Predictability of predictability: Time-varying momentum and reversal across assets and over time

Final Report on the research project funded by the SAS/IIF Grant "Predicting Predictability"

Valerio Potì[1,*]

Abstract

In this paper, we investigate predictability of predictability. Our emphasis is on how the distinct components of predictability, namely momentum and reversals, arise and on their variation over time and across assets. We find that, during recessions, it is profitable to initiate long-run reversal strategies on the S&P and short-run momentum strategies on gold. This is consistent with asset pricing models with slow moving capital since, during recessions (expansions), risk capital flows out of risky assets (safe heavens) and into safe havens (risky assets), thus allowing (forcing) the former to deviate from (converge to) its efficient price.

Keywords: Predictability, Momentum, Reversal, Horizon, Safe Havens, Market Efficiency

*Corresponding Author
Email address: valerio.poti@ucd.ie (Valerio Potì)

This research is generously supported by the SAS/IIF Grant to Promote Research on Forecasting. It forms part of ongoing research work on predictability with Professor Richard Levich from New York University and Dr Tom Conlon at UCD. The results and findings of this report will be included in a number of jointly authored and related papers that will be submitted for publication in peer-reviewed journals. Each one of these papers will acknowledge the generous support of the SAS/IIF Grant to Promote Research on Forecasting, which provided both fi-

1. Introduction

Recent literature, including Adrian *et al.* (2010), Duffie and Strulovici (2012), Mitchell and Pulvino (2012), Poti and Siddique (2013), Haddad (2014), Kondor and Vayanos (2014), has highlighted the asset pricing implications of time-varying capital availability and sluggish capital mobility. On a related note, Asness *et al.* (2013) find that ("cross-sectional") momentum and reversal are positively and negatively, respectively, related to liquidity risk, pointing to a possible link to availability of risk capital.

In this paper, we explore the relations between risk capital and predictability and, more generally, what drives variation of predictability over time and across asset classes, extending the work of Poti and Siddique (2013) on the role of risk capital as a key driver of variation of predictability. We place special emphasis on the possible interaction of risk capital availability with features of the market micro-structure, most prominently capital constraints and limited capital mobility, as key determinants of the magnitude and time variation of predictability, ultimately attempting to model 'predictability of predictability'. To this end, drawing on Vayanos and Woolley (2013), we extend the model proposed by Poti and Siddique (2013) so as to be able to explain the distinct components of predictability, namely momentum and reversals, and their variation over time and across assets. Our model predicts that short term momentum (reversal) strategies should be profitable during recessions (expansions) in the case of risky assets, when there is abundance (scarcity) of risk capital, and therefore scarcity (abundance) of mispricing, whereas the opposite pattern should hold in the case of 'safe heavens',

nancial assistance and precious intellectual stimulus to carry out this research. Support from FMC2 at University College Dublin, in the form of access to hedge fund data, is also gratefully acknowledged.

because capital moves from the former to the latter over the business cycle.[1]

Using data on the S&P500 and gold, taken to represent the universe of risky assets and safe heavens, respectively, we find evidence in support of our model. In particular, we find that, during recessions, it is profitable to initiate long-run reversal strategies on the S&P and short-run momentum strategies on gold. According to our model, this is because, during recessions (expansions), risk capital flows out of risky assets (safe heavens) and into safe havens (risky assets), thus allowing the former to deviate from its efficient price while forcing the latter to converge to its efficient price. We obtain similar results when we test the model using a wider set of risky assets (i.e., a set of International equity market indices, the Fama and French risk-factor mimicking portfolios, high interest rate currencies) and 'safe heavens' (including other precious metals and commodities as well as gold, low interest rate currencies). We do not report these additional results to save space but they are available upon request.

The recurring pattern is that short term momentum (reversal) strategies are profitable if started during recessions (expansions) in the case of risky assets, when there is scarcity of risk capital and therefore abundance of mispricing, whereas they are profitable if started during expansions (recessions) for safe havens, when risk capital has left the gold market to flow into equities.

[1] Recent and still relatively embryonic literature, including Lucey *et al.* (2006); Baur and Lucey (2010); Baur and McDermott (2010); Ranaldo and Soderlind (2010); Beckmann and Czudaj (2013); Bredin *et al.* (2015) examined asset classes such as precious metals, certain currencies, bonds issued by Sovereign entities considered especially stable and trustworthy, inquiring whether they exhibit features that qualify them as 'safe havens'. In spite of the lack of conclusive evidence on whether such assets do provide a safe haven in times of financial turmoil, including evidence that safe haven status might be time varying (e.g., Baur and Glover (2012)), it is clear that capital does flow out of risky assets and into perceived safe havens during times of financial or economic crisis, moving in the other direction during good times.

2. Predictability-based strategies

We represent the data-generating process (DGP) of the one-period excess-returns on the n assets in the economy as follows:

$$r_{t+h} = \mu_{t+h}\left(I_t\right) + u_{t+h} \tag{1}$$

$$\mu_{t+h} \equiv E\left(r_{t+h}|I_t\right) \equiv \mu_{t+h}\left(I_t\right) \tag{2}$$

Here, I_t is the information set at time t and $u_{t,t+h}$ is a zero-mean innovation, which is unpredictable with respect to the information set I_t. The information set includes not only the sigma-field generated by the past of $u_{t,t+h}$ but also all other available public and private information. Under rational valuation, the expected excess-return μ_{t+h} equals the time t discount rate $k_{t+h}(I_t)$ at which the marginal investor, assumed endowed with Rational Expectations (RE), values the excess return r_{t+h}. We define RE as the ability to formulate ex-ante forecasts that do not systematically diverge from ex-post Maximum Likelihood (ML) estimates of the DGP. This definition is consistent with Muth (1961) seminal article and the subsequent generalizations, including Sargent (1996). One well-known implication of this definition is that RE forecasts are such that abnormal returns, $e_{t+h} \equiv r_{t+h} - k_{t+h}\left(I_t\right)$, are unforecastable given the available information set I_t and, therefore, that abnormal expected returns, $\epsilon_{t+h} \equiv \mu_{t+h}\left(I_t\right) - k_{t+h}\left(I_t\right)$, have unconditionally zero mean, or $\alpha \equiv E_t\left(\epsilon_{t+1 \longrightarrow t+h}\right) = 0$, at all horizons $h \in \{1,\ 2,\ \}$, where $\epsilon_{t+1 \longrightarrow t+h} \equiv \prod_{s=1}^{h}(1 + \epsilon_{t+s})$.

We focus on 'predictability-based' strategies that allow an investor endowed with RE to take advantage of discrepancies between the (rational) expected rate of return and the discount rate by exploiting the resulting predictability. We denote the excess-return on a generic member of this class of strategies as $r^*_{t,t+h}$. *Momentum* and *reversal* strategies are two members of such class of strategies.

They exploit different components of predictability at different horizons. Momentum exploits short run positive autocorrelation of asset abnormal returns whereas reversal strategies exploit their negative autocorrelation at longer horizons.

We now derive the implications of RE for the entire class under a model in which assets are traded both in a wider capital market, where assets are held at the margin by a diversified investor, and in segmented markets where, due to exogenous variation in information gathering and processing costs, the assets are held at the margin by specialized and undiversified traders. In both situations, we assume that investors are greedy, risk-averse individuals bent on maximizing expected utility of lifetime wealth and endowed with RE. Also, investors are assumed to be capital-constrained, in the sense that the risk capital supply curve they face is upward-sloping. Here, risk capital is defined, as in Adrian and Shin (2010), as "balance sheet size". Finally, and importantly, we assume there are two types of information sets (public and private) required to formulate rational forecasts. One type (*type A*), denoted by $I_{A,t}$, is freely accessible by investors at no cost.[2] The other type (*type B*), denoted by $I_{B,t}$, can only be gathered and processed by incurring fixed transaction costs. Together, the two information sets add up to the entire information set available at time t. That is, $I_t = I_{A,t} \cup I_{B,t}$, where $I_{A,t} \cap I_{B,t} = \varnothing$. We also assume that fixed transaction costs are large enough and capital constraints are binding enough that, due to the need to exploit economies of scale while coping with capital-constraints, the incumbent will prefer to specialize in gathering a subset of $I_{B,t}$, $I_{B,i,t} \subseteq I_{B,t}$, and not to form diversified portfolios. The incumbent overall information set will therefore be $I_{i,t} \equiv I_A \cup I_{B,i,t}$. Here, for simplicity and without loss of generality, we may assume such that $\cup_{i\in[1,\dots,n]}(I_{B,i,t}) = I_{B,t}$ and $I_{B,i,t} \cap I_{B,j,t} = \emptyset$.

[2] Or, equivalently, at a cost proportional to the size of trading strategies required to exploit it.

Under this set of assumptions, asset payoffs will be traded in two parallel capital markets, namely a *wider capital market*, where assets are held at the margin by a diversified representative investor, and *segmented markets* populated by specialized traders who hold undiversified portfolios so as to maximally exploit economies of scale in the gathering and processing of type B information. In what follows, we shall refer to the marginal trader in the wider capital market as the *diversified marginal trader* (DMT) and to a marginal trader specialized in trading strategies in a segmented market as an *undiversified marginal trader* (UMT). Assets are held and priced in the wider capital markets as part of a static market portfolio whereas, in segmented markets, they are held and priced as part of dynamic and highly specialized (hence, undiversified) portfolios prescribed by trading strategies designed to exploit type B information.

Notably, when assets are priced under the coarse information set that only includes type A information, their returns exhibit predictability under the wider information set that includes type B information. In other words, excess-returns r_t priced under type A information exhibit excess-predictability (on a risk adjusted basis) that can be exploited and, hence, eliminated by strategies that use both type A and type B information. We denote by $r^*_{i,t,t+h} \equiv r^*_{t,t+h}(r_{i,t})$, $i = 1, 2, ..., n$, the excess-returns on the strategies with holding period h needed to exploit the predictability of the (one-period) excess-returns on the i-th asset under the information set $I_{i,t}$ and, therefore, type B information relevant to identify such predictability.

The economy is frictionless up to the different cost of acquisition of type A and B information. Therefore, investors will trade away all arbitrage opportunities under the relevant information set. That is, for every holding period h and denoting by of $r_{i,t,t+h}$ the i-th asset excess-return over holding-periods of length h, there exists analogously denoted positive holding period kernels $m_{t,t+h}$ and $m_{i,t,t+h}$ such that

$$E\left(r_{i,t,t+h}m_{t,t+h}|I_{A,t}\right)=0 \tag{3}$$

and

$$E\left(r^{*}_{i,t,t+h}m_{i,t,t+h}|I_{i,t}\right)=0 \tag{4}$$

hold for all traded assets and their predictability-based strategies, respectively (and, therefore for all $i = 1,\ 2,\ ,\ n$). Notably, (4) also holds with respect to the coarser information set $I_{A,t}$ for all time horizons that end before the time $t+\tau$ when the mispricing starts to correct. That is, even if $I_{A,t} \neq I_{i,t}$, $E\left(r^{*}_{i,t,t+h}m_{i,t,t+h}|I_{i,t}\right) = 0$, as long as $h < \tau$. If $I_{A,t} \neq I_{i,t}$, however, $E\left(r^{*}_{i,t,t+h}m_{i,t,t+h}|I_{i,t}\right) \neq 0\ \forall h \geq \tau$.

Under RE, these restrictions must also hold unconditionally. That is, $\forall i \in [1, 2, ..., n]$ and $\forall h \geq 1$,

$$E\left(r_{i,t,t+h}m_{t,t+h}\right)=E\left[E\left(r_{i,t,t+h}m_{t,t+h}|I_{A,t}\right)\right]=0 \tag{5}$$

$$E\left(r^{*}_{i,t,t+h}m_{i,t,t+h}\right)=E\left[E\left(r^{*}_{i,t,t+h}m_{i,t,t+h}|I_{i,t}\right)\right]=0 \tag{6}$$

We thus have[3]

$$E\left(r_{i,t1}\right)=-\frac{Cov\left(r_{i,t,t+h},m_{t,t+h}\right)}{E\left(m_{t,t+h}\right)}\cong\ -Cov\left(r_{i,t,t+h},m_{t,t+h}\right) \tag{7}$$

$$E\left(r^{*}_{i,t,t+h}\right)=-\frac{Cov\left(r^{*}_{i,t,t+h},m_{i,t,t+h}\right)}{E\left(m_{i,t,t+h}\right)}\cong\ -Cov\left(r^{*}_{i,t,t+h},m_{i,t,t+h}\right) \tag{8}$$

The restrictions (5) and (6) and the corresponding ones in (7) and (8), respectively, must hold for any admissible kernel, including the kernel with minimum variance, for the given set of priced assets.

