical confidence intervals of 10, 5 and 1% levels.

Table D.3 reports this measure for all predictors in columns boot-strap R^2. For the cross-section betas standard deviation in-sample R^2 of 0.4% is higher than the 95th bootstrapped percentile, but smaller than the 99th of 0.65%: therefore, given the empirical moments and persistence of the cross-section standard deviation of betas, we can only reject the null of no in-sample predictability of returns at a 5% confidence level. For winsorized versions of the standard deviation (that control for outliers) we always reject the null on no in-sample predictability at 1%. For the 80th and 70th betas interquartile ranges the we can also reject the null hypothesis of no predictability at the

[2.6]To compute the bootstrapped simulated series we use first and second sample moments for each regressor and also perform a full sample AR1 estimation model to compute the 1st order auto-correlation coefficient for our forecast candidate. We then compute in-sample R^2 for each of these simulated data and construct an empirical distribution of simulated R^2 with these 1000 bootstrap exercises. Note that these simulated variables, by construction, should have no in-sample predictability for market returns. We present confidence intervals of 10, 5 and 1% levels. We could alternatively generate the distribution of the F-statistic and present a formal test of the regression. We could have presented the empirical distribution of the F-statistic instead of the R^2

1% confidence level. For one-year ahead forecasts in-sample R^2 are 3.6% for the standard deviation of betas, significant at 5%. Winsorized versions are all significant at the 1% level, as well as interquartile ranges.

We also perform multi-variate in-sample regressions combining standard deviations and interquartile ranges measures. Results are in Table D.4 for the 24-month rolling betas. For one-month ahead returns, in general, adding two dispersion measures increase only marginally the in-sample R^2 and worsen statistical significance in our bootstrap methodology. However, for one-year ahead returns results improve substantially: adding both the standard deviation and interquartile ranges increase R^2 to 6.46% and up to 8.5% for the winsorized versions of standard deviations of betas. Results are all significant at least at a 5% level considering our bootstrap procedure R^2.

Table D.5 presents results for the rolling 36-month betas univariate forecast regressions. Overall, results are similar. One exception is the standard deviation without winsorization, now significant only marginally at 10%. Winsorized versions and interquartile ranges remain significant at 1% level. For one-year ahead returns results are also similar, albeit the majority of in-sample R^2 remain significant at a 5% confidence level. For multivariate versions, using a 36-month rolling beta of individual stocks does not change overall results. Actually, for some model combinations, results even improve in-sample: as one can see from Table D.6, one such example is the combined standard deviation with the 80th percentile interquartile range, which increase R^2 to 1.10 versus 0.77, now significant at a 1% level. However, in-sample results are worse if we increase our estimation window to a 48-months, especially for 1-year ahead returns: R^2 are on average significant only marginally at 10% under our bootstrap procedure.

We now turn to the out-of-sample performance of our proposed estimates of cross-section betas dispersion (CSBD) and their ability to forecast market returns.

2.3.3 Out-of-Sample Regressions

Another empirical problem that is pervasive in the ERP predictability literature is that the forecasting relationship, the point estimate b in equation (2.2), exhibit significant instability over time (see Koijen & Nieuwerburgh (2011)). It is a common feature that forecasting variables, like the dividend-to-price ratio (dp), even when present in-sample explanatory power, typically fail out-of-sample. Goyal & Welch (2008) document the failure of several such candidates to forecast the market returns out-of-sample. Even when out-of-sample predictability survives, it can be extremely sample dependent. In other words, it can be extremely sensitive to the training and testing window cut-offs. More recently, Kelly & Pruitt (2013) update these out-of-sample tests for common regressors in the literature and continue to find lack of out-of-sample predictability for several of these candidates.

We follow closely Goyal & Welch (2008) and Kelly & Pruitt (2013). We present the out-of-sample R^2 comparing the performance of the proposed regressor(s) with the up to time t sample average as a benchmark. We compute the mean squared error of the vector of recursive rolling errors of the model and the conditional mean (MSE_A and MSE_N), respectively. Define the vectors e_A (e_N) recursively, considering a training sample w and the full sample T:

$$\begin{aligned} e_{A,s} &= r^m_{s+1,s+k} - \widehat{r^m}_{s+1,s+k} \\ \widehat{r^m}_{s+1,s+k} &= a_{[w:(s-1)]} + b_{[w:(s-1)]} \cdot X_{s-1} + \epsilon_s \\ e_A &= [e_{A,(w+1)}, ..., e_{A,(T)}] \end{aligned}$$

where $\widehat{r^m}_{s+1,s+k}$ is the market return forecast at time $t = s-1$ using information up to that moment, $a_{[w:(s-1)]}$ and $b_{[w:(s-1)]}$ are the conditional OLS point estimates using data from the start of the training sample up to time ($t = s-1$), as well. Note that e_A is just a vector that stack all information generated with this recursive method[2.7]. The out-of-sample (OOS) statistic computes:

$$\text{OOS } R^2 = 1 - \frac{MSE_A}{MSE_N}$$

where $MSE_{\{A,N\}} = \sum_{s=w+1}^{s=T}(e_{\{A,N\},s})^2$.

Table D.7 on the Appendix D presents results for the rolling 24-month betas CSBD measures. We fix the sample split date on 1985 for easiness of comparison between models. For one-year ahead returns out-of-sample R^2 range between 4.7% for the model with cross-sectional betas standard deviation, to 9.9% for the 70th interquartile-range and 9.98% for winsorized version of betas standard deviation. For the one-month ahead returns OOS-R^2 range between 0.35% for the model with cross-sectional betas standard deviation, to 0.72% for the 70th interquartile-range and 0.71% for winsorized version of betas standard deviation. Table D.7 also presents multivariate versions, by combining more than one dispersion measure. For 1-year ahead horizon OOS-R^2 statistics range from 4.9% to 11.06% (0.32% to 0.72% for 1-

[2.7]For each iteration we estimate the OLS model in equation (2.2) from the start of the training sample w up to time $s-1$ and compute the one-step ahead forecast error $e_{A,s}$ for the model and also for the conditional sample mean up to time s, $e_{N,s}$. We then roll the sample forward and compute recursively these errors to form botg vectors e_N and e_A

month ahead returns), fixing the sample split date on 1985. Finally, we present in Table D.8 results for the 36-month rolling betas moments. They remain robust to this alternative estimation window, albeit with lower out-of-sample R^2 statistics: for one-year ahead statistics range from 1.01% to 8.25% (-0.23% to 0.70% for one-month ahead returns).

These figures suggest a high out-of-sample predictability. As a comparison, Kelly & Pruitt (2013) 3-step estimator using valuation ratios of 25 and 100 double sort Fama-French portfolios on size and book-value present an out-of-sample R^2 of 3.5% and 13.1% for one-year ahead returns, respectively[2.8]. Other famous candidates from the zoo of predictors usually deliver negative out-of-sample R^2 figures for 1-month and 1-year horizon returns (see Goyal & Welch (2008)).

We also present two tests for statistical significance of out-of-sample R^2. The first is the ENC-T, the test proposed by Diebold & Mariano (2002). The second is the ENC-New encompassing test statistic by Clark & McCracken (2001):

$$\text{ENC-N} = \text{MSE}_F = (T - h + 1) \cdot \frac{MSE_N - MSE_A}{MSE_A}$$

where h is the degree of overlap ($h = 1$ for no overlap). It tests for equal MSE of the unconditional forecast (in our case the conditional mean *benchmark)* and the conditional forecast ($\Delta MSE = 0$). Overall, both the univariate and multivariate models deliver highly significant out-of-sample R^2 for these tests.

Test sample selection can significantly change empirical results and out-of-sample predictability. One usual approach in the literature is to compute the statistic for several training sample cut-offs. Figure C.2 presents results for the betas standard deviation and interquartile ranges for several different training samples, both 1-year and 1-month ahead forecasts. On the X-axis we have the different sample date cut-offs for the training sample and on the Y-axis the out-of-sample R^2 relative to that sample split. As expected, the statistic changes substantially depending on the training sample selected. However, it strikes out that overall out-of-sample R^2 remain high, even when out-of-sample predictability reduces, as in the case of a period between 1972 and 1982 sample splits. They also increase at the end of the sample splits.

Figure C.3 on the Appendix C presents results for the winsorized version of cross-section standard deviations[2.9]. It can be seen that out-of-sample

[2.8]Their methodology consists of a 3 step statistic filtering method that explores the cross-section information valuation ratios for these portfolios

[2.9]Winsorization is a statistical technique that "shrinks" the extreme measures of a distribution. The first three series simply replace all Betas higher in module than the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value, the 70,80 and 90th percentile range of the individual Stocks Betas, respectively. The other methodology (*sigma* predictability of betas CSBD (cross-section dispersion) holds roughly with the same explanatory power. In Figure C.4 we shown that multivariate versions, that use both betas cross section standard deviation and interquartile ranges as combined regressors, also deliver high out-of-sample explanatory power regardless of the training sample considered. Finally, Figure C.5 presents one-year ahead statistics for the 36-month beta estimation window, as a robustness check. We present these results in a more detailed manner in Tables D.9 to D.12, for some of the CSBD measures computed from 24-month window individual S&P stocks betas. Besides out-of-sample R^2 figures we present statistics for both tests of no predictability improvement above the conditional historical mean: both ENC-New and ENC-T. As expected out-of-sample R^2 stats are highly significant, regardless of the sample test period, and robust to different model specifications.

Our proposed cross-section dispersion measure of demeaned betas (CSBD) has a high explanatory power for future market returns both in and out-of-sample[2.10]. It is also robust to several rolling betas window definitions and model specifications. The next section discusses the economic relevance of these predictability results.

2.3.4
Economical Interpretation and Relevance

A simple calculation suggested by Cochrane (2009) show that the Sharpe ratio S^* earned by an active investor exploiting predictive information based on a regression R-squared and a simple buy and hold strategy (S_0) can be related by the following equation. We consider, as a *benchmark* for the unconditional Sharpe ratio of a buy-and-hold strategy the estimate in Campbell & Thompson (2008a): dating back to 1871 data on aggregate stock market returns for the US, they compute Sharpe ratios of 0.108 (monthly) or 0.37 in annualized terms, respectively.

$$s^* = \sqrt{\frac{S_0^2 + R^2}{1 - R^2}}$$

The lower bounds of the out-of-sample predictive out-of-sample R^2 are of 0.45% for one-month and 4.70% for one-year ahead, the case of CSBD standard deviation (see Table D.7). This implies that an active investor exploring this predictability, in the absence of transaction costs, would increase monthly and annual Sharpe ratios to 0.125 and 0.443 or 16.1% and 18.4%, respectively.

winsor2) replaces the extreme values using the median absolute deviation as benchmark

[2.10] Remember that we take cross-section moments of demeaned betas: $\tilde{\beta_{i,T}} = \beta^i_T - \overline{\beta^i_T}$. $\overline{\beta^i_T} = T^{-1}\sum_{s=1}^{T}(\beta^i_s)$ is the time series average of conditional betas for stock i up to time $t = T$

Consider now the upper-bound of the out-of-sample R^2 estimates of 0.7% for one-month ahead and 10% for one year-ahead returns. For these figures, Sharpe ratios increase to 0.14 (monthly) and 0.52 (annualized) or 27.3% and 37.9%, respectively. These figures suggest that exploring dynamically the betas dispersion can improve risk adjusted returns substantially. As a matter of comparison, Kelly & Pruitt (2013) 3-pass regression filter methodology increases in monthly Sharpe ratios by roughly 30%, for an out-of-sample R^2 of 0.9% (1-month ahead returns).

What about the point estimates for the CSDB measures predictability coefficient? Table D.13 present in-sample OLS regression results for one-year ahead returns for all considered CSBD measures. Each column presents univariate regression results. Consider first the CSBD standard deviation measure ($\sigma_t(\beta^i)$): t's point estimate is -0.331, with an in-sample R^2 of 3.6%. A negative coefficient means that an increase in CSBD is related to a negative market return 1-year ahead. As we can infer from the table, point estimates are negative for all CSBD metrics. The section 2.4 discusses the economic interpretation of our results.

What about the size of the coefficient and it's economic relevance? The unconditional mean of $\sigma_t(\beta^i)$ is 0.44, with a standard deviation of 0.11. Therefore ,an increase in one standard deviation of this CSBD metric is associated with a decrease of approximately 3.7% in annualized market returns for the 1-year ahead horizon ($0.11 \cdot b = 0.037$). The same calculation for the 70th interquartile range (an incresase in 1 standard deviation) lead to a decrease of 4.8% in one-year ahead returns. Regardless of the CSBD metric considered, point estimates suggest relevant economic impacts on future market returns.

2.4 Robustness and Additional Results

2.4.1 Fama-French 150 univariate Portfolios Betas dispersion

The previous section presented results for market return predictability using individual stocks betas CSBD measures. This section presents, as a robustness check, results using portfolio data to estimate betas. We use, as common in the empirical finance literature, Fama and French‘s portfolios data-set.

We perform the computation of monthly rolling CAPM betas for the fifteen available uni-variate portfolio sorts based on characteristics, namely: size, book-to-market, operating profitability, investment, earnings-price, cashflow-price, dividend-yield, accruals, market betas, net share issuance, variance and residual variance and, finally, all three sorts based on prior returns (momentum, short term and long term reversal). There are 15 potential factors and 10 uni-variate sorts for each factor, for a total of 150 portfolios in the data-set. There is no data for several uni-variate sorts on these characteristics before 1965 on the authors website.

Rolling regressions use 24, 36 and 48 month windows to compute CAPM betas for each of the FF portfolios, running time-series regressions of the form: $R_t^{e,p} = \alpha_p + \beta_p^m \cdot r_t^{e,m} + \mu_t^p$, where p indexes the Fama-French uni-variate portfolio. We end up with a panel data set of portfolio betas, from 1967 to the end of 2018. We then compute, as in the individual stocks case, cross-sectional moments: for each t we measure the cross-section dispersion (CSBD) for conditional betas relative to their unconditional means: $\tilde{\beta_T^p} = \beta_T^p - \overline{\beta_T^p}$, where $\overline{\beta_T^p} = T^{-1}\sum_{s=1}^{T}(\beta_s^p)$ is the time-series average of the rolling-beta estimate up to time $t = T$.

In-sample predictability results are in Table D.14. For the cross-section standard deviation of portfolio betas, R^2 reach 0.62% for 1-month ahead return forecasts and we can reject the null of no predictability at 5%. Other dispersion measures, like interquartile ranges, have higher explanatory power: interquartile ranges deliver an in-sample R^2 that range from 1.07% to 1.29%, all significant at 1% level. Adding more than one variable typically increases in-sample R-squared as well. One-year ahead return forecasts regressions have higher R^2, but most of the dispersion measures are significant only at a 5% or less confidence levels, given the persistence of the regressors.

Out-of-sample predictability is also high when considering the Fama-French 150 portfolios CSDB. Table D.15 first panel presents a comparison of the out-of-sample-R^2 between models that use one single CSBD measure, together with encompassing statistics tests for one single sample split date for sake of brevity (1990): 1-year ahead out-of-sample range from a lower bound of 0.07% for the cross-section standard deviation of portfolio betas, not statistically significant. The upper bound reaches 5.55% for the 90th interquartile range and highly significant. One-month ahead returns statistics are lower and even negative in some cases, but typically this is a higher bar. In the bottom panel we can see that a model that uses both the cross-section standard deviation and the interquartile range delivers higher and significant results both for the one-month horizon (2.84%) and one-year horizon (11.35%). Contrary to the individual stock's case, for the portfolios maybe cross-sectional variation is better captured by more than one metric alone.

Figure C.9 shows that this out-of-sample forecastability is robust to different training samples. It plots out-of-sample R^2 statistic for the multivariate model that uses cross-section standard deviation and the 80th interquartile range. The out-of-sample R^2 Statistic is positive regardless of the cut-off, ranging for 1-year ahead forecasts, from negative in the beginning of the sample split dates to 10-14%, then falling again at the end of the training sample split (2000 and beyond). These figures, even though lower and more unstable than in the individual stocks case, provide additional evidence that combining cross-section dispersion with time variation in betas relative to their unconditional mean has strong predictive power for the equity risk premium.

What about the relative performance of our proposed CSBD to simple factor spreads? The value-spread, or the difference between betas of high and low book-to-market firms, is one of the several regressors tested in the zoo of predictability (Zhang, 2005). We compute a synthetic mean value spread of all the high-minus-low spreads of each individual 15 univariate sorts on characteristics (factors): $(15^{-1} \cdot \sum^{15} (\beta^H_{F,t} - \beta^L_{F,t}))$, where F represents each individual FF univariate portfolio. Factor spreads has a good relative performance relative to other CSBD measures considering the univariate models. However, it has worse out-of-sample results. The bottom panel of D.15 presents a negative out-of-sample statistic for the synthetic factor beta spread when considered individually, both for 1-month and 1-year ahead horizons. Multivariate versions that combine it with other CSBD measure can deliver positive out-of-sample R^2: they 2.08% or even 9.58% for 1-year ahead returns, but they always lower than those of multivariate regressions that use solely CSBD.

This section presented evidence of both in-sample and out-of-sample predictability for our proposed betas dispersion measures (CSBD) using Fama-French 150 univariate sorts on characteristics betas, instead of individual S&P500 stocks and. CSBD seems also a better out-of-sample forecaster of market returns than simple betas spreads, at least for the FF portfolios considered. We turn in the next section to the relation between CSBD and other standard predictors in the literature, like the dividend-to-price ration

2.4.2
Betas Dispersion and the Zoo of Predictors

It is a well established empirical fact that several candidates in the zoo of predictors of market returns, like the dividend-to-price ratio, have typically poor out-of-sample explanatory power and also unstable in-sample predictability (see Kelly & Pruitt (2013) and Goyal & Welch (2008)). Nevertheless, it is important to understand how our proposed measures correlate to these standard predictors in the literature. The main reason behind it is the clear theoretical link between valuation ratios and future returns, as given by present value relations like in Campbell & Shiller (1988)[2.11].

We present two exercises to address this question. In the first, we perform simple OLS regressions using our CSBD measures as the dependent variable and other usual regressors in the literature as explanatory variables. In the second, we perform our in-sample forecast regressions controlling additionally for these other regressors to check if our beta dispersion measures have explanatory power above and beyond these other candidates, in a horse race or *kitchen sink* approach.

We choose as regressors the following variables, all obtained in Goyal & Welch (2008) website. The first variable considered is the Stock Variance (svar), computed as the sum of squared daily returns on the S&P 500. The second is the Cross-Sectional Premium (csp) of Polk *et al.* (2006): their cross-sectional beta premium measures the relative valuations of high- and low-beta stocks. For valuation ratios we consider the following four: (i) dividend-to-price ratio (d/p), the difference between the log of dividends and the log of price; (ii) The earnings-to-price ratio (e/p) is the difference between the log of earnings (12-month moving sums of earnings on the S&P 500 index) and the log of prices; (iii) The book-to-market ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average. (iv) The dividend yield (d/y) is the difference between the log of dividends and the log of lagged prices. Finally, a typical macro factor considered is the Term Spread (tms), or the the difference between the long term yield on government bonds and the Treasury-bill for the US.

The first exercise explores the correlation, in a OLS regression setting, between the cross-section beta standard deviation ($\sigma_t(\beta^m_{i,t})$) and these candidates. Remember that point estimates for all dispersion measures in the in-sample forecasting regressions are negative, see for example Table D.13: an increase in CSBD leads to negative market returns for all horizons. Are these results consistent with the correlations in Table D.16? Let us take the *dp* ratio as an example. We know from the empirical literature that low prices relative to dividends tend to forecast higher subsequent returns for the market: that is, in a forecast regression between *dp* and future market returns, the coefficient is positive. That would, in turn, translate into a potential negative correlation between *dp* and CSBD measures. This is exactly what we get empirically, as

[2.11] As Cochrane (2008) suggests, given present value relations, if market returns are not predictable by valuation ratios, than the dividend growth must be predictable, to generate the observed variation in divided yields. It is exactly the absence of dividend growth predictability, rather than any potential finding of return predictability, that gives a stronger evidence for time variation in the equity risk premium we can see from Table D.16. As another example, consider an increase in the cross-section premium (*csp*), that leads to higher future market returns, as shown in Polk *et al.* (2006). One should expect a negative correlation between csp and CSBD, also what we get empirically. The only variable that has a positive correlation to the CSBD in betas is the term-spread (tms), which typically increases during recessions, when the FED tends to ease monetary policy aggressively. Finally, the last column presents the correlation to all these other variables combined together in a single regression: in-sample R^2 reaches only 13%, what suggests that there is still a lot of time series variation in CSBD that is not captured by these other typical regressors in the literature.

Our second exercise is just a *horse race* between our proposed betas CSBD measures and these other regressors. Table D.17 presents results for one-year ahead return forecasts using the standard deviation of betas as the CSBD measure. It survives the inclusion of all the above candidates, both in a pairwise fashion and also when we include all of them together (last column). Point estimates for $\sigma_t(\tilde{\beta}^i)$ remain negative across the board. in-sample R^2 increase to almost 19% (18% for the adjusted R^2) when controlling for all alternative regressors.

These correlation results should no be surprising. As noted by Cochrane (2009) "most of these variables are correlated with each other and correlated with or forecast business cycle. Expected returns vary over business cycles; it takes a higher risk premium to get people to hold stocks at the bottom of a recession. When expected returns go up, prices go down. We see the low prices, followed by the higher returns expected and required by the market".

Naturally, we haven't explored the correlation to all potential factors in the predictability zoo: Harvey *et al.* (2016) and Freyberger *et al.* (2020) show that there are hundreds of factors that potentially explain the cross-section of stock returns. And, as our paper suggests, any such variable would be a good candidate to also forecast the equity risk premium. However, our simple measure extracted from the cross-section information of betas has at least explanatory power above and beyond the most traditional valuation and macro factors in the literature. We next turn to how our proposed CSBD measures vary along the business cycle.

2.4.3
Betas Dispersion and the Business Cycle

We relate the cross-section dispersion measures (CSBD) to the NBER Recession indicators, as a first attempt to measure how they vary across the business cycle. Figure C.7 plots the time series of $\sigma^i(\beta^i_t)$ in the first panel (the

1st panel from top left to right) since 1930. NBER recession indicators are shaded areas in the chart. We also plot the time-series of some usual forecasting variables, like the dividend-to-price ratio (dp), the cross-section premium of Polk *et al.* (2006) and the aggregate market book-to-market ratio.

One can see from visual inspection that the CSBD measured by the cross-sectional standard deviation typically rises prior to recessions and falls sharply during recessions. The 2002 dot-com recession seems to be the exception, since CSBD fell only after the end of NBER dating dummy. Figure C.8 plots the same chart but changing the CSBD metric to the 70th interquartile range. The same previous pattern seems pervasive in the data, regardless of the metric: CSBD tend to rise prior to recessions and fall sharply during recessions. These results are qualitative compatible with our empirical findings. Remember that CSBD point estimates are negative for future market returns. Therefore, a high CSBD leading to a recession, when usually valuations are stretched, prices are high and leverage is high, is suggestive of negative future market returns ahead. During recessions, CSBD falls, which is empirically consistent with positive future market returns: recessions are moments of higher risk premium, when agents demand higher expected future returns to carry increased risk.

One other interesting empirical pattern of the cross-sectional dispersion in Betas is it's relation to the dividend-to-price ratio. Figure C.9 plots the empirical kernel density of σ_t^β on the x-axis for different sub-samples. The first density plots data for the whole sample period (1930-2017). We also split the sample in moments of high and low dividend-to-price Ratios (dp)[2.12]. A high dp is associated with low prices relative to dividends and bad economic states, like recessions. During those times, prices are depressed and expected future market returns are positive because agents demand higher risk premium to carry increased consumption risk.

One can see from the figure that the CSBD measure shifts left and becomes more compressed on the sub-sample of high dividend-to-price ratios. During economic bad times, when prices are low and dp is high, the empirical distribution of betas standard deviation shifts to the left, that is CSBD tends to fall. In other words, betas become closer to their "true" unconditional mean beta and also closer to each other. Conversely, on moments of low dp the empirical distribution of betas has even two tails. This empirical pattern also holds when considering the 70th percentile interquartile range (right panel): the IQR range shifts left in the sub-sample of high dp, that is, in bad times, individual stock betas become more closer to their unconditional mean and

[2.12]We split the sample formally into the high-dp bin (low bin) for months for which *dp* higher then the unconditional average of *dp* plus (minus) 1.5 times standard deviation the interquartile range decreases.

This empirical pattern is closely related to the beta compression result of Frazzini & Pedersen (2014): they show in their paper that betas tend to be compressed towards one in moments when leverage restrictions become binding. These are typically associated with recessions and bad economic times, when banks tend to be more conservative in their lending standards[2.13]. Our empirical findings suggest that betas also tend to be compressed to their unconditional mean during bad times. In addition, as the next section shows, our proposed CSBD metric has a stronger predictive power out-of-sample.

2.4.4
Do other Betas Dispersion Measures forecast the ERP?

This section presents brief empirical results of using the dispersion of stock's betas relative to the market beta of one as a forecasting variable for market returns. Following the intuition in Frazzini & Pedersen (2014), we compute $\beta^* = \beta_t^i - 1$ for all stocks and then calculate cross-section dispersion[2.14]. As previously pointed out, Table D.2 presents simple correlation (in-sample) for both metrics, ranging from 0.65 to 0.83: both dispersion measures have a strong correlation, at least unconditionally.

Figure C.10 presents out-of-sample R^2 statistics for alternative dispersion measures using β^* for several alternative training samples. As before, on the X-axis we have the different sample date cut-offs for the training sample and on the Y-axis the out-of-sample R^2 relative to that sample split. As one can see from the left panel, even when positive, they reach at most 2% for one-year ahead returns. The right panel presents results for winsorized versions of the cross-section dispersion measured by the standard-deviation ($\sigma_t(\beta^*)$): for them the statistic reach at most 2.5%. All these figures are much lower in comparison to CSBD out-of-sample R^2 statistics, which is suggestive of our measure's greater forecasting power for market returns.

