Sticky Expectations and Stock Market Anomalies*

PRELIMINARY VERSION – DO NOT CIRCULATE

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Abstract

We propose a simple model in which investors price a stock using a persistent signal and sticky belief dynamics à la Coibion and Gorodnichenko (2012). In this model, returns can be forecasted using (1) past profits, (2) past change in profits, and (3) past returns. The model thus provides a joint theory of two of the most economically significant anomalies, i.e. quality and momentum. According to the model these anomalies should be correlated, and be stronger when signal persistence is higher, or when earnings expectations are stickier. Using I/B/E/S data, we measure expectation stickiness at the analyst level. We find that analysts are on average sticky and, consistent with a limited attention hypothesis, more so when they cover more industries. We find strong support for the model's prediction in the data: both the momentum and the quality anomaly are stronger for stocks with more persistent profits, and for stocks which are followed by stickier analysts. Consistent with the model, both strategies also comove significantly.

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I Introduction

The existence of stock-return predictability is a central theme in the asset pricing literature: several stock-level characteristics beyond market betas significantly predict future stock-returns. A long-lasting debate pertains to the origin of such abnormal returns and to how they can exist in equilibrium without being arbitraged away. One strand of the literature is focused on interpreting abnormal returns as risk premia (see, for instance, Cochrane (2011))–implying they are only seemingly abnormal–while other authors attribute them to behavioral biases combined with limits to arbitrage (see, e.g., Barberis and Thaler (2003) or references therein, such as Daniel et al. (1998, 2001); Hirshleifer (2001)). Mispricing then relies on investors making systematic expectation errors, while rational arbitrageurs are unable to fully accommodate their demand because arbitrage is not risk-free. In this literature, the behavioral biases of the non-rational market-participants typically take the form of non-Bayesian expectations grounded in the psychology literature (see, e.g., Hong and Stein (1999) or Barberis et al. (1998)).

The focus of this paper is the "quality" anomaly: stocks with high profitability ratios tend to outperform on a risk-adjusted basis (Novy-Marx, 2013, 2015). Quality (or "profitability") has recently emerged as one of the stock-return anomalies with the largest economic significance. The corresponding long-short arbitrage strategy features high Sharpe ratios, no crash risk (Lemperiere et al., 2015), and very high capacity due to the high persistence of the profitability signal (e.g., operating cash-flow to asset ratio) on which the strategy sorts stocks (Landier et al., 2015). Our goal in this paper is to test if the quality anomaly can be directly related to a simple model of sticky expectations, in which investors update their beliefs too slowly.

We start by building a simple model in which risk-neutral investors price a stock, whose dividend is predictable with a persistent signal. These investors have "sticky" expectations à la Coibion and Gorodnichenko (2012, 2015), i.e. they are characterized by systematically under-reacting to new information (e.g., the release of earnings). Each period, they update their beliefs using all available information with a probability $1 - \lambda$. With probability λ, they stick to their previous beliefs. When solving this very simple model, we find that future stock returns can be forecasted using (1) past profits, (2) past changes in profits, and (3) past returns. Thus, the model provides a joint rationalization for quality and momentum, which are arguably the most significant anomalies documented in the literature (Frazzini et al., 2012). Another advantage of this model is that it incorporates rational expectations as a particular case.

We then examine whether the level of stickiness present in the data is big enough to explain the quality anomaly. We use observed earnings forecasts by financial analysts from I/B/E/S to test this hypothesis. Using directly observable expectations contained in financial analysts' EPS forecasts is a natural setting to study how beliefs of market participants potentially deviate from rational expectations. Analysts are professional forecasters and their forecasts are not cheap talk, which mitigates the legitimate skepticism for subjective answers found in surveys (see Bertrand and Mullainathan (2001)). Using these data, we find that the average forecaster reduces her distance to the rational forecast by about 15% per month, a level of stickiness consistent with evidence on macroeconomic forecasters (Coibion and Gorodnichenko, 2012, 2015).

We spell out several predictions that derive directly from of our simple model. First, our model predicts that firms subject to more sticky EPS forecast updating or more persistent cash-flows should also be more prone to both the quality and momentum anomalies. Second, the model also predicts that the quality and momentum anomalies should be positively correlated. In the data, we find strong evidence to support these two hypotheses: the magnitudes of both anomalies are increasing in expectation stickiness and cash-flow persistence. The tests of ancillary predictions also suggest that quality, like momentum, are well explained by the sticky expectation hypothesis.

Our analysis is mostly a contribution to the behavioral finance literature. Lakonishok et al. (1994) and Laporta (1996) both argue that the value premium is related to some level of extrapolative bias by analysts about glamor stocks. They do not directly look at analyst expectations but at earnings announcement returns. More recently, Brav et al. (2005) have looked at the predictability of returns expectation errors on a restricted set of strategies, but do not attempt to put economic structure on expectation dynamics. Our paper also relates to the old debate about under- vs overreaction. DeBondt and Thaler (1990) document patterns of overreaction by looking at analyst revisions. They find that forecasts by analysts tend to be too extreme vis-a-vis subsequent realizations of earnings. Abarbanell and Bernard (1992) show that these extreme forecasts are not due to overreaction to past earnings and find evidence that analysts actually under-react to past earnings, in line with our own results. More recently, Gennaioli et al. (2015) and Greenwood and Shleifer (2014) find that errors in CFO expectations of earnings growth are not rational and are compatible with a model of extrapolative expectations. Using somewhat different tests, and focusing on the cross-section instead of the time-series, our findings go in the direction of underreaction rather than overreaction. In this sense, our results are more consistent with papers that have documented the slow diffusion of information in markets (see, e.g., Hong et al. (2000); Hou (2007)). Finally, most related to our work is Engelberg et al. (2015), who document that predictable returns in various anomalies are concentrated around earnings announcements and days on which significant news is revealed. This is a direct prediction of our set-up which emphasizes sticky expectations about fundamentals: when investors are slow to adjust, expectation mistakes have a potentially larger impact on next period profits than on more distant cash-flows. Thus, excluding earnings announcement dates will significantly dampen the measured performance of the strategy.

In terms of theoretical asset-pricing models, an important strand of the behavioral literature has focused on explaining the value, momentum, and post-earnings announcement drift anomalies. Most related to our work are papers which propose non-Bayesian theories of beliefs dynamics that can explain these anomalies. Barberis et al. (1998) propose a model where investors try to estimate whether prices are in a trending regime or a mean-reverting regime. This generates simultaneously short-term underreaction of stock prices to news and overreaction to a series of good or bad news. Hong and Stein (1999) develop a model where two types of traders co-exist: traders who trade on news and trend-followers. The interaction between these traders generates an equilibrium that exhibits prices with both short-term momentum and long-term reversal. Because our paper focuses on the quality anomaly, we use a simple non-Bayesian set-up with only one type of agent. We directly measure analyst beliefs stickiness and test the comparative statics of the model which are highly constraining on the data: we show that the quality anomaly is stronger for stocks where the measured stickiness of analyst forecasts is higher. This is an indirect validation of the assumption that biases in analyst forecasts about future profitability can be seen as being representative of beliefs of investors.

In its methodology, our paper is also related to the recent macro literature on expectation formation. The model of expectations dynamics that we use is analyzed in Coibion and Gorodnichenko (2012), which was originally applied to professional inflation forecasts. In Mankiw and Reis (2001), agents also update beliefs infrequently due to fixed costs, which in turn leads to sticky prices.

The rest of the paper is organized as follows: The next section lays out the model of Coibion and Gorodnichenko (2012) and adapts it to the context of firm-level characteristics with predictive power on future profits. We derive structural predictions that link the persistence and predictive power of these firm-level characteristics, the level of beliefs stickiness from analysts, and the dynamics of their forecast errors. Section **III** describes the data. Section **IV** gathers our empirical results: First, we document the predictability of returns, earnings, and forecast errors by several firm-level characteristics observable at the time of forecast formation. Secondly, we test structural predictions of the model. Finally, Section **V** concludes.

II Model

A. Expectation Stickiness

We start by analyzing a model with expectation dynamics which can be directly tested without further assumption on the data. We take our model of expectation dynamics from the macro literature on information rigidity (see Mankiw and Reis (2002) or Reis (2006)). The intuition behind this model is that forecasters decide to update their expectations at discrete intervals, but fail to incorporate new and relevant information in the meanwhile.

We use notations from Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015). Let $F_t\pi_{t+h}$ be the expectation formed at t about profits at $t+h$, which we denote as π_{t+h}. Expectations are updated according to the following process:

$$F_t\pi_{t+h} = (1-\lambda)E_t\pi_{t+h} + \lambda F_{t-1}\pi_{t+h} \tag{1}$$

which is easy to interpret. The coefficient λ indicates the extent of expectation "stickiness." When $\lambda = 0$, expectations are perfectly rational. When λ is low, the forecaster rarely incorporates new information into her forecasts, when she does, she does it in a rational way. This framework accommodates patterns of both under-reaction ($0 < \lambda < 1$) and overreaction ($\lambda < 0$). It can be made consistent with models of Bayesian learning with private information (Coibion and Gorodnichenko, 2015). In this case, $0 < 1-\lambda < 1$ can, for instance, reflect the weight given to private signals.

As noted by Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015), this structure gives rise to straightforward testable predictions that are independent of the process underlying profits π_t:

Prediction 1 ***Inferring stickiness from forecast dynamics (Coibion and Gorodnichenko, 2015)***

Assuming expectations are sticky in the sense of equation (1), then the following two closely linked relationships should hold:

1. *Forecast errors should be predicted by past revisions:*

$$E_t\left(\pi_{t+1} - F_t\pi_{t+1}\right) = \frac{\lambda}{1-\lambda}(F_t\pi_{t+1} - F_{t-1}\pi_{t+1}) \tag{2}$$

2. *Revisions are autocorrelated over time:*

$$E_{t-1}\left(F_t\pi_{t+1} - F_{t-1}\pi_{t+1}\right) = \lambda\left(F_{t-1}\pi_{t+1} - F_{t-2}\pi_{t+1}\right) \tag{3}$$

The first relation can directly be tested on expectations data. Coibion and Gorodnichenko (2015) show its validity on inflation expectations. The strength of this relation is that it holds irrespective of the process that governs profits, or assumptions about the information available to forecasters. In that sense, it is a direct test of equation (1). The underlying intuition is that forecast revisions contain some element of new information, partially incorporated into expectations. When revisions predict expectation errors, it means that favorable information (as measured by revisions) leads forecasters to be systematically favorably surprised. The regression coefficient is increasing in the stickiness parameter λ.

The second prediction pertains to the dynamics of forecast errors. Namely, we find that there is momentum in forecasts, and that the intensity of the momentum is directly related to the stickiness of expectations. The intuition for this equation is fairly simple: forecast mistakes get "corrected" at speed λ. The proof is the following:

$$\begin{aligned}
\lambda \left(F_{t-1}\pi_{t+1} - F_{t-2}\pi_{t+1}\right) &= (1-\lambda)\left(E_{t-1}\pi_{t+1} - F_{t-1}\pi_{t+1}\right) \\
&= (1-\lambda)\left(E_{t-1}\pi_{t+1} - E_{t}\pi_{t+1}\right) \\
&+ (1-\lambda)\left(E_{t}\pi_{t+1} - F_{t}\pi_{t+1}\right) + (1-\lambda)\left(F_{t}\pi_{t+1} - F_{t-1}\pi_{t+1}\right) \\
&= (1-\lambda)\left(E_{t-1}\pi_{t+1} - E_{t}\pi_{t+1}\right) + \left(F_{t}\pi_{t+1} - F_{t-1}\pi_{t+1}\right)
\end{aligned}$$

We conclude by applying the operator E_{t-1} and noticing that $E_{t-1}E_t = E_{t-1}$.

The advantage of these two predictions is that they do not depend on further assumptions on the model. They are a direct test of the sticky expectation hypothesis.

B. *Earnings expectations*

We now further assume that firm profits π_{t+1} can be predicted with a signal s_t, that is

$$\pi_{t+1} = s_t + \epsilon_{t+1}, \tag{4}$$

where ϵ_{t+1} is a noise term. The signal is persistent, so that

$$s_{t+1} = \rho s_t + u_{t+1}, \tag{5}$$

where $\rho < 1$ and u_{t+1} is a noise term. One can think of s_t as a sufficient statistic capturing all public information useful to predict future profits. A particular case is to consider that s_t is simply equal to lagged profits or lagged cash-flows, but this is just a particular case. To obtain closed form solutions for conditional expectations, we also assume that ϵ_{t+1} and u_{t+1} follow a normal distribution, but the intuitions we derive in the paper do not hinge on this particular assumption.[1]

The expectation definition (1) can be rewritten as:

$$F_t\pi_{t+1} = (1-\lambda)\sum_{k\geq 0}\lambda^k E_{t-k}\pi_{t+1}$$

Given our assumptions about the profit process and the signal informativeness, we know that $E_{t-k}\pi_{t+1} = \rho^k s_{t-k}$, so that forecasts should write:

$$F_t\pi_{t+1} = (1-\lambda)\sum_{k\geq 0}(\lambda\rho)^k s_{t-k} \tag{6}$$

The econometrician does not observe the signal s_t, but observes the profit π_t, so we can formulate predictions on both the expected forecast *conditional* on π_t, and the conditional earnings surprise. Both predictions will reflect the interaction of signal persistence and slow updating in shaping expectations and expectation errors.

Prediction 2 ***Past profits predict future forecast errors***

Assuming expectations are sticky in the sense of equation (1), and profits can be forecasted using an autoregressive signal s_t, then earnings surprises should follow:

$$E_t\left(\pi_{t+1} - F_t\pi_{t+1}\middle|\, \pi_t\right) = \frac{\rho\lambda^2(1-\rho^2)}{1-\lambda\rho^2}\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t$$

This equation is straightforward to interpret. If expectations are rational ($\lambda = 0$), the earnings surprise should be uncorrelated with past realizations of profits. In fact, it should be zero. As soon as $\lambda > 0$, profits will predict future surprises, but only to the extent that the signal is persistent ($\rho > 0$). This is because past profits are indicative of future profits, but investors underestimate this persistence because they are slow at adjusting their beliefs. So to generate interesting predictions, we need both assumptions: Sticky expectations and persistent signals. The prefactor $\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}$ can be interpreted in a Bayesian manner as follows: When σ_ϵ is large, a high π_t is less likely to imply a high signal level and thus a large mistake. Conversely, when σ_u is large (fast moving signal), a high π_t is more likely to imply a high signal level *that got high only recently*, and thus implies a large mistake.

