Time-Varying Factor Allocation

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Abstract. In this empirical study, we provide evidence on how predictive information can help to profitably allocate a cross-asset factor portfolio, covering various well-known factors over the asset classes equity, commodity, fixed income, and foreign exchange. We investigate the performance of a meaningful set of predictors, which we broadly divide into macro and market indicators. Our analysis shows that tilting a global factor portfolio according to signals derived from business cycle indicators, inflation, and short-term interest rates, among other predictors, significantly outperforms a static factor benchmark. The established results are based on practical considerations, survive conservative transaction cost assumptions, and are validated over an extensive out-of-sample period. In sum, we highlight the potential benefits of an asset-allocation framework conditioned on predictive variables, but caution to time factors on a standalone basis.

Keywords. *factor investing, factor allocation, factor timing, factor tilting, multi-asset, return predictability, market indicators, macroeconomic indicators, asset management*

JEL Classification. *G11, D81*

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1 Introduction

Can selected state variables help investors to allocate across a broad factor universe?

Early work on explaining cross-sectional predictability found that investors should only expect to be compensated for the non-diversifiable risk inherent in a given asset (Treynor (1961), Sharpe (1964), Lintner (1965)). Later work established evidence for additional risk sources driving asset returns (for instance Fama and French (1993)). Since then, the concept of factor investing has emerged, allowing investors to analyze expected returns from a style-based rather than a typical asset class-based view. In parallel to the question of predicting the cross-section of asset returns, finance literature has also dealt with the predictability of the time-series of (aggregated) asset returns for quite some time. One of the most prominent and long-lasting subfields of study is the forecast of future stock market returns and implementations of stock market timing. The empirical results of this extensive research, conducted over decades, are rather mixed. As Dangl and Halling (2012) summarize, several papers find evidence for in-sample predictability, while there is no clear consensus about out-of-sample predictability.

Given the developments in the cross-sectional factor literature, the focus of some more recent papers has shifted to the predictability of other aggregated risk premia (or related smart beta ETF) returns and possible practical implementations. For example, Hodges et al. (2017) find evidence for the predictive power of business cycle information and the benefits of forecast combinations based on multiple predictors. However, the results of Asness et al. (2017) and Dichtl et al. (2019) take a more critical stance on factor return forecasting and viable benefits (after transaction costs) of timing for an investor in comparison to just holding an equally-weighted factor portfolio. While the mentioned (and other) papers often focus on a narrow investment universe and/or a limited number of constructed factors or analyzed predictors, recent work by Ilmanen et al. (2021) and Blin et al. (2021) takes a broader view. Ilmanen et al. (2021) cover the phenomena value, momentum, carry, and defensive applied in various asset classes over roughly a century of data, finding significant variation of factor premia over time and diversification benefits of combinations over factors and asset classes. Their findings further suggest that while some conditioning variables motivated by theory capture significant conditional return premia across asset classes, the profitability of timing measured via an implementation in real time and after transaction costs is limited. Blin et al. (2021) use a combination of macro, sentiment and valuation signals to dynamically allocate among a set of global alternative risk premia. The resulting portfolio outperforms an associated equal risk contribution benchmark and the performance does neither rely on any specific risk premia nor on any individual predictor.

In the spirit of Ilmanen et al. (2021) and Blin et al. (2021), we aim to shed further light on dynamically investing in factors based on predictive analysis, approaching a broad set of factors across several asset classes and various predictor variables. More in detail, we replicate several factors based on established phenomena, for instance value and momentum, across the four asset classes foreign exchange (FX), commodity, fixed income, and equity (the latter comprising U.S. single stocks and international equity indices), while considering transaction costs due for maintaining the long-short factor portfolios to establish a more realistic perspective. We arrive at an unbalanced sample of 21 factors, with the earliest time series dating back as far as July 1967. Subsequently, we gather a set of 15 predictors motivated by the relevant asset-pricing literature, which we broadly divide into macro and market indicators.

For each combination of factor and predictor, we construct a monthly return forecast, relying on a linear framework as an investor's heuristic to link future factor returns to the predictors. To estimate the model, we apply a Bayesian approach with a conservative prior, which stylizes an investor who is skeptical towards return predictability. We use these forecasts as inputs for a quantitative asset-allocation framework to tilt factors within a portfolio, assuming long-only and constant total portfolio weights over time. The results are then benchmarked against a static equally-weighted factor portfolio and compared among predictors. To check for robustness of our results, we conduct various further analyses. For instance, we study our optimized strategies over subsamples to assess the stability of out-performance over the course of time and calculate breakeven transaction costs to acknowledge the additional costs that come with maintaining an active investment style. Furthermore, we use our broad data set to explore the usage of predictive information in another out-of-sample setup, contrasting the diversified approach of our main analysis to investments in singular factors, where the time-varying exposure to a factor is adjusted according to the established return forecasts based on a given predictor.

We find that tilting a global factor portfolio according to signals derived from business cycle indicators, inflation, and short-term interest rates, among other predictors, significantly outperforms a static factor benchmark. These results survive our various robustness tests and are attributable both to enhanced returns as well as further diversification benefits achieved by the active management based on the predictors. While we find that some predictors arrive at similar allocation decisions, which could indicate mutual drivers, other predictors seem to deliver more distinct information, emphasizing potential benefits from using multiple predictors as independent variables in the prediction. Moreover, we show that the average of individually timed factors does not deliver as significant results as our asset-allocation approach, which demonstrates the additional benefits of applying the predictive information in a diversified portfolio context. The results are particularly relevant for investors, since we provide a transparent and replicable framework that incorporates practical considerations, conservative assumptions on transaction costs and out-of-sample validity.

The remainder of the paper is organized as follows: In Section 2, we start by outlining the contribution of the given paper to the literature and then put this into context by providing a brief overview of the related literature. In Section 3 we present our broad set of factors across several asset classes, starting with an explanation of the construction methodology. Subsequently, we show the heterogeneity of the constructed factors and stylize advantages of combining them in a diversified portfolio. Section 4 starts with outlining our set of predictive signals and the predictive regression framework. Afterwards, we introduce the applied asset-allocation framework and present the results of our empirical investigation. The section concludes with a discussion of the work, in which we compare our findings to those of other authors. In Section 5, we conclude with a short summary of our approach and findings as well as ideas for future research.

2 Contribution and Related Literature

Our analysis contributes to the existing literature in several ways. First, our investigation links established factors across multiple asset classes to a diverse set of predictors based on macro and market information. We construct, compared to other authors, a much broader, transparent, and reproducible cross-asset long-short factor universe, including available data from emerging and frontier markets starting in 1967. Second, we include transaction costs in our constructed factor set on a granular level to establish conservative and practice-oriented results. On top, we determine breakeven costs to find out at which threshold an outperforming active strategy is not lucrative anymore relative to the passive benchmark. Third, we compare the usefulness of predictive information on factor timing from a portfolio and individual factor perspective. Last, rather than identifying different regimes, we map a continuous predictor variable on expected returns.

To put our contributions into perspective, in the following we briefly outline other existing literature closest to this paper, while proving a more extensive literature overview in Appendix A.1. Blin et al. (2021) use a combination of macro, sentiment and valuation signals to dynamically allocate among a set of global alternative risk premia. The resulting portfolio, which derives its active weights from an adapted version of Black and Litterman (1992), outperforms an associated equal risk contribution benchmark and the performance does neither rely on any specific risk premia nor on any individual predictor. Dichtl et al. (2019) take a critical stance on factor return forecasting and viable benefits for an investor in comparison to just holding an equally-weighted factor portfolio. While the authors suggest factor timing and tilting, using technical and fundamental time-series predictors, is statistically significant, transaction costs erode much of the benefits. Hence, practitioners need to pay close attention to such costs. Ilmanen et al. (2021) test for factor return predictability across multiple asset-classes based on various conditioning variables motivated by theory. Their findings indicate that while value spreads and inverse volatility capture significant conditional return premia across asset classes, the profitability of timing measured via an implementation in real time and after transaction costs is limited. Finally, Hodges et al. (2017) investigate MSCI smart beta indices and find evidence for the predictive power of business cycle information and the benefits of forecast combinations based on multiple predictors.

3 Factor Data and Construction

We start this section with an introduction to our data and the signal construction for each asset class. Afterwards, we outline our methodology for the factor construction and point out differences between our factor set and others in the literature. The section concludes with a short descriptive presentation of the resulting cross-asset factor investment universe used for the following analysis in Section 4.

We construct factor returns across the asset classes FX, commodities, fixed income, as well as equity and all returns referred to hereafter are considered discrete[1] excess returns unless stated otherwise. First, we download price and asset characteristic data and construct end-of-month time series. Second, in order to construct each factor, we cross-sectionally rank assets by their associated factor characteristic and

[1] We follow authors such as Dichtl et al. (2019) in using discrete returns.

form long-short portfolios using the top/bottom 16.67% of assets. Moreover, we incorporate transaction costs on a granular level to form realistic - and often even conservative - estimates for actual asset returns. While our framework, which imposes time-invariant transaction costs on certain asset classes, may exaggerate or underestimate real traded costs at times[2], we aim for a pragmatic approach for approximation and want to impose as few assumptions on transaction costs as possible.

Table 1 gives an overview of replicated factors, the associated characteristics and measurements thereof, the factor-related academic literature, the financial instruments/indices associated with each asset class, as well as the number of assets within each asset class. In addition, Appendix A.3 provides more detailed descriptions of the factor construction across the different asset classes and Appendix A.4 highlights methodological differences to relevant academic literature. As in Blin et al. (2021), excess returns are scaled to an ex-ante volatility of 10% using all previous returns (i.e. applying an expanding window).[4] This simple approach has the advantage that each factor is sized with the same level of volatility to provide diversification and limit portfolio risk from any individual factor. Additionally, the ex-ante approach avoids look-ahead bias.

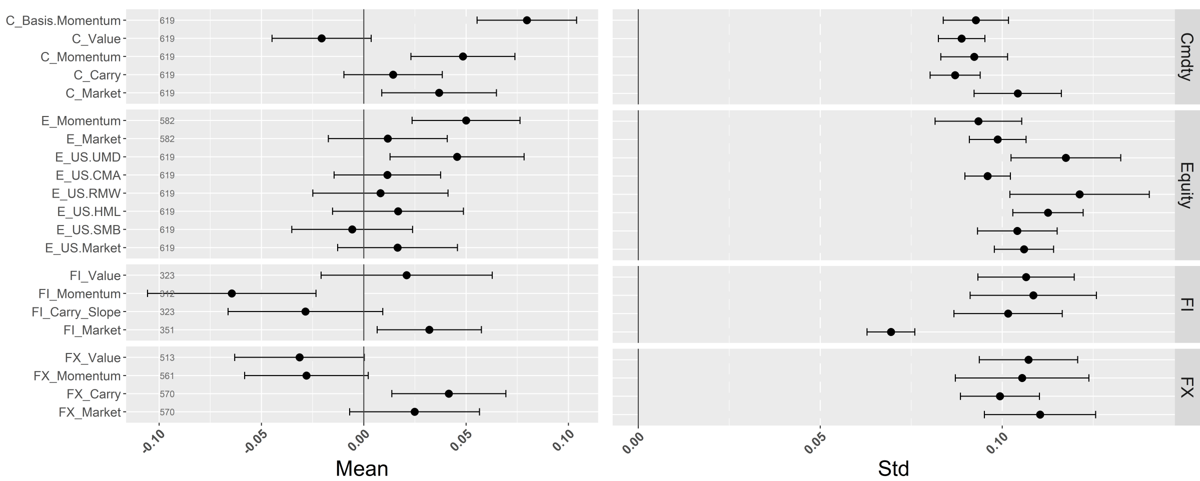

Fig. 1: Mean and Standard Deviation of Factor Excess Returns.
This figure presents summary statistics for our constructed set of 21 monthly factor excess return time series. In detail, the left panel reports the annualized arithmetic mean with associated two-sided 95% confidence intervals as box plots, while the right panel analogously reports the annualized standard deviation. The first letters of the factor labels (at the left margin) indicate the associated asset class of a given factor, where *C, E, FI*, and *FX* are abbreviations for *commodity, equity, fixed income*, and *foreign exchange*, respectively. The grey numbers on the right beside the factor labels report the available number of monthly observations per factor during our observation period starting in July 1967 and ending in December 2018. Standard errors for normal confidence intervals are obtained by bootstrap (see Appendix A.10 for more information). Monthly mean returns and their standard errors are annualized by multiplying with 12, while standard deviations and their standard errors are multiplied with $\sqrt{12}$. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

[2] We acknowledge in this context that transaction costs vary over time and have decreased historically on a broad basis due to progress in financial markets.

[3] See for instance Angelidis and Tessaromatis (2017).

[4] Moskowitz et al. (2012) use ex-ante exponentially weighted lagged squared daily returns, Hurst et al. (2017) aggregate 1-month, 3-month, and 12-month time series momentum strategies into a combined portfolio and scale it to an ex-ante annualized volatility of 10% over a rolling 3-year window).

Asset class	Factor	Characteristics	Measurement	Source	Transaction costs	Instrument	No. assets
FX	Market	Equally-weighted	$\frac{1}{N}$	Lustig et al. (2011)	Bid-ask spread	Forwards	69
	Carry	Implied-Yield	$\frac{f_t}{s_t}(1+r_t^d)-1$	Lustig et al. (2011)			
	Momentum	12-1 month return	$\prod_{s=t-11}^{t-1}(1+r_s)-1$	Menkhoff et al. (2012b)			
	Value	5-year change in real exchange rate	$\Delta_{t=60} s_t \frac{CPI_t^f}{CPI_t^d}$	Asness et al. (2013)			
Commodity	Market	Equally-weighted	$\frac{1}{N}$	Szymanowska et al. (2014)	4.4 bps rel. half-spread Marshall et al. (2012)	Futures	31
	Carry	Basis (First-to-Second)	$\frac{F_t^{T_2}}{F_t^{T_1}}-1$	Szymanowska et al. (2014)			
	Momentum	12-1 month return	$\prod_{s=t-11}^{t-1}(1+r_s^{T_1})-1$	Bakshi et al. (2019)			
	Value	Negative 5 year return	$-\left(\prod_{s=t-59}^{t}(1+r_s^{T_1})-1\right)$	Asness et al. (2013)			
	Basis-Momentum	12 month return difference	$\prod_{s=t-11}^{t}(1+r_s^{T_1})-\prod_{s=t-11}^{t}(1+r_s^{T_2})$	Boons and Prado (2019)			
Fixed Income	Market	Real GDP-weighted	$\frac{GDP_{t,i}^{real}}{\sum_i GDP_{t,i}^{real}}$	Dimson et al. (2006)	2.5x FX bid-ask spread (practitioner approximation)	Synthetic returns using zero coupon rates	45
	Carry	Slope	$y_t^{10y}-y_t^{5y}$	Koijen et al. (2018)			
	Momentum	12-1 month return	$\prod_{s=t-11}^{t-1}(1+r_s)-1$	Asness et al. (2013)			
	Value	Real interest rate	$y_t^{10y}-\frac{\Delta_{t=12}CPI_t}{CPI_{t-12}}$	Brooks and Moskowitz (2017)			
Equity Index	Market	Market-cap weighted	$\frac{MV_{t,i}}{\sum_i MV_{t,i}}$	Fama and French (1993)	10 bps p.m. [3]	MSCI Indices	49
	Momentum	12-1 month return	$\prod_{s=t-11}^{t-1}(1+r_s)-1$	Asness et al. (2013)			
Equity Single Stocks	Market	Market-cap weighted	$\frac{MV_{t,i}}{\sum_i MV_{t,i}}$	Fama and French (1993)	20 bps p.m. Detzel et al. (2021)	Stocks	24781
	Size	Market capitalization	MV_t	Fama and French (1993)			
	Momentum	12-1 month return	$\prod_{s=t-11}^{t-1}(1+r_s)-1$	Carhart (1997)			
	Value	Book-to-market	BtM_t	Fama and French (1993)			
	Quality	Operating Profitability	OP_t	Fama and French (2015)			
	Investment	Investment	ΔTA_t	Fama and French (2015)			

Table 1: Factor Replication Overview.
This table describes the construction of different asset class factors and links to the relevant literature. Each month we cross-sectionally rank the characteristics for each factor and go long (short) the top (bottom) 16.67% quantile of assets. f_t is the currency forward rate at time t, s_t is the spot exchange rate at time t, r_t^d is the domestic interest rate (here referred to the 1-month U.S. interest rate), $CPI_t^{f,d}$ is the consumer price index of the foreign (domestic) country f (d) at time t. $F_t^{T_i}$ is the value of the i-th nearby futures contract at time t expiring at time T, y_t^{i-y} is the i-year interest rate at time t, BtM_t is the book-to-market ratio, OP the operating profitability ratio and TA total assets. FX, commodity, fixed income and equity index data are from Bloomberg and Global Financial Data. Equity single stock factors are constructed using the CRSP/Compustat database. Figure A5 illustrates the performance of each factor.

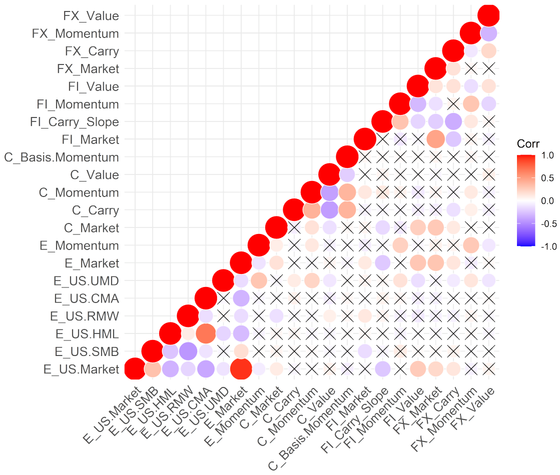

Fig. 2: Correlations of Factor Excess Returns.
This figure presents Pearson correlation coefficients for our constructed set of 21 monthly factor excess return time series as well as results of t-tests with the null hypothesis of no correlation. The correlation coefficient of a factor that significantly differs from zero at the 5% level is displayed as circle, where the size of the circle increases with the magnitude of the correlation and its color changes dependent on the sign of the correlation. In case the t-test indicates an insignificant coefficient, crosses are displayed instead of circles. The first letters of the factor labels indicate the associated asset class of a given factor, where *C, E, FI*, and *FX* are abbreviations for *commodity, equity, fixed income*, and *foreign exchange*, respectively. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

The constructed investment universe spans 21 factor strategies and respective market returns over the asset classes equity (comprising U.S. single stocks and international equity indices), commodity, fixed income, and FX.[5] While it would be ideal to analyze the monthly return data of these strategies over our full investigation period starting in July 1967 and ending in December 2018[6], this is not feasible for all constructed factors due to data constraints. As Table A5 indicates, our data set of monthly factor returns comprises 4878, 1309, 3095, and 2214 observations in the asset class segments equity, FI, Commodity, and FX, respectively. In sum, that leads to 11496 data points on cross-asset risk premia returns in an unbalanced panel for the following analyses.

Figure 1 lists the mean and standard deviation of the constructed factor returns individually, with associated two-sided 95% confidence intervals as box plots. Moreover, Table A5 reports detailed numbers and additional metrics (for instance Sharpe Ratios and certainty equivalents based on constant relative risk aversion (CRRA) utility, where the latter measure takes into account aversion to crash risk (Barroso and Santa-Clara (2015a)). The factors were constructed in a way to expect a positive sign of the mean return, however this is not always the case.

Explicitly, six out of the 21 presented factors have a negative mean return, whereby the mean of one factor is statistically significant below zero at the 5% level. 13 factors have a statistically indistinguishable return from zero, while the remaining seven factors are statistically significantly positive at the 5% level. We refrain from removing seemingly unattractive factors, as determined by mean returns, from our

[5] Contrary to Blin et al. (2021), we follow for instance Scherer and Apel (2020) and create all factors within each asset class separately, instead of mixing common factor styles across asset classes into a single factor portfolio, to control for asset-class specific homogeneity in the underlying return dynamics.
[6] The period is chosen with respect to the availability of data for risk premia construction.

sample. While constant exposure to such factors associated with negative returns certainly does not improve the overall performance of an investor, such factors may provide valuable characteristics within certain periods, which can be favoured by an active investment manager trying to successfully steer a portfolio through a particular period.

Even though we include all factors with a negative unconditional return, the factor universe still delivers a positive annualized excess return of on average 1.33%. Furthermore, as Table A5 reveals, all our factors exhibit excess kurtosis, with an average annualized excess kurtosis of 0.46, while the results in term of skewness are rather mixed, with an an average annualized skewness of -0.02. These observations are in line with those conducted by Blin et al. (2021) for their risk premia universe, who also find evidence supporting the possible explanation of out-performance as reward for exposure to extreme risks, but only find mixed evidence for the explanation as reward for considerably negatively-skewed returns, for example stated by Lemperiere et al. (2017).

Figure 2 illustrates the heterogeneous return behavior of our factors within and across different asset classes by plotting correlations.[7] Notably, 83.9% of the factor pairs exhibit a correlation lower than 0.25 in absolute terms and 48.53% show a negative sign, which both indicates potential diversification benefits for a cross-asset factor investor who seeks to combine them together in a portfolio.

