Stock Return Predictability: comparing Macro- and Micro-Approaches *

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Abstract

Economic theory identifies two potential sources of return predictability: time variation in expected returns (beta-predictability) or market inefficiencies (alpha-predictability). For the latter, Samuelson argued that macro-returns exhibit more inefficiencies than micro-returns, as individual stories are averaged out, leaving only harder-to-eliminate macro-mispricing at the index-level. To evaluate this claim, we compare macro- and micro-predictability on US data to gauge if the former turns out higher than the latter. Additionally, we extend over time the methodology of Rapach et al. (2011) to disentangle the two sources of predictability. We first find that Samuelson's view appears incorrect, as micro-predictability is not structurally lower than macro-predictability. Second, we find that our estimated alpha- and beta-predictability indices are coherent with their corresponding theoretical implications, thus suggesting that the two mechanisms are at play in our dataset. Notably, the alpha-predictability index appears as a theoretically based and easily updatable metric to spot irrational exuberance.

Keywords: out-of-sample return predictability; efficient market hypothesis; conditional beta pricing model; alpha predictability
JEL codes: C22, C53, G12, G14, G17

1 Introduction

Some forms of the Efficient Market Hypothesis (EMH) imply that stock returns are not predictable (Fama (1970), Pesaran (2010)). Since all available information is already embedded in asset prices, changes in the latter can only be caused by the arrival of new information which is by definition unpredictable. In other words, prices should follow a random walk, and running a regression of future returns, r_{t+1}, on past information, $\boldsymbol{X}_t$, should not yield predictive content.

At the same time, stock market efficiency may differ between a macro-perspective and a micro-perspective. Paul Samuelson argued in this sense (Jung and Shiller (2005)):

> *Modern markets show considerable micro efficiency (for the reason that the minority who spot aberrations from micro efficiency can make money from those occurrences). [...] In no contradiction to the previous sentence, I had hypothesized considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values.*

Samuelson's intuition amounts to a model where micro-returns are driven both by an idiosyncratic *efficient* component and by a common *inefficient* component (as micro-inefficiencies are arbitraged away by investors). If these idiosyncratic factors are independently distributed, they will average out in the aggregate, leaving at the index-level only the inefficient component of returns. Consequently, if stock return predictability is a gauge of inefficiency, and if Samuelson's view is correct, then we should observe higher levels of predictability at the macro- than at the micro-level.

The contribution of this paper is twofold. First, we compare, over time, macro- and micro-series of return predictability. Although the literature on this subject is enormous, to our knowledge we are the first ones to conduct this exercise in a time-varying manner.

Allowing time variation in our results matters, as return predictability appears largely to be a regime-dependent phenomenon (Henkel et al. (2011), Farmer et al. (2021)). Second, based on Rapach et al. (2011), we contribute to the literature aiming at identifying the drivers of return predictability by building a new indicator that is, theoretically, directly linked with market inefficiencies: the alpha-predictability index. On the result side, we first show that, contrary to Samuelson's view, aggregate returns do not exhibit higher levels of predictability compared to micro-returns. Second, we document that, as expected, our alpha-predictability index is positively linked with metrics of market effervescence.

However, more precisely, modern views of the EMH underline that a certain extent of return predictability can persist even in an efficient market setting. The aforementioned no-predictability paradigm implied that stock prices followed a random walk, and that expected returns were constant. On the contrary, Cochrane (2008) argues that, as investors' risk aversion varies over time, expected returns vary as well. Taking into account time variation in expected returns along the business cycle can therefore generate return predictability even in the absence of market inefficiencies.

To put it bluntly, in the midst of an economic crisis, investors become highly risk averse. This leads to a decline in stock prices and to an increase in expected returns. People could therefore predict that returns will be high in the future, but they are too concerned about their current situation to benefit from it. In the same strand of the literature, empirical papers also argued that this mechanism should be especially at play during economic downturns (Henkel et al. (2011), Dangl and Halling (2012), Rapach et al. (2010)).

Therefore, the interpretation of predictability time series is sensitive. High level of predictability can reflect market inefficiencies such as investors' irrationality or market frictions. But it can also mirror efficient variations in aggregate risk aversion. Conse-

quently, in order to clarify our framework, we present three hypotheses that summarise the different views on return predictability

In the first hypothesis, linked with the Samuelson's view, macro-predictability should be higher than micro-predictability, especially in times of irrational exuberance (e.g. during the dot-com bubble). The second hypothesis, in line with Cochrane's view, states that micro- and macro-predictability should not behave differently as they are influenced by the same factor: changes in aggregate risk aversion. They should therefore evolve in tandem and be higher during recessions. A third "in-between" hypothesis assumes that returns at the micro-level are driven by idiosyncratic factors that can be either efficient (e.g. news about cash flows) or inefficient (e.g. illiquidity issues). The former decrease micro-predictability, whereas the latter increase it. At the aggregate level, both types of individual factors are averaged out, so that micro-predictability can either be higher or lower than macro-predictability. Eventually, this third view is agnostic regarding the sources of macro-predictability, which can therefore be high both during recessions and during market effervescence periods.

We test the three different hypotheses on US post-war data, with an out-of-sample methodology that combines 23 models estimated on rolling windows. These models are commonly used in the return predictability literature and encompass both traditional econometric methods, factor modelling approaches and Machine Learning techniques. The large number of approaches considered here reflects the substantial model instability in forecasting returns exercises (Timmermann (2018)).

We find overall that our results corroborate the third hypothesis for at least two reasons. First micro-predictability is neither structurally higher nor lower than macro-predictability. On the contrary, micro-predictability "bounces around" macro-predictability. This result is in line with a model where micro-predictability level depends on the relative importance of efficient or inefficient idiosyncratic component of returns. Second, we ex-

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tend the methodology of Rapach et al. (2011) in a time-varying manner so as to disentangle the sources of macro-predictability. The two resulting series, the alpha-predictability and the beta-predictability indices, should track changes in macro-predictability due to market inefficiencies and due to time-varying risk aversion, respectively. In accord with the third hypothesis, we find that the alpha-predictability index is positively associated with metrics of market exuberance, whereas the beta-predictability index correlates with business cycle variables. This finding underlines that the two sources of return predictability are at play in our dataset, and therefore enables to reconcile the diverging views in the literature about the drivers of return predictability. Furthermore, from a policy perspective, the alpha-predictability index can also be used as an indicator in the financial stability toolkit to spot speculative bubbles. Along with other methodologies (Blot et al. (2018), Shiller et al. (2020)) it constitutes an easily updatable risk metric to gauge stock market irrational exuberance.

The rest of the paper is structured as follows: Section 2 details how the current paper is located in the return predictability literature, Section 3 describes the three theoretical hypotheses outlined above, Section 4 presents the methodology and the datasets used, Section 5 reports the empirical results, Section 6 provides different robustness checks and Section 7 concludes.

2   Return Predictability in the Literature

The literature on stock return predictability is extensive and has considerably evolved over time. Seminal papers focused on aggregate stock returns, most of the time reporting in-sample results within linear regression approaches. Various macro-financial variables appeared to have some predictive power, such as the dividend yield (Fama and French (1988), Campbell and Shiller (1988)), the term structure of interest rates (Campbell (1987)) or the consumption-wealth ratio (Lettau and Ludvigson (2001)). Nevertheless,

in sharp contrast with the previous studies, Welch and Goyal (2008) underline that the former results are hardly replicable. In a linear setting, return predictability appears as a spurious result, both in-sample and out-of-sample.

However, relying on more sophisticated techniques, subsequent papers claim to forecast future returns, although most of the time with relatively low R^2. These innovative approaches fall mainly in three non-exclusive categories.

First, return prediction is a specific forecasting exercise in itself, as the use of a performing model by investors is likely to erase the predictability pattern the model is based upon (Timmermann (2018)). The resultant instability in the predicting relationship paved the way for forecast averaging techniques, since they enable the econometrician not to rely on the assumptions of a single model. This includes notably simple and advanced forecast combination methods (Aiolfi and Timmermann (2006), Rapach et al. (2010), Elliott et al. (2013), Baetje (2018)) or Bayesian Model Averaging (Dangl and Halling (2012)). Second, in line with other financial market variables, stocks returns are mostly influenced by investors' expectations. These expectations constitute an unobserved variable, but can be included in the predictive model as a latent factor. Consequently, theory-driven approaches in the form of factor models have proven to perform relatively well at different frequencies (Binsbergen and Koijen (2010), Kelly and Pruitt (2013)). Third, given the complex structure of financial markets, it is unlikely that stock returns follow a linear process. As a result, different studies have explicitly investigated non-linear forecasting techniques. This comprises restricted linear models (Campbell and Thompson (2008)), nonlinear VARs (Henkel et al. (2011)), non-parametric approaches (Farmer et al. (2021)), or Machine Learning methodologies (Rapach et al. (2019), Chinco et al. (2019)).

Although all these analyses have exposed in-sample or out-of-sample forecastability, debate remains about the drivers of return predictability over time. Some papers underline

that, in line with Cochrane's view, predictability is a countercyclical phenomenon and is therefore elevated during economic downturns (Rapach et al. (2010), Henkel et al. (2011), Dangl and Halling (2012)). On the contrary, other studies argued that returns are especially predictable in bullish financial markets (Farmer et al. (2021)), while other identified specific periods of return predictability (e.g. surrounding the oil price shock of 1973, Welch and Goyal (2008), Timmermann (2008)).

Yet, return predictability is not the only available metric to gauge market inefficiencies. One intuitive way to do so is to estimate the informative content of stock prices (Bai et al. (2016)). In other words, are current prices useful to predict future cash flows? This recent work echoes older literature that evaluated to what extent stock returns were driven by future cash flows or by future returns (Campbell (1991), Campbell and Ammer (1993)). Another method amounts to estimate a fundamental value for stock prices, and to define market inefficiency as the departure of observed prices from this estimate (Lee et al. (1999)).

Most of these metrics of inefficiency are based on aggregate data. However some papers extended the above methodologies for individual stocks or for subgroups of stocks (Vuolteenaho (2002), Cohen et al. (2003), Dávila and Parlatore (2018)), sometimes with indicators that evolve over time (Farboodi et al. (2020)). Similarly, some studies evaluate return forecastability at the stock-level, but without reporting specifically micro-predictability (Avramov and Chordia (2006)), without time variation in the results (Rapach et al. (2011)) or without drawing a proper micro-macro analysis (Guidolin et al. (2013), Chinco et al. (2019)).

Compared to the aforementioned studies, the goal of the present paper is to compare, *over time*, *macro- and micro-predictability* so as to extract from this analysis a metric of market inefficiencies. This question has, to our knowledge, never been addressed in the literature.

There are indeed many reasons to presume that stock markets behave differently at the stock-level compared to the index-level. As stated before, Samuelson postulated that micro-efficient cash flow news were averaged out in the aggregate, leaving at the index-level merely the inefficient part of returns (Jung and Shiller (2005)). Effectively, some empirical papers underlined contrasting behaviours of micro-returns compared to macro-returns. Sadka and Sadka (2009) document that the positive relationship between earning growth and returns at the micro-level turns negative at the macro-level. Kothari et al. (2006) report similar findings between earning surprises and contemporaneous returns. Eventually, Hirshleifer et al. (2009) stress that elevated accruals predict negative future returns at the stock-level, but null or positive future returns at the index level. All these studies share a similar reasoning: cash flows are mainly idiosyncratic, whereas discount rates are common across firms. As such, drivers of stock returns may differ greatly depending on the scale we are considering. Allegedly, these drivers are more associated with expectations about future profitability at the micro-level, but, due to diversification effects, depend more on discount rate factors (such as investors' risk aversion) at the macro-level.