That both measures of cross-section dispersion have predictive power for the market returns provide additional empirical evidence of return predictability and, thus, of time varying equity risk premium. Our findings also present additional empirical evidence that betas dispersion across time is, by itself, a function of the same time varying risk premium.

[2.13] The author's show that funding shocks have further implications for the cross-section of asset returns. Specifically, a funding shock makes all security prices drop together, compressing betas toward one. Proposition 4 of Frazzini & Pedersen (2014) show that when the conditional variance of the stochastic discount factor rises (falls) the conditional return betas of all securities are compressed toward one (become more dispersed)

[2.14] Our CSBD measure is computed for each t from conditional CAPM betas deviations from the stock historical mean up to that moment ($\widetilde{\beta_t^i} = \beta_t^i - \bar{beta_t^i}$)

2.5 Conclusion

We propose novel forecasting variables for aggregate market returns that solely use cross-sectional information on CAPM betas moments. In a simple forecasting equation $E_t[R^m_{t+k}] = a + b \cdot X_t$ our idea is to identify z_t from the empirical distribution of conditional betas. Among other empirical moments, we consider measures of cross-sectional dispersion of betas relative to their unconditional mean $(\beta^i_t - \bar{\beta^i_t})$.

We show in this paper that time varying CAPM betas contain information about future expected returns. If the conditional CAPM holds, than there is a common element affecting both betas and the risk premium. But we know from Lewellen & Nagel (2006) and others that conditional models typically do not work well. However, the case we try to make is that even limited time series variability in the betas of individual stocks and portfolios, combined with cross-section information and moments, has enough informative power to forecast the Equity Risk Premium (ERP).

The cross-sectional dispersion of Betas (CSBD) forecast the market risk premium both in and out-of-sample. In-sample R^2 are significant using a bootstrap procedure to tackle the persistence of regressors bias. CSBD also forecasts market returns out-of-sample, delivering out-of-sample R^2 statistics that range between 4-10% for one-year ahead (0.4-0.7% for one-month ahead) returns. These levels of predictability match other recent work like Kelly & Pruitt (2013) with a much simpler and intuitive empirical methodology. CSBD out-of-sample forecasting power is also robust to several different training samples and tend to increase over time (see Figure C.2).

CSBD works independently of measurement: results are robust to alternative definitions of cross-section dispersion, like standard deviation, interquartile ranges and winsorized versions that control for potential outliers. CSBD also works when we consider betas of Fama-French univariate portfolio sorts on 15 characteristics to compute cross-section dispersion measures, instead of individual stocks.

Unlike most measures in the literature, ours is not a price- or valuation-based ratio. Our approach is also an alternative to models that use the cross-section of valuation ratios to infer the conditional market risk premium.

Cross-section dispersion (CSBD) is only mildly correlated with other standard predictors of market returns, such as dividend-to-price, dividend yield, book-to-market, market variance, cross-sectional premia. in-sample R^2 of univariate OLS regression on several such variables reach at most 20%, suggesting that there is still plenty of time variation of CSBD that is not captured by these other predictors in the literature. Despite being correlated, CSBD also has explanatory power above and beyond these standard predictors, surviving in-sample the inclusion of several of them in a typical *horse race* forecasting regression.

CSBD predictability is economically relevant: a investor that trades dynamically conditioning on CSBD can increase it's annualized Sharpe ratio up to 38% relative to buy and hold strategies. They also vary counter-cyclically with the business cycle: they tend to increase prior to NBER recessions, when prices are high, dividend-price ratios are low, firms agents and government tend to be leveraged, and future market returns tend to be negative. During NBER recessions CSBD tend to fall sharply, exactly when prices are low relative to dividends, dividend-price ratios and risk premia are high, exactly moments of future higher expected returns. These empirical findings provide not only additional evidence of market return predictability and time varying risk premium, but also that betas dispersion across time is, by itself, a function of time varying risk.

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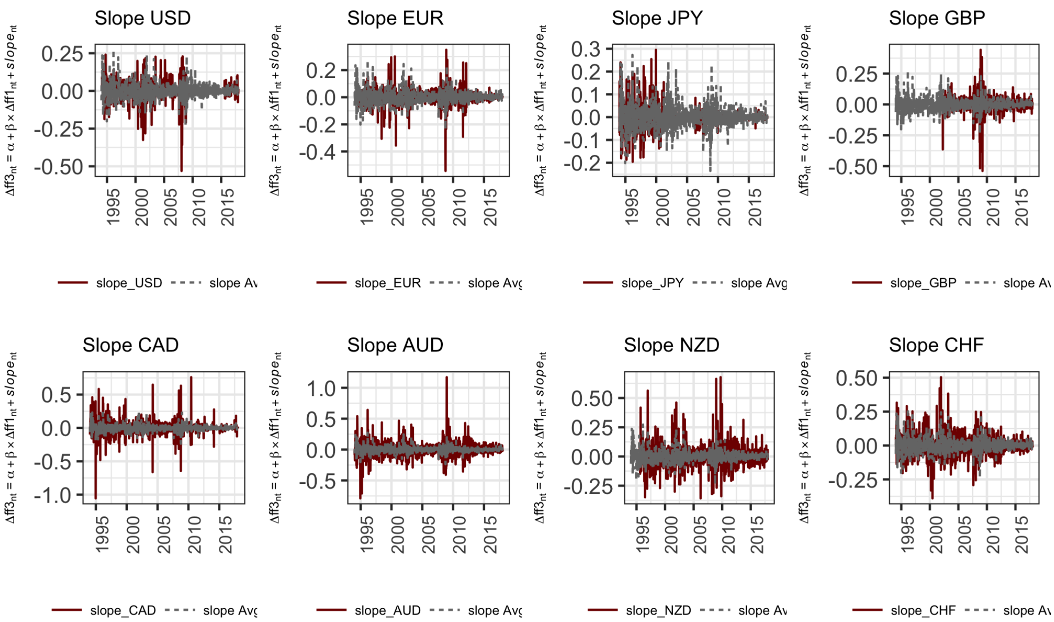
A
Figures of Chapter 1

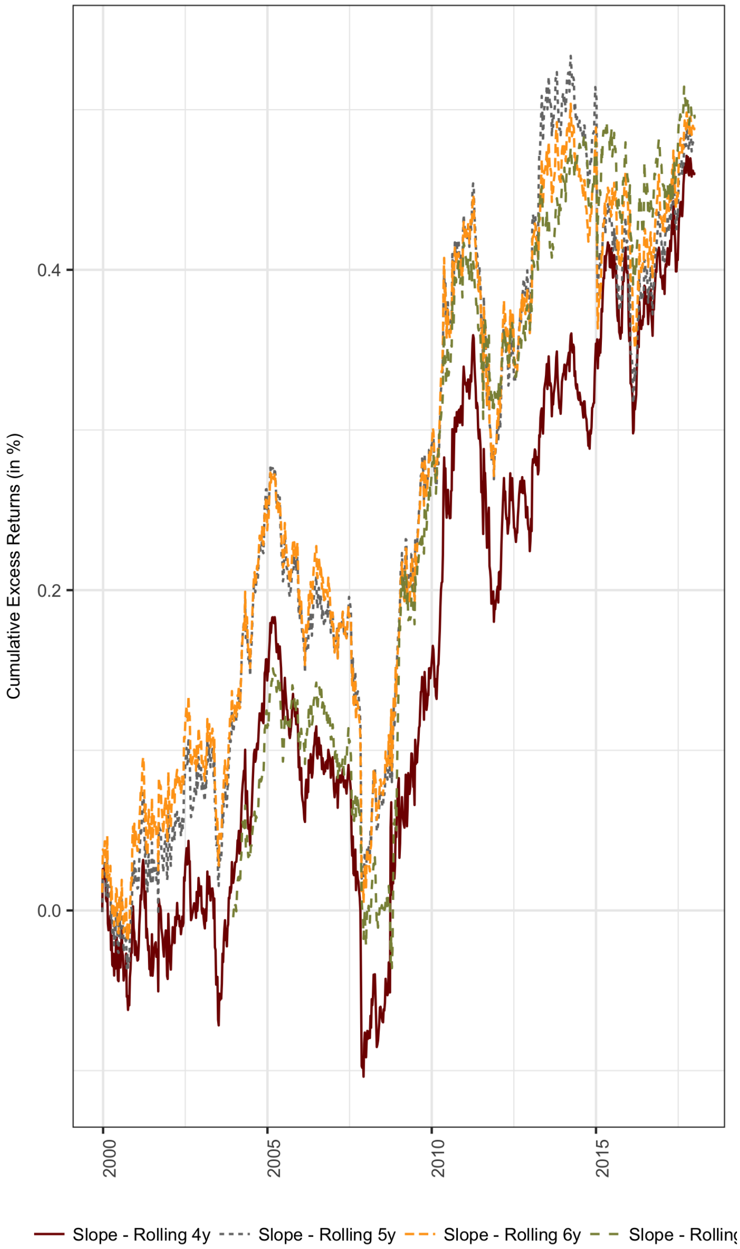
Figure A.1

Monetary *slope* by Country against G10 (average) – Full Sample Estimates



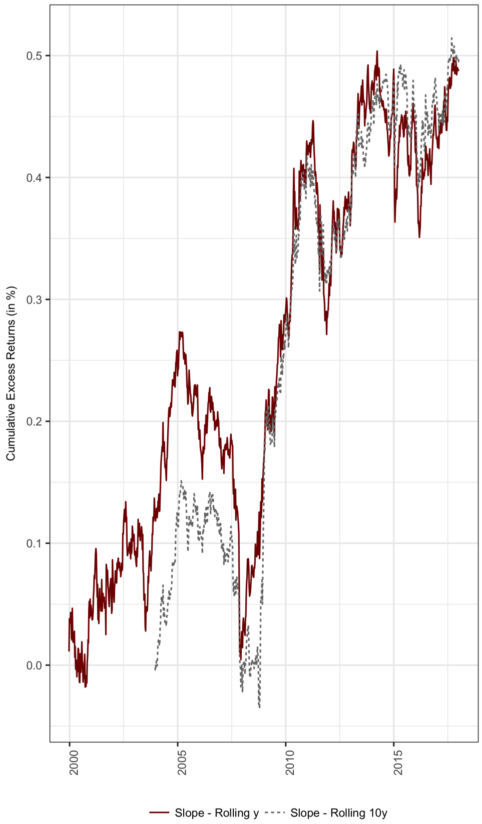
Note: Results presented consider *slope* first-stage estimation using all available data, using 3-month futures rates. $\text{slope}^3_{i,t}$ is defined as the residual of the regression of weekly changes in 3-month interest rate futures on weekly changes in one-month futures rates for each country. We run the following regression for each country in our sample using all available data across t: $\Delta ff^3_{i,t} = \alpha^n + \beta^n \cdot \Delta ff^1_{i,t} + \epsilon^3_{i,t}$ and define $\epsilon^3_{i,t} = \text{slope}^3_{i,t}$. We report weekly slope estimates for all G10 countries (red line) and also the synthetic G10 average (gray line). Sample from 1994-2007.

Figure A.2
Long - Short Country *slope* Portfolio Strategy

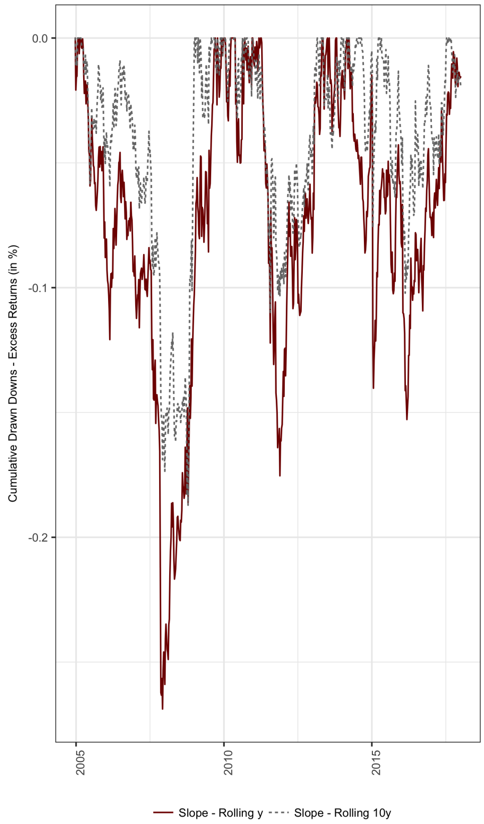


Note: Long-Short Country *slope* Portfolio. For each week we sort G10 countries (ex US) by their previous week point *slope* measure and divide them into 2 bins: High *slope* and Low *slope*. Following Panel regressions in-sample point estimates ($\phi_n < 0$), a positive slope for country i leads to positive currency return against the US dollar up to 4-week ahead. We go long the High *slope* bin and go short the Low *slope* bin. Cumulative portfolio excess returns in Panel for the whole sample for several measures of Recursive *slope* estimate training samples (4,5,6 and 10-year) (cumulative return$_t$ $= \sum_{s=0}^{t} rx_s$). We re-balance the portfolio each week. Sharpe ratios are adjusted for transaction costs following the limiting case estimates in Karnaukh (2020).

Figure A.3
Long - Short Country *slope* Portfolio Strategy



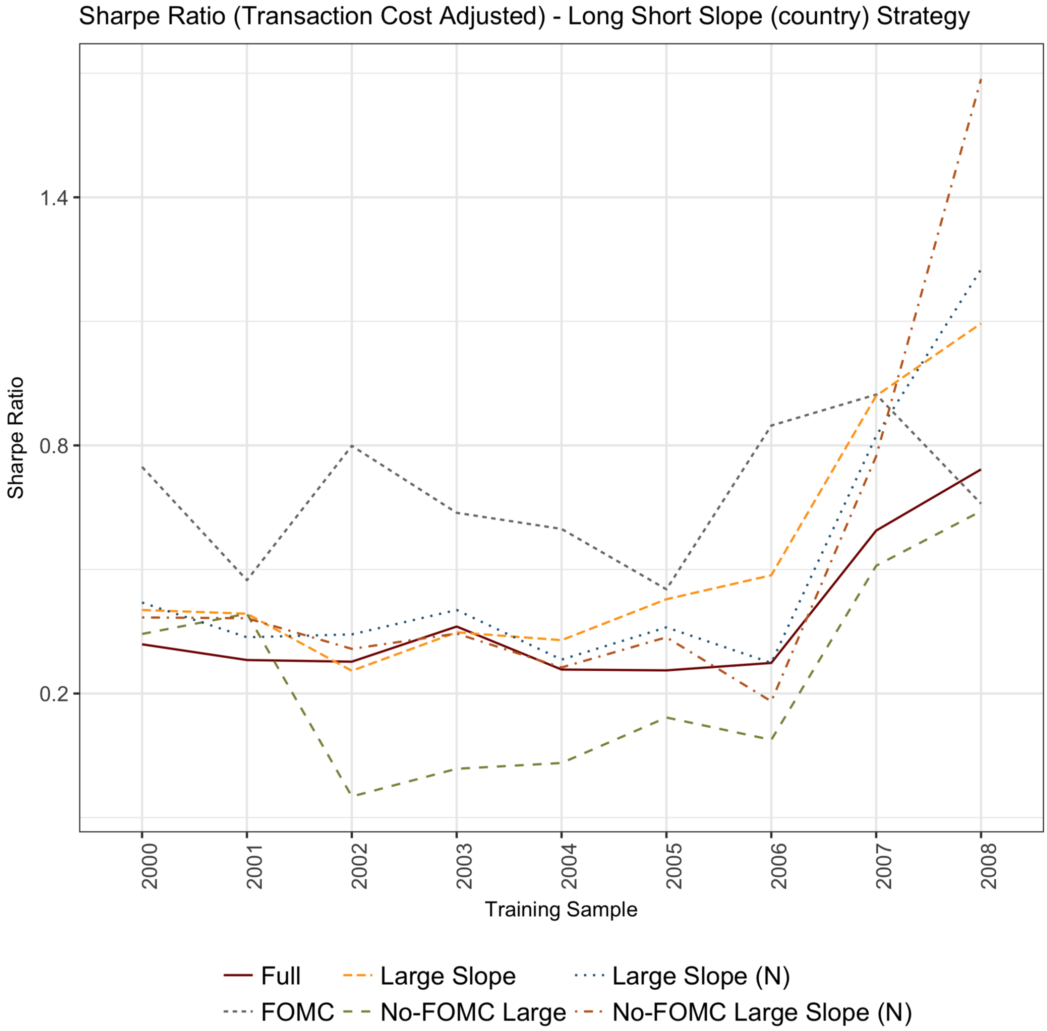
(a) Cumulative Returns



(b) Strategy Drawdown

Note: Long-Short Country *slope* Portfolio. For each week we sort G10 countries (ex US) by their previous week point *slope* measure and divide them into 2 bins: High *slope* and Low *slope*. Following Panel regressions in-sample point estimates ($\phi_n < 0$), a positive slope for country i leads to positive currency return against the US dollar up to 4-week ahead. We go long the High *slope* bin and go short the Low *slope* bin. Panel (a) present cumulative portfolio excess returns in Panel for the whole sample for 2 measures of Recursive *slope* estimate: 5-year training sample and 10-year training sample (cumulative return$_t = \sum_{s=0}^{t} rx_s$). Panel (b) computes the strategy draw-down up to time t (drawdown$_t = \sum_{s=0}^{t} rx_s - \max(\sum_{s=0}^{t} rx_s)$). We re-balance the portfolio each week. Sharpe ratios are adjusted for transaction costs following the limiting case estimates in Karnaukh (2020).

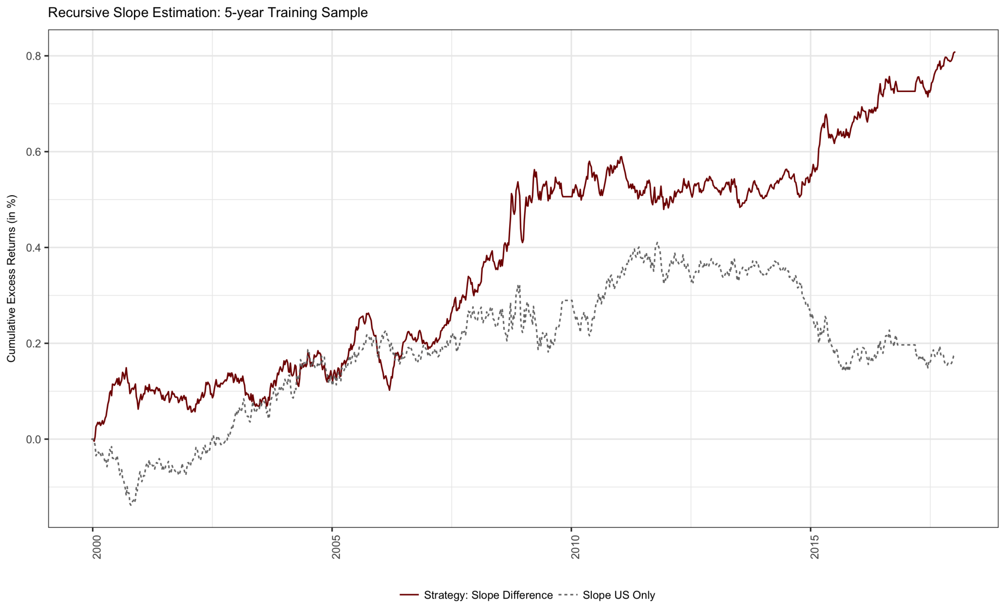
Figure A.4
Long - Short Country *slope* Portfolio Strategy – Different Training Samples (Recursive)



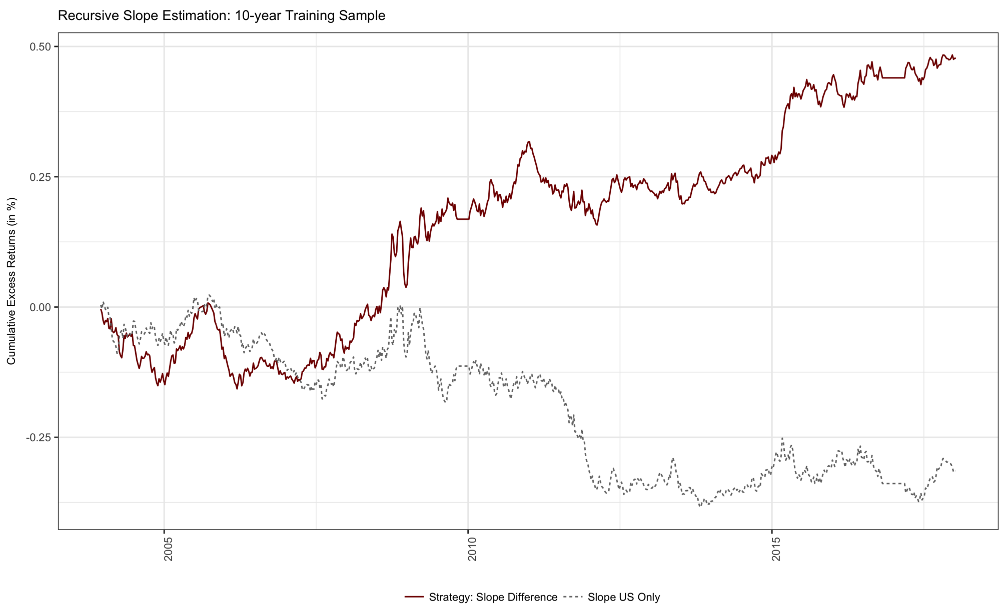
Note: Long-Short Country *slope* Portfolio annualized Sharpe ratios (Y-Axis). Sharpe ratios are adjusted for transaction costs following estimates in Karnaukh (2020). The X-Axis refers to each *slope* training window T_k: for each window we run the first stage *slope* model up to $t = T_k$, save coefficients and use them to compute *slope* measure from $(T_k : T)$. We then apply the strategy conditioning on each slope point estimate, re-balancing each week, and compute total Sharpe ratio of that strategy between $t = [t_k, T]$. Portfolio formation: for each week we sort G10 countries (ex US) by their previous week point slope estimate and divide them into 2 bins: High *slope* and Low *slope*. Following Panel regressions in-sample point estimates ($\phi_n < 0$) a positive slope at country i leads to a positive currency return against the US dollar. Therefore we go long the High *slope* bin and go short the Low *slope* bin.

Figure A.5

Tactical Dollar Portfolio Conditioning on *slope* – Cumulative Returns



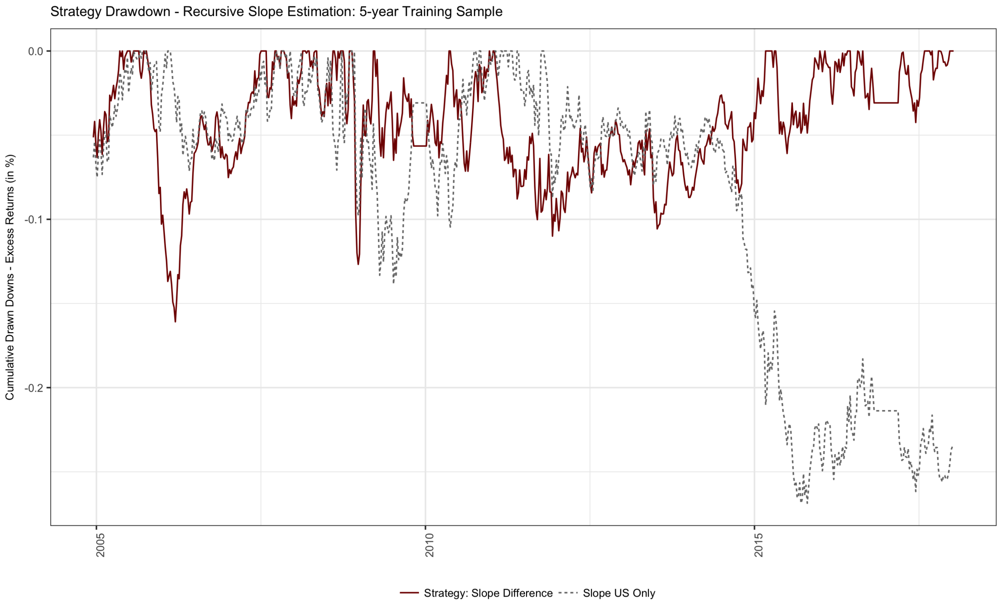
(a) 5-year Training Sample



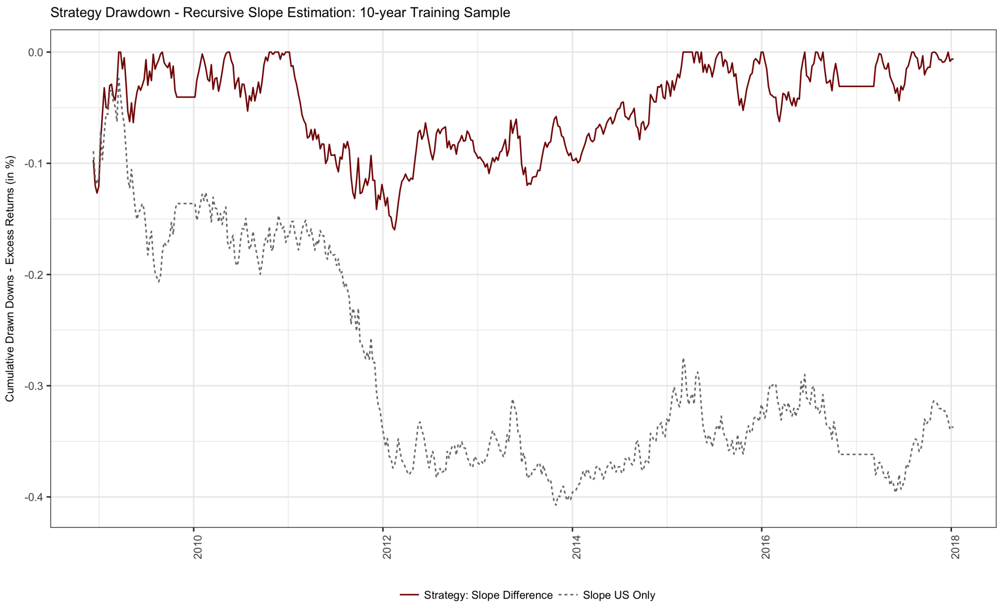
(b) 10-year Training Sample

Note: Long - Short G10 currencies Portfolio conditioning on *slope* estimates. We present results for 2 Models: Model I that conditions on *slope*-difference and Model III that conditions only on US *slope* information at $t-1$. Both panels report strategy portfolio excess returns up to time t. Panel (a) presents results for a 5-year training sample and Panel (b) for a 10-year training sample. Strategies are performed by computing recursive slope estimates: going either long-short G10 (ex us) currencies conditioning on slope information. Point estimate for slope-difference in Model I ($\phi_{\text{difference}}$ is positive, suggesting a strategy that goes long (short) G10 when average G10 slope difference against the US is positive (negative). We re-balance each week, accordingly. This is the tactical Long-Short Dollar Portfolio.