A natural approach for an investor with no expectations about the future development of available assets is to split his exposure equally across all assets to obtain a simple diversification benefit.[8] In this spirit, we construct the return of our naïve benchmark at a given point in time as the simple average of the returns of all premia with available data for this period in the data set. Given the ex-ante volatility scaling based on an expanding window, our factor universe embeds the character of risk parity to asset allocation. Therefore, our volatility-scaled equally-weighted benchmark implies an equal factor risk contribution (1/N allocation over the ex-ante scaled factor returns), where volatility represents the measure of risk. Figure 3 plots cumulative excess returns of all factors in our set and the naïve benchmark over our investigation period. Figure 3 (and Table A7) reveals that the equally-weighted benchmark indeed profits from diversification benefits, with a notable drop in volatility compared to the set of single factors and a higher Sharpe Ratio than nearly all of them (except for the commodity basis-momentum factor). In the next section, we will investigate whether an investor can enhance the performance of this simple benchmark using additional information to conduct conditional return predictions and to apply them in an asset-allocation framework.

4 Empirical Application

4.1 Predictors and Predictive Regressions

We gather a set of candidate predictors motivated by the relevant asset-pricing literature and show how they can be utilized in combination with factors. To determine our universe of indicators, we regard

[7] A numerical correlation matrix can be found in Table A6.

[8] The equally-weighted investment approach is a common benchmark in the literature. Moreover, several paper find that it is indeed a tough one to beat, see e.g. DeMiguel et al. (2007), Duchin and Levy (2009), and Jacobs et al. (2014).

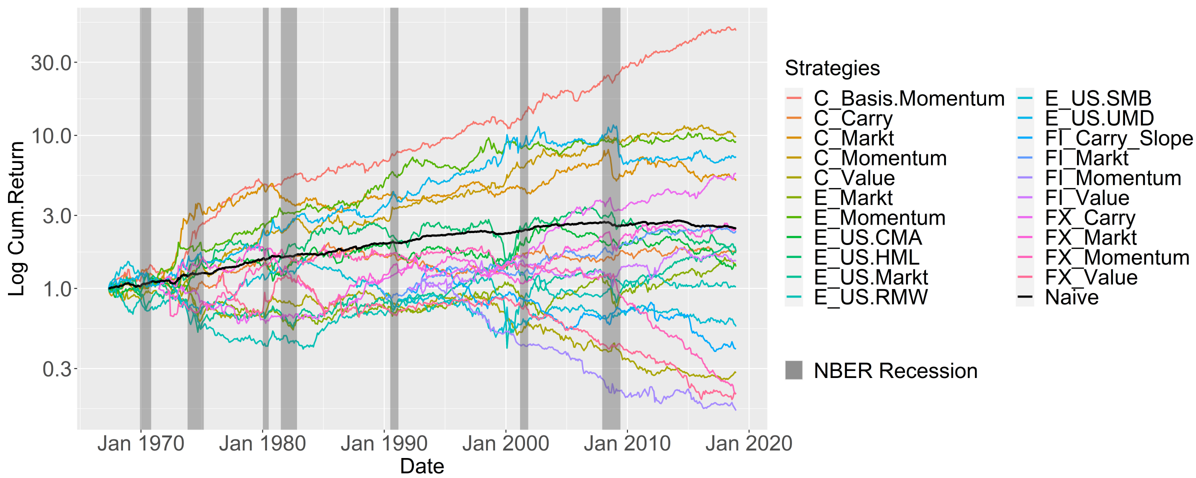

Fig. 3: Cumulative Excess Returns of Factors and Naïve Benchmark.
This figure plots cumulative excess returns of our constructed set of 21 monthly factor time series and of the naïve benchmark, which equally weights all available factors in our investment universe at a given point in time. The first letters of the factor labels indicate the associated asset class of a given factor, where *C, E, FI*, and *FX* are abbreviations for *commodity, equity, fixed income*, and *foreign exchange*, respectively. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

Ilmanen et al. (2021) as a starting point, who provide a broad selection of various measures. Asness et al. (2017) and Gupta and Kelly (2019) evaluate factor-specific characteristics, which we also include in our analysis. Similar to Bender et al. (2018), who aggregate predictors into valuation, sentiment and macroeconomic indicators, we group our set of indicators into two broad topical subsets, namely macro and market signals. Table 2 provides an overview of our selection.
Except for the factor specific indicators, all predictors represent proxies for global economic and financial conditions, as we aim to allocate a global factor universe. The indicators should be timely and accurately available which is particularly difficult with macroeconomic data, which are often subject to delayed publications and frequent revisions. For relevant macroeconomic indicators, we construct vintage time-series (as data are available) or lag predictors by an additional month.

We attempt to link the set of presented predictors to factor returns. Asness et al. (2013) show how value and momentum are exposed to liquidity shocks, which we represent using the TED spread (TED). To proxy for market uncertainty and arbitrage costs, we use the VIX and CBOE SKEW index (VIX, SPX.SKWNSS). Investment-based asset pricing literature (e.g. (Cochrane (1991), Cochrane (1996))) establishes a link between factors and economic shocks that affect future company investments. We select proxies for global growth (CFNAI), geopolitical risk (PLTCL.UNCRTNTY) and long-term costs of capital (RTS.10Y) to represent this category. In addition, we include the term spread (Steep_Yld_Crv) indicator which is closely related to the expectation theory of interest rates. Duration-based theories (e.g. Gormsen and Lazarus (2019)) investigate factor related sensitivity to discount rate shocks, which we represent with a short-term interest rates (RTS.3M) and money supply (GLBL.M2.SPPLY) indicator, both falling into the category of monetary policy. Furthermore, we use the indicators inflation (INFLTN) and global fiscal balance (BDGT.BLNC), which stand in relation to long-run consumption growth theories (e.g. Beeler and Campbell (2009), Breeden et al. (2015)). While the theoretic literature provides little reasoning on the economic foundation of factor-specific characteristics as predictors of future returns, we still include some prominent representatives of this category (Mom, Vola, Value, FCTR.SPRD) given their relevance in other related papers (see for instance Asness et al. (2017) and Gupta and Kelly (2019)). A more detailed explanation of each individual predictor, as well as its usage and foundation in the literature can be found in Appendix A.5. Finally, we acknowledge, as also stated in Ilmanen et al. (2021), that little theoretical guidance exists on the interaction of long-short factors and our set of predictors, especially with respect to the macroeconomic variables. We therefore aim to explore these interactions empirically to inspire new theories that can enhance our understanding of the underlying economic rationale.

Name	Symbol	Obs	Start	Min	Mean	Max	Std
		Macro Signals					
Chicago Fed National Activity Index	CFNAI	619 (100%)	Jun 1967	-4.298	-0.091	1.956	0.813
Inflation Regime	INFLTN	619 (100%)	Jun 1967	-0.010	0.038	0.148	0.029
Political Uncertainty	PLTCL.UNCRTNTY	264 (42.6%)	Jan 1997	52.484	111.296	275.519	44.648
Global Fiscal Balance	BDGT.BLNC	601 (97.1%)	Dec 1968	-0.078	-0.028	0.005	0.016
Short-term Interest Rate Regime	RTS.3M	357 (57.7%)	Apr 1989	0.005	0.030	0.086	0.019
Money Supply	GLBL.M2.SPPLY	619 (100%)	Jun 1967	1.683	19.826	57.571	17.030
		Market Signals					
Steepness of the Yield Curve	Steep_Yld_Crv	619 (100%)	Jun 1967	-0.027	0.016	0.044	0.012
VIX Index	VIX	397 (64.1%)	Dec 1985	0.095	0.202	0.614	0.079
TED Spread	TED	409 (66.1%)	Dec 1984	0.001	0.005	0.031	0.004
CBOE SKEW Index	SPX.SKWNSS	348 (56.2%)	Jan 1990	104.890	118.649	146.980	7.572
Long-term Interest Rate Regime	RTS.10Y	357 (57.7%)	Apr 1989	0.017	0.044	0.082	0.014
TS-Momentum	Mom						
TS-Volatility	Vola						
TS-Value	Value						
TS-Factor Spreads	FCTR.SPRD						

Table 2: Candidate Predictors.
This table lists our analyzed variables for conditioning factor excess returns by their names and associated shortcut symbols used in the rest of the paper. Additionally, column 'Obs' reports the available number of monthly observations per variable (together with the percentage describing to which extent the time series covers our total investigation period in parantheses), while the column 'Start' states the respective starting period. Moreover, in the last four columns the table provides summary statistics of the predictor time series, specifically the minimum and maximum monthly observation as well as monthly arithmetic mean and standard deviation. As the table indicates, the set is split into two broad topical subsets - macro and market signals. The last four market signals are not based on a single time series, but rather concepts applied for each factor individually, which result in distinct predictor signal time series for each factor. Therefore, the columns describing the properties of the time series are spared out in this case. Refer to Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability.

We follow the approach taken by Geyer and Lucivjanská (2016) and construct subjective views with different confidence levels in a predictive regression framework to receive fully systematic return estimates. This approach provides us with a tool to reconcile theory and data. The data-generating process is supposed to be

$$\begin{aligned} r_{t+1} =& \beta_0 + \beta_1 x_t + u_{t+1} \\ x_{t+1} =& \theta_0 + \theta_1 x_t + \nu_{t+1} \end{aligned} \tag{1}$$

where $\beta_0, \beta_1, \theta_0, \theta_1$ are the regression parameters, r_t is the factor excess return at time t, x_t is the predictor variable, assumed to follow a stationary AR(1) process, at time t and u_t, ν_t are normally distributed i.i.d. errors with mean zero and covariance matrix $\Sigma_{u,\nu}$. We estimate parameters $\beta_0, \beta_1, \theta_0, \theta_1$ and derive the predictive distribution for expected returns

$$\mu_t^{PR} = \beta_0 + \beta_1 x_t \tag{2}$$

including some degree of skepticism about the predictability of factor returns via informative views[9]. Wachter and Warusawitharana (2009) show the relationship between the population R^2 and the prior and we attribute to our regression a priori an R^2 of less than 1% ($\sigma_\eta = 0.08$), which is a very high level of skepticism toward predictability. This skepticism is a result of several authors who caution about the feasibility of factor timing (e.g. Asness (2016), Asness et al. (2017)). In Appendix A.6 we show how the skepticism toward predictability in form of a Bayesian prior impacts β_1 as opposed to estimating β_1 using a simple Frequentist approach.

As outlined in Equation 2, we note that only the slope coefficient β_1 directly translates the information of the explanatory variable x_t to a return estimation, whereas β_0 represents an intercept that includes information from average past returns. While including an intercept term in predictive regressions is standard, we caution that the predictive distribution of expected returns is partially influenced by past returns. Having derived the predictive distributions for expected returns from the Bayesian predictive regressions[10], we include them in a quantitative asset-allocation framework in Section 4.2. We want to point out that only the first line of Equation 1 and the parameters β_0, β_1 are relevant for deriving the predictive distribution outlined in Equation 2. Using only the first line of Equation 1 would imply $\mathbb{E}(u_{t-1}|x_t) = 0$. However, the vector x_t is in general stochastic, and hence some elements of x_t can be correlated with past disturbances. Using only the regression $r_{t+1} = \beta_0 + \beta_1 x_t + u_{t+1}$ would violate the standard Bayesian regression framework. Therefore, our presented approach includes the stochastic regressor x_t as dependent variable.[11]

4.2 Asset-Allocation Framework

We take the perspective of a global cross-asset risk premia investor. Our aim is to investigate whether predictor variables for future risk premia returns can help to profitably tilt the allocation to our investment universe in an out-of-sample framework. We measure the out-performance of our constructed strategies in comparison to the 'naïve' rebalanced 1/N benchmark introduced in Section 3, which does not need additional information for obtaining portfolio weights. Furthermore, we implement a benchmark strategy that obtains its weights from a mean-variance optimization approach with restrictions on short selling.[12] Concerning all constructed strategies in the following analysis, we point out that we refrain from shorting factors, but rather underweight them in case of an unfavourable prediction. This reluctance stems from the way our factor set is constructed, since we include bid-ask spreads directly into the returns. Simply

[9] The informative view enters the model in the form of a prior on the variance of the predictive regression coefficient β_1, where $\beta_1|\alpha, \theta_0, \theta_1, \Sigma \sim N(0, \sigma_\eta^2 \sigma_x^{-2} \Sigma_u)$.

[10] We generate a Markov Chain of 1000 draws and discard the first 10% in order to eliminate the impact of the starting value.

[11] For more details, see for example Kandel and Stambaugh (1996).

[12] A factor is initially included in the estimation for our mean-variance benchmark when there is enough return data to completely fill the estimation window.

flipping return signs would therefore incorrectly reflect realized returns[13]. In the following, we will describe the construction of our tilting strategies in detail.

Black and Litterman (1992) have proposed an innovative approach toward quantitative asset allocation with the merits of well-behaved and intuitive allocations compared to, for example, mean-variance optimized portfolios. For a portfolio with N assets (in our case factors), the $(N \times 1)$ return vector r is assumed to follow a normal distribution $r \sim N(\mu, \Sigma)$ with an $(N \times 1)$ vector of expected returns μ and an $(N \times N)$ covariance matrix Σ. The key ingredients are an equilibrium model

$$\Pi = \gamma \Sigma w_b, \tag{3}$$

where Π is an $(N \times 1)$ equilibrium return vector, γ a risk aversion scalar, Σ the $(N \times N)$ asset return covariance-matrix and w_b a $(N \times 1)$ benchmark weight vector, which we deem to be equally weighted. Equation 3 is then combined with expected return views and associated levels of confidence about these views,

$$P\mu \sim N(Q, \Omega), \tag{4}$$

where P is in our case an $(N \times N)$ identity matrix, Q is a $(N \times 1)$ vector quantifying the expected return views and an N-dimensional diagonal matrix Ω reflecting the uncertainty of these views.

A plain integration of the views into the standard Black-Litterman model does not satisfy all relevant practical constraints such as long-only investments or constant exposure (i.e. a fully invested portfolio with 100% exposure). Additionally, we aim to benchmark our active strategy and therefore resort to the practical approach taken by Da Silva et al. (2009), using the optimization

$$\begin{aligned} \max \quad & w_a^T \mu - \lambda w_a^T \Sigma w_a \\ \text{s.t.} \quad & w_a^T 1 = 0 \\ & w_a \geq -w_b, \end{aligned} \tag{5}$$

where w_a are the active and w_b the benchmark weights. The above constraints correspond to a fully invested portfolio ($(w_a + w_b)^T 1 = 1$ with a long-only constraint ($w_a \geq -w_b$). Hence, an active portfolio is constructed by building an alpha overlay portfolio. We follow Da Silva et al. (2009) and select the scaling parameter γ in Equation 3 so that the equilibrium excess returns provide an expected Sharpe ratio (SR_E) of 0.5 for the total portfolio[14]. Next, we will form active investment views on expected returns for all assets based on returns and variances from the predictive regressions. In order to avoid large deviations from the equally-weighted benchmark, we choose a total tracking error[15] (TE) of 2%[16], where

[13] A detailed description of limitations is presented in Appendix A.9.

[14] $SR_E(\gamma) = \frac{(\gamma \Sigma w_b)^T w_b}{w_b^T \Sigma w_b}$.

[15] Occasionally Σ is not positive definit, therefore we apply in this case the procedure from Higham (2002) to compute the nearest positive definit covariance matrix.

[16] The 2% tracking error is achieved via tuning of λ, which is the active risk aversion parameter

$$TE(w_a) = \sqrt{w_a^T \Sigma w_a}. \tag{6}$$

The period of historical return series varies among factors, therefore we include a factor only after its first out-of-sample return forecast is available.

To summarize, in our framework an investor stays 100% invested throughout the full horizon, but will overweight specific factors depending on the predictive signal. The investor's portfolio will then be benchmarked with an equally-weighted factor portfolio, which includes all available factors at the respective timepoint. The latter benchmark can be justified by assuming the view of an investor who does not believe in predictability of a provided signal and therefore recedes from over- or underweighting certain factors over time. Latter investor thus follows the idea of simple diversification. In consequence, the interpretation of the difference in out-of-sample performance between the predictor strategy and the naïve benchmark is rather simple: Every return deviation stems from the attempt to outperform the naïve benchmark by exploiting the results from the predictive signal.

4.3 Results

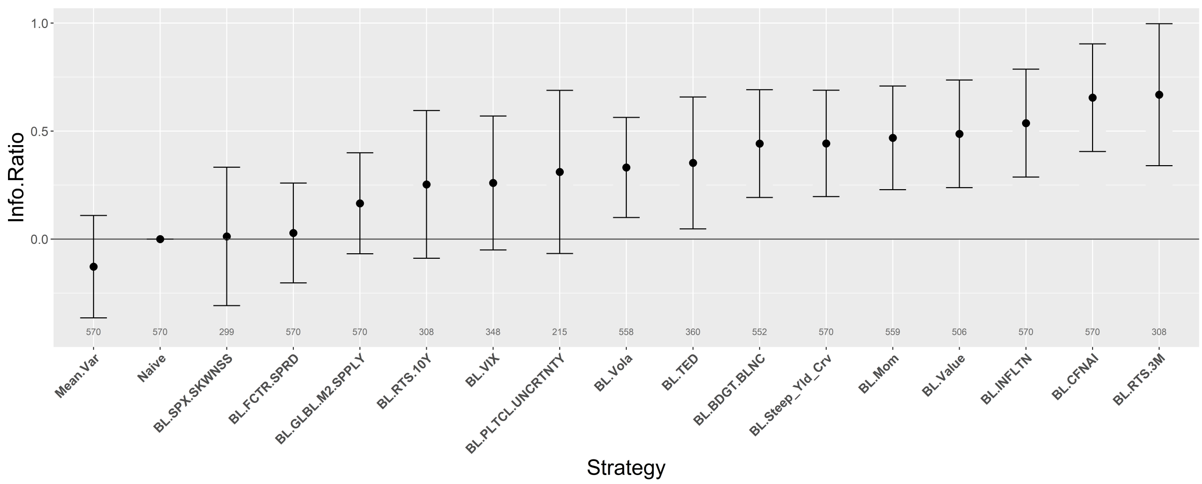

Fig. 4: Information Ratios of Tilting Strategies.
This figure presents information ratios for our set of 15 constructed tilting strategies (identifiable by the prefix 'BL') and for our two benchmarks, namely an equally-weighted 'naïve' allocation approach and an allocation deducted by mean-variance optimization. Standard errors for the one-sided 95% normal confidence intervals are obtained via bootstrapping (see Appendix A.10 for more information), the intervals are indicated in the chart as box plots. Information ratios and their standard errors are annualized, i.e. multiplied by $\sqrt{12}$. The grey numbers on top of each factor label report the available number of monthly observations per factor during our observation period starting in July 1967 and ending in December 2018. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

We calculate the information ratios of our tilting strategies against the equally-weighted benchmark, the latter consisting of all factors that are investable for the tilting strategy at hand.[17] In Figure 4, we

[17] For all our tilting strategies, with one exception, the corresponding naïve benchmark simply consists of all factors in our investment universe stated in Section 3. For the exception, namely our tilting strategy based

present the annualized estimated information ratios for our 15 tilting strategies and our two benchmarks, with associated one-sided 95% confidence intervals obtained via bootstrapping as box plots. Remarkably, all 15 strategies achieve a positive information ratio, and nine of them show a statistically significant out-performance at the 5% level compared to the equally-weighted benchmark.

To deal with data mining concerns, we adjust the calculated p-values for multiple testing using the approach of Holm (1979), acknowledging the fact that we tested several predictors as inputs for our allocation framework. After adjusting, still eight tilting strategies out-perform significantly at the 5% level in terms of information ratio.[18] Moreover, a broader analysis of out-performance, additionally considering other measures such as differences in mean returns, Sharpe Ratios, and certainty equivalents between optimized strategies and their naïve benchmark, delivers very similar results, as can be inferred by Table A7, which also additionally reports standard deviations and maximum drawdowns of the strategies.

To assess the stability of out-performance over the course of time, we divide the return time-series of our optimized tilting strategies in four (nearly) equal subsamples and estimate information ratios for each respective subperiod. The results are plotted in Figure A7. Ratios are not always comparable between different strategies, since we use an unbalanced sample of factors and predictors that leads to different starting points for the tilting strategies and, therefore, to subsamples of different length and over different time periods. Moreover, due to our unbalanced set, strategies with fewer observations will naturally be less likely to show significant results, no matter whether we take the whole sample or subsamples of equal length. We find that no optimized strategy shows significant out-performance at the 5% level in all four subsamples, and only one surpasses this threshold in at least three subsamples (BL.CFNAI). However, eight strategies manage to significantly beat their benchmark in at least two subsamples - in fact these are again the same strategies that survived the test for multi comparison over the full sample period.[19]

After having established that there are indeed different out-performing strategies, showing robust performance over different time intervals, we want to disentangle which kind of predictive signal (macro- or market-based) works best for our set of multiple factors across different asset classes. We find that four out of our six strategies based on macro signals achieve a statistically significant out-performance in terms of information ratio at the 5% level, while the same holds true for five out of our nine strategies based on market signals. Of those, four macro-based and four market-based strategies survive the test for multiple comparison.[20]

Notably, the three best-performing tilting strategies, of which we plot the logarithmic cumulative excess returns over time in Figure 5 and the aggregated weights over time in Figure 6, are all based on

on factor spreads, the corresponding naïve benchmark used in calculating the information ratio excludes the market factors in every asset class, since the tilting strategy does not invest in these factors (due to the fact that no spread data is available as information input for tilting these factors) and a comparison with a per se more diversified benchmark seems unfair when evaluating tilting capability.

[18] In detail, these strategies are BL.CFNAI, BL.INFLTN, BL.BDGT.BLNC, BL.RTS.3M, BL.Mom, BL.Vola, BL.Value and BL.Steep_Yld_Crv.