3 Working Hypotheses

We formalize in this section the three hypotheses outlined above. Following Avramov (2004) and Rapach et al. (2010) we express (excess) aggregate returns as:

$$r_{t+1} = \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}_t' \boldsymbol{f}_{t+1} + \epsilon_{t+1} \tag{1}$$

Where $\alpha(\boldsymbol{X}_t)$ represent the inefficient part of returns, $\boldsymbol{f}_{t+1}$ a vector of portfolio-based factors capturing systematic risk, $\boldsymbol{\beta}_t$ the corresponding vector of factor loadings and ϵ_{t+1} a disturbance term of mean zero.

Two sources of return predictability are potentially at play here. With time t variables, the econometrician is able to predict market inefficiencies $\alpha(\boldsymbol{X}_t)$. Additionally, return predictability can emerge from the forecastability of risk factors if we further assume that they evolve likewise:

$$\boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \tag{2}$$

Where $g(\boldsymbol{X}_t)$ is a vector of (forecastable) conditional expected returns for the risk factors and $\boldsymbol{u}_{t+1}$ a vector of mean-zero disturbance terms independent of ϵ_{t+1}.

Besides, we consider that micro-returns $r_{i,t+1}$ are affected by aggregate factors $\alpha(\boldsymbol{X}_t)$ and ϵ_{t+1}, but also by their individual counterparts: $\alpha_i(\boldsymbol{X}_t)$ and $\epsilon_{i,t+1}$ (that is, idiosyncratic inefficiencies and idiosyncratic unpredictable shocks). We assume that $\alpha_i(\boldsymbol{X}_t)$ and $\epsilon_{i,t+1}$ are centered around 0, and are diversified away at the macro-level. More precisely we write our system of macro- and micro-returns such as:

$$\begin{cases} r_{i,t+1} = \alpha_i(\boldsymbol{X}_t) + \omega_i \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \end{cases} \tag{3}$$

With ω_i and δ_i the exposures of $r_{i,t+1}$ to the common factors $\alpha(\boldsymbol{X}_t)$ and ϵ_{t+1}, respectively, and with $\epsilon_{i,t+1}$ being independent from ϵ_{t+1} and from $\boldsymbol{u}_{t+1}$. The system of equations 3 constitutes the basis for the three following hypotheses.

3.1 H_1, Samuelson's view

Our first hypothesis is built upon Samuelson's intuition and entails several implications.

First, we consider here that $\alpha_i(\boldsymbol{X}_t) = 0$ given that, in line with Samuelson, arbitrageurs

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should eradicate micro-mispricings. Second, at the time where Samuelson expressed this idea, the theory of return predictability driven by time-varying expected returns was not formulated yet. Some studies even modelled expected returns as a constant (Samuelson (1975)). We therefore suppose here that $g(\boldsymbol{X}_t) = \boldsymbol{c}$, with $\boldsymbol{c}$ a constant vector, so that $\boldsymbol{f}_{t+1} = \boldsymbol{c} + \boldsymbol{u}_{t+1}$. Third, as micro-inefficiencies are arbitraged away, and since the efficient idiosyncratic news are averaged out in the aggregate, it is assumed here that micro-returns are more driven by unpredictable components than macro-returns. Consequently, return predictability should be higher in the aggregate than at the micro-level[1]. Fourth, the common predictable factor $\alpha(\boldsymbol{X}_t)$ should especially be forecastable in times of elevated market inefficiency.

The System 3 can therefore be rewritten for H_1 as:

$$\begin{cases} r_{i,t+1} = \omega_i \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_{i,t} \boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = \boldsymbol{c} + \boldsymbol{u}_{t+1} \end{cases} \tag{4}$$

For illustrative purposes, we highlight in the top panel of Figure 1 how predictability should behave according to H_1. In that setting, return predictability only comes from the inefficient component of returns, $\alpha(\boldsymbol{X}_t)$. As $\alpha(\boldsymbol{X}_t)$ is mixed with unpredictable news ($\epsilon_{i,t+1}$) at the stock-level, micro-predictability (in blue) should be lower than macro-predictability (in red). Additionally, we consider here that markets are inefficient in times of irrational exuberance (Shiller (2015)) or during downturns as the proportion of noise traders may be especially high in recessions (Veldkamp (2005)). Accordingly, macro-predictability should peak during the late 90s dotcom-bubble, or during the Great

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[1]In other words, micro-returns are assumed to be essentially driven by "individual stories" (Jung and Shiller (2005)), whereas macro-returns are more affected by aggregate inefficiencies. More formally it would mean that the variance of the unpredictable factors of micro-returns ($\epsilon_{i,t+1} + \delta_i \epsilon_{t+1} + \boldsymbol{\beta}'_{i,t} \boldsymbol{u}_{t+1}$) dominates the variance of the predictable part ($\omega_i \alpha(\boldsymbol{X}_t)$). This is less true for the corresponding factors of macro-returns, respectively $\boldsymbol{\beta}'_t \boldsymbol{u}_{t+1} + \epsilon_{t+1}$ and $\alpha(\boldsymbol{X}_t)$.

Financial Crisis of 2008 (grey bars figure NBER US recessions).

Figure 1: Hypothetical Micro- and Macro-Predictability according to the different views
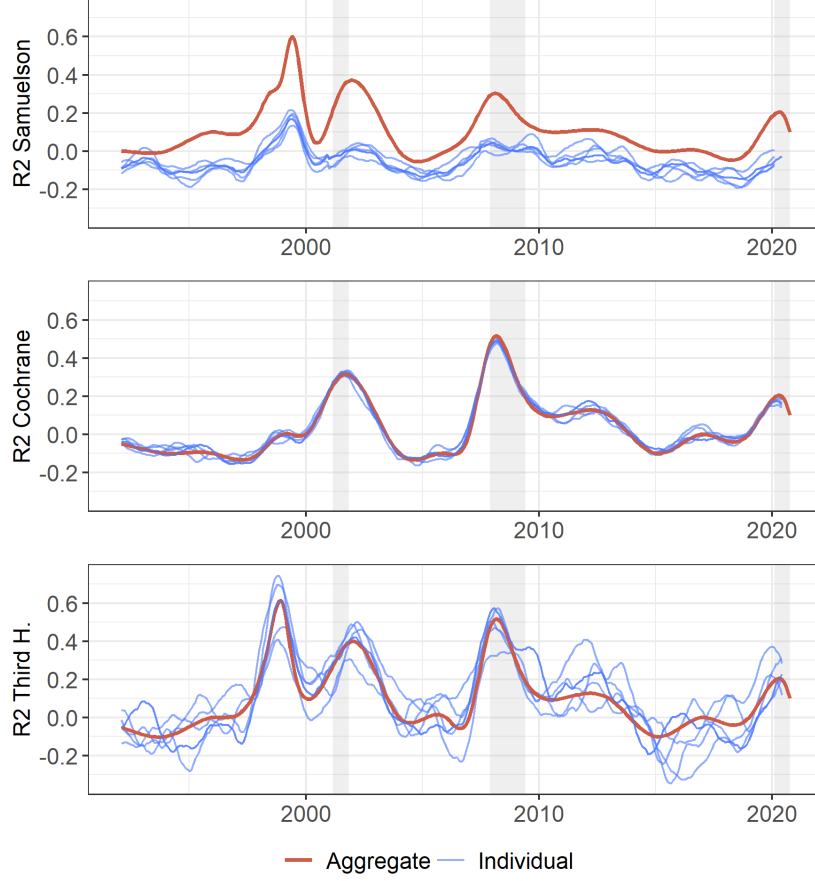
On the different graphs are represented the hypothetical macro- (in red) and micro- (in blue) predictability according to the three views outlined in Section 3. The graph is for illustrative purposes only and is not the result of an econometric estimation. The metric used is the out-of-sample R^2, later detailed in Section 4.2, that can take negative values. The grey vertical bands figure the NBER US recession dates.

3.2 H_2, Cochrane's view

Our second hypothesis dwells on Cochrane (2008), and assumes return predictability in the absence of market inefficiencies. Consequently, we consider here that $\alpha(\boldsymbol{X}_t) = \alpha_i(\boldsymbol{X}_t) = 0$. On the reverse, return predictability stems from time variation in expected

returns, that is from the predictability of the risk factors: $\boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1}$. In this setting, expected returns vary with risk aversion along the business cycles, for instance if investors fear to fall short on their consumption targets during downturns (Campbell and Cochrane (1999)). If at time t, a variable like the dividend yield is able to spot changes in contemporaneous risk aversion, and thus changes in expected returns, it can contain predictive content for future returns[2].

We then have for H_2 the following system:

$$\begin{cases} r_{i,t+1} = \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \end{cases} \qquad (5)$$

Here, micro- and macro-predictability are influenced by the same phenomenon: the forecastability of $\boldsymbol{f}_{t+1}$. As such, they should evolve in similar manners, although some differences may subsist depending on the values of $\boldsymbol{\beta}_{i,t}$ and $\boldsymbol{\beta}_t$, and on the realizations of $\epsilon_{i,t+1}$ and ϵ_{t+1}. This point is illustrated by the common trend in micro- (blue lines) and macro-predictability (red line) in the middle panel of Figure 1. Additionally, current returns may especially be influenced by expected returns during downturns, since expected returns are more volatile in recessions (Henkel et al. (2011)). Therefore, as underlined on Figure 1, both micro- and macro-predictability should behave in a counter-cyclical way, and rise in bad times.

3.3 H_3, Third view

Eventually, between the two precedent polar cases, the third view assumes that micro-returns can be *both* influenced by aggregate inefficiencies and by idiosyncratic mispricing, e.g. localized bubbles or specific illiquidity issues.

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[2]Note that, in that case, return predictability is not a "free lunch", investors have to take extra-risk to benefit from it (Kelly and Pruitt (2013)).

Leaning back on the previous representation, predictability could therefore emerge from "alpha"-predictability (aggregate or individual inefficiencies, $\alpha_i(\boldsymbol{X}_t)$ and $\alpha(\boldsymbol{X}_t)$), or from "beta"-predictability (due to time variation in expected returns, in line with H_2). If we also assume that the $\alpha_i(\boldsymbol{X}_t)$ and $\epsilon_{i,t+1}$ are diversified away at the aggregate level, H_3 would yield the exact same system of equations as System 3.

This view entails several implications illustrated on the bottom panel of Figure 1. First, depending notably on the relative importance of $\alpha_i(\boldsymbol{X}_t)$ and $\epsilon_{i,t+1}$, micro-predictability can be higher or lower than macro-predictability. Second, as these two variables are independently distributed, we would expect the average of micro-predictability indices across stocks to be similar to the macro-predictability series. Eventually, as macro-predictability can increase due to aggregate inefficiencies or to time variation in expected returns, it can both peak during speculative bubble periods or during downturns.

4 Data and Methodology

We assess the relevance of the three hypotheses with an out-of-sample methodology that tries to encompass the major modelling approaches in the literature. Our analysis is focused on postwar US monthly excess returns (from September 1945 to October 2020), but can easily be extended to other datasets.

4.1 Stock Return Data

Throughout this study we investigate the predictability of excess returns, i.e. total returns minus a risk-free rate. We extract monthly postwar US returns from Kenneth French website. This implies that:

1. We evaluate stock return predictability over a market constituted by all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. We take a as a risk-free rate the one-month Treasury bill rate from the same source.

2. We label "aggregate returns" the excess returns of the overall stock market, and "individual returns" the excess returns of the 25 Fama-French portfolios formed on Size and Book-to-Market.

Furthermore, we use supplementary variables as exogenous predictors in Section 4.2, or as covariates in the interpretative regressions of Section 5.2. Their collections and their constructions are more thoroughly detailed in Appendix A.2.