[1]Note that our assumption also imposes autocorrelation of profits: $\pi_{t+1} = \rho\pi_t + u_t + \epsilon_{t+1} - \rho\epsilon_t$, such that

$$Corr(\pi_{t+1},\pi_t) = \rho\left(1 - \frac{1}{1+\sigma_u^2/((1-\rho^2)\sigma_\epsilon^2)}\right).$$

C. Forecasting Stock Returns

We now assume that all investors are risk neutral and have the same expectation stickiness parameter λ. This is of course an approximation that states that a risk-neutral pricing kernel can be used, which would remain a valid approximation if some of the population is composed of risk-neutral sticky forecasters and the rest is composed of rational arbitrageurs with limits to arbitrage constraints. Our goal is to isolate the specific effect of expectation stickiness on asset prices. The stock price, just after receiving dividend π_t and observing signal s_t, is given by:

$$P_t = \sum_{k \geq 1} \frac{F_t \pi_{t+k}}{(1+r)^k} \tag{7}$$

Given that we know the process of profits and expectations updating, we can easily derive the prices and returns, defined as $R_{t+1} = (P_{t+1} + \pi_{t+1}) - (1+r)P_t$, as a function of past signals.

Proposition 1 *When all agents are risk-neutral λ-sticky, prices and returns are functions of past signals:*

$$P_t = m \sum_{k \geq 0} (\lambda \rho)^k s_{t-k}$$
$$R_{t+1} = m s_{t+1} + s_t + \epsilon_{t+1} - (1-\lambda)(1+m\rho) \sum_{k \geq 0} (\lambda \rho)^k s_{t-k}$$

where $m = \frac{1-\lambda}{1+r-\rho}$.

The econometrician does not observe the signal realization, but observes past returns and past profits. Our third prediction is that future returns can be forecasted using information available to the econometrician. This contrasts with the case where agents are rational ($\lambda = 0$). In that case the expected excess return is zero: $E_t R_{t+1} = m E_t(s_{t+1} - \rho s_t) = 0$. If one notes $P_t^\star$ the rational price (that prevails when $\lambda = 0$), another way to rewrite the dynamics of prices and interpret it further is as follows:

$$P_t = (1-\lambda) P_t^\star + \lambda \rho P_{t-1}$$

So, prices move to the rational price at speed $1 - \lambda$ and there is excess persistence of past prices, especially when ρ is large. The implications for stock returns predictability can be analyzed further: It turns out that the dependency of returns on past signals also predicts that four stock return anomalies documented in the literature should hold in the market we analyze. We describe these anomalies in terms of covariance of future returns with past predictive variables: in the rational case, this covariance should be null.

Prediction 3 ***Belief stickiness and stock-market anomalies***

Assuming expectations are sticky in the sense of equation (1), and profits can be forecasted using an autoregressive signal s_t, then, at the steady state:

1. *Past returns predict future returns (price momentum):*

$$cov(R_{t+1}, R_t) = (1 + m\rho)(m + \rho\lambda)\frac{\lambda\sigma_u^2}{1 - \lambda^2\rho^2} \approx \frac{1 + r}{(1 + r - \rho)^2}\sigma_u^2\lambda$$

2. *Earnings surprises predict future returns (post earnings announcement drift):*

$$cov(R_{t+1}, \pi_{t+1} - F_t\pi_{t+1}) = (1 + m\rho)\frac{\lambda\sigma_u^2}{1 - \lambda^2\rho^2} \approx \rho\left(\frac{1 + r}{1 + r - \rho}\right)\sigma_u^2\lambda$$

3. *Past profits predict future returns ("profitability"):*

$$cov(R_{t+1}, \pi_t) = (1 + m\rho)\frac{\rho\lambda^2}{1 - \lambda\rho^2}\sigma_u^2 \approx \rho\left(\frac{1 + r}{1 + r - \rho}\right)\sigma_u^2\lambda^2$$

4. *Increases in past profits predict future returns ("earnings momentum"):*

$$cov(R_{t+1}, \Delta\pi_t) = (1 + m\rho)\frac{\rho\sigma_u^2}{1 + \lambda\rho}\lambda^2$$

5. *Changes in the forecasts of profits predict future returns ("post-revision drift"):*

$$cov(R_{t+1}, F_t\pi_{t+1} - F_{t-1}\pi_{t+1}) \approx (1 + m\rho)\sigma_u^2\lambda$$

where the approximations are made for $\lambda << 1$ ("near-rational" expectations). Hence, under the "near rational" approximation, the forecasting power of these four variables increases with λ and ρ.

Obviously, all four items require that $\lambda > 0$, i.e. that there is some degree of stickiness in expectations. The forecasting power is, however, not in general a monotonic function of λ. For instance, when the signal has very little persistence, momentum is decreasing in λ when λ is large enough. This comes from the fact that investors do not make much mistakes by being "too slow". Another interesting by-product of our analysis is that sticky expectations have the power of explaining the last three items *if and only if* the signal is persistent. This ties again to the intuition that slow updating is not a big source of mispricing when recent news are not informative about the future. It makes returns more volatile (bigger mistakes are made every period), but does not generate persistence.

That items 1–5 of Prediction 3 hold in the data has been shown in the large empirical literature on asset pricing. Jegadeesh and Titman (1993) provide evidence of price momentum in equity markets. Post earnings announcement drift was already interpreted in the 1990s as evidence of investor underreaction to news about fundamentals (Abarbanell and Bernard, 1992). Novy-Marx (2013) shows the strength of the profitability anomaly and Landier et al. (2015) document that it is indeed a large anomaly, since a lot of money can be put at work in it without big transaction costs. Novy-Marx (2015) documents that changes in earnings also forecast returns, and Stickel (1991) and Chan et al. (1996) provide evidence that stock prices drift after analyst revisions.

In this paper, we go a step further and test the comparative statics suggested by the model on the cross-section of stock returns. These comparative statics are derived in the case where λ is small, which turns out to be the case in the data. In this case, a higher value of λ reinforces the anomaly. The same is true for stronger signal persistence (higher ρ). The second comparative statics property comes from the above mentioned fact that higher persistence makes slow expectations a larger source of mistake about the future. This is because current profits have the ability to forecast future ones. Also, when profits are more persistent, prices react more to small changes in current profits, so this acts as a multiplier of the first effect.

D. Comovement Between Portfolios

Our model also makes predictions about how different anomaly portfolios comove. So far we have focused on stock-level predictions, so let us build notations to analyze portfolio returns. Assume now N stocks indexed by i. N is large, but not infinite. R_t is the vector of stock returns R_{it}. For simplicity, ϵ_{it} is assumed to be i.i.d. in the time series (as before) and in the cross-section of stocks. Adding a common factor would not dramatically affect the results, as we will be focusing on long-short portfolios. Let w_t be a vector of portfolio weights w_{it} at date t. For instance, $w_t = \pi_t/N$ is the quality portfolio; $w_t = R_t/N$ is the momentum portfolio. Let $R^w_{t+1} = w'_t R_{t+1}$ be the portfolio return based on weights w.

Prediction 4 ***The positive correlation of arbitrage portfolios***

Assume that expectations are sticky in the sense of equation (1), and profits can be forecasted using an autoregressive signal s_t. Furthermore, assume near-rational expectations ($\lambda \ll 1$), then the expected PNL of the four above-mentioned anomalies should comove positively.

III Data

A. Data construction

To construct our sample of analyst expectations, we obtain earnings forecasts from the I/B/E/S Detail History file (unadjusted). We retain all forecasts that were issued 90 days *after* the previous earnings announcement date. We focus on analyst forecasts for the current fiscal year as well as earnings forecasts for one and two fiscal years ahead[2]. Given that firms typically report earnings about one month after the end of the fiscal year[3], the EPS forecasts for the current fiscal year have a horizon of between 11 and 8 months. Similarly, forecasts of next fiscal year's earnings have a horizon of about 23 to 20 months and forecasts for earnings two fiscal years ahead have an horizon of between 35 and 32 months.

We calculate the consensus forecast at a given horizon as the median analyst forecast of all analyst forecasts issued in the 90 days after the previous earnings announcement date. Next, we match actual reported EPS from the I/B/E/S unadjusted actuals file with the analyst forecasts we retain. As pointed out in prior research (see Robinson and Glushkov (2006), problems can arise when actual earnings from the Unadjusted Actuals file are matched with forecasts from the Unadjusted Detail History file. These problems are due to stock splits occurring between the EPS forecast and the actual earnings announcement: if a split occurs between an analyst's forecast and the associated earnings announcement, the forecast and the actual EPS value may be based on a different number of shares outstanding. To deal with this issue, we use the CRSP cumulative adjustment factors to put the forecasts from the Unadjusted Detail History and the actual EPS from the Unadjusted Actuals on the same share basis. Finally, we match stock return and accounting data from CRSP and Compustat respectively.

In order to test our hypotheses, we also construct a sample of monthly stock returns. To do so, we start with all firms in the monthly CRSP database between 1990 and 2013 having share codes 10 and 11. We keep only firms listed on NYSE, Amex, or Nasdaq[4] which we can match with COMPUSTAT. This is our CRSP–Compustat sample. For our stock-return tests we construct what we refer to as the IBES sample. We obtain this sample by keeping only stocks from the CRSP–Compustat sample for which we observe at least two sets of one and two year–ahead eanings forecasts between 1986 and 2013.

[Insert Table I about here.]

[2] We identify forecasts for the different fiscal years by the means of the I/B/E/S Forecast Period Indicator variable *FPI*

[3] The median difference between the earnings announcement date and the fiscal year end date in our sample is 38 days.

[4] Exchange codes 1,2 and 3

In Table I we report summary statistics for the main variables of the EPS forecast sample.

B. Replicating stock-return anomalies in our sample

We now calculate several signals based on firm-level stock market and accounting variables, which have been identified in prior studies to be associated with anomalous stock returns. We use the following five signals:

1. **Cash-flows** *(cf)* denotes the net cash-flow from the firm's operating activities. It is calculated as the ratio of Compustat item *oancf* and *at*. Cash-flows have been shown to be a very strong predictor of returns (see Asness et al. (2014), Landier et al. (2015)). One possible explanation is that cash-flows are a better measure of a firm's fundamental value, consistent with the idea that the difference between cash-flows and earnings predicts returns (Sloan, 1996).

2. **Return on Assets** *(roa)* is income before extraordinary scaled by total assets, that is *ib/at*. This measure of operating profitability has been shown to predict returns well (Asness et al. (2014), Novy-Marx (2013), Ball et al. (Forthcoming)).

3. **Return on Equity** *(roe)* is calculated as net income scaled by common equity, i.e., *ni/ceq*.

4. **Gross Profitability** *(gp)* is calculated according to Novy-Marx (2013) as revenues minus costs of goods sold scaled by total assets, i.e., *(revt-cogs)/at*.

5. **Momentum** (*mom*) is the cumulative firm-level return between months t-12 and t-2.

The first four signals correspond to various ways of measuring a firm's accounting profitability. We verify that the anomalies documented in the literature are indeed present in our CRSP–Compustat sample of monthly stock returns. Accounting signals are updated in the month following a firm's annual earnings announcement and accounting based signals remain valid until the month of the following annual earnings announcement. Earnings announcement dates are obtained from the Compustat Quarterly dataset. In Table A.I we report abnormal returns for the CRSP–Compustat sample[5]. For each of the above signals, we sort stocks at the beginning of each month into quintile portfolios and

[5]We restrict the sample to the 3,000 largest firm at the beginning of each year and require that the stock price of the firm is greater than \$5 at the point of time at which firms assigned to portfolios (i.e., at the beginning of the month). We further require that all four quality signals (i.e., cash-flows, return on assets, return on equity, and gross profitability) are available for a stock-month observation to be included in the portfolio sorts.

compute the monthly return in the next month. We report the returns of the 5 quintile and the long–short (Q5–Q1) portfolios. Portfolios are equally weighted. We report raw returns (Panel A), CAPM alphas (Panel B), and 3 Fama-French factor alphas (Panel C). We do not include momentum or profitability factors since these strategies are precisely those we are investigating in the present paper.

All strategies have highly significant alphas even without hedging. Cash-flow and Gross Profitability are the strategies generating the strongest abnormal returns (no hedging). Next are Momentum, ROE, and ROA. As a general observation, all strategies become more significant as soon as market risk is being hedged. In terms of 3 Factor risk-adjusted performance, the CRSP–Compustat sample is dominated by the cash-flow (t–stat=5.55), ROE (t–stat=3.82) and momentum (t–stat=3.59) strategies.

We now replicate the anomalies on the intersection of the I/B/E/S and the CRSP–Compustat Sample. We refer to this intersected sample as the IBES sample. This intersected sample consists of the firms in the CRSP–Compustat sample for which at least two sets of one- and two year ahead EPS forecasts are available in our earnings forecast dataset during 1986 and 2013. This constraint induces a considerable reduction in sample size. While the matched CRSP–Compustat sample has on average 4,622 firms (Minimum=3,430; Maximum=6,506) per year before applying the size (i.e., 3000 largest firms) and price filters (i.e., $p_{i,t-1} > \$5$), the IBES sample has on average 1,673 firms per year (Minimum 1,144 and maximum 1,964 firms) after applying the price filter. In Table II, we check that the anomalies documented in the literature are also present in our restricted IBES sample.

[Insert Table II about here.]

Table II shows the results for the cash-flow and momentum strategies, which both generate risk-adjusted excess returns independent of the hedging strategy. Statistical significance is lower than in the CRSP–Compustat sample, but remain at reasonable levels, in particular when strategies are hedged: the three FF factor alpha of the cash-flows strategy has a t–statistic of 4.94, while that of the Momentum strategy is 3.01. In Table A.II we report the risk-adjusted returns for the IBES Sample using alternative definitions of the profitability strategies. While the Gross Profitability strategy generates strongly significant risk-adjusted returns in the IBES sample independent of the hedging strategy, strategies based on ROA and ROE are not significant.