[19] In detail, these strategies are BL.CFNAI, BL.INFLTN, BL.BDGT.BLNC, BL.RTS.3M, BL.Mom, BL.Vola, BL.Value and BL.Steep_Yld_Crv.

[20] In detail, the surviving macro-based strategies are BL.CFNAI, BL.INFLTN, BL.BDGT.BLNC and BL.RTS.3M, while the market-based strategies are BL.Mom, BL.Vola, BL.Value and BL.Steep_Yld_Crv.

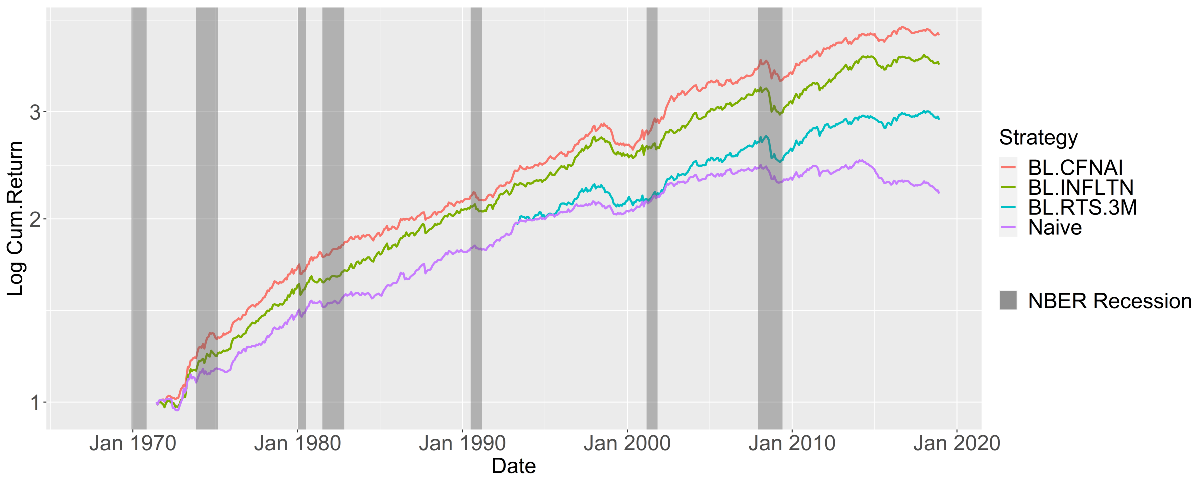

Fig. 5: Cumulative Logarithmic Excess Returns of Tilting Strategies and Naïve Benchmark.
This figure plots cumulative logarithmic excess returns of the three best-performing strategies (in terms of information ratio) from our constructed set of 15 constructed tilting strategies (identifiable by the prefix 'BL') and of the naïve benchmark, which equally weights all available factors in our investment universe at a given point in time. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

macro signals.[21] Figure 6 reveals that our optimized strategies, as intended, in general roughly follow the allocation proportions dictated by the equally-weighted benchmark, inducing a desirable degree of stability and diversification to the allocation over time. Still, and also as intended, the chart marks distinct deviations from the benchmark weights over the observation period, which indicate active allocation decisions based on the predictive regression framework and the strategy-specific predictor. As we can infer from Figure 5, these allocation decisions translate in an out-performance over time that presumably does not stem from a single event or period.

For gaining a better understanding of how the strategies based on the various predictors behave relatively to each other (and to the equally-weighted benchmark), we take a closer look on the active layer of each strategy, which represents the efforts of active management to generate out-performance by tilting away from the passive benchmark component. In Figure 7, we shows correlations between the active layer returns of all respective optimized strategies and the benchmark. Two main observations can be inferred from the chart. First, we generally detect a low correlation between the passive benchmark and our constructed strategies, specifically 0.02 on average. This indicates that the risk-adjusted out-performance observed for our optimal strategies not only stems from higher achieved returns, but also from incremental diversification benefits of combining the passive portfolio component with the active layer. Second, we find an average correlation of 0.11 across all tilting strategies, suggesting at least some further diversification benefits across different predictor-based strategies. However, as is evident in the chart, various strategy pairs with relatively high absolute correlations hide within this broad average, for instance BL.CFNAI and BL.Value (0.9) or BL.CFNAI and BL.Steep_Yld_Crv (0.9). This indicates that

[21] In another exercise, we confirm the strong results of the strategy based on the CFNAI by using another readily-available business cycle indicator in our framework, as can be seen more in detail in Appendix A.7.

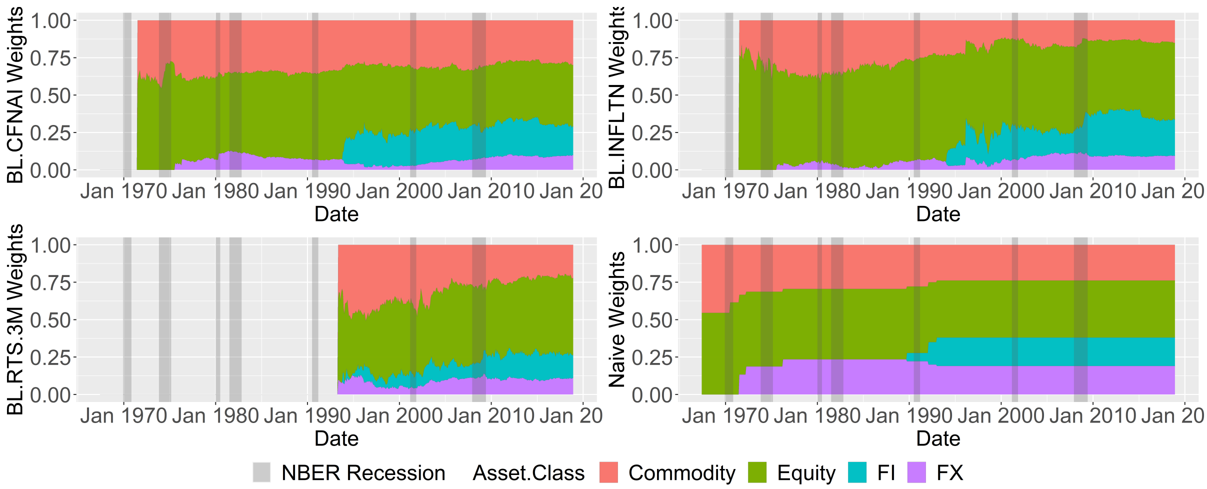

Fig. 6: Aggregated Portfolio Weights of Tilting Strategies and Naïve Benchmark.
This figure plots the aggregated portfolio weights of the three best-performing strategies (in terms of information ratio) from our constructed set of 15 constructed tilting strategies (identifiable by the prefix 'BL') and of the naïve benchmark, which equally weights all available factors in our investment universe at a given point in time. Portfolio weights in the original 21 factor strategies are aggregated over the factor-associated asset classes. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

the predictive framework based on different predictors has lead to relatively similar weighting decisions in our asset-allocation approach, questioning how distinct the information of some variables in our predictor set really is in comparison.

To further investigate whether either each factor delivers a positive contribution to the active layer or only a small amount of factors are responsible for the overall performance, we decompose the returns of the active layers into the individual factor components. The results are presented in Figure 8 for the BL.CFNAI strategy and in Table A8 aggregated over time for all strategies. As can be inferred from the chart, all four asset classes contribute on average to the overall out-performance of the BL.CFNAI active layer. However, there are still notable differences in annualized average contribution, with FI (0.15%) as main source of performance, followed by Commodity (0.13%), FX (0.05%), and Equity (0.02%). When averaging over all optimized strategies, we can observe a similar pattern, again with FI (0.12%) leading by far, followed by Commodity (0.04%), FX (0.03%), and Equity (0.02%).

Since maintaining an active investment style typically comes with additional costs[22] for an investor, for instance in terms of performing extensive analysis or additional trading, we want to explore whether the reported out-performance is robust to assumptions of further expenses associated with the tilting strategies. For this purpose, we focus on the turnover per strategy as a source of additional costs. In Table A7, we report the annualized turnover for all optimized strategies and benchmarks. On average, the tilting strategies exhibit an annual turnover of 117.82%, while forming and maintaining the naïve benchmark only leads to a turnover of 4.31%, marking a considerable increase in trading activity by a factor of around 27 compared to the passive portfolio. However, this high average turnover is partly driven

[22] In our setup, these *additional costs* are costs on top of those due to the construction of the singular long-short factor portfolios that comprise our investment universe.

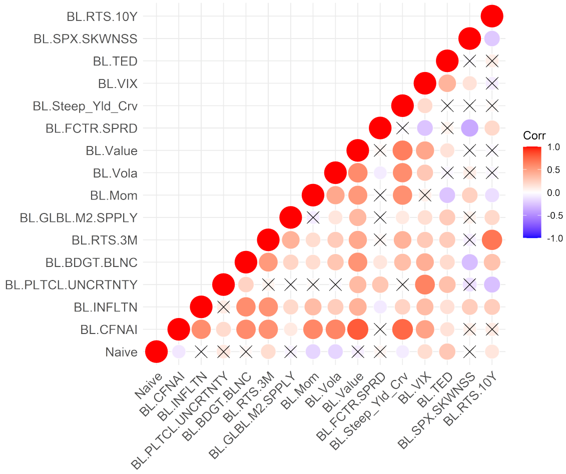

Fig. 7: Correlations of Active Layer Returns.
This figure presents Pearson correlation coefficients for the return of the respective active layer of our set of 15 constructed tilting strategies (identifiable by the prefix 'BL'), as well as for the return of the equally-weighted 'naïve' allocation approach, which represents the passive layer in each strategy. Moreover, the figure includes results of t-tests with the null hypothesis of no correlation. The correlation coefficient of a factor that significantly differs from zero at the 5% level is displayed as circle, where the size of the circle increases with the magnitude of the correlation and its color changes dependent on the sign of the correlation. In case the t-test indicates an insignificant coefficient, crosses are displayed instead of circles. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

by a few strategies (e.g. BL.GLBL.M2.SPPLY (304.23%) and BL.Value (203.08%)) with exceptionally high trading volume, as the median annual turnover of 103.19% reveals. Notably, some out-performing strategies exhibit in comparison a rather low turnover, for instance BL.CFNAI (58.02%).

As it is in done in Ilmanen et al. (2021) or Blin et al. (2021), we refrain from assuming specific transaction costs and rather focus on the constant cost per 100% turnover that would wipe out the out-performance, where we again consider the information ratio as measure. The results are reported in Table A7. On average, the out-performance of the tilting strategies would survive transaction costs of 82 bps, while some out-performing strategies show notable higher breakeven transaction costs, such as BL.CFNAI (227.13 bps). Overall, we find that while (turnover-based) transaction costs can indeed hamper out-performance, our tilting strategies based on various predictive signals are not homogeneously impacted, leaving many with considerably safety buffer for possible transaction costs.

4.4 Discussion

After having established strong results in an asset-allocation framework based on a diversified investment in our factor universe, we also analyze whether our predictors and the information of our predictive regression framework are useful to profitably time exposure of investments in individual factors. A detailed discussion of the framework and results can be found in Appendix A.8. To summarize these results, our evidence supports the critical view of some authors in the literature on profitably timing factors out-of-sample by scaling position size based on a predictor (see for instance Asness (2016), Asness

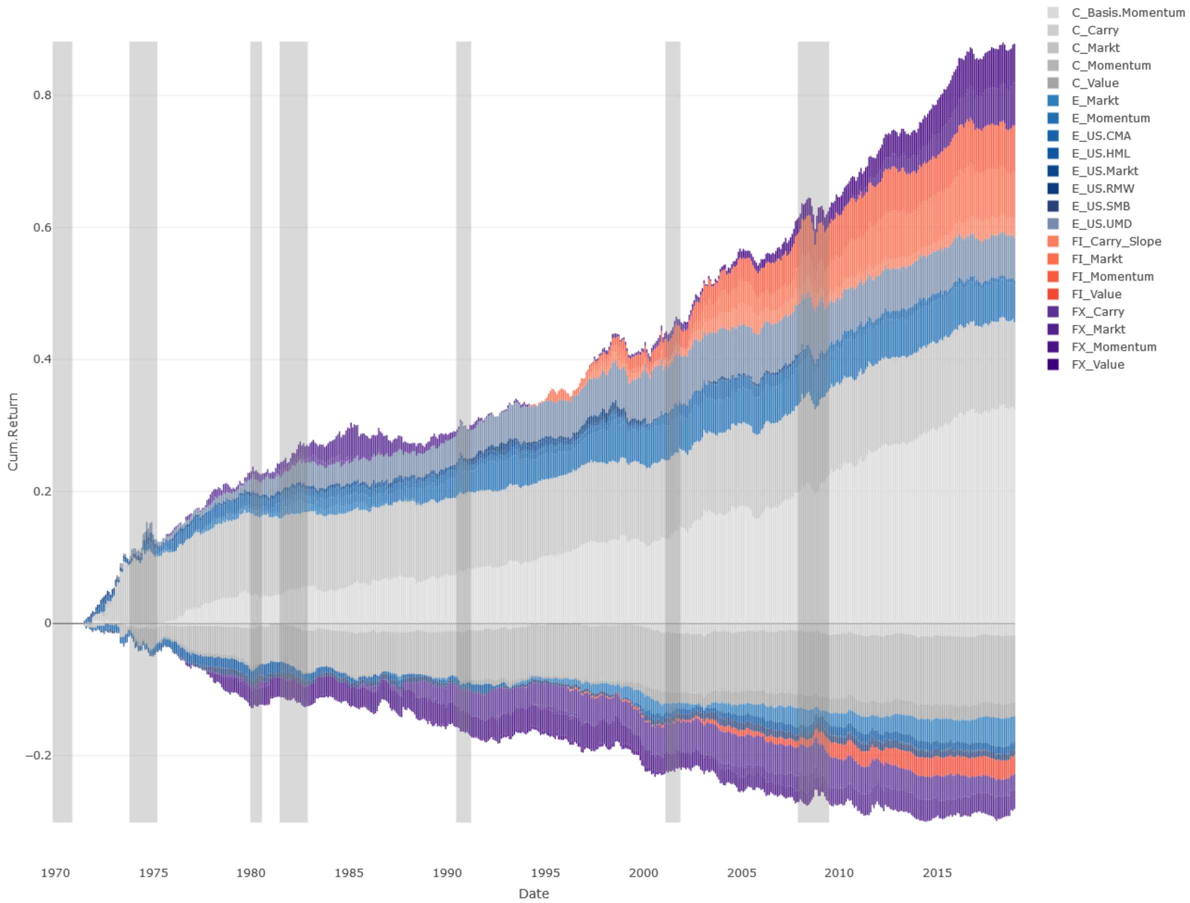

Fig. 8: Cumulative Returns of Active Layer (BL.CFNAI) by Asset Classes and Factors.
This figure presents the cumulative return of the active layer of the BL.CFNAI tilting strategy over time, while visually segregating the performance into the invested factors over our four asset classes. The first letters of the factor labels (at the right margin) indicate the associated asset class of a given factor, where *C, E, FI*, and *FX* are abbreviations for *commodity, equity, fixed income*, and *foreign exchange*, respectively. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

et al. (2017), or Ilmanen et al. (2021)). Even in our large sample, consisting of various factors across several asset classes and multiple predictor variables, we are not able to detect stable out-performance due to timing. Further on and more specifically, the results also contribute to the long-lasting discussion on equity market (factor) timing, suggesting that the equity market is as hard to time as the other analyzed factors are. Overall, the fact that the information from the regression framework does not seem helpful for the timing of individual factors suggests the increment value of applying this information instead in an asset-allocation framework, i.e. in a diversified manner.

Our results are broadly in line with Blin et al. (2021), who show how dynamically-tilted risk premia portfolios dominate a strategic equal risk contribution benchmark. While Dichtl et al. (2019) argue that for a global set of equity single stock factors transaction cost penalties and Black-Litterman shrinkage can only preserve timing but not tilting profitability, we present evidence that tilting delivers additional value after including conservative transaction costs for a factor universe consisting of multiple asset classes.

While latter authors reduce the set of predictors to the first principal component of their fundamental as well as of their technical indicators, we use a selected set motivated by asset-pricing theory. In our case, we receive a broader set of active strategies that may show high correlation of returns, given a potentially high correlation of the underlying predictors (see Figure 7). Whereas Hodges et al. (2017), Ilmanen et al. (2021) and Polk et al. (2020) assess the benefits of individually timed and subsequently blended factors, we provide an asset allocation optimization framework with tracking error and other constraints faced by practitioneers such as mutual fund managers.

Naturally, our research does not come without limitations. Therefore, we provide a transparent overview of various caveats, discretionary choices and possible variations associated with the presented analysis in Appendix A.9. Specifically, we start with arguments arising from our selected data set and factor methodology (for instance concerning data quality or volatility scaling), before stating and discussing limitations connected to our predictive regression and asset-allocation framework (for example dealing with possible non-linear effects).

5 Conclusion

Can meaningful predictors help investors to structure their investment in a broad factor universe, ranging across multiple asset classes?

Our paper provides empirical evidence of time-varying factor returns that can be exploited in an asset-allocation framework using information from relevant market and macro predictors. Starting with a list of predictors and a broad set of factors from different asset classes, we derive systematic views on expected returns using a predictive regression framework that includes a prior reflecting high skepticism toward predictability. The resulting views serve as input to tilt factor portfolios. We then show how factor portfolios using information from business cycle indicators, inflation, and short-term interest rates, among other predictors, significantly outperform an equally-weighted benchmark. The results survive various robustness tests, for instance the performance assessment over different subperiods or the inclusion of (multiple layers of) transaction costs. In an additional exercise, we show that the average of individually timed factors does not deliver comparably significant results, which demonstrates the additional benefits of applying the predictive information in a diversified manner and cautions to time factors on a standalone basis.

Our results are relevant for academics as well as practitioners and investors that aim at outperforming a factor benchmark. On the one hand, we provide new empirical evidence covering a long out-of-sample horizon of up to 51 years, adding to the literature on time-series predictability of factor returns and its exploitation for investment purposes. On the other hand, the results are particularly relevant for investors, given that we provide a transparent and replicable framework that incorporates practical considerations and conservative assumptions on transaction costs.

The presented work opens various paths for future research. For example, investors are often more concerned about surprises of market or macro indicators rather than their level, which would suggest to focus on unexpected news of these indicators and their impact on factor returns. Additionally, the results on factor tilting demonstrate a low correlation of active strategies between different indicators, suggesting that using multiple predictors simultaneously may result in improved estimates of expected returns or additional diversification. Finally, we hope that our work inspires new theories that can enhance our understanding of the economic mechanisms that drive these results.

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A Appendix: Supplementary Text

A.1 Literature Review of Factor Premium Predictability

The finance literature has dealt with the time-series predictability of (aggregated) asset returns for quite a while. A main focus of research in this area has been the predictability of equity market (excess) returns, with early studies dating back to just after the First World War (Dow (1920)). Over decades of research and many studies later[23], various variables have been proposed as viable predictors of the future stock market premium, whereby the consent concerning viability is not clear for the vast majority of variables and study results are in most cases not directly comparable, e.g. due to different investigation periods or analysis methods.

In this context, commonly used predictors for aggregated equity market returns are for instance various valuation ratios, e.g. the cyclically adjusted price-to-earnings ratio (CAPE) proposed by Campbell and Shiller (1998) based on the idea of mean-reversion over long investment horizons. Examples for other variables suggested by researchers are investor sentiment (Huang et al. (2015)), aggregated implied costs of capital (Li et al. (2013)), aggregated market volatility (Merton (1980);French et al. (1987)), the term spread (Campbell (1987)), expected GDP growth (e.g. measured by survey data, see Campbell and Diebold (2009)), and the ratio of new equity issues to total (equity and debt) issues (Baker and Wurgler (2000)).

To approach the mounting uncertainty about useful predictors (and equity premium predictability in general), Welch and Goyal (2007) undertake a comprehensive replication exercise and reexamine the empirical performance of variables taken from literature in a comparable setting. Their main finding is just as sober as it is well-known in the academic community: "By large, these models have predicted poorly both in-sample and out-of-sample for 30 years now." In a follow-up to their findings, Campbell and Thompson (2008) argued that predictions can outperform the historical average return in an out-of-sample test once theoretically motivated restrictions are imposed on the signs of coefficients and return forecasts. As Dangl and Halling (2012) summarize the situation in the literature four years later, several papers find evidence for in-sample predictability, while there is no clear consensus about out-of-sample predictability.

The focus of some more recent publications has shifted from the market (factor) to the return predictability of other aggregated risk premia[24] (or related smart beta ETFs) and possible practical implementations. For example, Hodges et al. (2017) investigate MSCI smart beta indices and find evidence for the predictive power of business cycle information and the benefits of forecast combinations based on multiple predictors. The results of Kirby (2019) highlight a pro-cyclical link between expected business conditions (measured by ex-ante forecasts of real GDP growth) and future returns of the U.S. equity value factor that is only uncovered after accounting for a structural break in the relationship over time. Moreira and Muir (2017) provide empirical evidence advocating the benefits of volatility timing for mean-variance investors using data for the U.S. market, size, value, momentum, profitability, and investment

[23] For example, Lettau and Ludvigson (2010) provide an overview over stock market predictability and discuss among others theoretical arguments, empirical findings, as well as statistical and conceptual pitfalls.

