Macro-based factors for the cross-section of currency returns

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Abstract

We use macroeconomic characteristics and exposures to Carry and Dollar as instruments to estimate a latent factor model with time-varying betas with the instrumented principal components analysis (IPCA) method by Kelly et al. (2020). On a pure out-of-sample basis, this model can explain up to 78% of cross-sectional variation of a Global panel of currencies excess returns, compared to only 27.9% for Dollar and Carry and 51% for a static PCA model. The latent factor and time-varying exposures are directly linked to macroeconomic fundamentals. The most relevant are exports exposures to commodities and US trade, credit over GDP, and interest rate differentials. This model, therefore, sheds light on how to incorporate macroeconomic fundamentals to explain time-series and cross-section.

1 Introduction

Macroeconomic fundamentals and currencies returns are, in many models, tightly connected (Hassan and Zhang 2021). However, in a seminal paper almost 40 years ago, Meese and Rogoff (1983), pointed out that the empirical evidence of this connection is relatively weak. While the search for macroeconomics drivers of currencies returns that could solve this apparent disconnect has been active to the asset-pricing and international macro literature since then (e.g. Lustig and Verdelhan 2007, Colacito et al. 2020 and Richmond 2019), the relation of macroeconomic fundamentals and returns is still elusive (Nucera et al. 2021). In parallel, a more recent strand literature, in particular Verdelhan (2018), shows that factor structures are essential to understanding currencies' total variation and the cross-section of returns. In fact, they show that Dollar and Carry are relevant priced factors

We leverage on both insights and propose a new empirical model that bridges macroeconomic intuition with the currencies factor structure. Broadly speaking, this model takes country-level macroeconomic variables, along exposures to Carry and Dollar, as instruments to jointly estimate interpretable latent factors and individual time-varying exposures, following the Instrumented Principal Components Analysis (IPCA) by Kelly et al. (2020). Our main result is that macroeconomic variables do matter to understand both time-series and cross-sectional currencies returns. In fact, we show that macroeconomic fundamentals bring information beyond what Dollar and Carry exposures can generate. This Macro based IPCA model (M-IPCA) can account for a high share of total returns variation while delivering low mispricing unconditional errors, even compared to benchmarks models. The results are valid for Developed, Emerging, and Global datasets of currencies' returns.

More importantly, by directly using economically motivated variables, both latent factors and time-varying exposures can shed light on *which* macroeconomic variables matter to understand this time-series and cross-section currencies returns. The most economically and statistically significant variables are exports exposures to the US and commodities, the share of international credit over Central Bank's reserves, total credit over GDP, and interest-rate differentials. Exposures to Carry and Dollar are also highly informative.

These macroeconomic variables have a dual role in the estimation and interpretation of the results. First, each of the estimated latent factors is approximately a managed portfolio of currencies with estimated weights directly linked to macro variables, thus retaining a direct economic interpretation. Second, these same macro fundamentals also determine the currency-level exposures to these latent factors. Since these variables vary over time, the exposures are naturally time-varying. These two M-IPCA features – interpretability and time-varying exposures – are departures of previous literature and are crucial to generating good statistical asset-pricing results while helping shed light on the macro-currencies returns' apparent disconnect.

Other methods for estimating latent factors, such as Principal Component Analysis (PCA) models, assume static exposures and are not directly interpretable. Also, most of the previous currencies factor literature (e.g., Verdelhan 2018, Lustig et al. 2011 and Lustig et al. 2014) sort portfolios based on some characteristic, such as interest-rate differential or dollar beta, and estimate rolling window regressions as a way to take the time-varying exposures into account. We use both the time-varying component of macroeconomic fundamentals and rolling exposures to Carry and Dollar as instruments to estimate and test the model without constructing portfolios sorted on a specific characteristic. Therefore, the M-IPCA framework allows us to estimate and test the model at the *currency-level*, which is a harder problem due to the role of potentially sizable idiosyncratic shocks for each of the currencies.

We find that the macro fundamentals matter for time-series and cross-section of currencies returns, which are the crucial dimensions of asset pricing tests. The M-IPCA model delivers small unconditional mispricing errors and high explanatory power of total risk variation. These results hold even when compared to a standard static Principal Component Analysis model or literature benchmarks that take some factors, such as Carry and Dollar, as observed (Lustig et al. 2014 and Verdelhan 2018). We estimate the M-IPCA using three different datasets: one with only developed countries, another with only emerging markets, and a third with all currencies (global). By doing this separation, we can test if there are meaningful differences in the risk-premium dynamics and exposures for emerging versus developed markets, which we indeed find relevant. Our dataset encompasses 36 currencies' monthly returns from 1988-2019 and nine macro variables on top of carry and dollar exposures. All variables are properly lagged to avoid using information unavailable to investors in real-time, and our results hold qualitatively on both in and out-of-sample procedures.

The first contribution of this paper is to show that the M-IPCA does a good job describing the cross-section variation of currencies excess-returns. The out-of-sample cross-sectional Pricing R^2 for the developed markets panel, which compares the realized versus model-predicted average return for each currency, is 66% for the M-IPCA with two factors specification. The benchmarks, a PCA with two factors and a model with Dollar and Carry as observed factors, generate, at most, 44%. If we increase the number of the M-IPCA factors to three, this metric goes up to 74.2%, while the PCA with three factors delivers only 48%. This result also holds in-sample, with the M-IPCA with three factors leading to a R^2 up to 79% while PCA does not get higher than 58% for a similar specification.

For the Global panel, a three-factor M-IPCA model delivers a R^2 of 74% out-of-sample and 65% in-sample, while benchmarks can get at most at 48% and 62%, respectively. This implicitly shows that pricing emerging markets is a harder problem. If we run the exercise only for these set of currencies, M-IPCA out-of-sample results would be only 46%, but benchmarks lead to a maximum of 28%. The relatively low R^2 could be due to a higher variance of idiosyncratic shocks in our sample.

It is important to note that these results do not rule out the relevance of Dollar and Carry factors. These factors are usually tested for a sorted portfolio of currencies in the literature and not at the individual level. Therefore, to compare our model performance with these benchmarks, we need to estimate time-varying exposures based on the rolling regressions of 36 months. One of the major advantages of using the IPCA is to estimate these time-varying exposures more efficiently. In fact, we find that some of the M-IPCA estimated latent factors are linked to the Carry and Dollar. which we discuss later.

Second, we show that the model also has successful time-series properties. The out-of-sample Total R^2 for a two-factor model, which is directly comparable to the Observed factors benchmarks, ranges from 35% to 50% across the three data panels, while benchmarks can deliver at most 36%. Similarly, the same pattern applies for in-sample results. It is essential to notice that all these tests are done at the *currency-level*, which has more noise than portfolios sorted on a specific characteristic.

Third, and more importantly, these results highlight that macro fundamentals are essential to understand the dynamics of currencies returns, both through time-varying exposures *and* macro-based factors. We can also test if the macroeconomic variables that matter for Developed Markets are, for example, the same as for Emerging markets, thus shedding light in the underlying sources of the risk-premium. Out of simplicity, we present the set of variables that matter the most for an in-sample fit with three factors. We then construct a minimum-variance efficient that appropriately combine the three factors into one. The resulting weights to these portfolios given by the macroeconomic variables can help us understand which of those are quantitatively more important to increase the explanatory power of the model.

For all panel of currencies, results are heavily influenced by exposure to dollar and carry factors. This shows the strength of previous results shown by the literature. However, other macroeconomic variables bring additional information to the table, in particular the ones related to financial vulnerability, trading linkages and exposures to commodities cycles. Interestingly, some variables tested by Meese and Rogoff (1983), such as those trade-related, are found relevant in our framework. For Developed Markets, the most important ones are international credit over central bank reserves, share of commodities over total exports and GDP per-capita. All these variables show up with a positive sign. Therefore, richer countries, more financially vulnerable and more reliant on commodities are, on average, more exposed to these global factor movements. For Emerging Markets, commodities exposure are also very relevant, followed by total credit over GDP (i.e. another financial vulnerability indicator), exports exposure to US, inflation and interest rate differentials. All these variables also show up with a positive sign.

Finally, we can use our framework to try to understand the macroeconomic drivers of exposure to the known Dollar factors. While the literature showed that this factor is relevant, it is unclear, in particular for the Dollar, why some countries are more or less exposed to it. To explore this dimension we use the same IPCA framework, but instead of jointly estimating time-varying betas and latent factors, we assume that the factors are actually observed. Therefore, these macroeconomic variables could only help through the time-varying exposures component, instead of the usual both channels. We can answer, than, why some currencies are more or less exposed to these factors. We do not consider dollar and carry exposures to let only macroeconomic variables to have a chance on explaining the exposures.

For the Developed Markets panel, essentially only exports to US are relevant. This means that the Developed Market countries exposed to the Dollar factor are those that have strong export links to the US. For Emerging Markets, however, the exposure is more complex. While exports links to US also matter with a positive sign, poorer emerging market countries with negative trade balance are also more exposed to this factor. Those that are less affected by commodities cycles and are less financially vulnerable also have a higher exposure. Thereafter, it looks that the underlying risk-premium sources of the Dollar factor is driven by multiple channels. These results suggest that the Macro-IPCA can help to disentangle the dollar risk into different conditional and unconditional factors, which themselves are linked to specific categories of macro-risks.

Our paper connects to a broad literature that tries to connect macro quantities to asset prices explicitly (Cochrane (2017)). Many macroeconomic variables have been proposed to be related to currencies returns. The search goes back to Meese and Rogoff (1983) that tested fundamentals such as GDP growth and per-capita level, trade balance, inflation, and interest differentials. More recently, the literature has proposed other variables such as exposures to commodities (Ready et al. 2017), output gap (Colacito et al. 2020) and trade-centrality (Richmond 2019). Also, Lowe and Borio (2002) and Gourinchas and Obstfeld (2012) point out the role of credit expansion as a financial vulnerability indicator, especially for emerging markets. We try to use the intuition given by these papers to construct simple metrics that can be applied for a large range of different countries to systematically test if they help to estimate latent factor models with time-varying exposures. Our paper is also related to Chernov et al. (2020), which tests models at the currency level.