IV Earnings Forecasts and Sticky Beliefs : Testing the Model

In this section, we now go on testing the predictions derived from the model of sticky beliefs that we presented in Section **II**.

A. Prediction (1): Measuring Stickiness

We start by providing graphical evidence on the relationship between forecast errors and forecast revisions. To do so, we calculate the forecast revision, which we define as the change in the consensus forecast of current fiscal year end earnings that was issued at the beginning of the fiscal year (i.e., $F_{t-1}\pi_{f,t}$) with respect to the consensus earnings forecast for current fiscal year earnings that was issued at the beginning of the previous fiscal year, i.e. $F_{t-2}\pi_{f,t}$. We normalize this revision of expectations by the stock price at the beginning of the previous fiscal year, that is $P_{f,t-2}$. The forecast revision for firm $f's$ earnings in fiscal year t is defined as $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$. Accordingly, we define the forecast error as the difference between earnings reported at the end of fiscal year t and the consensus forecast for fiscal year end earnings that was issued at the beginning of the fiscal year, which we again normalize by the stock price at the beginning of the previous fiscal year: $(\pi_{f,t} - F_{t-1}\pi_{f,t})/P_{f,t-2}$.

[Insert Figure 1 about here.]

In Figure 1 we show the forecast error as a function of forecast revisions. We sort all observations into vingtiles of the forecast revision $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$ and calculate average forecast error (defined as, $(\pi_{f,t} - F_{t-1}\pi_{f,t})/P_{f,t-2}$) and average forecast revision for each of the twenty ordered groups. The figure shows a strong monotonic relationship between the two.

Given the strong monotonic relationship between between forecast errors and revisions, we now use this insight to measure the stickiness of expectations. We first follow the approach initiated by Coibion and Gorodnichenko (2015) and summarized in our prediction 1. We run the following pooled regression where the time unit is fiscal years:

$$\frac{\pi_{f,t} - F_{t-1}\pi_{f,t}}{P_{f,t-2}} = a + b \cdot \frac{F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t}}{P_{f,t-2}} + c \cdot \ln(at)_{f,t-1} + \delta_t + \epsilon_{f,t} \tag{8}$$

In this regression, the coefficient b can be interpreted as a function of the stickiness parameter, so that $\lambda = b/(1+b)$. Hence, we regress expectation errors on forecast revisions. The more the two are related, the slower information is incorporated into forecasts. We include time (year) fixed effects in this regression to account for unanticipated aggregate shocks and also control for firm size. Error terms ϵ are allowed to be flexibly correlated within firm and within year.

[Insert Table III about here.]

We report regression results in Table III. In column (1) of Panel A, we directly estimate equation (8). We find $b = 0.177$, which means $\lambda = 0.15$. This suggests that, at the quarterly frequency, the weight of lagged forecasts is given by $0.15^{\frac{1}{4}} = 0.62$, very similar to what Coibion and Gorodnichenko (2015) find for quarterly revisions of inflation forecasts. In other words, analysts behave in aggregate as if they were revising their forecasts once every 7 months. Hence, our estimation of stickiness is in the ballpark of recent estimates coming from macro forecasts.

We then verify the robustness of this estimate in columns (2)–(4) of Panel A Table III. Although our model provides clear guidance as to how equation (8) should be specified, there may still be model specification errors, so we "stress-test" the model. In column (2), we include the two components of the revision separately, and find that they do not differ very much. In column (3), we only include the lagged forecast $F_{t-1}\pi_{f,t}/P_{f,t-2}$ and find a coefficient of similar size. In column (4), we further add firm fixed effects to account for the fact that analysts may have a specific constant bias for each firm. Again, the coefficient does not change very much.

In Panel B of Table III we use another strategy to estimate λ, which is based on the dynamics of forecasts revisions derived in prediction 2. The idea of this second approach is that the change in forecasts at time t contains an "echo" of the previous change in forecasts. The strength of that "echo" provides a measure of λ. More formally, we estimate

$$\frac{F_{t-1}\pi_t - F_{t-2}\pi_t}{P_{f,t-3}} = a + b \cdot \frac{F_{t-2}\pi_{f,t} - F_{t-3}\pi_{f,t}}{P_{f,t-3}} + c \cdot ln(at)_{f,t-2} + \delta_t + \epsilon_{f,t}, \tag{9}$$

When testing this prediction, we have to rely on analysts forecasts of three years ahead earnings, which makes our sample size drop substantially: we keep only about a third of our observations compared to Panel A where only two year ahead forecasts are needed.[6] Despite this constraint, we find an estimate of λ equal to 0.1 (see Column (1), Panel B, Table III), which is of a similar order of magnitude when compared to the estimate resulting from the strategy used in Panel A. The similar magnitude of the two coefficients is reassuring because the two estimation strategies are quite different in nature. The estimation in Panel B relies on the stickiness of expectations to be independent of the time distance to realization, which the strategy in Panel A, does not require. The second estimation is, however, less robust than the previous one due to the smaller sample size that the use of long-term forecasts impose.

[6]The drop in sample size is due to the fact that analyst forecasts drop sharply when moving to longer term forecasts such as three years and more.

B. Stickiness at the Analyst and Firm Levels

In this section, we extend our methodology to estimate firm–level and analyst–level stickiness parameters λ_a and λ_f. We then test whether certain firm– and/or analyst–level characteristics are correlated with higher levels of stickiness. For instance, if we interpret stickiness as resulting from time-constraints, we would expect analysts who follow more industries to exhibit more sticky expectations as they are more constrained in the time they can allocate to revising forecasts. In a similar vein, more experienced analysts might be more inclined to process material information more quickly, leading to less sticky expectations.

To test predictions of this kind, we proceed in two steps. First, we estimate the stickiness parameter for each analyst a and each firm f. In a second step, we relate the cross section of analyst and firm–level stickiness to observable analyst and firm characteristics.

Formally, we start by individually estimating the following regression for each analyst a

$$\frac{\pi_{f,t} - F_{a,t-1}\pi_{f,t}}{P_{f,t-2}} = a_a + b_a \cdot \frac{F_{a,t-1}\pi_{f,t} - F_{a,t-2}\pi_{f,t}}{P_{f,t-2}} + \epsilon_{a,f,t}. \tag{10}$$

Using the relation $\lambda_a = b_a/(1 + b_a)$ implied by the model, we can then back out the analyst level stickiness using the regression coefficient b_a from the above equation. Panel A of Table IV shows cross sectional descriptive statistics for the parameter λ_a.

[Insert Table IV about here.]

In total we are able to estimate the analyst level stickiness for 7,294 analysts. The median analyst–level stickiness is about 0.13, very similar to what we obtained from the pooled estimation in Panel A, Table III. The median analyst–level stickiness λ_a is estimated using 13 years of data (Median $N_{\lambda_a} = 13$). Note also that more than 25 percent of analysts have negative value for λ_a.

We now repeat the same procedure at the firm–level, which amounts to estimating the stickiness parameter of the median analyst covering a firm (i.e., using consensus forecast errors and revisions). More specifically, we estimate

$$\frac{\pi_{f,t} - F_{t-1}\pi_{f,t}}{P_{f,t-2}} = a_f + b_f \cdot \frac{F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t}}{P_{f,t-2}} + \epsilon_{f,t}, \tag{11}$$

and obtain the firm–level stickiness using the transformation $\lambda_f = b_f/(1 + b_f)$. The median firm–level stickiness λ_f is 0.12 and it is estimated using 11 years of data. Again, the stickiness parameter estimated at the firm–level is quite similar to what was obtained in the pooled estimation.

Next, we regress our estimated parameters λ_a (resp. λ_f) on analysts' (resp. firms') characteristics. Since we only have one observation per analyst, we use the median analyst characteristic during the sample period as explanatory variable and estimate the following cross sectional equation

$$\lambda_a = a + b \cdot x_a + \epsilon_a, \tag{12}$$

where x_a is, for instance, the median number of years an analyst has been forecasting earnings. We estimate a similar kind of regression at the firm–level, that is

$$\lambda_f = a + b \cdot x_f + \epsilon_f, \tag{13}$$

where x_f denotes, for instance, the median firm-size or EPS-Volatility of the firm throughout the sample period. The results for both types of regressions are reported in Table V.

[Insert Table V about here.]

In Panel A, we report results for the regression at the analyst level and find that analysts covering a larger number of industries have more sticky expectations, in line with a bounded rationality interpretation of the sticky forecasts model. Stickiness tends to decrease with the analyst's years of experience following the firm, but the result is insignificant once controlling for the number of firms and industries covered by the analyst. This might be due to the fact that more experienced analysts also follow more firms and industries.

In Panel B, we show the results from the firm–level regressions and find that stickiness is higher for firms with more volatile EPS, which can be interpreted as analysts "giving-up" on trying to make accurate forecasts for such firms. By contrast, when firms within an industry have heterogeneous EPS, stickiness is lower, suggesting a higher effort by analysts to differentiate firms. The same applies for industries in which forecast dispersion is higher.

C. Prediction (2): past profits predict forecast errors

Prediction 2 of the model suggests that if expectations are sticky, earnings surprises should be positively correlated with past realizations of a firm's profits (or cash-flows). To provide graphical evidence supporting this theoretical prediction, we sort observations into vingtiles of previous fiscal year end operating cash-flow over assets and calculate average forecast error and average operating cash-flow for each of the twenty groups.

[Insert Figure 2 about here.]

Figure 2 shows a strongly monotonic relationship between forecast errors and cash-flows, suggesting that analysts, in forming their expectations, do not take into account all available information.

To test this relationship more formally, we now relate the forecast error to various measures of profitability by running the following pooled regressions

$$\frac{\pi_{f,t} - F_{t-h}\pi_{f,t}}{P_{f,t-2}} = a + b_{t-h} \cdot \widetilde{\pi}_{f,t-h} + c \cdot ln(at)_{f,t-h} + \delta_t + \epsilon_{f,t} \tag{14}$$

for $h \in \{1, 2\}$. π denotes the EPS, which we normalize using the stock price at fiscal year end lagged twice, that is P_{t-2}. $\widetilde{\pi}$ denotes different proxies for profitability. In each regression, we control for firm size (logarithm of assets) and fiscal year dummies. We allow for error terms to be clustered within time and within firm.

If expectations were formed rationally, expectation errors $\pi_{f,t} - F_{t-h}\pi_{f,t}$ should have a zero mean conditional on information available at $t-h$, such as $\widetilde{\pi}_{f,t-1}$. If $b \neq 0$, then this suggests that forecasters underweight the information available in signals when forming their expectations. In our prediction 3, we provide a structural interpretation of the coefficient b for $\widetilde{\pi} = \pi$.

We allow for a non-zero constant a, which will capture the fact that expectations might have a constant positive bias as found in the literature (see e.g. Hong and Kacperczyk (2010), Guedj and Bouchaud (2005), or Hong and Kubik (2003)). In other words, we do not intend to analyze the average positive bias of analysts in this paper, but rather (1) the cross-section of their bias conditional on firm characteristics and (2) the dynamics of their bias over time. The results from these regressions are reported in Table VI.

[Insert Table VI about here.]

We find that the forecast error is systematically positively related to all past profitability measures, that is $b > 0$. This finding is consistent with the idea that analyst expectations are non-rational, and that analysts tend to under-react to some persistent signals that predict future profits. One possible interpretation is to simply view past profitability measures as the signal itself. But our model is more general, in that it does not impose that lagged profits be the only neglected signal.

D. Prediction (3): relating anomalies to structural parameters

D.1. Anomalies are stronger for firms followed by sticky analysts

In this section, we test the link made in Prediction (3) between the stickiness of analysts covering a given firm (λ_f), and the strength of the various asset pricing anomalies.

Our prediction is that when a firm is followed by more sticky analysts, these anomalies should be stronger. This is quite a direct test of our theory because it links asset prices to parameters of the model that are measured independently of stock-prices. Note that the underlying assumption is that the bias of analysts is also that of the marginal investor: if analysts were not representative of how the marginal investor is thinking, one would expect no link between their characteristics and stock prices. However, it seems quite plausible an assumption that the marginal investor anchors her beliefs on analyst forecasts.

[Insert Table VII about here.]

Table VII shows Fama and French (1993) three factor alphas for portfolios that are double sorted on firm-level stickiness (λ_f) and the cash-flow, change in cash-flow, and the momentum signal. We first sort stocks into terciles of the stickiness parameter λ_f. Within a tercile of the stickiness parameter, we then sort firms into quintiles of the anomaly signal. We get the Jensen's alpha of the Q5-Q1 portfolio in each stickiness tercile, using the usual Fama French three-factor model. We then test whether the alpha in the highest lambda tercile is greater than that in the lowest tercile. We generally find significant monotonicity in alphas. Our prediction is strongly supported in the data for the cash-flow and momentum signals and to a lesser extent for the change in cash-flows signal. Note that, consistent with our theory, portfolios double sorted on λ_f and other "profitability" signals (e.g., ROA, ROE, or Gross Profitability) and the difference of these are also highly monotonic in λ_f. The double-sorted portfolios using alternative profitability definitions are presented in Table A.IV.

As shown in item 5 of prediction (3), the model also implies that stock returns should covary more strongly with past forecast revisions if a stock is covered by stickier analysts: the covariance between stock-returns and forecast revisions is increasing in the firm level stickiness parameter λ_f. To test this theoretical prediction, we again carry out double sorts in which stocks are first sorted into terciles of λ_f, and within a tercile of the firm–level stickiness, stocks are sorted into quintiles of the begining of the fiscal year forecast revision (i.e., the consensus forecast at in the 90 days after the most recent annual earnings announcement). Forecast revision is as previously defined ($\frac{F_{t-1}\pi_{f,t}-F_{t-2}\pi_{f,t}}{P_{f,t-2}}$), that is the change in the forecast of current fiscal year earnings with respect to the forecast for the same earnings that was issued at the beginning of the previous fiscal year. The results, which are reported in Panel D of Tables VII show a monotonic relationship between the long-short three factor alpha and λ_f.

D.2. Anomalies are stronger for firms with highly persistent cash-flows

Another prediction of our model is that firms with more persistent cash-flows should also be subject to more pronounced stock return anomalies. The prime reason is that when cash-flows are highly persistent, slow updating leads to larger mistakes relative to rational Bayesian updating. We thus perform double-sort tests similar to the ones carried out above.