4.2 Constructing Raw Predictability Metrics

We present here our methodology to gauge the "raw predictability" of stock returns. We call raw predictability our mere ability to forecast future returns compared to a benchmark. This estimate will then be disentangled between alpha- and beta-predictability in Section 4.3.

As underlined in Section 2, an extensive number of models has been used in the return predictability literature. Besides, return-forecasting suffers from an elevated model instability as the popularity of performing approaches eradicates the predictive pattern they are based upon (Timmermann (2018)). We therefore adopt here an agnostic view, and centre our analysis on the estimation of $K = 23$ model types. These latter cover classic econometric models, forecast averaging methods, factor modelling approaches and Machine Learning tools. They are exhaustively described in Table A.1.

We evaluate return predictability with the out-of-sample R^2 of Campbell and Thompson (2008), a metric widely used in the literature (Welch and Goyal (2008)). This indicator documents how well a model performs compared with the prevailing mean as a benchmark. More formally, given $\bar{r}_t$ the prevailing mean of aggregate or individual returns from $t - L + 1$ to t, r_{t+1}^k the forecast of r_{t+1} of model k based on variables running from $t - L + 1$ to t, the out-of-sample R^2 for model k is defined as:

$$R_{os,k,t}^2 = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r_{i+1}^k)^2}{(r_{i+1} - \bar{r}_i)^2} \tag{6}$$

In line with Timmermann (2008), we use a rolling window estimation of length $L = 120$ months, and an averaging period for $R_{os,k,t}^2$ of length $n = 36$ months. Our model-selection strategy proceeds as follow:

First, given a specific series of aggregate or individual returns $\{r_{t+1}\}_{t=0}^{T-1}$, we evaluate the different K models on a rolling window of length L. For each model m, we thus obtain a series of out-of-sample forecast: $\{r_{t+1}^m\}_{t=L}^{T-1}$ [3].

Second, again for each model k, we compute the corresponding $R_{os,k,t}^2$ at each point in time from $L + n + 1$ to T.

Eventually, as in pseudo-real time strategies, we choose the model with the best average out-of-sample $R_{os,k,t}^2$ over the previous estimation period to perform the next-period forecast[4]. We can therefore build a series of final out-of-sample predictions $\{r_{t+1}^f\}_{t=L+n}^{T-1}$, where, potentially, at each point in time a different model is chosen for the final forecast. From the latter series, we can then construct our final metric of raw R^2 for r_{t+1}: $\{R_{os,t}^2\}_{t=L+n+1}^{T}$.

4.3 Disentangling the Sources of Predictability

Following the different hypotheses outlined in Section 3, return predictability can emerge from two different phenomenons: the exposure to predictable risk factors ($\boldsymbol{f}_{t+1}$) or to market inefficiencies ($\alpha(\boldsymbol{X}_t)$ and $\alpha_i(\boldsymbol{X}_t)$).

For each portfolio returns $r_{i,t+1}$, we compute the series of raw return predictability $R_{i,os,t}^2$

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[3] In line with Timmermann (2008), we apply a "sanity filter" to our forecasts. If a forecast exceeds any previous return of the estimation period (in absolute value) it is then replaced with a "no change" forecast. This type of filtering is common in the return predictability literature (Elliott et al. (2013)).

[4] Note that for an estimation period running from $t - L + 1$ to t, we need previous forecasts from $t - L - n + 2$ to $t - L + 1$ so as to build $R_{os,k,t-L+1}^2$. This latter variable will then be used in the model-selection to predict r_{t+1}.

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according to the methodology described in Section 4.2. In this section, to decompose this metric between the two sources of predictability, we extend the methodology proposed by Rapach et al. (2011).

We first build a "beta-pricing restricted" forecast of r_{t+1}: r_{t+1}^{β}. To that aim, we define as risk factors $\boldsymbol{f}_{t+1}$ the factors of the Fama-French three factor model, also extracted from Kenneth French website. We obtain the risk factors forecasts, $\boldsymbol{f}_{t+1}^{f}$, with the exact same prediction algorithm detailed in Section 4.2. Then, in line with Rapach et al. (2011), we estimate the risk loadings $\hat{\boldsymbol{\beta}}_{t}$ by regressing, over a rolling window and without constant, $\{r_s\}_{t-L+1}^{t}$ on $\{\boldsymbol{f}_s^{f}\}_{t-L+1}^{t}$. We can eventually construct:

$$r_{t+1}^{\beta} = \hat{\boldsymbol{\beta}}_{t}' \boldsymbol{f}_{t+1}^{f} \tag{7}$$

In other words, all predictability stemming from the exposure to time varying risk factors should be incorporated in the beta-pricing restricted forecast r_{t+1}^{β}. Any additional return predictability beyond this beta-predictability reflects the fact that $\alpha_i(\boldsymbol{X}_t) \neq 0$ or that $\alpha(\boldsymbol{X}_t) \neq 0$, and is therefore called the alpha-predictability.

We can thus represent the evolution over time of the beta-predictability and the alpha-predictability by decomposing the different $R_{i,os,t}^2$. To do so, we first compute the "beta-R^2": $R_{i,\beta,t}^2$. This metric documents the difference in predictive ability between the beta-pricing restricted forecast and the prevailing mean:

$$R_{i,\beta,t}^2 = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r_{i+1}^{\beta})^2}{(r_{i+1} - \bar{r}_i)^2} \tag{8}$$

We then gauge the performance of the unrestricted forecast (r_{t+1}^{f}) compared to the beta-pricing restricted forecast (r_{t+1}^{β}) by computing the "alpha-R^2": $R_{i,\alpha,t}^2$. This latter assesses the extra-predictability that can be gained beyond the exposition to predictable

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risk factors:

$$R_{i,\alpha,t}^2 = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r_{i+1}^f)^2}{(r_{i+1} - r_{t+1}^\beta)^2} \qquad (9)$$

In line with Rapach et al. (2011), we can show that:

$$R_{i,os,t}^2 = R_{i,\alpha,t}^2 + R_{i,\beta,t}^2 - R_{i,\alpha,t}^2 * R_{i,\beta,t}^2 \qquad (10)$$

Given that levels out-of-sample R^2 are particularly low in return forecasting exercises, we can therefore omit the cross-product and write:

$$R_{i,os,t}^2 \sim R_{i,\alpha,t}^2 + R_{i,\beta,t}^2 \qquad (11)$$

In other words, looking at raw macro- and micro-predictability, $R_{os,t}^2$ and $R_{i,os,t}^2$ is helpful to discriminate between the three different hypotheses of Section 3. But analyzing more closely the behaviours of $R_{i,\alpha,t}^2$ and $R_{i,\beta,t}^2$ enables to evaluate whether the two sources of predictability are indeed at play in the sample[5].

5 Empirical Results

This section first describes the raw predictability results over time, from both a micro- and a macro-perspective. It then outlines the decomposition of the raw predictability series between the alpha- and the beta-predictability, as well as the interpretation of the latter.

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[5]Note that $R_{i,\alpha,t}^2$ is not necessarily positive. Theory-driven forecasts (such as r_{t+1}^β) may perform better than unrestricted forecasts (here r_{t+1}^f) in out-of-sample comparisons (Rapach et al. (2011)).

5.1 Micro- and Macro- Raw Predictability

We represent on Figure 2 the raw predictability metrics for portfolio-returns ($R^2_{i,os,t}$, in blue) and for aggregate returns ($R^2_{os,t}$, in red). The 25 $R^2_{i,os,t}$ series are also plotted separately on Figure 6 of Appendix A.3.

Several findings emerge from Figure 2 that help to discriminate between the three hypotheses of Section 3. First micro-predictability is not structurally lower than macro-predictability. This result invalidates the main assumption of H_1, Samuelson's view, that macro-returns are more affected by market inefficiencies compared to micro-returns.

Figure 2: Micro- and Macro-Raw Predictability series, over time
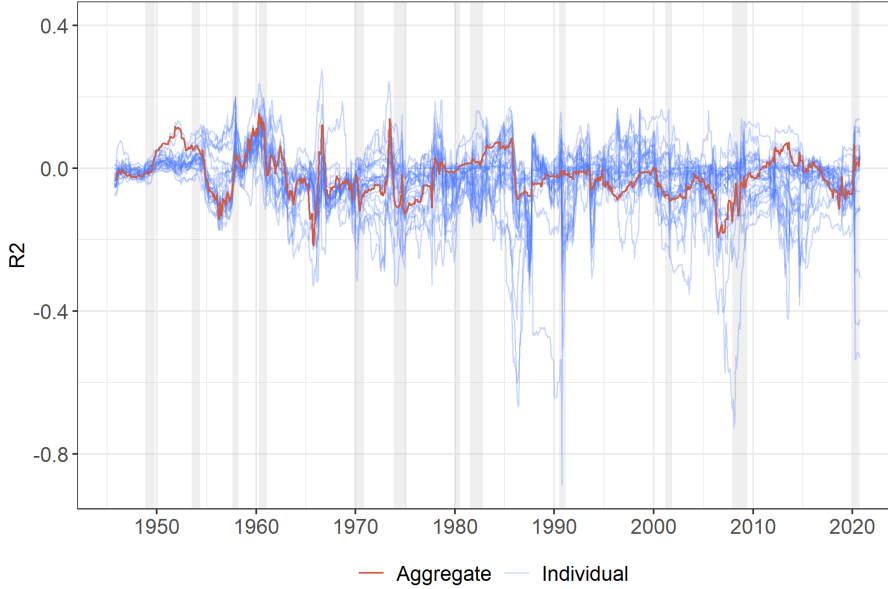
On the different graphs are represented the macro- ($R^2_{os,t}$, in red) and micro- ($R^2_{i,os,t}$, in blue) raw predictability indices according to the methodology outlined in Section 4.2. The metric used is the out-of-sample R^2, also detailed in Section 4.2, that can take negative values. The grey vertical bands figure the NBER US recession dates.

Second, micro-predictability does not seem to follow the exact same behaviour as the macro-predictability series. Although common factors are present in the micro-predictability series (as analyzed in Section 5.2), we notice that $R^2_{i,os,t}$ is sometimes significantly lower

or higher than $R^2_{os,t}$. This finding contradicts H_2 (Cochrane's view) according to which micro- and macro-predictability should behave similarly.

Eventually, two observations appear to corroborate the last hypothesis (H_3, the "third view"). First, we remark on Figure 2 that the variances of $R^2_{i,os,t}$ are considerably higher than for $R^2_{os,t}$. Second we plot on Figure 3 the average of the micro-predictability series over the I different portfolios ($\overline{R^2}_{i,os,t} \equiv I^{-1} \sum_{1 \leq i \leq I} R^2_{i,os,t}$, in dark blue) along the macro-predictability series ($R^2_{os,t}$, in red).