This paper also connects to the latent factor model estimation for international assets literature. Rey (2015) and Miranda-Agrippino and Rey (2021) show that global assets display a strong factor structure that is related to financial and commodities cycles. Verdelhan (2018) suggests that at least a two-factor model is necessary to account for the currencies dynamics. Lustig and Verdelhan (2007), Lustig et al. (2011) and Lustig et al. (2014) try to explain the cross-section implications of carry trades and its relation with some macroeconomic variables. Finally, another paper that is closely related to ours is Nucera et al. (2021). They assume that some factors can be weak and potentially omitted and estimate a latent factor model combining Lettau and Pelger (2020) and Giglio and Xiu (2021) methods. After estimating the risk-premium of macroeconomic variables, they find that they are not strong. We show that they can be relevant for the dual latent factor with time-varying exposures estimation.

We also add to the IPCA literature developed by Kelly et al. (2019). Using characteristics as instruments to estimate latent factor models with time-varying betas has been successful for different asset classes, especially equities (Kelly et al. 2020 and Bybee et al. (2022)) and corporate bonds (Kelly et al. (2022)). We show that macroeconomic fundamentals as instruments can also help to explain the dynamics of currencies returns.

The difference in our approach, compared to previous literature, is the flexibility of the M-IPCA. This method looks for systematic risks estimated through macro fundamentals, thus retaining direct economic interpretation. We show that the model does an excellent job in both asset-pricing relevant dimensions - time and cross-sections. These factors turn out to have exciting but not targeted cross-sectional implications.

The following section discusses the latent factor with time-varying exposures motivation for currencies returns. Next, in section 3 we discuss how we choose the macroeconomic variables that are the candidates for the estimation procedure. Then we show the details of how the M-IPCA and benchmarks are estimated in section 4 , followed by a discussion of how the data is constructed in section 5. Section **??** describe and discuss the results, showing both the asset-pricing properties and the interpretation of the macroeconomic variables that matter for currencies' returns. In section 7, we discuss how our results compare to the Carry and Dollar factors.

2 M-IPCA motivation

We start from the International APT model proposed by Solnik (1983). From the perspective of an American investor, each currency excess return i, $r_{t+1}^{x,i}$, is assumed to follow equation 1, where f_t is the vector of the latent factors and ε_t^i the idiosyncratic shock of country i. Since returns are always relative to the dollar, there is an additional term – the US idiosyncratic shock ε_{t+1}^{US} – which loads *equally* on all currencies. It is assumed that $E_t[\varepsilon_{t+1}^i] = E_t[\varepsilon_{t+1}^i f_{t+1}] = 0$ for all i, including the US.

$$r_{t+1}^{x,i} = \beta_t^i f_{t+1} - \varepsilon_{t+1}^i + \varepsilon_{t+1}^{US} \tag{1}$$

Factors can be assumed to be observed and potentially motivated by economic intuition – such as the Carry and Dollar (Verdelhan 2018) and output gap (Colacito et al. 2020), for example – or latent, and then estimated by some Principal Component Analysis method (Nucera et al. 2021). In both cases, to deal with the time-varying exposures, most papers use portfolios of currencies sorted in a particular characteristic, assuming a constant exposure, or by running rolling regressions at the currency level. We depart from the literature in two dimensions. We use macroeconomic motivated fundamentals as instruments to estimate both a latent factor model and time-varying exposures. By doing that, we retain the macroeconomic motivation of factors construction while estimating time-varying exposures more efficiently by combining the standard rolling regression exposures to Carry and Dollar to the natural time-varying component of macroeconomic characteristics.

The estimation closely follows the Instrumental Principal Component Analysis (IPCA) in Kelly et al. (2020). Instead of using stock-level characteristics, we are going to use macroeconomic fundamentals of each currency as instruments to the estimation of the model. We assume that time-varying exposures are given by equation 2, where $z_{i,t}$ is a vector of characteristics, Γ_β a matrix of coefficients and $\nu_{\beta,i,t}$ an error term such that $E[\nu_{\beta,i,t}] = E[\nu_{\beta,i,t} z'_{i,t}] = 0$. Both Γ_β and the latent factors are estimated simultaneously – estimation and derivation details are available in section 4. Characteristics are rank-standarized between -0.5 and 0.5 to account for different variables' different volatility and to retain the long-short interpretability of the factors.

$$\beta_{i,t} = z'_{i,t}\Gamma_\beta + \nu_{\beta,i,t} \tag{2}$$

The latent factor estimates correspond to portfolios of the underling country returns where the portfolio weights are determined by the country characteristics through Γ_β. Therefore, If macroeconomic fundamentals are relevant for currencies returns, the coefficients in the Γ_β matrix should be economically significant, pinning down both time-varying exposures and latent factor estimates. As an example, suppose that GDP growth is a relevant variable. The estimated latent factor will be approximately equal to a long-short portfolio of currencies sorted by the variable, and the currencies more exposed to this factor are going to be those with the highest GDP growth. As time passes, the ranking of those countries based on the variable can change, thus mechanically reordering the exposure to the factor. If more than one variable is relevant, the Γ_β matrix gives the relative weights to each of the relevant macroeconomic fundamentals that are relevant to explain currencies movements.

Our main goal is to determine if and which macroeconomic fundamentals matter for currencies returns –, that is, the macroeconomic variables that have economically significant loadings in the matrix Γ_β. Before that, however, we need to show that the resulting asset pricing model implications are satisfied. We analyze the asset pricing fit in two dimensions, related to time-series and cross-section properties. First, it should successfully explain the total risk dynamics of currencies excess returns (total variation). Second, it must be able to explain the unconditional cross-section of returns by generating low mispricing errors. On top of that, we need to show that this macroeconomic variables bring new information to the estimation relative to what is already known. For that, we use literature benchmarks to evaluate the asset-pricing results in absolute and relative terms.

To evaluate these three metrics, however, we need to consider the additional term that does not show up in factor structures of assets that are not relative prices like currencies – the US idiosyncratic shock. This additional term can complicate the analysis in the currency level, especially for those that do not have long enough time-series. To see how this could be problematic, take the cross-section implications of a good asset pricing model. In order for a model to successfully explain the unconditional cross-section of returns, pricing errors of all currencies, α^i in equation 3, should be be zero.

$$\alpha^i = E[r^{x,i}_{t+1}] - E[\beta^i_t f_{t+1}] \tag{3}$$

However, this implicitly assumes that the sample is long enough such that the realized average idiosyncratic shocks are zero. In reality, however, currencies have short time series. This could lead to significantly non-zero US idiosyncratic shocks for some of the assets. For example, suppose that the average US idiosyncratic component deviates largely from zero in the chosen sample. In that case, the realized excess return estimation is going to be equal to the US idiosyncratic realized shock plus the predicted value from the factor structure, while the model is only going to capture the second channel. Therefore, the mispricing is going to be determined by a shock that is outside the scope of the model.

More worryingly, in an unbalanced panel of currencies, the size of the shock realization is going to depend on the specific sample for each currency, which is the case for all our panels. It is important to emphasize that if a particular currency has non-zero idiosyncratic shocks average realization due to short sample sizes, this is also going to impact the mispricing by forces outside the scope of the factor model. However, its impact is diluted for one out of N currencies. By increasing the number of currencies, this problem can be attenuated. It is only the US idiosyncratic shock that loads equally for all of them, so the effect is not damped by increasing the cross-section.

The comparison across different models can also become problematic. Some factors proposed by the literature are not dollar-neutral (i.e. are not long-short portfolios) and thus are going to embed the US idiosyncratic term mechanically and artificially increase the explanation power of the risk dynamics, as discussed by Boudoukh et al. (2018). Take the Dollar factor as an example. This factor is defined by the cross-sectional average of all currencies for each period, RX_{t+1}. As seen in equation 4, for a sufficiently large number of currencies, the average of idiosyncratic shocks for all i other than the US goes to zero, but the last term is still there. Therefore, if you run a regression specification such as equation 5 where you assume the factor of equation 1 is RX, then both left and right hand sides have ε^{US}, increasing the explanatory power over the total variation of the excess return [1].

$$RX_{t+1} = \frac{1}{N}\sum_i r^{x,i}_{t+1} = \frac{1}{N}\sum_i \beta^i_t f_{t+1} + \varepsilon^{US}_{t+1} \tag{4}$$

$$r^{x,i}_{t+1} = \delta^i_t RX_{t+1} + u^i_t = \delta^i_t \frac{1}{N}\sum_i \beta^i_t f_{t+1} + \delta^i_t \varepsilon^{US}_{t+1} + u^i_t \tag{5}$$

A final potential issue is that the IPCA estimation may interpret the US idiosyncratic shock as an additional factor with a unitary constant exposure for all currencies [2]. To avoid all these potential pitfalls of the co-founding effects of the US idiosyncratic shock, we subtract equation 4 from each currency as in equation 1 from the model, and then get the following equation 6, where $\bar{\beta}_t$ is the cross-sectional average of β^i_t and $\tilde{\beta}_t$ the demeaned exposure. In this specification, the returns in excess of the cross-section average in each period, $\tilde{r}^{x,i}_{t+1}$, do not depend anymore on the US idiosyncratic shock and have the standard factor structure more common in the equities literature.

$$\tilde{r}^{x,i}_{t+1} = r^{x,i}_{t+1} - RX_{t+1} = \left(\beta^i_t - \bar{\beta}_t\right) f_{t+1} - \varepsilon^i_{t+1} = \tilde{\beta}^i_t f_{t+1} - \varepsilon^i_{t+1} \tag{6}$$

In the proposed framework, latent factors and time-varying exposures are jointly estimated using macroeconomic fundamentals. We are going to use the cross-section given by equation 6 to estimate and test the M-IPCA and the benchmarks. In the next section we show which macroeconomic variables we consider in the estimation of the model.