In a first step, we measure each firm's cash-flow persistence ρ_f. We do so by estimating the following regression for each firm f individually

$$cf_{f,t} = a + \rho \cdot cf_{f,t-1} + \epsilon_{f,t} \tag{15}$$

The median cash-flow persistence is about $\rho_f \approx 0.27$ and this median cash-flow persistence is estimated using 13 yearly observations ($N_{\rho_f} = 13$). (see Panel B of Table IV). In a second step, we check that the profitability, the momentum, and the post revisiona anomaly are more pronounced among high ρ_f firms. To do so we first sort firms into Terciles of ρ_f and secondly into quintiles of the cash-flows, change in cash-flows, the momentum signal, and the beginning of the fiscal year forecast revision.

[Insert Table VIII about here.]

The results are reported in Table VIII. We find that all the three factor alphas of all three strategies are monotonic in ρ_f. This prediction holds particularly well for the change in cash-flows strategy and for momentum. This result also holds somewhat for alternative profitability definitions (see Table A.V), in particular for gross profitability and the difference thereof. Post–revision drift is also stronger for firms with more persistent cash flows.

E. Prediction (4): the correlation of anomalies

A last prediction of our model is that the three strategies in Table II should be positively correlated. We report in Table IX the realized pairwise correlations between the returns of the Q5-Q1 Long–Short portfolios from Table II. These correlations are reported for both Equal and Value Weighted portfolios. In Panel A, correlations are calculated between the raw Long–Short returns. In Panel B, we report correlations for market hedged Long–Short returns: hedged returns are calculated by estimating the exposure of the long–short portfolio to the market portfolio for rolling windows of 36 months and subtracting the estimated market exposure. In Panel C, to make sure that correlations across strategies are not simply driven by similarities in the relative size of long and short holdings, we use both the market and the Fama and French Size factor SMB in our hedging of each strategy. The results strongly support the theoretical prediction that the three strategies are positively correlated and that these correlations are not driven by exposure to the market factor or similarities in the size composition of portfolios.

V Conclusion

In this paper, we propose a model that predicts that the quality (or "profitability") anomaly arises if market participants update expectations of future profits too slowly, and if the level of profits can be predicted by persistent publicly observable signals. Assuming that financial analyst forecasts are representative of the beliefs of market participants, our theory suggests that two of the most economically significant anomalies, i.e. momentum and quality (or "profitability"), should be more pronounced for stocks which (1) are followed by analysts characterized by more sticky expectations or (2) firms subject to more persistent profits. According to the model the returns of the two anomalies should also be correlated. The theoretical predictions are borne out by the data. Finally, we also explore cross-sectional determinants of the expectation stickiness measure we propose in this paper. It turns out that analysts that follow more industries or who have less experience tend to have more sticky beliefs, in-line with a limited attention interpretation of our results.

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Figures

Figure 1

Forecast Error and Forecast Revisions

This figure shows the forecast errors as a function of forecast revisions. We sort observations into vingtiles of the forecast revision $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$ and calculate average forecast error (defined as, $(\pi_{f,t} - F_{t-1}\pi_{f,t})/P_{f,t-2}$) and average forecast revision for each of the twenty ordered groups.

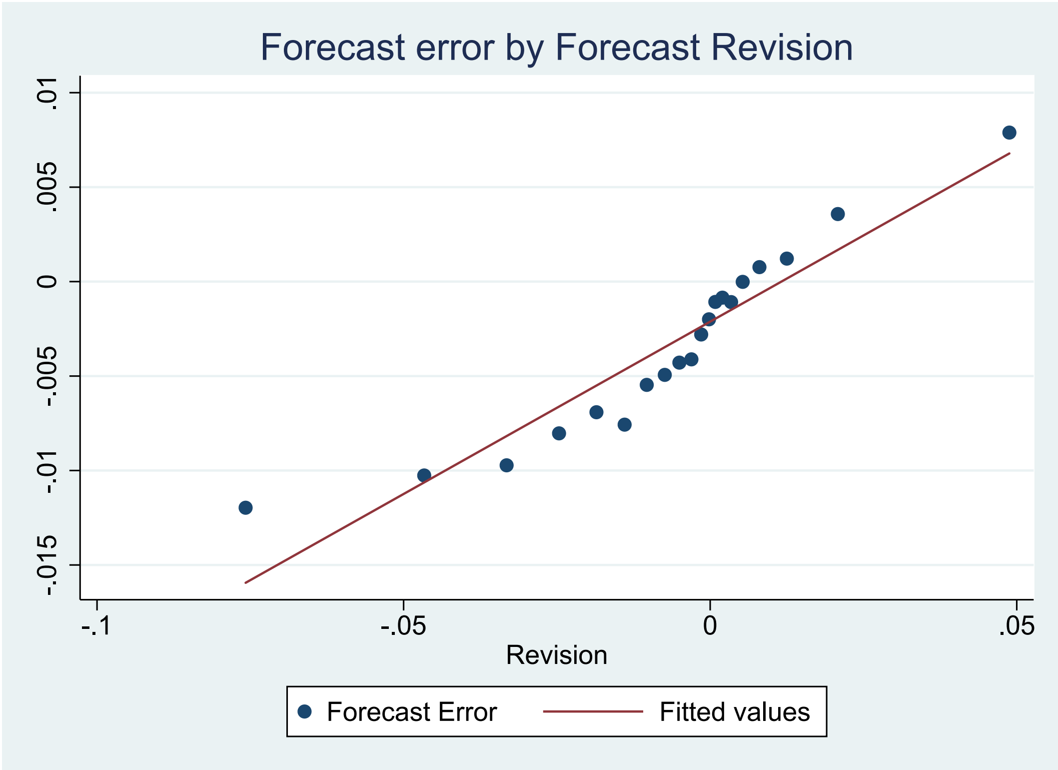
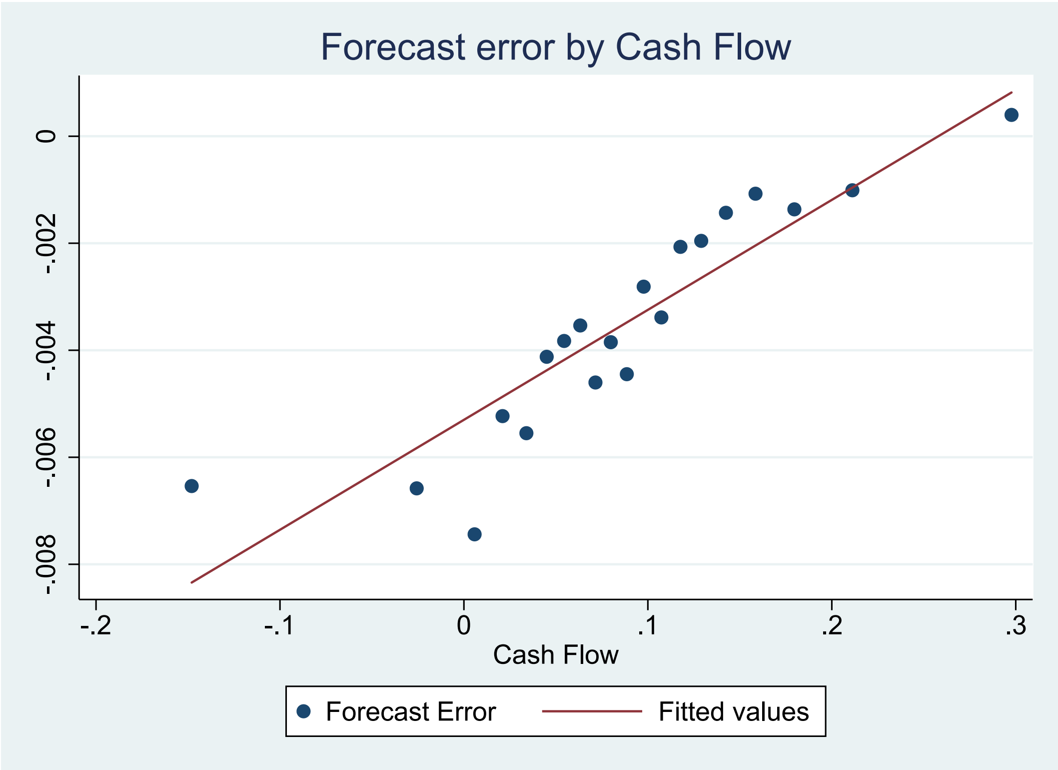


Figure 2

Forecast Error and Cash-Flow

This figure shows forecast error as a function of past cash-flows. We sort observations into vigintiles of the most recent operating cash-flow to assets ratio and calculate average forecast error and average cash-flow to assets for each of the 20 ordered groups.



Tables

Table I

Summary statistics

This table shows summary statistics for the I/B/E/S earnings forecasts sample (1986–2013). $\pi_{f,t}$ is the actual EPS reported in I/B/E/S. $F_{t-1}\pi_{f,t}$, $F_{t-2}\pi_{f,t}$, and $F_{t-3}\pi_{f,t}$ are the one, two, and three year consensus forecasts for earnings at date t, which we calculate as the median earnings forecast of all forecasts issued during the 90 days following the respective earnings announcement at $t-1$, $t-2$, and $t-3$. *Numest1*, *numest2*, and *numest3* are the number of forecasts used to calculate these consensus forecasts. $\left(\pi_{f,t} - F_{t-1}\pi_{f,t}\right)/P_{f,t-2}$, $\left(\pi_{f,t} - F_{t-2}\pi_{f,t}\right)/P_{f,t-3}$, and $\left(\pi_{f,t} - F_{t-3}\pi_{f,t}\right)/P_{f,t-3}$ are the forecast errors with respect to the one, two, and three year earnings forecast. $P_{f,t-n}$ denotes the stock price at fiscal year end $t-n$. $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$ and $(F_{t-2}\pi_{f,t} - F_{t-3}\pi_{f,t})/P_{f,t-3}$ are the forecast revisions of the one and two year earnings forecasts. *cf* is Compustat item *oancf* devided by item *at*. *roa* is *ib/at*. *roe* is *ni/ceq*. *gp* is *(revt-cogs)/at*. *cret* is the cumulative firm-level return between months t-12 and t-2. All variables are trimmed by removing observations for which the value of a variable deviates from the median by more than five times the interquartile range.

	(1)							
	count	mean	sd	min	p25	p50	p75	max
$\pi_{f,t}$	48523	2.5014	58.9490	-31.0000	0.7100	1.4500	2.4400	6232.0000
$F_{t-1}\pi_{f,t}$	48523	2.5968	55.2721	-19.1900	0.8200	1.5425	2.5000	6035.0300
$F_{t-2}\pi_{f,t}$	44686	2.7598	53.6678	-11.0700	1.0050	1.7300	2.7100	6387.0000
$F_{t-3}\pi_{f,t}$	16223	2.6024	3.6529	-13.4625	1.2250	2.1000	3.3000	307.9297
numest1	48523	8.7367	7.1228	1.0000	3.0000	7.0000	12.0000	56.0000
numest2	44733	7.9662	6.4662	0.0000	3.0000	6.0000	11.0000	52.0000
numest3	16271	2.6766	2.6693	0.0000	1.0000	2.0000	3.0000	25.0000
$\left(\pi_{f,t} - F_{t-1}\pi_{f,t}\right)/P_{f,t-2}$	48523	-0.0034	0.0236	-0.0938	-0.0108	-0.0004	0.0056	0.0924
$\left(\pi_{f,t} - F_{t-2}\pi_{f,t}\right)/P_{f,t-3}$	44319	-0.0104	0.0384	-0.1808	-0.0249	-0.0043	0.0064	0.1709
$\left(\pi_{f,t} - F_{t-3}\pi_{f,t}\right)/P_{f,t-3}$	15414	-0.0137	0.0487	-0.2336	-0.0332	-0.0072	0.0078	0.2182
$F_{t-1}\pi_{f,t}/P_{f,t-2}$	48242	0.0644	0.0475	-0.1944	0.0386	0.0627	0.0877	0.3202
$F_{t-2}\pi_{f,t}/P_{f,t-2}$	44496	0.0714	0.0409	-0.1698	0.0468	0.0698	0.0926	0.3077
$F_{t-3}\pi_{f,t}/P_{f,t-3}$	15471	0.0764	0.0441	-0.1696	0.0489	0.0747	0.0970	0.3256
$(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$	43728	-0.0066	0.0246	-0.1092	-0.0152	-0.0021	0.0042	0.1044
$(F_{t-2}\pi_{f,t} - F_{t-3}\pi_{f,t})/P_{f,t-3}$	15143	-0.0046	0.0269	-0.1210	-0.0148	-0.0015	0.0065	0.1173
cf(t)	44485	0.0948	0.0855	-0.3959	0.0487	0.0910	0.1397	0.5620
roa(t)	47723	0.0485	0.0676	-0.2976	0.0147	0.0447	0.0817	0.3743
roe(t)	46749	0.1136	0.1382	-0.5557	0.0631	0.1208	0.1744	0.7790
gp(t)	48494	0.3206	0.2515	-1.1235	0.1281	0.2790	0.4566	1.8383
mom(t-1)	37952	0.1582	0.4314	-0.9841	-0.1011	0.1075	0.3508	2.4400
mom(t-2)	34332	0.1748	0.4352	-0.9841	-0.0886	0.1180	0.3640	2.4506
Observations	48523							