Figure 3: Macro-Raw Predictability series and averaged Micro-Raw Predictability, over time
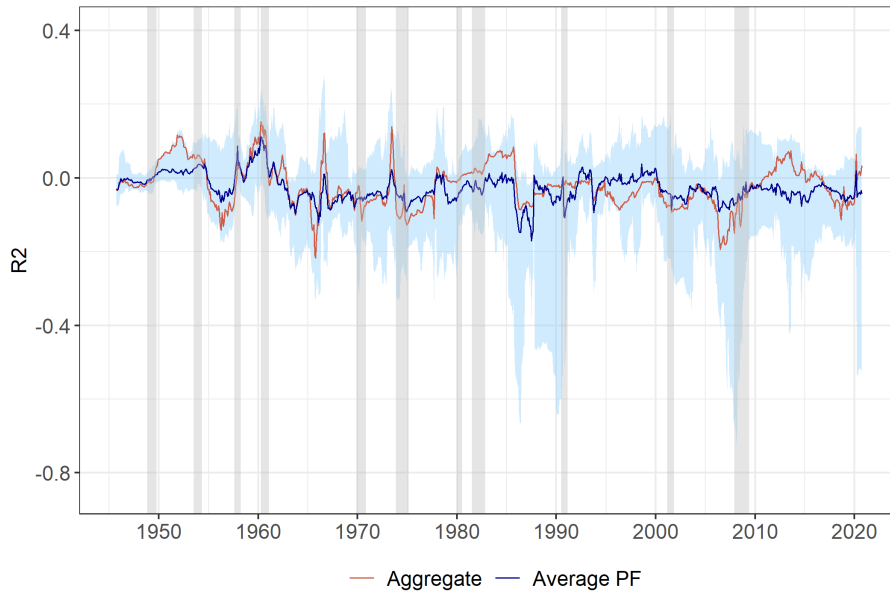
On the graph are represented the macro-raw predictability ($R^2_{os,t}$, in red) and the average micro-raw predictability across portfolios ($\overline{R^2}_{i,os,t}$, in blue). The details of the methodology are outlined in Section 4.2. The light blue area represents the gap between the minimum and the maximum values taken by the different portfolio-raw predictability series ($R^2_{i,os,t}$). The metric used is the out-of-sample R^2, also detailed in Section 4.2, that can take negative values. The grey vertical bands figure the NBER US recession dates.

We observe that pooling the different $R^2_{i,os,t}$ results in a time series that is significantly more correlated with $R^2_{os,t}$ than the individual micro-predictability series. Both of these findings are in line with the implications of H_3. In this setting, micro-predictability is

affected upward by idiosyncratic inefficiencies ($\alpha_i(\boldsymbol{X}_t)$) and downward by idiosyncratic news ($\epsilon_{i,t+1}$). As these two components are centered around 0, they do not translate to macro-returns. Accordingly, macro-predictability should be less volatile than micro-predictability, whereas the average of the micro-predictability series should mimic the evolution of the macro-predictability series. We find both of these results on Figure 2 and 3.

Eventually, the results outlined in this section, regarding the means and the variances of the macro- and micro-predictability series, as well as regarding the strong correlation of $\overline{R^2}_{i,os,t}$ with respect to $R^2_{os,t}$, are detailed in Figure 7 of Appendix A.4 [6]. Moreover, in Appendix A.5, we take into account the uncertainty regarding the coefficient estimates by first fitting ARMA(1,1) processes on the $R^2_{i,os,t}$ and $R^2_{os,t}$, and then by performing 500 bootstrap simulations. The Figure 8 of Appendix A.5 depicts the different coefficients along with their standard errors. We can thus notice that the mean of $R^2_{os,t}$ is similar to the means of $R^2_{i,os,t}$, while the standard deviation of $R^2_{os,t}$ appears significantly lower than the standard deviations of $R^2_{i,os,t}$.

5.2 Alpha- and Beta-Predictability

5.2.1 Building Alpha- and Beta-Predictability

The findings highlighted with Figure 2 and 3 enabled to discard the first two hypotheses: Samuelson's and Cochrane's views. On the reverse, the third view, H_3, seems to fit well with the behaviours of the micro- and macro- raw predictability series outlined above. However, H_3 has also implications regarding the time variation of macro-predictability. Since macro-predictability is influenced by alpha- and beta-predictability, it should be significant both in times of elevated market inefficiencies and during economic downturns.

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[6]Note that all the aforementioned results concerning $R^2_{i,os,t}$ and $R^2_{os,t}$ cannot be explained by the variances of the input returns $r_{i,t+1}$ and r_{t+1}. We plot on Figure 9 and 10 of Appendix A.4 the standard deviations of stock returns against either the level or the variance of their corresponding raw predictability indices. For both graphs the relationships between these variables appear weak at best.

As such, Figures 2 and 3 do not help disentangling these two potential factors, since drops in alpha-predictability may counterbalance rises in beta-predictability (and the reverse).

We therefore attempt in this section to better understand the sources of variation of macro-predictability over time. To do so, we take as a starting point the individual portfolio returns $(r_{i,t+1})$ that we use to estimate the individual series of alpha-predictability $(R^2_{i,\alpha,t})$ and beta-predictability $(R^2_{i,\beta,t})$ with the methodology detailed in Section 4.3. Eventually, we represent on Figures 4 and 5 the behaviours of, respectively, the pooled series $\overline{R^2}_{i,\alpha,t} \equiv I^{-1} \sum_{1 \le i \le I} R^2_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t} \equiv I^{-1} \sum_{1 \le i \le I} R^2_{i,\beta,t}$ [7].

We draw several conclusions from these figures. First remember that, in line with H_3, we expect $\overline{R^2}_{i,\alpha,t}$ to rise in periods of market exuberance, and $\overline{R^2}_{i,\beta,t}$ to increase during recessions. In order to better visualize their time variations, we plot along $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ the opposite of the "Excess CAPE yield" (ECY, built as the inverse of the CAPE ratio minus a risk-free rate) and the Unemployment rate. The former has been advocated to be a good metric of market effervescence[8] (Shiller et al. (2020)), while the latter stands as an intuitive variable to spot changes in the business cycle. Regarding the behaviour of $\overline{R^2}_{i,\alpha,t}$ on Figure 4, the series appears positively correlated with the opposite of the US ECY. As expected, $\overline{R^2}_{i,\alpha,t}$ is relatively high in periods of market booms. These periods include notably the "Kennedy-Johnson peak" (Shiller (2015)) around 1966, the dotcom bubble of the late 90s and finally the period preceding the Great Financial Crisis of 2007.

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[7]On Figures 4 and 5 we center the R^2 metrics around the mid-point of their estimation periods. In other words, whereas in Section 4.2 we had $R^2_{os,m,t} = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1}-r^m_{i+1})^2}{(r_{i+1}-\bar{r}_i)^2}$, here we consider that $R^2_{os,m,t} = 1 - \sum_{i=t-n/2}^{t-1+n/2} \frac{(r_{i+1}-r^m_{i+1})^2}{(r_{i+1}-\bar{r}_i)^2}$, with n an even number. We do this as, for the out-of-sample predictive algorithm, we need all the previous forecasting errors to perform our model selection. However, for interpretative purposes, building the R^2 metrics with only past data will tend to artificially shift the series with respect to the other external variables.

[8]Adjusting likewise the CAPE ratio enables to take into account the role of the fall in risk-free rates for stock valuations in the recent years. In line with Chatelais and Stalla-Bourdillon (2020) we multiply the ECY by -1 throughout the rest of this paper, so that an increase in this metric reflects stronger stock valuations (with respect to bonds).

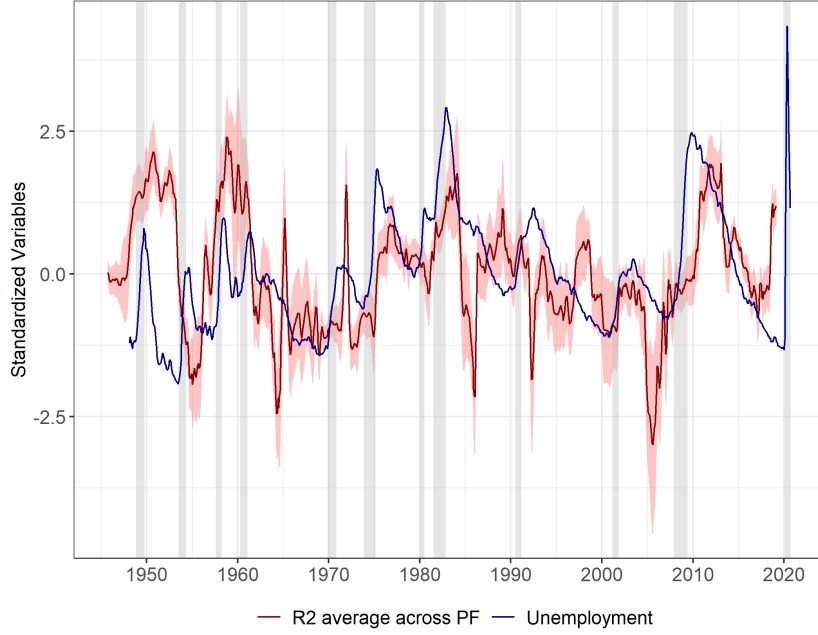Figure 4: $\overline{R^2}_{i,\alpha,t}$ and US ECY, over time
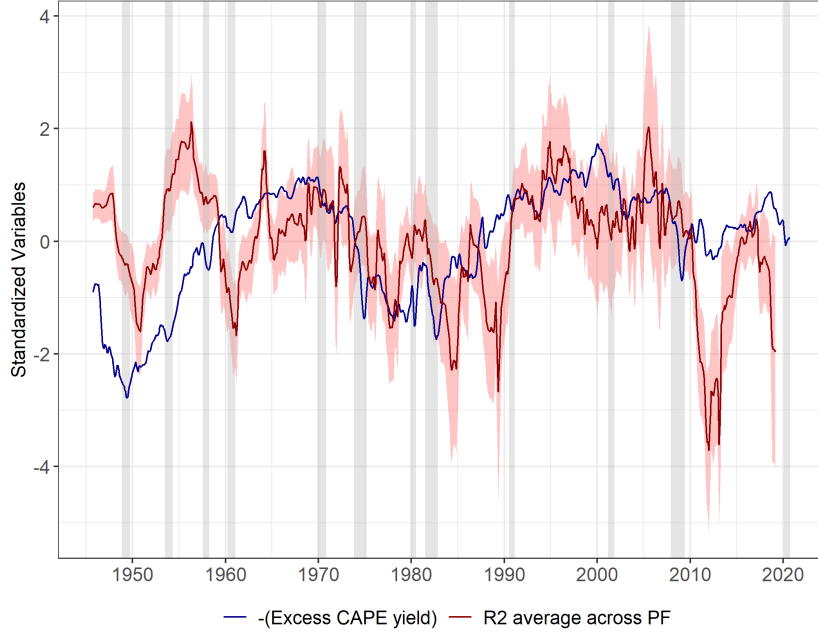
On the graph are represented the average across portfolios of the alpha-predictability series ($\overline{R^2}_{i,\alpha,t}$, in red) and the US Excess CAPE yield multiplied by -1 (in blue). These monthly series have been standardized to fit in the same graph, and, for visual purposes, they have been smoothed over a 3-month period. Raw series of $\overline{R^2}_{i,\alpha,t}$ are yet available in the Figure 11 of Appendix A.6. The red area figures the cross-sectional dispersion around $\overline{R^2}_{i,\alpha,t}$ (+/-1 standard deviation). The metric used is the out-of-sample alpha-predictability $R^2_{i,\alpha,t}$, detailed in Section 4.3, that can take negative values. The grey vertical bands figure the NBER US recession dates.

As for $\overline{R^2}_{i,\beta,t}$, the series appears also positively associated with the US Unemployment rate. It rises during economic downturns, for example throughout the 1960-61 recession, in the neighbouring of the 1973- oil shock, along the Great Financial Crisis or during the recent Covid crisis[9].

Second, the red areas surrounding $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ figure the cross-sectional dispersion of alpha- and beta-predictability across portfolios. We thus notice that the series of $R^2_{i,\alpha,t}$

---

[9]Note that, following the Covid-shock, all predictability appears to stem from the beta-predictability. This finding is in line with other recent studies, such as Gormsen and Koijen (2020). This latter argue that the apparent disconnection between the macroeconomic situations and the US stock market wasn't due to irrational investors' behaviours, but could be rationalized through the fall in long-term sovereign rates.