[24] For a broader picture of the related factor literature, please refer to Appendix A.2.

factors, as well as a currency carry factor. Bender et al. (2018) express their view that while factor timing comes with diverse caveats[25], it still can be a useful tool for an investor with a sufficiently long investment horizon and awareness of the accompanied pitfalls.

Gupta and Kelly (2019) examine 65 U.S. equity factors and find that profitable timing based on recent performance is possible for the bulk of individual factors as well as for a combined approach relying on all factors. Furthermore, equity factor momentum seems to define a complementary phenomenon to stock momentum, which appears substantially more stable in terms of how momentum is measured[26] and is robustly traceable in a global equity sample, according to their empirical results.

Yara et al. (2020) investigate value strategies across various asset classes and find that respective value spreads are useful conditioning variables for the future returns of these strategies. Moreover, they decompose the value spread into two components, a common component and an asset-class-specific component, to establish an estimate of the relative contribution of both parts to predictability. According to their analysis, the common component captures roughly two-thirds of the variation in expected value returns in the pool of asset classes and the time variation of this common component can be largely explained by the dividend yield, intermediary leverage, and an illiquidity premium. Yara et al. (2020) interpret this finding together with the fact that expected value returns seem counter-cyclical as evidence for a risk-based story of the value premium.

Haddad et al. (2020) emphasize the relationship between factor predictability, resulting timing benefits in an optimal portfolio, and the stochastic discount factor (SDF). In case factor timing proves relevant for the optimal portfolio, this fact should be considered in the estimation of the SDF, they argue. Due to the vast amount of factors in the literature that are potentially available for timing, estimation however proves challenging and prone to spurious findings. Therefore, they propose a new approach relying on the concept of no near-arbitrage opportunities to structure a large number of factor returns, thereby facilitating the estimation process through a reduction in dimensionality.[27] After applying their methodology to U.S. equity data and fifty factors suggested by literature while using valuation ratios as conditioning information, they report high predictability of the principal components of their factor set. Based on these principal components, they derive predictions of individual factor returns that deliver significant out-performance in out-of-sample R^2 compared to individual factor forecasts. Hence, the results of Haddad et al. (2020) strongly suggest the profitability of factor timing and relevant implications for the SDF.

Polk et al. (2020) examine time-series variation in U.S. and international equity factors and link their return behavior over time to their sensitivity to aggregated news about future cash-flows. They show that

[25] The three main demanding tasks according to Bender et al. (2018) are to deal with (1) time-varying relationships, (2) the selection of predictors based on hindsight and potential data mining, as well as (3) the problem of data revisions.

[26] In contrast to stock momentum that typically only works at short horizons, Gupta and Kelly (2019) report large positive momentum across factors for look-back periods ranging from one month up to five years.

[27] In detail, Haddad et al. (2020) assume that average conditional Sharpe Ratios are capped by a constant, following the argument of Kozak et al. (2018) that these opportunities would soon be exploited by arbitrageurs in equilibrium. They highlight that this "forbids “good deals” on average, but not always". The further implication of this assumption is that measuring the predictability of the largest principal components of the set of factors is sufficient to characterize expected returns.

the documented heterogeneity in sensitivities across factors motivates real-time long-only factor tilting strategies relying on business cycle information. Within their analysis, they provide empirical evidence of sizable out-performance when comparing these strategies to a static multi-factor allocation and prove that their findings are robust after correcting for transaction costs as well as across market cap and geographic segments.

Scherer and Apel (2020) assess the dependency of various alternative risk premia strategies, constructed across several asset classes, to business cycle regimes and report a significant relationship. Moreover, they show that this observation can be exploited to over- and underweight a static portfolio accordingly, which significantly increases the performance while maintaining low turnover. To make up for the rather short investigation period of their data exercise[28], they cross-validate their results by applying the analysis to other investment universes.

On the other side, authors such as Asness (2016), Asness et al. (2017), and Dichtl et al. (2019) take a critical stance on factor return forecasting and viable benefits (after transaction costs) for an investor in comparison to just holding an equally-weighted factor portfolio. Given the disruption that smart beta vehicles have brought to the (fees of the) active asset management industry[29], Asness (2016) highlights the incentive of asset managers to potentially sell factor timing skills as something worth charging additional fees for.

In addition to this selection of recent journal publications, more working papers on factor predictability and timing are in the making. For instance, Blin et al. (2021) build on the work of Scherer and Apel (2020) and use a combination of macro, sentiment and valuation signals to dynamically allocate among a set of global alternative risk premia. The resulting portfolio, which derives its active weights from an adapted version of Black and Litterman (1992), outperforms an associated equal risk contribution benchmark and the performance does neither rely on any specific risk premia nor on any individual predictor.

Ilmanen et al. (2021) examine an exceptionally long[30] set of monthly asset returns covering international single stocks as well as equity indices, government bonds, currencies and commodities. They construct long-short factor portfolios in association with four phenomena (value, momentum, carry and defensive), for which the finance literature has established profound in- and out-of-sample evidence in the cross-section of returns over various asset classes, and report notable variation in factor returns over time. Given this discovered time-variation in factor premia, Ilmanen et al. (2021) subsequently use their rich data set to test for factor return predictability based on various conditioning variables motivated by theory. They point out that the ambition of timing studies can be typically divided into three categories, namely the exploration of (1) a single factor within a single asset class focusing on a single conditioning variable, (2) multiple factors within a single asset class using one or more predictors, and (3) a single factor across multiple asset classes with related predictors, while the focus of their paper is the exploration of multiple factors across multiple asset classes with various predictors. Their findings indicate that while value spreads and inverse volatility capture significant conditional return premia across asset classes, the

[28] Their portfolio performance data are only calculated from January 2010 to August 2018.
[29] The last paragraph of Appendix A.2 provides more context concerning this disruption.
[30] While their earliest time series starts in February 1877, the majority of series begins in the 1920s.

profitability of timing measured via an implementation in real time and after transaction costs is limited. Additionally, they detect stronger predictability performance for models imposing restrictions based on economic theory (similar to the findings of Campbell and Thompson (2008) concerning stock market predictability) and combining multiple predictors. Finally, Ilmanen et al. (2021) fail to link economic measures suggested by the asset-pricing literature, such as macroeconomic, business cycle, tail risk, or sentiment, to the variation in factor premia and therefore provide challenging empirical results for these theories.

A.2 Literature Review of Factor Investing

The theoretical work on asset pricing of Ross (1976) was influential for what today is called factor or risk premia investing. The fundamental idea generalizes and expands the CAPM by linearly relating the expected return of an asset in equilibrium to its sensitivity to a set of common, undiversifiable risk factors, whereby the choice of adequate factors is a key question for the application of the theory.

A famous answer to this question is the three-factor model by Fama and French (1993). During the 1980s, empirical evidence had mounted that firm characteristics such as size (proxied by market capitalization) and value (proxied by book-to-market equity) have explanatory power for the cross-section of average equity returns, while the theoretically-sound CAPM had only shown weak empirical predictive power. As a result of this development, Fama and French (1993) extended the CAPM by adding both firm characteristics in the form of factor-mimicking portfolios to the asset-pricing framework.[31] Their accompanied argument is that these variables are related to economic fundamentals and act as proxy for common risk factors.

Nowadays, factors are booming after the empirical discovery of additional anomalies in the cross-section of returns, especially in the equity literature. Based on the findings of Jegadeesh and Titman (1993), Carhart (1997) adds the momentum factor to the existing set of equity factors by Fama and French (1993) and empirically shows that this setup is able to explain persistence in mutual fund returns. Inspired by investment-based asset pricing, Hou et al. (2015) propose an investment and a profitability factor to explain the cross-section of stock returns and also Fama and French (2015) revisit their famous three-factor model and add the aforementioned two factors, while questioning the importance of value in the resulting five-factor model according to their empirical results.

The list of additional factors proposed in the literature is long. Harvey et al. (2016) report 316 variables shown to predict cross-sectional equity returns. In this context, Cochrane (2011) introduced the term 'factor zoo' to critically address the vast amount of proposed factors in the literature. He further highlighted the challenge to examine which characteristics actually provide independent information about average returns and which are subsumed by others. The challenge to get a more profound theoretical and empirical understanding of the multiverse of factors in relation to returns is still ongoing.

For instance, Campbell and Vuolteenaho (2004) follow a present-value argument to highlight the two theoretical reasons for changing expected market returns, namely (1) changes in expected cash flows

[31] As mentioned by Cochrane (2011) in his critical reflection, the methodology of Fama and French (1993) has become a standard procedure in contemporary asset pricing literature.

and (2) changes in discount rates. They point out that both components should be evaluated differently by a sufficiently risk-averse long-term equity investor, implying a higher demanded compensation for assets that covary with cash-flow news of the market compared to assets that covary with discount rate news.[32] In this sense, the authors argue for a split-up of the CAPM's beta into two separate coefficients associated with the two sources of risk. After framing their idea within the intertemporal capital asset pricing model (ICAPM) of Merton (1973), they fit their model to U.S. stock portfolios sorted by size, book-to-market ratios, and CAPM betas and find remarkable improvements in explanatory performance relative to the single factor CAPM, putting more into perspective the empirically observed high average return that motivated the size and value factors mainly in the first place. Harvey et al. (2016) argue for new significance standards in the asset-pricing literature, with hurdles that are increasing over time to account for the limited amount of data, decreasing costs of data mining over time and a more and more crowded field of discoveries. The findings of McLean and Pontiff (2016) suggest that at least some of the original cross-sectional predictability of U.S. stock returns is the result of mispricing and that investors learn about mispricing from academic publications, leading to a subsequent deterioration of predictability and associated out-performance. Based on their sample, they report a decrease in portfolio returns of 26% out-of-sample and 58% post-publication for the 97 variables studied. In another study, Green et al. (2017) test simultaneously 94 characteristics and find that the information of only 12 variables subsume the remaining characteristics for reliably and independently determining non-microcap U.S. stocks over their sample from 1980 to 2014. Moreover, they note a drop in return predictability in 2003 with only two variables being independent determinants since then. In a recent study, DeMiguel et al. (2020) show analytically as well as empirically using U.S. stock data that combining characteristics reduces transaction costs due to more efficient net re-balancing of the underlying stocks, since trades to re-balance different characteristics often cancel each other out. They empirically investigate the number of jointly significant characteristics with and without transaction costs and state a higher number of significant factors after combining characteristics and considering transaction costs. They conclude that transaction costs provide an economic rationale for considering a larger number of factors jointly. Similarly, Fisher et al. (2016) analyze long-only U.S. equity investing and show the superior performance of a strategy that simultaneously depends on value and momentum compared to a strategy that just combines two independently-formed value and momentum portfolios. They describe two advantages of the integrated strategy leading to this result, namely the decrease in transaction costs and the better exploitation of value and momentum information in a long-only portfolio.

While a large part of the literature examines the (U.S.) equity cross-section, the idea of factors has also spread to other asset classes.[33] In the FX market, the failure of the uncovered interest parity is a long- and well-known anomaly (see e.g. Bilson (1980), Hansen and Hodrick (1980) or Fama (1984) for

[32] Campbell and Vuolteenaho (2004) argue that in the case of bad cash-flow news, the result is a decrease in wealth and unchanged investment opportunities, while in the case of news concerning higher discount ratios, wealth decreases whereas future investment opportunities enhance. Therefore, the risk premium compensating for covariance with the market's cash-flow beta should be higher than the premium for covariance with discount rate news, since in the latter case the effects on wealth and future investment opportunities partially offset each other.

[33] In this context, evidence that a certain factor theme (by some called 'style') shows relevance and is applicable across asset classes is typically viewed as a sign of robustness (Asness (2016)).

an early investigation and Burnside et al. (2008) for a more recent contribution). This economic theory predicts – based on the assumption of rational risk neutral investors and a no-arbitrage consideration – that the interest rate differential between countries is an unbiased estimator of the future exchange rate change. In other words, given a positive interest rate differential between two currencies, there should be on average a devaluation of the high-yielding currency of a magnitude so that both currencies have identical expected returns. Since empirical tests of the uncovered interest parity typically reject this relationship and rather find that high-yielding currencies appreciate on average (see for example Froot and Thaler (1990)), the carry strategy, consisting of a long basket of high-yielding currencies and a short basket of low-yielding currencies, has emerged in the literature as well as in practice. The explanation of the historically observed out-performance is still debated in the literature and possibly multi-dimensional, as different approaches and findings suggest (see e.g. Brunnermeier and Pedersen (2009), Burnside et al. (2011) , Lustig et al. (2011) and Menkhoff et al. (2012a)). Similar to the outlined developments in the equity literature, more characteristic-based factors have emerged over the years, promising predictive power about cross-sectional FX returns, for example value and momentum (e.g Asness et al. (2013), Menkhoff et al. (2012b), Pedersen (2019)). Moreover, Lustig et al. (2011) introduce a level factor, defined as average FX excess return of the underlying set of currencies against the U.S. dollar, called the 'Dollar risk factor'. As they argue, this factor is connected to a home risk premium (for U.S. investors, in this context), which delivers average excess returns to compensate for home country risk.

Similar to the developments in the equity and FX literature, more variables have joined the competition of explaining bond returns. For example, Elton et al. (1995) additionally examine a bond market factor in the spirit of the equity market factor as well as two factors based on unexpected changes in macro variables (inflation and economic performance) referring to Chen et al. (1986) among others. According to the findings of Asness et al. (2013), the concepts of value and momentum are also relevant for predicting international government bonds returns. Moreover, Koijen et al. (2018) demonstrate that also carry described in the context of currencies shows predictive power for global bonds returns.

Initial explanations of commodity returns root back to the 1930s, when Kaldor (1939) introduced the 'theory of storage', which suggests a link between commodity future prices and variables such as the interest rate, the convenience yield and storage costs, whereby the convenience yield is related to inventory levels. Keynes (1930) introduced another perspective on commodity future prices called the 'theory of normal backwardation'. This theory argues that there should be a premium in the market for risk-averse speculators for taking the long-side of a commodity future trade, since inventory holders such as commodity producers by assumption want to hedge their exposure by taking the short-side. Gorton et al. (2012) formulate an analytical model building on both theories and empirically investigate the derived link between inventories and risk premia on commodity futures in a broad cross-section of 31 commodities. They find a negative, nonlinear relation between the convenience yield and the level of inventories as confirming evidence for their theory. Moreover, their results suggest that future as well as spot prices comprise relevant information about current inventories and that prior futures returns, prior spot price changes, and the futures basis are correlated with futures risk premia, as predicted by their analytical results. Szymanowska et al. (2014) show that the cross-sectional and time-series variation in expected returns of commodity futures is dependent on characteristics such as momentum, volatility or basis rather than on the sectors or industries the commodities can be attributed to. Particularly, they use one basis factor for spot premia and two additional basis factors for term premia to price the cross-section of commodity futures returns. Bakshi et al. (2019) examine cross-sectional commodity returns and propose a model including an average commodity factor, a carry factor as well as a momentum factor that is able to explain the cross-section of commodity returns. As an economic rationale, they show dependencies of portfolios formed on carry with innovations in global equity volatility and of portfolios formed on momentum with speculative activity in commodity markets. Boons and Prado (2019) detect a strong risk premium in portfolios sorted on a combination of slope and curvature of the futures term structure. They connect this finding with imbalances in supply and demand of future contracts that require a premium from an investor's perspective.

In a recent working paper, Ilmanen et al. (2021) examine an exceptionally long[34] set of monthly asset returns covering international single stocks as well as equity indices, government bonds, currencies and commodities. To explore factor performance as well as variation over time, they construct long-short factor portfolios in association with four phenomena (value, momentum, carry and defensive), for which the finance literature has established profound in- and out-of-sample evidence in the cross-section of returns over various asset classes. They report positive and statistically significant premia for each factor within each asset class over their full sample of roughly a century and find evidence promoting diversification benefits of combinations over different factors and asset classes. Furthermore, the analyzed factor premia significantly vary over time, as their results indicate. While additional tests suggest that this variation can partly be explained by poorer out-of-sample performance due to over-fitting in the original sample, Ilmanen et al. (2021) find only little evidence for variation stemming from arbitrage activity after the wide-spread discovery (proxied by academic publication) of these factors.

While factors have received growing attention in the literature, the idea of factor investing has also spread in the asset management industry, or as Dimson et al. (2017) phrase it: "Factor investing and smart beta strategies are in vogue". Whereas in the past active asset managers mostly competed among each other and their value-weighted benchmarks, nowadays new challengers have emerged: Smart beta ETFs (see e.g. Asness and Liew (2014) or Kahn and Lemmon (2016)). These exchange-traded and readily-accessible financial products use characteristics identified in the factor literature and apply them (individually or in combination) within a ruled-based approach to derive portfolio weights. Typically, smart beta is structured as long-only strategy that deviates from a value-weighted benchmark according to the documented return effect of the characteristic(s) and that gets re-balanced regularly. Kahn and Lemmon (2016) picture smart beta as a disruptive financial innovation that delivers transparent low-cost access to return components previously attributed to the performance of active management. Further on, they project that the active asset management industry will progress in two distinct product types, low-cost smart-beta products and pricier strategies delivering pure alpha, and recommend managers currently in between to decide which road to follow. Blitz (2016) empirically documents that it may not be straightforward to gain desired factor exposure via smart beta products and emphasizes that

[34] While their earliest time series starts in February 1877, the majority of series begins in the 1920s.

understanding the specific construction procedure of the ETF is essential for obtaining the desired exposure. Smart beta may be a prominent one, but clearly not the only solution to implement factor investing in the real world. For example, Bass et al. (2017) propose a strategic approach to map assets to macro factors and subsequently allocate between these factors. They point out the benefits of its adoption for institutional investors compared to a traditional asset class allocation.

A.3 Details to Factor Construction

For the set of global **currencies** we use monthly spot and forward exchange rates in U.S. dollars and build end-of-month series starting from January 1971 to December 2018. The data are primarily sourced from Bloomberg and missing data was filled with data from GFD[35]. Using bid-ask data, we can account for transaction costs during trading. The total sample contains 69 currencies and detailed information on each currency are presented in Table A1 in the Appendix. We note that the effective sample size of available currencies can vary over time, given that some emerging country currencies become available only at later time periods and other currencies cease to exist i.e. due to the adoption of the Euro. We exclude countries within the euro area after they adapted the euro starting in January 1999. To illustrate the availability of all currencies and other asset classes at each particular time point, we plot the time-varying sample size in Figure A4. Our data cleansing process includes data removals in case of large deviation of the covered interest rate parity. We remove negative ask and mid implied yields in non-developed markets, ask and mid implied yields in developed markets below -5%, and ask and mid implied yields above 150% in all markets. Additionally we remove data where bid implied yields are above 150%.

To proxy for a currency market factor, we follow the approach of Lustig et al. (2011) and construct the dollar factor. The dollar factor describes a long position in the set of all available currencies against the U.S. dollar and the performance is measured over a 1-month holding period.

Our measure of carry is the implied yield in line with literature. The implied yield for long positions is calculated using the current 1-month forward bid rate (f^b) and the current spot ask rate (s^a), given that an investor would purchase the forward at the bid price and sell after the 1 month holding period at the spot ask price

$$IY_t^l = \frac{f_t^b}{s_t^a}(1 + r_t^d) - 1, \tag{7}$$

where r_t^d is the (domestic) U.S. dollar interest rate. Given that covered interest rate parity holds, the implied yield should approximate the interest rate differential between the USD and the respective foreign currency (Riddiough and Sarno (2018)). Furthermore, the implied yield for short positions is calculated in an analogous way, using the current 1-month forward ask rate (f^a) and the current spot bid rate (s^b) instead

$$IY_t^s = \frac{f_t^a}{s_t^b}(1 + r_t^d) - 1 \tag{8}$$

[35] Methodology inherited from Dockner et al. (2018).

For currency momentum, we sort according to the historical 12-month currency excess return and leave out the most recent month

$$M_t = \prod_{s=t-11}^{t-1} (1 + r_s) - 1, \tag{9}$$

where r_t is the currency spot return. For the value measure, we refer to the concept of purchasing power parity in order to determine whether a currency is under- or overvalued. Our measure is the five-year change in the real exchange rate, which can be formulated as the 5-year currency spot rate adjusted by the consumer price index of the foreign country relative to the U.S. over the same period. We therefore use the same methodology as Asness et al. (2013), who restrict their analysis to the G10 countries, and extend it to a broader currency sample.

For our global **fixed income** universe we construct zero curves for 45 international local currency government bond markets (21 developed and 24 emerging countries) starting in December 1994 and ending in December 2018 using data from Bloomberg. Detailed bond data information are provided in Table A2. Moreover, we use monthly data, i.e. end-of-month data of local bond yields and, analogously to currencies, build end-of-month time series. In order to have meaningful duration-representative returns, we aggregate returns into a bucket where bonds with a time to maturity of five to ten years are grouped. This maturity-bucketing is analog to the methodology used by JP Morgan[36], who also form several maturity buckets for instance within their JPM GBI index. Sovereign bond returns will be presented from the perspective of a U.S. investor. Similar to currencies, we note that the effective sample size of available countries can vary over time, given limited data availability for particular countries. The time-varying sample size of the high duration bucket is illustrated in Figure A4.

We introduce a number of risk premia evident in the fixed income universe. The market factor constitutes of a GDP-weighted long position in the seven largest countries[37] in terms of real GDP[38] and a short position in the risk-free rate[39].