[1]In fact, Chernov et al. (2020) finds that only 1% of the variation of this Dollar factor is priced. Later in this paper, we show that in our specification, the Dollar factor is also priced in our cross-section.

[2]When we estimate the IPCA, one of the variables is the the intercept – unitary for all currencies in all periods. In theory the Γ_β could load up only for the intercept, thus recovering a factor that in reality is the US idiosyncratic shock.

3 Which macro fundamentals should matter

There are potentially many channels through which macroeconomic variables can matter for currencies returns. In this paper, we will focus on a subset of standard potentially relevant macroeconomic fundamentals that have been previously proposed in the theoretical and empirical literature. We acknowledge that there are potentially many other channels, but since the cross-section of currencies returns is small, we select only a few of these characteristics to avoid overfitting. Thereafter, the main exercise of this paper is not to select the most relevant macroeconomic variables among a high-dimensional data set. Instead, we show that even if we consider a small subset among the potentially high-dimensional, we can add information that is not embedded in the literature benchmarks. This would help to establish a link between currencies' risk-premium and macroeconomic fundamentals, which so far has been hard to be be pinned down.

The first set of varaiables we consider in our model closely follows Meese and Rogoff (1983). In particular, we test if inflation, GDP level and growth, interest differential, and trade-balance as candidates to have economic meaningful Γ_β loadings. More intuitively, under this M-IPCA framework, this implies we are testing if, for example, currencies with high inflation are more or less exposed to a specific latent factor of currencies approximated to a long-short portfolio sorted on the level of inflation. If inflation is relevant to the M-IPCA model with positive loadings in the Γ_β, we are showing that a (i) factor that resambles a managed portfolio based on this metric helps to explain the time-series and cross-section of currencies returns and that (ii) high inflation countries have a higher unconditional risk-premium.

Second, trade-related variables other than trade balance have also been proposed to be relevant for currencies returns. In particular, Richmond (2019) links the dollar factor to trade network centrality measures. Following this intuition, we include the trade share of each country to the US economy as a potential relevant additional fundamental. Thereafter, this variable is a proxy to the exposure to the US economy through direct trade relations. While we could include network based metrics, we use this as a simple proxy to a potentially complicated measure. On top of that, we also use the commodity share of exports, following (Rey 2015 amd Miranda-

Agrippino and Rey 2021), that show that commodities price swings are linked to a Global Financial Cycle measure and drive returns of many different global asset classes. Intuitively, countries that are more exposed to commodity cycles could demand a higher risk-compensation due to the pro-cyclical nature of commodities prices.

Finally, we use two metrics related to financial stability. Recent literature Borio et al. (2018) emphasize the role financial cycles to predict economic variables such recession. Out of simplicity and data availability, we use Credit over GDP as a metric for the M-IPCA framework. The goal is to measure if highly leveraged economies are also more exposed to systemic risks, both for Developed and Emerging Markets. On top of that, we also take the role of international reserves as another indicator of financial vulnerability, For Emerging Markets in particular, but not only, the Central Banks' reserves adequacy is an object of interest of the International Monetary Fund (e.g. IMF (2011)) since it is related to the ability of preventing sudden stops and currencies crisis. As a proxy to this risk we use the share of Central Banks' share of international credit (i.e. credit exposed to foreign buyers) with respect to Central Banks's international reserves. By using both of these metrics we hope to uncover if exposures to financial cycles are also relevant to understand currencies average returns.

Next, we show how to estimate the M-IPCA model.

4 Models details

4.1 M-IPCA

To estimate the M-IPCA model we closely follow Kelly et al. (2020). We start from the equation 6 that takes into account the US idiosyncratic shock to avoid all the potential pitfalls discussed in previous sections. To estimate both the latent factors and time-varying exposures we solve the optimization problem in equation 7, where $\tilde{R}_t$ is a $Nx1$ vector of $\tilde{r}_t^{x,i}$ and Z_t the NXL stacked matrix of L rank-standardized macroeconomic characteristics.

$$\min_{\Gamma,\{f_t\}} \sum_{t=1}^{T} \left(\tilde{R}_t - Z_{t-1}\Gamma f_t\right)' \left(\tilde{R}_t - Z_{t-1}\Gamma F_t\right) \tag{7}$$

The first order conditions conditions are given by 8 and 9. The iterative algorithm to recover these objects are described in detail in Kelly et al. (2019) and Kelly et al. (2020).

$$\hat{f}_{t+1} = \left(\hat{\Gamma}'_\beta Z'_t Z_t \hat{\Gamma}_\beta\right)^{-1} \hat{\Gamma}'_\beta Z'_t \tilde{R}_{t+1}, \qquad \forall\ t \tag{8}$$

$$vec\left(\hat{\Gamma}'_\beta\right) = \left(\sum_{t=1}^{T-1} Z_t Z'_t \otimes \hat{f}_{t+1}\hat{f}'_{t+1}\right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t \otimes \hat{f}_{t+1}\right]' \tilde{R}_{t+1}\right) \tag{9}$$

4.2 Asset Pricing Tests

We propose that in order to evaluate the M-IPCA asset pricing features we need to measure two dimensions: time-series total risk explanatory power and the size of mispricing errors. To do that, all at the currency-level, we proceed as fallowing.

First, intuitively, M-IPCA finds factors and exposures that maximize the explanatory power of the risk model for a panel of currencies excess returns. This is the the time-series dimensions metric that we use. We call it Total R^2 metric which is given by equation 10 where $\bar{z}_t$, summarizes this dimension. The goal of this metric is evaluate one the asset-pricing properties – how well can each of these models explain the risk-dynamics of a panel of currencies returns? In fact, Verdelhan (2018) has showed that currencies have a strong factor structure, and that most of the total variation of currencies returns can be attributed to exposures to a Dollar factor (i.e. the cross-sectional average of the returns in each period). Therefore, for our model to be successful we need to also be able to explain a relevant share of currencies variation with our latent factor method.

$$Total R^2 = 1 - \frac{\sum_{i,t}\left[\tilde{r}_{i,t+1} - (z_{i,t} - \bar{z}_t)'\left(\hat{\Gamma}_\beta \hat{f}_{t+1}\right)\right]^2}{\sum_{i,t} \tilde{r}^2_{i,t+1}} \tag{10}$$

It is important to note that the Total R^2 is a targeted object on the optimization problem of the M-IPCA. However, we show that our results hold both for the in-sample results as well a out-of-sample.

More importantly, the second dimension of asset pricing properties – the low mispricing errors implied by the model – are not targeted moments. In this dimension, the goal is to be able to explain the cross-sectional of currencies returns – can we understand why, on average, some currencies deliver a high unconditional return than others? To summarize the explanatory power on the unconditional cross-section we are using the Pricing R^2, which is sample equivalent of the weighted average of $\tilde{\alpha}_i = E[\tilde{r}_{t+1}] - E[\tilde{\beta}_t^t f_{t+1}]$, where $\mathcal{T}_i$ determines the period of currency i that we have the data and w_i is equal to the number of observations that currency i is in our sample divided by total amount of observations we have for all currencies.

$$PricingR^2 = 1 - \frac{\sum_i w_i \left[\frac{1}{|\mathcal{T}_i|}\sum_{t\in\mathcal{T}_i}\left(\tilde{r}_{i,t+1} - (z_{i,t} - \bar{z}_t)'\left(\hat{\Gamma}_\beta \hat{f}_{t+1}\right)\right)\right]^2}{\sum_i w_i \left(\frac{1}{|\mathcal{T}_i|}\sum_{t\in\mathcal{T}_i}\tilde{r}_{i,t+1}\right)^2} \tag{11}$$

If M-IPCA is a successful model it should explain the total variation of currencies returns and predictability while delivering small mispricing such that we have high Total and Pricing R^2s, respectively. We estimate the model with up to five different factors.

4.3 Benchmarks

To compare the results of the M-IPCA, we also consider two different benchmarks. The first is based on a static Principal Component Analysis model. The second uses observed factors, in particular Dollar and Carry. All the benchmarks models are also tested at the currency-level, which can lead to different magnitudes compared to previous literature which focuses on returns of portfolios sorted in certain characteristics.

4.3.1 PCA model

The first benchmark is a PCA model estimated using the same panel of currencies returns $r^{x,i}_{t+1}$. used on M-IPCA estimation.[3] After estimating the latent factors, we consider two alternative estimation methods for the currencies' exposure to the factors. In the first, unconditional-PCA (U-PCA), the loadings are estimated using the whole sample of returns, recovering a static $\tilde{\beta}^i$ for each currency. This is a standard approach, but in the M-IPCA specification we have time-varying exposures, which can help to explain a good part of our results. Therefore, we make the PCA method more flexible to allow for some time-varying exposures. In the second method, which we call conditional-PCA (C-PCA), we use 36-month rolling windows to estimate time-varying $\tilde{\beta}^i_t$. By doing that we hope to give this benchmark a fairer chance of matching the M-IPCA results.

4.3.2 Observed factors

The second benchmark model assumes that the factors are observed – Dollar and Carry. Both factors are constructed using long-short portfolios sorted on each currency's dollar exposure or the interest-rate differentials. Notice that this procedure avoids embedding the factors with the US idiosyncratic shocks because the shocks are netted out. Following the PCA benchmark, we also estimate equation 6 with either a sample that uses the whole sample, Unconditional Observed model (U-Obs), or by running rolling regressions to recover time-varying exposures, the Conditional Observed model (C-Obs).

4.4 Out-of-sample procedure

Given that the estimation procedure of methods such as M-IPCA and PCA is more involved than simple regressions used in the observed benchmark cases, we construct out-of-sample estimations to avoid overfitting pitfals, in particular over the time-series metric that is a targeted moment of this method. We also consider how our procedure performs against the same set of benchmarks

[3]Since we have an unbalanced panel, we estimate PCA using the expectation maximization (EM) approach proposed by Stock and Watson (2002).

in an out-of-sample environment. To form our training and evaluation samples we use a standard *expanding training sample* procedure. That is, we start with a training sample consisting of 4 years of data and evaluate the performance of models estimated over this training sample for the next month (out-of-sample). We then expand the training sample by one month and repeat the procedure. We continue to expand our training sample until the full sample of data has been exhausted, ultimately leaving us with 27 years of test sample data. Note that the C-Obs is already an out-of-sample metric under this perspective. Also, both U-Obs and U-PCA are only estimated for in-sample results by construction. We show results for both these sampling exercises.