Figure A.6
Tactical Dollar Portfolio Conditioning on *slope* – Drawdowns



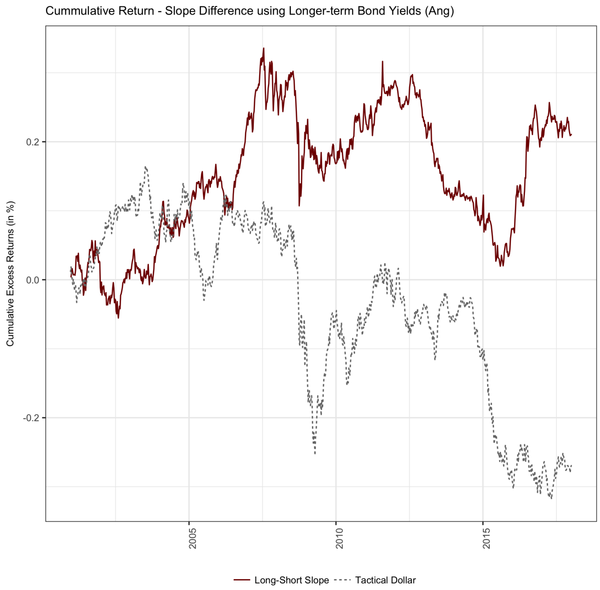
(a) 5-year Training Sample



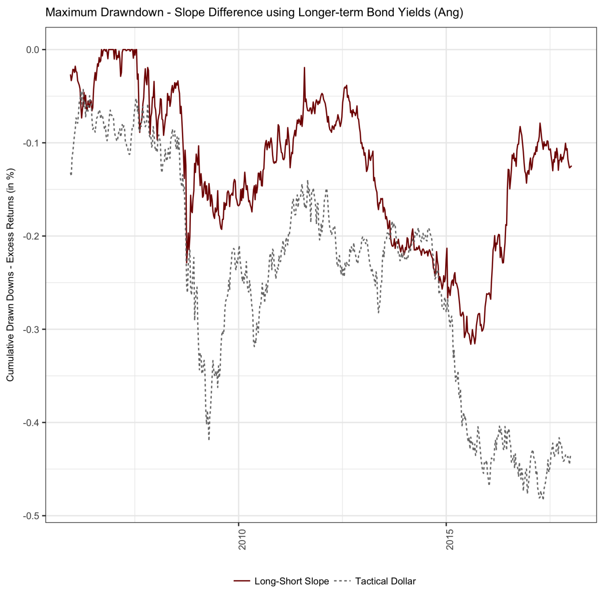
(b) 10-year Training Sample

Note: Long - Short G10 currencies Portfolio conditioning on *slope* estimates. We present results for 2 Models: Model I that conditions on *slope*-difference and Model III that conditions only on US *slope* information at $t-1$. Both panels report strategy portfolio excess returns maximum drawn-down up to time t: drawdown$_t$ $= \sum_{s=0}^{t} rx_s - \max(\sum_{s=0}^{t} rx_s))$. Panel (a) presents results for a 5-year training sample and Panel (b) for a 10-year training sample. Strategies are performed by computing recursive slope estimates: going either long-short G10 (ex us) currencies conditioning on slope information. Point estimate for slope-difference in Model I ($\phi_{\text{difference}}$ is positive, suggesting a strategy that goes long (short) G10 when average G10 slope difference against the US is positive (negative). We re-balance each week, accordingly. This is the tactical Long-Short Dollar Portfolio.

Figure A.7
Long-Short Currency Strategy Conditioning on Long-Term Yields *slope*



(a) Total Return



(b) Maximum Drawn-Down

Note: Long-Short Country *slope* Portfolio using 10-year Bond Yields minus 3-month *slope*. For each week we sort G10 countries (ex US) by their previous week point *long-term slope* measure and divide them into 2 bins: High *slope* and Low *slope*. Following Ang & Chen (2010) empirical results, a positive 10-year *slope* for country i leads to negative currency return against the US dollar over the medium term. Contrary to our empirical findings, we build this portfolio going long the Low *slope* bin and go short the High *slope* bin. Cumulative portfolio excess returns in the left Panel for both the long-short and also the tactical-Dollar strategy (cumulative return$_t$ $= \sum_{s=0}^{t} rx_s$). The right panel computes the strategy maximum drawn-down. We re-balance the portfolio each week. Sharpe-ratios are adjusted for transaction costs following the limiting case estimates in Karnaukh (2020).

B
Tables of Chapter 1

Table B.1
Currency Portfolios Sharpe Ratios (Annualized)

Unconditional Currency Strategies

	Full	Large *slope*	No-FOMC and Large	FOMC
Long G10 (Dollar Portfolio)	0.15	0.21	0.13	-0.14
Carry Trade	0.3	0.33	0.23	0.38

slope Conditional Currency Strategies

	Full	Large *slope*	No-FOMC and Large	FOMC
Long-Short Currency *slope*[a]	0.38	0.50	0.52	0.68
Tactical Dollar Portfolio[b]	0.4	0.56	0.90	0.26

Notes: All figures are annualized Sharpe ratios, approximately adjusted for transaction costs. For all strategies, we compute returns on different sub-samples: all sample weeks, on FOMC Weeks only, on weeks with large G10 average slope (bigger in absolute values than 0.5 times the standard deviation, always computed up to the week we are forming the portfolio), in No-FOMC weeks with large G10 slope. Currency returns are measured using London fixing (Wed-Wed carry adjusted returns). *slope* for the US and Canada is constructed using Tue-Tue weekly data to assure we have all information when forming portfolios. Measures used to construct slope conditional portfolios are recursively computed. Long-G10 is the simple the average unconditional return of an equally weighted long G10 currencies and short the US Dollar. The carry-trade is the unconditional carry strategy, to adjusted for transa in our G10 sub-sample: for each week we sort currencies based on their interest rate differential relative to the US, going long the high carry and short the low carry currencies. Novel Currency strategies: (a) strategy that uses individual country *slope* information at t to construct a long-short portfolio. Panel regressions point estimates suggest a negative delayed reaction for *slope*. We use this information to sort countries based on their *slope* measure in week t into a High and a Low *slope* bin. We go long the high and short the low bin each week, re-balancing weekly; (b) we use information on *slope* difference between a synthetic G10 average and the US to tactically trade the Dollar portfolio: when slope difference is positive (negative) we go long (short) the G10 equally weighted currency portfolio, re-balancing weekly

Table B.2: Monetary *slope* Model Estimation by Country

	USD	EUR	JPY	GBP	CAD	AUD	NZD	CHF
constant	$-.00$	$-.00$	$.00$	$-.00$	$-.00$	$-.00$	$-.00$	$-.00$
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Δff_N^1	$.63^{***}$	$.79^{***}$	1.12^{***}	$.70^{***}$	$.78^{***}$	$.81^{***}$	$.73^{***}$	$.86^{***}$
	(.04)	(.07)	(.09)	(.08)	(.06)	(.10)	(.03)	(.05)
R^2	.42	.57	.58	.59	.57	.51	.56	.54
Adj. R^2	.42	.57	.58	.59	.57	.51	.56	.54
Num. obs.	1157	1216	1253	824	1253	1253	1174	1253

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We report boot-strapped standard errors in parentheses to account for constructed regressor bias. Results presented consider *slope* first-stage estimation using all available data, using 3-month futures rates. $\text{slope}^3_{i,t}$ is defined as the residual of the regression of weekly changes in 3-month interest rate futures on weekly changes in one-month futures rates for each country. We run the following regression for each country in our sample using all available data across t: $\Delta ff^3_{i,t} = \alpha^n + \beta^n \cdot \Delta ff^1_{i,t} + \epsilon^3_{i,t}$ and define $\epsilon^3_{i,t} = \text{slope}^3_{i,t}$.

Table B.3

Full Sample Adjusted *slope* Correlation: $\Delta ff^3_{i,t} = \alpha^n + \beta^n \cdot \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$

	G10 (avg)	EURGBP (avg)	EUR	JPY	GBP	CAD	AUD	NZD	CHF
G10	1	0.53	0.50	0.32	0.03	0.48	0.76	0.71	0.62
EURGBP	0.53	1	0.67	0.82	0.07	0.11	0.12	0.12	0.29
EUR	0.50	0.67	1	0.13	0.01	0.26	0.22	0.12	0.29
GBP	0.32	0.82	0.13	1	0.10	0.06	0.01	0.07	0.17
JPY	0.03	0.07	0.01	0.10	1	0.05	0.08	0.08	0.01
CAD	0.48	0.11	0.26	0.06	0.05	1	0.15	0.14	0.10
AUD	0.76	0.12	0.22	0.01	0.08	0.15	1	0.60	0.41
NZD	0.71	0.12	0.12	0.07	0.08	0.14	0.60	1	0.30
CHF	0.62	0.29	0.29	0.17	0.01	0.10	0.41	0.30	1

Notes: Simple pairwise correlation coefficient for *slope* ($\text{slope}^3_{i,t}$), estimated using all available data. G10 synthetic *slope* is a cross-sectional average computed for each t using individual country *slope* measures. EURGBP is the simple average of the Euro area and Great Britain *slope* estimates, the most liquid and traded interest futures markets.

Table B.4
Interest Rate Futures and Monetary *slope* Descriptive Statistics by Country

Variable	Stat	USD	EUR	JPY	GBP	CAD	AUD	NZD	CHF
$\text{slope}^3_{i,t}$	μ	0	0	0	0	0	0	0	0
	$P_{10\%}$	−4.04	−4.68	−3.03	−5.26	−8.84	−11.21	−9.68	−7.71
	$P_{90\%}$	4.96	4.58	2.31	5.50	7.92	10.83	8.96	7.60
	σ	0.16	0.15	0.11	0.23	0.28	0.32	0.19	0.20
$\text{slope}^3_{i,t}$	μ	0	0	0	0	0	0	0	0
	$P_{10\%}$	−5.35	−6.42	−3.75	−11.45	−11.39	−7.05	−5.47	−4.81
	$P_{90\%}$	4.91	5.96	3.90	10.80	10.84	7.54	5.51	4.50
	Std	0.16	0.21	0.12	0.38	0.31	0.20	0.25	0.14
$ff^1_{i,t}$	μ	2.59	2.49	0.45	3.01	3.05	4.80	5.27	1.18
	σ	0.07	0.05	0.01	0.07	0.05	0.05	0.07	0.04
$ff^1_{3,t}$	μ	2.61	2.45	0.51	2.45	3.18	4.94	5.35	1.35
	σ	0.07	0.06	0.02	0.07	0.06	0.05	0.06	0.04
$\Delta ff^1_{i,t}$	μ	−0.15	−0.51	−0.14	−0.58	−0.19	−0.25	−0.57	−0.36
	σ	0.22	0.22	0.11	0.38	0.41	0.40	0.41	0.26
$\Delta ff^3_{i,t}$	μ	−0.30	−0.69	−0.13	−0.65	−0.22	−0.27	−0.47	−0.31
	Std	0.21	0.23	0.17	0.35	0.42	0.45	0.41	0.30

Notes: All data are in basis points (percentage points * 100). μ and σ are the cross-sectional (country) mean and standard deviation across t. $P_{10\%}$ and $P_{90\%}$ are the 10th and 90th percentile across t for each metric. $ff^1_{i,t}$ and $ff^3_{i,t}$ are, respectively, the 1-month and 3-month future interest rate level. $\Delta ff^1_{i,t}$ is the weekly change in futures. Short-term structure *slope* or *monetary slope* ($\text{slope}^{3,6}_{US,G10}$) is defined as the residual of the regression of weekly changes in 3-6 month interest rate futures on weekly changes in one-month futures rates for each country. We run the following regression: $\Delta ff^3_{i,t} = \alpha + \beta \cdot \Delta ff^1_{i,t} + \epsilon^3_{i,t}$ and define $\epsilon^3_{i,t} = \text{slope}^3_{i,t}$) for each G10 country

Table B.5
G10 (ex US) Currency Returns – Descriptive Statistics by Country

Variable	Stat	EUR	JPY	GBP	CAD	AUD	NZD	CHF
$f^i_t - s^i_t \approx i^n_t - i^{us}_t$	μ	−0.63	−2.65	0.70	0.07	2.00	2.61	−1.89
	σ	0.04	0.06	0.03	0.03	0.05	0.04	0.04
$rx^i_{t\to t+1}$	μ	2.49	−2.47	0.24	0.34	2.46	3.43	−0.25
	σ	3.59	2.20	1.84	1.73	2.47	2.61	2.32
	Sharpe Ratio	0.14	−0.23	0.03	0.04	0.20	0.27	−0.02
$rx^i_{t\to t+4}$	μ	2.50	−2.83	0.32	0.22	2.58	3.72	−0.44
	σ	1.77	1.14	0.90	0.81	1.22	1.27	1.14
	Sharpe Ratio	0.14	−0.26	0.04	0.03	0.22	0.30	−0.04
$rx^i_{t\to t+52}$	μ	2.06	−2.70	−0.01	0.02	2.06	2.85	−0.55
	σ	0.47	0.32	0.25	0.23	0.38	0.41	0.28
	Sharpe Ratio	0.13	−0.25	−0.001	0.002	0.16	0.21	−0.06

Notes: Interest rates and returns data are presented in annualized terms and percentage points. Sharpe ratio is unconditional buy-and-hold full sample strategy annualized return μ is the simple cross-sectional arithmetic mean and σ is the standard deviation (across t). Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f^i_t is the (log) currency forward rate and s^i_t is the (log) exchange rate against the dollar, so that an increase in s_t means a depreciation of the foreign currency against the dollar. Interest rate differential against the US is measured by the forward discount ($f^i_t - s^i_t \approx i^n_t - i^{us}_t$). All currency-returns are measured against the US dollar

Table B.6
Currency Portfolios Returns – Descriptive Statistics

Portfolio	Stats	Full	Large *slope*	No-FOMC and Large	FOMC
Long G10 (*Dollar*)	Sharpe ratio	0.15	0.21	0.13	−0.14
	μ	2.28	3.59	2.18	−2.26
	p-val	0.49	0.54	0.73	0.80
	σ	108.77	120.99	119.06	116.60
	N	1,065	431	356	170
Carry G10	Sharpe ratio	0.31	0.33	0.23	0.38
	μ	7.33	8.91	5.97	9.50
	p-val	0.16	0.34	0.55	0.49
	σ	171.63	193.65	189.73	179.77
	N	1,063	430	355	170

Notes: All returns are in basis-points (bps), Weekly observations. Sharpe Ratio in annualized terms. μ is the unconditional mean return across t, σ is the standard deviation of the mean (across t). N is the number of weekly observations for that portfolio and sub-sample. The long G10-short US dollar portfolio (Dollar portfolio) goes long all available G10 currencies in a given week against the US dollar (simple weighted average). The carry G10 is a carry trade portfolio restricted to our sample of countries: a strategy that goes long countries with high interest rate differentials (in the cross-section) and shorts low interest rate differential countries, against the US. We re-balance the carry-trade portfolio weekly. All returns are gross of transaction costs but are excess returns relative to the risk-free rate.

Table B.7: Panel of G10 Countries Full Sample – Current Week Impact

	Current-Week Return - Model I ($rx^i_{t-1\to t} = \phi_1 \cdot$ *slope* difference$_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{i,t}$))							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\text{slope}^{i,\Delta ff_3}_{diff}$	$.021^{***}$	$.022^{***}$	$.021^{***}$	$.021^{***}$	$.021^{***}$	$.021^{***}$	$.021^{***}$	$.021^{***}$
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
$\Delta ff^{i,1}_{\text{difference}}$		$.000^{*}$						$-.000$
		(.000)						(.000)
rx^i_{t-1}			$-.017$					$-.019$
			(.014)					(.016)
VIX				$-.000$				$-.000$
				(.000)				(.000)
$\text{ts}^{us}10\text{yr}$					.000			$-.001$
					(.000)			(.001)
$\text{ts}^{i}10\text{yr}$					.000			$.002^{**}$
					(.000)			(.001)
dp						-4.451		-4.278
						(3.099)		(3.018)
ff target							$-.000$	$-.002^{*}$
							(.000)	(.001)
R^2	.012	.013	.013	.014	.013	.013	.013	.018
Adj. R^2	.011	.012	.012	.013	.012	.012	.012	.016
Num. obs.	7640	7640	7623	7573	7359	7573	7640	7343

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions of the form: $rx^i_{t-1\to t} = \phi_1 \cdot \text{slope difference}_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t-1\to t}$ is the individual country currency return against the USD in the current week, slope difference$_{i,t}$ is the *slope* difference measure ($\text{slope}_{i,t} - \text{slope}_{US,t}$) estimated in the first stage regressions, μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). Full Sample *slope* measure obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available data. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_i - \Delta ff^1_{US}$), lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the country 10 year bond term spread ($tsN10yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target).

Table B.8: Panel of G10 Countries Full Sample – Forecastability (1-week Ahead Returns)

1-Week Ahead Return - Model I ($rx^i_{t\rightarrow t+1} = \phi_1 \cdot$ *slope* difference$_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{i,t}$))

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\text{slope}^{i,\Delta ff_3}_{diff}$	.009***	.009***	.009***	.009***	.010***	.009**	.009***	.010***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
$\Delta ff^{i,1}_{\text{difference}}$		.000						−.000
		(.000)						(.000)
rx^i_{t-1}			−.014					−.019
			(.019)					(.020)
VIX				−.000				−.000
				(.000)				(.000)
ts^{us}10yr					.000*			−.001
					(.000)			(.001)
ts^i10yr					.000			.001
					(.000)			(.001)
dp						−3.132		−2.693
						(3.206)		(3.087)
ff target							−.000	−.001
							(.000)	(.001)
R^2	.002	.003	.002	.002	.004	.002	.003	.006
Adj. R^2	.001	.002	.001	.001	.003	.001	.001	.005
Num. obs.	7632	7632	7615	7566	7353	7566	7632	7337

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions of the form: $rx^i_{t\rightarrow t+1} = \phi_1 \cdot \text{slope difference}_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t\rightarrow t+1}$ is the one-week ahead individual country currency return against the USD, slope difference$_{i,t}$ is the *slope* difference measure ($\text{slope}_{i,t} - \text{slope}_{US,t}$) estimated in the first stage regressions, μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\rightarrow t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). Full Sample *slope* measure obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available data. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_i - \Delta ff^1_{US}$), lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the country 10 year bond term spread ($tsN10yr$), US Equity dividend-price ratio (CRSP) (*dp*), and the federal fund rates target (ff target).

Table B.9: Predictive Regressions Panel of G10 Countries
Model I: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope difference}^{\Delta ff_3}_{i,t} + \mu_i + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{diff}$	.022***	.009***	.007	.021***	.009***	.007
	(.005)	(.003)	(.005)	(.005)	(.003)	(.005)
$\Delta ff^{i,1}_{\text{difference}}$	.000*	.000	.001**	.000	.000	.001
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
R^2	.013	.003	.002	.016	.003	.001
Adj. R^2	.012	.002	.001	.014	.001	-.001
Num. obs.	7640	7632	7611	3875	3877	3876

	FOMC Weeks			No-FOMC and Large Weeks*		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{diff}$	.028***	.015***	.000	.018***	.007**	.010**
	(.005)	(.003)	(.005)	(.005)	(.003)	(.005)
$\Delta ff^{i,1}_{\text{difference}}$	.001***	.000	−.000	.000	.000	.001**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
R^2	.038	.011	.000	.011	.002	.003
Adj. R^2	.032	.005	-.007	.009	-.001	.000
Num. obs.	1211	1211	1211	3323	3324	3323

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for different horizons ($rx^i_{t-j\to t+k}$): (i) impact on current week ($rx_t = rx_{t-1\to t}$, where $j = 1$ and $k = 0$), (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to t+k}$, where $j = 0$ and $k = \{1, 4\}$). Selected Sub-samples: (i) Full sample (all country-week observations), unbalanced panel; (ii) Large *slope* Weeks (weeks with $|\text{slope diff}_{i,t}| > [\mu^n_{\text{slope diff}} + 0.5 \cdot \sigma^n_{\text{slope diff}}]$); (iii) FOMC Weeks only and (iv) No FOMC and Large *slope* weeks (unconditional μ^n and σ^n computed excluding FOMC weeks). Panel regressions of the form: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope difference}_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t-j\to t+k}$ is the individual country currency return against the US, slope difference$_{i,t}$ is the *slope* difference measure ($\text{slope}_{i,t} - \text{slope}_{US,t}$) estimated in the first stage regressions, μ_i are individual country fixed effects. These regressions don't control for additional variables ($X_{i,t}$). Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t + k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). Full Sample *slope* measure obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available data.

Table B.10: Predictive Regressions Panel of G10 Countries
Model II: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_3}_{us,t} + \phi_2 \cdot \text{slope}^{\Delta ff_3}_{i,t} + \mu_i + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{US}$	$-.020^{**}$	$-.010$	$-.003$	$-.019^{*}$	$-.011$	$-.004$
	(.010)	(.007)	(.012)	(.010)	(.007)	(.012)
$\text{slope}^{\Delta ff_3}_{G10\text{ avg}}$	$.022^{***}$	$.009^{***}$	.007	$.021^{***}$	$.008^{***}$	$.008^{*}$
	(.007)	(.003)	(.005)	(.007)	(.003)	(.005)
R^2	.012	.002	.000	.016	.003	.001
Adj. R^2	.011	.001	-.001	.014	.001	-.002
Num. obs.	7640	7632	7611	3875	3877	3876

	FOMC Weeks			No-FOMC and Large Weeks*		
	rx_t	rx_{t+1}	rx_{t+4}	rx_{t0}	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{US}$	$-.007$	$-.029^{***}$	$.020^{*}$	$-.021^{**}$	$-.005$	$-.011$
	(.010)	(.007)	(.012)	(.010)	(.007)	(.012)
$\text{slope}^{\Delta ff_3}_{G10\text{ avg}}$	$.034^{***}$	$.011^{***}$	.006	$.017^{**}$	$.008^{***}$	$.009^{*}$
	(.007)	(.003)	(.005)	(.007)	(.003)	(.005)
R^2	.040	.016	.002	.011	.002	.001
Adj. R^2	.033	.009	-.005	.009	-.001	-.002
Num. obs.	1211	1211	1211	3323	3324	3323

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for different horizons ($rx^i_{t-j\to t+k}$): (i) impact on current week ($rx_t = rx_{t-1\to t}$, where $j = 1$ and $k = 0$), (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to t+k}$, where $j = 0$ and $k = \{1, 4\}$). Selected Sub-samples: (i) Full sample (all country-week observations), unbalanced panel; (ii) Large *slope* Weeks (weeks with $|\text{slope difference}_{i,t}| > [\mu^n_{\text{slope difference}} + 0.5 \cdot \sigma^n_{\text{slope difference}}]$); (iii) FOMC Weeks only and (iv) No FOMC and Large *slope* weeks (unconditional μ^n and σ^n computed excluding FOMC weeks). Panel regressions of the form: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope difference}_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t-j\to t+k}$ is the individual country currency return against the US, $\text{slope difference}_{i,t}$ is the *slope* difference measure ($\text{slope}_{i,t} - \text{slope}_{US,t}$) estimated in the first stage regressions, μ_i are individual country fixed effects. These regressions don't control for additional variables ($X_{i,t}$). Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t + k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available.

Table B.11: Panel of G10 Countries Full Sample – Current Week Impact

Model II ($rx^i_{t-1\to t} = \phi_1 \cdot \; slope_{us,t} + \phi_2 \cdot \; slope_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{i,t})$)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\text{slope}^{\Delta ff_3}_{US}$	$-.013$	$-.020^{**}$	$-.020^{**}$	$-.020^{**}$	$-.021^{**}$	$-.019^{*}$	$-.019^{*}$	$-.020^{**}$	$-.022^{**}$
	(.011)	(.010)	(.010)	(.010)	(.009)	(.010)	(.010)	(.010)	(.009)
$\text{slope}^{\Delta ff_3}_{i}$		$.022^{***}$	$.022^{***}$	$.022^{***}$	$.022^{***}$	$.022^{***}$	$.022^{***}$	$.022^{***}$	$.021^{***}$
		(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Δff^1_i			.000						$-.000$
			(.000)						(.000)
Δff^1_{US}			$-.000^{*}$						.005
			(.000)						(.004)
rx^i_{t-1}				$-.017$					$-.019$
				(.014)					(.016)
VIX					$-.000$				$-.000$
					(.000)				(.000)
ts^{us}10yr						.000			$-.001$
						(.000)			(.001)
ts^{i}10yr						.000			$.002^{**}$
						(.000)			(.001)
dp							-4.461		-3.957
							(3.111)		(3.064)
ff target								$-.000$	$-.007^{*}$
								(.000)	(.004)
R^2	.002	.012	.013	.013	.014	.013	.013	.013	.019
Adj. R^2	.001	.011	.012	.011	.012	.012	.012	.012	.017
Num. obs.	8072	7640	7640	7623	7573	7359	7573	7640	7343

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for current-week returns. Panel regressions of the form: $rx^i_{t-1\to t} ==$ $\phi_1 \cdot \text{slope}_{us,t} + \phi_2 \cdot \text{slope}_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t\to t+1}$ is the individual country currency return against the US one week ahead, slope $_{i,t}$ is the *slope* for country i measure and $\text{slope}_{US,t}$) is the US measure, both estimated in the first stage regressions. μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_i - \Delta ff^1_{US}$), lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the country 10 year bond term spread ($tsN10yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target).