Table II

Anomalies in the IBES Sample

This table presents excess returns (Panel A), CAPM alphas (Panel B), and three factor alphas based on the Fama and French 1993 model (Panel C) for quintile portfolios which are constructed based on a cash-flows (cf) based profitability and a momentum signal. The sample period runs from 1990 to 2013. Accounting based signals are assumed to be available, and thus updated, one month after the firm's annual earnings announcement. They are valid until the month of the next annual earnings announcement. Cash-flows *(cf)* is defined as Compustat item *oancf* divided by item *at*. Δcf is the difference between this year's and last year's *cf*. Momentum *(mom)* is the cumulative firm–level return between months $t-12$ and $t-2$. Q5-Q1 is the long–short portfolio which is long the 20% firms with the highest values of the signal (Fifth quintile) and short the 20% of firms with the lowest values (First quintile). Standard errors are adjusted for heteroskedasticity and autocorrelations up to 12 lags. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: Excess Return						
cf	0.00956**	0.0104***	0.0108***	0.0116***	0.0133***	0.00376**
	(2.51)	(3.45)	(3.90)	(4.24)	(4.91)	(2.44)
Δcf	0.0111***	0.00907***	0.00893***	0.0108***	0.0143***	0.00320***
	(3.42)	(3.16)	(3.15)	(3.81)	(4.52)	(3.00)
mom	0.00859**	0.00857***	0.00936***	0.0114***	0.0172***	0.00856**
	(2.17)	(2.84)	(3.61)	(4.32)	(4.30)	(2.25)
Panel B: CAPM						
cf	0.00153	0.00388**	0.00454**	0.00522***	0.00672***	0.00520***
	(0.80)	(2.09)	(2.35)	(2.74)	(3.63)	(4.38)
Δcf	0.00358*	0.00270	0.00298	0.00454**	0.00698***	0.00340***
	(1.90)	(1.45)	(1.59)	(2.56)	(3.22)	(3.34)
mom	0.0000482	0.00220	0.00372**	0.00560***	0.00980***	0.00975***
	(0.02)	(1.01)	(2.14)	(3.06)	(3.80)	(2.81)
Panel C: FF1993						
cf	0.0000849	0.00196**	0.00268***	0.00367***	0.00592***	0.00584***
	(0.09)	(2.36)	(2.70)	(3.48)	(4.82)	(4.94)
Δcf	0.00221**	0.000904	0.00106	0.00294***	0.00572***	0.00351***
	(2.22)	(0.98)	(1.34)	(3.31)	(4.60)	(3.36)
mom	-0.00177	0.000125	0.00200**	0.00411***	0.00918***	0.0110***
	(-0.84)	(0.09)	(2.07)	(4.79)	(4.47)	(3.01)

Table III

Estimating Expectation Stickiness

In Panel A, we relate the forecast error with respect to the one year forecast, that is $\left(\pi_{f,t} - F_{t-1}\pi_{f,t}\right)/P_{f,t-2}$, to the forecast revision, i.e. the difference between the consensus earnings forecasts at $t-1$ and $t-2$. We also regress the forecast error on the individual elements of the forecast revision. In Panel B, we use the forecast revision at date $t-1$ $\left(F_{t-1}\pi_t - F_{t-2}\pi_t\right)/p_{t-3}$ as the dependent variable and relate it to the forecasts at dates $t-2$, $t-3$, and the revision at date $t-2$, that is $(F_{t-2}\pi_{f,t} - F_{t-3}\pi_{f,t})/P_{f,t-3}$. Standard errors are double clustered at the firm–year level. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Panel A: Dependent variable: $\left(\pi_{f,t} - F_{t-1}\pi_{f,t}\right)/P_{f,t-2}$				
	(1)	(2)	(3)	(4)
$(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$	0.177***			0.122***
	(12.45)			(8.21)
$F_{t-1}\pi_{f,t}/P_{f,t-2}$		0.169***	0.020***	
		(11.98)	(3.18)	
$F_{t-2}\pi_{f,t}/P_{f,t-2}$		-0.201***		
		(-12.22)		
Observations	43,785	43,785	43,785	43,785
R^2	0.068	0.071	0.033	0.198
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes
Panel B: Dependent variable: $\left(F_{t-1}\pi_t - F_{t-2}\pi_t\right)/p_{t-3}$				
	(1)	(2)	(3)	(4)
$(F_{t-2}\pi_{f,t} - F_{t-3}\pi_{f,t})/P_{f,t-3}$	0.096***			0.008
	(3.87)			(0.21)
$F_{t-1}\pi_{f,t}/P_{f,t-3}$		0.059**	-0.051***	
		(2.29)	(-4.00)	
$F_{t-2}\pi_{f,t}/P_{f,t-3}$		-0.142***		
		(-5.19)		
Observations	15,359	15,359	15,359	15,359
R^2	0.094	0.110	0.091	0.327
Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes

Table IV

Descriptive Statistics (λ and ρ at the firm and analyst levels)

In Panel A, we report descriptive statistics for several analyst–level variables. The parameter λ_j is the analyst stickiness parameter obtained from running the following regression

$$\frac{\pi_{f,t} - F_{a,t-1}\pi_{f,t}}{P_{f,t-2}} = a_a + b_a \cdot \frac{F_{a,t-1}\pi_{f,t} - F_{a,t-2}\pi_{f,t}}{P_{f,t-2}} + \epsilon_{a,f,t} \tag{16}$$

for each analyst separately. $F_{a,t-1}\pi_{f,t}$ is the current fiscal year EPS forecasts issued by analyst a for firm f. This regression identifies the analyst level stickiness parameter λ_a using forecasts issued by the same analyst for different firms. The stickiness parameter λ_a is simply the coefficient b in the above regression, which is estimated for each analyst separately. N_{λ_a} is the number of analyst–level observations used to identify λ_a. *Experience* is median experience of an analyst during the sample period. We calculate *Experience* as the difference between the current year and the year an analyst has first appeared in the I/B/E/S database. *Firm Experience* is the median firm–specific experience of an analyst, which we define as the difference between the current year and the year in which an analyst has issued an EPS forecast for a given firm for the first time. *Industry experience* is the median number of years an analyst has been forecasting earnings for the industry to which the firm belongs. *Covered Industries* is the median number of SIC2 industries covered by the analyst. Analogously *Covered Firms* is the median number of firms an analyst covers.

In Panel B, we report descriptive statistics for firm–level variables and parameters obtained from estimating the pooled regression

$$\frac{\pi_{f,t} - F_{t-1}\pi_{f,t}}{P_{f,t-2}} = a_f + b_f \cdot \frac{F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t}}{P_{f,t-2}} + \epsilon_{f,t} \tag{17}$$

for each firm separately. This regression identifies the firm–level stickiness parameter λ_f by using the entire history of consensus forecasts for a given firm. λ_f is simply the coefficient b in the above regression. N_{λ_f} is the number of firm–level observations used to identify the λ_f stickiness parameter. ρ_f is obtained from estimating $cf_{f,t} = a + \rho \cdot cf_{f,t-1} + \epsilon_{f,t}$ for each firm, where cf is *oancf/at*. N_{ρ_f} is the number of observations at the firm level. *Firm Size* is the *ln(at)*. *EPS Volatility* is the standard deviation of EPS at the firm level. *Firm Level Forecast Dispersion* is the standard deviation of analyst forecasts issued for the firm. *Within Industry EPS (Forecast) Dispersion* is the dispersion of Earnings (Forecasts) within a SIC2 industry. All variables are trimmed by removing observations for which the value of a variable deviates from the median by more than five times the interquartile range.

Panel A: Analyst level

	(1)							
	count	mean	sd	min	p25	p50	p75	max
λ_a	7294	0.0976	0.3928	-1.6362	-0.0388	0.1292	0.2791	1.8768
N_{λ_a}	7294	26.5022	33.7159	2.0000	5.0000	13.0000	35.0000	463.0000
Experience	7294	5.3624	3.6605	0.0000	3.0000	4.0000	7.0000	25.5000
Firm Experience	7285	2.9645	1.5994	0.0000	2.0000	3.0000	4.0000	13.0000
Industry Experience	7286	4.4594	3.0042	0.0000	2.0000	4.0000	6.0000	24.0000
Covered Industries	7294	2.7878	2.0453	1.0000	1.0000	2.0000	4.0000	26.0000
Covered Firms	7294	9.6419	7.1871	1.0000	5.0000	9.0000	12.0000	144.0000
Observations	7294							

Panel B: Firm level

	(1)							
	count	mean	sd	min	p25	p50	p75	max
λ_f	3406	0.0731	0.3693	-1.6193	-0.0724	0.1202	0.2733	1.8459
N_{λ_f}	3406	12.3914	7.2202	2.0000	7.0000	11.0000	17.0000	28.0000
ρ_f	3330	0.2488	0.3968	-2.2447	0.0019	0.2722	0.5270	2.4391
N_{ρ_f}	3335	15.2258	7.0965	2.0000	9.0000	15.0000	22.0000	26.0000
Firm Size	3406	7.0786	1.8898	2.2459	5.7399	6.8595	8.2581	14.6739
EPS Volatility	3402	0.0460	0.0288	0.0003	0.0245	0.0386	0.0615	0.2018
Firm Level Forecast Dispersion	3331	0.1069	0.0987	0.0000	0.0437	0.0730	0.1301	0.5736
Within Industry Forecast Dispersion	3405	0.0413	0.0101	0.0111	0.0341	0.0408	0.0480	0.0709
Within Industry EPS Dispersion	3405	0.0517	0.0121	0.0017	0.0442	0.0509	0.0612	0.0843
Observations	3406							

Table V

Explaining λ_a and λ_j

In Panel A, we relate the analyst–level stickiness parameter λ_a to various analyst characteristics. In Panel B, we relate the firm–level stickiness parameter λ_f to various firm characteristics. For variable definitions, see previous table. Standard errors account for heteroskedasticity. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Panel A: Dependent variable λ_a (Analyst level)						
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	-0.004***					-0.003
	(-3.42)					(-1.25)
Firm Experience		-0.010***				-0.007*
		(-3.66)				(-1.70)
Industry Experience			-0.005***			0.002
			(-3.80)			(0.54)
Covered Industries				0.005**		0.009***
				(2.52)		(3.95)
Covered Firms					-0.001*	-0.002***
					(-1.77)	(-2.71)
Constant	0.119***	0.128***	0.120***	0.084***	0.109***	0.121***
	(12.83)	(11.69)	(13.16)	(10.45)	(12.18)	(9.23)
Observations	7,294	7,285	7,286	7,365	7,365	7,283
R^2	0.001	0.002	0.002	0.001	0.000	0.004
Panel B: Dependent variable λ_f (Firm level)						
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Size	0.003					0.004
	(0.81)					(1.05)
EPS Volatility		1.244***				1.556***
		(5.02)				(5.54)
Firm Level Forecast Dispersion			0.012			-0.071
			(0.17)			(-0.92)
Within Industry Forecast Dispersion				-1.344**		0.621
				(-2.05)		(0.39)
Within Industry EPS Dispersion					-1.157**	-2.638**
					(-2.10)	(-2.02)
Constant	0.052*	0.015	0.071***	0.129***	0.133***	0.088*
	(1.90)	(1.11)	(7.63)	(4.60)	(4.54)	(1.95)
Observations	3,406	3,402	3,331	3,405	3,405	3,326
R^2	0.000	0.009	0.000	0.001	0.001	0.014

Table VI

Forecast Errors and Profitability Signals

In this table we present the results from regressing firm level EPS forecast errors on a number of profitability signals that have been identified to positively predict expected returns. The dependent variable in Panel A is the forecast error based on the consensus forecast for the current fiscal year earnings, that is $\left(\pi_{f,t} - F_{t-1}\pi_{f,t}\right)/P_{f,t-2}$. Analogously, the dependent variable in Panel B is the forecast error with respect to the consensus forecast that was issued in the previous fiscal year, i.e., $\left(\pi_t - F_{t-2}\pi_t\right)/P_{t-2}$. $\pi_{f,t-1}/p_{f,t-2}$ is the actual last fiscal year EPS from I/B/E/S normalied by the fiscal year end stock price lagged twice. *cf* is Compustat item *oancf* devided by item *at*. *roa* is *ib/at*. *roe* is *ni/ceq*. *gp* is *(revt-cogs)/at*. Standard errors are clustered at the firm level. All regressions control for year dummies and firm size. Standard errors are double clustered at the firm–year level. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Panel A: $\left(\pi_t - F_{t-1}\pi_t\right)/P_{t-2}$ regressed on various signals s_{t-1}					
	(1)	(2)	(3)	(4)	(5)
$\pi_{f,t-1}/P_{f,t-2}$	0.025***				
	(4.34)				
cf(t-1)		0.019***			
		(8.58)			
roa(t-1)			0.017***		
			(4.18)		
roe(t-1)				0.010***	
				(5.61)	
gp(t-1)					0.002**
					(2.56)
Observations	42,587	43,370	47,779	46,798	48,523
R^2	0.033	0.035	0.031	0.032	0.029
Panel B: $\left(\pi_t - F_{t-2}\pi_t\right)/P_{t-2}$ regressed on various signals s_{t-2}					
	(1)	(2)	(3)	(4)	(5)
$\pi_{f,t-2}/P_{f,t-3}$	0.017				
	(1.37)				
cf(t-2)		0.038***			
		(8.14)			
roa(t-2)			0.030***		
			(4.54)		
roe(t-2)				0.015***	
				(4.67)	
gp(t-2)					0.006***
					(2.91)
Observations	37,845	39,773	44,693	43,769	45,272
R^2	0.045	0.050	0.045	0.047	0.043