5 Data

5.1 Currencies Returns

The excess return of currency i at time t, $r_{i,t}$, is defined by equation 12, where $i_{i,t}$ is the implied interest-rate differential by forward prices and $s_{i,t}$ is the spot return.

$$r^{x,i}_{i,t+1} = i_{i,t} - i_{US,t} - (s_{i,t+1} - s_{i,t}) \tag{12}$$

We use monthly returns for 36 currencies, from January 1988 to November 2019, divided into Emerging and Developed markets groups [4]. Data for spot returns and implied interest rates are from Datastream. In table 1 we present the start and end dates for each currency in our dataset, as well as the number of monthly observations.

5.2 Macroeconomic fundamentals

Table 2 describes the source of each series, how the measure is calculated, how many lags we use, and the frequency of the data. We use data from Oxford Economics, BIS, IMF, and Penn Table for the macro variables. Importantly, we lag variables according to the release window to only

[4] We exclude currencies when they were pegged to the dollar. After the introduction of the Euro, we treat Germany as the equivalent area.

Table 1: Sample description of currencies panel – we define the Developed Market and Emerging Markets in Panel A and B, respectively. For each of these currencies we report when they get in the data set in the start date columns and when they leave. The column Obs shows the final number of monthly observations available for each of the currencies.

Country	**Start date**	**End date**	**Obs**
Panel A: Developed Markets			
Australia	Dec-88	Nov-19	372
Austria	Jan-97	Nov-98	23
Belgium	Dec-88	Nov-98	41
Canada	Dec-88	Nov-19	372
Denmark	Dec-88	Nov-19	372
Finland	Jan-97	Nov-98	23
France	Dec-88	Nov-98	120
Germany	Jan-91	Nov-19	347
Ireland	Oct-93	Nov-98	62
Italy	Dec-88	Nov-98	120
Japan	Dec-88	Nov-19	372
Netherlands	Dec-88	Nov-98	120
New Zealand	Dec-88	Nov-19	372
Norway	Dec-88	Nov-19	372
Portugal	Jan-97	Nov-98	23
Singapore	Dec-88	Nov-19	372
Spain	Jan-97	Nov-98	23
Sweden	Dec-88	Nov-19	372
Switzerland	Dec-88	Nov-19	372
UK	Dec-88	Nov-19	372
Panel B: Emerging Markets			
Brazil	Mar-04	Nov-19	189
Chile	Mar-04	Nov-19	189
Colombia	Mar-04	Nov-19	189
Czech Republic	Jan-97	Nov-19	275
Greece	Jan-97	May-00	41
Hungary	Oct-97	Nov-19	266
India	Oct-97	Nov-19	266
Indonesia	Jun-07	Nov-19	150
Malaysia	Jul-05	Nov-19	173
Mexico	Jan-97	Nov-19	275
Poland	Feb-02	Nov-19	214
Russia	Mar-04	Nov-19	189
South Africa	Jan-00	Nov-19	239
South Korea	Feb-02	Nov-19	214
Thailand	Jan-97	Nov-19	275
Turkey	Jan-97	Nov-19	261

consider variables in the investor's information set. All characteristics are rank-standardized within each of the three panel of currencies between -0.5 and 0.5 for each period. Therefore, the estimated latent factors retain a more natural managed portfolios intuition of under and overweight of certain characteristics.

Table 2: Macroeconomic fundamentals – here we define which of the macroeconomic variables we are considering in our M-IPCA specification. All the variables are rank-standardized between -0.5 and 0.5. We indicate the variable, the frequency of the data, the source, how many lags to take into account release windows and which transformation of the data we are using. YoY stands for Year over Year, 4qma is the four quarters moving average and level is the data without any transformations.

Variable	**Frequency**	**Source**	**Lags (months)**	**Measure**
CPI	Quarterly	Datastream	6	YoY 4qma
Real GDP Growth	Quarterly	Datastream	6	YoY 4qma
Interest rate differential	Monthly	Datastream	0	Level
Commodity share of exports	Annual	Datastream	18	Level
US trade share	Annual	Datastream	18	Level
Trade Balance over GDP	Quarterly	Datastream	9	4qmma
GDP per-capita (USD)	Annual	Datastream	15	Level
Total Credit over GDP	Quarterly	BIS	12	Level
International credit/international reserves	Quarterly	BIS/IMF	9	Level

5.3 Factor exposures

In addition to the macro variables, we also use the currency's Dollar and Carry betas as a characteristic in the estimation procedure. Since the literature has showed a strong information for both these factors, we believe that these exposures may capture information that not necessarily is embedded in the standard macroeconomic series. More specifically, for each month and currency, the beta is calculated by regressing the currency's monthly return ex-Dollar on Verdelhan (2018)'s Global Dollar and Carry factors. We use data from the previous 36 months for each regression.

In the next sections we show how pricing and macroeconomic fundamental variables help to explain currencies cross-sectional and time-series properties.

6 Macro matters for currencies returns

First we show that the M-IPCA does a good job describing total risk dynamics while maintaining out-of-sample unconditional small mispricing errors for all panels of currencies. We also show that these results hold in-sample and provide the estimated Γ_β for an in-sample specification with three factors to show which macroeconomic variables matter for currencies return.

6.1 Developed Markets

A good asset-pricing model should have small unconditional pricing errors. We use the Pricing R^2 to evaluate how well M-IPCA and all benchmarks compare in the unconditional out-of-sample cross-sectional dimension. In Panel A of table 3 we show that M-IPCA specification can explain from 32.5% to 78.5% of the unconditional cross-sectional variation for developed markets. Therefore, despite being estimated and tested at the *currency*-level, the M-IPCA can explain most of the cross-sectional dispersion. Note that the M-IPCA estimation does not target this measure, so there should be no mechanic relation of number of factors and high Pricing R^2s.

More importantly, when compared to benchmarks, M-IPCA does a significantly good job over this dimension. The PCA model can only explain 51% of the cross-sectional variation at most. For a parsimonious model of three factors, in particular, the differences are even more striking – 74.2% for the M-IPCA compared to only 48% for the PCA. On top of that, M-IPCA does much better than the second benchmark. For the two observed factors ,Carry and Global Dollar the explanatory power is, at maximum, 27.9%, while the M-IPCA model with two factors can account for 66%.

The second dimension that a good asset-pricing model should satisfy is the total risk dynamics of returns, which we measure using the Total R^2. As discussed before, currencies have a strong factor structure which can be easily identified with high R^2 over the time-series of each of the series. Note that the maximization of Total R^2 is the optimization problem that these models target, but as we run the analyzis in a out-of-sample fashion, the overfitting issues are lessened, even as we increase the number of factors that, in-sample, should mechanically be monotonically increasing. Interestingly, M-IPCA also does much better than the two benchmarks over this dimension, explaining up to 71.8% over this dimension while benchmarks can get only up to 45%. Again, a parsimonious model of $K = 3$ can explain u to 60%, while benchmarks can only up to 41.4%.

Table 3: Out-of-sample R^2s results – in this table we show the Total and Pricing R^2 as defined by equations 10 and 11, respectively. Total R^2 measures the explanatory power of each of the models on the total variation of currencies returns, therefore the risk dynamics. Pricing R^2 measures the ability of the model to explain the cross-section of those returns. All returns are measured in excess of the cross-sectional average in each period. The frequency of returns is monthly, starting in December 1988 and ending on November 2019. The panel of returns is unbalanced, therefore not all currencies data start or end in the same period. The three panels – Developed, Global and Emerging Markets – are defined in Table 1. We estimate the M-IPCA model, which is the IPCA specification with macroeconomic variables and exposures to Dollar and Carry factors as characteristics. C-Obs assumes that the factors are observed and estimates time-varying exposures with rolling windows of 36 months. C-PCA specification fits a PCA model and a rolling window estimation to the exposures, like for the C-Obs. All results are out-of-sample – we estimate each of the models, M-IPCA, C-PCA and C-Obs on an expanding window with initial size of 48 months of observations. For C-PCA and M-IPCA we show the each of the results for specifications of 1 to 5 factors (K). M-IPCA delivers has the highest R^2s in both dimensions compared to the two other benchmarks.

	Pricing $R\hat{2}$					**Total $R\hat{2}$**				
	K1	**K2**	**K3**	**K4**	**K5**	**K1**	**K2**	**K3**	**K4**	**K5**
	Panel A: Developed Markets Panel									
M-IPCA	32.5	66.3	74.2	76.7	78.5	28.0	49.8	60.0	66.3	71.8
C-Obs		27.9					33.7			
C-PCA	32.2	43.8	48.1	52.2	51.4	19.3	36.0	41.4	45.0	48.2
	Panel B: Global Markets Panel									
M-IPCA	14.9	55.6	65.4	62.6	67.9	20.1	36.8	43.5	47.5	52.0
C-Obs		48.1					35.3			
C-PCA	31.6	37.4	44.4	41.3	53.7	14.0	24.3	30.0	37.7	43.7
	Panel C: Emerging Markets Panel									
M-IPCA	19.4	17.6	46.3	39.9	32.0	15.5	34.9	48.7	55.6	61.3
C-Obs		-3.9					26.9			
C-PCA	25.6	27.6	8.7	19.2	30.6	13.0	25.5	35.9	44.6	48.3

6.2 Global Markets

When we estimate the M-IPCA and PCA pooling both emerging and developed markets currencies, results are qualitatively similar to the previous two panels as can be seen in Panel B of Table 3. Pricing R^2 ranges from 14.9% to 67.9% for the M-IPCA, but only 53.7% for the benchmarks. Again, using the three factors specification, M-IPCA delivers a 65.4% R^2, while PCA and Observed model only 37.4% and 48.1%, respectively. Therefore, our model still delivers around 17 percentage points more of explanatory power over the cross-sectional compared to the two benchmarks used in this paper. The same idea also applied to the Total R^2, which are at least 8 percentages points higher for this specification compared to C-Obs and C-PCA. Again, the flexibility of M-IPCA with respect to the macroeconomic variables seem to provide additional information compared to the results found before by the literature. It is

6.3 Emerging Markets

The final panel uses only Emerging Market currencies. The idea is that the underlying risk-premium dynamics for these currencies is potentially distinct from the others Developed Markets. Therefore by fitting two M-IPCA models separately we could disentangle these two sources different set of variables that could matter for Γ_β. First we need to ensure that M-IPCA has a good performance, both in absolute and relative terms, in the two asset pricing dimensions.