Table B.12: Panel of G10 Countries Full Sample – Forecastability (1-week Ahead Returns)

	Model II ($rx^i_{t\to t+1} = \phi_1 \cdot \; slope_{us,t} + \phi_2 \cdot \; slope_{i,t} + \Omega \cdot X_{i,t} + \mu_i + \epsilon_{i,t})$)								
$\text{slope}^{\Delta ff_3}_{US}$	$-.007$	$-.010$	$-.010$	$-.010$	$-.010$	$-.013^{*}$	$-.009$	$-.010$	$-.014^{*}$
	(.006)	(.007)	(.007)	(.007)	(.008)	(.007)	(.008)	(.007)	(.008)
$\text{slope}^{\Delta ff_3}_{i}$		$.009^{***}$	$.009^{***}$	$.009^{***}$	$.009^{***}$	$.008^{***}$	$.008^{***}$	$.009^{***}$	$.008^{***}$
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Δff^1_i			.000						$-.000$
			(.000)						(.000)
Δff^1_{US}			$-.000$						$-.003$
			(.000)						(.006)
rx^i_{t-1}				$-.014$					$-.020$
				(.019)					(.020)
VIX					$-.000$				$-.000$
					(.000)				(.000)
ts^{us}10yr						$.001^{*}$			$-.001$
						(.000)			(.001)
ts^{i}10yr						.000			.001
						(.000)			(.001)
dp							-3.128		-2.794
							(3.214)		(3.151)
ff target								$-.000$	.002
								(.000)	(.006)
R^2	.001	.002	.003	.002	.002	.005	.002	.003	.007
Adj. R^2	-.000	.001	.002	.001	.001	.003	.001	.001	.005
Num. obs.	8064	7632	7632	7615	7566	7353	7566	7632	7337

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for 1-week ahead returns. Panel regressions of the form: $rx^i_{t\to t+1} = \phi_1 \cdot \text{slope}_{us,t} + \phi_2 \cdot \text{slope}_{i,t} + \Omega X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t\to t+1}$ is the individual country currency return against the US one week ahead, slope $_{i,t}$ is the *slope* for country i measure and $\text{slope}_{US,t}$) is the US measure, both estimated in the first stage regressions. μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^3_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{i,t}$) for each country using full-sample available. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_i - \Delta ff^1_{US}$), lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the country 10 year bond term spread ($tsN10yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target).

Table B.13: Panel of G10 Countries Large *slope* Weeks – 1-Week Returns

Model I ($rx^i_{t\to t+1} = \phi_1 \cdot$ *slope difference*$_{i,t} + \Omega \cdot X_{i,t} + \mu_i + \epsilon_{i,t})$)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\text{slope}^{i,\Delta ff_3}_{diff}$	.009***	.009***	.009***	.009***	.010***	.009***	.009***	.010***	
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	
$\Delta ff^{i,1}_{\text{difference}}$		.000						−.000	
		(.000)						(.000)	
rx^i_{t-1}			−.029					−.035*	
			(.019)					(.020)	
VIX				−.000				−.000	
				(.000)				(.000)	
ts^{us}10yr					.000			−.001	
					(.000)			(.001)	
ts^{i}10yr					−.000			.001	
					(.000)			(.001)	
dp						−1.668		−.002	
						(3.206)		(3.087)	
ff target							−.000	−.001	
							(.000)	(.001)	
R^2	.003	.003	.004	.003	.006	.003	.003	.010	
Adj. R^2	.001	.001	.002	.001	.003	.001	.001	.006	
Num. obs.	3877	3877	3868	3853	3700	3853	3877	3692	

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for current-week returns, Large *slope* Weeks sub-sample (weeks with $|\text{slope difference}_{i,t}| > [\mu^n_{\text{slope difference}} + 0.5 \cdot \sigma^n_{\text{slope difference}}]$). Panel regressions: $rx^i_{t\to t+1} = \phi_1 \cdot \text{slope}_{i,t} + \phi_2 \cdot \text{slope}_{us,t} + \Omega \cdot X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t\to t+1}$ is the individual country currency return against the US one week ahead, $\text{slope}_{i,t}$ is the *slope* measure estimated in the first stage regressions, μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_i - \Delta ff^1_{US}$), lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the country 10 year bond term spread ($tsN10yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target).

Table B.14: Panel of G10 Countries Large *slope* Weeks – Forecastability (1-week Ahead Returns)

Model II $(rx^i_{t\to t+1} = \phi_1 \cdot \; slope_{us,t} + \phi_2 \cdot \; slope_{i,t} + \Omega \cdot X_{i,t} + \mu_i + \epsilon_{i,t}))$

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\text{slope}^{\Delta ff_3}_{US}$	−.008	−.011	−.011	−.011	−.012	−.014*	−.011	−.011	−.016**
	(.006)	(.007)	(.007)	(.007)	(.008)	(.007)	(.008)	(.007)	(.008)
$\text{slope}^{\Delta ff_3}_{i}$		.008***	.008***	.009***	.008***	.008***	.008***	.008***	.008***
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Δff^1_i			.000						−.000
			(.000)						(.000)
Δff^1_{US}			−.000						−.004
			(.000)						(.006)
rx^i_{t-1}				−.029					−.036*
				(.019)					(.020)
VIX					−.000				−.000
					(.000)				(.000)
ts^{us}10yr						.000			−.001
						(.000)			(.001)
ts^{i}10yr						−.000			.001*
						(.000)			(.001)
dp							−1.645		−.280
							(3.214)		(3.151)
ff target								−.000	.003
								(.000)	(.006)
R^2	.001	.003	.004	.004	.004	.006	.003	.004	.012
Adj. R^2	-.001	.001	.001	.002	.001	.003	.001	.001	.007
Num. obs.	4103	3877	3877	3868	3853	3700	3853	3877	3692

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for current-week returns, Large *slope* Weeks sub-sample (weeks with $|\text{slope difference}_{i,t}| > [\mu^n_{\text{slope difference}} + 0.5 \cdot \sigma^n_{\text{slope difference}}])$. Panel regressions: $rx^i_{t\to t+1} = \phi_1 \cdot \text{slope}_{i,t} + \phi_2 \cdot \text{slope}_{us,t} + \Omega \cdot X_{i,t} + \mu_i + \epsilon_{n,t+k}$, where $rx^i_{t\to t+1}$ is the individual country currency return against the US one week ahead, $\text{slope}_{i,t}$ is the *slope* measure estimated in the first stage regressions, μ_i are individual country fixed effects and $X_{i,t}$ is a vector of controls that vary across time and (potentially) across country. Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Additional Controls*: we include changes to one-month futures rates differential $(\Delta ff^1_i - \Delta ff^1_{US})$, lagged individual country returns (rx^i_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread $(tsUS10yr)$, the country 10 year bond term spread $(tsN10yr)$, US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target).

Table B.15: Panel Regressions (G10) – *slope* measure using 6-month futures
Model II: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_6}_{us,t} + \phi_2 \cdot \text{slope}^{\Delta ff_6}_{i,t} + \mu_i + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_6}_{US}$	$-.014$	$-.007$	$-.001$	$-.012$	$-.008$	$-.001$
	(.011)	(.006)	(.011)	(.011)	(.006)	(.011)
$\text{slope}^{\Delta ff_6}_{G10}$	.021***	.009***	.008	.020***	.009***	.009*
	(.008)	(.003)	(.005)	(.008)	(.003)	(.005)
R^2	.012	.002	.000	.015	.003	.001
Adj. R^2	.010	.001	-.001	.012	.001	-.001
Num. obs.	7640	7632	7611	3875	3877	3876

	FOMC Weeks			No-FOMC and Large Weeks*		
	rx_{t0}	rx_{t+1}	rx_{t+4}	rx_{t0}	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_6}_{US}$	.003	$-.026$***	.022*	$-.017$	$-.003$	$-.008$
	(.011)	(.006)	(.011)	(.011)	(.006)	(.011)
$\text{slope}^{\Delta ff_6}_{G10}$	.035***	.013***	.010**	.016**	.007**	.008*
	(.008)	(.003)	(.005)	(.008)	(.003)	(.005)
R^2	.040	.018	.002	.010	.002	.001
Adj. R^2	.033	.011	-.004	.008	-.001	-.002
Num. obs.	1211	1211	1211	3323	3324	3323

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for different horizons ($rx^i_{t-j\to t+k}$): (i) impact on current week ($rx_t = rx_{t-1\to t}$, where $j = 1$ and $k = 0$), (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to t+k}$, where $j = 0$ and $k = \{1, 4\}$). Selected Sub-samples: (i) Full sample (all country-week observations), unbalanced panel; (ii) Large *slope* Weeks (weeks with $|\text{slope difference}_{i,t}| > [\mu^n_{\text{slope difference}} + 0.5 \cdot \sigma^n_{\text{slope difference}}]$); (iii) FOMC Weeks only and (iv) No FOMC and Large *slope* weeks (unconditional μ^n and σ^n computed excluding FOMC weeks). Panel regressions of the form: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_6}_{us,t} + \phi_2 \cdot \text{slope}^{\Delta ff_6}_{i,t} + \mu_i + \epsilon_{t+k}$, where $rx^i_{t-j\to t+k}$ is the individual country currency return against the US, $\text{slope}^{\Delta ff_6}_{i,t}$ is the *slope* measure for country i constructed using 6-month interest rates futures changes in the first stage regression, $\text{slope}^{\Delta ff_6}_{us,t}$ is the US slope measure. μ_i are individual country fixed effects. These regressions don't control for additional variables ($X_{i,t}$). Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^6_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{6,t})$ for each country using full-sample available.

Table B.16: Panel Regressions (G10) – *slope* measure using US-Orthogonal Slope

Model II: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_3}_{us,t} + \phi_2 \cdot \text{slope}^{\Delta ff_3}_{G10\perp US} + \mu_i + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{US}$	$-.019^{*}$	$-.007$	.000	$-.010$	$-.010^{*}$	.009
	(.010)	(.005)	(.012)	(.010)	(.005)	(.012)
$\text{slope}^{\Delta ff_3}_{G10\perp US}$	$.010^{**}$	$-.002$	$-.005$	.003	$-.002$	$-.008$
	(.005)	(.004)	(.006)	(.005)	(.004)	(.006)
R^2	.004	.001	.000	.001	.001	.001
Adj. R^2	.003	-.001	-.001	-.001	-.001	-.002
Num. obs.	6645	6637	6616	3171	3171	3170

	FOMC Weeks			No-FOMC and Large Weeks*		
	rx_{t0}	rx_{t+1}	rx_{t+4}	rx_{t0}	rx_{t+1}	rx_{t+4}
$\text{slope}^{\Delta ff_3}_{US}$	$-.032^{***}$	$-.007$	.017	$-.008$	$-.011^{**}$	.001
	(.010)	(.005)	(.012)	(.010)	(.005)	(.012)
$\text{slope}^{\Delta ff_3}_{G10\perp US}$	$.013^{***}$	$-.001$	.006	.003	$-.003$	$-.009$
	(.005)	(.004)	(.006)	(.005)	(.004)	(.006)
R^2	.011	.000	.001	.001	.002	.001
Adj. R^2	.003	-.007	-.007	-.002	-.001	-.002
Num. obs.	1054	1053	1053	2710	2711	2710

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly panel regressions for different horizons ($rx^i_{t-j\to t+k}$): (i) impact on current week ($rx_t = rx_{t-1\to t}$, where $j = 1$ and $k = 0$), (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to t+k}$, where $j = 0$ and $k = \{1, 4\}$). Selected Sub-samples: (i) Full sample (all country-week observations), unbalanced panel; (ii) Large *slope* Weeks (weeks with $|\text{slope difference}_{i,t}| > [\mu^n_{\text{slope difference}} + 0.5 \cdot \sigma^n_{\text{slope difference}}]$); (iii) FOMC Weeks only and (iv) No FOMC and Large *slope* weeks (unconditional μ^n and σ^n computed excluding FOMC weeks). Panel regressions of the form: $rx^i_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_6}_{us,t} + \phi_2 \cdot \text{slope}^{\Delta ff_6}_{i,t} + \mu_i + \epsilon_{t+k}$, where $rx^i_{t-j\to t+k}$ is the individual country currency return against the US, $\text{slope}^{\Delta ff_6}_{i,t}$ is the *slope* measure for country i constructed using 6-month interest rates futures changes in the first stage regression, $\text{slope}^{\Delta ff_6}_{us,t}$ is the US slope measure. μ_i are individual country fixed effects. These regressions don't control for additional variables ($X_{i,t}$). Country G10 currency returns data built from Thomson Reuters. Currency (log) excess returns for country n from week t to $t+k$ is defined as $rx^i_{t\to t+k} = f^i_t - s^i_t - \Delta s^i_{t+1}$, where f_t is the (log) currency forward rate and s_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^6_{i,t} = \Delta ff^1_{i,t} + \text{slope}^3_{6,t}$) for each country using full-sample available.

Table B.17

Long-Short Country *slope* Portfolio Sharpe Ratio

		Training Sample for Rolling *slope* Estimation								
Sub-Sample Weeks	**Avg***	2000	2001	2002	2003	2004	2005	2006	2007	2008
Full Sample	**0.374**	0.319	0.281	0.277	0.362	0.258	0.256	0.274	0.594	0.742
FOMC Weeks	**0.682**	0.748	0.474	0.799	0.637	0.598	0.452	0.848	0.923	0.659
Large *slope* (US, $\overline{G10}$)	**0.517**	0.402	0.393	0.255	0.348	0.329	0.428	0.486	0.92	1.095
No FOMC and Large (US, $\overline{G10}^a$)	**0.235**	0.344	0.393	-0.049	0.018	0.032	0.142	0.088	0.509	0.641
Large *slope* ((slope$_n$)^b)	**0.496**	0.42	0.336	0.343	0.402	0.282	0.36	0.274	0.823	1.226
No FOMC and Large ((slope$_n$)^b)	**0.518**	0.384	0.382	0.308	0.345	0.263	0.336	0.181	0.774	1.686

Notes: Table reports Sharpe ratios (annualized) adjusted for Transaction Costs of a strategy that uses individual country monetary slope information at t to construct a long short portfolio. Panel regressions point estimates suggest a positive momentum for individual country slopes: when $\text{slope}_{i,t} > 0$, that is the change in interest rate futures term structure slope is positive, there is a positive return for the currency over 1-4 weeks ahead in addition to the positive impact observed on current weeks. We sort currencies by their slope point estimate every week, going long the currencies with higher slope and short currencies with lower slope estimates. We re-balance this portfolio every week. The columns in the table are fixed yearly cut-offs for both the estimation of first stage regression and for the computation of out-of-sample Sharpe ratios of the conditional long-short *slope* strategy: for each training sample (Ts) we estimate the model in equation (1.15) using data up to Ts, save for each country i the coefficients of the first stage regression α^n_{Ts} and β^n_{Ts} estimates up to $t = Ts$. We then use them to compute $\text{slope}^n_{\{Ts+1,\dots,T\}}$ and use this conditional *slope* measure to form portfolios of long-short country *slope* for each week until the end of our sample. We re-balance each week and calculate Sharpe ratios of this strategy from year Ts until 2017 (the end of our sample), adjusting from approximate transaction costs of each re-balancing. This test is therefore implicitly controlling for both a potential instability in the first stage regression and also of the strategy conditional return and volatility. $*$ The column Average is the simple average of all yearly cut-off Sharpe ratios. We also implement this strategy on different sub-samples: (i) all sample weeks, (ii) on FOMC Weeks only; (iii) on weeks with large G10 average slope ($\overline{G10}^a$): weeks with $|\text{slope}^{G10}_t| > \mu_T + 0.5 \cdot \sigma_T$, where slope^{G10} is a synthetic G10 *slope* average; (iv) in No-FOMC weeks with large G10 slope; (v) weeks with large individual country slopes in each bin (long and short): $|\text{slope}^n_t| > \mu^n_T + 0.5 \cdot \sigma^n_T$), that is we include all weeks when at least the *slope* in the long and short bins are higher than this threshold and (vi) no-FOMC weeks with large individual *slopes*

Table B.18

Long-Short Country *slope* Portfolio Loadings on Currency Risk-Factors

(a) Monthly Currency Risk-Factors based on Verdelhan *et al.* (2011)

	Rolling *slope* 2-Year			Rolling *slope* 5-Year			Rolling *slope* 10-Year		
Monthly α^j	.0037*	.0041*	.0037*	.0034*	.0036**	.0034*	.0044**	.0044***	.0044**
	(.0021)	(.0021)	(.0021)	(.0018)	(.0016)	(.0018)	(.0017)	(.0016)	(.0017)
Carry-Trade Factor (HmL)	.0571		.0690	.0459		.0405	−.0211		−.0066
	(.0829)		(.0915)	(.0860)		(.0914)	(.0890)		(.1079)
Dollar Factor		−.0274	−.0541		.0364	.0213		−.0452	−.0421
		(.1025)	(.1139)		(.0939)	(.1005)		(.0982)	(.1196)
R^2	.0017	.0002	.0025	.0019	.0008	.0022	.0005	.0016	.0017
Adj. R^2	-.0023	-.0038	-.0055	-.0027	-.0038	-.0071	-.0055	-.0043	-.0103
Num. obs.	253	253	253	218	218	218	170	170	170

(b) Weekly G10 Sample Currency Risk Factors

	Rolling *slope* 2-Year			Rolling *slope* 5-Year			Rolling *slope* 10-Year		
Weekly α^j	.0009*	.0009**	.0009*	.0008**	.0008**	.0008**	.0010***	.0010***	.0010***
	(.0005)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0003)	(.0003)	(.0003)
Carry-Trade Factor (G10 weekly HmL)	.0429		−.0092	−.0537		−.0623*	−.0155		−.0092
	(.0346)		(.0558)	(.0346)		(.0353)	(.0387)		(.0419)
Dollar Factor (G10 weekly)		−.2977	−.2993		−.0092	−.0409		.0332	.0273
		(.2452)	(.2628)		(.0419)	(.0410)		(.0481)	(.0523)
R^2	.0023	.0461	.0458	.0075	.0001	.0089	.0010	.0016	.0019
Adj. R^2	.0014	.0452	.0440	.0064	-.0010	.0068	-.0004	.0002	-.0009
Num. obs.	1096	1098	1096	940	942	940	734	734	734

Notes: Long-short *slope* portfolio spanning by other currency risk factors. Panel (a) monthly returns of two risk factors in the currency literature: the carry trade factor and the dollar factor. Data for these factors returns are based on Verdelhan *et al.* (2007) and Verdelhan *et al.* (2011) updated version on the author's website. We combine our weekly portfolio data-set with monthly factor data by summing our weekly returns based strategies in a given month. Naturally this may lead to measurement error. In panel (b) We use as risk factors the carry-trade portfolio and the Dollar portfolio from our weekly return data set for G10 countries. Long-Short *slope* portfolio sort currencies by their slope point estimate every week, going long the currencies with lower slope and short currencies with higher slope estimates. We re-balance this portfolio every week. Results reported for recursively Adjusted *slope* Measures: for each training sample (2-year, 5-year and 10-year) we estimate the model in equation (1.15), compute for each country i estimates up to $t = Ts$ and use them to compute $\text{slope}^n_{\{Ts+1,\dots,T\}}$. We then use this conditional *slope* measure to form portfolios of long-short country *slope*, re-balancing for each week until the end of our sample

Table B.19: Predictive Regressions Dollar Portfolio
Model I: $rx^{G10}_{t-j\to t+k} = \phi_1 \cdot \text{slope difference}^{\Delta ff_3}_{G10,t} + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks			No-FOMC and Large Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
constant	.000	.000	.001	.000	.000	.002**	.000	−.000	−.000
	(.000)	(.000)	(.001)	(.000)	(.000)	(.001)	(.001)	(.001)	(.002)
$\text{slope}^{i,\Delta ff_3}_{diff}$	.025***	.010*	.007	.025***	.010*	.005	.016**	.014	.026*
	(.007)	(.006)	(.011)	(.008)	(.006)	(.012)	(.008)	(.010)	(.016)
R^2	.019	.003	.000	.026	.005	.000	.021	.010	.010
Adj. R^2	.018	.002	-.001	.025	.003	-.001	.015	.004	.004
Num. obs.	1157	1156	1153	638	638	638	173	173	173

	FOMC Weeks			Pre-2008 Weeks			No-FOMC and Large Weeks**		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
constant	.001	−.000	.000	.000	.000	.001	.001	.000	.001
	(.001)	(.001)	(.002)	(.000)	(.000)	(.001)	(.001)	(.001)	(.001)
$\text{slope}^{i,\Delta ff_3}_{diff}$	.033	.021	.009	.019**	.008	.003	.015**	.006	.014
	(.023)	(.014)	(.025)	(.008)	(.006)	(.012)	(.007)	(.007)	(.015)
R^2	.042	.017	.001	.015	.003	.000	.010	.002	.002
Adj. R^2	.037	.011	-.005	.013	.001	-.001	.007	-.001	-.001
Num. obs.	183	183	183	714	714	714	321	321	321

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly predictive regressions of the long G10 currencies (Short US dollar). Models use the *slope* difference measure (slope $\text{difference}_{G10,t} = \text{slope}_{G10,t} - \text{slope}_{US,t}$)). Table presents different return horizons :(i) impact on current week ($rx_t = rx_{t-1\to t}$, (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to\ t+k}$. Selected Sub-samples: (i) Full sample; (ii) Large *slope* Weeks (weeks with $|\text{slope difference}_{G10,t}| > [\mu^{G10}_{\text{slope difference}} + 0.5 \cdot \sigma^{G10}_{\text{slope difference}}]$); (iii) No FOMC and Large *slope* weeks (μ^{G10} and σ^{G10} computed excluding FOMC weeks); (iv) FOMC Weeks only, (v) Pre 2008 sample (to exclude Quantitative easing period in the US and other developed countries) and (vi) No Fomc and Large, a cut that considers 1/4 of *slope* standard deviation rather than 1/2. Variables: $rx^{G10}_{t-j\to t+k}$ is the long G10 currency portfolio (short dollar), estimated in the first stage regressions. These regressions don't control for additional variables (X_t). Dollar portfolio (log) excess returns computed using equal weighted averages: $rx^{G10}_{t\to t+k} = N^{-1}\sum^i (f^i_t - s^i_t - \Delta s^i_{t+k})$, where f^i_t is the (log) currency forward rate and s^i_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Full Sample slope measure*: obtained from the first stage regression for each country using full-sample. *slope* G10 is the simple cross-section average of individual country slopes

Table B.20: Regressions of Long G10 Portfolio Full Sample – Current Week Impact

	slope Difference and Controls (Model I) - Current Week Return ($rx_{t-1\to t}$)							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
constant	.000	.000	.000	.002*	−.001	.001*	.001	.003
	(.000)	(.000)	(.000)	(.001)	(.001)	(.000)	(.000)	(.002)
$\text{slope}_{diff}^{\Delta ff_3}$	.025***	.026***	.025***	.026***	.026***	.025***	.026***	.028***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
$\Delta ff^1_{\text{difference}}$		.001						.002
		(.004)						(.004)
rx^{G10}_{t-1}			.015					.005
			(.031)					(.031)
VIX				−.000				−.000
				(.000)				(.000)
ts US10yr					.000*			−.001
					(.000)			(.001)
ts G1010yr					.000			.002**
					(.000)			(.001)
dp						−4.288		−4.528
						(3.127)		(3.181)
ff target							−.000	−.002*
							(.000)	(.001)
R^2	.019	.019	.019	.023	.022	.021	.019	.033
Adj. R^2	.018	.017	.017	.021	.019	.019	.018	.026
Num. obs.	1157	1157	1157	1146	1144	1146	1157	1144

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly Impact regressions of the Dollar Portfolio (a Long G10 currencies and Short Dollar, simple weighted) for one current week returns, using the Full Sample: $rx^{G10}_{t-1\to t} = \phi_1 \cdot \text{slope difference}_{G10,t} + \Omega X_{i,t} + \epsilon_{G10,t+k}$, where $rx^{G10}_{t\to t+1}$ is the Dollar portfolio return1-week ahead, $\text{slope difference}_{G10,t}$ is the *slope* difference measure ($\text{slope}_{G10,t} - \text{slope}_{US,t}$) estimated in the first stage regressions and $X_{i,t}$ is a vector of controls that vary across time. Country G10 currency returns data built from Thomson Reuters. *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^3_{G10,t} = \Delta ff^1_{G10,t} + \text{slope}^3_{G10,t})$ where $\Delta ff^1_{G10,t}$ is the simple average of changes in 1-week forwards at week t. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_{G10} - \Delta ff^1_{US}$), lagged individual country returns (rx^{G10}_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the average G10 10 year bond term spread ($tsG1010yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target)