Figure 5: $\overline{R^2}_{i,\beta,t}$ and US Unemployment rate, over time

On the graph are represented the average across portfolios of the beta-predictability series ($\overline{R^2}_{i,\beta,t}$, in red) and the US Unemployment rate (in blue). These monthly series have been standardized to fit in the same graph, and, for visual purposes, they have been smoothed over a 3-month period. Raw series of $\overline{R^2}_{i,\beta,t}$ are yet available in the Figure 12 of Appendix A.6. The red area figures the cross-sectional dispersion around $\overline{R^2}_{i,\beta,t}$ (+/-1 standard deviation). The metric used is the out-of-sample beta-predictability $R^2_{i,\beta,t}$, detailed in Section 4.3, that can take negative values. The grey vertical bands figure the NBER US recession dates.

are way more dispersed than the series of $R^2_{i,\beta,t}$. This result is quite intuitive as well: in line with H_3, alpha-predictability depends on the importance of both idiosyncratic and aggregate factors, $\alpha_i(\boldsymbol{X}_t)$ and $\alpha(\boldsymbol{X}_t)$. On the reverse, beta-predictability should reflect a single phenomenon, the predictability of $\boldsymbol{f}_{t+1}$. Therefore we should indeed observe more dispersion among the different $R^2_{i,\alpha,t}$ than for the different $R^2_{i,\beta,t}$.

These two findings appear in accordance with the implications of H_3 regarding either the timing of alpha-predictability and beta-predictability peaks, or the dispersion among portoflio returns for these series. However, to better assess the drivers of $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ beyond pure visual examination, we turn to regression analysis in the next sec-

tion.

5.2.2 Interpreting Alpha- and Beta-Predictability

According to the different implications of H_3, three variable types may affect $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$. First, $\overline{R^2}_{i,\alpha,t}$ is supposed to increase during periods of either elevated market frictions, or of irrational exuberance. Conversely, following Henkel et al. (2011), $\overline{R^2}_{i,\beta,t}$ should especially be high during economic downturns. Thus, let $j \in \{\alpha, \beta\}$, we look at regressions of the form:

$$\overline{R^2}_{i,j,t} = c_j + \boldsymbol{\gamma}'_{IE,j}\boldsymbol{X}_{IE,j,t} + \boldsymbol{\gamma}'_{FC,j}\boldsymbol{X}_{FC,t} + \boldsymbol{\gamma}'_{RA,j}\boldsymbol{X}_{RA,t} + \epsilon_{j,t} \tag{12}$$

With $\boldsymbol{X}_{IE,t}$ spotting periods of irrational exuberance (valuation ratios or speculative bubble indicators), $\boldsymbol{X}_{FC,t}$ indicating financial constraints which prevent arbitrageurs from exploiting potential mispricings (stock return volatility, financial intermediary leverage) and $\boldsymbol{X}_{RA,t}$ following closely the business cycles (unemployment level).

H_3 has several implications for the signs of the different coefficients. If we assume that increases in $\boldsymbol{X}_{IE,t}$, $\boldsymbol{X}_{FC,t}$ and $\boldsymbol{X}_{RA,t}$ reflect an increase in market effervescence, an aggravation of financial constraints and a strengthening of economic activity, respectively, we would expect, in line with Section 3, that $\boldsymbol{\gamma}_{IE,\alpha} > 0$, $\boldsymbol{\gamma}_{FC,\alpha} > 0$ and that $\boldsymbol{\gamma}_{RA,\beta} < 0$. Furthemore, we would also expect that a tightening of financial conditions leaves beta-predictability unaffected as the latter shouldn't be influenced by market frictions. Eventually, we remain agnostic regarding the link between economic expansions and alpha-predictability. Alpha-predictability can either be positively influenced by the former (if an improvement in macroeconomic conditions triggers investor's excessive enthusiasm) or negatively (if noise traders are especially present during recessions, Veldkamp (2005)). Therefore, we expect $\boldsymbol{\gamma}_{FC,\beta}$ to be non-significant while we do not form any expectation regarding the sign of $\boldsymbol{\gamma}_{RA,\alpha}$.

To test these implications on the US stock market, we first use for $\boldsymbol{X}_{IE,t}$ two different valuation ratios: the Excess CAPE yield, already described in Section 5.2.1, and the S&P 500 Price Earning Ratio. Additionally, we also look at survey variables to gauge market exuberance in the form of the U.S. One-Year Confidence Index of Yale university. Second, we consider for $\boldsymbol{X}_{FC,t}$ three different metrics to reflect funding constraints. The first one is stock return volatility, the second one the Baa-Aaa corporate bond spread and the third one the seasonally adjusted changes in U.S. broker-dealer leverage (LF_t, Adrian et al. (2014)). Following Farmer et al. (2021), we take LF_t as proxy of funding constraints, since lower leverage is associated with a reduced availability of arbitrage capital. Eventually, for the business cycles variables, $\boldsymbol{X}_{RA,t}$, we take as a main proxy the US unemployment rate, but we also use the Consumer Sentiment Index from the University of Michigan in the robustness checks of Section 6. These different covariates, as well as their originating sources are more precisely detailed in Table 5 of Appendix A.2.

The regression results are presented in Table 1 and Table 2. For the alpha-predictability, we notice in Table 1 that whatever the proxy for $\boldsymbol{X}_{IE,t}$, the associated coefficient $\boldsymbol{\gamma}_{IE,\alpha}$ is significantly positive in the nine specifications outlined here. This finding suggests that alpha-predictability is particularly at play in times of elevated market effervescence. As for the business cycles variables, we observe that the corresponding slopes $\boldsymbol{\gamma}_{RA,\alpha}$ are always significant and positive. This last result indicates that alpha-predictability tends to be especially high in times of bullish stock market combined with sound macroeconomic conditions. Conversely, the mechanism outlined by Veldkamp (2005) does not seem to play any role here. Eventually, for all the different regressions, the coefficients $\boldsymbol{\gamma}_{FC,\alpha}$ are either non-significant or (significantly) positive. Thus, although financial constraints' coefficients have most of the time the expected sign, these variables appear to have only a secondary importance in the drivers of alpha-predictability.

Table 1: Regression results for the Alpha-Predictability

					Dependent variable:				
					Alpha-predictability: $\overline{R^2}_{i,\alpha,t}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$-ecy_t$	0.240***	0.443***	0.243***						
	(0.068)	(0.130)	(0.069)						
pe_t				0.001***	0.001***	0.001***			
				(0.0002)	(0.0001)	(0.0002)			
$Yale_t$							0.002***	0.002***	0.002***
							(0.0004)	(0.0003)	(0.0004)
$-unemp_t$	0.007***	0.006**	0.007***	0.008***	0.010***	0.007***	0.013***	0.015***	0.014***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
$vol_{1,t}$	−0.00001			−0.001			0.003***		
	(0.001)			(0.001)			(0.001)		
$-LF_t$		0.0001			−0.00002			0.001*	
		(0.0002)			(0.0002)			(0.001)	
Baa_t			0.003			−0.004			0.021***
			(0.008)			(0.008)			(0.007)
Const.	0.032***	0.032***	0.032***	0.018*	0.033***	0.017*	−0.101***	−0.050*	−0.113***
	(0.010)	(0.012)	(0.010)	(0.010)	(0.011)	(0.010)	(0.033)	(0.027)	(0.034)
Obs.	856	597	856	856	597	856	214	214	214
R^2	0.175	0.265	0.175	0.166	0.250	0.166	0.363	0.427	0.380
Adj. R^2	0.172	0.261	0.172	0.163	0.246	0.163	0.354	0.418	0.371

Note: ⁣ *p<0.1; **p<0.05; ***p<0.01

On the table are represented the different regression results with $\overline{R^2}_{i,\alpha,t}$ as a predicted variable.
$t-$statistics have been computed using Newey-West standard errors. Variables are rearranged so
that an increase in $\boldsymbol{X}_{IE,t}$, $\boldsymbol{X}_{FC,t}$ and $\boldsymbol{X}_{RA,t}$ reflects, respectively, a surge in market effervescence,
an aggravation of financial constraints and a strengthening of economic activity.

Regarding the beta-predictability, we remark in Table 2 that, as expected, a decrease in economic activity is related to an increase in beta-predictability ($\gamma_{RA,\beta} < 0$) for all nine regressions, in line with Henkel et al. (2011). Similarly, beta-predictability seems to coincide with bearish financial markets, as the coefficients $\gamma_{IE,\beta}$ are significantly negative irrespective of the chosen metric. Eventually, again as expected, financial constraints do not seem to play a role in determining the level of beta-predictability, as coefficients $\gamma_{FC,\beta}$ are non-significant across all specifications of Table 2.

The results of Tables 1 and 2 bring new additional evidence in favor of H_3: all the different coefficients exhibited the expected signs according to this hypothesis. The findings highlighted in this section as well as in Section 5.1 corroborate the two main ideas of this paper: First, that there is indeed a diversification effect of efficient and inefficient individual factors when we compare micro-returns to macro-returns. Second, that regarding more specifically the drivers of macro-predictability, both types of return predictability, alpha- and beta-predictability, seem at play at the same time in our dataset. This last finding contrasts with the return predictability literature, where previous studies tended to oppose these two mechanisms.

6   Robustness checks

We provide here different robustness checks for the results outlined in Section 5.2.

First, to build the alpha- and the beta-predictability indices, we relied on the 3 factor-model of Fama and French (1993) as proxies for the risk factors $\boldsymbol{f}_{t+1}$, namely the excess return on the market, the size factor and the value factor. On Figures 11 and 12 of Appendix A.6, we also plotted the resulting $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ whether we rely on the 1-factor (in green), the 3-factor (in red) or the 5-factor (in blue) Fama-French models [10].

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[10]The two last factors "Robust Minus Weak" and "Conservative Minus Aggressive" are also extracted from Kenneth French website. Due to their limited availability, the $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ for the 5-factor model start later than for the 1-factor or 3-factor models.

Table 2: Regression results for the Beta-Predictability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable:								
	Beta-predictability: $\overline{R^2}_{i,\beta,t}$								
$-ecy_t$	-0.582^{***}	-0.214^{*}	-0.598^{***}						
	(0.101)	(0.125)	(0.102)						
pe_t				-0.001^{***}	-0.0004^{***}	-0.001^{***}			
				(0.0003)	(0.0001)	(0.0003)			
$Yale_t$							-0.002^{***}	-0.002^{***}	-0.002^{***}
							(0.0005)	(0.0004)	(0.0005)
$-unemp_t$	-0.005^{***}	-0.011^{***}	-0.007^{***}	-0.008^{***}	-0.013^{***}	-0.008^{***}	-0.014^{***}	-0.017^{***}	-0.015^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$vol_{1,t}$	-0.0002			0.001			-0.001		
	(0.001)			(0.001)			(0.001)		
$-LF_t$		-0.0002			-0.0001			-0.001	
		(0.0002)			(0.0002)			(0.001)	
Baa_t			-0.013			-0.0003			-0.006
			(0.008)			(0.008)			(0.009)
Const.	-0.067^{***}	-0.094^{***}	-0.067^{***}	-0.042^{***}	-0.093^{***}	-0.042^{***}	0.073^{*}	0.026	0.076^{**}
	(0.011)	(0.012)	(0.011)	(0.016)	(0.011)	(0.016)	(0.038)	(0.032)	(0.038)
Ob.	856	597	856	856	597	856	214	214	214
R^2	0.234	0.302	0.242	0.109	0.305	0.108	0.395	0.468	0.395
Adj. R^2	0.231	0.298	0.240	0.106	0.301	0.105	0.386	0.460	0.387

Note: *p<0.1; **p<0.05; ***p<0.01

On the table are represented the different regression results with $\overline{R^2}_{i,\beta,t}$ as a predicted variable.
$t-$statistics have been computed using Newey-West standard errors. Variables are rearranged so
that an increase in $\boldsymbol{X}_{IE,t}$, $\boldsymbol{X}_{FC,t}$ and $\boldsymbol{X}_{RA,t}$ reflects, respectively, a surge in market effervescence,
an aggravation of financial constraints and a strengthening of economic activity

We notice on both figures that, despite some discrepancies for the 1-factor model indices, the different metrics behave in a very similar way. These similarities are noticeable whether we look at the pooled series ($\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$) or at the dispersion around the latter (the shaded areas on Figures 11 and 12).