Just like to the Developed and Global Markets panels of currencies returns, M-IPCA does a good job both in absolute and relative terms, describing the cross-sectional of returns and unconditional risk-dynamics. Panel C of Table **??** shows that pricing R^2 range from 19.4% to 46.3%, significantly higher than all benchmarks. However, there are a few differences compared to previous panels. First, the R^2s metrics are much lower, potentially reflecting the higher idiosyncratic variance of Emerging Markets returns or a shorter sample for most of the countries. Second, this problem is particularly acute for the benchmarks. The C-Obs model, for example, has a *negative* pricing R^2. C-PCA also does poorly, with a 30.6% result on this metric, but only on the five factor specification. For our preferable model, R^2 is only 9%. Finally, interestingly the best out-of-sample model for the M-IPCA is the parsimonious version with only three factors.

Next we show that results hold also in the in-sample sample before we move to the analysis of the Γ_β that can allow us to check the differences of exposures of Emerging and Developed Markets, if any.

6.4 In-sample Evaluation

In this section we report the results for the in-sample models. This is important for two reasons. First because we want to analyze the resulting Γ_β matrix for the interpretation of the model. The in-sample model results in only in just one of those matrices, making the analyses simpler. Second, the sample of our results is relatively small, so that we this as an additional robustness exercise. Note that in this setting in addition to the C-Obs and C-PCA benchmarks we can also construct static versions of these models, the U-Obs and U-PCA.

In table 4 we report the results for M-IPCA and benchmarks, again using up to five factors for the factor models. Compared to the out-of-sample, results are somewhat better for the Developed Markets panel, but much improved for the Emerging Markets version. This latter result could be linked to a less noisy estimation given the lack of cross-sectional and time-series data for the emerging markets currencies returns.

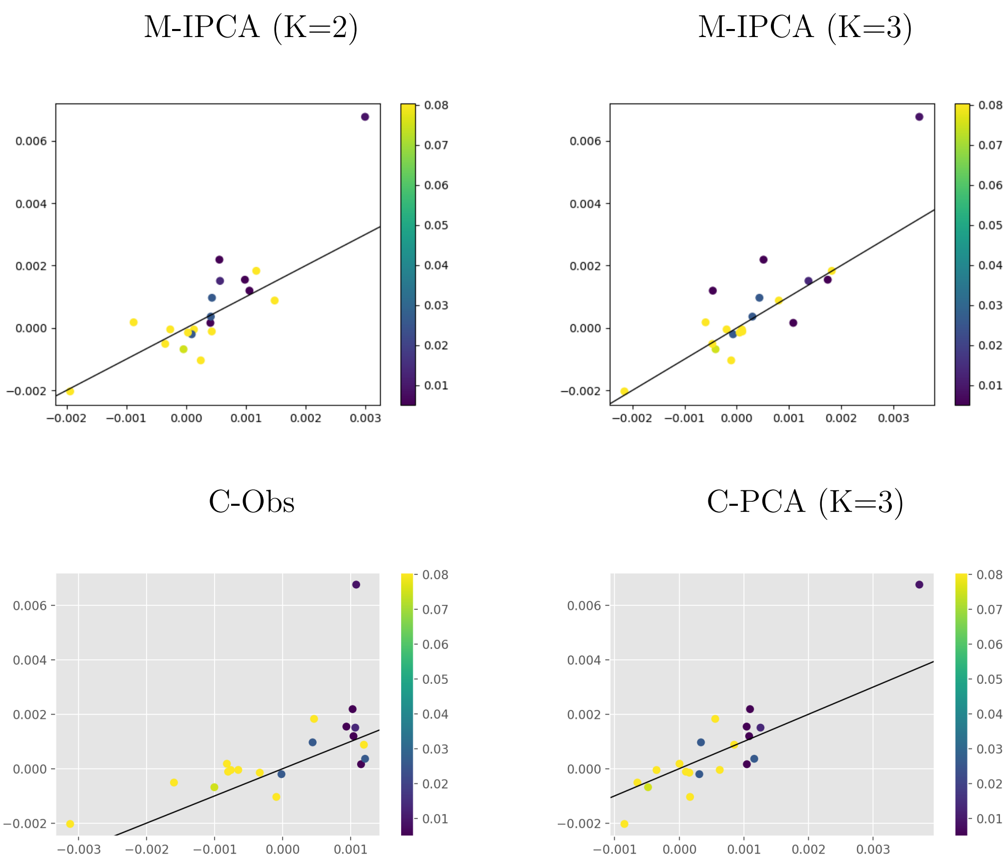
In general, however, M-IPCA beats the benchmark in the in-sample sample. The only exceptions are the five factor specification of the U-PCA that has a Pricing R^2 of 91%. If, however, we only consider a more parsimonious specification of up to three factors, M-IPCA is always better to explain the cross-section of returns. This indicates a potential problem of overfitting for these PCA models, especially the unconditional one, since the out-of-sample results get significantly worse than the in-sample. It is important to emphasize that in-sample Total R^2s are targeted moment in all the estimations, thereafter the in-sample properties are less informative about which of the models does a better job explaining the time-series dimension of returns.

In Figures 1, 2, 3 we visually represent the pricing R^2 results for Developed, Global and Emerging Markets panels, respectively. We plot realized average return for each of the currencies in each of the panels against version of expected returns and a 45 degrees line. We also present more clearly the weights that each of the currency has for the metric calculation by using different colors. There we can see the same pattern as in the previous table, where M-IPCA does a better job explaining the cross-sectional dispersion of currencies excess returns compared to C-Obs and C-PCA benchmarks.

Table 4: In-sample R^2s results – in this table we show the Total and Pricing R^2 as defined by equations 10 and 11, respectively. Total R^2 measures the explanatory power of each of the models on the total variation of currencies returns, therefore the risk dynamics. Pricing R^2 measures the ability of the model to explain the cross-section of those returns. All returns are measured in excess of the cross-sectional average in each period. The frequency of returns is monthly, starting in December 1988 and ending on November 2019. The panel of returns is unbalanced, therefore not all currencies data start or end in the same period. The three panels – Developed, Global and Emerging Markets – are defined in Table 1. We estimate the M-IPCA model, which is the IPCA specification with macroeconomic variables and exposures to Dollar and Carry factors as characteristics. C-Obs assumes that the factors are observed and estimates time-varying exposures with rolling windows of 36 months. U-Obs is the unconditional version of the C-Obs, where exposures are static and estimated only once in-sample. C-PCA specification fits a PCA model and a rolling window estimation to the exposures, like for the C-Obs. Agains, U-PCA estimates the exposure as static. Results are in-sample. For C-PCA, U-PCA, and M-IPCA we show the each of the results for specifications of 1 to 5 factors (K). M-IPCA delivers has the highest R^2s in both dimensions compared to the two other benchmarks.

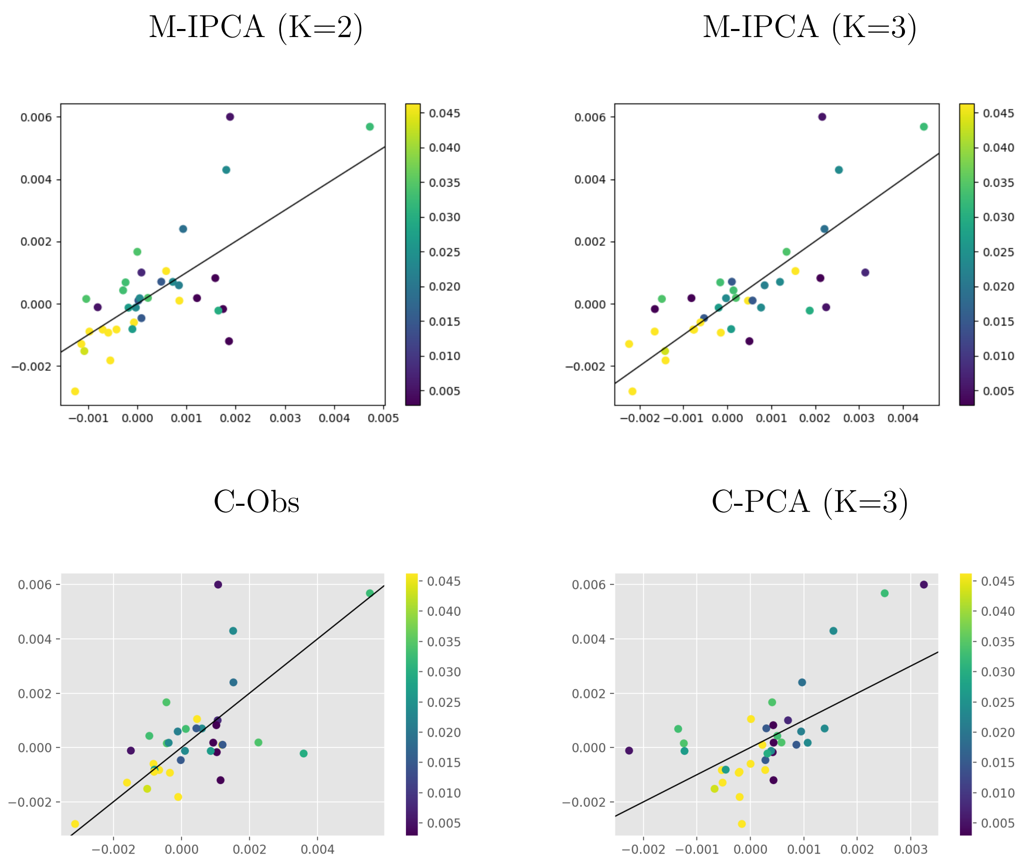
	Pricing $R\hat{2}$					**Total $R\hat{2}$**				
	K1	**K2**	**K3**	**K4**	**K5**	**K1**	**K2**	**K3**	**K4**	**K5**
	Panel A: Developed Markets Panel									
M-IPCA	21.4	61.0	79.4	83.6	84.0	35.6	55.9	65.3	71.5	76.6
C-Obs		27.9					33.7			
U-Obs		-0.1					17.2			
C-PCA	34.6	39.8	51.6	63.5	66.6	31.4	48.2	67.9	76.9	83.1
U-PCA	30.7	45.5	58.3	88.8	90.6	29.0	42.1	61.8	70.4	76.0
	Panel B: Global Markets Panel									
M-IPCA	53.7	67.7	74.3	79.4	82.7	24.2	46.0	51.9	56.7	60.1
C-Obs		48.1					35.3			
U-Obs		62.2					19.4			
C-PCA	-18.1	42.1	38.9	65.2	71.0	19.6	37.4	47.5	57.2	65.0
U-PCA	5.1	37.6	42.0	69.1	73.5	14.5	27.9	34.0	46.3	53.1
	Panel C: Emerging Markets Panel									
M-IPCA	59.6	78.1	69.0	64.1	70.4	27.9	48.9	58.7	66.0	72.3
C-Obs		-3.9					26.9			
U-Obs		27.1					13.5			
C-PCA	-15.8	19.8	47.6	60.2	70.5	21.4	42.7	57.9	67.1	76.1
U-PCA	3.8	32.1	46.4	55.4	63.2	16.3	34.0	45.9	54.4	63.2