Table B.21: Regressions of Long G10 Portfolio Full Sample – Forecastability (1-week Ahead Returns)

	slope Difference and Controls (Model I) - One-Week Ahead Returns ($rx_{t \to t+1}$)							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
constant	.000	.000	.000	.000	−.001	.001	.001	.001
	(.000)	(.000)	(.000)	(.001)	(.001)	(.001)	(.001)	(.002)
$\text{slope}^{\Delta ff_3}_{diff}$	.010*	.010*	.010*	.010*	.011*	.010*	.010*	.011*
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
$\Delta ff^1_{\text{difference}}$		−.001						−.000
		(.004)						(.004)
rx^{G10}_{t-1}			−.001					−.008
			(.033)					(.033)
VIX				−.000				−.000
				(.000)				(.000)
ts US10yr					.000			−.001
					(.000)			(.001)
ts G1010yr					.000			.001
					(.000)			(.001)
dp						−2.854		−3.380
						(3.280)		(3.353)
ff target							−.000	−.001
							(.000)	(.001)
R^2	.003	.003	.003	.003	.005	.004	.004	.008
Adj. R^2	.002	.001	.001	.001	.002	.002	.002	.001
Num. obs.	1156	1156	1156	1145	1143	1145	1156	1143

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly predictive regressions of the Dollar Portfolio (a Long G10 currencies and Short Dollar, simple weighted) for one week ahead returns, using the Full Sample: $rx^{G10}_{t \to t+1} = \phi_1 \cdot \text{slope difference}_{G10,t} + \Omega X_{i,t} + \epsilon_{G10,t+k}$, where $rx^{G10}_{t \to t+1}$ is the Dollar portfolio return1-week ahead, slope difference$_{G10,t}$ is the *slope* difference measure ($\text{slope}_{G10,t} - \text{slope}_{US,t}$) estimated in the first stage regressions and $X_{i,t}$ is a vector of controls that vary across time. Country G10 currency returns data built from Thomson Reuters. *Full Sample slope measure*: obtained from the first stage regression $\Delta ff^3_{G10,t} = \Delta ff^1_{G10,t} + \text{slope}^3_{G10,t}$) where $\Delta ff^1_{G10,t}$ is the simple average of changes in 1-week forwards at week t. *Additional Controls*: we include changes to one-month futures rates differential ($\Delta ff^1_{G10} - \Delta ff^1_{US}$), lagged individual country returns (rx^{G10}_{t-1}), the VIX as a volatility measure, the US 10 year bond term spread ($tsUS10yr$), the average G10 10 year bond term spread ($tsG1010yr$), US Equity dividend-price ratio (CRSP) (dp), and the federal fund rates target (ff target)

Table B.22: Predictive Regressions Dollar Portfolio
Model II: $rx^{G10}_{t-j\to t+k} = \phi_1 \cdot \text{slope}^{\Delta ff_3}_{US,t} + \phi_2 \cdot \text{slope}^{\Delta ff_3}_{G10,t} + \epsilon_{t+k}$

Selected Sub-Samples

	Full Sample			Large *slope* Weeks			No-FOMC and Large Weeks		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
constant	.000	.000	.001	.000	.000	.002**	.000	.000	−.000
	(.000)	(.000)	(.001)	(.000)	(.000)	(.001)	(.001)	(.001)	(.002)
$\text{slope}^{\Delta ff_3}_{US}$	−.023***	−.010*	−.004	−.022***	−.011*	−.002	−.018**	−.012	−.022
	(.007)	(.006)	(.011)	(.007)	(.007)	(.012)	(.008)	(.010)	(.019)
$\text{slope}^{\Delta ff_3}_{i}$	.031***	.011	.014	.031**	.009	.009	.002	.023	.048
	(.011)	(.008)	(.016)	(.012)	(.008)	(.016)	(.011)	(.015)	(.031)
R^2	.020	.003	.001	.028	.005	.001	.034	.014	.016
Adj. R^2	.018	.001	-.001	.025	.002	-.003	.023	.002	.004
Num. obs.	1157	1156	1153	638	638	638	173	173	173
	FOMC Weeks			**Pre-2008 Weeks**			**No-FOMC and Large Weeks****		
	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}	rx_t	rx_{t+1}	rx_{t+4}
constant	.001	−.000	.000	.000	.000	.001	.001	.000	.001
	(.001)	(.001)	(.002)	(.000)	(.000)	(.001)	(.001)	(.001)	(.001)
$\text{slope}^{\Delta ff_3}_{US}$	−.015	−.028*	.020	−.018**	−.009	−.000	−.018**	−.006	−.010
	(.019)	(.014)	(.032)	(.007)	(.006)	(.011)	(.007)	(.008)	(.014)
$\text{slope}^{\Delta ff_3}_{i}$	.059*	.010	.006	.020*	.007	.007	.006	.007	.027
	(.032)	(.019)	(.034)	(.012)	(.008)	(.018)	(.009)	(.011)	(.023)
R^2	.077	.023	.004	.015	.003	.000	.014	.002	.004
Adj. R^2	.067	.012	-.007	.012	.000	-.003	.008	-.005	-.002
Num. obs.	183	183	183	714	714	714	321	321	321

Notes: Significance Values $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports weekly predictive regressions of the long G10 currencies (Short US dollar). Models use the both *slope* measures ($\text{slope}_{G10,t}$) and $\text{slope}_{US,t}$). Table presents different return horizons :(i) impact on current week ($rx_t = rx_{t-1\to t}$, (ii) forecast 1 and 4-weeks ahead ($rx_{t+k} = rx_{t\to t+k}$. Selected Sub-samples: (i) Full sample; (ii) Large *slope* Weeks (weeks with $|\text{slope difference}_{G10,t}| > [\mu^{G10}_{\text{slope difference}} + 0.5 \cdot \sigma^{G10}_{\text{slope difference}}]$); (iii) No FOMC and Large *slope* weeks (μ^{G10} and σ^{G10} computed excluding FOMC weeks); (iv) FOMC Weeks only, (v) Pre 2008 sample (to exclude Quantitative easing period in the US and other developed countries) and (vi) No Fomc and Large, a cut that considers 1/4 of *slope* standard deviation rather than 1/2. Variables: $rx^{G10}_{t-j\to t+k}$ is the long G10 currency portfolio (short dollar), estimated in the first stage regressions. These regressions don't control for additional variables (X_t). Dollar portfolio (log) excess returns computed using equal weighted averages: $rx^{G10}_{t\to t+k} = N^{-1}\sum^{i}(f^i_t - s^i_t - \Delta s^i_{t+k})$, where f^i_t is the (log) currency forward rate and s^i_t is the (log) exchange rate against the dollar (an increase in s_t means a depreciation of the foreign currency against the dollar). *Full Sample slope measure*: obtained from the first stage regression for each country using full-sample. *slope* G10 is the simple cross-section average of individual country slopes

Table B.23

Long-Short Dollar Portfolio Conditioning on Monetary *slope*
Sharpe Ratio – Rolling *slope* Estimates

	Full Sample			Large *slope* Weeks			FOMC Weeks			No-FOMC and Large		
Train Sample	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Mean	0.398	-0.148	-0.262	0.56	0.321	0.444	0.26	0.192	0.309	0.901	0.519	0.275
Rolling:1998	0.342	-0.08	-0.152	0.344	0.104	0.106	0.151	-0.04	-0.005	1.181	0.729	0.519
Rolling:1999	0.466	0.077	-0.005	0.488	0.22	0.505	0.273	0.175	0.42	1.179	0.687	0.318
Rolling:2000	0.431	-0.123	-0.018	0.585	0.154	0.602	0.374	0.113	0.562	1.165	0.457	0.377
Rolling:2001	0.331	-0.609	-0.516	0.57	0.111	0.374	0.321	0.071	0.318	0.865	-0.246	0.101
Rolling:2002	0.318	-0.55	-0.563	0.514	0.252	0.41	0.102	0.045	0.171	0.787	-0.066	0.157
Rolling:2003	0.311	-0.43	-0.42	0.565	0.409	0.72	0.16	0.151	0.511	0.721	0.243	0.338
Rolling:2004	0.509	0.081	-0.146	0.777	0.456	0.52	0.452	0.368	0.536	0.766	0.942	0.059
Rolling:2005	0.491	-0.021	-0.177	0.842	0.685	0.703	0.52	0.484	0.633	0.823	0.815	0.258
Rolling:2006	0.521	0.086	-0.18	0.783	0.74	0.637	0.4	0.487	0.434	0.67	0.909	0.574
Rolling:2007	0.545	0.204	-0.238	0.505	0.534	0.287	0.139	0.435	0.089	0.78	1.031	0.266

Notes: Table reports Sharpe ratios (annualized) adjusted for Transaction Costs of a strategy that uses *slope* difference information at t to go long or short the *Dollar Portfolio*. Point estimates suggest a positive momentum for the US slope and a negative for G10 average slope. We re-balance this portfolio every week. We implement this strategy on different sub-samples: all sample weeks, on FOMC Weeks only, on weeks with large G10 average slope (bigger in absolute values than 0.5 times the standard deviation, always computed up to the week we are forming the portfolio) and in No-FOMC weeks with large G10 slope ($|\text{slope}_t^{G10}| > \mu_T^{G10} + 0.5 \cdot \sigma_T^{G10}$). Recursively Adjusted *slope* Measures: for each training sample (Ts) we estimate the model in equation (1.15), compute the $\alpha_{Ts}^{G10,us}$ and $\beta_{Ts}^{G10,us}$ estimates up to $t = Ts$ and use them to compute $\text{slope}_{\{Ts+1,\ldots,T\}}^{G10,us}$. We present here results for the baseline models: M1 uses *slope* difference (slope difference_{G10}); M2 both US and G10 *slope* to condition (since $\phi_1^{US} > 0$ and $\phi_2^{G10} < 0$ we consider weeks when either US *slope* measure is positive or G10 *slope* measure is negative to go long the US dollar and short other G10 currencies); M3 use only US monetary slope estimated from 3-month forwards)

Table B.24
Out-of-Sample R-Squared Dollar Portfolio – Baseline Models

	Full Sample					Large *slope* Weeks				
Stats	N	M1	M2	M3	M4	N	M1	M2	M3	M4
IS R-Squared	1154	0.18	0.19	0.12	0.71	616	0.34	0.36	0.23	1.31
IS Adj.R-Squared	1154	0.1	0.02	0.04	0.53	616	0.18	0.04	0.07	1.69
slope Rolling: 12-1998	910	-0.77	-1.03	-0.94	-1.02	349	0.1	-0.49	-0.32	-0.4
slope Rolling: 12-1999	859	-0.39	-0.65	-0.59	-0.67	324	0.09	-0.45	-0.29	-0.47
slope Rolling: 12-2000	807	-0.27	-0.47	-0.41	-0.67	303	0.14	-0.24	-0.09	-0.23
slope Rolling: 12-2001	755	-0.38	-0.49	-0.44	-0.5	272	0.22	0.02	0.12	0.01
slope Rolling: 12-2002	703	-0.54	-0.62	-0.57	-.39	239	0.23	0.1	0.21	0.47
slope Rolling: 12-2003	651	-0.71	-0.79	-0.74	-0.55	215	0.18	0.03	0.15	0.43
slope Rolling: 12-2004	599	-0.74	-0.82	-0.78	-0.55	202	0.19	0.06	0.2	0.48
slope Rolling: 12-2005	547	-0.78	-0.86	-0.82	-0.56	175	0.28	0.12	0.25	0.6
slope Rolling: 12-2006	495	-1.02	-1.1	-1.05	-0.78	153	0.29	0.15	0.3	0.61
slope Rolling: 12-2007	443	-1.36	-1.44	-1.37	-1.09	115	0.22	0.08	0.26	0.62

Notes: Out-of-sample R-squared statistic from Campbell and Thompson (2008). Weekly rolling predictive regressions of the *Dollar Portfolio* (a Long G10 currencies and Short Dollar) for one week ahead returns. FX Portfolio weekly return data built using individual G10 country currency returns from Thomson Reuters. For each Training Sample $t = [1 : T_0]$ we estimate the *slope* model until T_0. We then use the estimated coefficients up to T_0 compute out-of-sample slope point estimates from $t = [T0, T]$ and compute recursively the out-of-sample R-squared statistic. We present here results for the baseline models: M1 uses the slope differential ($\text{slope}_{\text{diff}} = \text{slope}^{\Delta ff3}_{G10} - \text{slope}^{\Delta ff3}_{US}$), M2 uses both US slope and G10 (avg) and M3 uses only US monetary slope to forecast currency returns out-of-sample. We present results for the full sample and also for the large slope sub-sample and No-FOMC Weeks and Large *slope* sub-sample ($|\ \text{slope}^n_t\ | > \mu^n(\text{slope}^n_t) + 0.5 \times \sigma^n(\text{slope}^n_t)$))

Table B.25

Dynamically Traded Long G10-Short US dollar Portfolio Loadings on Currency Risk-Factors

(a) Monthly Currency Risk-Factors based on Verdelhan *et al.* (2011)

	Rolling *slope* 2-Year			Rolling *slope* 5-Year			Rolling *slope* 10-Year		
Monthly α^j	.0023	.0021	.0023	.0039**	.0041***	.0040**	.0031	.0033*	.0032
	(.0017)	(.0015)	(.0017)	(.0018)	(.0015)	(.0017)	(.0021)	(.0018)	(.0020)
Carry-Trade Factor (HmL)	−.0703		−.0342	−.0286		.0250	−.0798		.0509
	(.0860)		(.0879)	(.0886)		(.1050)	(.1126)		(.1405)
Dollar Factor		−.1719	−.1582		−.1941	−.2038		−.3348**	−.3595*
		(.1374)	(.1461)		(.1303)	(.1535)		(.1460)	(.1874)
R^2	.0053	.0180	.0191	.0008	.0244	.0250	.0051	.0676	.0694
Adj. R^2	.0012	.0140	.0111	-.0040	.0198	.0157	-.0009	.0620	.0579
Num. obs.	248	248	248	213	213	213	166	166	166

(b) Weekly G10 Sample Currency Risk Factors

	Rolling *slope* 2-Year			Rolling *slope* 5-Year			Rolling *slope* 10-Year		
Weekly α^j	.0005	.0005	.0005	.0009**	.0009**	.0009**	.0007*	.0007*	.0007*
	(.0003)	(.0003)	(.0003)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)
Carry-Trade Factor (G10 weekly HmL)	−.0454		−.0395	−.0388		−.0417	−.0668*		−.0339
	(.0351)		(.0375)	(.0370)		(.0371)	(.0399)		(.0390)
Dollar Factor (G10 weekly)		.0515	.0344		.0111	−.0142		.1657**	.1441*
		(.1081)	(.1143)		(.0773)	(.0791)		(.0833)	(.0866)
R^2	.0051	.0027	.0062	.0041	.0001	.0043	.0125	.0276	.0303
Adj. R^2	.0041	.0017	.0043	.0030	-.0010	.0021	.0111	.0262	.0275
Num. obs.	1042	1044	1042	908	910	908	705	705	705

Notes: Dynamically traded long G10 Portfolio spanning by other currency risk factors. Panel (a) monthly returns of two risk factors in the currency literature: the carry trade factor and the dollar factor.Data for these factor returns are based on Verdelhan *et al.* (2007) and Verdelhan *et al.* (2011) updated version on the author's website. We combine our weekly portfolio data-set with monthly factor data by summing our weekly returns based strategies in a given month. Naturally this may lead to measurement error. In panel (b) We use as risk factors the carry-trade portfolio and the Dollar portfolio using our weekly return data set. *Tactical Dollar portfolio*: we use average G10 *slope* difference (against the US) information at t to go long or short an average of G10 currencies against the US dollar, re-balancing weekly according to *slope* signal. Results reported for recursively Adjusted *slope* Measures: for each training sample (2-year, 5-year and 10-year) we estimate the model in equation (1.15), compute for each country i estimates up to $t = Ts$ and use them to compute $\text{slope}^n_{\{Ts+1,\ldots,T\}}$. We then use this conditional *slope* measure to form portfolios of long-short country *slope*, re-balancing for each week until the end of our sample

Table B.26

US Slope Predicts Future US Rates Changes

$$i^{us}_{t+k} = \theta_0 + \theta_1 \cdot \text{slope}^{3,6}_{US,t} + \mu_{t+k}$$

	Interest Rate on Deposits				One-Month Interest Rates Futures				Future FED Funds	
	i^{us}_{t+4}	i^{us}_{t+8}	i^{us}_{t+12}	i^{us}_{t+24}	$ff^{1,us}_{t+4}$	$ff^{1,us}_{t+8}$	$ff^{1,us}_{t+12}$	$ff^{1,us}_{t+24}$	fed_{t+4}	fed_{t+12}
constant	$-.011^{*}$	$-.023^{**}$	$-.035^{***}$	$-.086^{***}$	$-.011^{**}$	$-.023^{***}$	$-.035^{***}$	$-.085^{***}$	$-.001$	$-.001$
	(.006)	(.009)	(.013)	(.021)	(.005)	(.008)	(.012)	(.021)	(.012)	(.021)
$\text{slope}^{\Delta ff_3}_{US}$	1.163^{***}	1.751^{***}	2.157^{***}	3.129^{***}	$.983^{***}$	1.621^{***}	2.282^{***}	3.265^{***}	0.659^{***}	2.010^{***}
	(.111)	(.167)	(.229)	(.387)	(.084)	(.152)	(.211)	(.379)	(.194)	(.337)
R^2	.087	.087	.072	.055	.108	.091	.093	.062	.017	.051
Adj. R^2	.087	.086	.071	.054	.107	.090	.092	.061	.016	0.049
Num. obs.	1151	1147	1143	1131	1151	1147	1143	1131	656	656

Notes: This table reports weekly predictive regressions of changes in future realized US interest rates on short-term US *slope* extracted from 3-month interest rates futures contracts. We compute forward-looking future 4,8,12 and 24-months changes for several interest rates measures: the first is derived from interest-rates on deposits. The second is derived directly from future changes in the 1-month future FED Funds contract k-months ahead. The third is the future change in the Effective Fed Fund

Table B.27

Slope Difference Predicts future Interest Rates Differential

$[i^{G10}_{t+k} - i^{us}_{t+k}] = \theta_0 + \theta_1 \cdot [\text{slope}^3_{G10,t} - \text{slope}^3_{US,t}] + \mu_{t+k}$

	4-Week Ahead Interest Rate Differential ($i^{G10}_{t+4} - i^{us}_{t+4}$)						
	EUR	JPY	GBP	CAD	AUD	NZD	CHF
constant	$-.010^{*}$	.003	$-.016^{**}$	$-.008$	$-.008$	$-.013$	$-.002$
	(.006)	(.005)	(.008)	(.007)	(.008)	(.009)	(.006)
slope difference$_i^{\Delta ff_3}$	$.579^{***}$	$.770^{***}$	$.660^{***}$	$.325^{***}$	$.422^{***}$	$.249^{***}$	$.423^{***}$
	(.086)	(.081)	(.099)	(.076)	(.076)	(.092)	(.077)
R^2	.039	.074	.054	.016	.026	.007	.026
Adj. R^2	.038	.073	.053	.015	.025	.006	.025
Num. obs.	1112	1135	787	1135	1135	1085	1135

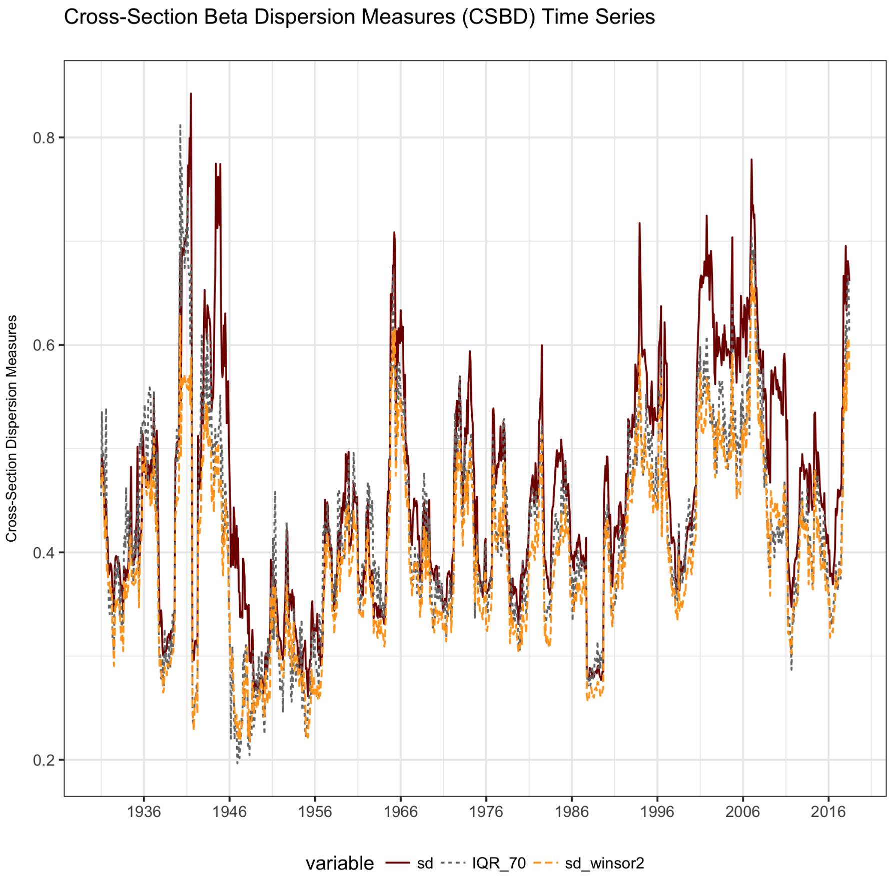
	8-Week Ahead Interest Rate Differential ($i^{G10}_{t+8} - i^{us}_{t+8}$)						
	EUR	JPY	GBP	CAD	AUD	NZD	CHF
constant	$-.020^{**}$	.009	$-.029^{**}$	$-.011$	$-.014$	$-.024^{*}$	$-.007$
	(.010)	(.009)	(.012)	(.010)	(.012)	(.014)	(.010)
slope difference$_i^{\Delta ff_3}$	$.919^{***}$	1.107^{***}	$.918^{***}$	$.321^{***}$	$.737^{***}$	$.395^{***}$	$.536^{***}$
	(.143)	(.138)	(.154)	(.097)	(.111)	(.140)	(.118)
R^2	.036	.053	.043	.009	.037	.007	.018
Adj. R^2	.035	.053	.042	.009	.036	.006	.017
Num. obs.	1121	1144	783	1144	1144	1091	1144

	12-Week Ahead Interest Rate Differential ($i^{G10}_{t+12} - i^{us}_{t+12}$)						
	EUR	JPY	GBP	CAD	AUD	NZD	CHF
constant	$-.023^{*}$	.016	$-.043^{***}$	$-.012$	$-.011$	$-.031^{*}$	$-.007$
	(.013)	(.012)	(.016)	(.011)	(.016)	(.018)	(.012)
slope difference$_i^{\Delta ff_3}$	1.385^{***}	1.443^{***}	1.246^{***}	$.410^{***}$	$.953^{***}$	$.568^{***}$	$.760^{***}$
	(.194)	(.189)	(.200)	(.114)	(.142)	(.183)	(.147)
R^2	.044	.049	.048	.011	.039	.009	.023
Adj. R^2	.043	.048	.046	.011	.038	.008	.022
Num. obs.	1100	1123	776	1123	1123	1073	1123

Notes: This table reports weekly predictive regressions of changes in future realized interest rates differentials between G10 countries and the US using as regressors current *slope difference* extracted from 3-month interest rates futures contracts from G10 and the US. We compute forward-looking future 4,8 and 12-months changes for interest rates differences extracted from currency futures discounts ($i^{G10}_{t+k} \approx s^i_{t+k+1} - f^i_{t+k}$).

C
Figures of Chapter 2

Figure C.1
Cross-Section Beta Dispersion Measures (CSBD) Time Series

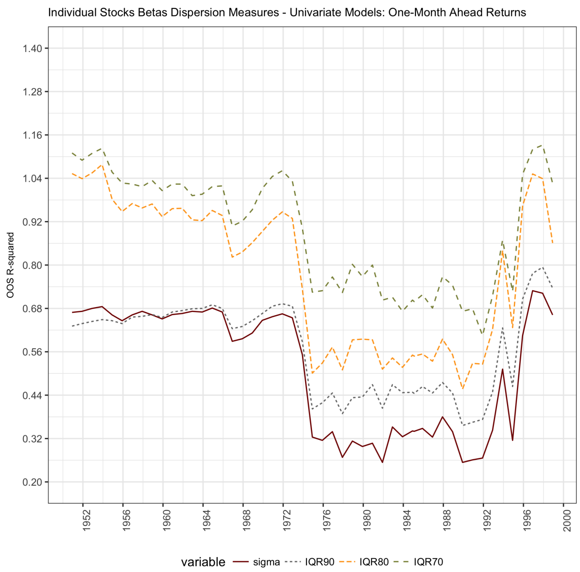


Note: Time Series for Cross-Section Dispersion Measures (CSBD) for CAPM Rolling 24-month betas. Variables in the chart correspond to: (i) *sd* cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) IQR_{80} and IQR_{70} are 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) sd winsor2 is one of the winsorized versions of Betas standard deviation (statistical technique that "shrinks" the extreme measures of a distribution): this *winsorization*version replaces the extreme values using the median absolute deviation as benchmark.