The minimum-variance kernel that satisfies (5) and (6) for all assets and static combinations thereof traded in the wider capital market is the Inter-temporal

[3]When pricing excess-returns, and for realistically low levels of the risk free rate, the mean of the kernel is essentially not identified and thus it can be well approximated by setting it to unity.

marginal Rate of Substitution (IMRS), $\phi_{t,t+h}$, of the marginal investor in such market. We model this IRMS as a linear function[4] of a set of factors $f_{t,t+h}$ and setting its mean equal to one (again, this is legitimate because we are working with excess-returns):

$$\varphi_{t,t+h} = a + b' f_{t,t+h} = 1 + b' f_{t,t+h} \tag{9}$$

Then, from 7 and (9), we have

$$E(r^*_{i,t,t+h}) \cong -Cov(r^*_{i,t,t+h}, \varphi_{t,t+h}(f_{t,t+h})) = -b'Cov(r^*_{i,t,t+h}, f_{t,t+h}) = \beta(r^*_{i,t,t+h})'\lambda_{i,t} \tag{10}$$

Here, the elements of the vector $\beta(r^*_{i,t,t+h})$ are the coefficients of the regression of $r^*_{i,t,t+h}$ on the factors and $\lambda_{i,t} \cong -b'Var(f_{t,t+h})^{-1}Cov(r^*_{i,t,t+h}, f_{t,t+h})$ is a conformable vector of risk-premia.

The minimum-variance kernel that satisfies (6) and (8) for the predictability-based strategies on asset i is the IMRS of the investor who, at the margin, trades $r^*_{i,t,t+h}$. The fixed transaction costs entailed by trading this payoff impact the investors' problem in the direction of increasing the optimal scale of trading, thus creating an entry barrier. The marginal trader is the incumbent in the segmented market for the trading strategy payoff. For ease of argument but without loss of generality, we assume that average unit fixed transaction costs are, at the incumbent's optimal scale, negligible. Thus, at such scale, the incumbent can invest at the margin in the strategy even though she cannot optimally hold a diversified portfolio. Hence, from (8), we have that maximization of the incumbent's expected

[4]The representative investor's IMRS will be a function of the payoff on a portfolio of risky assets that represents the efficient allocation for all investors. Such a function will be unconditionally linear (static CAPM) or non linear (e.g., higher-moment versions of the static CAPM, conditional CAPM) depending, in general, on the functional specification of the investors' utility functions and their wealth allocations.

utility implies the following restriction on the strategy expected excess-returns:

$$E\left(r^*_{i,t,t+h}\right) \ = -Cov\left(r^*_{i,t,t+h}, \varphi_{i,t,t+h}\right) = \sigma\left(r^*_{i,t,t+h}\right)\sigma\left(\varphi_{i,t,t+h}\right) \tag{11}$$

Here, $\varphi_{i,t,t+h}$ denotes the incumbent's IMRS. The right-most equality follows from the fact that, since the market for the strategy is *segmented* from the rest of the capital market due to the entry barrier and the incumbent is undiversified, $\varphi_{i,t,t+h}$ is perfectly negatively correlated to the strategy since the latter makes up her entire portfolio.

It remains to establish the relation between $\varphi_{i,t,t+h}$ and $\varphi_{t,t+h}$ at the equilibrium allocation. Investors with access to Type B information have also access to Type A information. Hence, if *capital is perfectly mobile*, investors with access to Type B information can also trade the assets traded by investors with access to Type A only. Therefore, $\forall\ i \in [1,\ 2,\ n]$, it must be that

$$E\left(x_{i,t+h}\varphi_{i,t,t+h}|I_{i,t}\right) = \mathbf{0} \tag{12}$$

Here, $x_{i,t,t+h} = [r_{t,t+h}\ r^*_{i,t,t+h}]'$. This means that $\varphi_{i,t,t+h}$ prices both $r_{t,t+h}$ and $r^*_{i,t,t+h}$ and, therefore, it must be at least as volatile as $\varphi_{t,t+h}$, which prices only $r_{t,t+h}$. That is, it must be

$$\sigma^2\left(\varphi_{i,t,t+h}\right) \geq \sigma^2\left(\varphi_{t,t+h}\right) \tag{13}$$

Moreover, the investor that holds at the margin the portfolio of risky assets traded in the wider capital market can always choose to undertake the fixed costs and become an undiversified trader. Unless the optimal scale of trading allows for only a limited number of incumbents, which seems implausible, and if the incumbent's risk capital is large enough, competitive pressure and the threat posed by potential entrants will rule out $\sigma^2\left(\varphi_{i,t,t+h}\right) > \sigma^2\left(\varphi_{t,t+h}\right)$because, as implied by

Proposition I in Ross (2005)[5], investors with concave and non-decreasing utility of wealth prefer an investment opportunity set priced by a more volatile minimum-variance kernel. This turns the weak inequality in (13) into an equality. That is, in equilibrium with perfect capital mobility, we have

$$\sigma^2\left(\varphi_{i,t,t+h}\right) = \sigma^2\left(\varphi_{t,t+h}\right) \tag{14}$$

Therefore, (9) and (12) jointly imply

$$SR^2\left(r^*_{i,t,t+h}\right) \equiv \frac{E(r^*_{i,t,t+h})^2}{\sigma^2(r^*_{i,t,t+h})} \cong \sigma^2\left(\varphi_{i,t,t+h}\right) = \sigma^2\left(\varphi_{t,t+h}\right) \tag{15}$$

Here, SR denotes the strategy Sharpe Ratio. That is, since the strategy cannot be traded at the margin by a diversified investor, we should observe a quest for reward for total risk, instead of systematic risk alone. We use (9) and (15), together with the well-known duality between the volatility of the minimum-variance kernel and the economy maximal SR, and obtain the following more practical restriction

$$SR^2\left(r^*_{i,t,t+h}\right) \cong \sigma^2\left(\varphi_{i,t,t+h}\right) = b'\sigma^2\left(f_{t+h}\right)b = \lambda'\sigma^{-2}\left(f_{t+h}\right)\lambda \tag{16}$$

This can be seen as the squared hurdle SR that predictability-exploiting trades must offer to be entered into by proprietary traders. A higher hurdle rate would

[5]The volatility of the minimum-variance kernel, as an implication of the familiar Hansen and Jagannathan (1991) bound, coincides with the SR attainable by trading the available assets. Therefore, if this weak inequality did not hold, the unconditional maximal SR attainable by trading the currency would exceed the unconditional maximal SR attainable in the wider capital markets. For the investor holding the market portfolio, this would represent an opportunity to increase expected utility by switching risk capital to currency trading. As shown by Ross (2005), this is true even if the investor's preferences are defined over third and higher order moments of her portfolio return. In this case, the investor can simply use a dynamic trading strategy to trade off the conditional SR for conditional higher moments to achieve a more desirable combination. This is the intuition behind Ross (2005) Proposition I. For a formal statement and proof, see pp. 28-29 in Ross (2005).

imply, for the providers of risk capital, missing out on investment opportunities that are more advantageous than those they typically undertake. The equilibrium SR in the left-hand side of (16) should be seen as net of all transaction costs, including the price impact of trades. As illustrated in Appendix, there is a duality between the coefficient of determination of predictive regressions and the SR of the strategies that exploit the predictability picked up by such regressions. Hence, the restriction in (16) is consistent with the volatility bound in (A.4) in Appendix and, therefore, with the restriction on predictability explored by Levich and Poti (2015).

Next, we consider the equilibrium when *capital is imperfectly mobile.* To this end, we note that it cannot be ruled out that the incumbents, in spite of committing all their risk capital to trading a particular strategy, may still face a binding capital constraint when $\sigma^2\left(\varphi_{i,t,t+h}\right) > \sigma^2\left(\varphi_{t,t+h}\right)$. In this case, SRs would exceed the bound in (13) by a non-negative amount until enough new risk capital arrives, i.e. until potential entrants decide to undertake the fixed entry cost. Due to limited capital mobility à la Duffie (2010) and Duffie and Strulovici (2012), this may take some time and occur somewhat sluggishly, giving rise to predictable co-variation with the availability of risk-capital[6], i.e.

$$SR_t^2\left(r^*_{i,t,t+h}\right) - \sigma^2\left(\varphi_{t,t+h}\right) = -\theta\left[SR_{t-1}^2\left(r^*_{i,t-1,t-1+h}\right) - \sigma^2\left(\varphi_{t,t+h}\right)\right] + e_t \qquad (17)$$

where $h \geq 1$, $0 < \theta \leq 1$ and e_t is a random error term. The error-correction parameter θ, in the context of our stylized model, is proportional to the risk capital of the marginal trader of the strategy with excess-return $r^*_{i,t,t+h}$ and, in the presence of imperfect capital mobility, we have $\theta < 1$ whereas, in case of

[6]Of course, the economy maximal SR also likely co-varies with risk-capital but the testable implication here is that currency strategies SRs should co-vary more with risk capital than the economy maximal SR does.

perfect capital mobility, $\theta = 1$. To conceptualize such risk capital, we follow the capital allocation literature (e.g., Matten (1996); Chorafas (2004)) and define it as the difference between the market value of the marginal trader's assets and the quantile of the distribution of the latter under which the marginal trader is forced to liquidate her positions, to meet liabilities. The latter may include debt-type obbligations, such as margin calls, and, if the marginal trader is a fund manager, investors' redemptions. Then, according to the above discussion, we must have that

$$\frac{\partial \theta_t}{\partial q_t} > 0$$

If we model the marginal trader as a hedge fund manager, we may assume a logistic relation between θ_t and asset under management (AUM) flow $g_{AUM,t}$ centred at a (possibly time-varying) steady-state AUM flow $\bar{g}_{AUM}$. In this case, we have

$$\theta_t = \theta_a + \theta_b \left\{ 1 - \left[1 + e^{-\gamma(g_{AUM,t} - \bar{g}_{AUM})} \right]^{-1} \right\} \tag{18}$$

This specification implies an autoregressive process with time-varying coefficients

$$SR_t^2(r^*_{i,t,t+h}) = (1 - \theta_t)\sigma^2(\varphi_{t,t+h}) - \theta_t SR_{t-1}^2(r^*_{i,t-1,t-1+h}) + e_t \tag{19}$$

or, using the shorthand notation $y_t = SR_t^2(r^*_{i,t,t+h})$,

$$\begin{aligned} y_t = \beta_{a,0} + \beta_{b,0}(\gamma, g_{AUM,t}\bar{g}_{AUM}) \\ + \beta_{a,1} y_{t-1} + \beta_{b,1}(\gamma, g_{AUM,t}, \bar{g}_{AUM}) \times y_{t-1} + e_t \end{aligned} \tag{20}$$

where

$$\begin{aligned} \beta_{a,0} &= (1 - \theta_a)\sigma^2(\varphi_{t,t+h}) \\ \beta_{0,b} &= \theta_b \left\{ 1 - \left[1 + e^{-\gamma(g_{AUM,t} - \bar{g}_{AUM})} \right]^{-1} \right\} \sigma^2\left(\varphi_{t,t+h}\right)) \\ \beta_{a,1} &= \theta_a \\ \beta_{b,1} &= \theta_b \left\{ 1 - \left[1 + e^{-\gamma(g_{AUM,t} - \bar{g}_{AUM})} \right]^{-1} \right\} \end{aligned} \tag{21}$$

In this model, $G(\gamma, g_{AUM,t}, \bar{g}_{AUM}) \equiv 1 - \left[1 + e^{-\gamma(g_{AUM,t} - \bar{g}_{AUM})}\right]^{-1}$ is a transition function bounded between 0 and 1 and depends upon the location parameter $\bar{g}_{AUM}$ and the scale parameter γ. For identification purposes, γ is restricted to be positive. In principle, $\bar{g}_{AUM}$ could be time-varying, if the steady-state growth rate of AUM changes over time. The above suggests a negative relation between the rate of change of the SR available from exploiting predictability and the risk capital committed to do so. For values of $g_{AUM,t}$ below $\bar{g}_{AUM}$, the value of the transition function $G(\gamma, g_{AUM,t}, \bar{g}_{AUM})$ tends to zero and, therefore, the coefficient vector is $(\beta_{a,0}, \beta_{a,1})$, as in a standard auto-regressive model. For values above this threshold, $G(\gamma, g_{AUM,t}, \bar{g}_{AUM})$ tends to one and, therefore the coefficient vector is $(\beta_{a,0} + \beta_{b,0}, \beta_{a,1} + \beta_{b,1})$, as in a threshold model with break at $g_{AUM,t}$. The specification of $G(\gamma, g_{AUM,t}, \bar{g}_{AUM})$, for $\gamma < \infty$, implies a smooth transition between these two regimes. For $\gamma \to \infty$, however, the model converges to a standard (non-smooth) threshold autoregression with break at $g_{AUM,t}$. Availability of risk capital in the wider capital market drives instead fluctuations in the economy-wide SR, i.e. in the right-hand side of (16), whereas funding liquidity in any given currency predicts spot returns on holdings of assets denominated in that currency, as shown by Adrian *et al.* (2010).