Our measure of carry is defined similar to Koijen et al. (2018) as the term spread within the maturity bucket:

$$C_t = y_t^{10y} - y_t^{5y}. \tag{10}$$

For momentum we take again the common measure of the 12-1 month historical U.S. dollar return, i.e.

$$M_t = \prod_{s=t-11}^{t-1} (1 + r_s^{m_t}) - 1, \tag{11}$$

[36] Brooks and Moskowitz (2017) follow the same approach.
[37] United States, Great Britain, Japan, China, Germany, India, France
[38] We acknowledge that the introduction of GDP-weighting leads to a slight look-ahead bias, since GDP might not have been (precisely) available at each timepoint.
[39] ICE LIBOR USD 1-month rate is taken from Bloomberg.

where $r_t^{m_t}$ is the return of a bond at time t with remaining maturity m_t. Our measure of value is defined as the nominal yield (y) on the bond minus current inflation[40] (Inf^{yoy}) to derive a real bond yield level:

$$V_t = y_t - Inf_t^{yoy}. \tag{12}$$

As stated in Brooks and Moskowitz (2017), our measures of carry, momentum and value can be interpreted in a natural economic way, namely that carry provides information about expected future yields without changes to the yield curve, momentum signals trends in yield changes and value indicates the level of yields with respect to a fundamental anchor namely inflation.

Our **commodity** data collection includes liquid and exchange-traded commodity futures contracts for 31 commodities sourced via Bloomberg. The majority of contracts is identical to those used by Szymanowska et al. (2014) and Boons and Prado (2019). Our sample of futures data starts in July 1959 and ends in December 2018. Data descriptions and results are indicated in Table A3. The returns of individual commodities are calculated using a roll-over strategy as done by the authors above. In line with their reasoning, we calculate first and second nearby contract returns given these are usually more liquid. In order to avoid contract positions close to expiration and the resulting notice days or erratic volume and price behavior, we restrict expiration of each commodity contract to be after $t+2$. To account for transaction costs, we will apply a relative half spread of 4.4 basis points suggested by Marshall et al. (2012).

For commodities the market factor is, analog to currencies, a long position in the set of all available commodity futures at any specific timepoint. Our carry signal is derived from the basis (B_t), which indicates whether a commodity futures curve is in contango (positive basis) or in backwardation (negativ basis):

$$B_t = \frac{F_t^{T_2}}{F_t^{T_1}} - 1, \tag{13}$$

where $F_t^{T_n}$ is the n-th nearby futures contract at time t. We take long (short) positions in commodities in backwardation (contango), i.e. purchase (sell) relatively cheap (expensive) first-nearby futures contracts given the term-structure of the futures curve.

For momentum we use in accordance with previous asset classes the 12-1 month historical return of the first-nearby futures contract as signal

$$M_t = \prod_{s=t-11}^{t-1} (1 + r_s^{T_1}) - 1, \tag{14}$$

where $r_s^{T_1}$ is the return of the first nearby (T_1) futures contract at time s[41].

[40] Opposed to expected inflation as is used e.g. in Brooks and Moskowitz (2017) or Asness et al. (2013).

[41] We require at least one return $r_s^{T_1}$ for the calculation of the momentum signal above, i.e. in case of missing data we will still be able to generate a momentum signal and therefore expand the momentum signal availability in the cross-section.

The commodity value measure is based on the negative five year cumulative return[42] commonly used by other authors such as Asness et al. (2013):

$$V_t = -\Big(\prod_{s=t-59}^{t} (1 + r_s^{T_1}) - 1 \Big) \tag{15}$$

The last and most recent commodity factor is basis-momentum, which is defined as a combination of (B_t) and momentum (M_t):

$$BM_t = \prod_{s=t-11}^{t} (1 + r_s^{T_1}) - \prod_{s=t-11}^{t} (1 + r_s^{T_2}). \tag{16}$$

The motivation of the signal according to Boons and Prado (2019) is that it contains relevant slope and curvature information, determined by market participants seeking positions on the futures curve at different locations.

For our analysis on international **equity indices** we include a total of 49 Morgan Stanley Capital International (MSCI) country total return indices, all sourced via Bloomberg, to our equity cross-section and construct end-of-month series starting in January 1970. The respective indices are all quoted in USD. Detailed information to the indices is provided in Table A4. As outlined by Zaremba (2019), MSCI indices, followed by Datastream Global Equity Indices, are the most popular choice on a country-level equity perspective, given the calculation transparency, consistency in index calculation and result comparability across a broad number of countries. Bhojraj and Swaminathan (2006) investigate factor momentum on equity index level from 1970 to 1999 using MSCI data and find momentum during the first year and reversals during the following year. We acknowledge the heterogenity among the selected countries and therefore are cautious with the final results of the factor construction.

In our analysis, we proxy transaction costs with 10 basis points for each country index in each month. Analog to the other asset classes, we assume this proxy will be again more conservative given full transaction costs are incurred monthly, even when the position remains unchanged.

We construct a market-capitalization weighted equity index benchmark with the seven largest countries in terms of market capitalization to represent the equity market factor financed with the risk-free rate. Given market capitalization data from the country indices becomes available not until August 1995, we proxy the equity market returns solely with the U.S. equity index returns, starting in 1970. Our equity index momentum measure is the 12-1 month cumulative return as in Equation 11. [43] Finally, we replicate the five classical U.S. **equity single stock** factors (from Fama and French (1993) and Fama and French (2015)) as well as the momentum factor from Carhart (1997) and add them to our factor universe.

At the end of month t we rank assets according to the above described signals and form six portfolios. In the case of an available total sample size below six, at least one asset will be selected for the top and

[42] Analog to momentum, we will require at least one return $r_s^{T_1}$ for the calculation of the value signal in order to broaden the cross-sectionally available assets.

[43] Opposed to the other presented asset classes, we refrain from constructing a **carry** and **value** factor within the equity index space due to the heterogeneity of countries.For carry the dividend yield could be considered as underlying characteristic measurement and for value the cyclically-adjusted price earnings ratio. However, perceived discrepancies in terms of e.g. shareholder value and accounting methodologies, among other differences, across the presented countries led us to refrain from constructing such factors.

bottom sixth portfolio. This selection approach has the advantage that it can account for a varying sample size. We take long (short) positions in assets based on the top (bottom) sextile in accordance with the standard methodology i.e. done by Lustig et al. (2011) for currencies. At the end of each month, the portfolios are rebalanced. Each asset in the long (short) portfolio is then weighted equally.

A.4 Differentiation to Literature

For **currencies**, in contrast to most other literature (i.e. Menkhoff et al. (2012b) or Lustig et al. (2011) we include the United States, i.e. USD, to the currency sample. All currencies above are generally quoted against the USD, however with the inclusion of the USD as a separate investable currency, this has the effect that the pair USD/USD constitutes a neutral portfolio position. From a practical perspective, this gives an investor the chance to stay in USD (i.e. invest into the currency pair USD/USD) in case the other investment opportunities are less attractive, i.e. due to negative carry across all currencies. In addition, we use inflation and GDP data from local sources (including several emerging market countries) and rely on the credibility of local authorities supplementing sound data. As mentioned in the Appendix A.3, we apply a data cleansing procedure when covered interest parity is violated.

For **fixed income**, opposed to currency data, we do not have bid-ask data available for the zero-coupon yield curves. In order to account for transaction costs, we therefore approximate the zero-coupon bond spreads using currency-related spreads for each country.[44] Our heuristics includes a spread multiple of 1.5 of the country-representative FX-spread. Given that we calculate returns from the perspective of a U.S. investor, total transaction costs (including currency conversion costs) for a fixed income investor consist therefore of a 2.5 multiple of currency transaction costs. Given that total transaction costs are incurred at each month, even if the bond is not entirely sold but only rebalanced, we assume this approach will be more conservative than in practice. Total fixed income transaction costs will be represented as follows:

$$s_t^{spread} = \left| s_t^a - s_t^b \right|, \tag{17}$$

where s_t^a (s_t^b) is the ask (bid) spot exchange rate at time t. Equation 17 represents the currency spot spread.

$$rx_{t+1} = \frac{s_{t+1}^b - 1.5 s_{t+1}^{spread}}{s_t^a} - 1 \tag{18}$$

where rx_t is the currency spot excess return at time t.

Following the construction of fixed income returns including transaction costs, we construct a long-term maturity bucket averaging returns between tenors of five to ten years. We consider this duration bucket to proxy for returns with highest loadings on duration risk. Especially for the included frontier markets, the assumed fixed income spread may be partially too tight. However, we want to place as few assumptions on such costs as is necessary, staying in line with transaction costs for other asset classes.

[44] González-Rozada and Yeyati (2008) show that time variation in bond spreads is explained by global factors which we assume are also implicit in currency spreads.

Hence, while the approach might over- or underestimated costs for specific markets, the assumption of full monthly turnover and associated transaction costs places already a substantially conservative assumption on such costs.

We use a broader cross-section of 31 **commodities** to construct factors for this asset class (cp. Boons and Prado (2019) and Szymanowska et al. (2014) who use 21 commodities respectivley).

Given the global representativeness of the asset-classes currencies, fixed income and commodities, we follow suit with **equities** and resort to MSCI equity indices. From a practical perspective and given real-world investment constraints, country indices provide investors with a simple, mostly feasible, diversified and cost-efficient way to implement an equity factor strategy. However, we acknowledge that there is great heterogeneity across the different countries and the results of global factor portfolios based on heterogeneous country specific indicators shall be treated cautiously. This great heterogeneity among countries leads us to construct only a market and momentum factor, which can be constructed most consistently in our view, for equity indices.

A.5 Details to Predictors

There is some evidence in the literature that business conditions and the business cycle have predictive power for future aggregated asset returns.[45] Therefore, we include a variable that captures the dynamics of the U.S. business cycle as a proxy for the global cycle. As signal, we take the **Chicago Fed National Activity Index**, a weighted average of 85 monthly indicators of national economic activity provided by the Federal Reserve Bank of Chicago in a monthly frequency, which is e.g. used in Lustig and Verdelhan (2012) or Hodges et al. (2017) to proxy the business cycle in 'real-time'[46]. To be specific, we focus on the available three-month moving average of the CFNAI as e.g. Brave (2009) suggests, since the index is very volatile at times.

Furthermore, we include the **Aruoba-Diebold-Scotti Business Conditions Index** (ADS) as second U.S. business cycle predictor to check for robustness of the results based on the CFNAI. The indicator (as well as vintage data starting with the inception of the index in December 2008) is openly available from the Federal Reserve Bank of Philadelphia and is based on the framework proposed in Aruoba et al. (2009) for measuring economic activity at high frequency while relying on data available at different frequencies. To use the daily time series in our monthly framework, we have to convert the index to a monthly frequency. Instead of simply taking the last value of the month, we aggregate the index via averaging over all daily observations in the given month to reduce noise and to include potentially some of the intra-month extra information. Given the lack of vintage data prior to their initial release dates, we have to interpret the results of both business cycle related predictors with caution.

[45] Fama and French (1989) is an early example, while Lustig and Verdelhan (2012), Dangl and Halling (2012), Hodges et al. (2017), Ilmanen et al. (2021), Scherer and Apel (2020) and Polk et al. (2020) give a more recent perspective. In addition to this selection of academic journal publications, more practice-oriented working papers such as Varsani and Jain (2018) also investigate this topic.

[46] We use the vintage data provided on the homepage of the Chicago Fed (`https://www.chicagofed.org/publications/cfnai/index`). As Lustig and Verdelhan (2012) notice, the data are not perfectly 'real-time', since the data prior to the initial release of the index (January 2001) is not vintage. Additionally, the authors emphasize that the invention of the CFNAI was dependent on relevant progress in the econometric literature.

The impact of monetary policy on asset prices is a particularly relevant component of a central banks' policy decision and an abundance of literature exists on analyzing the impact of policy changes and market prices[47]. To analyze factor return predictability of monetary policy, we use a measure of **money supply**, specifically M2 supply, of the four largest global central banks which includes the Federal Reserve, the Bank of England (BoE), the Bank of Japan (BoJ) and the European Central Bank (ECB). All indices are expressed in USD and downloaded from Bloomberg. We calculate monthly changes in money supply for each central bank's M2 supply respectively and calculate a level-dependent overall money supply change index. The U.S. M2 money supply has the longest time series, dating back to at least 1960, followed by the BoE in 1986, the ECB in 1999 and the BoJ in 2003.

The monetary-policy framework of inflation-targeting (see e.g. Bernanke and Mishkin (1997)) indicates the relevance of inflation levels to the economy. Naturally, the investigation of the predictive power linking inflation to future aggregated asset returns has been the subject of various studies.[48] To analyze different **inflation regimes**, we resort to the inflation levels of the seven largest countries in terms of economic output. This includes the U.S., U.K., Japan, China, Germany, India and France. For each country, we source the year-on-year inflation changes from Global Financial Data, weight them in terms of GDP and calculate a representative global inflation index.

To account for fiscal policy, we approximate a **global fiscal balance** measure using a GDP-weighted index consisting of the same seven largest countries as used in our inflation regime indicator. For each country, we source from Bloomberg the budget balance in percentage of GDP and derive a global budget balance index. The interdependence between asset prices and fiscal policy behavior is theoretically and empirically discussed by numerous authors. For example, Blanchard (1981) defines a theoretic model to determine economic output, stock market, and term structure, which captures the link of changes in stock prices and output to (the disclosure of) changes in fiscal (and monetary) policy. Similarly, the formal model of Shah (1984) relates equity prices with fiscal (and monetary) policy. Moreover, Tavares and Valkanov (2001) find empirically that fiscal policy shows roughly a similar level of importance for asset return variability as does monetary policy. Furthermore, Eschenbach and Schuknecht (2002) establish a link between asset prices and public finances, whereas Jaeger and Schuknecht (2007) study fiscal policy during boom-bust phases and conclude that economic activity in such phases tends to be persistent with cyclical turning points that are hard to forecast. Laopodis (2009) investigates the effect of fiscal policy measures on the U.S. stock market from 1968 until 2005 and concludes that the market shows signs of inefficiency associated with pricing-in future fiscal policy steps, after presenting results relating past

[47] For example, Blanchard (1981) defines a theoretic model to determine economic output, stock market, and term structure, which captures the link of changes in stock prices and output to (the disclosure of) changes in monetary and fiscal policy. Similarly, the formal model of Shah (1984) relates equity prices with monetary and fiscal policy. Boyle and Peterson (1995) also specify a theoretical framework, in which stock prices are impacted by macroeconomic uncertainty via two channels, namely by altering expected returns and expected future dividends, where the degree of the second effect is notably driven by monetary policy. Tavares and Valkanov (2001) find empirically that monetary policy roughly shows a similar level of importance for asset return variability as does fiscal policy. Rigobon and Sack (2004) find empirically that responses of market interest rates and asset prices can be estimated from policy shocks. Rosa (2012) filters the surprise component of large-scale asset purchase announcements to determine the asset price impact within the U.S.. In a more recent study, Gospodinov and Jamali (2018) investigate the dependency of returns from commodity futures of 20 commodities to uncertainty in monetary policy.

[48] See for instance Ilmanen et al. (2021) and Dichtl et al. (2019).

fiscal deficits and current returns. In a recent study, Marfatia et al. (2020) investigate the (potential time-varying) relationship between fiscal policy changes and historical return and volatility patterns in U.S. stocks and bonds, spanning a period of 125 years with their extensive data set.

We downloaded the **Global Economic Policy Uncertainty Index** from Davis (2016) on May 17, 2020. The index starts in January 1997 and is a GDP-weighted economic policy uncertainty measure comprised of 21 countries. While there are two versions available (based on current-price and purchasing power parity (PPP)-adjusted GDP), we choose the PPP-adjusted GDP index which is aligned with other GDP-weighted measures in this paper.

Previous studies have repeatedly analyzed long- and short-term interest rates as predictors of asset returns.[49] Therefore, we source the three-month and ten-year zero coupon rates from Bloomberg and calculate a global short-term and long-term **interest rate regime** index, based on the seven largest countries measured in terms of economic output. The relative weight of country interest rates is specified by the relative magnitude of the economic output. We categorize the three-month interest rate, which is mostly driven by the influence of the central banks, as macro indicator. Moreover, the three-month interest rate shows, opposed to the central bank rate, more dynamics that could convey potentially important information for asset prices. On the other hand, we assign the ten-year interest rate, which is driven rather by other market participants, to our set of market indicators.

Our measure of market-implied volatility is the **VIX Index**[50], which expresses expected return fluctuations of the S&P500 index, using data provided from the CBOE. We extend the volatility time series using the VXO index, i.e. used by Ang et al. (2006), to proxy for volatility before the start of the VIX availability in 2003. The VXO index measure accounts for the implied volatility of the S&P100 index from January 1986 to December 2003. We splice the series with the VIX index thereafter. Additionally, to measure the slope of the implied volatility curve, we use the **CBOE SKEW Index**. The index is, similar to the VIX index, another measure of potential downside risk in the U.S. equity market but reflects perceived tail risk by measuring increasing relative demand for low strike puts.

The difference of the ten-year and three-month zero coupon interest rate, sourced via Bloomberg, is used to calculate the **steepness of the yield curve**. The yield curve, particularly in the case of higher short-term than long-term interest rates, is widely perceived as a predictor of future economic activity (cp. Estrella and Trubin (2006), Wright (2006), Haubrich et al. (2006)) and therefore attracts wide attention among investors and researchers of return predictability.[51]

We consider the TED spread as proxy of **market liquidity** and calculate it from the difference of the three-month U.S. Libor and U.S. treasury bill yield. The time series is available starting in December 1984 and can be seen as a measure of funding conditions for global banks and a systemic stress measure in the interbank market (see for instance Bianchi et al. (2010),González-Hermosillo and Hesse (2011)).

Additionally, we include signals that we derive using past return data of the factors, namely momentum, value and volatility, as other authors before have investigated the predictive power of these known

[49] See for instance Dichtl et al. (2019).

[50] For other papers that rely on the VIX for the prediction of asset returns, see for example Ilmanen et al. (2021).

[51] See as example Dichtl et al. (2019).

technical indicators concerning future aggregated asset returns.[52] In detail, the time series of the **momentum** signal of a given factor is calculated as rolling arithmetic mean return estimated over the previous twelve months. The **volatility** signal for factor i at time t is dervied as follow:

$$\text{Vol}_t^i = Std_{t-1}^i - Std_t^i, \tag{19}$$

where $Std_{i,t}$ is the historic return volatility of factor i estimated at time t over the last twelve months. The **value** signal is inspired by Asness et al. (2013) and is given for factor i at time t by

$$\text{Val}_t^i = ln(\frac{\bar{P}_{t-60}^i}{P_t^i}), \tag{20}$$

where P_t^i is the price index of factor i at time t and $\bar{P}_{t-60}^i$ is the average price index five years ago, estimated from $t-65$ to $t-54$.

As last conditioning variable, we extract the spread of the underlying cross-sectional valuation signal of each factor (excluding market factors of each asset class) to infer a measure of historical factor valuation; we term this measure **factor spread**.[53] The factor spreads used in our analysis are presented in Table 1.

A.6 Bayesian vs. Frequentist Regression Framework

To reconcile our Bayesian (presented in Section 4.2) with a standard frequentist regression approach, we compare our estimated betas with those of an expanding OLS regression. As an example, we plot estimated regression betas using both approaches for all market factors and the CFNAI as predictive variable in Figure A1. As we can see, the betas of the Bayesian estimation are tilted to zero and less extreme compared to those of the OLS estimation, while they still show a similar dynamic over time. This observation is in line with our chosen prior in the Bayesian framework, which reflects a very high level of skepticism toward predictability.

A.7 Variation of Business Cycle Indicator

Our results presented in Section 4.3 show a strong outperformance when relying on the CFNAI as predictive variable in the tilting framework. To check whether this still holds true when using a different (U.S.) business cycle indicator, we additionally reproduce the analysis with the freely-available Aruoba-Diebold-Scotti Business Conditions Index (ADS). [54] As we can see in Figure A2, cumulative returns of both strategies show only minor differences, suggesting that the result is robust against the specific choice of the indicator.

[52] See for instance Lewellen (2002), Teo and Woo (2004), Barroso and Santa-Clara (2015b), Hodges et al. (2017), Gupta and Kelly (2019), Dichtl et al. (2019) and Ilmanen et al. (2021).

[53] Similar concepts are applied, for example, by Asness et al. (2017), who investigate the equity value spread, which is the valuation difference of equities with greatest and least exposure to the value factor, or by Ilmanen et al. (2021), who analyze characteristic spreads of different factors.

[54] More information on the index can be found in Appendix A.5.