Figure C.2

S&P 500 Individual Stocks Betas – Simple Dispersion Measures:
Out-of-sample R-squared by Sample Split Date – Rolling Betas (24 Months)

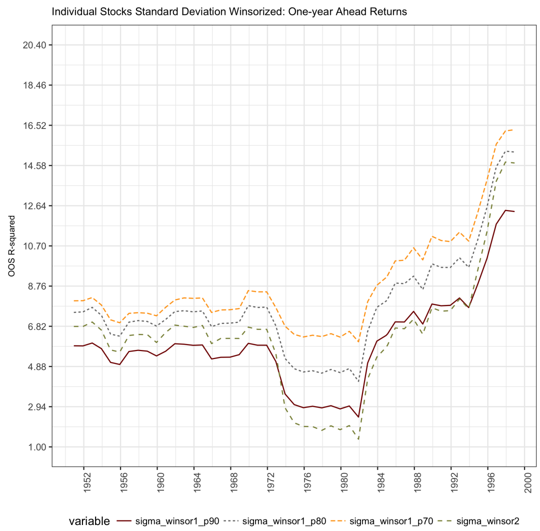
(a) One-Year Ahead Returns ($hpr_{t\to t+12}$)



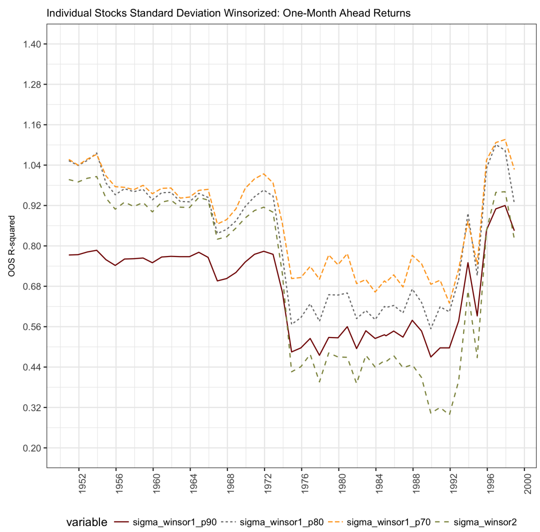
(b) One-Month Ahead Returns ($hpr_{t\to t+1}$)

Note: out-of-sample Statistics for Market Return Predictions 1-year ahead ($hpr_{t\to t+12}$) and 1-Month ahead Returns ($hpr_{t\to t+1}$) using Individual Stocks Betas Dispersion Measures. In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for four different Betas dispersion measures: (i) *sigma* is the cross-section standard deviation of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation; (ii) $IQR_{\{P70,P80,P90\}}$ are the cross-sectionals 70,80 and 90th percentile range of the individual Stocks Betas. Betas for each individual stocks in the S&P 500 are computed using monthly data with a 24, 36 and 48 Month Rolling Window Estimate. In these charts we report results using the 24-Month window.

Figure C.3
S&P 500 Individual Stocks Betas Standard Deviation Controlling for Outliers: OOS R-squared by Sample Split Date – Rolling Betas (24 Months)



(a) One-Year Ahead Returns ($hpr_{t \to t+12}$)

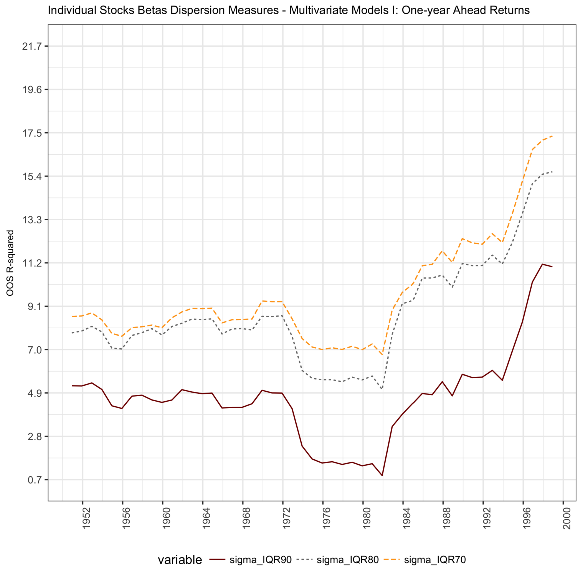


(b) One-Month Ahead Returns ($hpr_{t \to t+1}$)

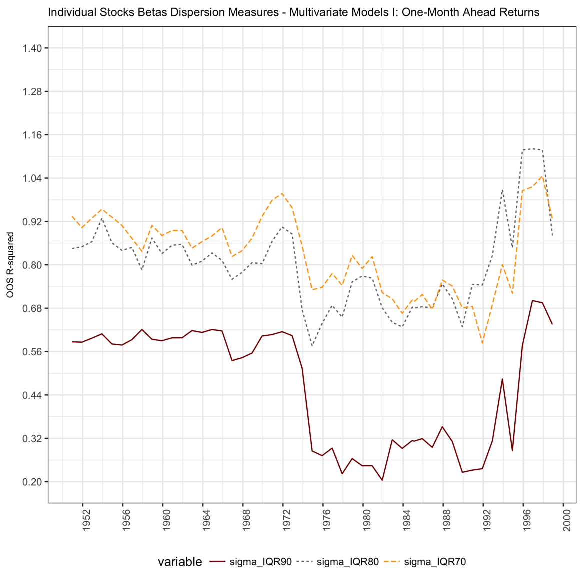
Note: out-of-sample Statistics for Market Return Predictions 1-year ahead ($hpr_{t \to t+12}$) and 1-Month ahead Returns ($hpr_{t \to t+1}$) using Individual Stocks Betas Dispersion Measures, controlling for Outliers using Winsorizing Methods (more below). In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for the cross-section Beta standard deviation *sigma* of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation. Betas for each individual stocks in the $S\&P500$ are computed using monthly data with a 24, 36 and 48 Month Rolling Window Estimate. In these charts we report results using the 24-Month window. Winsorization is a statistical technique that "shrinks" the extreme measures of a distribution. The first three series simply replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value, the 70,80 and 90th percentile range of the individual Stocks Betas, respectively. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark.

Figure C.4

S&P 500 Individual Stocks Betas Dispersion Multivariate Models: OOS R-squared by Sample Split Date – Rolling Betas (24 Months)



(a) One-Year Ahead Returns ($hpr_{t \to t+12}$)

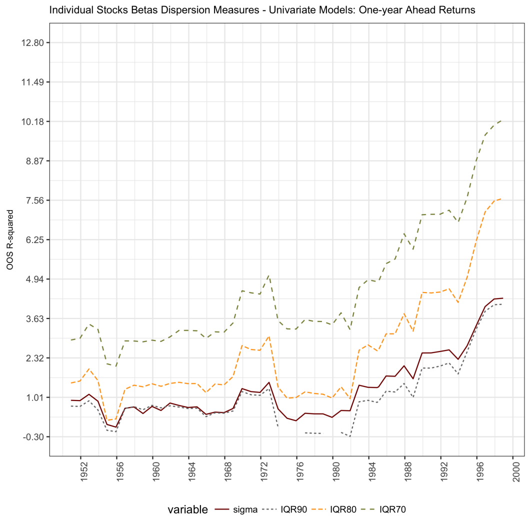


(b) One-Month Ahead Returns ($hpr_{t \to t+1}$)

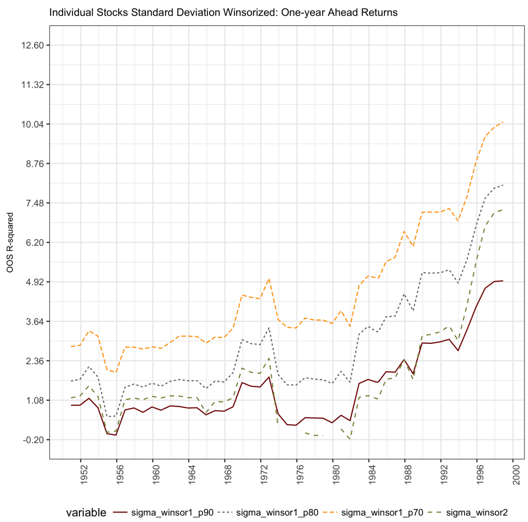
Note: out-of-sample Statistics for Market Return Predictions 1-year ahead ($hpr_{t \to t+12}$) and 1-Month ahead Returns ($hpr_{t \to t+1}$) using Individual Stocks Betas Dispersion Measures. In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for multivariate models of dispersion measures. For all models we include the standard deviation and additional an interquartile range: (i) *sigma* is the cross-section standard deviation of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation; (ii) $IQR_{\{P70,P80,P90\}}$ are the cross-sectionals 70,80 and 90th percentile range of the individual Stocks Betas. Betas for each individual stocks in the $S\&P500$ are computed using monthly data with a 24, 36 and 48 Month Rolling Window Estimate. In these charts we report results using the 24-Month window.

Figure C.5

S&P 500 Individual Stocks Betas - Simple Dispersion Measures: Out-of-sample R-squared by Sample Split Date – One-Year Ahead Returns ($hpr_{t \to t+12}$) – Rolling Betas (36 Months)



(a) $\sigma_t(\beta^m_{i,t})$ and interquartile Ranges

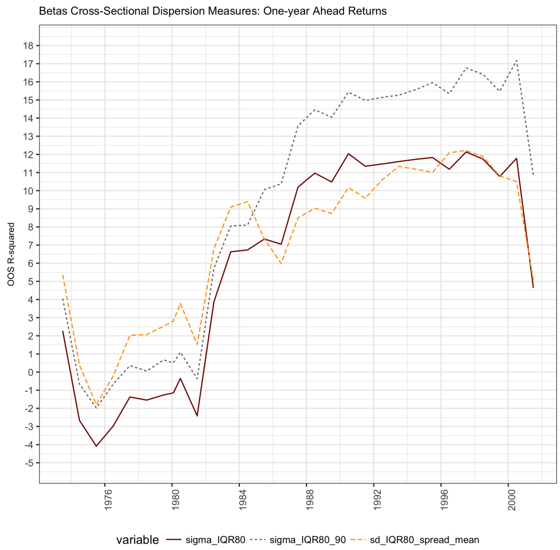


(b) $\sigma_t(\beta^m_{i,t})$ Controlling for Outliers

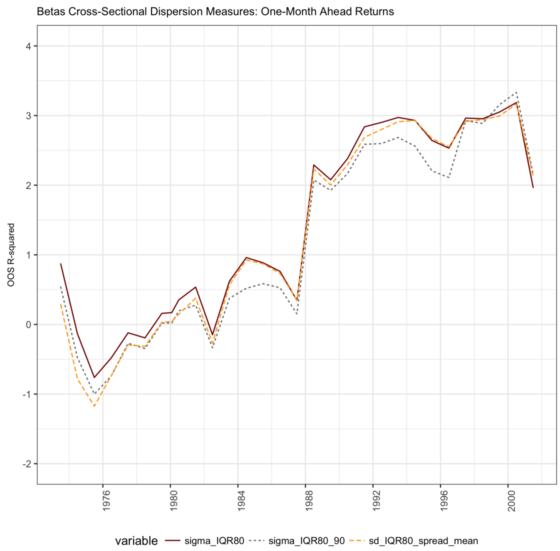
Note: out-of-sample Statistics for Market Return Predictions 1-year ahead ($hpr_{t \to t+12}$) ($hpr_{t \to t+1}$) using Individual Stocks Betas Dispersion Measures. In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for four different Betas dispersion measures: (i) *sigma* is the cross-section standard deviation of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation; (ii) $IQR_{\{P70,P80,P90\}}$ are the cross-sectionals 70,80 and 90th percentile range of the individual Stocks Betas. Betas for each individual stock in the S&P 500 are computed using in this chart with the 36-Month window. Winsorization is a statistical technique that "shrinks" the extreme measures of a distribution. The first three series simply replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value, the 70,80 and 90th percentile range of the individual Stocks Betas, respectively. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark.

Figure C.6

Dispersion Measures of FF 150 univariate Portfolio Betas:
Out-of-sample R-squared by Sample Split Date



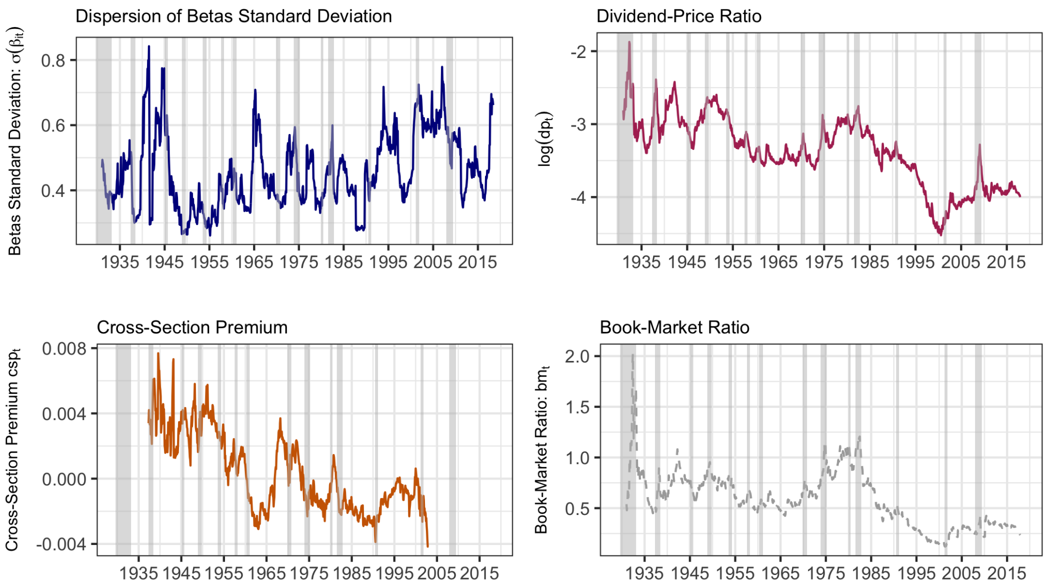
(a) One-Year Ahead Returns ($hpr_{t \to t+12}$)



(b) One-Month Ahead Returns ($hpr_{t \to t+1}$)

Note: out-of-sample Statistics for Market Return Predictions 1-year ahead ($hpr_{t \to t+12}$) and 1-Month ahead Returns ($hpr_{t \to t+1}$) using Fama-French 150 uni-variate Sorts Betas Dispersion Measures based on 15 characteristics. In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for multivariate models of dispersion measures. For all models we include the standard deviation and additionally an interquartile range: (i) *sigma* is the cross-section standard deviation of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation; (ii) $IQR_{\{P70,P80,P90\}}$ are the cross-sectionals 70,80 and 90th percentile range of the individual Stocks Betas. Betas for each individual stocks in the $S\&P500$ are computed using monthly data with a 24, 36 and 48 Month Rolling Window Estimate. In these charts we report results using the 24-Month window.

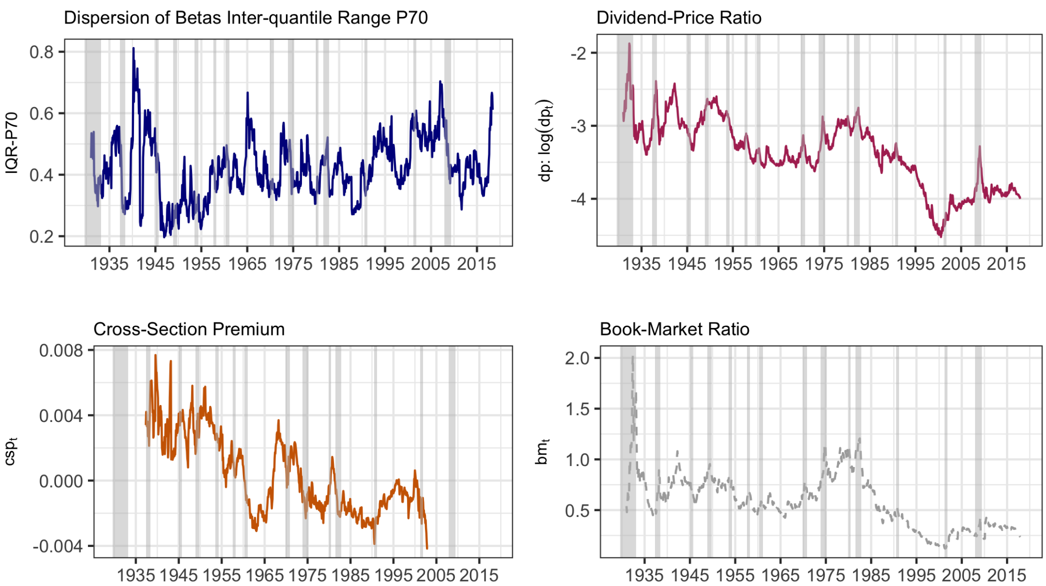
Figure C.7
Betas Cross Section Dispersion x Standard Regressors and US Recessions



Note: Time Series for Cross-Section Dispersion Measures (CSBD) for CAPM Rolling 24-month betas. Shaded areas represent US recessions as measured by the NBER indicator. Variables in the chart correspond to, from top left to right-bottom: (i) *sd* cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$); (ii) dividend-to-price Ratio (d/p), the difference between the log of dividends and the log of price; (iii) Cross-Sectional Premium (csp) of Polk *et al.* (2006): their cross-sectional beta premium measures the relative valuations of high- and low-beta stocks and (iv) The book-to-market ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average. Other regressors obtained in Goyal & Welch (2008) website.

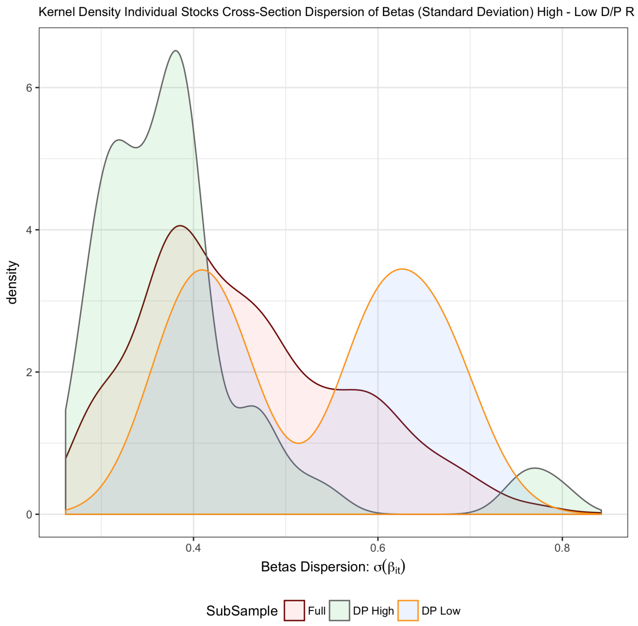
Figure C.8

Betas Cross Section Dispersion x Standard Regressors and US Recessions

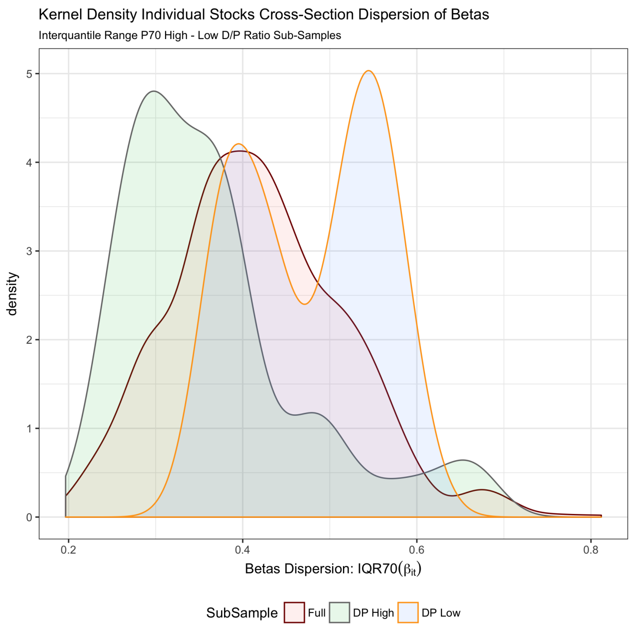


Note: Time Series for Cross-Section Dispersion Measures (CSBD) for CAPM Rolling 24-month betas. Shaded areas represent US recessions as measured by the NBER indicator. Variables in the chart correspond to, from top left to right-bottom: (i) IQR_{70} is 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (ii) dividend-to-price Ratio (d/p), the difference between the log of dividends and the log of price; (iii) Cross-Sectional Premium (csp) of Polk *et al.* (2006): their cross-sectional beta premium measures the relative valuations of high- and low-beta stocks and (iv) The book-to-market ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average. Other regressors obtained in Goyal & Welch (2008) website

Figure C.9
Kernel Density Plot – CSBD Measures in High/Low Dividend-to-Price sub-samples



(a) Betas Cross-Sectional Standard deviation ($\sigma_i(\beta_t^i)$)



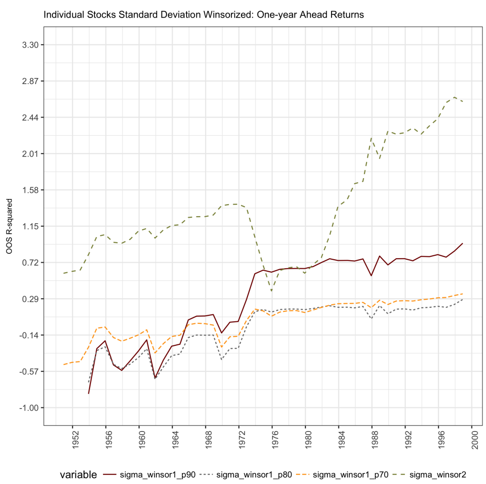
(b) Betas Cross-Sectional 70th interquartile range deviation ($\mathrm{IQR}_{70}^i(\beta_t^i)$)

Note: Empirical kernel density plot of σ_t^{β} (left panel) and 70th interquartile-range of CAPM individual stocks betas on the x-axis for different sub-samples. The first density plots data for the whole sample period (1930-2017). We also split the sample in moments of high and low Dividend-to-Price Ratios (dp). We split the sample formally into the high-dp bin (low bin) for months for which *dp* higher then the unconditional average of *dp* plus (minus) 1.5 times standard deviation. A high dp can be associated with low prices relative to dividends and bad economic states, like recessions, when prices are depressed and expected future market returns are positive because agents demand higher risk premium to carry increased consumption risk.

Figure C.10

Alternative Dispersion Measure of S&P 500 Individual stock betas difference relative to the Market Beta of 1 ($\beta_t^i - \beta^m$) – Out-of-sample R-squared by Sample Split Date One-Year Ahead Returns ($hpr_{t \to t+12}$) – Rolling Betas (24 Months)

(a) $\sigma_t(\beta_{i,t}^m)$ and interquartile Ranges



(b) $\sigma_t(\beta_{i,t}^m)$ Controlling for Outliers

Note: out-of-sample Statistics for Market Return Predictions 1-year ahead returns ($hpr_{t \to t+12}$) ($hpr_{t \to t+1}$) using an alternative individual stocks betas dispersion measure, relative to the market beta of one. For each t we compute $\beta^* = \beta_t^i - 1$ and then calculate cross-section dispersion, following the intuition in Frazzini & Pedersen (2014). In the X-Axis we present out-of-sample statistic for each training window split, recursively forecasting returns going forward. Sample Split starts in 1950. The Y-axis is the value of the out-of-sample statistic (in percentage points) measuring forecast improvement relative to the historical mean as in Goyal & Welch (2008). We present statistics for four different Betas dispersion measures: (i) *sigma* is the cross-section standard deviation of rolling Betas estimation. For each t we compute for the N individual stocks betas the cross-section standard deviation; (ii) $IQR_{\{P70,P80,P90\}}$ are the cross-sectionals 70,80 and 90th percentile range of the individual Stocks Betas. Betas for each individual stock in the S&P 500 are computed using monthly data with a 24-month window in this chart. Winsorization is a statistical technique that "shrinks" the extreme measures of a distribution. The first three series simply replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value, the 70,80 and 90th percentile range of the individual Stocks Betas, respectively. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark.