We can generalize this model to allow for more lags, extra predetermined regressors and a different specification of the transition function as follows:

$$y_t = X_t'\beta_a + X_t'\beta_b G_t + e_t \tag{22}$$

where X_t contains a constant, lags of the dependent variables, lags of $g_{AUM,t}$ and possibly other predetermined variables, i.e. known at time $t-1$. Also, $G_t = G(\gamma, S_{t-d}, c)$ is the transition function, $d \geq 1$ an integer, S_{t-d} is the variable that drives the transition (e.g., $g_{AUM,t-1}$ in (20)) and c is the threshold, which could be a fixed parameter or a variable in I_{t-d}. We can write such a model as follows, in a format that will facilitate the reporting (tabulation) and discussion of the model estimates:

$$
\begin{aligned}
y_t = &\beta_{a,0} + \beta_{a,1,1} y_{t-1} + ... + \beta_{a,1,s} y_{t-s} \\
&+ \beta_{a,2,1} g_{AUM,t-1} + ... + \beta_{a,2,r} g_{AUM,t-r} \\
&+ \beta'_{a,3,1} Z_{t-1} + ... + \beta'_{a,3,p} Z_{t-p} \\
&+ f_t g_t + e_t
\end{aligned}
\tag{23}
$$

where

$$
\begin{aligned}
f_t = &\beta_{b,0} + \beta_{b,1,1} y_{t-1} + ... + \beta_{b,1,s} y_{t-s} \\
&+ \beta_{b,2,1} g_{AUM,t-1} + ... + \beta_{b,2,r} g_{AUM,t-r} \\
&+ \beta'_{b,3,1} Z_{t-1} + ... + \beta'_{b,3,p} Z_{t-p}
\end{aligned}
\tag{24}
$$

and

$$
g_t = 1 - (1 + exp(\gamma(S_{t-d} - c)))^{-1} \tag{25}
$$

Here, Z_t is a vector of possible additional explanatory variables. This more general specification can be seen as an ADL($s, max(r, p)$) model with a smooth transition between regimes. Overall, under this stylized model, the availability of risk capital committed to trading a given asset drives down excess-predictability of the asset returns, i.e. deviations from the steady-state equilibrium described by (15) and (16).

3. Methodology

Under imperfect capital mobility, our model predicts a negative relation between the rate of change of the SR available from exploiting predictability and the risk capital committed to do so. Testing this prediction requires estimates of (a) the SR of trading strategies that exploit predictability and (b) measures of risk capital availability.

The *trading strategies* we consider are the ones that most commonly are deployed to exploit the two main manifestations of predictability, namely momentum and reversal. These are the most natural strategies if one intends to exploit delayed discounting of information on the part of the market. Clearly, we could have engaged in a search over trading strategies and we would most likely have found strategies that, at least in sample, perform much better but this would have exposed to the risk of data snooping.

As for *measures of risk capital availability*, our approach to their identification is twofold. First, because risk capital is arguably more plentiful during times of economic expansion, we proxy for availability of risk capital by using business cycles variables, such as the NBER classification of time periods into expansions and recessions and estimated probabilities that the economy is in a recession. Second, following Jylha and Suominen (2011) and Poti and Siddique (2013), we use relatively direct albeit noisy measures of risk capital availability, such as the flow of asset under management to the hedge fund industry. This choice is motivated by the fact that hedge fund managers arguably represent ideal candidates to epitomize the informed trader who, at the margin, deploys the predictability-based strategies.

Unfortunately, both approaches provide proxies for risk capital availability that are very broad in nature and do not give any indication on the amount of risk capital directed towards specific strategies and asset classes. Also, not all risk capital flowing in and out of assets throughout the economic cycle is allocated by informed traders, giving rise to a possible error in variable (EIV) problem. To partially obviate to these shortcomings, we group traded assets in two broad asset classes, namely *risky assets* and *safe havens*, and study relative time-variation of the SRs of predictability-based strategies based on these two asset classes. Our rationale is that, in spite of the lack of conclusive evidence on whether such assets do provide a safe haven in times of financial turmoil, including evidence that safe haven status might be time varying (e.g., Baur and Glover (2012)), it is clear that capital does flow out of risky assets and into perceived safe havens during times of financial or economic crisis, especially into gold, moving in the other direction during good times. This fact offers the opportunity to test the asset pricing implications of time-varying capital availability, including sluggish capital mobility, posited by our model. In capital markets with mobile but sluggish capital, there should be relative scarcity of risk capital allocation to risky assets during recessions and abundance during expansion, whereas the opposite should be the case for safe havens. That is, for assets that enjoy safe haven status, there should be more plentiful capital allocation during recessions than during expansions. This should have implications for the relative efficiency of the pricing of safe havens and risky assets over the business cycle and, therefore, for the timing of momentum and reversal strategies. Because these two asset classes benefit from risk capital flows at opposite times, their SRs should change across the business cycle and react to measures of *broad* risk capital availability in the opposite manner. In this regard, our econometric strategy for identifying the effect of risk capital availability is to compare the profitability of predictability-based strategies that experience opposite capital flows in different states of the economy *while* conditioning on the state of the economy. Our working assumptions, underpinning this econometric identification strategy by linking our chosen predictability-based strategies to our chosen measures of risk capital availability, are that (a) informed risk capital always does its best to correct/exploit mispricing (no strategic with-holding of firepower or "bubble-riding") and (b) momentum, as well as reversal, works because it exploits/corrects mispricing.

In our context, we are interested in excess-predictability rather in predictability per se because, by definition, only the former can translate into trading profits on a risk-adjusted basis and is of interest from a policy of point of view. To measure excess-predictability we must measure inefficient pricing relative to the RE benchmark. The required measure of excess-predictability must reflect all mispricing, whether captured by momentum or reversal strategies and, for each strategy initiation time, across all lookback and holding periods. We define two such basic measures of mispricing and, therefore, excess-predictability. The first one is a measure of excess-reward to total risk of predictability-based strategies and is the relevant measure of excess-predictability if the strategies are traded by a UMT, which is the case under the assumed presence of economies of scale for gathering and processing Type B information. The second one is a measure of excess-reward to systematic risk and would be the relevant measure of excess-predictability if the strategies were traded by a UMT, which would happen if there were no such economies of scale. More in detail, the first of such measures is

$$ESR_{i,t}^{*2} \equiv SR_{i,t}^{*2} - \sigma(\varphi_{t,t+h})^2 \tag{26}$$

Here, $SR_{i,t}^{*2} \equiv \lim_{h\to\infty} SR_t^2(r_{i,t,t+h}^*)$, where $SR_t^2(r_{i,t,t+h}^*) \equiv \frac{\mu_t^2(r_{i,t,t+h}^*)}{\sigma_{t-1}^2(r_{i,t,t+h}^*)}$, is the squared holding-period SR of a strategy that exploits all predictability of $r_{i,t}$ and $\sigma(\varphi_{t,t+h})^2$ is the variance of the capital market's IMRS which, as per (16), bounds from above the maximal attainable squared SR on any strategy. The second one is the squared information ratio of a strategy that exploits all the predictability of $r_{i,t}$, i.e.

$$IR_{i,t}^{*2} \equiv \lim_{h\to\infty} IR_t^2(r_{i,t,t+h}^*) \tag{27}$$

Here, $IR_t^2(r_{i,t,t+h}^*) \equiv \frac{\alpha_t^2(r_{i,t,t+h}^*)}{\sigma_t^2(u_{i,t,t+h}^*)}$, $\alpha_t^2(r_{i,t,t+h}^*) \equiv \mu_t^2(r_{i,t,t+h}^*) - \beta(r_{i,t,t+h}^*)'\lambda_{i,t}$ and $u_{i,t,t+h}^* = r_{i,t,t+h}^* - \mu_{i,t,t+h}^*$, where $\beta(r_{i,t,t+h}^*)$ and $\lambda_{i,t}$ are defined as in (10). Notice that, in the definitions above, we must let $h \to \infty$ because the strategy with excess-return $r_{i,t,t+h}^*$ must have a long enough holding period for it to be open when mispricing corrects and predictability becomes observable.

This leaves open the issue of how to empirically proxy for such measures. Pragmatically, we shall adopt the approach of estimating these quantities for averages of $r^*_{i,t,t+h}$ across different predictability-based strategies and for a relatively long holding period, i.e. setting $h = 60$ months, so that we can expect that we capture as much as possible of the mispricing present at time t and most of such mispricing has been corrected by the market by time $t + h$. We shall denote such "average" predictability based strategies as

$$r^*_{t,t+h} \equiv \sum_i w_i r^*_{i,t,t+h} \tag{28}$$

Here, w_i are the weights with which the individual strategies are combined in the average one, $i \in 1, 2, ..., n$.

To make inferences on $ESR^2_t(r^*_{i,t,t+h})$ and $IR^{*2}_{i,t}$, we use two closely related statistics. To make inferences on $ESR^2_t(r^*_{i,t,t+h})$, we use the Jobson and Korkie (1981b) z statistic of the difference between $SR_t(r^*_{i,t,t+h})$ and the holding-period SR of the market portfolio, i.e.

$$JK(r^*_{i,t,t+h}) \equiv \sqrt{T}\frac{\hat{\sigma}(r^*_{i,t,t+h})\hat{\mu}(r^*_{m,t,t+h}) - \hat{\sigma}(r^*_{m,t,t+h})\hat{\mu}(r^*_{i,t,t+h})}{\sqrt{2\hat{\sigma}^2(r^*_{m,t,t+h})\hat{\sigma}^2(r^*_{i,t,t+h}) - \hat{\sigma}(r^*_{m,t,t+h})\hat{\sigma}(r^*_{i,t,t+h})}} \tag{29}$$

Here, $r^*_{m,t,t+h}$ denotes the holding-period excess-return on the market portfolio. To make inferences on $IR^2(r^*_{i,t,t+h})$, we use the OLS t-statistics of Jensen's alpha, which we denote as $\tau(r^*_{i,t,t+h}) \equiv t(\alpha^2_t(r^*_{i,t,t+h}))$. Under the null of no excess-predictability, both statistics are normally distributed with zero mean and unit variance.[7].

From these measures of excess-predictability, we also construct an additional statistic specifically designed to test the implications of our model. It is defined as

$$diff_i \equiv JK^2(r^*_{i,t,t+h}) - \tau^2(r^*_{i,t,t+h}) \tag{30}$$

[7]We also experimented with GMM adjustments for heteroskedasticity and autocorrelation. Our inferences are both qualitatively and, to a large extent, quantitatively unchanged. These results are not reported to save space but are available upon request.