Figure 1: Developed Markets Expected Returns



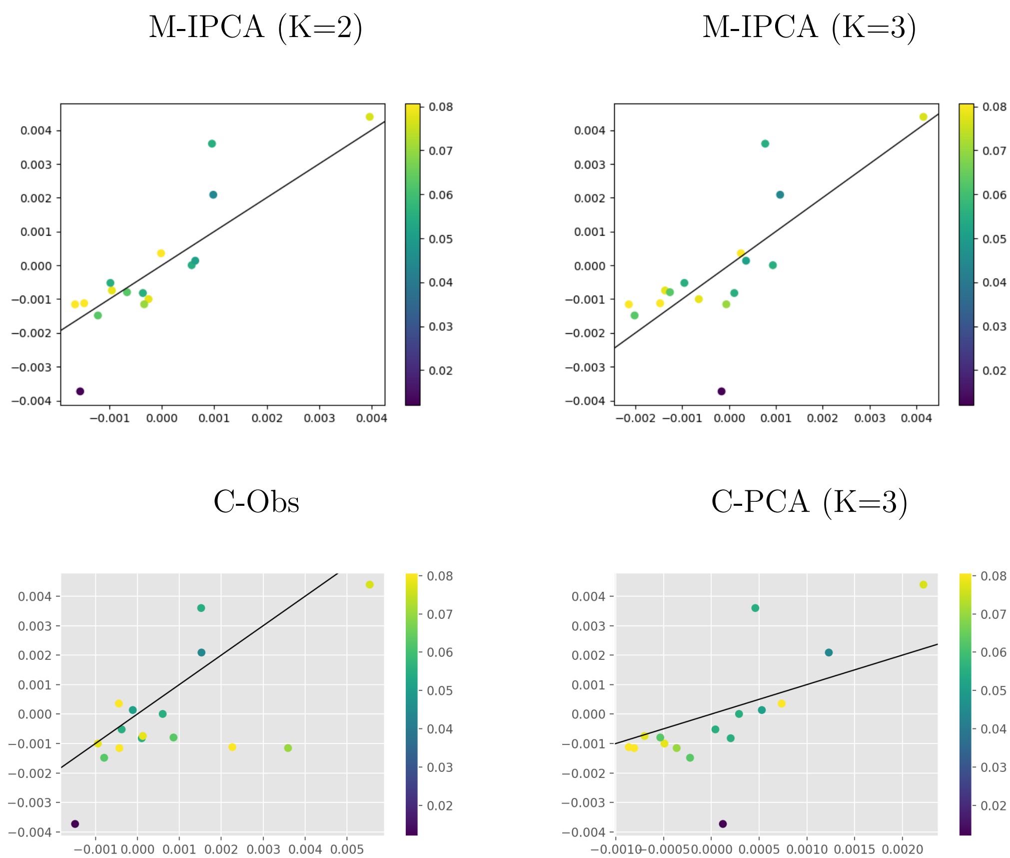
Note: Here we show the $E[\tilde{r}]$ on y-axis versus $E[\tilde{\beta} f_{t+1}]$ on the x-axis for each of the currencies on the DM panel for M-IPCA and benchmarks under the in-sample specification. Colours are determined by w_i. We compare M-IPCA with two and three factors, the C-Obs model and the C-PCA specification with three factors. This is a visual analogue to the Pricing R^2 metric. A good fit is the one where expected values is closely aligned to the realized averages – close to the 45 degrees line.

Figure 2: Global Expected Returns



Note: Here we show the $E[\tilde{r}]$ on y-axis versus $E[\tilde{\beta} f_{t+1}]$ on the x-axis for each of the currencies on the Global panel for M-IPCA and benchmarks under the in-sample specification. Colours are determined by w_i. We compare M-IPCA with two and three factors, the C-Obs model and the C-PCA specification with three factors. This is a visual analogue to the Pricing R^2 metric. A good fit is the one where expected values is closely aligned to the realized averages – close to the 45 degrees line.

Figure 3: Emerging Markets Expected Returns



Note: Here we show the $E[\tilde{r}]$ on y-axis versus $E[\tilde{\beta} f_{t+1}]$ on the x-axis for each of the currencies on the EM panel for M-IPCA and benchmarks under the in-sample specification. Colours are determined by w_i. We compare M-IPCA with two and three factors, the C-Obs model and the C-PCA specification with three factors. This is a visual analogue to the Pricing R^2 metric. A good fit is the one where expected values is closely aligned to the realized averages – close to the 45 degrees line.

6.5 Which Characteristics Matter?

Now that we have established that M-IPCA does a good job explaining currencies returns, both in-sample and out-of-sample, we can go to the next step. As shown in the previous section, macroeconomic fundamentals are important to estimate both latent factors and time-varying exposures. In this section we explore *which* variables are relevant for all three panels of currencies. We focus on a Γ_β specification of three factors estimated in-sample, but in Appendix A.1 we show results for different number of factors. This is the chosen specification by the parsimony

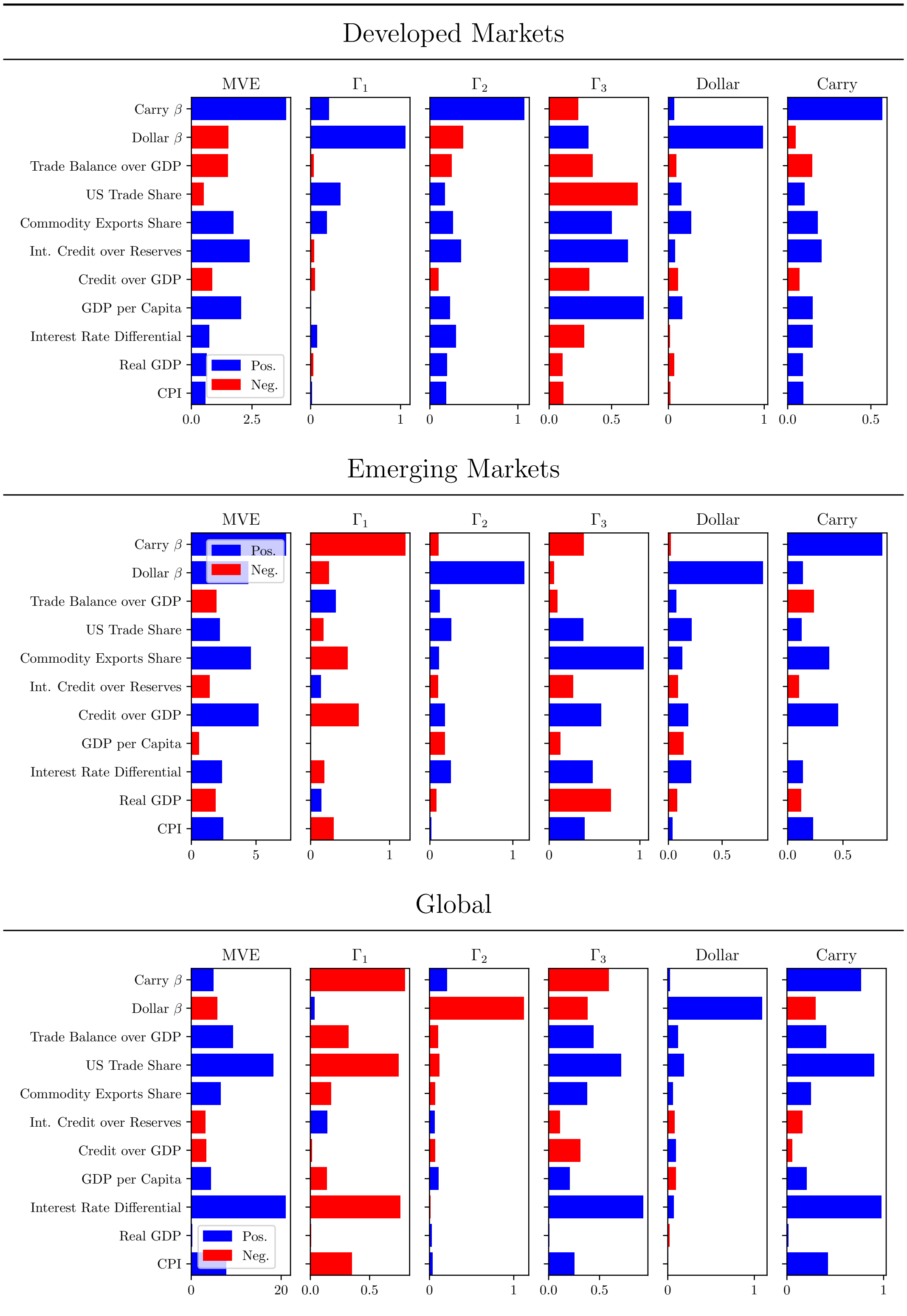
Figure 4 summarizes these results for the developed, emerging, and global panels of countries. The middle three columns present the separate loadings for each of the corresponding three latent factors. However, the individual columns of Γ_β are rotationally unidentified. To address this issue, we also include several summaries of Γ_β which impose a particular rotation matrix. The first column presents results where the mean-variance efficient portfolio weights for the latent factors are used to identify Γ_β. This is formed by taking the inner product of the original Γ_β and the MVE portfolio weights. The last two columns present similar results where the rotation matrix is formed by regressing the dollar and carry factors on our estimated latent factors.