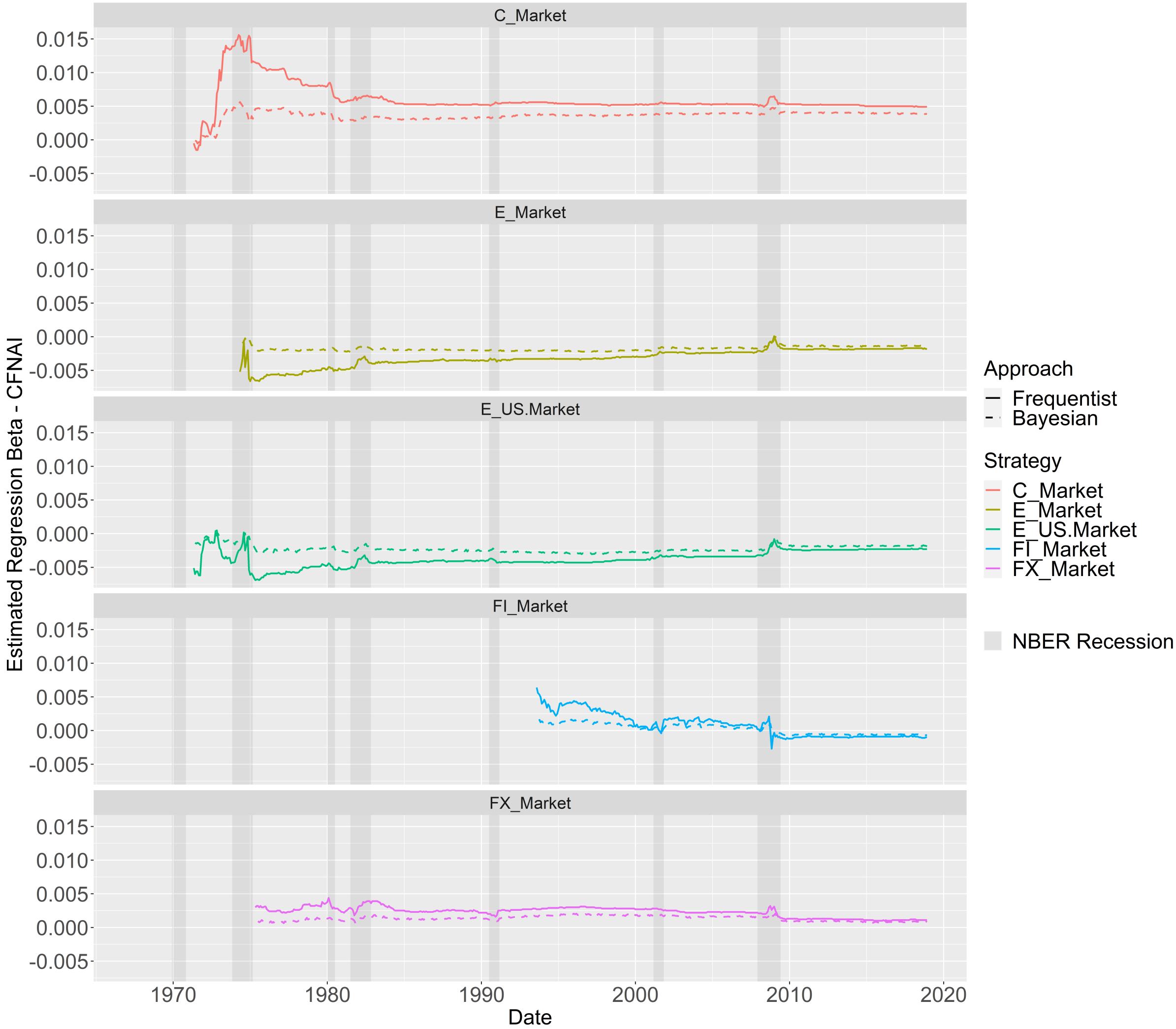

Fig. A1: Expanding Regression Betas of Market Factors.
This figure presents estimated regression betas (estimated with expanding window) of all market factors, based on the Chicago Fed National Activity Index (CFNAI) as independent variable to predict future factor returns. For each factor, regressions are estimated in two ways, a frequentist approach (OLS) and our Bayesian approach presented in Section 4.2 (both including the intercept). For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability.

A.8 Timing of Individual Factors

Our previous findings suggest that applying the information of certain return predictors within an asset-allocation framework provides value to a cross-asset factor investor. In the following, we want to further analyze whether these results stem from our selected portfolio approach, which is anchored on a diversified benchmark and able to actively tilt the whole cross-section of available factors in case predictability is detected, or rather from the fact that our set of chosen variables merely succeeds in predicting the time-series dynamics of individual factors. For this purpose, we investigate factor timing capability by constructing an investment strategy per combination of factor and predictor based on the results of our predictive regression framework, similar to Gupta and Kelly (2019) or Ilmanen et al. (2021). The strategy is rebalanced monthly, whereby the weight $w_t^{i,k}$ invested in the ith factor at the end of period t can vary

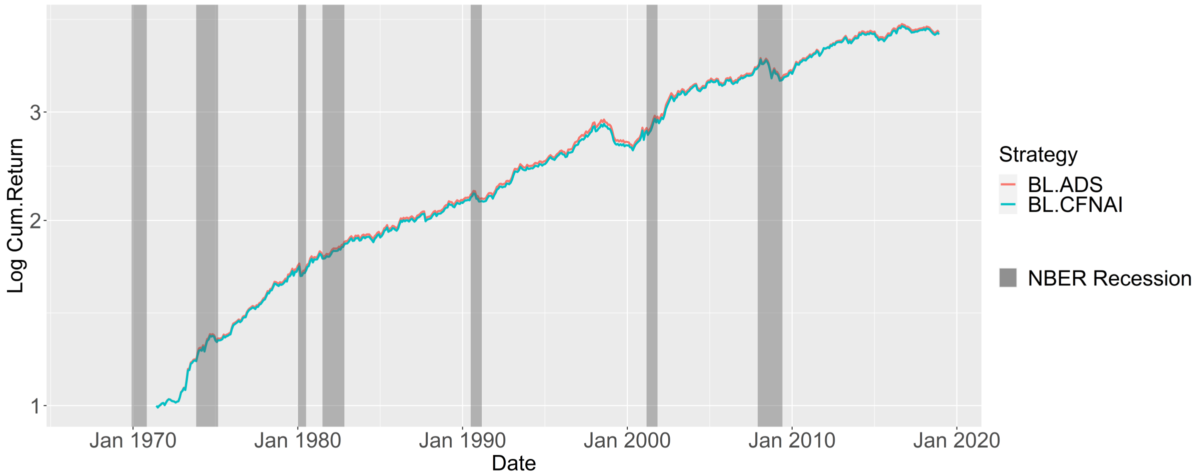

Fig. A2: Cumulative Logarithmic Excess Returns of Tilting Strategies Based on Business Cycle Indicators. This figure plots cumulative logarithmic excess returns of two tilting strategies based on different business cycle indicators, namely the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti Business Conditions Index (ADS). For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

between 2 and 0 and is set according to expectations about the return in the next period derived from the predictive regressions using predictor k

$$\mathrm{w}_t^{i,k} = min\left(max\left(\frac{\hat{r}_{t\to t+1}^{i,k}}{2\hat{\sigma}_t^i} + 1, 0\right), 2\right). \tag{21}$$

More detailed, the strategy overweights the factor if the predicted return $\hat{r}_{t\to t+1}^{i,k}$ is positive and scales the position size relatively to the magnitude of the return prediction. In case of a negative predicted return, the strategy underweights the factor exposure.[55] As in Gupta and Kelly (2019) and Ilmanen et al. (2021), we standardize the predicted return by calculating z-scores, where $\hat{\sigma}_t^i$ is the annualized factor volatility, estimated at time t using an expanding window.

We derive the monthly returns of the timing strategy as

$$\mathrm{r}_{t+1}^{i,k} = w_t^{i,k} \times r_{t+1}^i. \tag{22}$$

To measure the timing benefits of a given factor-predictor combination, we calculate the annualized information ratio as in Ilmanen et al. (2021), using the return time-series of the timed strategy and the associated static factor (with a constant weight of 1 over the same period) as benchmark. Since the timing strategies can exhibit heterogenous exposure over time compared to each other and the static strategies, which could lead to a potentially unfair performance comparison, we scale all (timing and static) strategies ex-post to a volatility of 10% before calculating information ratios. For establishing statistical inference, we perform bootstraps with 1000 replications to estimate standard errors and p-values (see Appendix A.10 for more information).

[55] Given the way our factor set is constructed, we refrain from shorting factors, see Section 4.1.

Our set of factors and predictors leaves us with a total of 324 strategy combinations to test for factor timing capabilities, after adding the equally-weighted benchmark as an additional strategy[56]. Figure A3 shows the annualized information ratios for all possible factor-predictor combinations, with associated one-sided 95% confidence intervals as box plots.[57] As is evident by the chart, the timing of single factors is - generally speaking - not working well in our data set. More in detail, 56.48% of the timing strategies deliver a negative information ratio. In line with these results, the average information ratio of all strategies is negative (-4.47%).

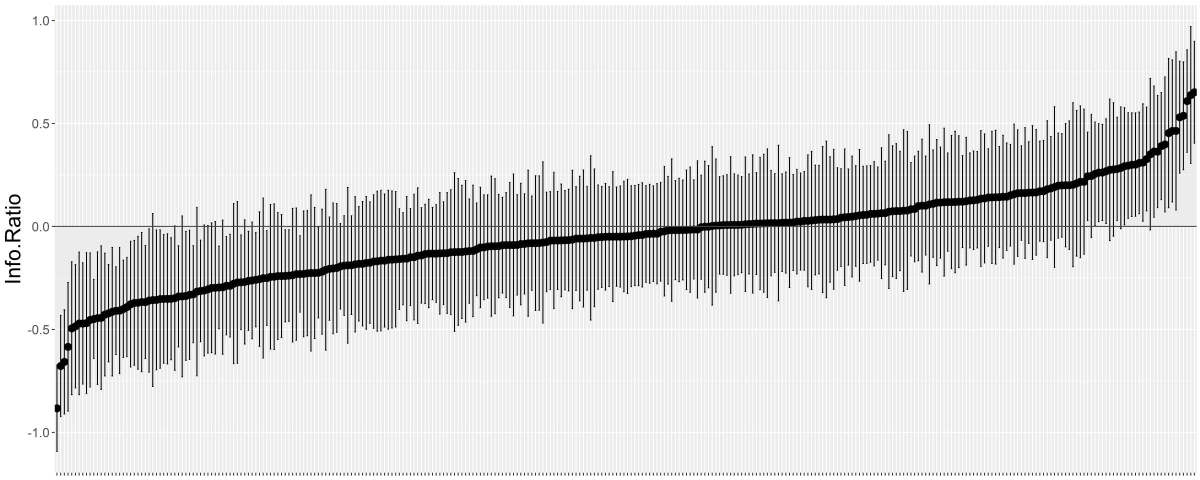

Fig. A3: Information Ratios of Timing Strategies.
This figure presents information ratios for our entire set of 324 constructed timing strategies, with associated one-sided 95% confidence intervals as box plots. Standard errors for normal confidence intervals are obtained by bootstrap (see Appendix A.10 for more information). Information ratios and their standard errors are annualized, i.e. multiplied by $\sqrt{12}$. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, details on the applied factor timing methodology can be found in Section A.8.

Changing the focus to the profitable segment of timing strategies, we find that 8.33% of all strategies show a significant positive IR at the 5% level.[58] While this observation might sound encouraging to some extent, we are left with justified data mining concerns due to our extensive set of tested factor-predictor combinations. To deal with these concerns, we again adjust the calculated p-values for multiple testing using the approach of Holm (1979). After the adjustment, only 1.23% of all strategies survive the multiple testing procedure.

To summarize, our evidence supports the critical view of some authors in the literature[59] on profitably timing factors out-of-sample by scaling position size based on a predictor. Even in our large sample,

[56] Ilmanen et al. (2021) also time multifactor portfolios consisting of all factors within an asset class. While it is not the focus of this paper to dive deeper in the exposure timing of multifactor portfolios, we acknowledge the interest in whether one of our predictors delivers information to profitably time the overall equally-weighted 'market' of our cross-asset universe.

[57] The text of the x-axis of the chart, containing the extensive list of all tested factor-predictor combinations, was not well readable, so we spared it out.

[58] Figure A6 in the Appendix, which presents a subset of Figure A3, provides a clearer look on the most promising predictor-factor combinations.

[59] See for instance Asness (2016) and Asness et al. (2017).

consisting of various factors across several asset classes and multiple predictor variables, we are not able to detect stable out-performance due to timing. Further on and more specifically, the results also contribute to the long-lasting discussion on equity market (factor) timing, suggesting that the equity market is as hard to time as the other analyzed factors are. Overall, the fact that the information from the regression framework does not seem helpful for the timing of individual factors suggests the increment value of applying this information instead in an asset-allocation framework, i.e. in a diversified manner.

A.9 Limitations

Limitations due to Construction of Factor Universe

The impact of volatility scaling of factor returns can be significant for the validity of our results. Kim et al. (2016) acknowledge the risk parity concept of Moskowitz et al. (2012), but find that their core results are mainly driven by the volatility-scaling of returns which is also of concern for us. Nevertheless, we believe the relative risk contribution of factor returns shall be equally distributed, whereas unscaled factor returns can result in single factors driving overall returns. Maillard et al. (2010) show that volatility of risk parity portfolios is located between minimum variance and equally-weighted portfolios and we therefore believe to have found a compromise with our approach in terms of factor weighting.

While we put special emphasis on determining transaction costs of underlying securities, we have to approximate such costs particularly for equity indices, single stocks, fixed income, and commodities based on realistic (practical) assessment and based on other literature. Only for currencies we have bid-ask quotes available, which we can use to calculate the effective realized excess return after transaction costs.

An additional concern, especially since we include a number of emerging and frontier markets in our analysis, is the data quality. For our fixed income factors we construct zero coupon yield curves based on linear interpolation of individual points on the yield curve. Therefore, an incorrect yield curve level can affect overall fixed income performance. Moreover, shorting illiquid emerging and frontier market assets may be rather difficult and involves prohibitive transaction costs, which we aim to reflect in factor excess returns. Linear interpolation is a fairly simple approach toward constructing a yield curve and there is a large strand of academic literature on more sophisticated methods of yield curve construction. While our approach may not reflect individual tenors very precisely, we calculate an average return for bonds between five and ten year duration with the effect of averaging out yields at individual tenors.

In our equity single stocks factor universe, we resort to the classical U.S. factors only due to their special status in the literature, which stands in contrast to other asset classes that have a more global focus. Therefore, we could further include international (Fama-French) factors to better represent global equity single stock factors. However, given the already comparably large number of equity factors in this analysis, we refrained from doing so, since further additions would lead to a further overrepresentation of this asset class.

Our factor construction approach considers the top (bottom) 16.67% of assets to form long (short) portfolios[60] and we note that the top (bottom) 20.00% of assets or other versions thereof could be considered.

While we have used MSCI indices for our equity index factors, one could use equity index futures that potentially provide more precise bid-ask spreads. This approach, however, reduces the universe of included countries in our analysis and as stated by Zaremba (2019), MSCI indices belong to the most popular choice on a country-level equity perspective.

Theoretically, an investor could be able to short factors, which is not feasible in the way our factor universe is constructed. For example taking into account the bid-ask spread of currencies in order to calculate excess returns, we would have to use different data to calculate excess returns of short excess returns of a factor.

Limitations due to Predictive Regression and Asset-Allocation Framework

Some predictors, especially macroeconomic indicators, are usually slow-moving in levels and it may be sensible to construct longer-term factor return forecasts. We use a one-month prediction horizon to forecast returns, which may be a too short interval to translate economic data on asset prices. We use an expanding window regressions, which may not consider changes in relationships of predictors and factors but provides rather stable return forecasts and therefore weights to the asset allocation optimization. Another extension of the analysis could involve the inclusion of multiple predictors to forecast factor returns. Our assumption, which is in line with Wachter and Warusawitharana (2009), is that a single predictor can provide forecasts to multiple factors. Multiple predictors could potentially provide more information, but could also complicate the situation without providing a better intuition to expected returns. Finally, our approach is only concerned with linear relationships, while there is no reason ro rule out non-linear effects.

A.10 Details to Bootstrap Methods and Inference

To calculate standard errors for different summary statistics (e.g. mean or standard deviation) of a return time series, we rely on non-parametric bootstrapping (see for instance Davison and Hinkley (1997)). In detail, we generate 1000[61] bootstrap samples, each of which has the same size as the original time series, by randomly drawing monthly observations with replacement from the original sample. Subsequently, we compute the different summary statistics under consideration for each bootstrap sample and derive the standard errors of the statistics.

For standard errors of information ratios and to additionally calculate p-values of tests with the null hypothesis of a similar or smaller statistic ("no outperformance") than that of a given benchmark return time-series over the same time period, we employ a slightly different procedure. We construct the 500 bootstrap samples by randomly drawing monthly observation pairs with replacement of the original

[60] We started off with currency factors and used the same approach as Lustig et al. (2011).For the other factors, we insisted on consistency and therefore remained with this approach.

[61] With the number of samples, we follow authors such as Brandt et al. (2009) or Barroso and Santa-Clara (2015a) (as the former state in their study and the latter in the Online Appendix of their work).

sample, which in this case contains the return time series under investigation and the benchmark series, both of equal length. Afterwards, we calculate the different summary statistics per bootstrap sample for both the series under investigation and the benchmark series and test whether the statistic under investigation is smaller than or equal to the analogues statistic of the benchmark series. The p-value is then derived as the number of bootstrap samples with a statistic smaller than or equal to the benchmark divided by the total number of bootstrap samples.

Using the standard errors from the non-parametric bootstrap, we construct (non-bias-adjusted, i.e. centered around the original estimate of the statistic) normal confidence intervals, one- or two-sided depending on application.

B Appendix: Additional Tables and Figures

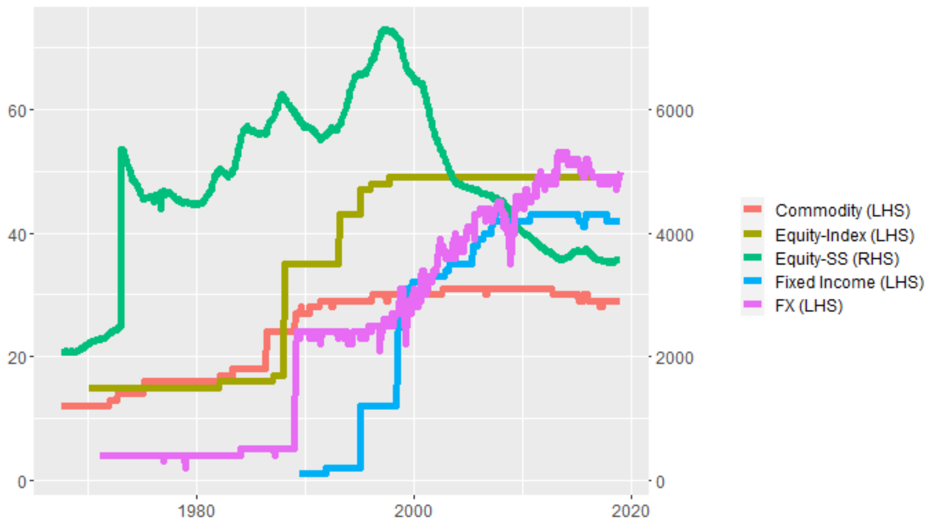

Fig. A4: Cross-Asset Sample Size.
This figure presents the total number of available asset for the asset classes FX (FX), fixed income (Fixed Income), commodity (Commodity), equity index (Equity-Index) and equity single stock (Equity-SS). As illustrated, the number of available assets within each asset class can vary over time. LHS refers to the left-hand side of the (primary) y-axis, RHS to the right-hand side (secondary y-axis). For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

Name	Mnemonic	First obs.	N	Avg. ret.	St. dev.
British Pound	GBP	1971-02	572	0.35	9.92
Czech Koruna	CZK	1997-01	260	-0.75	12.26
Danish Krone	DKK	1989-01	356	0.92	10.05
Euro	EUR	1999-02	238	-0.73	9.95
Hungarian Forint	HUF	1998-08	227	0.25	13.58
Iceland Krona	ISK	2004-09	152	-2.03	14.79
Norwegian Krone	NOK	1989-01	358	-0.65	10.83
Polish Zloty	PLN	1998-08	245	1.37	13.66
Russian Ruble	RUB	2001-09	207	-1.70	14.70
Swedish Krona	SEK	1989-01	360	-0.89	11.37
Swiss Franc	CHF	1971-02	573	0.28	11.78
Turkish Lira	TRY	1997-01	246	1.65	17.17
Ukraine Hryvnia	UAH	2005-05	160	1.29	18.64
Argentine Peso	ARS	2000-08	202	12.56	15.23
Brazil Real	BRL	1999-05	225	5.86	17.23
Canadian Dollar	CAD	1971-02	572	-0.41	6.65
Chilean Peso	CLP	2000-08	216	0.57	10.50
Colombian Peso	COP	1999-09	228	0.71	12.64
Mexican Peso	MXN	1997-12	253	1.24	10.65
Peruvian Sol	PEN	2000-08	216	0.81	5.08
Australian Dollar	AUD	1984-01	418	1.92	11.72
China Offshore Spot	CNH	2010-09	100	0.88	3.96
Indian Rupee	INR	1999-01	238	1.58	7.22
Indonesian Rupiah	IDR	2001-05	208	3.75	11.12
Japanese Yen	JPY	1989-03	353	-2.05	10.72
Malaysian Ringgit	MYR	2004-10	170	-1.32	7.48
New Zealand Dollar	NZD	1989-01	355	2.25	11.40
Philippines Peso	PHP	1999-01	239	-3.02	6.75
Singapore Dollar	SGD	1989-01	359	-0.62	5.57
South Korean Won	KRW	1999-01	237	1.42	10.58
Taiwan Dollar	TWD	1999-01	236	-2.51	4.68
Thai Baht	THB	1995-10	275	-0.79	10.75
Egyptian Pound	EGP	2007-08	130	4.90	16.07
Ghana Cedi	GHS	2013-01	70	-9.59	15.08
Kenyan Shilling	KES	2008-08	105	6.31	7.65
Nigeria Naira	NGN	2011-04	81	6.20	12.56
Ugandan Shilling	UGX	2002-02	129	-3.25	9.69
South African Rand	ZAR	1989-01	359	-1.61	14.10
Israeli Shekel	ILS	1998-08	228	-0.16	8.02
Austrian Schilling	ATS	1989-02	117	0.75	10.80
Belgian Franc	BEF	1989-01	117	1.51	10.40
Estonian Kroon	EEK	1999-02	141	2.02	10.99
Finnish Markka	FIM	1989-01	119	-0.65	11.84
French Franc	FRF	1989-01	120	2.54	10.49
German Mark	DEM	1989-01	118	1.29	10.93
Greek Drachma	GRD	1989-01	137	-9.04	10.28
Irish Punt	IEP	1989-01	116	2.50	10.57
Italian Lira	ITL	1989-01	119	-3.86	10.97
Latvian Lat	LVL	2001-03	136	0.20	10.23
Maltese Lira	MTL	1999-11	91	-3.07	7.28
Dutch Guilder	NLG	1989-01	118	-0.44	10.87
Portuguese Escudo	PTE	1989-01	120	4.11	10.47
Slovakia Koruna	SKK	1999-10	67	7.05	12.15
Slovenia Tolar	SIT	2004-07	30	5.09	8.44
Spanish Peseta	ESP	1989-01	117	-0.85	11.53
Cypriot Pound	CYP	2002-01	67	-1.91	8.04

Hong Kong Dollar	HKD	1989-01	360	-0.25	0.56
Romanian Leu	RON	2005-03	156	-0.04	11.11
Vietnam Dong	VND	1999-05	125	2.01	6.81
Zambian Kwacha	ZMW	2013-02	70	-2.76	20.96
Kazakhstan Tenge	KZT	2005-11	156	-3.00	11.04
Tanzanian Shilling	TZS	2002-04	127	-8.41	5.67
New Mozambique Metical	MZN	2012-04	37	-30.83	14.48
Uruguay Peso	UYU	2010-01	86	-7.19	9.56
Georgia Lari	GEL	2010-12	95	-15.05	9.33
Kuna	HRK	2002-04	188	3.21	10.02
Mongolia Togrog	MNT	2009-04	116	-10.82	7.48
Serbian Dinar	RSD	2011-08	88	-5.68	10.59
Us Dollar	USD	1971-02	575	0.00	0.00

Table A1: Overview of FX Universe.
This table presents the analysed currency universe with a total of 69 currencies between 1971 and 2018. The data are primarily sourced from Bloomberg and missing data was filled with data from GFD. The table shows the Bloomberg name, the Bloomberg mnemonic, the first observation of a currency excess return, the total number of observed returns, the arithmetic average return and the standard deviation of returns.