This measure, as the difference between a (squared) measure of reward for total risk and a (squared) measure of reward for systematic risk, will be highest when risk capital is scarce, because exploiting the predictability of $r_{i,t}$ to generate this high SR is a risk-arbitrage that requires risk capital. In this regard, it is important to remember that, in our model (i.e., (16)), capital-constrained risk-arbitrageurs disregard alphas and seek instead reward for total risk because, from their point of view, the risk involved in the risk-arbitrage activity is non-marginal and, hence, undiversifiable. In (30), therefore, the role of $\tau^2(r^*_{i,t,t+h})$ is to provide a reference point for the reward for risk in the wider capital market whereas the role of $JK^2(r^*_{i,t,t+h})$ is to measure reward for risk in the market for the predictability-based strategies.

4. Data

Our main dataset are monthly chained front-month futures price data from 1982-2013 on the S&P 500 and gold, taken to represent the universe of risky assets and safe heavens and obtained from Bloomberg. Working with futures data means that excess-returns and rates of returns are the same. That is, we do not have to subtract the risk free rate and add the dividend rate to get the former from the latter.

For comparison and performance attribution purposes, we also use data on the Fama and French (1996) risk factor-mimicking portfolios, rmrf_t, smb_t and hml_t taken from the online library of Professor Kenneth French.

We use data HFR data to construct, as done by Jylha and Suominen (2011), a measure of aggregate asset under management flows to the hedge fund industry, which we denote as $g_{AUM,t}$ and, following Kruttli *et al.* (2015), a measure of aggregate illiquidity of holdings in this industry. Finally, we use data on a number of other variables to construct proxy measures of the state of the economy and possible determinants of predictability. The NBER classification of time periods into expansions and recessions, the related smoothed recession probability estimates and time-series of estimates of economic and equity market uncertainty produced by Baker *et al.* (2015) are obtained from the St Luis Federal Reserve database (FRED Economic data).

5. Construction of predictability-based strategies

We construct momentum strategies by forming dynamic portfolios rebalanced monthly based on a signal represented by past returns. We form the strategies by varying both the *look-back period* and the *holding period*. Here, by look-back period we mean the number of months we lag returns to define the signal used to form a new portfolio each month whereas, by holding period, we mean the number of months we hold each portfolio after it has been formed. For each asset s and month t, we define the signal to be positive if the excess return over the past k months is positive, and negative otherwise. In “un-weighted” versions of the strategies, we go long a fixed amount of the asset if the signal is positive and short if negative, holding the position for h months. In “weighted” versions of the strategies, we set the position size to be proportional to the signal thus defined and inversely proportional to the asset ex ante volatility each month. Sizing each position in each strategy to have constant ex ante volatility filters out noise from the estimate of the signal provided by the past return. As such, the“weighted” strategies can be seen as instances of the class of strategies that combine a directional signal with a volatility filter. As noted by Moskowitz *et al.* (2012), the volatility-weighting makes it easier to aggregate strategies across assets with very different volatility levels and it is helpful econometrically because it yields a time series with relatively stable volatility, which is not dominated by a few volatile periods.

For each trading strategy (k,h), we derive a time series of non-overlapping monthly returns even if the holding period h is more than one month. We do so following the methodology proposed by Jegadeesh and Titman (1993) and used by Moskowitz *et al.* (2012). The return at time t represents the average return across all portfolios at that time, namely the return on the portfolio that was constructed last month, the month before that (and still held if the holding period h is greater than two), and so on for all currently "active" portfolios. In what follows, we shall use a terminology popular among financial traders and refer to all such active portfolios as "positions". Specifically, for each asset and trading time period t, we start by constructing the position initiated in the last time period based on the sign of the past asset return from time t-k-1 to t-1 and compute, for the period from t-1 to t, a one period rate of return on this position. We then continue by constructing the position initiated in the previous time period based on the sign of the past asset return from time t-k-2 to t-2 and compute, for the period from t-1 to t, a one period rate of return on this position. We continue in this fashion until we compute the rate of return from t-1 to t on the oldest position that is still open at t-1, based on the sign of the past return from t-k-h to t-h. This way, for each (k,h), we get a single time series of monthly returns by computing the average return of all of these h currently "active" portfolios (i.e., the portfolio that was just formed and those that were formed in the past and are still held at time t-1). We refer to it as the series of one-period returns on trading strategy (k,h) and denote it as $R_{i,k,h,t}$, where $t = k+1$, ..., T and T is the number of monthly observation in the sample period.

Importantly and more innovatively, for each trading strategy (k,h), we also construct two time series of non-overlapping monthly returns on positions formed at the same time, to which we refer as $RI_{i,k,h,t}$. Here, $RI_{i,k,h,t}$ is a time series of returns on positions **initiated** at time t only. Positions are allocated to trading period t depending on when they are opened, regardless of when the returns that they generate occur. For each trading period t, such positions are then aggregated into a total position for the trading period and a time series of rates of returns for an holding period h is then calculated, without or with volatility-weighting. As an application of this approach, for each trading strategy (k,h), we also construct two time series of non-overlapping monthly returns on portfolios formed during either recessions or expansions only, to which we refer as $RI^{j}_{i,k,h,t} \in \{RI^{rec}_{i,k,h,t},\ RI^{exp}_{i,k,h,t}\}$. Here, $RI^{rec}_{i,k,h,t}$ and $RI^{exp}_{i,k,h,t}$ are time series of returns on strategies comprising positions initiated only during recessions and only during expansions, respectively. Positions are allocated to a subset corresponding to either period depending on when they are opened, regardless of when the returns that they generate occur. Positions within each subset are then aggregated and a time series of one-period returns is then calculated (separately for recessionary and expansionary periods) following the Moskowitz et al (2012) methodology, without or with volatility-weighting.

6. Predictability of S&P vs. Gold

In Table 1, for the full sample period, we report SRs for 'un-weighted' (i.e., without volatility-weighting) and 'weighted' (i.e., with volatility-weighting) versions of the momentum strategy considered by Moskowitz *et al.* (2012) for lookback periods $k \in K$ of 1 to 12 months, as well as 15, 18, 21 and 24 months, matching the holding-period with the look-back period length in each case. For each holding period (and lookback period) k, the reported SRs are calculated as

$$\frac{\hat{\mu}(R_{i,k,k,t}|\{t-1-k,...,t-1\} \in S)}{\hat{\sigma}(R_{i,k,k,t}|\{t-1-k,...,t-1\} \in S)} \tag{31}$$

where $\hat{\mu}()$ and $\hat{\sigma}()$ denote the sample mean and the sample standard deviation operator, respectively, and $S = \{t-1-k, 2, ..., T\}$ is the sets of observations on the strategy returns over the full sample period. In the last row of the table, labelled "Avg", we also report the SRs for the strategy that invests with equal weights in all the individual trading strategies (k, k), namely the equally weighted average trading strategy with return $R_{i,avg,t} = (1/16)\sum_{k\in K} R_{i,k,k,t}$.

In Table 2, we report SRs for the same strategies "**initiated**" during recessionary (in Panel A) and expansionary periods (in Panel B). In each case, the reported SRs are calculated as

$$\frac{\hat{\mu}(RI^{j}_{i,k,h,t})}{\hat{\sigma}(RI^{j}_{i,k,h,t})} \tag{32}$$

Here, as explained earlier, $RI^{j}_{i,k,h,t} \in \{RI^{rec}_{i,k,h,t}, RI^{exp}_{i,k,h,t}\}$ are time series of returns on strategies comprising positions initiated either only during recessions $(RI^{rec}_{i,k,h,t})$ or only during expansions $(RI^{rec}_{i,k,h,t})$. Importantly, the SRs thus calculated do not refer to the performance of the strategy during either expansions or recessions but rather to their performance over time depending on whether they were started during an expansion or a recession.

We see an almost perfect reversal pattern during recessions across the S&P and gold, which is especially clear in the case of the volatility-weighted strategies, though there are little differences during times of economic expansions. During recessions, momentum strategies based on the S&P, which acts in our analysis as the representative risky asset, are profitable at short horizons and unprofitable at longer horizons. Since the losses incurred by momentum strategies imply profitability of the corresponding reversal strategy, the SR estimates in the panels of Table 2 imply that, during recessions, reversals strategies based on the S&P are loss-making at short horizons and profitable at longer horizons. For gold, during recessions, the pattern is the exact opposite. That is, momentum strategies are profitable at longer horizons whereas, at short horizons, it is reversal strategies to be profitable. During recessions, moreover, the simple 'buy and hold' strategy is profitable only for gold, consistent with the safe haven property of this asset, and for the S&P at the longest horizon. During expansions, all strategies appear to be profitable for both the S&P and gold, with the exception of short term momentum on the S&P.

The fact that short term momentum strategies initiated during recessions are profitable in the case of the S&P but not in the case of gold is consistent with positing that, during recessions, there is less risk capital allocated to the risky asset and more risk capital allocated to the safe haven, resulting in the mispricing of the former and the efficient pricing of the latter. The mispricing of the S&P is the basis for the profitability of the short-term momentum strategies based on it whereas the efficient pricing of gold brought about by the risk capital flows is the reason for the unprofitability of the short-term momentum strategies on this asset.

At longer horizons, gold momentum strategies are more profitable than S&P momentum strategies for most horizons, both during recessionary and expansionary periods, possibly due to the greater liquidity and overall maturity of the equity market compared to gold markets.

7. Predictability of predictability

As a further check on the predictability of predictability-based strategies, we carry out an analysis along the lines of Asness *et al.* (2001). These authors were interested in whether there is 'stale pricing' in hedge fund returns. We are interested in whether there is stale (i.e., sluggish) discounting of information regarding time-variation of predictability determinants.

In Table 3, we report estimates of the first order autocorrelation coefficient, ρ, together with the associated GLS t-statistic, the coefficient of determination, R^2, of the first order autoregression used to estimate ρ and the variance ratio (the ratio of the sample variance of annual excess-returns to the annualized sample variance of monthly excess-returns), for the un-weighted (in Panel A) and volatility-weighted momentum strategies (in Panel B) on the **S&P** with holding period and lookback period of k months (specified in the first column), as well as the average momentum strategy on the **S&P** without and with volatility-weighting, which, in each panel, are reported in the rows labelled as "Avg". The sample period, in all cases, is the full one, namely the period 1982-2013. In Table 4, we report estimates of the same measures of serial correlation for the corresponding momentum strategies on **gold**. In Table 5, for comparison, we do so also for the strategies represented by the Fama and French (1996) risk factor mimicking portfolios.

There is clear evidence of both predictability of the momentum returns and heterogeneity of this predictability across trading horizons (holding periods and/or lookback period) and assets (S&P and Gold). This results in time-varying predictability of S&P and gold returns.

These results imply that there is indeed stale (i.e., sluggish) discounting of information regarding time-variation of predictability and, therefore, that predictability is indeed predictable. The fact that momentum returns are themselves predictable (mainly mean-reversion) suggests this is a possibility, but we need to establish whether it arises from time-variation of risk capital availability. For it to be the case, such availability would have to be itself predictable, and the market pricing mechanism would have had to either overlook this predictability or not be in a position to exploit it (e.g., if traders who knew of the usefulness of deploying more risk capital were unable to find it).

In Figure 1 and 2, we treat the holding the S&P index as a benchmark and plot two different measures of excess-reward for risk estimated over rolling 5-year windows of monthly excess-returns on the "overall" (i.e., average) momentum strategies on the S&P and gold, respectively. The first of such measures, denoted by a jagged red line, is the Jobson and Korkie (1981a) z statistic, which is zero under the null that the Sharpe ratios of the momentum strategy and of the benchmark (holding the S&P) are equal. As such, it is a measure of reward for total risk (i.e., both systematic and idiosyncratic risk) The second of such measures, denoted by a continuous blue line, is the more familiar Jensen's alpha, which is zero under the null that the intercept of the regression of the excess-return on the momentum strategy on the S&P excess-return is zero. As such, it is a measure of reward for systematic risk only.

In the case of the S&P, the Jobson and Korkie (1981) z statistic closely tracks the alpha of the momentum strategy and their volatility is comparable (i.e., 1.13% and 1.25%, respectively). For gold, to the contrary, the time series of these two measures of excess-reward for risk are noticeably different. The time series of the rolling alphas is almost always above the time series of the rolling Jobson and Korkie (1981) z statistics and their volatility is quite different (i.e., 1.52% and 1.31%, respectively).