Unsurprisingly, the results suggest that dollar and carry βs are relevant for the corresponding observed factors, however, the MVE and latent factors have meaningful loadings on other characteristics as well. Therefore, macroeconomic variables bring new information beyond the usual exposures to Carry and Dollar already proposed by previous literature. In particular, in the 3 factor model, the first two factors primarily correspond to the dollar and carry βs while the third factor is a mix of other characteristics.

The exact characteristics vary somewhat across the panels considered. US trade share and the interest rate differential seem to matter for the global and developed panel, while commodity exports share is slightly more important for emerging markets. Financial vulnerability measures such as credit over GDP as international credit over reserves are also relevant for both Developed and Emerging markets, indicating the risk information embedded in financial vulnerability relevance. Interestingly, for the variables testes by Meese and Rogoff (1983), only interest rate differentials seem to matter, while the impacts of GDP growth, trade balance over GDP and inflation are small. The other channels, more related to the recent literature, such as financial vulnerability, trade linkages and exposure to commodities cycles seem to be the most relevant among this small subset of potential macroeconomic fundamentals.

For the MVE rotation, which more easily summarizes all the information in the Γ_β matrix,

Figure 4: Risk Factor Interpretation at the Characteristic Level



Note: This figure reports the Γ_β estimates for various panels as well as rotated versions of Γ_β. The first column reports results where the rotation matrix is the MVE portfolio weights. The last two columns reports results where the rotation matrix is the dollar and carry observed factors.

most of the macroeconomic characteristics with meaningful magnitude enter with a positive sign. Again, all these three classes of macroeconomic fundamentals appear in the loadings of these matrices – financial vulnerability, trade and commodities exposures. The interpretation is that countries more exposed to commodities cycles, those that have a higher leverage, or the economies that are more directly linked to the US should also command a higher return on average.

Also, we find that the Γ_β matrices are only somewhat different comparing Developed and Emerging Markets specifications. While we find that M-IPCA does a much better job explaining the cross-section of Developed Market currencies excess returns relative to the Emerging Markets panel, the characteristics that influence each of these models is only somewhat difference. We conjecture that the worse performance over the Emerging Markets is due to a higher share of idiosyncratic shocks not captured by the latent factor structure and by a smaller sample size relative to Developed Markets, even though further works needs to be done to pin down this evidence more precisely.

Finally, while the variables used in this framework is far from exhaustive, even this small subset of potential macroeconomic variables can already bring powerful new information that can help to understand the cross-sectional dispersion of currencies returns. In the next section we use the M-IPCA framework to try to understand the drivers of already known factors, in particular, Carry and Dollar.

7 Interpreting Carry and Dollar factor βs

When factors are taken as observed, IPCA still provides an useful method to estimate instrumented βs as an alternative to standard rolling estimation. As discussed, much of the past literature does the analysis at the portfolio level, which are sorted using rolling windows regressions. This could be inefficient, in particular when the whole exercise is in the currency-level. Therefore, our goal in this section is to use M-IPCA to estimate only these time-varying exposures. This has two main advantages. First, it is potentially a more efficient way to calculate this object. Second, and more importantly, it helps to answer a still not fully appreciated question – why some currencies are more exposed to the Dollar relative to the others? These instrumented exposures are inherently more interpretable than rolling βs because their variation can be traced back to individual macro characteristics.

Given that our goal here is to interpret the dollar and carry βs, we drop the rolling estimates of these from our set of characteristics. In our main exercise in the previous sections these exposures were used for the M-IPCA estimation on top of the macroeconomic fundamentals. Here, on the other hand, we want to understand which of variables could be used as instruments to be (potentially) better and more interpretable time-varying exposures.

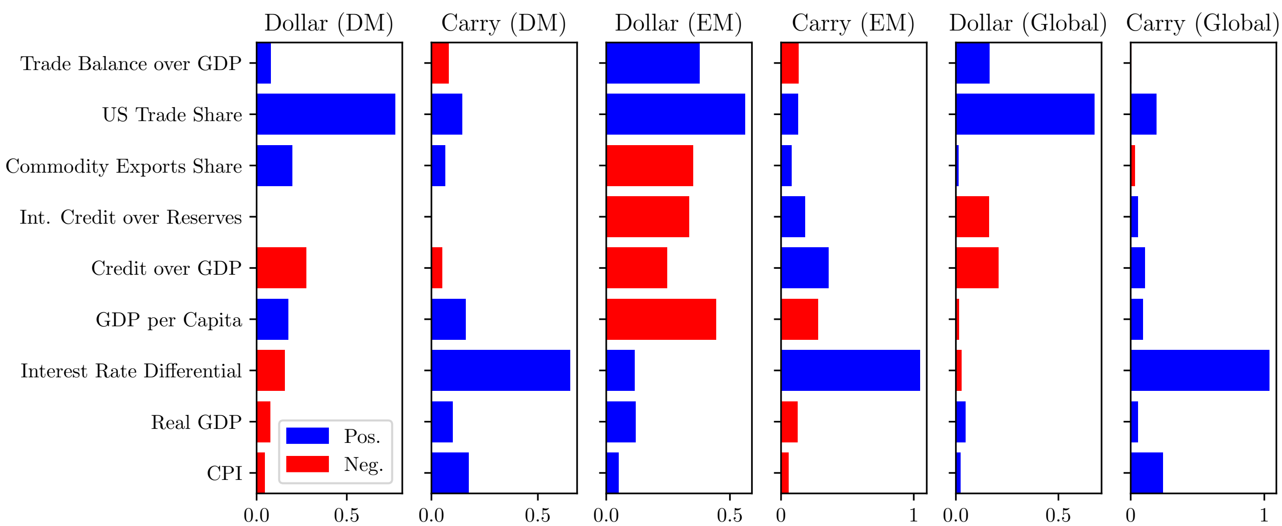
Figure 5 summarizes the loadings for these βs for each of the three panels for the M-IPCA estimation taking Dollar and Carry as observed factors. For all three panels, the dollar factor seems linked with the US trade-share – currencies with higher dollar beta are in fact those that have a higher direct dependence of US external side. In other words, if most of the exports of a country go to the US, they are more exposed to the Dollar factor, and therefore demand a higher risk-premium compensation. On the other hand, interest rate differential and inflation do not affect these exposures. Also, for the DM and Global panels, these trade links seem to be the only important aspect of the dollar factor.

However, interestingly, for Emerging Markets the dollar factor is also linked to others external variables. In fact, currencies with a higher trade-balance that are also richer are more exposed to the dollar, as well as those with *less* exposure to commodities cycles as a share of exports and less financially vulnerable. This suggests a richer description of Dollar exposures that could be only linked with exposures to US, as is the case for Developed Markets, or a richer and higher dimensional problem in the case of Emerging Markets.

For the carry, unsurprisingly, the most relevant characteristic is the interest-rate differential itself – no other characteristics have a relatively large loading in the Γ_β matrix. It is important to note, though, this particular variables does not show up in any of the panels for the Dollar exposure. Thereafter, we find evidence that the set of characteristics that matter for Carry is distinct for the Dollar. This could mean that the underlying macroeconomic sources of risk-premium dynamics are indeed different.

Again, in theory we could have added many more macroeconomic variables into the estimation procedure. This exercise's only goal was to highlight that M-IPCA can also be applied to give more interpretation to the exposures of already known priced factors. We showed that trade linkages and exposures to commodities cycles are the ones that matter the most for the Dollar, while only interest rate differentials are relevant for Carry. But other macroeconomic fundamentals can describe these exposures more efficiently.

Figure 5: Observed Factor Interpretation at the Characteristic Level



Note: This figure reports Γ_β where dollar and carry are used in place of estimated latent factors. The first two columns report the Γ_β entries for dollar and carry over the developed markets panel, the second two columns report comparable results for the emerging markets panel and the last two columns report comparable results for the global panel.

8 Conclusion

We show that the M-IPCA model provides a novel method to help understand the drivers of currency returns. Our results suggest that M-IPCA factor can leverage macroeconomic characteristics information and therefore do a better job of explaining cross-sectional variation in currency returns out of sample relative to existing approaches. Our results hold both in and out-of-sample, and are evaluated in the cross-sectional and time-series properties of these returns. In fact, we show that M-IPCA does a particular good job pricing the unconditional average of excess returns for all groups of countries.

Also, these macroeconomic fundamentals bring new information compared to only Dollar and Carry exposures, providing hope that the macro and currencies bridge can be more easily be established. The set of characteristics that matter vary only somewhat across different panels, but the most important ones are related to trade exposures to the US, exposure to commodity cycles and financial vulnerability indicators.