Second, we provide on Table 6 of Appendix A.7 additional regression results in line with our analysis of Section 5.2. We use as an alternative business cycle variable the Consumer Sentiment Index from the University of Michigan, and as a supplementary financial friction proxy a different metric of stock market volatility (computed by estimating a GARCH(1,1) on daily stock returns instead of taking the monthly average of squared returns). We thus notice in Table 6 that these modifications leave the main results unchanged: we still have $\gamma_{IE,\alpha}$ and $\gamma_{RA,\beta}$ significantly positive and negative, $\gamma_{FC,\alpha}$, $\gamma_{FC,\beta}$ non-significant, and $\gamma_{RA,\alpha}$ positive (although not significantly).

7 Conclusion

Based on US postwar data, we manage in this paper to discriminate between three opposite hypotheses regarding the behaviours of micro- and macro-stock return predictability. Overall, by looking at raw predictability metrics, we find that our results are consistent with a model (H_3) that lies in-between Samuelson's and Cochrane's views (H_1 and H_2). Indeed, micro-predictability series do not appear to be structurally higher or lower than macro-predictability indices, but tend to "bounce" around the latter. Furthermore, pooling micro-predictability series across portfolios yields an index that is significantly more correlated with the macro-predictability metric. All these observations corroborate an hypothesis where individual returns are mostly affected by idiosyncratic efficient and inefficient components, but also by common factors. If the former are diversified away at the index-level, we should indeed observe more variability in micro-predictability series, but also an averaged micro-predictability index that mimic the macro-predictability

series.

Additionally, by extending over time the framework by Rapach et al. (2011), we are able to disentangle the two sources of return predictability, the alpha- and the beta-predictability. Here again, our results underpin an intermediate view where return predictability is both affected by these two mechanisms. As a matter of fact, our two estimated indices match the expected theoretical patterns: alpha-predictability rises in period of market effervescence whereas beta-predictability increases during downturns. This last finding enables to reconcile two opposite blocks of the literature: whereas previous papers tend to stress a specific source of predictability (Farmer et al. (2021), Dangl and Halling (2012)), our results suggest that the two phenomenons are at play in our sample.

Eventually, we argue that our estimated alpha-predictability index $(\overline{R^2}_{i,\alpha,t})$ constitutes a theoretically based and easily updatable series to assess periods of irrational exuberance in real time. Along with other metrics of speculative bubbles (Shiller et al. (2020), Blot et al. (2018)), it can be used for financial stability purposes to gauge potential overvaluations on the stock market.

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A Appendix

A.1 List of estimated Models

With r_{t+1} the predicted variable (index or portfolio excess returns) and r_{t+1}^f the model-forecast.

Table 3: Estimated Models

Name	Model description	References
Model 1	*Simple Exponential Smoothing* • $p_{t+1} = \alpha p_t + (1-\alpha)r_t$ • With $p_1 = r_1$	Timmermann (2008)
Model 2	*Double Exponential Smoothing* • $p_{t+1} = \alpha(p_t + \lambda_{t-1}) + (1-\alpha)r_t$ • $\alpha_t = \beta(p_{t+1} - p_t) + (1-\beta)\lambda_{t-1}$ • With $p_1 = 0$, $f_2 = r_2$ and $\lambda_2 = r_2 - r_1$	Timmermann (2008)
Model 3	*Autoregressive Model (BIC)* • $r_{t+1} = \alpha + \beta(L)r_t + u_t$ • Number of lags chosen with the Bayesian Information Criterion	Timmermann (2008)
Model 4	*Autoregressive Model (AIC)* • $r_{t+1} = \alpha + \beta(L)r_t + u_t$ • Number of lags chosen with the Aikake Information Criterion	Elliott and Timmermann (2013)
Model 5	*Smooth Transition Autoregressive Model 1* • $r_{t+1} = \boldsymbol{\theta}_0' \boldsymbol{\eta}_t d_t + \boldsymbol{\theta}_1' \boldsymbol{\eta}_t + u_{t+1}$ • $d_t = 1/(1 + exp(\gamma_0 + \gamma_1(r_t - r_{t-6}))$ • With $\boldsymbol{\eta}_t = (1, r_t)'$	Timmermann (2008)

Table 3: Estimated Models

Name	Model description	References
Model 6	*Smooth Transition Autoregressive Model 2* • $r_{t+1} = \boldsymbol{\theta}_0'\boldsymbol{\eta}_t d_t + \boldsymbol{\theta}_1'\boldsymbol{\eta}_t + u_{t+1}$ • $d_t = 1/(1 + exp(\gamma_0 + \gamma_1 r_{t-3})$ • With $\boldsymbol{\eta}_t = (1, r_t)'$	Timmermann (2008)
Model 7	*Neural net model 1* • $r_{t+1} = \theta_0 + \sum_{i=1}^{n} \theta_i g(\boldsymbol{\beta}_i'\boldsymbol{\eta}_t) + u_{t+1}$ • With g the logistic function, $\boldsymbol{\eta}_t = (1, r_t, r_{t-1}, r_{t-2})'$ and $n = 2$	Timmermann (2008)
Model 8	*Neural net model 2* • $r_{t+1} = \theta_0 + \sum_{i=1}^{n_1} \theta_i g(\sum_{j=1}^{n_2} \beta_j g(\boldsymbol{\alpha}_j'\boldsymbol{\eta}_t)) + u_{t+1}$ • With g the logistic function, $\boldsymbol{\eta}_t = (1, r_t, r_{t-1}, r_{t-2})'$, $n_1 = 2$ and $n_2 = 1$	Timmermann (2008)
Model 9 to Model 18	*Univariate regressions* • $r_{t+1} = \theta_0 + \theta_1 x_t + u_{t+1}$ • With x_t (univariate) exogenous regressors from the list detailed in Table 4	Welch and Goyal (2008)
Model 19	*"Kitchen sink" regression* • $r_{t+1} = \theta_0 + \boldsymbol{\theta}_1'\boldsymbol{X}_t + u_{t+1}$ • With $\boldsymbol{X}_t$ the exogenous regressors from the list detailed in Table 4	Welch and Goyal (2008)
Model 20	*"Model selection" from* Goyal and Welch (2008) • With all the potential combinations $\boldsymbol{X}_{i,t}$ from the list detailed in Table 4, we evaluate: • $r_{t+1} = \theta_{i,0} + \boldsymbol{\theta}_{i,1}'\boldsymbol{X}_{i,t} + u_{i,t+1}$ • At each point in time, we choose the model with the smallest out-of-sample R^2	Welch and Goyal (2008)

Table 3: Estimated Models

Name	Model description	References
Model 21	*Factor model from* Kelly and Pruitt (2013) • Only for aggregate return predictions • With bm_{it} the book-to-market ratio of portfolio i and F_t the estimated factor, we run the following three regressions: • $bm_{i,t} = \theta_{i,0} + \theta_{i,1}r_{t+1} + e_{i,t}$ (time series) • $bm_{i,t} = c_t + F_t\hat{\theta}_{i,1} + u_{i,t}$ (cross section) • $r_{t+1} = \gamma_1 + \gamma_2\hat{F}_t + \epsilon_{i,t+1}$ (time series)	Kelly and Pruitt (2013)
Model 22	*Forecast averaging - equally weighted* • Let $p_{j,t+1}$ the forecasts from the J precedent models, we use a simple equally-weighted forecast averaging of the form: • $p_{t+1} = \sum_{j=1}^{J} p_{j,t+1}$	Timmermann (2008)
Model 23	*Model selection - in-sample* • From the J precedent models (apart from Model 22), we evaluate the in-sample RMSE for each single model and take as a prediction the forecast of the model with the lowest RMSE.	Timmermann (2008)

A.2 Datasets

Table 4: External regressors used in Model 9 to 20 in Table 3

Variable	Description	Sources
tms_t	*Term spread* • 10 Year Treasury rate minus the 3-Month T-Bill rate	Amit Goyal website (before January 2020), FRED (after January 2020)
$cape_{1,t}$	*Cyclically-adjusted PE (CAPE) ratio 1* • Real S&P 500 Prices divided by the 10-year moving average of the corresponding real Earnings	Robert Shiller website
$cape_{2,t}$	*Cyclically-adjusted PE (CAPE) ratio 2* • CAPE ratio with scaled Earnings (i.e. adjusted to account for changes in corporate payout policy)	Robert Shiller website
pe_t	*PE ratio* • Nominal S&P 500 prices divided by corresponding nominal Earnings	Robert Shiller website
bm_t	*Book-to-Market ratio* • Median Book-to-Market ratio of Fama-French 100 portfolios	Kenneth French website
ecy_t	*Excess CAPE yield* • Inverse of $cape_{1,t}$ minus the 10-year real sovereign rate	Robert Shiller website
dp_t	*Dividend-Price ratio* • Log of S&P 500 nominal dividends minus log of S&P 500 contemporaneous nominal dividends (as in Goyal and Welch (2008))	Robert Shiller website
dy_t	*Dividend Yield* • Log of S&P 500 nominal dividends minus log of S&P 500 previous nominal dividends (as in Goyal and Welch (2008))	Robert Shiller website
$vol_{1,t}$	*Return Volatility 1* • Monthly average of daily squared aggregate returns, as in Goyal and Welch (2008)	Kenneth French website
$vol_{2,t}$	*Return Volatility 2* • Monthly average of daily aggregate return volatility estimated with a GARCH(1,1)	Kenneth French website
$index_t$	*Index level* • S&P 500 index level	Robert Shiller website
IP_t	*Industrial Production* • US Industrial Production	FRED

*Above listed variables are available over the all estimation period (September 1945-October 2020).*

Table 5: Additional external regressors used in Sections 5.2 and 6

Variable	Description	Sources
$Michigan_t$	*Consumer Sentiment* • Consumer Sentiment Index from the University of Michigan	FRED
$unemp_t$	*Unemployment rate* • US Unemployment rate	FRED
Baa_t	*Baa-Aaa spread* • Moody's Seasoned Baa Corporate Bond Yield minus Aaa Corporate Bond Yield	FRED
LF_t	*U.S. broker-dealer leverage* • Seasonally adjusted changes in U.S. broker-dealer leverage (Adrian, Etula and Muir (2014))	Tyler Muir website
$Yale_t$	*Confidence Index of Yale University* • Seasonally adjusted changes in U.S. broker-dealer leverage (Adrian, Etula and Muir (2014))	Yale University website

Various variables also used in the regressions of Section 5.2 and 6 are already detailled in Table A.2: ecy_t, pe_t, $vol_{1,t}$ and $vol_{2,t}$.