As a more direct check on the implications of our model, we focus on $DIFF_t$ in (30). In Figure 3, we plot $DIFF_t$ for the S&P against the flow of AUM to the hedge fund industry. We see a striking comovement, which suggests that predictability and market efficiency, on the one hand, and hedge funds capital flows, on the other hand, are indeed closely related. The close comovement suggests that investors' capital is attracted to the hedge fund industry at times of high predictability and ow market efficiency. We do not report the corresponding figures for gold and other assets to save space (but they are available upon request). In all cases, we find a positive association but weaker and less clear than in the case of the S&P. This is not surprising because, if it is true that risk capital to the hedge fund industry flows when predictability is high, the greatest driver will be the predicability on the most heavily traded assets and asset classes, as they will have more capacity to absorb the AUM flows.

According to the model in (20)-(21), the growth of AUM above its steady state should negatively predict predictability. Hence, it should forecast a drop of $DIFF_t$.

To test whether the co-movement is of the type predicted by the model, we estimate (20) for both the S&P and gold. In the model in (20), the dependent variable is $y_t = SR_t^2(r^*_{i,t,t+h})$ but we also estimate it with using $DIFF_t$ as the dependent variable, i.e. with with $y_t = DIFF_t$, since the former is a positive function of $SR_t^2(r^*_{i,t,t+h})$ and, because it is defined as a difference between a measure of reward for total risk and reward for systematic risk, it is more likely to pick up genuine variation in predictability, under the null of our model, rather than spurious in-sample performance of the predictability based strategies. This is because the UMT cares about reward for total risk rather than reward for systematic risk and she will arbitrage excessive levels of the former and disregard the latter away excess-is scarce. Hence, when risk capital sluggishly becomes available after a period of scarcity, reward for total risk should drop more than reward for systematic risk, leading $DIFF_t$ to decrease.

In Table 6, we report estimates of specifications of the model in (24), which extends the baseline model in (20), with either $y_t = DIFF_t$ or $y_t = SR_t^2(r^*_{i,t,t+h})$, i.e. with either $DIFF_t$ or $SR_t^2(r^*_{i,t,t+h})$ as the dependent variable. As for the transition variable, i.e. S_{t-d} in (25), we experiment with both $g_{AUM,t-1}$ and $SR_{t-1}^2(r^*_{i,t-1,t-1+h})$. All reported p-values are based on Newey and West (1987) standard errors with 60 lags (to account for the error serial correlation induced by the unavoidable overlapping observation problem). Unfortunately, for this problem, no other remedy is available as the specialized corrections proposed by the literature so far, e.g. the method of Hodrick (1992) is not applicable because it requires one-period returns whereas we work with multi-period SRs ($SR_t^2(r^*_{i,t,t+h})$) or functions thereof ($DIFF_t$). The p-values for the tests concerning sums of coefficients are obtained using the delta-method. The sample period is from 1991:01 to 2011:01, the longest possible given that data on aggregate hedge fund flows $g_{AUM,t}$ is not available before 1991:01 and that, because of the length of the holding period, the final month for which we can compute SR_t^2 is 2011:01. To save space, we do not report the individual autoregressive coefficients $\beta_{a,1,i}, i = 1, 2, ..., s$, and $\beta_{b,1,i}, i = 1, 2, ..., s$. In Table 7, we report corresponding estimates for gold. Notably, apart from the case of the model in the third column which failed to converge, the sign of the recession variable is the opposite as in the corresponding estimates for the S&P, consistent with the conjecture that capital moves in and out of these two asset classes at different points of the business cycle and, therefore, confirming the importance of risk capital flow for predictability determination.

As shown by the estimates reported in the table, a number of the coefficients of $g_{AUM,t}$ are negative to statistically significant extent. In the case of the coefficients of $g_{AUM,t}$ in the "ADL" part (i.e., the $\beta_{a,2,i}$ coefficients) of the model, their sum is negative and, when the dependent variable is $SR_t^2(r_{i,t,t+h}^*)$, also statistically significant. Not surprisingly, these coefficients are not negative at all lags, as perhaps suggested by popular but simplistic views of the relation between risk capital and profitability of trading rules. Our model implies that risk capital flows and predictability are jointly determined in dynamic market equilibrium, in that excess-predictability attracts, albeit sluggishly, risk capital and the latter, when its flow grows above its steady-state magnitude, reduces excess-predictability. From this point of view, (20) and the more general version thereof in (25) should be seen as reduced form representations of this dynamic equilibrium, in which a negative relation between risk capital and excess-predictability only takes hold with delay. In fact, Figure (3) shows that, on a contemporaneous basis, this relation is clearly positive (consistent with the fact that risk capital flows by informed investors are high when the reward on this capital, due to excess-predictability, is high).

One shortcoming of the relatively general specifications examined in the previous two Tables is the large number of variables, which makes interpretation difficult and, due to possible collinearity among some of the regressors, may affect the significance of the coefficient estimates. In Table 8, to obviate to this shortcoming, we therefore report estimates of more parsimonious variations on the model in (24), with $y_t = SR_t^2(r^*_{i,t,t+h})$ as the dependent variable, without regime transition ("no threshold") and with regime transition. When a regime transition is allowed, it is restricted to affect only the coefficients of the lags of $g_{AUM,t}$ and it is governed by a function of the lagged squared SR and a threshold, with the latter specified either as a fixed parameter or as a multiple of the lagged variance of the market portfolio and with two alternative specifications for the transition function (i.e., the logistic, as before, and an exponential specification, as in an ESTAR model). The multiple of the variance of the market portfolio is a proxy for the SR bound in (16), with the factor in (9) given by the market porfolio excess-return, based on the predictability bound in (A4) in Appendix. Hence, in the specification in which the threshold is a multiple of the lagged variance of the market portfolio, the multiple plays the role of the squared relative risk aversion (RRA) of the marginal trader, as per (A4) in Appendix. As before, all reported p-values are based on Newey and West (1987) standard errors with 60 lags (to account for the error serial correlation induced by the unavoidable overlapping observation problem). As shown in Panel A, hedge funds AUM flows $g_{AUM,t}$ predict a decrease of $SR_t^2(r^*_{i,t,t+h})$ and, therefore, a decrease of predictability. This is consistent with our predictability determination model in (17). Also consistent with our model is the fact that the sum of the coefficients of $g_{AUM,t}$ is negative either in the autoregressive part of the model or in the part that multiplies the transition function, though this sum of coefficients if never statistically significant. The estimates for the threshold, in the models in which the latter is specified as a fixed parameter, are consistent (i.e., $c = 0.25$ in models 2 and 3) with a squared SR of $c = 0.25$ per annum, or a SR of 0.5 per annum, which is a very reasonable estimate. Similarly, in the models with dynamic threshold specified as a multiple of the lagged variance of the return on the market portfolio (the S&P), the multiple is $c = 28.72$, which implies a marginal trader RRA given by $RRA_t = \sqrt{28.72} = 5.35$, which is in line with the RRA bound proposed by Ross (2005) and used by Poti and Wang (2010).

8. Conclusions and final remarks

In this paper, our focus is on the determination of predictability of financial asset returns or, equivalently, on predictability of predictability in financial markets. Building on Poti and Siddique (2013), we develop a model in which capital constraints and limited capital mobility determine the magnitude and variation of predictability over time and across assets. To test this model, we explore the different properties of momentum and reversal strategies on gold and the S&P, taken to represent safe haven and risky assets, during different stages of the economic cycle.

Conventional wisdom has it that momentum strategies fail during volatile times, hence they should fail during recessions. The point, however, is the relative strength of the trend vs. the volatility of the traded asset. If volatility is high but, due to delayed absorption of information, the trend is even stronger, momentum will make money. The strategy would have to be started, however, at a time of relative capital scarcity (i.e., recessions in the case of the S&P and expansions in the case of gold), as otherwise prices would not discount information with a delay and no trend would ensue. Hence, momentum strategies on safe assets will do well if started during a recession but momentum strategies on safe haven will do well if started during expansions, which are times of capital outflows from safe havens and, therefore, times of capital scarcity.

A related issue is the one raised by Asness *et al.* (2013) in their 2013 article in the Journal of Finance (page 962). They write:

"*Why does momentum load positively and value load negatively on liquidity* *risk? ... Further investigation into the opposite signed exposure of value and momentum to liquidity risk is an interesting research question, but beyond the scope of this paper*".

Our results suggest that the explanation is precisely the different timing of risk capital flows to safe haven and risky assets we propose. More specifically, momentum loads positively on liquidity because liquidity is a proxy for risk capital so, when it flows into a market, the latter becomes more efficient and prices slowly move towards the fair value, whether from below or from above (depending on where they were before the liquidity flow). The opposite is the case for value (reversal). It is profitable to start a contrarian strategy (with a suitably long time horizon) when risk capital moves out of a market and prices get out of line with fundamentals. If this explanation is correct, an implication is that "alphas" should be more persistent than Sharpe ratios both for momentum and reversal strategies. We leave the investigation of this implication for further research.

The usefulness of our results is that they clarify the circumstances when one can expect financial asset returns to be predictable. For risky assets, as we have seen, this is during recessions and when risk capital leave the hedge fund industry. For safe havens, this is at the opposite times. Further worthwhile steps, which will be taken next in the research program to which this report belongs, include the identification of estimators of predictability that can be used in real time. All known estimators of predictability require knowledge, explicitly or implicitly, of the ex-post performance of predictability-based strategy. For example, $SR_t^2(r^*_{i,t,t+h})$ requires knowledge of the performance between t and $t+h$ of the predictability-based strategy $r^*_{i,t,t+h}$, i.e. the average momentum/reversal strategy in our context. The coefficient of determination of predictive regressions and variance ratios (used, among others, by Campbell and Thompson (2008) and, in conjunction with a predictability bound, by Levich and Poti (2015); but see also Cochrane (2005) for a systematic and lucid discussion) suffer from the same shortcoming because they represent measures of predictability that can only be exploited by entering a suitable trading strategy at the beginning of the estimation period and keeping it in place until the end. One possibility, which we shall explore next, is to extract predictability estimates from traded option prices. By applying our model to a time series of these predictability estimates, it would then be possible to obtain "real time" forecasts of how this preditability would evolve. An obvious possible applications would be to help decide whether to commit capital (i.e., invest) to the exploitation of predictability, e.g. whether to open a trading desk. Another less obvious application would be in terms of econometric modeling and forecasts of predictability can be used to refine priors about predictability itself and related parameters in econometric models in a number of contexts, e.g. in making inferences on asset pricing models.