On top of that we showed that the M-IPCA framework can help to explain why some currencies have, for example, a higher exposure to the Dollar factor. We find that for Developed Markets it is mostly due to exports exposures to the US, while for Emerging Markets only fundamentals also matter.

What we have not explored, however, is if there are additional macroeconomic fundamentals outside our sample that can be used to explain these cross-sections more efficiently. In this paper we only showed that macroeconomic fundamentals can indeed bring new information on top of dollar and carry exposures, giving hope that the apparent disconnect of macro and currencies is not so disconnected. We leave for future work to pin down exactly which is the most efficient approach to link time-varying exposures and latent factor estimations using the right set of macroeconomic fundamentals.

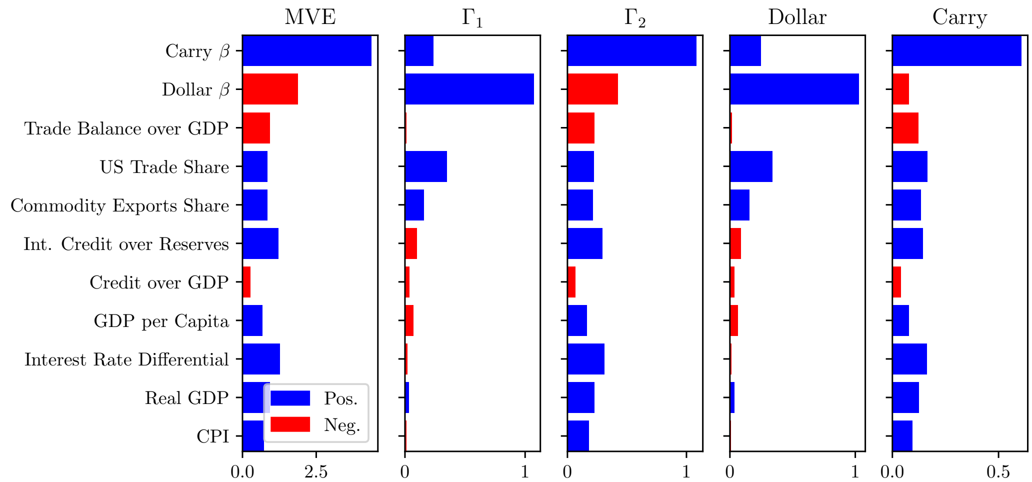
A Appendix

A.1 Different factor specifications

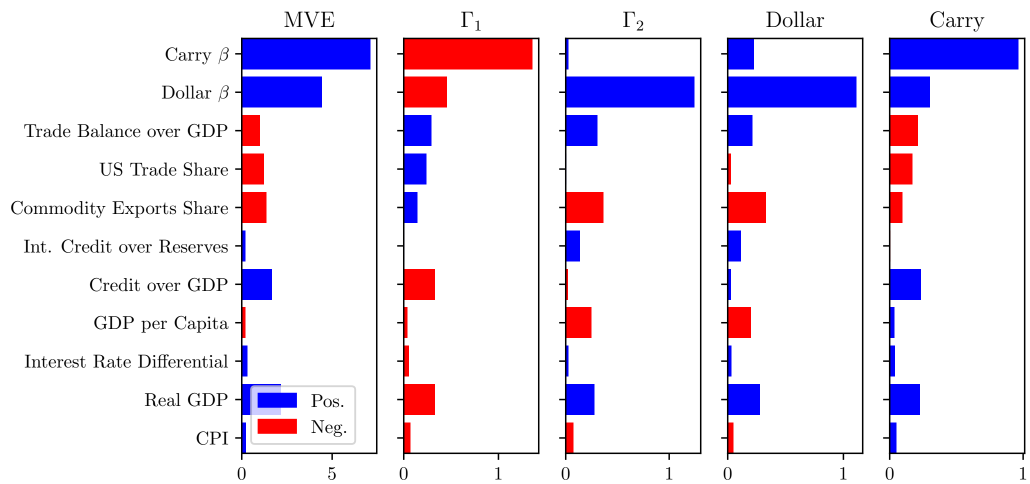
This section presents summaries for Γ_β for several alternative factor count choices. We show results for both cases with 2 and 4 factors in addition to the 3 factor model presented in the main text. These results are contained in figures 6 and 7 respectively.

Figure 6: Risk Factor Interpretation at the Characteristic Level (K=2)

Developed Markets



Emerging Markets



Global

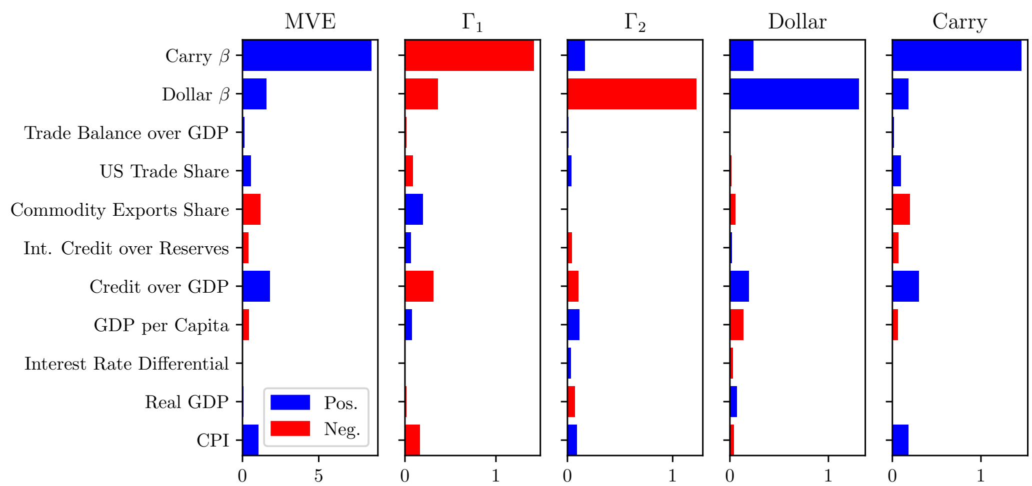
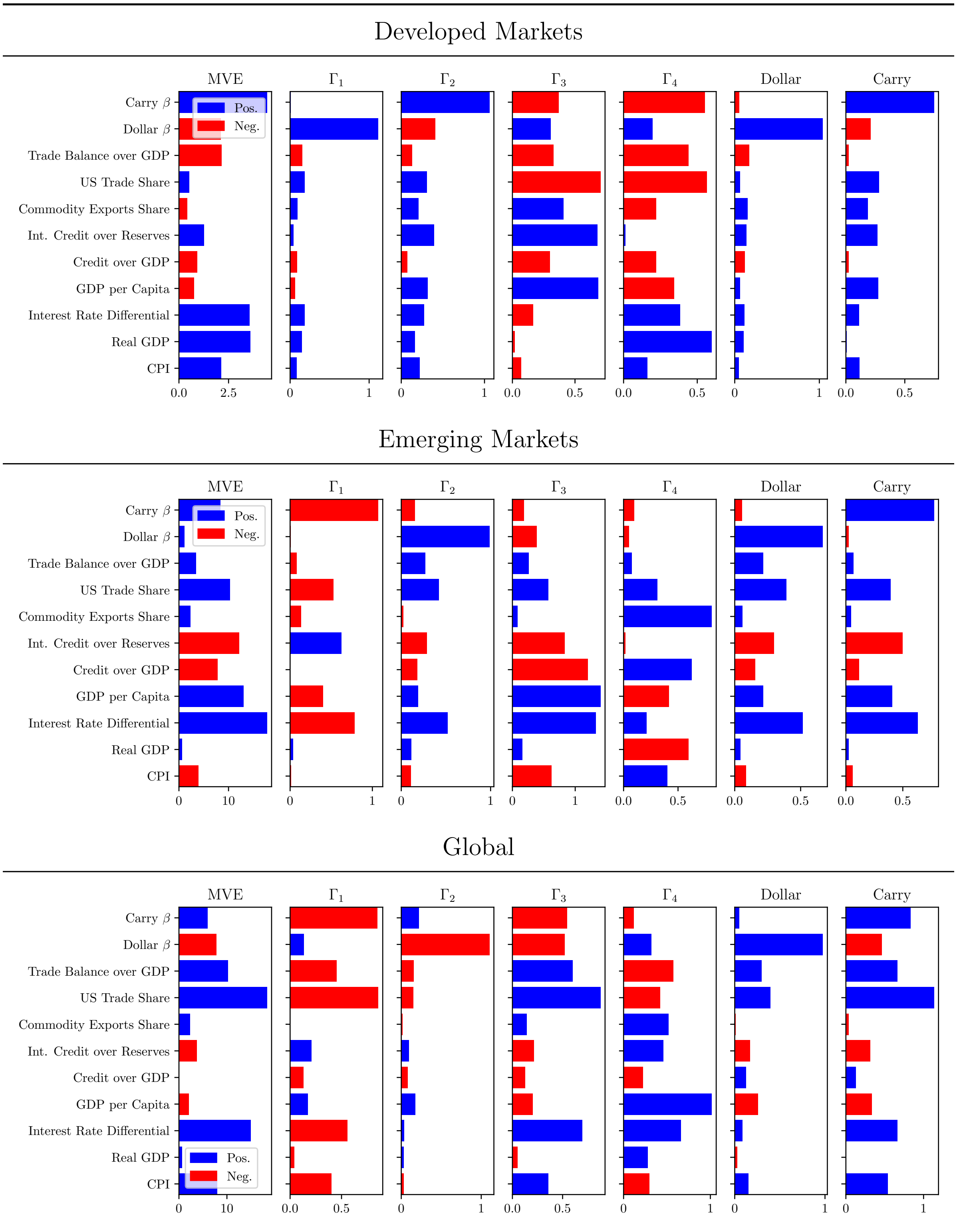


Figure 7: Risk Factor Interpretation at the Characteristic Level (K=4)



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