Table VII

Anomalies and λ_f

This table shows Fama and French (1993) three factor alphas for portfolios that are double sorted on λ_f and the respective signal. We first sort stocks into Terciles of the stickiness parameter λ_f. Within a Tercile of the stickiness parameter, we then sort firms into Quintiles of the signal. We consider the cash-flows signal *(cf)* in Panel A, the change in cash-flows *(*Δcf*)* in Panel B, and the momentum signal *(mom)* in Panel C. In Panel D, we use on the consensus forecast revision at the beginning of the fiscal year, i.e. $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$, as a signal. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: cf						
T1	0.00131	0.00246**	0.00269***	0.00396***	0.00440***	0.00308**
	(1.11)	(2.17)	(2.70)	(3.16)	(3.33)	(2.34)
T2	0.000213	0.00248**	0.00320***	0.00371***	0.00661***	0.00639***
	(0.18)	(2.26)	(2.72)	(3.72)	(4.39)	(4.48)
T3	-0.00111	0.00127	0.00210*	0.00321***	0.00652***	0.00763***
	(-0.91)	(1.18)	(1.72)	(3.16)	(5.46)	(4.89)
T3 - T1	-0.00242*	-0.00119	-0.000591	-0.000751	0.00213***	0.00455***
	(-1.77)	(-0.77)	(-0.61)	(-0.93)	(2.64)	(3.40)
Panel B: Δcf						
T1	0.00241**	0.000733	0.00150	0.00322***	0.00467***	0.00227
	(2.14)	(0.69)	(1.53)	(2.89)	(2.91)	(1.39)
T2	0.00227*	0.00217**	0.00223**	0.00252***	0.00608***	0.00380***
	(1.81)	(2.16)	(1.99)	(2.95)	(4.18)	(3.33)
T3	0.00174	-0.000145	-0.000227	0.00312***	0.00622***	0.00448***
	(1.61)	(-0.13)	(-0.25)	(2.69)	(5.72)	(3.32)
T3 - T1	-0.000670	-0.000878	-0.00172	-0.0000985	0.00155	0.00222
	(-0.57)	(-0.93)	(-1.50)	(-0.11)	(1.11)	(1.22)
Panel C: mom						
T1	-0.000698	0.000318	0.00209**	0.00361***	0.00894***	0.00964**
	(-0.32)	(0.25)	(1.99)	(3.10)	(3.52)	(2.43)
T2	0.000211	0.000236	0.00181	0.00412***	0.00898***	0.00877***
	(0.10)	(0.15)	(1.39)	(4.46)	(4.55)	(2.63)
T3	-0.00497**	0.000400	0.00238***	0.00380***	0.00973***	0.0147***
	(-2.18)	(0.29)	(2.64)	(4.94)	(4.70)	(3.72)
T3 - T1	-0.00427***	0.0000824	0.000281	0.000189	0.000785	0.00506***
	(-3.60)	(0.08)	(0.40)	(0.22)	(0.51)	(3.03)
Panel D: $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$						
T1	0.00391**	0.00144	0.00139	0.000457	-0.0000188	-0.00393**
	(2.20)	(0.98)	(1.31)	(0.37)	(-0.01)	(-2.07)
T2	0.00254	0.00184*	0.00288***	0.00237**	0.00296*	0.000422
	(1.38)	(1.77)	(2.90)	(2.07)	(1.78)	(0.24)
T3	-0.00303**	-0.000577	0.00121	0.00231*	0.00585***	0.00887***
	(-2.29)	(-0.56)	(1.24)	(1.83)	(3.92)	(4.20)
T3 - T1	-0.00694***	-0.00202	-0.000174	0.00185**	0.00586***	0.0128***
	(-4.91)	(-1.34)	(-0.21)	(2.04)	(4.72)	(7.54)

Table VIII

Anomalies and ρ_f

This table shows Fama and French (1993) three factor alphas for portfolios that are double sorted on ρ_f, which measures the persistence of *cf*, and the respective signal. We first sort stocks into terciles of their persistence parameter ρ_f. Within a Tercile of the persistence parameter, we then sort firms into Quintiles of the signal. We consider the cash-flows signal *(cf)* in Panel A, the change in cash-flows Δcf in Panel B, and the momentum signal *(mom)* in Panel C. In Panel D, we use on the consensus forecast revision at the beginning of the fiscal year, i.e. $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$, as a signal. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q5	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: cf						
T1	-0.000454	0.00146	0.00256**	0.00227**	0.00409***	0.00455***
	(-0.37)	(1.62)	(2.35)	(2.05)	(3.56)	(2.98)
T2	0.00152	0.00225**	0.00261**	0.00362***	0.00584***	0.00432***
	(1.28)	(2.39)	(2.21)	(3.11)	(3.65)	(3.00)
T3	-0.00105	0.00109	0.00304***	0.00496***	0.00763***	0.00867***
	(-0.84)	(1.29)	(2.91)	(3.99)	(5.79)	(5.06)
T3 - T1	-0.000594	-0.000373	0.000486	0.00269***	0.00353***	0.00413**
	(-0.43)	(-0.39)	(0.80)	(2.67)	(3.72)	(2.20)
Panel B: Δcf						
T1	0.00313**	0.000283	0.00000437	0.00197**	0.00329***	0.000165
	(2.27)	(0.30)	(0.00)	(2.33)	(2.86)	(0.13)
T2	0.00187*	0.00197	0.00132	0.00314***	0.00622***	0.00435***
	(1.68)	(1.62)	(1.22)	(2.87)	(4.14)	(2.91)
T3	0.000109	0.000599	0.00158*	0.00374***	0.00772***	0.00761***
	(0.10)	(0.65)	(1.76)	(3.56)	(5.30)	(5.78)
T3 - T1	-0.00302**	0.000316	0.00157*	0.00177*	0.00442***	0.00744***
	(-2.37)	(0.33)	(1.73)	(1.90)	(4.43)	(5.37)
Panel C: mom						
T1	-0.00213	-0.000326	0.00167	0.00308***	0.00693***	0.00906**
	(-0.91)	(-0.25)	(1.55)	(3.53)	(3.74)	(2.41)
T2	-0.00174	0.000521	0.00181*	0.00435***	0.00993***	0.0117***
	(-0.81)	(0.38)	(1.73)	(4.00)	(4.75)	(3.46)
T3	-0.00234	0.000315	0.00205*	0.00448***	0.0107***	0.0130***
	(-1.10)	(0.23)	(1.95)	(5.30)	(4.23)	(3.21)
T3 - T1	-0.000209	0.000641	0.000380	0.00140*	0.00374***	0.00394***
	(-0.16)	(0.97)	(0.53)	(1.93)	(3.14)	(2.63)
Panel D: $(F_{t-1}\pi_{f,t} - F_{t-2}\pi_{f,t})/P_{f,t-2}$						
T1	-0.000157	0.000777	0.000884	-0.0000915	0.00124	0.00139
	(-0.11)	(0.84)	(0.90)	(-0.07)	(0.83)	(0.76)
T2	0.00220	0.00133	0.00171	0.00199*	0.00146	-0.000738
	(1.17)	(1.11)	(1.62)	(1.67)	(0.97)	(-0.34)
T3	0.00133	0.000622	0.00325***	0.00236**	0.00594***	0.00460***
	(0.80)	(0.48)	(3.46)	(2.02)	(4.70)	(2.80)
T3 - T1	0.00149	-0.000155	0.00236***	0.00246***	0.00470***	0.00321**
	(1.03)	(-0.16)	(3.26)	(3.04)	(4.65)	(1.99)

Table IX

Correlations (Q5-Q1 Long–Short)

This table reports correlations between the returns of the Q5-Q1 Long–Short portfolios from Table II. *cf* is *oancf/at*, Δcf the change in *cf*, and *mom* denotes the firm-level return between months $t-12$ and $t-2$. We report correlations for both Equal and Value Weighted portfolios. In Panel A, correlations are calculated between the raw Long–Short returns. In Panel B, we report correlations for market hedged Long–Short returns. Market hedged returns long–short returns for signal x are denoted as *Hx*. Market hedged returns are calculated by estimating the exposure of the long–short portfolio to the market portfolio for rolling windows of 36 months and subtracting in each month the predicted exposure to the market portfolio from the raw return of the long–short portfolio: $Hx = r_{market\_hedged,Q5-Q1,t} = r_{Q5-Q1,t} - \hat{\beta}_{mkt,t} \times r_{mktrf,t}$, where $r_{Q5-Q1,t}$ denotes the raw return for the long–short return based on signal x, $\hat{\beta}_{mktrf,t}$ the exposure of the Long-Short portfolio to the market factor estimated for rolling windows of 36 months, and $r_{mktrf,t}$ the return of the market portfolio. In Panel C, we use market and size hedged long-short returns, which we denote by *H1x*. We use the official Fama and French Size factor SMB and we calculate market-size hedged returns as follows: $H1x = r_{market\_size\_hedged,Q5-Q1,t} = r_{Q5-Q1,t} - \hat{\beta}_{mktrf,t} \times r_{mktrf,t} - \hat{\beta}_{smb,t} \times SMB_t$, where SMB_t denotes the official size factor and $\hat{\beta}_{smb,t}$ the exposure of the raw return to the size factor SMB. To account for outliers, we remove months in which returns for the long–Short momentum portfolio (mom) exceed the 1st or 99th percentile. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Panel A: Raw						
	Equal Weighted			Value Weighted		
	cf	Δcf	mom	cf	Δcf	mom
cf	1.00			1.00		
Δcf	0.35***	1.00		0.13*	1.00	
mom	0.18**	0.24***	1.00	0.24***	0.14*	1.00
Panel B: Market Hedged						
	Hcf	HΔcf	Hmom	Hcf	HΔcf	Hmom
Hcf	1.00			1.00		
HΔcf	0.31***	1.00		0.16*	1.00	
Hmom	0.10	0.26***	1.00	0.20***	0.12	1.00
Panel C: Market–Size Hedged						
	H1cf	H1 Δcf	H1mom	H1cf	H1 Δcf	H1mom
H1cf	1.00			1.00		
H1 Δcf	0.37***	1.00		0.16*	1.00	
H1mom	0.19**	0.22***	1.00	0.27***	0.11	1.00

APPENDIX : TABLES

Table A.I

Anomalies in the CRSP–Compustat Sample

This table presents excess returns (Panel A), CAPM alphas (Panel B), and Fama and French 1993 alphas (Panel C) for quintile portfolios which are constructed based on different signals. The sample period runs from 1990 to 2013. The sample is restricted to the 3000 largest firms (measured by market capitalization in each December) of the CRSP universe for which the respective signal can be calculated. Accounting based signals are assumed to be available, and thus updated, three months after fiscal year end. *cf* is Compustat item *oancf* divided by item *at*. *roa* is *ib/at*. *roe* is *ni/ceq*. *gp* is *(revt-cogs)/at*. Δx is the difference between this year's and last year's signal x. *mom* is the cumulative firm–level return between months $t-12$ and $t-2$. Q5-Q1 is the long–short portfolio which is long the 20% firms with the highest values and short the 20% of firms with the lowest. Standard errors are adjusted for heteroskedasticity and autocorrelations up to 12 lags. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q5	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: Excess Return						
cf	-0.00146	0.00569*	0.00772***	0.00911***	0.0106***	0.0121***
	(-0.32)	(1.71)	(2.64)	(3.27)	(3.78)	(4.21)
roa	0.00252	0.00700**	0.00713**	0.00777***	0.00887***	0.00636**
	(0.50)	(2.31)	(2.56)	(2.75)	(3.15)	(2.02)
roe	0.00231	0.00583*	0.00754***	0.00829***	0.00932***	0.00701**
	(0.48)	(1.87)	(2.75)	(3.08)	(3.27)	(2.23)
gp	0.00424	0.00526	0.00626*	0.00793***	0.00959***	0.00535***
	(1.23)	(1.63)	(1.94)	(2.65)	(3.18)	(2.80)
Δcf	0.00526	0.00683**	0.00650**	0.00779***	0.00846**	0.00320***
	(1.54)	(2.31)	(2.31)	(2.65)	(2.54)	(3.83)
Δroa	0.00589	0.00729**	0.00783***	0.00831***	0.00699**	0.00110
	(1.57)	(2.42)	(2.72)	(3.07)	(2.09)	(0.99)
Δroe	0.00600	0.00700**	0.00775***	0.00822***	0.00734**	0.00134
	(1.56)	(2.40)	(2.91)	(3.03)	(2.22)	(1.22)
Δgp	0.00513	0.00683**	0.00772***	0.00850***	0.00800**	0.00287***
	(1.45)	(2.25)	(2.70)	(3.01)	(2.44)	(3.24)
mom	0.00227	0.00654**	0.00764***	0.00921***	0.0119***	0.00960***
	(0.53)	(2.09)	(2.82)	(3.36)	(3.06)	(2.65)
Panel B: CAPM						
cf	-0.0101***	-0.00124	0.00136	0.00269	0.00387**	0.0140***
	(-4.22)	(-0.78)	(0.78)	(1.48)	(2.14)	(4.69)
roa	-0.00682***	0.00135	0.00122	0.00135	0.00199	0.00881***
	(-3.17)	(0.58)	(0.63)	(0.69)	(1.10)	(3.08)
roe	-0.00695***	-0.000861	0.00178	0.00236	0.00276	0.00971***
	(-3.14)	(-0.48)	(0.94)	(1.16)	(1.52)	(3.17)
gp	-0.00208	-0.00117	-0.000967	0.000707	0.00260	0.00468**
	(-1.17)	(-0.77)	(-0.53)	(0.44)	(1.34)	(2.29)
Δcf	-0.00247	0.000306	0.000653	0.00138	0.000780	0.00325***
	(-1.34)	(0.17)	(0.37)	(0.90)	(0.45)	(4.09)
Δroa	-0.00218	0.00118	0.00256	0.00230	-0.000880	0.00130
	(-1.12)	(0.58)	(1.14)	(1.19)	(-0.53)	(1.05)
Δroe	-0.00201	0.000814	0.00229	0.00219	-0.000315	0.00169
	(-1.11)	(0.43)	(1.11)	(1.13)	(-0.20)	(1.41)
Δgp	-0.00282	0.000578	0.00234	0.00231	0.000420	0.00324***
	(-1.62)	(0.29)	(1.06)	(1.29)	(0.23)	(3.42)
mom	-0.00645***	0.000130	0.00205	0.00351**	0.00447*	0.0109***
	(-2.74)	(0.07)	(1.16)	(2.11)	(1.95)	(3.33)
Panel C: FF1993						
cf	-0.0103***	-0.00302***	-0.000515	0.00113	0.00290***	0.0132***
	(-6.43)	(-3.80)	(-0.60)	(1.16)	(2.62)	(5.55)
roa	-0.00741***	-0.00111	-0.000790	-0.0000968	0.00141	0.00882***
	(-4.62)	(-1.08)	(-0.80)	(-0.08)	(1.24)	(3.46)
roe	-0.00744***	-0.00272***	-0.0000906	0.000620	0.00163	0.00907***
	(-4.87)	(-3.50)	(-0.11)	(0.59)	(1.46)	(3.82)
gp	-0.00378***	-0.00302***	-0.00256**	-0.000324	0.00168	0.00545***
	(-3.02)	(-3.16)	(-2.37)	(-0.38)	(1.50)	(3.00)
Δcf	-0.00355***	-0.00147	-0.00125	-0.000262	-0.000175	0.00337***
	(-3.77)	(-1.63)	(-1.64)	(-0.36)	(-0.21)	(4.27)
Δroa	-0.00350***	-0.000975	0.000253	0.000715	-0.00154*	0.00196*
	(-3.04)	(-1.06)	(0.25)	(0.65)	(-1.83)	(1.71)
Δroe	-0.00358***	-0.00122	0.000368	0.000681	-0.00130*	0.00228*
	(-3.64)	(-1.42)	(0.34)	(0.61)	(-1.77)	(1.94)
Δgp	-0.00374***	-0.00145	0.000116	0.000509	-0.000613	0.00312***
	(-4.18)	(-1.62)	(0.11)	(0.62)	(-0.63)	(3.49)
mom	-0.00810***	-0.00193*	0.000204	0.00200***	0.00412**	0.0122***
	(-4.28)	(-1.72)	(0.24)	(2.99)	(2.41)	(3.59)