9. Appendix

Consider the regression model, or an estimate (of a possibly reduced form representation) thereof, of the data generation process (DGP) given in equation (1) of the main text of the article. The coefficient of determination $R^2 \equiv \frac{\sigma_\mu^2}{\sigma_r^2}$ of such a model, where $\sigma_\mu^2 \equiv \sigma^2(\mu_{t+1}(I_t))$ is the unconditional variance of conditional mean excess-returns and $\sigma_r^2 \equiv \sigma^2(r_{t+1})$ is the unconditional variance of excess-returns, can be decomposed as follows:

$$\begin{aligned} R^2 \equiv \frac{\sigma_\mu^2}{\sigma_r^2} &= \frac{E\left(\mu_{t+1}^2\right) - E\left(\mu_{t+1}\right)^2}{\sigma_r^2} \\ &= \frac{E\left(\mu_{t+1}^2\right)}{\sigma_u^2/(1-R^2)} - \frac{E\left(\mu_{t+1}\right)^2}{\sigma_r^2} \\ &= E\left(\frac{\mu_{t+1}^2}{\sigma_u^2}\right)\left(1-R^2\right) - E\left(\frac{\mu_{t+1}}{\sigma_r}\right)^2 \\ &= E\left(\left(\frac{\mu_{t+1}}{\sigma_u}\right)^2\right)\left(1-R^2\right) - SR\left(r_{t+1}\right)^2 \end{aligned}$$

In the first term on the right-hand side of this equation, the expression inside the expectation can be seen as the squared conditional Sharpe Ratio (SR) in the special case of constant conditional volatility[8], whereas the second term is simply the squared unconditional SR attainable by holding the asset with excess-return r_{t+1} (the currency, in our case). We can thus write:

$$R^2 = E\left(SR_t\left(r_{t+1}\right)^2\right)\left(1-R^2\right) - SR\left(r_{t+1}\right)^2 \quad \text{(A.1)}$$

In this study, we are only concerned with the predictability of excess-returns. When pricing excess-returns, the risk-free rate can be treated as if it were constant and known. In this case, as shown by Cochrane (1999),[9] the squared un-

[8]Or simply neglecting heteroskedasticity as a further possible source of predictability and hence profitability

[9]See p. 75-76 in the appendix of Cochrane (1999).

conditional SR is the expectation of the squared conditional SR, i.e. $SR(r_{t+1})^2 = E\left(SR_t\left(r_{t+1}\right)^2\right)$. In the case of a predictability-based strategy that involves only a single risky asset (alongside the risk-free one), its conditional SR is generated by time-varying positions in such asset. Hence, the conditional SR of the strategy that exploits the predictability of the asset with excess-return r_{t+1}, to which we refer as the *rational* trading rule on such asset, is generated by a time varying position in the asset itself. Letting r^*_{t+1} denote (as in the main text of the article) the excess-return on such strategy, its unconditional squared SR is thus $SR\left(r^*_{t+1}\right)^2 = E\left(SR_t\left(r^*_{t+1}\right)^2\right) = E\left(SR_t\left(r_{t+1}\right)^2\right)$. We can therefore rewrite (A.1) as follows:

$$R^2 = SR\left(r^*_{t+1}\right)^2\left(1 - R^2\right) - SR^2\left(r_{t+1}\right) \qquad \text{(A.2)}$$

The equality in (A.2), in turn, can be solved for the unconditional squared SR of r^*_{t+1}:

$$SR\left(r^*_{t+1}\right)^2 = \frac{SR^2(r_{t+1}) + R^2}{1 - R^2} \qquad \text{(A.3)}$$

Hence, the SR of r^*_{t+1} can be decomposed in the SR of a 'static' long position in the currency and the coefficient of determination R^2 of the dynamic strategy that exploits its predictability. This shows that there exists a duality between the R^2 of a given predictive model and the SR attainable by exploiting the predictability captured by the model. As a consequence of (A.3), we also have $R^2 \leq SR\left(r^*_{t+1}\right)^2$. That is, the R^2 of a given predictive regression is no greater than the squared SR of the rational trading rule that exploits the predictability captured by the regression itself.

Following Poti and Wang (2010), who build on Ross (2005), one way to restrict the attainable SR is to directly restrict the curvature of the marginal trader's utility function by imposing a relative risk aversion (RRA) upper bound RRAV, i.e. imposing

$$SR\left(r^*_{t+1}\right)^2 \leq \sigma\left(m_{t+1}\right)^2 \leq \sigma\left(\varphi_{V,t+1}\right)^2 \cong RRA_V^2\sigma(r_{m,t+1})^2 \equiv \phi \qquad \text{(A.4)}$$

Here, $\varphi_{V,t+1}$is the IMRS between present and future wealth of an investor with relative risk aversion RRA_V and $\sigma\left(r_{m,t+1}\right)$ is the volatility of the market portfolio. The latter should be seen as the portfolio of risky assets held by the marginal investor active in the wider capital market (the potential entrant in the market for predictability-based strategies in the context of the UMTM). The right-hand side of (A.4), which we denote in short as $\phi \equiv RRA_V^2\sigma\left(r_{m,t+1}\right)^2$, represents an upper bound to the variance of the pricing kernel. Poti and Wang (2010) demonstrate that, as long as the RRA bound holds, the corresponding bound on the volatility of the kernel holds even when the marginal investor exhibits non-constant RRA and thus her preferences are defined over moments of possibly third and higher orders. [10]

[Table 1 about here.]

[Table 2 about here.]

[Table 3 about here.]

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

[Table 8 about here.]

[10] In particular, Poti and Wang (2010) argue that the IMRS volatility bound must hold in world where, consistent with 3 and 4 moment extensions of the CAPM, co-skewness and co-kurtosis risk carry a non-zero price.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

10. References

Adrian, T., Etula, E., Shin, H.S. (2010). Risk Appetite and Exchange Rates. *Federal Reserve Bank of New York Staff Report no. 361.*

Asness, C. S., Krai, R.l, Liew, J. (2001). Do hedge funds hedge? *Journal of Portfolio Management*, **28**(1).

Asness, Clifford S., Moskowitz, Tobias J., Pedersen, Lasse Heje. (2013). Value and Momentum Everywhere. *The Journal of Finance*, **68**(3), 929–985.

Baker, Scott R., Bloom, Nicholas, Davis, Steven J. (2015 (October)). *Measuring Economic Policy Uncertainty.* Working Paper 21633. National Bureau of Economic Research.

Baur, D., Lucey, B. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review*, **45**, 217–229.

Baur, Dirk G., McDermott, Thomas K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, **34**(8), 1886–1898.

Baur, G., Glover, K. (2012). The Destruction of a Safe Haven Asset?

Beckmann, Joscha, Czudaj, Robert. (2013). Gold as an inflation hedge in a time-varying coefficient framework. *The North American Journal of Economics and Finance*, **24**(0), 208–222.

Bredin, Don, Conlon, Thomas, Poti, Valerio. (2015). Does Gold Glitter in the Long-Run? Gold as a Hedge and Safe Haven Across Time and Investment Horizon. *International Review of Financial Analysis*, **Forthcoming**.

Campbell, John Y., Thompson, Samuel B. (2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies*, **21**(4), 1509–1531.

Chorafas, D.N. (2004). *Economic Capital Allocation with Basel II.* Elsevier.

Cochrane, J.H. (1999). *Portfolio advice for a multifactor world.* Report. National Bureau of Economic Research.

Cochrane, J.H. (2005). *Asset pricing.* Princeton: Princeton University Press.

Duffie, Darrell. (2010). Presidential Address: Asset Price Dynamics with Slow-Moving Capital. *The Journal of Finance*, **65**(4), 1237–1267.

Duffie, Darrell, Strulovici, Bruno. (2012). Capital Mobility and Asset Pricing. *Econometrica*, **80**(6), 2469–2509.

Fama, E.F., French, K.R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 55–84.

Haddad, V. (2014). Concentrated Ownership and Equilibrium Asset Prices.

Hodrick, Robert J. (1992). Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. *Review of Financial Studies*, **5**(3), 357–386.

Jegadeesh, N., Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 65–91.

Jobson, J. D., Korkie, Bob M. (1981a). Performance Hypothesis Testing with the Sharpe and Treynor Measures. *The Journal of Finance*, **36**(4), 889–908.

Jobson, J.D., Korkie, B.M. (1981b). Performance Hypothesis Testing with the Sharpe and Treynor Measures. *Journal of Finance*, **36**(4).

Jylha, P., Suominen, M. (2011). Speculative capital and currency carry trades. *Journal of Financial Economics*, **99**, 60–75.

Kondor, P., Vayanos, D. (2014). Liquidity Risk and the Dynamics of Arbitrage Capital.

Kruttli, Mathias S., Patton, Andrew J., Ramadorai, Tarun. (2015). The Impact of Hedge Funds on Asset Markets. *Review of Asset Pricing Studies.*

Levich, Richard M., Poti, Valerio. (2015). Predictability and "good deals" in currency markets. *International Journal of Forecasting*, **31**(2), 454–472.

Lucey, B., Tully, E., Poti, V. (2006). International Portfolio Formation, Skewness and the Role of Gold. *Frontiers in Finance and Economics*, 49–68.

Matten, C. (1996). *Managing Bank Capital: Capital Allocation and Performance Measurement.* Chichester, UK: John Wiley & Sons.

Mitchell, Mark, Pulvino, Todd. (2012). Arbitrage crashes and the speed of capital. *Journal of Financial Economics*, **104**(3), 469–490.

Moskowitz, T.J., Ooi, Yao Hua, Pedersen, Lasse Heje. (2012). Time series momentum. *Journal of Financial Economics*, **104**(2), 228 – 250. Special Issue on Investor Sentiment.

Newey, W.K., West, K.D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica: Journal of the Econometric Society*, **55**, 703–708.

Poti, V., Wang, D.L. (2010). The coskewness puzzle. *Journal of Banking & Finance*, **34**(8), 1827–1838.

Poti, Valerio, Siddique, Akhtar. (2013). What drives currency predictability? *Journal of International Money and Finance*, **36**(0), 86–106.

Ranaldo, Angelo, Soderlind, Paul. (2010). Safe Haven Currencies. *Review of Finance*, **14**(3), 385–407.

Ross, S.A. (2005). *Neoclassical finance.* Princeton Univ Pr.

Vayanos, Dimitri, Woolley, Paul. (2013). An Institutional Theory of Momentum and Reversal. *Review of Financial Studies*, **26**(5), 1087–1145.

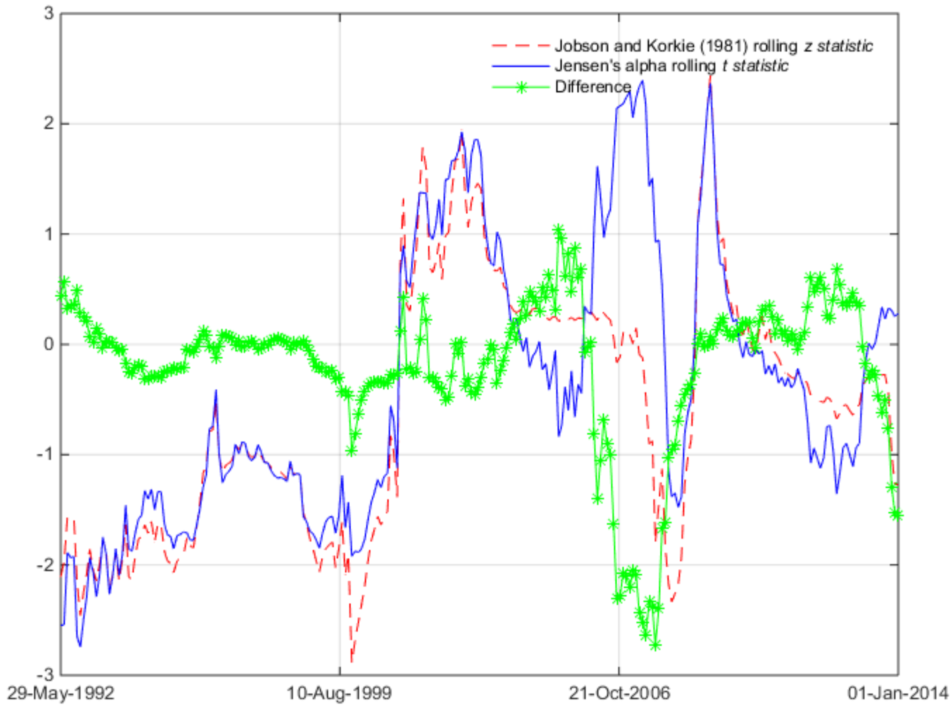

Figure 1: This Figure plots the time series of the Jobson and Korkie (1981) rolling z statistic and of Jensen's Alpha estimated over rolling 5-year windows of monthly data on S&P excess-returns.