Name	First obs.	N	Avg. ret.	St. dev.
Australia	1995-01	288	5.91	12.66
Austria	1998-05	248	5.71	10.90
Belgium	1998-05	248	5.88	11.21
Brazil	2007-04	141	10.95	30.73
Canada	1995-01	288	6.04	9.37
Chile	2005-11	142	3.46	13.70
China	2010-09	100	0.83	4.93
Colombia	2005-05	164	8.66	21.61
Croatia	2007-02	140	-3.00	12.93
Czech Republic	1998-06	247	5.24	16.29
Denmark	1995-01	288	5.83	10.42
Finland	1998-07	246	5.59	10.74
France	1998-05	201	5.44	11.87
Germany	1991-11	326	6.61	10.54
Great Britain	1995-01	288	5.17	8.93
Greece	2000-09	220	17.93	44.34
Hong Kong	1998-06	247	6.34	8.19
Hungary	1998-07	246	2.39	23.49
India	1998-12	241	6.15	10.76
Indonesia	2003-03	190	6.44	24.25
Ireland	1998-05	248	6.93	14.40
Italy	1998-10	243	5.59	13.47
Japan	1989-05	356	4.34	12.43
Malaysia	1999-10	231	3.48	9.06
Mexico	2002-10	195	2.77	16.45
Netherlands	1998-05	248	5.56	10.71
New Zealand	1995-01	288	4.57	13.25
Norway	1998-08	245	0.69	11.85
Peru	2006-05	152	5.29	12.53
Philippines	1998-09	106	20.55	23.98
Poland	1998-06	247	4.24	19.58
Portugal	1998-05	248	7.92	17.65
Russia	2007-02	143	-3.90	29.00
Singapore	1998-07	246	2.96	9.28
Slovakia	2005-05	164	5.59	11.48
South Africa	1995-01	288	-0.22	23.33
South Korea	1998-07	246	9.25	18.38
Spain	1998-05	248	6.59	13.12
Sweden	1995-01	288	3.94	11.68
Switzerland	1995-01	288	4.15	11.40
Taiwan	1999-04	237	1.33	6.12
Thailand	1995-01	288	1.24	14.21
Turkey	2005-05	164	1.65	34.42
Ukraine	2015-09	40	-14.07	11.66
United States	1995-01	288	7.15	6.98

Table A2: Overview of Fixed Income Universe.
This table presents the analysed fixed income universe with a total of 45 countries between 1991 and 2018. The underlying yield curves are sourced from Bloomberg. The table shows the country name, the first observation of a fixed income excess return, the total number of observed returns, the arithmetic average return and the standard deviation of returns.

				$R^{T_1}_{fut,i,t+1}$			$R^{T_2}_{fut,i,t+1}$	
Name	Mnemonic	First obs.	N	Avg. ret.	St. dev.	N	Avg. ret.	St. dev.
Crude Oil	CL	1983-04	429	7.11	32.65	429	7.63	30.76
Gasoline	HU	1986-05	391	14.81	32.97	390	12.80	30.03
Heating Oil	HO	1986-05	392	8.57	30.78	392	8.47	29.09
Natural Gas	NG	1990-05	344	-7.88	47.80	344	-3.17	41.22
Propane	PN	1989-01	334	19.39	41.42	327	17.87	34.86
Rough Rice	RR	1989-01	358	-6.65	25.55	358	-3.48	23.97
Sugar	SB	1961-02	695	4.79	41.76	695	6.16	38.07
Corn	C.	1959-08	713	-2.20	23.77	713	-0.86	22.89
Oats	O.	1959-08	713	-0.22	29.06	712	0.06	26.85
Wheat	W.	1959-08	713	-1.83	25.20	713	-0.40	24.23
Canola	RS	1982-02	443	-0.65	19.67	431	1.10	19.26
Barley	WA	1991-04	262	-2.35	20.79	247	2.31	19.86
Cotton	CT	1959-08	713	2.22	23.47	713	3.87	22.01
Lumber	LB	1986-05	392	-4.72	27.37	389	-0.55	23.40
Rubber	RT	2002-07	198	-0.77	31.27	198	-0.27	32.32
Feeder Cattle	FC	1971-12	565	3.52	16.61	560	4.52	15.93
Live Cattle	LC	1964-12	649	4.73	16.23	649	4.74	14.30
Lean Hogs	LH	1986-05	392	-2.33	23.81	391	4.52	20.55
Pork Bellies	PB	1961-10	654	1.09	32.18	643	3.26	30.23
Gold	GC	1975-02	527	1.42	19.00	527	1.28	19.02
Silver	SI	1975-02	527	2.55	31.60	527	2.78	31.69
Copper	HG	1989-01	360	7.51	24.97	360	8.29	24.18
Palladium	PA	1986-05	392	12.28	31.45	366	13.02	29.53
Platinum	PL	1986-05	392	4.13	21.71	384	3.48	21.75
Soybean Oil	BO	1959-08	713	5.23	28.57	713	4.78	27.36
Soybean Meal	SM	1959-08	713	9.36	29.08	713	9.60	27.97
Soybeans	S.	1959-08	713	5.06	25.50	713	6.29	25.25
Coffee	KC	1972-09	556	3.99	36.51	556	2.67	34.40
Orange Juice	JO	1967-03	622	5.06	32.50	622	4.76	31.26
Cocoa	CC	1959-08	713	2.96	30.46	713	2.86	28.94
Milk	DA	1989-07	273	4.15	25.50	270	3.89	21.82

Table A3: Overview of Commodity Universe.
This table presents the analysed commodity universe with a total of 31 commodities between 1959 and 2018. The underlying yield curves are sourced from Bloomberg. The table shows the commodity name, the commodity mnemonic, the first observation of a commodity excess return, the total number of observed returns of the first and second nearby futures, the arithmetic average return of the first and second nearby futures and the standard deviation of the first and second nearby returns.

Name	Mnemonic	First obs.	N	Avg. ret.	St. dev.
Argentina	MXAR	1988-01	372	23.47	51.30
Australia	MSDUAS	1970-01	588	10.01	23.59
Austria	MSDUAT	1970-01	588	7.75	23.36
Belgium	MSDUBE	1987-01	384	6.15	20.19
Brazil	MXBR	1988-01	372	23.77	48.37
Canada	MSDUCA	1970-01	588	8.42	19.29
Chile	MXCL	1988-01	372	14.04	23.83
China	MSEUSCF	1993-01	312	3.96	32.90
Colombia	MXCO	1993-01	312	14.45	30.40
Czech Republic	MSEUSCZ	1995-01	288	8.12	27.34
Denmark	MSDUDE	1970-01	588	11.08	19.30
Egypt	MSIUEG	1997-09	256	9.02	32.87
Finland	MSDUFI	1988-01	372	10.20	29.71
France	MSDUFR	1970-01	588	8.30	22.07
Germany	MSDUGR	1970-01	588	8.37	21.58
Great Britain	MSDUUK	1970-01	588	11.06	21.30
Greece	M3GR	1988-01	372	2.20	38.45
Hong Kong	MSDUHK	1970-01	588	15.40	33.46
Hungary	MSEUSHG	1995-01	288	14.75	35.44
India	MSEUSIA	1993-01	312	10.71	28.70
Indonesia	MSEUSINF	1988-01	372	16.16	45.39
Ireland	MSDUIE	1988-01	372	4.27	21.70
Israel	MXIL	1993-01	312	7.06	22.84
Italy	MSDUIT	1988-01	372	3.93	24.08
Japan	MSDUJN	1970-01	588	9.02	20.62
Jordan	MSEUSJO	1988-01	372	0.83	18.04
Malaysia	MSDUMAF	1988-01	372	7.53	26.57
Mexico	MXMX	1988-01	372	18.16	29.49
Morocco	MSIUMOR	1995-01	288	6.10	18.46
Netherlands	MSDUNE	1970-01	588	8.64	18.86
New Zealand	MSDUNZ	1982-01	444	9.76	24.65
Norway	MSDUNO	1970-01	588	10.27	26.63
Pakistan	MSEUSPF	1995-12	277	5.42	35.06
Peru	MXPE	1993-01	312	18.27	30.11
Philippines	MSEUSPHF	1988-01	372	9.37	29.11
Poland	MSEUSPO	1993-01	312	16.05	44.20
Portugal	MSDUSPT	1988-01	372	2.73	22.71
Russia	MXRU	1995-01	288	22.72	49.38
Singapore	MSDUSG	1988-01	372	7.94	23.46
South Africa	MSEUSSA	1993-01	312	9.25	26.17
South Korea	MSEUSKO	1988-01	372	10.49	34.85
Spain	MSDUSP	1970-01	588	6.05	23.29
Sri Lanka	MSEUSSL	1993-01	312	7.03	33.41
Sweden	MSDUSW	1970-01	588	11.45	23.36
Switzerland	MSDUSZ	1970-01	588	9.77	17.77
Taiwan	MSEUSTW	1988-01	372	9.26	33.16
Thailand	MSEUSTHF	1988-01	372	10.88	34.87
Turkey	MSEUSTK	1988-01	372	16.25	53.03
United States	MXUS	1970-01	588	8.57	15.05

Table A4: Overview of Equity Index Universe.
This table presents the analysed equity index universe with a total of 49 countries between 1970 and 2018. The MSCI indices are sourced from Bloomberg. The table shows the equity index name, the index mnemonic, the first observation of an equity index excess return, the total number of observed returns, the arithmetic average return of the index and the standard deviation of the returns.

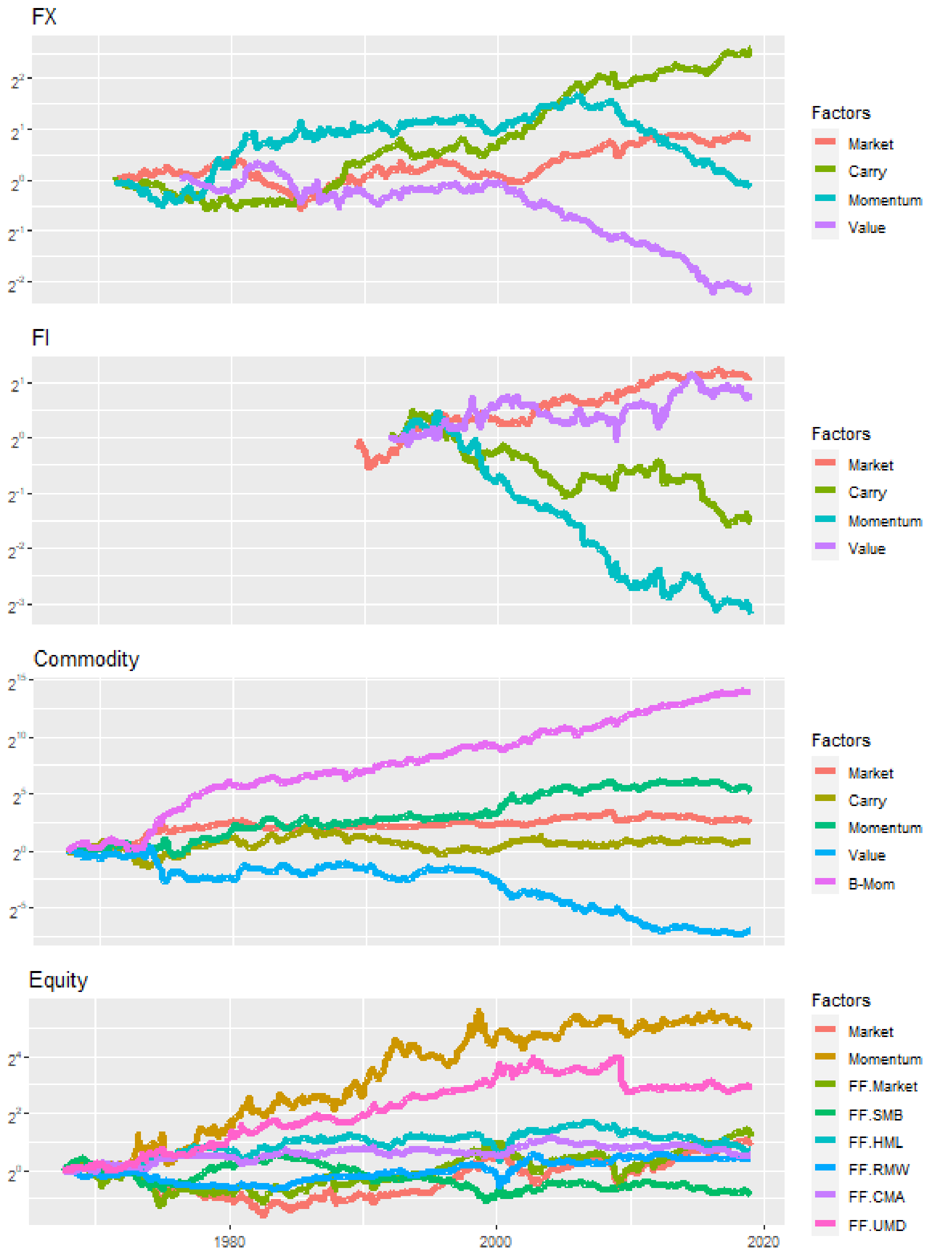

Fig. A5: Factor Performance Overview.
This figure presents the performance of replicated factors across the asset classes FX, fixed income, commodities and equities. Within equities, the (global) equity index market and momentum factor is represented as well as the classical US factors. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

	Obs	Mean		Std		Kurtosis	Skewness	SR		CE	
					Equity						
US.Market	619	1.65	(1.49)	10.60	(0.42)	0.15	-0.16	0.16	(0.14)	-0.67	(1.57)
US.SMB	619	-0.57	(1.51)	10.42	(0.56)	0.47	0.16	-0.05	(0.15)	-2.70	(1.49)
US.HML	619	1.67	(1.63)	11.26	(0.49)	0.20	0.01	0.15	(0.14)	-0.87	(1.66)
US.RMW	619	0.81	(1.69)	12.13	(0.98)	1.25	-0.30	0.07	(0.14)	-2.53	(2.16)
US.CMA	619	1.15	(1.33)	9.60	(0.32)	0.05	0.05	0.12	(0.14)	-0.68	(1.32)
US.UMD	619	4.56	(1.67)	11.75	(0.77)	0.68	-0.31	0.39	(0.16)	1.55	(1.94)
Market	582	1.17	(1.48)	9.88	(0.4)	0.17	-0.16	0.12	(0.15)	-0.84	(1.55)
Momentum	582	5.00	(1.35)	9.35	(0.61)	0.68	0.22	0.53	(0.14)	3.30	(1.33)
					Commodity						
Market	619	3.68	(1.43)	10.43	(0.61)	0.60	0.29	0.35	(0.13)	1.59	(1.39)
Carry	619	1.43	(1.23)	8.71	(0.35)	0.16	-0.04	0.16	(0.14)	-0.10	(1.26)
Momentum	619	4.85	(1.3)	9.23	(0.47)	0.34	0.19	0.53	(0.14)	3.19	(1.27)
Value	619	-2.06	(1.24)	8.89	(0.33)	0.12	-0.02	-0.23	(0.14)	-3.65	(1.25)
Basis.Momentum	619	7.97	(1.24)	9.28	(0.46)	0.34	0.04	0.86	(0.14)	6.26	(1.26)
					Fixed Income						
Market	351	3.20	(1.3)	6.94	(0.33)	0.11	0.09	0.46	(0.19)	2.25	(1.29)
Carry	323	-2.85	(1.93)	10.16	(0.76)	0.42	-0.04	-0.28	(0.19)	-4.96	(2)
Momentum	312	-6.45	(2.1)	10.85	(0.88)	0.53	0.08	-0.59	(0.21)	-8.82	(2.12)
Value	323	2.10	(2.13)	10.66	(0.68)	0.29	-0.07	0.20	(0.2)	-0.22	(2.2)
					FX						
Market	570	2.48	(1.62)	11.04	(0.78)	0.79	0.24	0.22	(0.14)	0.11	(1.59)
Carry	570	4.16	(1.42)	9.94	(0.55)	0.41	-0.26	0.42	(0.15)	2.08	(1.53)
Momentum	561	-2.80	(1.54)	10.55	(0.94)	1.45	-0.48	-0.27	(0.14)	-5.37	(1.93)
Value	513	-3.14	(1.62)	10.72	(0.69)	0.53	0.10	-0.29	(0.15)	-5.44	(1.65)

Table A5: Summary Statistics of Factors.
This table presents summary statistics for our constructed set of 21 monthly factor excess return time series, which are split up in the four asset classes equity, commodity, fixed income and FX. In detail, we report in the first column the number of monthly return observations during our investigation period starting in July 1967 and ending in December 2018, followed by annualized arithmetic mean returns (as percentages) with standard errors in parantheses, annualized standard deviations (as percentages) with standard errors in parantheses, annualized excess kurtosis, annualized skewness, annualized Sharpe Ratios with standard errors in parantheses, and annualized certainty equivalents (applying a CRRA utility with $\gamma = 4$; as percentages) with standard errors in parantheses. Monthly mean returns, certainty equivalents and their standard errors are annualized by multiplying with 12, while standard deviations, Sharpe Ratios and their standard errors are multiplied with $\sqrt{12}$. We annualize monthly excess kurtosis by multiplying with $\frac{1}{12}$ and skewness by multiplying with $\frac{1}{\sqrt{12}}$. Standard errors are obtained by bootstrap (see Appendix A.10 for more information). For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

Table A6: Correlation Matrix of Factor Excess Returns.
This table presents Pearson correlation coefficients for our constructed set of 21 monthly factor excess return time series, which are split up in the four asset classes equity, commodity, fixed income and FX. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3.