D
Tables of Chapter 2

Table D.1
Descriptive Time-series Statistics of S&P500 Individual Stocks Cross-Section Betas Moments

Beta Metric	Dispersion Measure	Mean	Median	sd	Max	Min
(a) CSBD $[\tilde{\beta} = \beta_t^i - \bar{\beta}]$	$\sigma_t(\beta_{i,t}^m)$	0.46	0.44	0.11	0.84	0.26
N = 1111	$IQR_{90,t}(\beta_{i,t}^m)$	1.09	1.06	0.26	1.83	0.53
	$IQR_{80,t}(\beta_{i,t}^m)$	0.69	0.68	0.16	1.16	0.32
	$IQR_{70,t}(\beta_{i,t}^m)$	0.42	0.42	0.10	0.81	0.20
	Winsor $2[\sigma_t\, \beta]$	0.40	0.39	0.09	0.68	0.22
	skewness	0.35	0.28	0.60	3.03	−1.15
	kurtosis	4.63	4.07	2.34	21.37	2.25
(b) Alternative $(\beta^* = \beta_t^i - 1)$	$\sigma_t(\beta_{i,t}^m)$	0.58	0.55	0.16	1.13	0.31
N = 1111	$IQR_{90,t}(\beta_{i,t}^m)$	1.41	1.33	0.35	2.69	0.72
	$IQR_{80,t}(\beta_{i,t}^m)$	0.92	0.88	0.22	1.57	0.47
	$IQR_{70,t}(\beta_{i,t}^m)$	0.57	0.55	0.14	1.01	0.28
	Winsor $2[\sigma_t\, \beta]$	0.52	0.49	0.11	0.85	0.28
	skewness	0.61	0.50	0.46	2.33	−0.43
	kurtosis	4.05	3.79	1.40	13.76	1.86

Notes: Descriptive Statistics in the time series for cross-sectional dispersion measures and moments of the market-betas of Individual S&P500 Stocks rolling 24-month regressions. We consider two alternative Beta metrics. The first is our proposed CSBD, that computes cross-section moments of stocks Betas relative to their unconditional time series mean: $\tilde{\beta} = \beta_t^i - \bar{\beta}$. The second follows Frazzini & Pedersen (2014) and compute moments for the dispersion of betas around one (the market beta). For each t we compute for both metrics: (i) the cross-section standard-deviation $(\sigma_t(\beta_{i,t}^m))$, (ii) the 90-th, 80-th and 70th Betas interquartile-range $(IQR_t(\beta_{i,t}^m)$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark; (iv) skewness and kurtosis are also measured in the cross-section

Table D.2

Correlation S&P500 Individual Stocks Cross-Section Betas Moments

	Alternative ($\beta^* = \beta_t^i - 1$)				CSBD ($[\tilde{\beta} = \beta_t^i - \bar{\beta}]$)			
	$\sigma_t(\beta^*_{i,t})$	$IQR_{90,t}(\beta^*_{i,t})$	$IQR_{80,t}(\beta^*_{i,t})$	$IQR_{70,t}(\beta^*_{i,t})$	$\sigma_t(\tilde{\beta}_{i,t})$	$IQR_{90,t}(\tilde{\beta}_{i,t})$	$IQR_{80,t}(\tilde{\beta}_{i,t})$	$IQR_{70,t}(\tilde{\beta}_{i,t})$
$\sigma_t(\beta^*_{i,t})$	1	0.97	0.91	0.83	0.83	0.77	0.72	0.69
$IQR_{90,t}(\beta^*_{i,t})$	0.97	1	0.94	0.87	0.77	0.73	0.69	0.66
$IQR_{80,t}(\beta^*_{i,t})$	0.91	0.94	1	0.95	0.72	0.70	0.69	0.67
$IQR_{70,t}(\beta^*_{i,t})$	0.83	0.87	0.95	1	0.66	0.65	0.66	0.65
$\sigma_t(\tilde{\beta}_{i,t})$	0.83	0.77	0.72	0.66	1	0.95	0.92	0.89
$IQR_{90,t}(\tilde{\beta}_{i,t})$	0.77	0.73	0.70	0.65	0.95	1	0.96	0.91
$IQR_{80,t}(\tilde{\beta}_{i,t})$	0.72	0.69	0.69	0.66	0.92	0.96	1	0.96
$IQR_{70,t}(\tilde{\beta}_{i,t})$	0.69	0.66	0.67	0.65	0.89	0.91	0.96	1

Notes: Simple in-sample Correlation coefficients for two alternative dispersion measures of the Market-Betas of Individual S&P500 Stocks rolling 24-month regressions. We consider two alternative Beta metrics. The first is our proposed CSBD that computes cross-section moments of stocks Betas relative to their unconditional time series mean: $\tilde{\beta} = \beta_t^i - \bar{\beta}$. The second follows Frazzini & Pedersen (2014) and compute moments for the dispersion of betas around one (the market beta). For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark

Table D.3

Model Comparison S&P500 Individual Stocks Betas Dispersion Measures – Rolling 24 Months

One-Month Ahead Returns ($hpr_{t \to t+1}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	0.40	0.30	4.20	0.04	0.25	0.34	0.65	$-3,199.33$
$IQR_{90,t}(\beta^m_{i,t})$	0.38	0.29	4.02	0.04	0.25	0.34	0.60	$-3,199.16$
$IQR_{80,t}(\beta^m_{i,t})$	0.66	0.56	6.95	0.01	0.26	0.39	0.61	$-3,202.07$
$IQR_{70,t}(\beta^m_{i,t})$	0.65	0.55	6.84	0.01	0.28	0.40	0.58	$-3,201.96$
Winsor[σ_t β] P_{80}	0.64	0.55	6.80	0.01	0.27	0.37	0.60	$-3,201.92$
Winsor[σ_t β] P_{70}	0.62	0.52	6.51	0.01	0.25	0.35	0.64	$-3,201.64$
Winsor 2[σ_t β]	0.59	0.50	6.26	0.01	0.22	0.31	0.54	$-3,201.38$
$log[\sigma_t\ \beta]$	0.45	0.35	4.72	0.03	0.25	0.36	0.55	$-3,199.85$
$log[IQR_{80,t}\ \beta]$	0.64	0.54	6.73	0.01	0.24	0.35	0.60	$-3,201.86$
$log[IQR_{70,t}\ \beta]$	0.58	0.48	6.09	0.01	0.28	0.38	0.60	$-3,201.22$

One-Year Ahead Returns ($hpr_{t \to t+12}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	3.61	3.52	39.08	0	1.84	2.59	4.26	-483.22
$IQR_{90,t}(\beta^m_{i,t})$	3.54	3.45	38.32	0	1.79	2.61	4.16	-482.49
$IQR_{80,t}(\beta^m_{i,t})$	5.73	5.64	63.43	0	1.86	2.74	4.56	-506.48
$IQR_{70,t}(\beta^m_{i,t})$	5.82	5.73	64.48	0	1.83	2.63	4.40	-507.46
Winsor[σ_t β] P_{80}	5.64	5.55	62.33	0	2.07	2.96	4.53	-505.44
Winsor[σ_t β] P_{70}	5.52	5.43	60.97	0	1.67	2.60	4.34	-504.15
Winsor 2[σ_t β]	5.43	5.34	59.87	0	1.80	2.41	4.15	-503.11
$log[\sigma_t\ \beta]$	3.94	3.85	42.77	0	2.04	2.71	4.55	-486.78
$log[IQR_{80,t}\ \beta]$	5.26	5.17	57.96	0	1.98	2.77	4.48	-501.30
$log[IQR_{70,t}\ \beta]$	5.30	5.21	58.39	0	1.88	2.54	5.00	-501.71

Notes: In-Sample One-Month and One-Year Ahead Market Excess Returns Forecast Regressions: $hpr_{t \to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t \to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of one cross-sectional dispersion measure of the Market-Betas of Individual S&P500 Stocks. We perform rolling regressions using 24 to 48 months to compute Market-Betas for each of the S&P500 stocks time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$. Results in this table are for 24-month window. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark. The bootstrapped R^2 is designed to tackle the potential spurious predictability arising from time-series persistence of regressors. For each model we simulate 1000 bootstrapped samples using an estimated Arima (1,0,0) with the original regressors and then compute the 90, 95 and 99 percent cut-offs for these 1000 in-sample R^2 empirical distribution. AIC is the Akaike information criteria

Table D.4
Model Comparison S&P500 Individual Stocks Betas Multivariate Models – Rolling 24 Months

One-Month Ahead Returns ($hpr_{t\rightarrow t+1}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t + IQR_{90,t}(\beta)$	0.40	0.21	2.11	0.12	0.42	0.54	0.85	$-3,197$
$\sigma_t + IQR_{80,t}(\beta)$	0.77	0.58	4.05	0.02	0.42	0.58	0.92	$-3,201$
$\sigma_t + IQR_{70,t}(\beta)$	0.69	0.50	3.62	0.03	0.45	0.56	0.85	$-3,200.38$
winsor P90$\sigma_t + IQR_{80,t}(\beta)$	1.00	0.81	5.29	0.005	0.45	0.58	0.84	$-3,203$
winsor P80$\sigma_t + IQR_{80,t}(\beta)$	0.67	0.48	3.54	0.03	0.45	0.58	0.91	$-3,200$
winsor 2$\sigma_t + IQR_{80,t}(\beta)$	0.68	0.49	3.58	0.03	0.42	0.54	0.78	$-3,200$
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	0.47	0.28	2.47	0.08	0.41	0.53	0.80	$-3,198$
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	0.67	0.48	3.53	0.03	0.43	0.54	0.78	$-3,200$

One-Year Ahead Returns ($hpr_{t\rightarrow t+12}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t + IQR_{90,t}(\beta)$	3.66	3.48	19.82	0	3.20	4.01	6.07	-481.80
$\sigma_t + IQR_{80,t}(\beta)$	6.46	6.28	36.00	0	3.04	4.27	6.35	-512.60
$\sigma_t + IQR_{70,t}(\beta)$	6.14	5.96	34.06	0	3.15	4.01	6.21	-508.96
winsor P90$\sigma_t + IQR_{80,t}(\beta)$	8.45	8.28	48.11	0	3.23	4.09	6.17	-535.08
winsor P80$\sigma_t + IQR_{80,t}(\beta)$	5.79	5.61	32.02	0	3.37	4.32	6.99	-505.11
winsor 2 : $\sigma_t + IQR_{80,t}(\beta)$	5.75	5.56	31.76	0	3.23	4.05	5.85	-504.62
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	3.96	3.77	21.47	0	3.16	4.05	5.83	-484.99
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	5.38	5.20	29.62	0	3.22	4.35	5.98	-500.57

Notes: In-Sample One-Month and One-Year Ahead Market Excess Returns Forecast Regressions: $hpr_{t\rightarrow t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\rightarrow t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a pair of cross-sectional dispersion measures of the Market-Betas of Individual S&P500 Stocks. We perform rolling regressions using 24 to 48 months to compute Market-Betas for each of the S&P500 stocks time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$. The models in this table consider Multivariate model that use cross-sectional statistics to measure the dispersion in Betas at each point in time, combining two-metrics at a time. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark. The bootstrapped R^2 is designed to tackle the potential spurious predictability arising from time-series persistence of regressors. For each model we simulate 1000 bootstrapped samples using an estimated Arima (1,0,0) with the original regressors and then compute the 90, 95 and 99 percent cut-offs for these 1000 in-sample R^2. AIC is the Akaike information criteria

Table D.5
Model Comparison S&P500 Individual Stocks Betas Dispersion Measures – Rolling 36 Months

One-Month Ahead Returns ($hpr_{t\rightarrow t+1}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	0.31	0.22	3.28	0.07	0.26	0.34	0.57	$-3,198.41$
$IQR_{90,t}(\beta^m_{i,t})$	0.32	0.23	3.39	0.07	0.24	0.33	0.55	$-3,198.52$
$IQR_{80,t}(\beta^m_{i,t})$	0.79	0.70	8.34	0.004	0.25	0.34	0.55	$-3,203.46$
$IQR_{70,t}(\beta^m_{i,t})$	0.43	0.34	4.53	0.03	0.23	0.34	0.68	$-3,199.66$
Winsor[$\sigma_t\ \beta$] P_{80}	0.75	0.65	7.88	0.005	0.25	0.36	0.58	$-3,203.00$
Winsor[$\sigma_t\ \beta$] P_{70}	0.41	0.31	4.27	0.04	0.24	0.35	0.56	$-3,199.40$
Winsor 2[$\sigma_t\ \beta$]	0.64	0.55	6.77	0.01	0.24	0.33	0.53	$-3,201.90$
$log[\sigma_t\ \beta]$	0.39	0.29	4.08	0.04	0.23	0.31	0.50	$-3,199.22$
$log[IQR_{80,t}\ \beta]$	0.72	0.63	7.65	0.01	0.27	0.38	0.61	$-3,202.77$
$log[IQR_{70,t}\ \beta]$	0.42	0.32	4.37	0.04	0.25	0.36	0.65	$-3,199.50$

One-Year Ahead Returns ($hpr_{t\rightarrow t+12}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	1.18	1.09	12.48	0	2.00	2.88	4.63	-457.21
$IQR_{90,t}(\beta^m_{i,t})$	1.36	1.27	14.42	0	1.85	2.50	4.09	-459.13
$IQR_{80,t}(\beta^m_{i,t})$	3.22	3.13	34.69	0	1.94	2.68	4.86	-478.97
$IQR_{70,t}(\beta^m_{i,t})$	3.58	3.48	38.70	0	1.70	2.56	4.29	-482.85
Winsor[$\sigma_t\ \beta$] P_{80}	3.15	3.06	33.93	0	2.15	3.03	4.80	-478.23
Winsor[$\sigma_t\ \beta$] P_{70}	3.38	3.29	36.53	0	1.72	2.48	4.33	-480.76
Winsor 2[$\sigma_t\ \beta$]	2.84	2.75	30.50	0	1.80	2.56	3.96	-474.90
$log[\sigma_t\ \beta]$	1.48	1.38	15.66	0	1.95	2.67	4.44	-460.36
$log[IQR_{80,t}\ \beta]$	2.98	2.88	31.99	0	2.08	2.80	4.37	-476.36
$log[IQR_{70,t}\ \beta]$	3.03	2.94	32.62	0	2.04	2.81	4.80	-476.96

Notes: In-Sample One-Month and One-Year Ahead Market Excess Returns Forecast Regressions: $hpr_{t\rightarrow t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\rightarrow t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of one cross-sectional dispersion measure of the Market-Betas of Individual S&P500 Stocks. We perform rolling regressions using 24 to 48 months to compute Market-Betas for each of the S&P500 stocks time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$. Results in this table are for 36-month window. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark. The bootstrapped R^2 is designed to tackle the potential spurious predictability arising from time-series persistence of regressors. For each model we simulate 1000 bootstrapped samples using an estimated Arima (1,0,0) with the original regressors and then compute the 90, 95 and 99 percent cut-offs for these 1000 in-sample R^2. AIC is the Akaike information criteria

Table D.6

Model Comparison S&P500 Individual Stocks Betas Multivariate Models – Rolling 36 Months

One-Month Ahead Returns ($hpr_{t\to t+1}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t + IQR_{90,t}(\beta)$	0.33	0.14	1.72	0.18	0.42	0.54	0.75	$-3,196.57$
$\sigma_t + IQR_{80,t}(\beta)$	1.10	0.92	5.85	0.003	0.41	0.54	0.80	$-3,204.80$
$\sigma_t + IQR_{70,t}(\beta)$	0.43	0.24	2.27	0.10	0.41	0.56	0.92	$-3,197.67$
winsor P90$\sigma_t + IQR_{80,t}(\beta)$	1.64	1.45	8.70	0	0.41	0.49	0.72	$-3,210.44$
winsor P80$\sigma_t + IQR_{80,t}(\beta)$	0.92	0.73	4.85	0.01	0.42	0.54	0.73	$-3,202.82$
winsor 2 : $\sigma_t + IQR_{80,t}(\beta)$	0.88	0.69	4.66	0.01	0.39	0.50	0.73	$-3,202.44$
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	0.39	0.20	2.04	0.13	0.41	0.50	0.77	$-3,197.22$
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	0.83	0.64	4.40	0.01	0.40	0.53	0.80	$-3,201.93$

One-Year Ahead Returns ($hpr_{t\to t+12}$)

	In-Sample Statistics				bootstrap R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t + IQR_{90,t}(\beta)$	1.37	1.18	7.22	0.001	3.33	4.17	6.05	-457.16
$\sigma_t + IQR_{80,t}(\beta)$	4.73	4.55	25.89	0	3.50	4.42	5.97	-493.46
$\sigma_t + IQR_{70,t}(\beta)$	4.73	4.55	25.89	0	3.21	4.21	5.65	-493.46
winsor P90$\sigma_t + IQR_{80,t}(\beta)$	6.62	6.44	36.91	0	3.26	4.12	5.87	-514.32
winsor P80$\sigma_t + IQR_{80,t}(\beta)$	3.28	3.09	17.66	0	3.44	4.35	6.22	-477.61
winsor 2 : $\sigma_t + IQR_{80,t}(\beta)$	3.31	3.13	17.84	0	3.13	4.08	5.62	-477.97
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	1.49	1.30	7.88	0	3.25	4.14	6.43	-458.48
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	3.59	3.40	19.39	0	3.08	3.96	6.64	-480.97

Notes: In-Sample One-Month and One-Year Ahead Market Excess Returns Forecast Regressions: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is combines two cross-sectional dispersion measures of the Market-Betas of Individual S&P500 Stocks. We perform rolling regressions using 24 to 48 months to compute Market-Betas for each of the S&P500 stocks time-series regressions of the form: $R_t^i = \alpha_i + \beta_i^m \cdot r_t^m + \mu_t^i$. Results in this table are for 36-month window. The models in this table consider Multivariate model that use cross-sectional statistics to measure the dispersion in Betas at each point in time. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta_{i,t}^m)$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta_{i,t}^m)$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark. The bootstrapped R^2 is designed to tackle the potential spurious predictability arising from time-series persistence of regressors. For each model we simulate 1000 bootstrapped samples using an estimated Arima (1,0,0) with the original regressors and then compute the 90, 95 and 99 percent cut-offs for these 1000 in-sample R^2. AIC is the Akaike information criteria

Table D.7

Out-of-Sample R^2 Model Comparison S&P500 Individual Stocks Betas – Rolling 24 Months

(a) Univariate Models - Training Sample Split 1985

	One-Year Ahead Return($hpr_{t\to t+12}$)			One-Month Ahead Return($hpr_{t\to t+1}$)		
Model	OOS-R^2	ENC-N	ENC-T	OOS-R^2	ENC-N	ENC-T
$\sigma_t(\beta^m_{i,t})$	4.70	22.10	19.21	0.35	2.48	1.36
$IQR_{90,t}(\beta^m_{i,t})$	5.80	23.63	24.02	0.46	2.57	1.82
$IQR_{80,t}(\beta^m_{i,t})$	8.21	34.20	34.87	0.55	3.44	2.17
$IQR_{70,t}(\beta^m_{i,t})$	9.91	34.78	42.89	0.72	3.28	2.82
Winsor[$\sigma_t\ \beta$] P_{90}	7.03	26.43	29.50	0.55	2.81	2.15
Winsor[$\sigma_t\ \beta$] P_{80}	8.91	34.26	38.13	0.62	3.37	2.45
Winsor[$\sigma_t\ \beta$] P_{70}	9.98	33.73	43.22	0.71	3.14	2.81
Winsor 2[$\sigma_t\ \beta$]	6.74	32.13	28.18	0.47	3.42	1.86
$log[\sigma_t\ \beta]$	3.00	20.29	12.07	0.24	2.43	0.94
$log[IQR_{90,t}\ \beta]$	4.48	19.16	18.29	0.38	2.02	1.49
$log[IQR_{80,t}\ \beta]$	6.79	27.97	28.39	0.52	2.97	2.03
$log[IQR_{70,t}\ \beta]$	8.23	28.61	34.97	0.68	2.78	2.69

(b) Multivariate Models - Training Sample Split 1985

Model	One-Year Ahead Return($hpr_{t\to t+12}$)			One-Month Ahead Return($hpr_{t\to t+1}$)		
Model	OOS-R^2	ENC-N	ENC-T	OOS-R^2	ENC-N	ENC-T
$\sigma_t + IQR_{90,t}(\beta)$	4.87	22.70	19.98	0.32	2.45	1.25
$\sigma_t + IQR_{80,t}(\beta)$	10.47	37.30	45.58	0.68	3.34	2.69
$\sigma_t + IQR_{70,t}(\beta)$	11.06	36.60	48.50	0.72	3.10	2.82
σ_t[winsor P90] + $IQR_{80,t}(\beta)$	8.66	35.14	36.98	0.21	2.68	0.80
σ_t[winsor P80] + $IQR_{80,t}(\beta)$	4.25	31.28	17.30	0.14	3.30	0.53
σ_t[winsor P70] + $IQR_{80,t}(\beta)$	7.81	34.66	33.03	0.44	3.32	1.72
σ_t[winsor 2] + $IQR_{80,t}(\beta)$	7.86	33.48	33.27	0.53	3.26	2.10
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	2.53	19.34	10.13	0.13	2.24	0.52
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	7.02	28.35	29.45	0.57	2.93	2.22
$log[\sigma_t(\beta)] + log[IQR_{70,t}(\beta)]$	7.39	28.63	31.10	0.53	2.79	2.08

Notes: out-of-sample Statistics for Market Return Predictions. Out-of-sample procedure in this table split the sample in 1985 as a training window and recursively forecast returns going forward. Results for a wide range of sample splits are presented in Figures C.2 and C.3. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Models: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of the S&P500 Index Individual Stocks Betas Dispersion Measures. Models in this table consider both Univariate in panel (a) and Multivariate models in panel (b) that use cross-sectional dispersion in Betas for a rolling 24-month window. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark; (iv) we take logs of the simple dispersion measures

Table D.8
Out-of-Sample R^2 Model Comparison S&P500 Individual Stocks Betas – Rolling 36 Months

Univariate Models Forecast Regressions - Training Sample Split 1985

Model	One-Year Return($hpr_{t\to t+12}$)			One-Month Return($hpr_{t\to t+1}$)		
	OOS-R^2	ENC-N	ENC-T	OOS-R^2	ENC-N	ENC-T
$\sigma_t(\beta^m_{i,t})$	1.72	7.89	6.82	−0.22	1.12	−0.86
$IQR_{90,t}(\beta^m_{i,t})$	1.21	7.54	4.79	−0.12	1.15	−0.47
$IQR_{80,t}(\beta^m_{i,t})$	3.12	17.14	12.56	−0.03	2.97	−0.13
$IQR_{70,t}(\beta^m_{i,t})$	5.45	21.20	22.49	0.52	2.10	2.03
Winsor[σ_t β] P_{90}	2.00	9.52	7.97	0.05	1.63	0.20
Winsor[σ_t β] P_{80}	3.79	17.42	15.36	0.19	2.98	0.75
Winsor[σ_t β] P_{70}	5.58	20.37	23.03	0.56	2.03	2.18
Winsor 2[σ_t β]	1.76	14.59	7.00	−0.28	2.34	−1.09
$log[\sigma_t\ \beta]$	1.13	8.10	4.45	−0.50	0.96	−1.95
$log[IQR_{90,t}\ \beta]$	1.07	6.71	4.21	−0.18	0.90	−0.71
$log[IQR_{80,t}\ \beta]$	2.73	14.21	10.93	−0.07	2.28	−0.28
$log[IQR_{70,t}\ \beta]$	4.63	16.51	18.91	0.43	1.77	1.69

Multivariate Models Forecast Regressions - Training Sample Split 1985

Model	One-Year Return($hpr_{t\to t+12}$)			One-Month Return($hpr_{t\to t+1}$)		
	OOS-R^2	ENC-N	ENC-T	OOS-R^2	ENC-N	ENC-T
$\sigma_t + IQR_{90,t}(\beta)$	1.01	6.86	3.99	−0.23	1.11	−0.91
$\sigma_t + IQR_{80,t}(\beta)$	5.91	19.51	24.52	0.70	3.50	2.74
$\sigma_t + IQR_{70,t}(\beta)$	8.64	26.57	36.88	0.14	1.81	0.56
σ_t[winsor P90] + $IQR_{80,t}(\beta)$	8.25	29.61	35.09	0.54	4.25	2.11
σ_t[winsor P80] + $IQR_{80,t}(\beta)$	−1.15	12.45	−4.45	−2.22	1.04	−8.46
σ_t[winsor P70] + $IQR_{80,t}(\beta)$	3.82	18.70	15.49	−1.53	1.18	−5.86
σ_t[winsor 2] + $IQR_{80,t}(\beta)$	3.33	16.55	13.44	0.20	2.80	0.80
$log[\sigma_t(\beta)] + log[IQR_{90,t}(\beta)]$	1.03	7.89	4.07	−0.54	0.89	−2.10
$log[\sigma_t(\beta)] + log[IQR_{80,t}(\beta)]$	4.45	15.04	18.18	0.26	2.36	1.00
$log[\sigma_t(\beta)] + log[IQR_{70,t}(\beta)]$	5.52	17.75	22.80	−0.37	1.18	−1.42

Notes: out-of-sample Statistics for Market Return Predictions. Out-of-sample procedure in this table split the sample in 1985 as a training window and recursively forecast returns going forward. Results for a wide range of sample splits are presented in Figures C.2 and C.3. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Models: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of the S&P500 Index Individual Stocks Betas Dispersion Measures. Models in this table consider both Univariate in panel (a) and Multivariate models in panel (b) that use cross-sectional dispersion in Betas for a rolling 36-month window. For each t we compute: (i) the cross-section standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th Betas interquartile-range ($IQR_t(\beta^m_{i,t})$), (iii) Winsorized Betas standard deviation: statistical technique that "shrinks" the extreme measures of a distribution, the first three series replace all Betas higher in module that the equivalent percentile (IQR$\{P70, P80, P90\}$) by the percentile value. The other methodology (*sigma winsor2*) replaces the extreme values using the median absolute deviation as benchmark; (iv) we take logs of the simple dispersion measures.