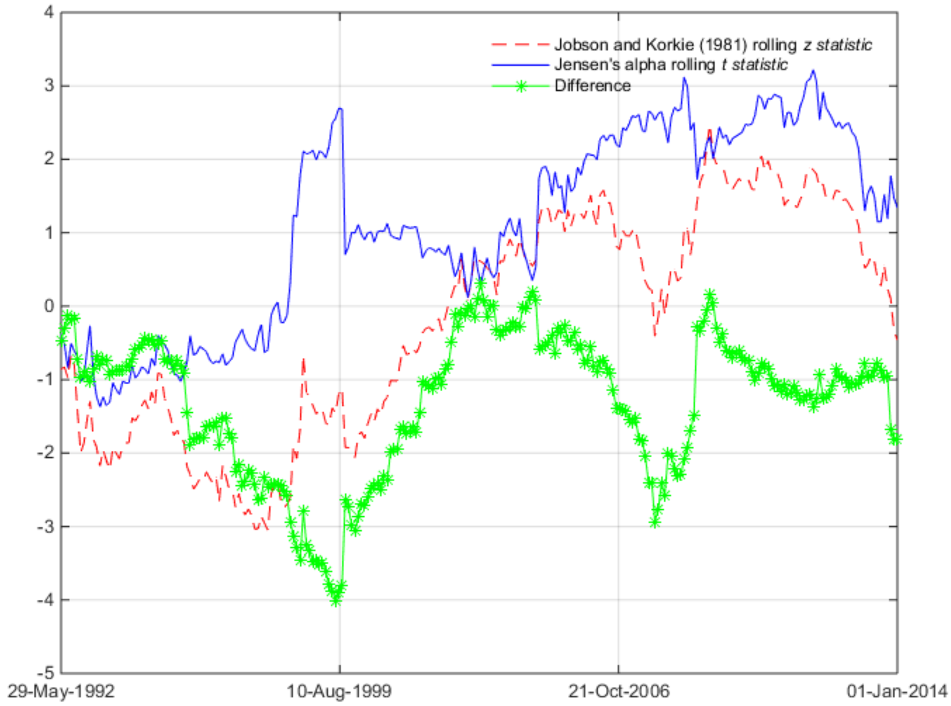

Figure 2: This Figure plots the time series of the Jobson and Korkie (1981) rolling z statistic and of Jensen's Alpha estimated over rolling 5-year windows of monthly data on excess-returns on gold.

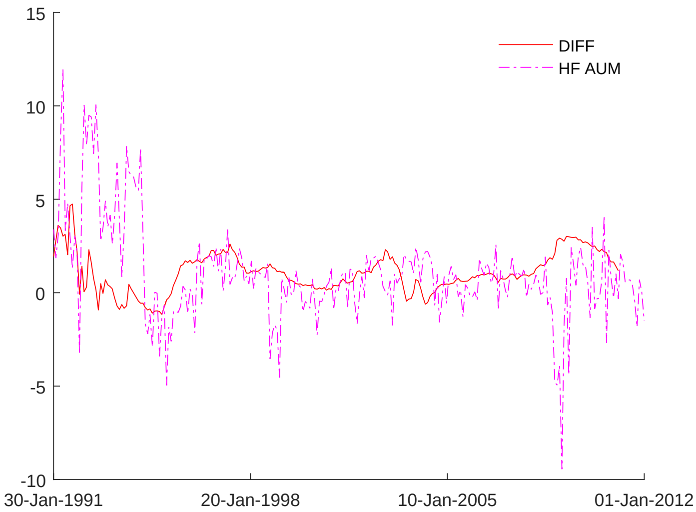

Figure 3: This Figure plots the time series of the difference between the squared Jobson and Korkie (1981) rolling z statistic and the squared Jensen's Alpha estimated over rolling 5-year windows of monthly data on S&P excess-returns.

Table 1: This table reports annualized **ex-post Sharpe Ratios** over the full sample period 1982-2013 for momentum strategies (in the column labelled "Momentum") and volatility-weighted momentum strategies (in the column labelled "Weighted Momentum") characterized by differing holding periods, as well as the equally weighted average of these strategies (in the row labeled by "Average") and, for comparison, for 'buy & hold' strategies with the same holding period. The strategies use the sign of returns over a lookback period to signal the position to be held for a holding period. In each case, **both the lookback period and the holding period equal** k. **Weighted momentum corresponds to a strategy taking a volatility-weighted position**.

	Momentum		Weighted Momentum		Buy & Hold	
k	S&P	Gold	S&P	Gold	S&P	Gold
1	0.19	-0.07	0.21	0.02	0.45	0.24
2	0.08	-0.08	0.09	-0.06	0.44	0.24
3	0.20	0.08	0.16	0.12	0.44	0.24
4	0.20	0.16	0.22	0.14	0.44	0.25
5	0.41	0.16	0.37	0.16	0.43	0.25
6	0.43	0.22	0.42	0.25	0.43	0.25
7	0.42	0.35	0.46	0.34	0.43	0.25
8	0.46	0.36	0.53	0.39	0.43	0.25
9	0.51	0.41	0.55	0.41	0.43	0.25
10	0.51	0.45	0.53	0.48	0.43	0.26
11	0.44	0.46	0.48	0.48	0.44	0.26
12	0.46	0.48	0.47	0.47	0.44	0.26
15	0.44	0.43	0.44	0.40	0.44	0.27
18	0.37	0.39	0.41	0.32	0.44	0.28
21	0.38	0.38	0.42	0.26	0.44	0.29
24	0.34	0.38	0.40	0.25	0.44	0.29
Avg	0.45	0.41	0.49	0.35	0.43	0.26

Table 2: This table reports Sharpe Ratios for positions **initiated** during recessionary (Panel A) and expansionary periods for differing investment strategies over the period 1982-2013. Momentum strategies use the sign of returns over the lookback period k to signal the position to be held for the holding period. In each case, the lookback period is equal to the holding period. Weighted momentum corresponds to a strategy taking a volatility weighted position. The signal is based upon the sign of the return over the entire lookback only. For comparison, we also report Sharpe Ratios for 'buy & hold' strategies with the same holding periods.

Panel A (Recession)

	Momentum		Weighted Momentum		Buy & Hold	
k	S&P	Gold	S&P	Gold	Gold	S&P
1	0.85	-0.55	1.21	-0.53	0.29	-0.78
2	0.48	-0.81	0.50	-0.70	0.29	-0.78
3	0.63	-0.65	0.52	-0.66	0.29	-0.78
4	0.61	-0.03	0.49	-0.04	0.29	-0.78
5	0.57	-0.52	0.38	-0.52	0.29	-0.78
6	0.49	-0.08	0.28	-0.11	0.29	-0.78
7	0.37	0.09	0.20	0.04	0.29	-0.78
8	0.34	0.17	0.23	0.14	0.29	-0.78
9	0.39	0.07	0.37	0.06	0.29	-0.78
10	0.32	0.14	0.33	0.14	0.29	-0.78
11	0.34	0.10	0.40	0.10	0.29	-0.78
12	0.28	0.24	0.32	0.26	0.29	-0.78
15	0.22	0.34	0.31	0.35	0.29	-0.78
18	0.05	0.35	0.24	0.36	0.29	-0.78
21	0.01	0.52	0.25	0.51	0.29	-0.78
24	-0.11	0.48	0.14	0.49	0.29	-0.78

Panel B (Expansion)

	Momentum		Weighted Momentum		Buy & Hold	
k	S&P	Gold	S&P	Gold	Gold	S&P
1	0.07	0.02	0.07	0.11	0.23	0.70
2	0.01	0.17	0.01	0.13	0.24	0.70
3	0.14	0.18	0.14	0.18	0.26	0.69
4	0.13	0.18	0.16	0.18	0.26	0.67
5	0.36	0.26	0.37	0.25	0.28	0.66
6	0.47	0.32	0.46	0.29	0.26	0.67
7	0.50	0.46	0.51	0.40	0.24	0.67
8	0.51	0.45	0.52	0.38	0.28	0.70
9	0.50	0.50	0.51	0.45	0.30	0.71
10	0.50	0.53	0.49	0.50	0.33	0.71
11	0.40	0.48	0.39	0.44	0.33	0.71
12	0.41	0.46	0.39	0.40	0.34	0.71
15	0.36	0.38	0.34	0.30	0.36	0.71
18	0.36	0.36	0.33	0.29	0.35	0.71
21	0.37	0.32	0.34	0.27	0.37	0.73
24	0.32	0.32	0.30	0.28	0.39	0.72

Table 3: This table reports, for the excess-return on several strategies, estimates of the first order autocorrelation coefficient, ρ, and the associated GLS t-statistic, the coefficient of determination, R^2, of the first order autoregression used to estimate ρ and the variance ratio (the ratio of the variance of annual excess-returns to the annualized variance of monthly excess-returns). The strategies under consideration are the un-weighted (in Panel A) and volatility-weighted momentum strategies (in Panel B) on the **S&P** with holding period and lookback period of k months (specified in the first column), as well as the corresponding equally-weighted strategies (in the rows labelled as "Avg"). The sample period is the full one, 1982-2013.

Strategy	ρ	t	R^2	**Variance ratio**
k		**Panel A**		
1	0.02	0.36	0.00	0.97
2	0.05	0.89	0.00	0.97
3	0.09	1.60	0.01	1.00
4	0.07	1.34	0.01	0.86
5	0.07	1.21	0.01	1.12
6	0.10	1.84	0.01	1.17
7	0.12	2.13	0.01	1.11
8	0.13	2.32	0.02	1.08
9	0.08	1.41	0.01	1.04
10	0.09	1.53	0.01	1.15
11	0.07	1.21	0.01	1.24
12	0.07	1.19	0.00	1.29
15	0.05	0.87	0.00	1.49
18	0.03	0.48	0.00	1.58
21	-0.01	-0.12	0.00	1.84
24	0.01	0.14	0.00	2.05
Avg	-0.01	-0.12	0.00	1.40
k		**Panel B**		
1	0.12	2.16	0.01	1.27
2	0.04	0.77	0.00	0.85
3	0.05	0.92	0.00	0.84
4	0.03	0.46	0.00	0.98
5	0.02	0.27	0.00	1.16
6	0.07	1.23	0.01	1.28
7	0.10	1.77	0.01	1.26
8	0.10	1.76	0.01	1.20
9	0.04	0.63	0.00	0.98
10	0.03	0.50	0.00	0.90
11	0.01	0.23	0.00	0.91
12	0.00	-0.06	0.00	0.95
15	0.01	0.20	0.00	1.10
18	0.04	0.65	0.00	1.36
21	0.01	0.26	0.00	1.54
24	0.02	0.33	0.00	1.37
Avg	-0.02	-0.30	0.00	1.19

Table 4: This table reports, for the excess-return on several strategies, estimates of the first order autocorrelation coefficient, ρ, and the associated GLS t-statistic, the coefficient of determination, R^2, of the first order autoregression used to estimate ρ and the variance ratio (the ratio of the variance of annual excess-returns to the annualized variance of monthly excess-returns). The strategies under consideration are the un-weighted (in Panel A) and volatility-weighted momentum strategies (in Panel B) on **gold** with holding period and lookback period of k months (specified in the first column), as well as the corresponding equally-weighted strategies (in the rows labelled as "Avg"). The sample period is the full one, 1982-2013.

Strategy	ρ	t	R^2	**Variance ratio**
k		**Panel A**		
1	-0.11	-1.89	0.01	0.74
2	-0.03	-0.51	0.00	0.84
3	-0.04	-0.72	0.00	0.79
4	-0.13	-2.37	0.02	0.84
5	-0.06	-1.02	0.00	0.81
6	-0.09	-1.54	0.01	1.06
7	-0.08	-1.41	0.01	1.08
8	-0.10	-1.87	0.01	1.13
9	-0.15	-2.62	0.02	0.95
10	-0.14	-2.49	0.02	1.08
11	-0.14	-2.57	0.02	1.06
12	-0.14	-2.44	0.02	1.32
15	-0.13	-2.38	0.02	1.50
18	-0.14	-2.53	0.02	1.78
21	-0.14	-2.59	0.02	1.65
24	-0.15	-2.72	0.02	1.60
Avg	-0.14	-2.61	0.02	1.17
k		**Panel B**		
1	-0.10	-1.80	0.01	0.67
2	0.00	-0.06	0.00	0.86
3	-0.02	-0.38	0.00	0.58
4	-0.07	-1.25	0.01	0.63
5	-0.06	-1.09	0.00	0.79
6	-0.10	-1.72	0.01	0.84
7	-0.08	-1.46	0.01	0.85
8	-0.10	-1.82	0.01	0.79
9	-0.14	-2.50	0.02	0.69
10	-0.14	-2.56	0.02	0.70
11	-0.15	-2.69	0.02	0.72
12	-0.15	-2.64	0.02	0.73
15	-0.15	-2.72	0.02	0.98
18	-0.15	-2.66	0.02	1.07
21	-0.14	-2.43	0.02	1.15
24	-0.13	-2.42	0.02	1.52
Avg	-0.16	-2.90	0.03	0.70

Table 5: This table reports, for the excess-return on several strategies, estimates of the first order autocorrelation coefficient, ρ, and the associated GLS t-statistic, the coefficient of determination, R^2, of the first order autoregression used to estimate ρ and the variance ratio (the ratio of the variance of annual excess-returns to the annualized variance of monthly excess-returns). The strategies under consideration are the risk-factor mimicking portfolios. The sample period is the full one, 1982-2013.