		Equity								Commodity					Fixed Income				FX			
		US.Mkt	US.SMB	US.HML	US.RMW	US.CMA	US.UMD	Mkt	Mom	Mkt	C	Mom	Val	BM	Mkt	C	Mom	Val	Mkt	C	Mom	Val
Eq	US.Mkt	1.00	0.32	-0.33	-0.18	-0.38	-0.12	0.93	-0.08	0.10	-0.04	-0.01	0.07	-0.07	-0.02	-0.24	0.00	0.27	0.20	0.13	-0.06	0.06
	US.SMB	0.32	1.00	-0.25	-0.45	-0.12	-0.03	0.17	0.01	0.05	0.02	0.02	-0.03	-0.01	-0.15	-0.04	0.10	0.02	0.02	0.06	-0.01	0.00
	US.HML	-0.33	-0.25	1.00	0.10	0.68	-0.18	-0.29	-0.05	0.04	0.04	-0.03	-0.04	0.01	0.03	0.01	-0.05	-0.01	-0.03	-0.01	0.02	-0.04
	US.RMW	-0.18	-0.45	0.10	1.00	-0.14	0.03	-0.15	-0.02	-0.13	-0.03	-0.02	0.08	0.04	0.12	0.05	-0.06	-0.09	-0.06	-0.06	0.05	-0.03
	US.CMA	-0.38	-0.12	0.68	-0.14	1.00	-0.03	-0.32	-0.04	-0.01	0.07	0.00	-0.07	0.04	-0.01	0.06	0.04	-0.07	-0.06	-0.01	-0.01	0.02
	US.UMD	-0.12	-0.03	-0.18	0.03	-0.03	1.00	-0.15	0.30	-0.03	0.10	0.22	-0.10	0.01	0.05	0.03	0.15	-0.14	-0.04	-0.09	0.13	-0.11
	Mkt	0.93	0.17	-0.29	-0.15	-0.32	-0.15	1.00	-0.12	0.15	-0.01	-0.02	0.05	-0.04	0.11	-0.23	-0.01	0.29	0.30	0.13	-0.08	0.03
	Mom	-0.08	0.01	-0.05	-0.02	-0.04	0.30	-0.12	1.00	0.09	-0.03	0.12	-0.06	-0.02	-0.07	-0.02	0.24	-0.03	0.07	0.05	0.28	-0.10
Cdty	Mkt	0.10	0.05	0.04	-0.13	-0.01	-0.03	0.15	0.09	1.00	-0.07	0.15	-0.13	0.03	0.05	-0.16	-0.09	0.25	0.28	0.11	0.01	-0.01
	C	-0.04	0.02	0.04	-0.03	0.07	0.10	-0.01	-0.03	-0.07	1.00	0.40	-0.42	0.39	-0.05	-0.03	-0.02	-0.07	-0.07	-0.13	0.08	-0.06
	Mom	-0.01	0.02	-0.03	-0.02	0.00	0.22	-0.02	0.12	0.15	0.40	1.00	-0.41	0.38	0.12	0.11	0.07	-0.09	0.05	-0.03	0.11	-0.06
	Val	0.07	-0.03	-0.04	0.08	-0.07	-0.10	0.05	-0.06	-0.13	-0.42	-0.41	1.00	-0.21	0.01	0.05	0.02	0.01	-0.04	0.00	-0.01	0.08
	BM	-0.07	-0.01	0.01	0.04	0.04	0.01	-0.04	-0.02	0.03	0.39	0.38	-0.21	1.00	0.04	0.02	0.02	0.01	0.05	0.01	0.04	-0.01
FI	Mkt	-0.02	-0.15	0.03	0.12	-0.01	0.05	0.11	-0.07	0.05	-0.05	0.12	0.01	0.04	1.00	0.02	-0.10	-0.03	0.47	-0.24	0.05	-0.06
	C	-0.24	-0.04	0.01	0.05	0.06	0.03	-0.23	-0.02	-0.16	-0.03	0.11	0.05	0.02	0.02	1.00	0.31	-0.18	-0.21	-0.35	0.12	0.04
	Mom	0.00	0.10	-0.05	-0.06	0.04	0.15	-0.01	0.24	-0.09	-0.02	0.07	0.02	0.02	-0.10	0.31	1.00	-0.30	-0.13	0.06	0.30	-0.18
	Val	0.27	0.02	-0.01	-0.09	-0.07	-0.14	0.29	-0.03	0.25	-0.07	-0.09	0.01	0.01	-0.03	-0.18	-0.30	1.00	0.14	0.15	-0.14	0.15
FX	Mkt	0.20	0.02	-0.03	-0.06	-0.06	-0.04	0.30	0.07	0.28	-0.07	0.05	-0.04	0.05	0.47	-0.21	-0.13	0.14	1.00	0.15	0.04	0.01
	C	0.13	0.06	-0.01	-0.06	-0.01	-0.09	0.13	0.05	0.11	-0.13	-0.03	0.00	0.01	-0.24	-0.35	0.06	0.15	0.15	1.00	-0.10	0.20
	Mom	-0.06	-0.01	0.02	0.05	-0.01	0.13	-0.08	0.28	0.01	0.08	0.11	-0.01	0.04	0.05	0.12	0.30	-0.14	0.04	-0.10	1.00	-0.32
	Val	0.06	0.00	-0.04	-0.03	0.02	-0.11	0.03	-0.10	-0.01	-0.06	-0.06	0.08	-0.01	-0.06	0.04	-0.18	0.15	0.01	0.20	-0.32	1.00

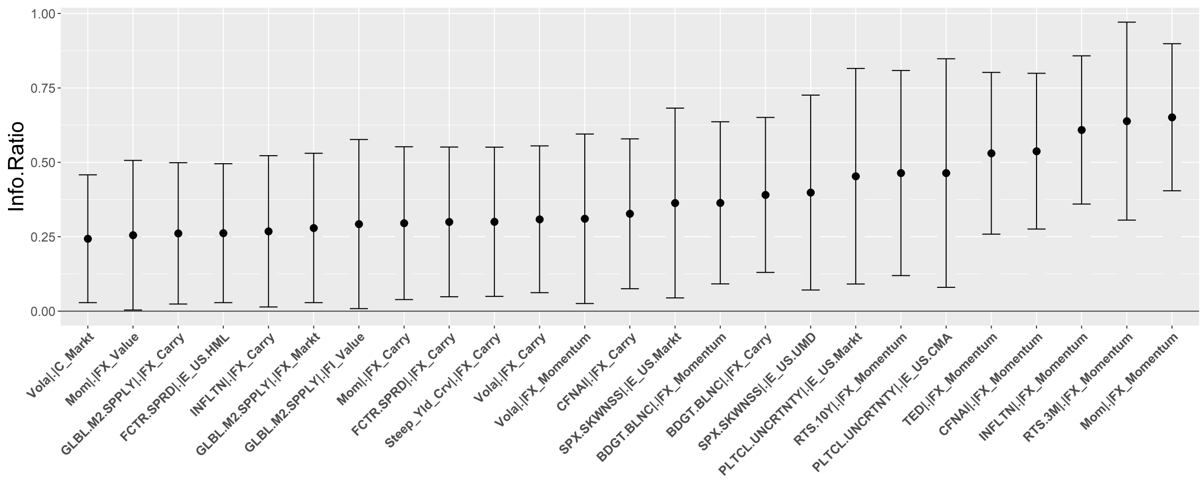

Fig. A6: Information Ratios of Significant Timing Strategies.
This figure presents information ratios for only those of our entire set of 324 constructed timing strategies, which show a significant positive IR at the 5% level. Associated one-sided 95% confidence intervals are indicated as box plots. Standard errors for normal confidence intervals are obtained by bootstrap (see Appendix A.10 for more information). Information ratios and their standard errors are annualized, i.e. multiplied by $\sqrt{12}$. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, details on the applied factor timing methodology can be found in Section A.8.

	Obs	Mean	Std	SR	CE	Info.Ratio	Skewness	Kurtosis	MD	MD.Period	Turnover	Breakeven_TC
Mean.Var	570	1.52	2.05	0.74	1.44	-12.76	-0.08	0.09	-10.72	Feb 2014 - Dec 2018	12.01	-172.06
BL.CFNAI	570	2.97 ***	2.85	1.04 ***	2.81 ***	65.46 ***	-0.07	0.23	-9.39	Aug 1998 - May 2000	58.02	227.13
BL.INFLTN	570	2.74 ***	2.99	0.92 **	2.56 ***	53.68 ***	-0.12	0.37	-9.76	Feb 2008 - Apr 2009	132.42	79.83
BL.PLTCL.UNCRTNTY	215	0.92 ·	3.21	0.29	0.72	31.09 ·	0.08	0.11	-9.17	Jun 2008 - Jun 2009	88.52	70.92
BL.BDGT.BLNC	552	2.58 ***	3.04	0.85 ·	2.40 **	44.21 ***	-0.19	0.31	-10.66	Feb 2008 - May 2009	60.56	140.51
BL.RTS.3M	308	1.56 ***	2.92	0.53 ***	1.39 ***	66.86 ***	-0.23	0.19	-9.34	Jun 2008 - Apr 2009	133.60	82.94
BL.GLBL.M2.SPPLY	570	2.21	3.78	0.59	1.93	16.57	0.16	0.63	-10.56	Apr 2014 - Dec 2018	304.23	17.13
BL.Mom	559	2.82 **	2.98	0.95 *	2.64 **	46.86 **	0.00	0.25	-6.87	Feb 2008 - Oct 2008	101.14	111.39
BL.Vola	558	2.59 **	3.03	0.85	2.41 *	33.15 **	0.15	0.28	-9.14	Jun 1998 - May 2000	89.07	92.04
BL.Value	506	2.37 ***	2.83	0.84 *	2.21 ***	48.72 ***	-0.14	0.21	-7.92	Feb 2008 - May 2009	203.08	46.95
BL.FCTR.SPRD	570	1.57	3.78	0.41	1.28	2.81	0.09	0.32	-21.48	Sep 2002 - Dec 2018	69.02	11.55
BL.Steep_Yld_Crv	570	2.65 ***	3.00	0.88 *	2.47 **	44.28 ***	0.00	0.15	-7.50	Feb 2014 - Sep 2018	55.31	178.30
BL.VIX	348	1.23 ·	3.00	0.41	1.05	25.98 ·	-0.09	0.23	-10.59	Dec 1998 - Feb 2000	103.82	45.74
BL.TED	360	1.59 *	3.49	0.46	1.35 ·	35.26 *	-0.16	0.14	-13.16	Dec 1997 - May 2000	103.19	78.15
BL.SPX.SKWNSS	299	0.47	4.23	0.11	0.10	1.22	-0.21	0.42	-20.14	Apr 2013 - Dec 2018	139.67	3.18
BL.RTS.10Y	308	1.01	3.24	0.31	0.79	25.30	-0.20	0.15	-11.96	Oct 2007 - Feb 2009	125.62	44.23
Naive	570	1.69	2.53	0.67	1.57	0.00	-0.07	0.28	-11.83	Apr 2014 - Dec 2018	4.31	

Table A7: Summary Statistics of Tilting Strategies.
This table presents summary statistics for our set of 15 constructed tilting strategies (identifiable by the prefix 'BL') and for our two benchmarks, namely an equally-weighted 'naïve' allocation approach and a mean-variance optimized allocation. In detail, we report in the first column the number of monthly return observations during our investigation period starting in July 1967 and ending in December 2018, followed by annualized arithmetic mean returns (as percentages) with associated significance levels, annualized standard deviations (as percentages), annualized Sharpe Ratios with associated significance levels, annualized certainty equivalents (applying a CRRA utility with $\gamma = 4$; as percentages) with associated significance levels, annualized information ratios (as percentages) with associated significance levels, annualized excess kurtosis, annualized skewness, maximum drawdowns (as percentages) as well as the time period in which these drawdowns occured, annualized turnover (as percentages) and breakeven transaction costs (in basis points per 100% turnover) in the other respective columns. Monthly mean returns and certainty equivalents are annualized by multiplying with 12, while standard deviations, Sharpe Ratios and information ratios are multiplied with $\sqrt{12}$. We annualize monthly excess kurtosis by multiplying with $\frac{1}{12}$ and skewness by multiplying with $\frac{1}{\sqrt{12}}$. For the performance measures, i.e. mean, Sharpe Ratio, certainty equivalent and information ratio, we additionally report significance levels of tests with the null hypothesis of no outperformance compared to the relevant estimate of the equally-weighted benchmark over the same period, whereby p-values are obtained via bootstrapping (see Appendix A.10 for more information). In this sense, the levels ***,**,*,$^{\cdot}$ indicate whether a given estimate is significantly greater as the relevant estimate of the equally-weighted benchmark at the 0,01%, 1%, 5% or 10% level, respectively. For the maximum drawdown period, we specifically report the start date of the maximum drawdown period and the date the maximum drawdown was reached. Breakeven transaction costs are calculated in term of information ratio relatively to the equally-weigted benchmark. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

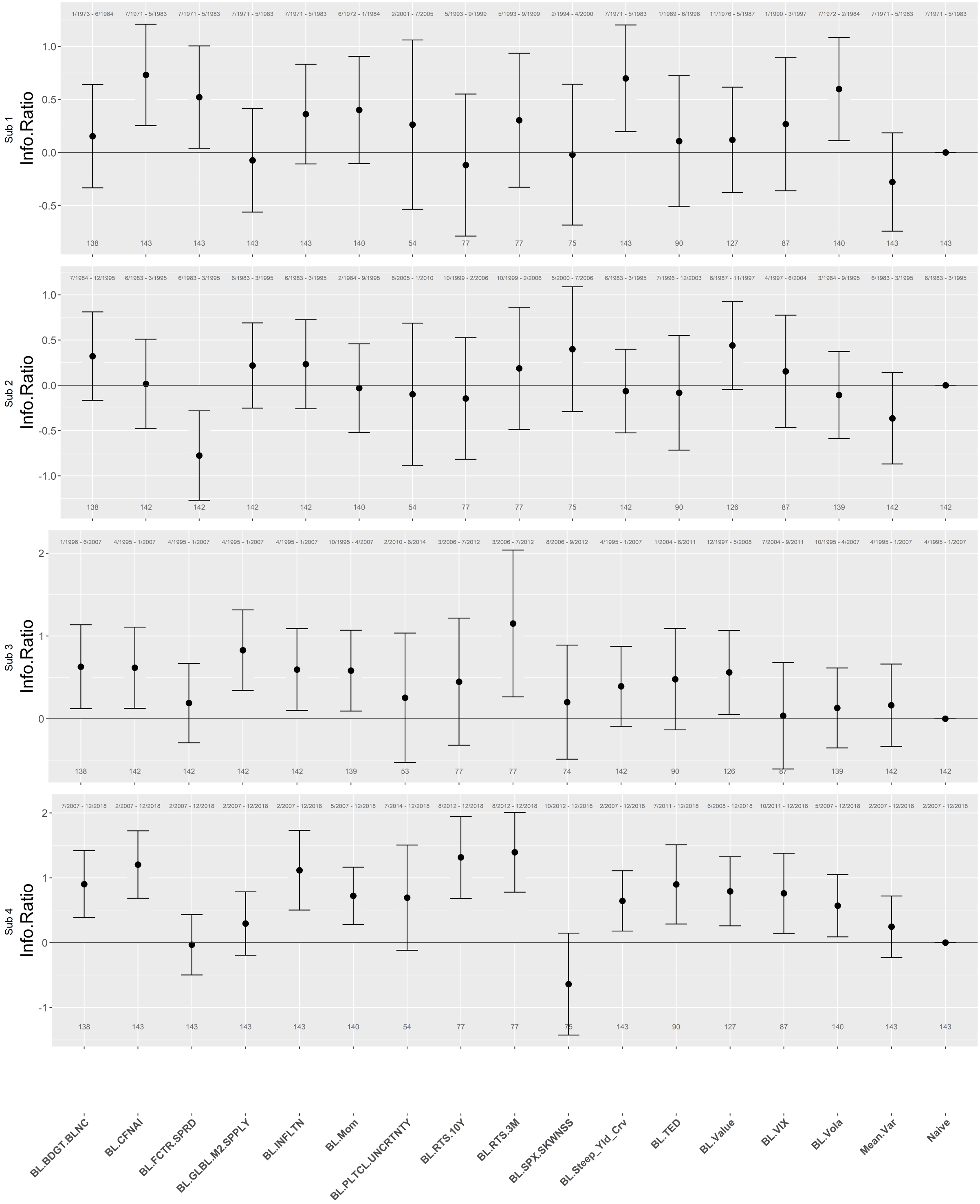

Fig. A7: Information Ratios of Tilting Strategies for Subperiods. (Caption on the next page.)

Fig. A7: Information Ratios of Tilting Strategies for Subperiods.
This figure presents information ratios for our set of 15 constructed tilting strategies (identifiable by the prefix 'BL') and for our two benchmarks, namely an equally-weighted 'naïve' allocation approach and an allocation deducted by mean-variance optimization. In detail, we divide the return time series of our optimized tilting strategies in four (nearly) equal subsamples and estimate information ratios for each respective subperiod, where the results are plotted in the four respective panels of the chart. The grey numbers on the bottom of each panel report the available number of monthly observations per factor during the subperiod, while the respective time period covered is stated on the top. Standard errors for the one-sided 95% normal confidence intervals are obtained via bootstrapping (see Appendix A.10 for more information), the intervals are indicated in the chart as box plots. Information ratios and their standard errors are annualized, i.e. multiplied by $\sqrt{12}$. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.

	E_US.Markt	E_US.SMB	E_US.HML	E_US.RMW	E_US.CMA	E_US.UMD	E_Markt	E_Momentum	C_Markt	C_Carry	C_Momentum
BL.CFNAI	-0.002	-0.016	-0.023	-0.003	0.014	0.137	-0.087	0.127	0.280	-0.037	-0.213
BL.INFLTN	0.203	-0.007	0.068	0.054	-0.049	0.091	-0.218	0.201	0.244	-0.065	-0.207
BL.PLTCL.UNCRTNTY	-0.110	-0.022	-0.209	0.076	0.208	0.003	0.226	0.079	0.039	-0.022	0.021
BL.BDGT.BLNC	0.214	0.047	-0.098	-0.051	0.138	0.162	-0.112	0.177	0.213	-0.055	-0.169
BL.RTS.3M	-0.087	-0.045	-0.061	-0.005	-0.014	0.112	0.023	-0.105	0.024	-0.007	-0.131
BL.GLBL.M2.SPPLY	-0.018	-0.223	-0.071	0.039	-0.013	0.103	0.190	0.117	0.540	-0.051	-0.148
BL.Mom	-0.104	0.145	0.020	0.026	0.029	0.033	-0.075	0.098	-0.018	-0.072	0.331
BL.Vola	-0.090	0.024	0.178	-0.134	-0.074	-0.078	-0.137	0.090	0.448	-0.000	0.068
BL.Value	0.038	-0.007	0.055	-0.009	-0.038	0.222	-0.111	0.070	0.013	-0.043	-0.031
BL.FCTR.SPRD		-0.299	0.111	0.011	-0.010	0.442		0.153		0.051	-0.009
BL.Steep_Yld_Crv	-0.074	0.007	0.074	-0.066	-0.069	0.144	-0.091	0.053	0.275	-0.030	-0.200
BL.VIX	0.053	0.032	-0.239	0.001	0.085	0.153	0.122	-0.013	-0.021	-0.011	-0.101
BL.TED	0.372	-0.022	-0.084	0.064	-0.021	-0.036	-0.092	0.086	0.036	0.006	-0.220
BL.SPX.SKWNSS	0.047	0.066	-0.117	-0.147	0.003	0.073	0.334	-0.059	-0.053	-0.070	-0.201
BL.RTS.10Y	-0.153	-0.134	-0.012	-0.125	-0.022	0.053	0.143	-0.133	-0.029	-0.041	-0.184

	C_Value	C_Basis.Momentum	FI_Markt	FI_Carry_Slope	FI_Momentum	FI_Value	FX_Markt	FX_Carry	FX_Momentum	FX_Value
BL.CFNAI	-0.045	0.680	0.278	0.123	0.326	-0.121	-0.070	-0.052	0.153	0.151
BL.INFLTN	0.074	0.083	0.144	-0.006	0.312	0.071	-0.094	0.088	0.111	0.152
BL.PLTCL.UNCRTNTY	0.142	-0.332	-0.153	0.123	0.244	-0.061	-0.215	-0.104	0.400	0.334
BL.BDGT.BLNC	0.022	0.239	-0.111	0.096	0.326	-0.054	-0.049	-0.233	0.122	0.089
BL.RTS.3M	-0.061	0.437	0.035	0.097	0.322	-0.067	-0.117	0.187	0.372	0.228
BL.GLBL.M2.SPPLY	-0.057	0.234	0.109	0.041	0.170	0.022	-0.070	-0.246	-0.079	0.013
BL.Mom	-0.036	-0.241	0.717	0.126	0.299	0.079	-0.110	0.095	0.134	0.157
BL.Vola	-0.350	0.602	0.103	0.195	0.315	-0.088	-0.069	-0.173	0.113	0.132
BL.Value	-0.047	0.346	0.156	0.178	0.245	-0.099	-0.035	-0.162	0.238	0.154
BL.FCTR.SPRD	0.103	-0.456		-0.052	0.428	-0.051		-0.255	-0.015	0.093
BL.Steep_Yld_Crv	-0.031	0.923	0.316	0.144	0.326	-0.049	-0.070	-0.088	-0.069	-0.102
BL.VIX	-0.060	0.321	-0.038	0.031	0.326	-0.043	-0.134	-0.154	0.098	0.144
BL.TED	-0.001	0.769	-0.154	0.092	-0.240	-0.076	-0.097	-0.091	0.323	0.180
BL.SPX.SKWNSS	-0.269	-0.326	0.966	0.183	0.327	-0.067	-0.097	-0.301	-0.101	-0.069
BL.RTS.10Y	-0.048	0.342	-0.095	-0.039	0.318	-0.083	-0.083	0.304	0.387	0.194

Table A8: Cumulative Returns of Active Layer by Factors.
This table presents cumulative returns (as percentages) for the active layers of our set of 15 tilting strategies over our full investigation period, decomposed into the individual factor components. To enable comparisons of the unbalanced set of data series, returns were annualized. The first letters of the factor labels indicate the associated asset class of a given factor, where *C, E, FI* and *FX* are abbreviations for *commodity, equity, fixed income* and *foreign exchange*, respectively. For an overview of all analyzed factor time series, refer to Table 1 and Section 3, while detailed information on the underlying factor time series, for instance covering the sourced data across asset classes and the construction methodology, are provided in Appendix A.3. Similarly, refer to Table 2 as well as Section 4.1 for a broad perspective on the Bayesian regression analysis and the considered candidate predictors, and to Appendix A.5 for details on the variables tested for predictability. Finally, for information on the applied asset-allocation framework, see Section 4.2.