Table A.II

Anomalies in the IBES Sample (Alternative Profitability Definitions)

This table presents excess returns (Panel A), CAPM alphas (Panel B) and FF1993 three factor alphas (Panel C) for quintile portfolios which are constructed based on several alternative profitability definitions. The sample is restricted to firms for which the firm–level stickiness parameter λ_f is available (See Table IV for more information). *roa* is *ib/at*. *roe* is *ni/ceq*. *gp* is the *(revt-cogs)/at*. Δx is the difference between this year's and last year's signal x. Standard errors are adjusted for heteroskedasticity and autocorrelations up to 12 lags. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q5	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: Excess Return						
roa	0.0123***	0.00968***	0.0103***	0.0112***	0.0123***	0.00000613
	(2.99)	(3.36)	(3.72)	(4.16)	(4.34)	(0.00)
roe	0.0126***	0.0104***	0.0101***	0.0105***	0.0120***	-0.000553
	(3.13)	(3.51)	(3.73)	(3.92)	(4.39)	(-0.29)
gp	0.00836***	0.00925***	0.0114***	0.0124***	0.0143***	0.00593***
	(2.60)	(2.88)	(3.83)	(4.30)	(4.95)	(4.16)
Δroa	0.0117***	0.0100***	0.00893***	0.0102***	0.0133***	0.00157
	(3.30)	(3.42)	(3.31)	(3.73)	(4.06)	(1.19)
Δroe	0.0113***	0.0103***	0.00939***	0.0108***	0.0123***	0.00104
	(3.06)	(3.62)	(3.59)	(4.02)	(3.86)	(0.80)
Δgp	0.0106***	0.00963***	0.00877***	0.0109***	0.0142***	0.00363***
	(3.15)	(3.25)	(3.17)	(3.97)	(4.44)	(3.17)
Panel B: CAPM						
roa	0.00381*	0.00367*	0.00416**	0.00491**	0.00534***	0.00153
	(1.79)	(1.93)	(2.10)	(2.56)	(2.93)	(1.07)
roe	0.00406*	0.00385*	0.00413**	0.00429**	0.00556***	0.00150
	(1.91)	(1.90)	(2.21)	(2.36)	(3.26)	(0.94)
gp	0.00216	0.00229	0.00446**	0.00550***	0.00749***	0.00533***
	(1.24)	(1.14)	(2.24)	(2.85)	(3.74)	(3.34)
Δroa	0.00385*	0.00376*	0.00329*	0.00401**	0.00576***	0.00191
	(1.83)	(1.95)	(1.73)	(2.12)	(2.75)	(1.39)
Δroe	0.00349*	0.00400**	0.00362*	0.00460**	0.00496**	0.00147
	(1.73)	(2.02)	(1.93)	(2.44)	(2.58)	(1.09)
Δgp	0.00283	0.00326	0.00298	0.00470**	0.00691***	0.00408***
	(1.54)	(1.63)	(1.59)	(2.54)	(3.19)	(3.29)
Panel C: FF1993						
roa	0.00194	0.00146*	0.00229**	0.00361***	0.00502***	0.00309**
	(1.61)	(1.74)	(2.15)	(3.34)	(3.95)	(2.09)
roe	0.00246*	0.00187**	0.00244***	0.00289***	0.00466***	0.00221
	(1.90)	(2.07)	(2.77)	(2.79)	(4.13)	(1.45)
gp	0.000234	0.000214	0.00292***	0.00457***	0.00638***	0.00615***
	(0.24)	(0.19)	(2.80)	(3.97)	(5.16)	(4.35)
Δroa	0.00225*	0.00177*	0.00132	0.00253**	0.00488***	0.00262**
	(1.73)	(1.85)	(1.55)	(2.36)	(4.00)	(2.00)
Δroe	0.00171	0.00202**	0.00198*	0.00322***	0.00382***	0.00211
	(1.47)	(2.13)	(1.76)	(3.10)	(3.55)	(1.60)
Δgp	0.00177*	0.00137	0.000952	0.00303***	0.00563***	0.00386***
	(1.69)	(1.42)	(1.11)	(3.22)	(4.55)	(3.43)

Table A.III

Correlations Long-Short-Return (All Profitability Definitions)

This table reports correlations between the returns of Q5-Q1 Long–Short portfolios for all profitability measures. We report correlations for both Equal and Value Weighted portfolios. In Panel A, correlations are calculated between the raw Long–Short returns. In Panel B, we report correlations for market hedged Long–Short returns. Market hedged returns are calculated by estimating the exposure of the portfolio to the market portfolio for rolling windows of 36 months and subtracting from the raw return of the portfolio the predicted exposure to the market portfolio: $r_{market\_hedged,Q5-Q1,t} = r_{Q5-Q1,t} - \hat{\beta}_{mkt,t} \times r_{mktrf,t}$, where $r_{Q5-Q1,t}$ denotes the raw return, $\hat{\beta}_{mktrf,t}$ the exposure of the Long-Short portfolio to the market factor estimated for rolling windows of 36 months, and $r_{mktrf,t}$ the return of the market portfolio. In Panel C, we use market and size hedged long-short returns. We use the official Fama and French Size factor SMB and we calculate market-size hedged returns as follows: $r_{market\_size\_hedged,Q5-Q1,t} = r_{Q5-Q1,t} - \hat{\beta}_{mktrf,t} \times r_{mktrf,t} - \hat{\beta}_{smb,t} \times SMB_t$, where SMB_t denotes the official size factor and $\hat{\beta}_{smb,t}$ the exposure of the raw return to the size factor SMB. To account for outliers, we remove months in which returns for the Momentum Long–Short portfolio (mom) exceed the 1st or 99th percentile. ($p < 0.10$, $+\ p < 0.05$, $*\ p < 0.01$)

Panel A: Long Short return

	Equal Weighted									Value Weighted								
	cf	roa	roe	gp	Δcf	Δroa	Δroe	Δgp	mom	cf	roa	roe	gp	Δcf	Δroa	Δroe	Δgp	mom
cf	1.00									1.00								
roa	0.75*	1.00								0.83*	1.00							
roe	0.71*	0.84*	1.00							0.51*	0.77*	1.00						
gp	0.30*	0.41*	0.10	1.00						0.68*	0.70*	0.44*	1.00					
Δcf	0.35*	0.24*	0.24*	0.09	1.00					0.13+	0.14+	0.15*	0.07	1.00				
Δroa	0.25*	0.43*	0.31*	0.20*	0.49*	1.00				-0.10	0.10	0.15*	0.05	0.41*	1.00			
Δroe	0.26*	0.44*	0.38*	0.12+	0.44*	0.90*	1.00			-0.00	0.23*	0.27*	0.11	0.38*	0.80*	1.00		
Δgp	0.25*	0.25*	0.29*	0.07	0.50*	0.59*	0.57*	1.00		-0.09	0.01	0.18*	-0.01	0.40*	0.55*	0.46*	1.00	
mom	0.18*	0.18*	0.11	0.10	0.24*	0.32*	0.27*	0.13+	1.00	0.24*	0.31*	0.21*	0.28*	0.14+	0.22*	0.36*	0.13+	1.00

Panel B: Market Hedged

	Hcf	Hroa	Hroe	Hgp	HΔcf	HΔroa	HΔroe	HΔgp	Hmom	Hcf	Hroa	Hroe	Hgp	HΔcf	HΔroa	HΔroe	HΔgp	Hmom
Hcf	1.00									1.00								
Hroa	0.73*	1.00								0.80*	1.00							
Hroe	0.63*	0.78*	1.00							0.43*	0.69*	1.00						
Hgp	0.43*	0.53*	0.18*	1.00						0.66*	0.67*	0.35*	1.00					
HΔcf	0.31*	0.19*	0.16*	0.11	1.00					0.16+	0.19*	0.20*	0.08	1.00				
HΔroa	0.23*	0.45*	0.27*	0.22*	0.50*	1.00				-0.07	0.19*	0.19*	0.10	0.47*	1.00			
HΔroe	0.23*	0.43*	0.32*	0.16*	0.45*	0.92*	1.00			-0.01	0.26*	0.25*	0.11	0.42*	0.83*	1.00		
HΔgp	0.19*	0.18*	0.20*	0.09	0.49*	0.56*	0.56*	1.00		-0.09	0.01	0.14+	-0.00	0.42*	0.58*	0.49*	1.00	
Hmom	0.10	0.10	-0.05	0.13+	0.26*	0.35*	0.29*	0.07	1.00	0.20*	0.30*	0.09	0.26*	0.12	0.29*	0.37*	0.09	1.00

Panel C: Market–Size Hedged

	H1cf	H1roa	H1roe	H1gp	H1Δcf	H1Δroa	H1Δroe	H1Δgp	H1mom	H1cf	H1roa	H1roe	H1gp	H1Δcf	H1Δroa	H1Δroe	H1Δgp	H1mom
H1cf	1.00									1.00								
H1roa	0.74*	1.00								0.81*	1.00							
H1roe	0.59*	0.82*	1.00							0.43*	0.72*	1.00						
H1gp	0.59*	0.65*	0.45*	1.00						0.70*	0.71*	0.51*	1.00					
H1Δcf	0.37*	0.24*	0.26*	0.08	1.00					0.16+	0.18*	0.23*	0.06	1.00				
H1Δroa	0.31*	0.50*	0.41*	0.19*	0.50*	1.00				-0.05	0.19*	0.33*	0.03	0.44*	1.00			
H1Δroe	0.28*	0.48*	0.45*	0.14+	0.45*	0.91*	1.00			-0.00	0.27*	0.36*	0.06	0.40*	0.81*	1.00		
H1Δgp	0.20*	0.20*	0.25*	0.05	0.51*	0.57*	0.57*	1.00		-0.10	-0.01	0.16*	-0.01	0.42*	0.57*	0.48*	1.00	
H1mom	0.19*	0.15+	0.06	0.11	0.22*	0.35*	0.28*	0.10	1.00	0.27*	0.34*	0.25*	0.24*	0.11	0.19*	0.31*	0.11	1.00

Table A.IV

Anomalies and λ_f (Alternative Profitability Definitions)

This table shows Fama and French (1993) three factor alphas for portfolios that are double sorted on λ_f and alternative profitability signals. We first sort stocks into Terciles of the stickiness parameter λ_f. Within a Tercile of the stickiness parameter, we then sort firms into Quintiles of the profitability signal. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q5	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: roa						
T1	0.00432**	0.00208***	0.00108	0.00317***	0.00416***	-0.000162
	(2.50)	(2.66)	(0.93)	(2.92)	(2.94)	(-0.09)
T2	0.00190	0.00160*	0.00339***	0.00375***	0.00556***	0.00366**
	(1.25)	(1.67)	(2.88)	(3.46)	(3.76)	(2.41)
T3	-0.000684	0.000932	0.00215*	0.00445***	0.00514***	0.00582***
	(-0.62)	(0.71)	(1.77)	(3.25)	(3.96)	(3.18)
T3 - T1	-0.00501***	-0.00115	0.00106	0.00128	0.000976	0.00598***
	(-2.81)	(-0.93)	(1.16)	(1.59)	(0.83)	(3.10)
Panel B: roe						
T1	0.00466***	0.00210**	0.00190**	0.00209*	0.00407***	-0.000595
	(2.64)	(2.43)	(2.05)	(1.75)	(3.26)	(-0.33)
T2	0.00199	0.00354***	0.00301***	0.00311***	0.00454***	0.00256*
	(1.29)	(3.38)	(2.75)	(2.60)	(3.53)	(1.84)
T3	0.000642	-0.0000226	0.00270***	0.00302***	0.00564***	0.00500**
	(0.48)	(-0.02)	(2.72)	(2.76)	(4.20)	(2.46)
T3 - T1	-0.00402**	-0.00213*	0.000806	0.000928	0.00157	0.00559***
	(-2.31)	(-1.91)	(1.06)	(1.00)	(1.44)	(3.22)
Panel C: gp						
T1	0.00146	-0.000510	0.00261**	0.00451***	0.00674***	0.00527***
	(1.13)	(-0.42)	(2.26)	(3.40)	(5.19)	(2.96)
T2	0.000791	0.00102	0.00365***	0.00446***	0.00628***	0.00549***
	(0.83)	(0.83)	(2.67)	(4.19)	(4.09)	(3.67)
T3	-0.00169	0.000536	0.00229*	0.00444***	0.00641***	0.00810***
	(-1.45)	(0.44)	(1.94)	(3.45)	(4.79)	(4.72)
T3 - T1	-0.00316**	0.00105	-0.000326	-0.0000689	-0.000328	0.00283*
	(-2.45)	(1.05)	(-0.34)	(-0.06)	(-0.30)	(1.88)
Panel E: Δroa						
T1	0.00364**	0.00195*	0.00182**	0.00178	0.00336**	-0.000276
	(2.37)	(1.86)	(2.11)	(1.40)	(2.30)	(-0.18)
T2	0.00307**	0.00256**	0.00196*	0.00324***	0.00460***	0.00153
	(2.03)	(2.23)	(1.78)	(2.91)	(3.13)	(1.05)
T3	-0.000530	0.00123	-0.0000595	0.00310**	0.00656***	0.00710***
	(-0.51)	(1.08)	(-0.06)	(2.46)	(5.55)	(5.10)
T3 - T1	-0.00417***	-0.000724	-0.00187**	0.00133	0.00320**	0.00737***
	(-3.66)	(-0.73)	(-2.44)	(1.44)	(2.51)	(5.42)
Panel F: Δroe						
T1	0.00328***	0.00158	0.00244*	0.00207**	0.00316**	-0.000114
	(2.63)	(1.44)	(1.97)	(2.08)	(2.31)	(-0.09)
T2	0.00274*	0.00317***	0.00263**	0.00375***	0.00313***	0.000390
	(1.84)	(2.97)	(2.18)	(3.02)	(2.69)	(0.26)
T3	-0.000348	0.00135	0.000346	0.00398***	0.00498***	0.00532***
	(-0.29)	(1.48)	(0.30)	(3.30)	(4.48)	(3.58)
T3 - T1	-0.00363***	-0.000232	-0.00210**	0.00190**	0.00181	0.00544***
	(-3.18)	(-0.27)	(-2.43)	(2.27)	(1.51)	(4.53)
Panel G: Δgp						
T1	0.00204*	0.00255**	0.000585	0.00243**	0.00493***	0.00289*
	(1.66)	(2.45)	(0.60)	(2.28)	(2.95)	(1.69)
T2	0.00274**	0.00208**	0.00199**	0.00393***	0.00469***	0.00196
	(2.07)	(2.02)	(2.19)	(3.27)	(3.18)	(1.44)
T3	0.0000550	0.0000458	0.0000513	0.00302***	0.00714***	0.00709***
	(0.05)	(0.04)	(0.05)	(2.82)	(6.04)	(5.08)
T3 - T1	-0.00199*	-0.00251***	-0.000533	0.000590	0.00221	0.00420**
	(-1.88)	(-2.97)	(-0.64)	(0.57)	(1.40)	(2.48)