Strategy	ρ	t	R^2	**Variance ratio**
rmrf	0.11	2.03	0.01	1.27
hml	-0.04	-0.70	0.00	0.78
smb	0.13	2.38	0.02	1.51
umd	0.08	1.40	0.01	1.19

Table 6: The panels of this table report alternative models, specified in the headings of the panel themselves, of the measure of excess-predictability $DIFF_t$, of strategies on the S&P with 5-year holding periods initiated at time t. The sample period is from 1991:01 to 2011:01, the longest possible given that data on aggregate hedge fund flows $g_{AUM,t}$ is not available before 1991:01 and that, because of the length of the holding period, the final month for which we can compute SR_t^2 is 2011:01. To save space, we do not report the individual autoregressive coefficients $\beta_{a,1,i}, i = 1, 2, ..., s$, and $\beta_{b,1,i}, i = 1, 2, ..., s$. All p-values are based on Newey and West (1987) HAC standard errors with 60 lags. The p-values for the tests concerning sums of coefficients are obtained using the delta-method.

Transition variable:	$g_{AUM_{t-1}}$		SR_{t-1}^2
Independent variable:	$DIFF_t$	$SR_t^2(r_{i,t,t+h}^*)$	$DIFF_t$
$\sum \beta_{a,1,i}$	0.90	0.89	0.87
	(0.000)	(0.000)	(0.000)
$\sum \beta_{a,2,i}$	-0.04	-0.01	-0.03
	(0.149)	(0.000)	(0.150)
$\sum \beta_{b,1,i}$	-0.05	0.02	0.09
	(0.910)	(0.320)	(0.220)
$\sum \beta_{b,2,i}$	-0.00	0.01	0.01
	(0.764)	(0.951)	(0.593)
$\beta_{a,2,1}$	-0.01	-0.01	0.03
	(0.657)	(0.000)	(0.000)
$\beta_{a,2,2}$	-0.02	0.00	-0.03
	(0.008)	(0.000)	(0.053)
$\beta_{a,2,3}$	-0.01	0.00	0.00
	(0.108)	(0.225)	(0.707)
$\beta_{a,2,4}$	0.00	0.00	-0.03
	(0.004)	(0.014)	(0.176)
$\beta_{a,VXO}$	0.51	0.15	1.14
	(0.018)	(0.000)	(0.006)
$\beta_{a,rec}$	0.07	0.02	0.00
	(0.000)	(0.018)	(0.988)
$\beta_{a,unc}$	-0.03	-0.01	-0.07
	(0.231)	(0.000)	(0.228)
$\beta_{b,2,1}$	-0.04	0.00	-0.03
	(0.001)	(0.000)	(0.026)
$\beta_{b,2,2}$	0.05	0.01	0.03
	(0.023)	(0.000)	(0.122)
$\beta_{b,2,3}$	0.10	0.00	0.03
	(0.000)	(0.000)	(0.258)
$\beta_{b,2,4}$	-0.10	0.01	-0.02
	(0.000)	(0.000)	(0.000)
$\beta_{b,VXO}$	6.38	-0.07	-2.09
	(0.091)	(0.027)	(0.000)
$\beta_{b,rec}$	0.18	-0.02	0.15
	(0.695)	(0.123)	(0.000)
$\beta_{b,unc}$	0.24	0.01	0.23
	(0.095)	(0.000)	(0.008)
γ	16218.28	242.06	8005.71
	(0.999)	(0.031)	(0.000)
c	4.32	0.00	0.19
	(0.000)	(0.000)	(0.991)
$\overline{R}^2$	0.87	0.86	0.88

Table 7: The panels of this table report alternative models, specified in the headings of the panel themselves, of the measure of excess-predictability $DIFF_t$, of strategies on gold with 5-year holding periods initiated at time t. The sample period is from 1991:01 to 2011:01, the longest possible given that data on aggregate hedge fund flows $g_{AUM,t}$ is not available before 1991:01 and that, because of the length of the holding period, the final month for which we can compute SR_t^2 is 2011:01. To save space, we do not report the individual autoregressive coefficients $\beta_{a,1,i}, i = 1, 2, ..., s$, and $\beta_{b,1,i}, i = 1, 2, ..., s$. All p-values are based on Newey and West (1987) HAC standard errors with 60 lags. The p-values for the tests concerning sums of coefficients are obtained using the delta-method.

Transition variable:	$g_{AUM_{t-1}}$		SR^2_{t-1}
Independent variable:	$DIFF_t$	$SR_t^2(r^*_{i,t,t+h})$	$DIFF_t$
$\sum \beta_{a,1,i}$	0.82	0.94	0.88
	(0.053)	(0.000)	(0.000)
$\sum \beta_{a,2,i}$	-0.15	0.00	0.01
	(0.072)	(0.029)	(0.054)
$\sum \beta_{b,1,i}$	0.13	0.01	-1617.87
	(0.074)	(0.780)	(1.000)
$\sum \beta_{b,2,i}$	0.5	-0.00	119.87
	(0.082)	(0.184)	(0.587)
$\beta_{a,2,1}$	-0.03	0.00	0.01
	(0.549)	(0.639)	(0.486)
$\beta_{a,2,2}$	-0.05	0.00	-0.01
	(0.016)	(0.715)	(0.099)
$\beta_{a,2,3}$	0.01	0.00	-0.01
	(0.000)	(0.103)	(0.323)
$\beta_{a,2,4}$	-0.09	0.00	0.03
	(0.073)	(0.103)	(0.009)
$\beta_{a,VXO}$	0.22	0.04	-2.04
	(0.810)	(0.014)	(0.021)
$\beta_{a,rec}$	-0.41	-0.01	0.72
	(0.010)	(0.004)	(0.000)
$\beta_{a,unc}$	0.10	0.00	-0.56
	(0.270)	(0.000)	(0.000)
$\beta_{b,2,1}$	0.04	0.00	591.45
	(0.221)	(0.502)	(0.000)
$\beta_{b,2,2}$	0.04	0.00	-3583.56
	(0.136)	(0.381)	(0.000)
$\beta_{b,2,3}$	-0.02	0.00	1411.09
	(0.242)	(0.321)	(0.000)
$\beta_{b,2,4}$	0.09	0.00	1700.81
	(0.057)	(0.082)	(0.000)
$\beta_{b,VXO}$	-4.77	-0.05	-84560.35
	(0.000)	(0.286)	(0.000)
$\beta_{b,rec}$	1.06	0.01	-32666.22
	(0.000)	(0.348)	(0.000)
$\beta_{b,unc}$	-0.66	0.01	6577.06
	(0.000)	(0.002)	(0.000)
γ	2718.63	204.85	62.25
	(0.000)	(0.002)	(0.000)
c	0.17	0.00	0.33
	(0.000)	(0.000)	(0.000)
$\overline{R}^2$	0.84	0.93	0.79

Table 8: The panels of this table report alternative models, specified in the headings of the panel themselves, of the average squared Sharpe ratio, SR_t^2, of strategies with 5-year holding periods initiated at time t. The sample period is from 1991:01 to 2011:01, the longest possible given that data on aggregate hedge fund flows $g_{AUM,t}$ is not available before 1991:01 and that, because of the length of the holding period, the final month for which we can compute SR_t^2 is 2011:01.

Panel A (No threshold)

$$SR_t^2 = \beta_0 + \beta_{1,1}SR_{t-1}^2 + ... + \beta_{1,s}SR_{t-s}^2 + g_{AUM,t-1} \times SR_{t-1}^2 + u_t$$

	β_0	SR_{t-1}^2	SR_{t-2}^2	SR_{t-3}^2	$g_{AUM,t-1}$	$g_{AUM,t-1} \times SR_{t-1}^2$	$\overline{R}^2$
1.	0.08	0.45	0.30	0.18	-0.49	2.10	0.83
	(0.023)	(0.000)	(0.000)	(0.003)	(0.003)	(0.030)	

Panel B.1 (LSTAR Exogenous time-invariant threshold)

$$SR_t^2 = \beta_0 + \beta_{1,1}SR_{t-1}^2 + ... + \beta_{1,4}SR_{t-4}^2$$
$$+\beta_{2,1}g_{AUM,t-1} + ... + \beta_{2,4}g_{AUM,t-4} + f_t g_t + u_t,$$
$$f_t = const. + \beta_{3,1}g_{AUM,t-1} + ... + \beta_{3,4}g_{AUM,t-4},$$
$$g_t = 1 - (1 + exp(\gamma(SR_{t-1}^2 - c)))^{-1}$$

	$\sum \beta_{1,i}$	$\sum \beta_{2,i}$	$\sum \beta_{3,i}$	γ	c	$\overline{R}^2$
2.	1.03	-0.37	1.75	17115.27	0.25	0.85
	(0.000)	(0.153)	(0.000)	(0.987)	(0.000)	

Panel B.2 (ESTAR Exogenous time-invariant threshold)

$$SR_t^2 = \beta_0 + \beta_{1,1}SR_{t-1}^2 + ... + \beta_{1,4}SR_{t-4}^2$$
$$+\beta_{2,1}g_{AUM,t-1} + ... + \beta_{2,4}g_{AUM,t-4} + f_t g_t + u_t$$
$$f_t = const. + \beta_{3,1}g_{AUM,t-1} + ... + \beta_{3,4}g_{AUM,t-4},$$
$$g_t = 1 - exp(-\gamma(SR_{t-1}^2 - c)^2)$$

	$\sum \beta_{1,i}$	$\sum \beta_{2,i}$	$\sum \beta_{3,i}$	γ	c	$\overline{R}^2$
3.	0.96	14.36	-14.65	19474.23	0.25	0.85
	(0.000)	(0.003)	(0.001)	(0.000)	(0.000)	

Panel C.1 (LSTAR Exogenous time-varying threshold)

$$SR_t^2 = \beta_0 + \beta_{1,1}SR_{t-1}^2 + ... + \beta_{1,4}SR_{t-4}^2$$
$$+\beta_{2,1}g_{AUM,t-1} + ... + \beta_{2,4}g_{AUM,t-4} + f_t g_t + u_t,$$
$$f_t = const. + \beta_{3,1}g_{AUM,t-1} + ... + \beta_{3,4}g_{AUM,t-4},$$
$$g_t = 1 - (1 + exp(\gamma(SR_{t-1}^2 - c \times \sigma^2(r_{m,t-1}))))^{-1}$$

	$\sum \beta_{1,i}$	$\sum \beta_{2,i}$	$\sum \beta_{3,i}$	γ	c	*Restrictions*	$\overline{R}^2$
4.a	-0.035	0.55	-1.60	0.58	28.72		0.86
	(0.493)	(0.271)	(0.200)	(0.031)	(0.028)		
4.b	-0.030	0.55	-1.13	0.68	25.00	$c \leq 25$	0.86
	(0.446)	(0.441)	(0.258)	(0.000)	(0.000)		
4.c	0.084	0.46	-1.36	5.56	5.00	$c \leq 5$	0.86
	(0.303)	(0.592)	(0.471)	(0.000)	(0.000)		

Panel C.2 (ESTAR Exogenous time-varying threshold)

$$SR_t^2 = \beta_0 + \beta_{1,1}SR_{t-1}^2 + ... + \beta_{1,4}SR_{t-4}^2$$
$$+\beta_{2,1}g_{AUM,t-1} + ... + \beta_{2,4}g_{AUM,t-4} + f_t g_t + u_t,$$
$$f_t = const. + \beta_{3,1}g_{AUM,t-1} + ... + \beta_{3,4}g_{AUM,t-4},$$
$$g_t = 1 - exp(-\gamma(SR_{t-1}^2 - c \times \sigma^2(r_{m,t-1})))$$

	$\sum \beta_{1,i}$	$\sum \beta_{2,i}$	$\sum \beta_{3,i}$	γ	c	$\overline{R}^2$
5.	0.16	-0.21	0.50	0.56	20.16	0.86
	(0.052)	(0.451)	(0.265)	(0.058)	(0.000)	