A.3 Raw Predictability series: individual graphs

Figure 6: Individual Micro- and Macro-Raw Predictability series, over time
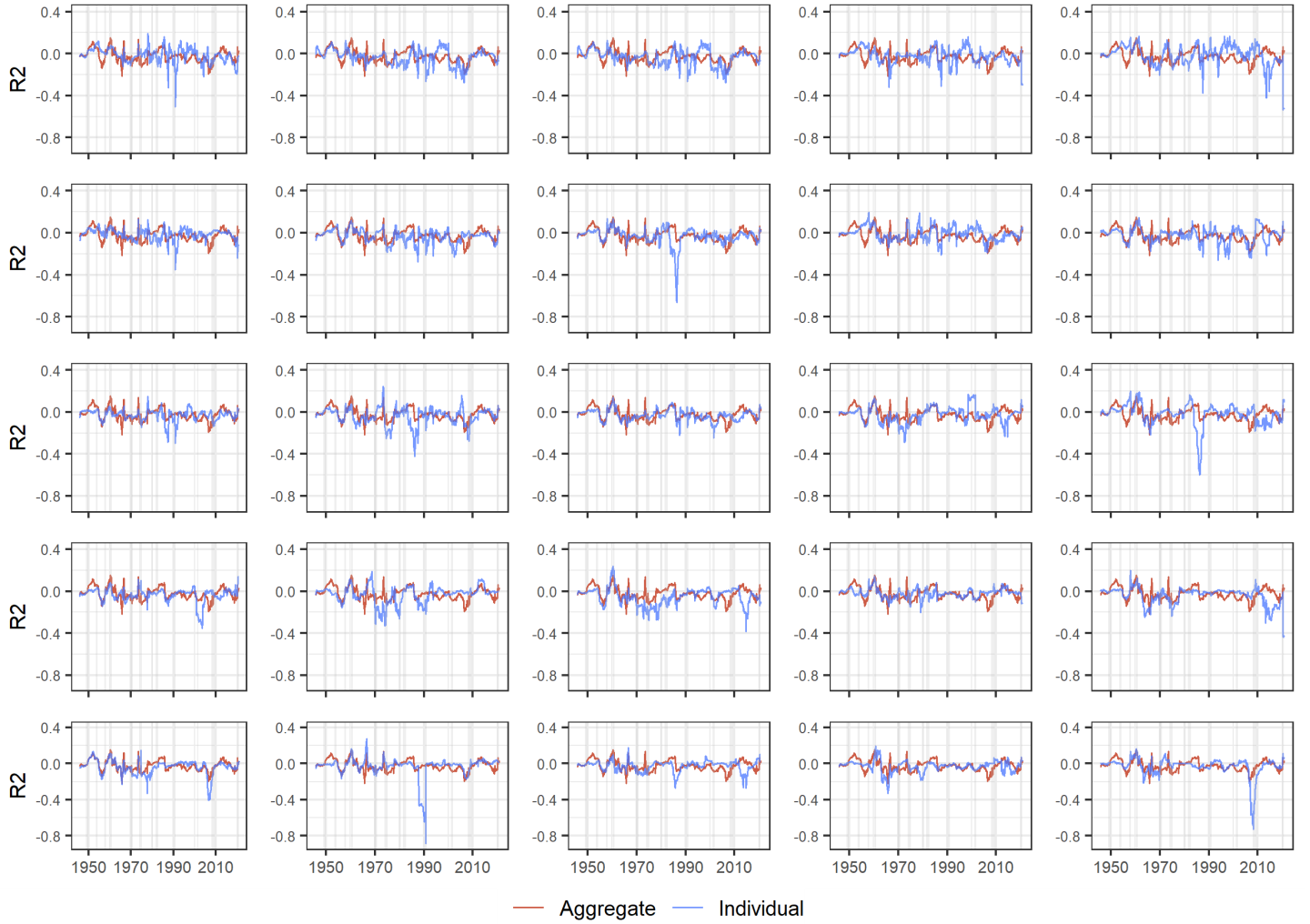
On the different graphs are represented the macro- ($R^2_{os,t}$, in red) and micro- ($R^2_{i,os,t}$, in blue) raw predictability indices according to the methodology outlined in Section 4.2. The metric used is the out-of-sample R^2, also detailed in Section 4.2, that can take negative values. The grey vertical bands figure the NBER US recession dates.

A.4 Moments of the raw return predictability series

Figure 7: Distribution of Micro-Raw Predictability Statistics
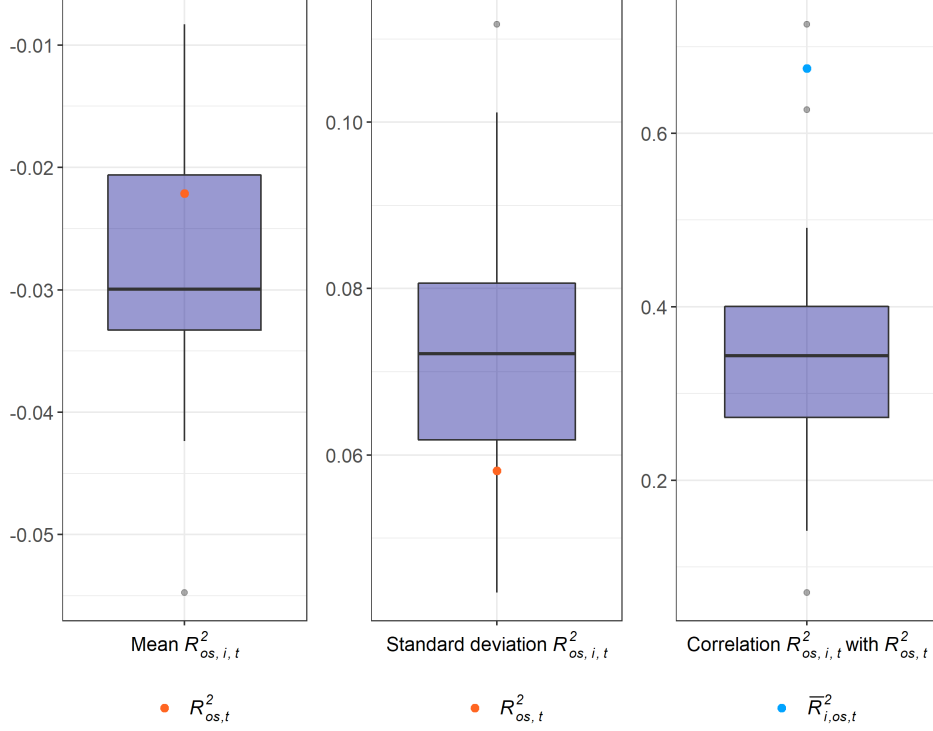
On the different graphs are represented the distributions (in blue) of different statistics of the I series $R^2_{i,os,t}$: their means, their standard deviations and their correlations with respect to $R^2_{os,t}$. The grey points represent the outliers of the aforementioned distributions. The coloured point represent the corresponding statistics either for $R^2_{os,t}$ or for $\overline{R^2}_{i,os,t}$. We thus notice, along Section 5.1: first that the mean of $R^2_{os,t}$ is in line with the means of the different $R^2_{i,os,t}$, second that the standard deviation of $R^2_{os,t}$ stands below the first quartile of $R^2_{i,os,t}$, eventually that pooling the different series $R^2_{i,os,t}$ into $\overline{R^2}_{i,os,t}$ sharply increases the correlation with $R^2_{os,t}$. The metric used is the out-of-sample R^2, also detailed in Section 4.2, that can take negative values.

A.5 Standard errors, mean and standard deviations of raw predictability series

To assess the difference in means and standard deviations of $R^2_{os,t}$ with respect to $R^2_{i,os,t}$, we fit an ARMA(1,1) on each series. More precisely, with Y_t being either $R^2_{os,t}$ or $R^2_{i,os,t}$, we estimate:

$$Y_t = c + \gamma Y_{t-1} + \theta \epsilon_{t-1} + \epsilon_t \text{ and } E(\epsilon_t^2) = \sigma_\epsilon^2 \tag{13}$$

For each series, we then compute their estimated unconditional means m as:

$$\hat{m} = \frac{\hat{c}}{1 - \hat{\gamma}} \tag{14}$$

And their variances σ^2 as:

$$\hat{\sigma}^2 = \frac{(1 + 2\hat{\gamma}\hat{\theta} + \hat{\gamma}^2)\hat{\sigma_\epsilon}^2}{1 - \hat{\gamma}^2} \tag{15}$$

Standard errors for these two estimates are obtained with 500 bootstrap simulations. Mean and standard deviation for $R^2_{os,t}$ are depicted in red in Figure 8, and in blue for the 25 $R^2_{i,os,t}$. Black error bands figure +/- 1 standard error confidence intervals along the estimates. We thus notice on Figure 8, in line with Section 5.1, that, although the means of $R^2_{os,t}$ and $R^2_{i,os,t}$ appear indistinguishable from each other, the standard deviation of $R^2_{os,t}$ is significantly lower than for $R^2_{i,os,t}$.

Figure 8: Mean and standard deviations of raw predictability series: confidence intervals
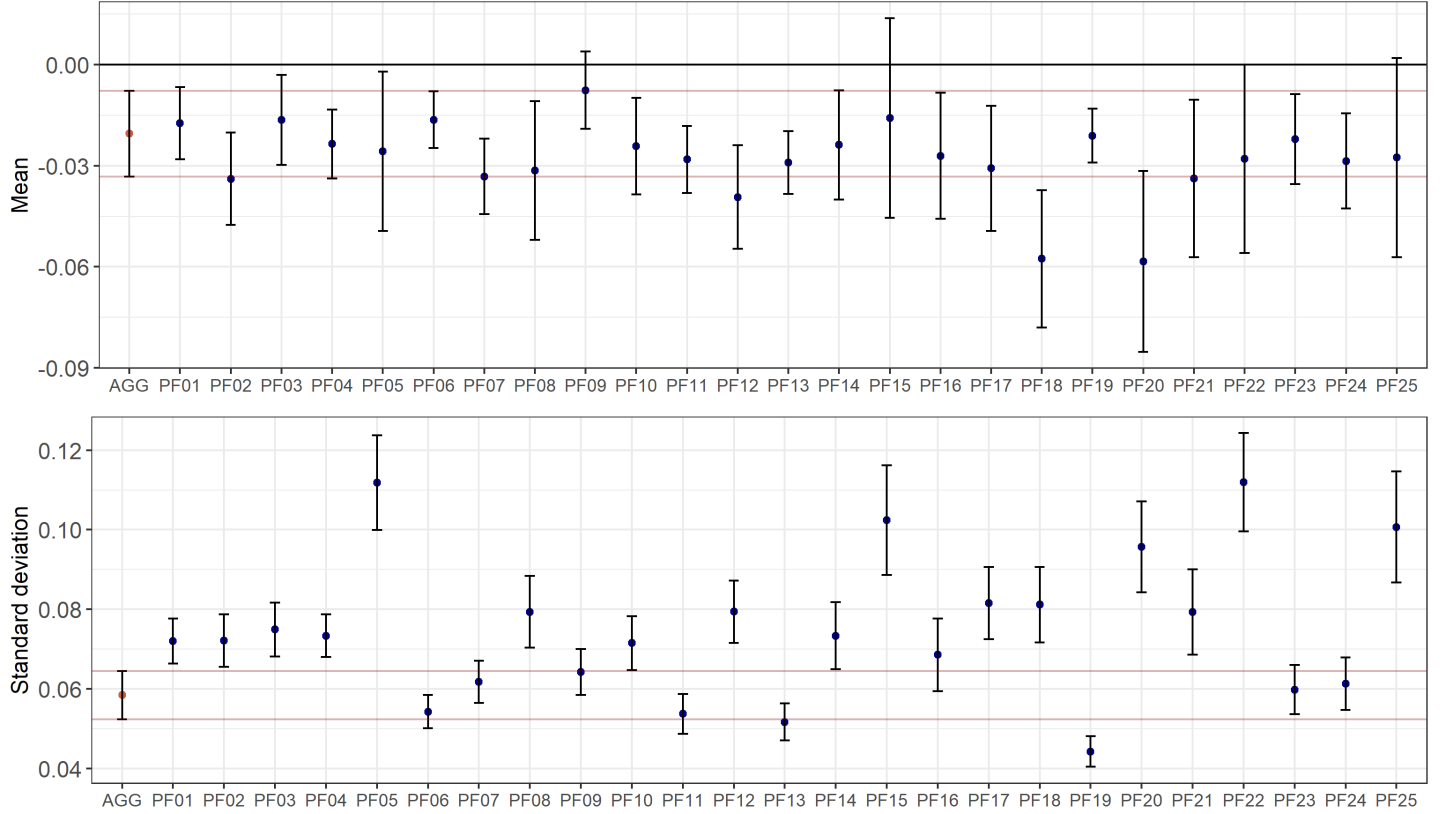
On the graph are represented the unconditional means (upper panel) and the standard deviations (lower panel) of $R^2_{os,t}$ (in red) $R^2_{i,os,t}$ (in blue). The coefficients are obtained by fitting the series with ARMA(1,1) processes, as described in Equations 14 and 15. The standard errors are obtained with 500 bootstrap simulations. Black error bands figure +/- 1 standard error confidence intervals.