Table D.9
Out-of-sample R^2 CSBD Model σ_t – Rolling Betas (24 Months)

Train-sample	One-Year Returns ($hpr_{t \to t+12}$)			One-Month Returns ($hpr_{t \to t+1}$)			$P/R = \pi$
Split	OOS R^2	ENC-N	ENC-T	OOS R^2	ENC-N	ENC-T	
1950-12-01	5.22	41.26	44.62	0.67	5.00	5.46	3.36
1955-12-01	4.11	33.11	32.14	0.65	4.62	4.88	2.64
1960-12-01	4.54	32.71	32.80	0.66	4.40	4.61	2.01
1965-12-01	4.12	27.77	27.08	0.67	4.09	4.25	1.57
1970-12-01	4.83	28.36	28.95	0.66	3.82	3.77	1.24
1975-12-01	1.64	18.31	8.52	0.32	2.78	1.61	0.99
1976-12-01	1.71	17.97	8.69	0.34	2.78	1.69	0.94
1977-12-01	1.55	17.03	7.66	0.27	2.54	1.31	0.90
1978-12-01	1.66	16.75	7.99	0.31	2.63	1.49	0.86
1979-12-01	1.48	15.79	6.95	0.30	2.56	1.38	0.82
1980-12-01	1.59	15.87	7.28	0.31	2.59	1.38	0.78
1981-12-01	1.10	14.95	4.86	0.25	2.45	1.12	0.75
1982-12-01	3.15	19.81	13.86	0.35	2.64	1.50	0.71
1983-12-01	3.69	20.82	15.87	0.32	2.52	1.35	0.68
1984-12-01	4.20	21.36	17.64	0.34	2.52	1.38	0.65
1985-02-01	4.27	21.43	17.85	0.34	2.51	1.36	0.62
1985-12-01	4.70	22.10	19.21	0.35	2.48	1.36	0.59
1986-12-01	4.63	21.50	18.37	0.32	2.45	1.23	0.56
1987-12-01	5.25	22.52	20.28	0.38	2.71	1.40	0.53
1988-12-01	4.57	19.87	16.93	0.34	2.51	1.21	0.51
1989-12-01	5.60	21.22	20.30	0.25	2.27	0.87	0.48
1990-12-01	5.44	20.27	18.97	0.26	2.29	0.86	0.46
1991-12-01	5.46	19.61	18.37	0.27	2.29	0.85	0.43
1992-12-01	5.79	19.36	18.80	0.34	2.32	1.05	0.41
1993-12-01	5.30	17.23	16.47	0.51	2.41	1.51	0.39
1994-12-01	6.72	18.38	20.31	0.32	1.97	0.89	0.37
1995-12-01	8.11	19.86	23.84	0.60	2.26	1.64	0.35
1996-12-01	10.04	22.03	28.81	0.73	2.31	1.89	0.33
1997-12-01	10.91	22.56	30.12	0.72	2.23	1.79	0.31
1998-12-01	10.78	21.34	28.27	0.66	2.20	1.56	0.29
1999-12-01	10.91	20.56	27.19	0.70	2.21	1.57	0.27
2000-12-01	10.41	19.90	24.41	0.38	1.82	0.80	0.25

Notes: out-of-sample Statistics for Market Return Predictions using Individual Stocks Betas Dispersion Measures: $hpr_{t \to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t \to t+k}$ is the cumulative (log) excess return of the market between months t and $t + k$. The model in this table uses as explanatory variable X_t the cross-section standard deviation in betas σ_t computed for each t. Out-of-sample procedure in this table split the sample in several training windows (in each row) and recursively forecast returns going forward. Results for a wide range of sample splits are presented in . $\phi = P/R$ is the number of recursive out-of-sample forecasting periods divided by the training period) close to 1. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Rolling regressions betas window 24-months for S&P500 individual stocks time-series regressions of the form: $R_t^i = \alpha_i + \beta_i^m \cdot r_t^m + \mu_t^i$

Table D.10
Out-of-sample R^2 CSBD Model $IQR_t(\beta^{70}_{i,t})$ – Rolling Betas (24 Months)

Train-sample	One-Year Returns ($hpr_{t\to t+12}$)			One-Month Returns ($hpr_{t\to t+1}$)			$P/R = \pi$
Split	OOS R^2	ENC-N	ENC-T	OOS R^2	ENC-N	ENC-T	
1950-12-01	8.21	57.19	72.48	1.11	7.17	9.10	3.36
1955-12-01	7.13	47.05	57.58	1.03	6.34	7.78	2.64
1960-12-01	7.96	47.19	59.67	1.02	5.91	7.14	2.01
1965-12-01	7.66	41.35	52.27	1.02	5.37	6.49	1.57
1970-12-01	8.63	41.72	53.84	1.04	5.08	6.02	1.24
1975-12-01	6.10	31.59	33.16	0.73	3.95	3.75	0.99
1980-12-01	6.33	28.26	30.42	0.80	3.81	3.63	0.78
1981-12-01	5.75	26.64	26.73	0.70	3.52	3.10	0.75
1982-12-01	7.83	31.76	36.16	0.71	3.49	3.05	0.71
1983-12-01	8.64	33.26	39.15	0.67	3.32	2.80	0.68
1984-12-01	9.03	33.35	39.92	0.70	3.34	2.85	0.65
1985-02-01	9.15	33.50	40.29	0.70	3.31	2.82	0.62
1985-12-01	9.91	34.78	42.89	0.72	3.28	2.82	0.59
1986-12-01	9.95	34.03	41.78	0.68	3.20	2.59	0.56
1987-12-01	10.58	34.86	43.31	0.77	3.50	2.83	0.53
1988-12-01	9.98	31.83	39.27	0.74	3.29	2.66	0.51
1989-12-01	11.14	33.40	42.87	0.67	3.06	2.31	0.48
1990-12-01	10.92	31.86	40.46	0.68	3.05	2.26	0.46
1991-12-01	10.87	30.58	38.77	0.60	2.89	1.93	0.43
1992-12-01	11.37	30.25	39.25	0.72	2.93	2.20	0.41
1993-12-01	10.92	27.68	36.03	0.87	2.98	2.58	0.39
1994-12-01	12.39	29.02	39.87	0.73	2.61	2.07	0.37
1995-12-01	14.03	30.83	44.06	1.05	2.92	2.87	0.35
1996-12-01	15.88	32.83	48.70	1.12	2.86	2.92	0.33
1997-12-01	16.57	32.81	48.85	1.13	2.80	2.82	0.31
1998-12-01	16.63	31.43	46.69	1.03	2.69	2.42	0.29
1999-12-01	16.89	30.37	45.13	1.17	2.78	2.62	0.27
2000-12-01	16.56	29.31	41.67	0.70	2.18	1.48	0.25

Notes: out-of-sample Statistics for Market Return Predictions using Individual Stocks Betas Dispersion Measures: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t + k$. The model in this table uses as explanatory variable X_t the cross-section interquartile-ranges using the 70th Percentile $(IQR_t(\beta^{70}_{i,t})$ computed for each t. Out-of-sample procedure in this table split the sample in several training windows (in each row) and recursively forecast returns going forward. Results for a wide range of sample splits are presented in . $\phi = P/R$ is the number of recursive out-of-sample forecasting periods divided by the training period) close to 1. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Rolling regressions betas window 24-months for S&P500 individual stocks time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$

Table D.11
Out-of-sample R^2 CSBD Model $\sigma(\beta)_{i,t}$winsorized P70 – Rolling Betas (24 Months)

Train-sample Split	One-Year Returns ($hpr_{t\to t+12}$)			One-Month Returns ($hpr_{t\to t+1}$)			$P/R=\pi$
	OOS R^2	ENC-N	ENC-T	OOS R^2	ENC-N	ENC-T	
1950-12-01	8.05	54.08	70.92	1.06	6.74	8.65	3.36
1955-12-01	6.99	44.46	56.37	0.98	5.96	7.39	2.64
1960-12-01	7.74	44.42	57.85	0.97	5.54	6.77	2.01
1965-12-01	7.49	39.13	50.99	0.97	5.04	6.15	1.57
1970-12-01	8.48	39.73	52.84	1.00	4.79	5.75	1.24
1971-12-01	8.48	38.82	51.73	1.01	4.75	5.71	1.19
1972-12-01	7.72	35.51	45.68	0.99	4.55	5.44	1.13
1973-12-01	6.83	33.58	39.12	0.87	4.16	4.67	1.08
1974-12-01	6.43	31.79	35.87	0.70	3.76	3.70	1.03
1975-12-01	6.30	30.77	34.32	0.71	3.74	3.63	0.99
1980-12-01	6.58	27.68	31.68	0.78	3.60	3.52	0.78
1981-12-01	6.07	26.22	28.33	0.69	3.34	3.03	0.75
1982-12-01	8.01	30.97	37.09	0.70	3.32	3.00	0.71
1983-12-01	8.80	32.41	39.94	0.66	3.16	2.76	0.68
1984-12-01	9.17	32.46	40.59	0.70	3.18	2.82	0.65
1985-02-01	9.28	32.58	40.89	0.69	3.16	2.79	0.62
1985-12-01	9.98	33.73	43.22	0.71	3.14	2.81	0.59
1986-12-01	10.01	32.95	42.04	0.68	3.06	2.58	0.56
1987-12-01	10.61	33.71	43.44	0.77	3.36	2.85	0.53
1988-12-01	10.03	30.78	39.45	0.75	3.15	2.67	0.51
1989-12-01	11.16	32.32	42.98	0.69	2.94	2.36	0.48
1990-12-01	10.96	30.84	40.62	0.70	2.94	2.32	0.46
1991-12-01	10.91	29.60	38.93	0.63	2.78	2.02	0.43
1992-12-01	11.37	29.25	39.24	0.73	2.82	2.25	0.41
1993-12-01	10.93	26.84	36.08	0.87	2.86	2.59	0.39
1994-12-01	12.33	28.10	39.65	0.74	2.52	2.12	0.37
1995-12-01	13.89	29.79	43.56	1.05	2.82	2.88	0.35
1996-12-01	15.61	31.57	47.71	1.11	2.75	2.89	0.33
1997-12-01	16.25	31.49	47.72	1.12	2.68	2.78	0.31
1998-12-01	16.31	30.15	45.60	1.03	2.59	2.43	0.29
1999-12-01	16.57	29.15	44.09	1.16	2.67	2.60	0.27
2000-12-01	16.37	28.30	41.11	0.71	2.09	1.49	0.25

Notes: out-of-sample Statistics for Market Return Predictions using Individual Stocks Betas Dispersion Measures: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$. The model in this table uses as explanatory variable X_t is the cross-section winsorized standard deviation of individual betas $\sigma(\beta)_{i,t}$winsorized P70 computed for each t: it simply replaces all betas higher in module than the 70th-percentile (IQR$\{P70\}$) by the percentile value. Out-of-sample procedure in this table split the sample in several training windows (in each row) and recursively forecast returns going forward. Results for a wide range of sample splits are presented in . $\phi = P/R$ is the number of recursive out-of-sample forecasting periods divided by the training period) close to 1. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Rolling regressions betas window 24-months for S&P500 individual stocks time-series regressions of the form: $R_t^i = \alpha_i + \beta_i^m \cdot r_t^m + \mu_t^i$

Table D.12
Out-of-sample R^2 CSBD Multivariate Models $\sigma(\beta)_{i,t} + IQR_t(\beta^{70}_{i,t}$ – Rolling Betas
(24 Months)

Train-sample	One-Year Returns ($hpr_{t\to t+12}$)			One-Month Returns ($hpr_{t\to t+1}$)			$P/R = \pi$
Split	OOS R^2	ENC-N	ENC-T	OOS R^2	ENC-N	ENC-T	
1950-12-01	8.60	58.02	76.25	0.94	6.27	7.65	3.36
1955-12-01	7.65	48.39	62.10	0.91	5.72	6.88	2.64
1960-12-01	8.54	48.62	64.43	0.90	5.24	6.23	2.01
1965-12-01	8.29	42.80	56.97	0.90	4.80	5.74	1.57
1970-12-01	9.32	43.19	58.59	0.98	4.69	5.63	1.24
1975-12-01	7.00	33.22	38.40	0.74	3.79	3.79	0.99
1980-12-01	7.27	29.76	35.29	0.82	3.67	3.74	0.78
1981-12-01	6.76	28.21	31.78	0.72	3.38	3.19	0.75
1982-12-01	8.92	33.53	41.70	0.71	3.29	3.03	0.71
1983-12-01	9.76	35.08	44.79	0.67	3.12	2.78	0.68
1984-12-01	10.15	35.11	45.41	0.70	3.15	2.84	0.65
1985-02-01	10.27	35.26	45.78	0.70	3.13	2.81	0.62
1985-12-01	11.06	36.60	48.50	0.72	3.10	2.82	0.59
1986-12-01	11.13	35.84	47.35	0.68	3.01	2.58	0.56
1987-12-01	11.78	36.67	48.89	0.76	3.28	2.80	0.53
1988-12-01	11.22	33.65	44.73	0.74	3.11	2.64	0.51
1989-12-01	12.37	35.23	48.29	0.68	2.91	2.35	0.48
1990-12-01	12.17	33.63	45.72	0.68	2.89	2.28	0.46
1991-12-01	12.11	32.26	43.80	0.58	2.68	1.87	0.43
1992-12-01	12.61	31.89	44.17	0.69	2.73	2.13	0.41
1993-12-01	12.18	29.33	40.78	0.80	2.74	2.38	0.39
1994-12-01	13.58	30.60	44.32	0.72	2.49	2.05	0.37
1995-12-01	15.15	32.29	48.23	1.00	2.76	2.74	0.35
1996-12-01	16.69	33.75	51.68	1.02	2.65	2.65	0.33
1997-12-01	17.14	33.25	50.89	1.05	2.61	2.60	0.31
1998-12-01	17.34	32.10	49.10	0.93	2.49	2.19	0.29
1999-12-01	17.66	31.07	47.61	1.10	2.63	2.48	0.27
2000-12-01	17.53	30.23	44.64	0.63	2.02	1.33	0.25

Notes: out-of-sample Statistics for Market Return Predictions using Individual Stocks Betas Dispersion Measures: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t + k$. The model in this table uses as explanatory variable X_t is the multivariate version that uses both cross-section standard deviation of individual betas $\sigma(\beta)_{i,t}$ and the 70th interquatile range of betas $IQR_t(\beta^{70}_{i,t}$, both computed for each t. Out-of-sample procedure in this table split the sample in several training windows (in each row) and recursively forecast returns going forward. Results for a wide range of sample splits are presented in . $\phi = P/R$ is the number of recursive out-of-sample forecasting periods divided by the training period) close to 1. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic and ENC-T Model is the Diebold and Mariano (1995). Rolling regressions betas window 24-months for S&P500 individual stocks time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$

Table D.13

In-Sample Regressions: Dispersion Measures of S&P Individual Stocks Betas – Rolling 24 Months

One-Year Ahead Returns ($hpr_{t\to t+12}$)										
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
constant	.217***	.222***	.269***	.268***	.233***	.268***	.262***	.273***	−.064***	−.011
	(.021)	(.022)	(.023)	(.022)	(.022)	(.023)	(.022)	(.023)	(.019)	(.013)
$\sigma_t(\beta^i)$	−.331***									
	(.046)									
$IQR_t^{P90}(\beta^i)$		−.145***								
		(.021)								
$IQR_t^{P80}(\beta^i)$			−.296***							
			(.036)							
$IQR_t^{P70}(\beta^i)$				−.481***						
				(.055)						
$\sigma_t(\beta^i)_{\text{winsor P90}}$					−.484***					
					(.067)					
$\sigma_t(\beta^i_{\text{winsor P80}})$						−.769***				
						(.093)				
$\sigma_t(\beta^i_{\text{winsor P70}})$							−1.092***			
							(.129)			
$\sigma_t(\beta^i_{\text{winsor 2}})$								−.522***		
								(.061)		
$log[\sigma_t]$									−.160***	
									(.021)	
$log[IQR_t^{P80}]$										−.190***
										(.024)
R^2	.036	.035	.057	.058	.040	.056	.055	.054	.039	.053
Adj. R^2	.035	.035	.056	.057	.039	.055	.054	.053	.038	.052
Num. obs.	1045	1045	1045	1045	1045	1045	1045	1045	1045	1045

Notes: In-Sample One-Month Ahead Market Excess Returns Forecast Regressions: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of cross-sectional dispersion measures of the Market-Betas of the S&P 500 Stocks. We perform rolling regressions using 24,36 and 48 months to compute Market-Betas for each of the individual stocks running time-series regressions of the form: $R_t^i = \alpha_i + \beta_i^m \cdot r_t^m + \mu_t^i$. The models in this table consider simple cross-sectional statistics to measure the dispersion in Betas at each point in time. For each t we compute: (i) the cross-section standard-deviation of individual stocks betas ($\sigma_t(\beta_{i,t}^m)$), (ii) the 90-th, 80-th and 70th 150 interquartile-ranges ($IQR_t(\beta_{i,t}^m)$, (iii) winsorized versions of the Betas standard deviation and (iv) logs of the standard deviation and IQRs. Standard errors in parentheses are computed using Newey-west corrections. For a more rigorous test of statistical significance for each model report to Table D.2 where we present the boot-strapped R^2,designed to tackle the potential spurious predictability arising from time-series persistence of regressors

Table D.14

Model Comparison: Dispersion Measures of FF 150 univariate Portfolio Betas – Rolling 24 Months

One-Month Ahead Returns ($hpr_{t\to t+1}$)

	In-Sample Statistics				bootstrapped R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	0.62	0.46	3.98	0.05	0.36	0.49	0.80	$-2,159.68$
$IQR_{90,t}(\beta^m_{i,t})$	1.29	1.13	8.37	0.004	0.39	0.59	1.01	$-2,164.04$
$IQR_{80,t}(\beta^m_{i,t})$	1.07	0.91	6.92	0.01	0.42	0.58	0.88	$-2,162.61$
$IQR_{70,t}(\beta^m_{i,t})$	1.13	0.98	7.33	0.01	0.38	0.52	0.86	$-2,163.02$
$IQR_{80,t} + \sigma_t$	2.68	2.38	8.82	0	0.66	0.84	1.15	$-2,171.20$
$IQR_{90,t} + IQR_{80,t} + \sigma_t$	2.89	2.43	6.34	0	0.88	1.05	1.40	$-2,170.56$
$\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$	0.44	0.29	2.89	0.09	0.42	0.67	1.09	$-2,207.62$
$\sigma_t(\beta^m_{i,t}) + \mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$	0.80	0.49	2.58	0.08	0.72	0.94	1.33	$-2,158.87$
$IQR_{80,t} + \sigma_t + \mu_t$	2.83	2.38	6.21	0	0.93	1.15	1.52	$-2,170.19$

One-Year Ahead Returns ($hpr_{t\to t+12}$)

	In-Sample Statistics				bootstrapped R^2			
Model	R^2	Adj-R^2	F-stat	F-pval	P90	P95	P99	AIC
$\sigma_t(\beta^m_{i,t})$	3.17	3.02	20.65	0	3.77	4.79	7.97	-485.63
$IQR^{80}_t(\beta^m_{i,t})$	5.83	5.68	39.03	0	3.62	5.20	8.38	-503.25
$IQR^{90}_t(\beta^m_{i,t})$	5.55	5.40	37.03	0	3.68	4.94	8.46	-501.35
$IQR^{70}_t(\beta^m_{i,t})$	4.00	3.84	26.21	0	3.69	5.13	8.06	-491.02
$IQR_{80,t} + \sigma_t$	10.24	9.96	35.89	0	6.18	7.53	9.88	-531.55
$IQR_{90,t} + IQR_{80,t} + \sigma_t$	12.47	12.05	29.83	0	8.18	9.47	13.03	-545.46
$\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$	5.58	5.43	37.90	0	3.48	4.89	7.81	-522.80
$\sigma_t(\beta^m_{i,t}) + \mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$	6.64	6.34	22.35	0	6.24	7.86	10.68	-506.65
$IQR_{80,t} + \sigma_t + \mu_t$	13.42	13.01	32.46	0	8.00	9.73	12.47	-552.35

Notes: In-Sample one-month and one-year ahead Market excess returns forecast regressions: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and t+k; X_t is a vector of cross-sectional dispersion measures of the Market-Betas of Fama-French univariate Portfolio sorts. We consider sorts on all potential risk factors: Size, Value (book-to-market), Operating Profitability, Investment, Earnings-to-Price, Cashflow-to-Price, Dividend-Yield, Accruals, Market Beta, Net Share Issues, Daily Variance, Daily Residual Variance and portfolios formed on past performance (momentum, short-term and long-term reversal). We have 15 potential factors and 10 univariate sorts for each factor for a total of 150 portfolios. We perform rolling regressions using 24 months to compute Market-Betas for each of the FF portfolios running time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$. The models in this table consider simple cross-sectional statistics to measure the dispersion in Betas at each point in time. For each t we compute: (i) the cross-section 150 Portfolios standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th 150 Portfolio Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) The mean Factor beta spread, measured as the cross-sectional mean of all 15 Factors High minus low Beta portfolio. Formally for each t we compute $\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$, where F is the corresponding Fama-French univariate sort factor mimicking portfolio. The bootstrapped R^2 is designed to tackle the potential spurious predictability arising from time-series persistence of regressors. For each model we simulate 1000 bootstrapped samples using an estimated Arima (1,0,0) with the original regressors and then compute the 90, 95 and 99 percent cut-offs for these 1000 in-sample R^2. AIC is the Akaike information criteria

Table D.15

Dispersion Measures of FF 150 univariate Portfolio Betas – Summary of out-of-sample Statistics

Betas Rolling 24 Months

	One-Year Returns ($hpr_{t\to t+12}$)		One-Month Returns ($hpr_{t\to t+1}$)	
Moments	OOS R^2	ENC-N	OOS R^2	ENC-N
$\sigma_t(\beta^m_{i,t})$	0.07	0.24	−1.12	−3.73
$IQR^{80}_t(\beta^m_{i,t})$	3.92	13.75	0.31	1.05
$IQR^{90}_t(\beta^m_{i,t})$	5.55	19.80	0.22	0.74
$IQR^{70}_t(\beta^m_{i,t})$	1.04	3.54	−0.97	−3.24
$\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$	−1.84	−6.09	−0.44	−1.48
$\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right) + IQR^{80}_t(\beta^m_{i,t})$	2.08	7.16	−0.33	−1.11
$IQR_{80,t} + \sigma_t$	11.35	43.15	2.84	9.85
$IQR_{90,t} + IQR_{80,t} + \sigma_t$	14.97	59.33	2.59	8.96
$IQR_{80,t} + \sigma_t + \mu_t$	9.58	35.71	2.69	9.32

Notes: out-of-sample Statistics for Market Return Predictions. Out-of-sample procedure in this table split the sample in 1990 as a training window and recursively forecast returns going forward. The 1990 split was chosen to keep R/P (the number of recursive out-of-sample periods divided by the training period) close to 1. We report test statistics for the out-of-sample R^2 under the alternative assumption of no forecast improvement against the historical mean: ENC-New is the Clark and McCraken's (2001) encompassing test statistic. Models: $hpr_{t\to t+k} = \alpha + \Phi \cdot X_t + \epsilon_{t+1}$, where $hpr_{t\to t+k}$ is the cumulative (log) excess return of the market between months t and $t+k$; X_t is a vector of Beta cross-section dispersion measures for the FF150 univariate sorts portfolios. For each t we compute: (i) the cross-section 150 Portfolios standard-deviation ($\sigma_t(\beta^m_{i,t})$), (ii) the 90-th, 80-th and 70th 150 Portfolio Betas interquartile-range ($IQR_t(\beta^m_{i,t})$, (iii) The mean Factor beta spread, measured as the cross-sectional mean of all 15 Factors High minus low Beta portfolio within that univariate sort. Formally for each t we compute $\mu_t\left(\beta^H_{F,t} - \beta^L_{F,t}\right)$, where F is the corresponding Fama-French univariate sort factor mimicking portfolio. Rolling regressions for betas using 24 60 months to compute Market-Betas for each of the FF portfolios running time-series regressions of the form: $R^i_t = \alpha_i + \beta^m_i \cdot r^m_t + \mu^i_t$

Table D.16
Individual Stocks Betas Dispersion – Standard Deviation Regression on ERP Standard Regressors

	Dependent variable: Standard Deviation of Betas ($\sigma_t(\beta^m_{i,t})$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
svar	−2.01***							−3.80***
	(0.62)							(1.11)
csp		−5.79***						2.57
		(1.68)						(2.05)
dp			−0.09***					0.17**
			(0.01)					(0.09)
ep				−0.09***				−0.06***
				(0.01)				(0.02)
tms					1.52***			1.66***
					(0.27)			(0.35)
bm						−0.14***		0.10***
						(0.01)		(0.04)
dy							−0.09***	−0.24***
							(0.01)	(0.09)
Constant	0.46***	0.44***	0.15***	0.22***	0.43***	0.54***	0.14***	−0.03
	(0.004)	(0.004)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.09)
Observations	1,044	788	1,044	1,044	1,044	1,044	1,044	788
R^2	0.01	0.01	0.15	0.11	0.03	0.12	0.15	0.13

Notes: In-Sample Regression of individual stocks betas dispersion measure defined as the cross-section betas standard deviation on all standard return forecast regressors. We run $\sigma_t(\beta^m_{i,t}) = \alpha + \beta^k X_t$, where X_t are: Stock Variance (svar), Cross-Sectional Premium (csp) of Polk *et al.* (2006), dividend-to-price Ratio (d/p), the earnings-to-price ratio (e/p), the book-to-market ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average and the dividend yield (d/y) and the Term Spread (tms). See Goyal & Welch (2008)

Table D.17

Return Forecast Regression using Individual Stocks Betas Dispersion

	One-Year Ahead Return Forecast Regression ($hpr_{t\to t+k}$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma_t(\beta^m_{i,t})$	-0.32^{***}	-0.29^{***}	-0.24^{***}	-0.26^{***}	-0.39^{***}	-0.22^{***}	-0.24^{***}	-0.21^{***}
	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)
svar	1.77^{*}							-0.58
	(1.08)							(1.56)
csp		1.37						-9.07^{***}
		(2.43)						(2.87)
dp			0.06^{***}					0.10
			(0.01)					(0.12)
ep				0.06^{***}				0.11^{***}
				(0.01)				(0.03)
tms					3.24^{***}			2.96^{***}
					(0.47)			(0.50)
bm						0.14^{***}		-0.18^{***}
						(0.02)		(0.05)
dy							0.06^{***}	0.03
							(0.01)	(0.12)
Constant	0.21^{***}	0.19^{***}	0.37^{***}	0.34^{***}	0.19^{***}	0.08^{**}	0.37^{***}	0.94^{***}
	(0.03)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.04)	(0.13)
Observations	1,044	788	1,044	1,044	1,044	1,044	1,044	788
R^2	0.04	0.04	0.05	0.05	0.08	0.07	0.05	0.19

Notes: In-Sample market return forecast regression using, in addition to individual stocks betas dispersion measure, other usual regressors in the literature in a *kitchen sink* approach. We run $r^m_{t+1\to t+12} = \alpha + \gamma \cdot \sigma_t(\beta^m_{i,t}) + \Omega X_t$, where X_t are the following variables: Stock Variance (svar), Cross-Sectional Premium (csp) of Polk *et al.* (2006), dividend-to-price Ratio (d/p), the earnings-to-price ratio (e/p), the book-to-market ratio (b/m) is the ratio of book value to market value for the Dow Jones Industrial Average and the dividend yield (d/y) and the Term Spread (tms). See Goyal & Welch (2008)