Figure 9: Raw Predictability levels vs. Returns standard deviations
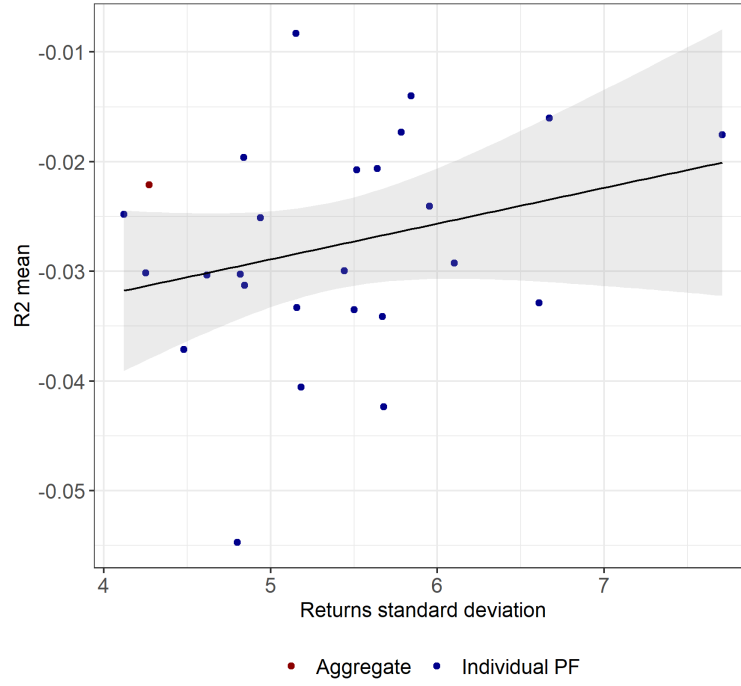
On the scatter plot are represented, for $r_{i,t+1}$ (in blue) and r_{t+1} (in red), the standard deviations of the returns series on the x-axis, and the mean of their raw predictability, $R^2_{i,os,t}$ or $R^2_{os,t}$, on the y-axis. The metric used for the y-axis is the out-of-sample R^2, detailed in Section 4.2, that can take negative values.

Figure 10: Raw Predictability standard deviations vs. Returns standard deviations
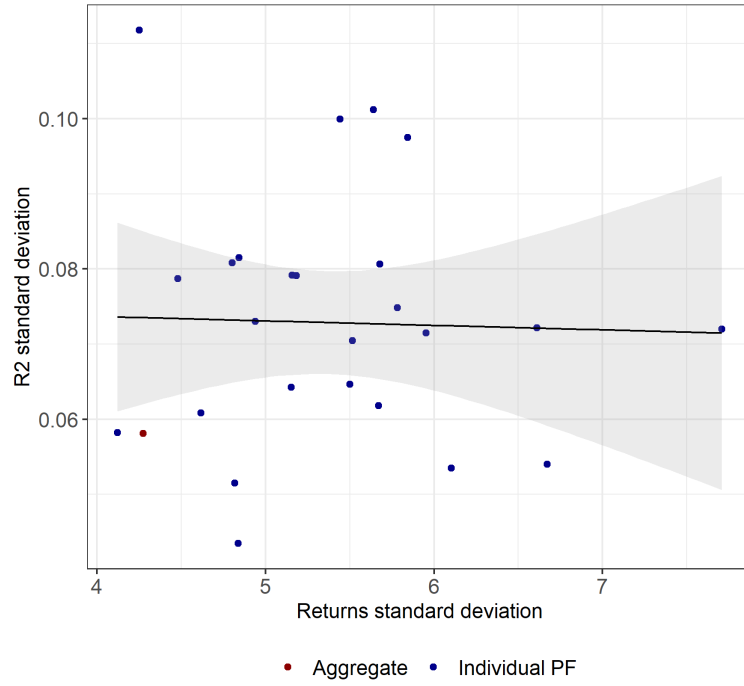
On the scatter plot are represented, for $r_{i,t+1}$ (in blue) and r_{t+1} (in red), the standard deviations of the returns series on the x-axis, and the standard deviations of their raw predictability, $R^2_{i,os,t}$ or $R^2_{os,t}$, on the y-axis. The metric used for the y-axis is the out-of-sample R^2, detailed in Section 4.2, that can take negative values.

A.6 Robustness checks: alternative risk factors

Figure 11: $\overline{R^2}_{i,\alpha,t}$ with different Factor Specifications
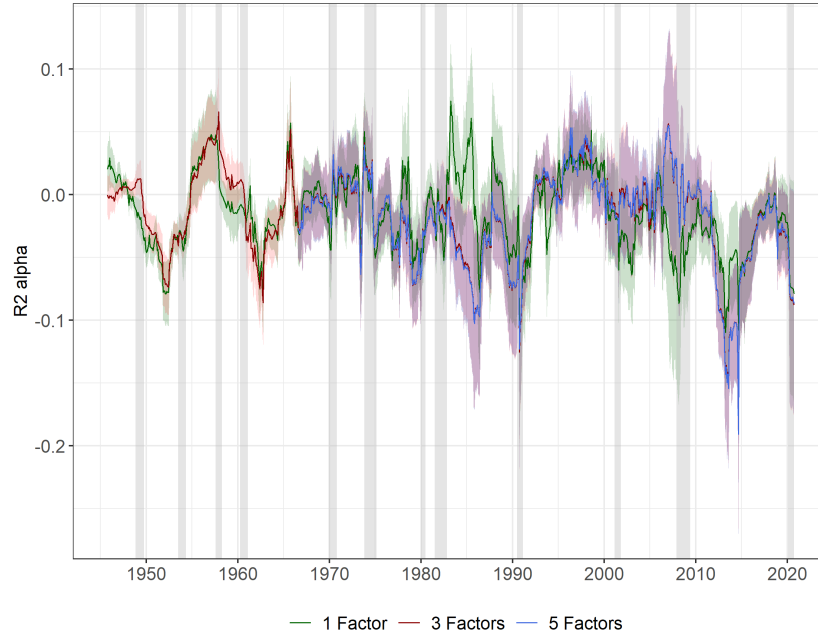
On the graph are represented the average across portfolios of the alpha-predictability series ($\overline{R^2}_{i,\alpha,t}$) computed using the 1-factor (in green), the 3-factor (in red) or the 5-factor (in blue) Fama-French models. The coloured areas figure the corresponding cross-sectional dispersion around the different $\overline{R^2}_{i,\alpha,t}$ (+/-0.5 standard deviation). The metric used is the out-of-sample alpha-predictability $R^2_{i,\alpha,t}$, detailed in Section 4.3, that can take negative values. The grey vertical bands figure the NBER US recession dates.

Figure 12: $\overline{R^2}_{i,\beta,t}$ with different Factor Specifications
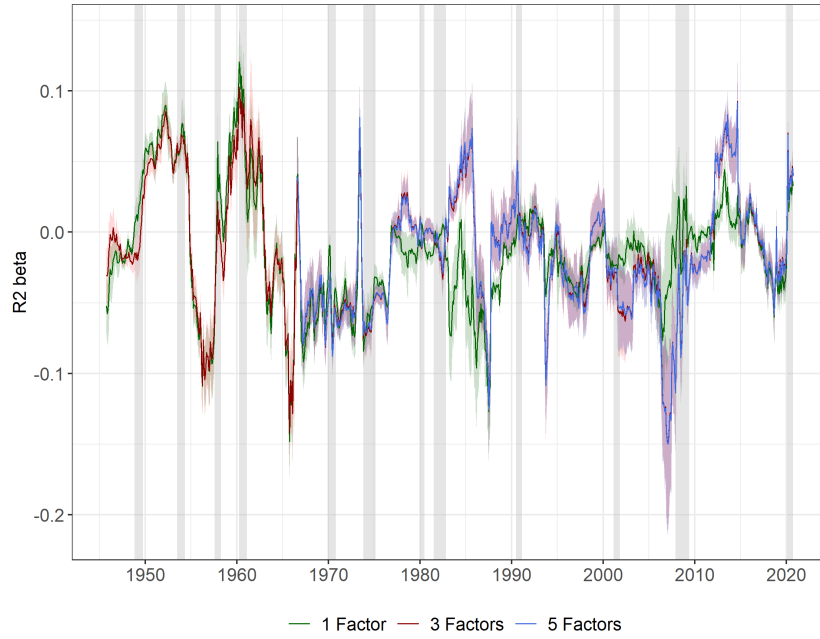
On the graph are represented the average across portfolios of the beta-predictability series ($\overline{R^2}_{i,\alpha,t}$) computed using the 1-factor (in green), the 3-factor (in red) or the 5-factor (in blue) Fama-French models. The coloured areas figure the corresponding cross-sectional dispersion around the different $\overline{R^2}_{i,\beta,t}$ (+/-0.5 standard deviation). The metric used is the out-of-sample beta-predictability $R^2_{i,\beta,t}$, detailed in Section 4.3, that can take negative values. The grey vertical bands figure the NBER US recession dates.

A.7 Robustness checks: regression results

Table 6: Additional Regression Results for the Alpha- and Beta-Predictability

	Dependent variable:			
	Alpha-pred.: $\overline{R^2}_{i,\alpha,t}$		Beta-pred.: $\overline{R^2}_{i,\beta,t}$	
	(1)	(2)	(1)	(2)
pe_t	0.001**	0.001***	−0.001***	−0.001***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)
$Michigan_t$	0.0004		−0.001***	
	(0.0003)		(0.0002)	
$-unemp_t$		0.008***		−0.008***
		(0.002)		(0.002)
vol_t	−0.0004		0.0004	
	(0.001)		(0.001)	
$vol_{2,t}$		−0.002		0.002
		(0.002)		(0.001)
Const.	−0.074***	0.017*	0.063***	−0.041***
	(0.026)	(0.010)	(0.022)	(0.016)
Obs.	496	856	496	856
R²	0.077	0.168	0.086	0.107
Adj. R²	0.071	0.165	0.086	0.107

Note:	*p<0.1; **p<0.05; ***p<0.01

On the table are represented the different regression results with $\overline{R^2}_{i,\alpha,t}$ and $\overline{R^2}_{i,\beta,t}$ as a predicted variables. t−statistics have been computed using Newey-West standard errors. Variables are rearranged so that an increase in $\boldsymbol{X}_{IE,t}$, $\boldsymbol{X}_{FC,t}$ and $\boldsymbol{X}_{RA,t}$ reflects, respectively, a surge in market effervescence, an aggravation of financial constraints and a strengthening of economic activity