Table A.V

Anomalies and ρ_f (Alternative Profitability Definitions)

This table shows Fama and French (1993) three factor alphas for portfolios that are double sorted on ρ_f, which measures the persistence of *cf*, and alternative profitability signals. We first sort stocks into terciles of their persistence parameter ρ_f. Within a Tercile of the persistence parameter, we then sort firms into Quintiles of the profitability signal. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

	(1) Q1	(2) Q2	(3) Q5	(4) Q4	(5) Q5	(6) Q5-Q1
Panel A: roa						
T1	0.0000432	0.00126	0.00220*	0.00303**	0.00339***	0.00335**
	(0.04)	(1.34)	(1.84)	(2.54)	(2.64)	(2.52)
T2	0.00340**	0.00178*	0.00218*	0.00411***	0.00436***	0.000958
	(2.31)	(1.83)	(1.71)	(3.28)	(3.02)	(0.56)
T3	0.00111	0.00154	0.00204*	0.00460***	0.00638***	0.00526***
	(0.70)	(1.49)	(1.88)	(4.09)	(4.92)	(2.66)
T3 - T1	0.00107	0.000280	-0.000161	0.00157*	0.00298***	0.00192
	(0.77)	(0.37)	(-0.23)	(1.66)	(3.42)	(1.18)
Panel B: roe						
T1	0.000666	0.00280***	0.000860	0.00211*	0.00349***	0.00282**
	(0.60)	(3.13)	(0.85)	(1.92)	(2.98)	(2.19)
T2	0.00411**	0.00106	0.00335***	0.00310**	0.00421***	0.0000924
	(2.54)	(0.97)	(3.14)	(2.34)	(3.21)	(0.05)
T3	0.00146	0.00194**	0.00246**	0.00386***	0.00596***	0.00450**
	(0.90)	(1.98)	(2.46)	(3.87)	(5.15)	(2.28)
T3 - T1	0.000795	-0.000859	0.00160*	0.00175**	0.00247***	0.00168
	(0.56)	(-1.22)	(1.90)	(2.03)	(3.43)	(1.01)
Panel C: gp						
T1	-0.000283	0.000266	0.00178	0.00357***	0.00461***	0.00489***
	(-0.25)	(0.22)	(1.30)	(3.05)	(4.14)	(3.27)
T2	0.000823	-0.0000743	0.00348***	0.00496***	0.00666***	0.00584***
	(0.76)	(-0.06)	(2.65)	(3.73)	(4.30)	(3.35)
T3	-0.000490	0.0000876	0.00308***	0.00513***	0.00787***	0.00836***
	(-0.43)	(0.08)	(3.00)	(4.62)	(5.45)	(5.12)
T3 - T1	-0.000207	-0.000179	0.00130	0.00156*	0.00326***	0.00347**
	(-0.21)	(-0.16)	(1.54)	(1.79)	(3.47)	(2.37)
Panel D: Δroa						
T1	0.00199	0.000701	0.000779	0.00171	0.00305***	0.00106
	(1.45)	(0.71)	(0.86)	(1.53)	(2.65)	(0.91)
T2	0.00276*	0.00275**	0.00210**	0.00231*	0.00466***	0.00190
	(1.79)	(2.37)	(2.41)	(1.68)	(3.28)	(1.14)
T3	0.00172	0.00119	0.000936	0.00380***	0.00632***	0.00460***
	(1.25)	(1.15)	(0.81)	(3.31)	(4.02)	(2.71)
T3 - T1	-0.000271	0.000488	0.000157	0.00208**	0.00327**	0.00354**
	(-0.22)	(0.64)	(0.18)	(2.32)	(2.41)	(2.26)
Panel E: Δroe						
T1	0.00147	0.000807	0.000826	0.00279**	0.00234**	0.000867
	(1.29)	(0.75)	(0.76)	(2.41)	(2.40)	(0.86)
T2	0.00214	0.00372***	0.00240*	0.00244*	0.00388***	0.00174
	(1.49)	(3.48)	(1.91)	(1.93)	(2.77)	(0.92)
T3	0.000562	0.00146	0.00195	0.00531***	0.00468***	0.00411***
	(0.43)	(1.35)	(1.64)	(4.90)	(3.82)	(2.72)
T3 - T1	-0.000908	0.000648	0.00113	0.00251***	0.00234**	0.00325**
	(-0.78)	(0.79)	(1.51)	(2.70)	(2.35)	(2.46)
Panel F: Δgp						
T1	0.00244**	-0.0000119	0.000527	0.00270***	0.00259*	0.000157
	(2.03)	(-0.01)	(0.52)	(2.76)	(1.94)	(0.15)
T2	0.000940	0.00269**	0.00162*	0.00195	0.00739***	0.00645***
	(0.84)	(2.13)	(1.86)	(1.43)	(5.04)	(4.20)
T3	0.00161	0.000458	0.00108	0.00446***	0.00634***	0.00473***
	(1.18)	(0.45)	(1.14)	(4.70)	(4.70)	(3.18)
T3 - T1	-0.000827	0.000470	0.000555	0.00176**	0.00375***	0.00458***
	(-0.68)	(0.54)	(0.54)	(2.02)	(4.05)	(3.45)

APPENDIX : PROOFS

A Proof of Proposition 1

Our goal here is to compute prices and returns. Start from the definition of sticky expectations:

$$\begin{aligned} F_t(\pi_{t+k}) &= (1-\lambda)\sum_{j\geq 0}\lambda^j E_{t-j}\pi_{t+k} \\ &= (1-\lambda)\rho^{k-1}\sum_{j\geq 0}\lambda^j\rho^j s_{t-j} \end{aligned}$$

We can then plug this back into prices:

$$\begin{aligned} P_t &= \sum_{k\geq 1}\frac{F_t\pi_{t+k}}{(1+r)^k} \\ &= \sum_{k\geq 1}\frac{1}{(1+r)^k}((1-\lambda)\rho^{k-1}\sum_{j\geq 0}\lambda^j\rho^j s_{t-j}) \\ &= \sum_{j\geq 0}\sum_{k\geq 1}\frac{1}{(1+r)^k}((1-\lambda)\rho^{k-1}\lambda^j\rho^j s_{t-j}) \\ &= \sum_{j\geq 0}\frac{1-\lambda}{1+r}[\sum_{k\geq 0}\frac{\rho^k}{(1+r)^k}](\lambda^j\rho^j s_{t-j}) \\ &= \sum_{j\geq 0}\frac{1-\lambda}{1+r}[\frac{1}{1-\rho/(1+r)}](\lambda^j\rho^j s_{t-j}) \\ &= \frac{1-\lambda}{1+r-\rho}\sum_{j\geq 0}\lambda^j\rho^j s_{t-j} \end{aligned}$$

Finally, we can compute dollar returns as:

$$\begin{aligned} R_{t+1} &= P_{t+1}+\pi_{t+1}-(1+r)P_t \\ &= ms_{t+1}+s_t+\epsilon_{t+1}-zm\sum_{k\geq 0}(\lambda\rho)^k s_{t-k} \end{aligned}$$

B Proof of Prediction 2

First notice that $Cov(s_{t-k}, s_t) = \rho^k Var(s_t)$.

From Equation (6):

$$E_t\left(F_t\pi_{t+1}|\,\pi_t\right) = (1-\lambda)\sum_{k\geq 0}(\lambda\rho)^k E_t(s_{t-k}|\pi_t)$$

Since s_t and π_t are Gaussian stationnary random variables centered on zero, we can write the conditional expectations as simple projections.

- for $k > 0$:

$$\begin{aligned}
E_t(s_{t-k}|\pi_t) &= \frac{Cov(s_{t-k},\pi_t)}{Var(\pi_t)}\pi_t \\
&= \frac{Cov(s_{t-k},s_{t-1}+\epsilon_t)}{Var(s_t)+\sigma_\epsilon^2}\pi_t \\
&= \frac{Cov(s_{t-(k-1)},s_t)}{Var(s_t)+\sigma_\epsilon^2}\pi_t \\
&= \rho^{k-1}\frac{Var(s_t)}{Var(s_t)+\sigma_\epsilon^2}\pi_t \\
&= \rho^{k-1}\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t
\end{aligned}$$

  because $Var(s_t) = \rho^2 Var(s_t) + \sigma_u^2$.

- for $k = 0$:

$$\begin{aligned}
E_t(s_t|\pi_t) &= \frac{Cov(s_t,\pi_t)}{Var(\pi_t)}\pi_t \\
&= \frac{Cov(s_t,s_{t-1}+\epsilon_t)}{Var(s_t)+\sigma_\epsilon^2}\pi_t \\
&= \rho\frac{Var(s_t)}{Var(s_t)+\sigma_\epsilon^2}\pi_t \\
&= \rho\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t
\end{aligned}$$

So:

$$\begin{aligned}
E_t\left(F_t\pi_{t+1}|\,\pi_t\right) &= (\rho+\lambda\rho\sum_{k\geq 0}\lambda^k\rho^{2k})(1-\lambda)\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t \\
&= (1-\lambda)\rho(1+\frac{\lambda}{1-\lambda\rho^2})\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t
\end{aligned}$$

The second prediction follows directly from:

$$\begin{aligned}
E_t\left(\pi_{t+1}\middle|\,\pi_t\right) &= E(s_t|\pi_t)\\
&= \frac{Cov(s_t,\pi_t)}{Var(\pi_t)}\pi_t\\
&= \frac{Cov(s_t,s_{t-1})}{Var(\pi_t)}\pi_t\\
&= \rho\frac{\sigma_u^2}{\sigma_u^2+(1-\rho^2)\sigma_\epsilon^2}\pi_t
\end{aligned}$$

C Proof of existence of well-known strategies

We know that prices and returns are given by the following formulas:

$$\begin{aligned}
P_t &= m.\sum_{k\geq 0}(\lambda\rho)^k s_{t-k}\\
R_{t+1} &= ms_{t+1}+s_t+\epsilon_{t+1}-zm\sum_{k\geq 0}(\lambda\rho)^k s_{t-k}
\end{aligned}$$

where $m=\frac{1-\lambda}{1+r-\rho}$ and $z=1+r-\rho\lambda$. It is useful to note that $zm=(1-\lambda)(1+m\rho)$ and replace it in the above expression.

Note $a_k = cov\left(R_{t+1},s_{t-k}\right)$. After some tedious algebra, we can prove that:

$$a_k=(1+m\rho)\frac{\lambda\sigma_u^2}{1-\lambda\rho^2}(\lambda\rho)^k$$

A. Profitability Anomaly

$$\begin{aligned}
cov(R_{t+1},\pi_t) &= cov(R_{t+1},s_{t-1})\\
&= a_1\\
&= \sigma_s^2\left[m\rho^2+\rho-(1-\lambda)(1+m\rho)\left(\rho+\frac{\lambda\rho}{1-\lambda\rho^2}\right)\right]\\
&= (1+m\rho)\lambda\rho\sigma_s^2\left(1+\frac{1-\lambda}{1-\lambda\rho^2}\right)
\end{aligned}$$

B. Momentum

The covariance between consecutive returns is given by:

$$cov(R_{t+1},R_t)=ma_0+a_1-zm\sum_{k\geq 0}(\lambda\rho)^k a_{k+1}$$

We inject the values of the a's coefficients into the above equation, and obtain:

$$cov(R_{t+1}, R_t) = (1 + m\rho)(m + \rho\lambda^2)\frac{\lambda\sigma_u^2}{1 - \lambda\rho^2}$$

which immediately shows that momentum is positive as soon as $\lambda > 0$.

C. Earnings momentum

We need to compute $cov(R_{t+1}, \Delta\pi_t)$. Quite simply:

$$cov(R_{t+1}, \Delta\pi_t) = a_1 - a_2$$

Thus:

$$cov(R_{t+1}, \Delta\pi_t) = (1 + m\rho)(1 - \lambda\rho)\frac{\lambda^2\rho\sigma_u^2}{1 - \lambda^2\rho^2}$$

D. Forecast revisions

Last, we show that returns covary with past forecast revisions.
Start with

$$F_t(\pi_{t+1}) = (1 - \lambda)E_t(\pi_{t+1}) + \lambda F_{t-1}(\pi_{t+1}).$$

From which it follows that:

$$\begin{aligned} Update_t &= F_t(\pi_{t+1}) - F_{t-1}(\pi_{t+1}) \\ &= (1 - \lambda)[S_t - (1 - \lambda)\rho \sum_{j \geq 0} (\lambda\rho)^j S_{t-1-j}] \\ &= (1 - \lambda)[S_t - \frac{1 - \lambda}{\lambda} \sum_{j > 0} (\lambda\rho)^j S_{t-j}] \end{aligned}$$

Which we want to correlate with:

$$R_{t+1} = ms_{t+1} + s_t + \epsilon_{t+1} - (1 - \lambda)(1 + m\rho) \sum_{k \geq 0} (\lambda\rho)^k s_{t-k}$$

We decompose this into different terms:

$$\begin{aligned} Term_1 &= cov(S_t, R_{t+1}) \\ &= (1 - \lambda)[\rho m + 1 - (1 - \lambda)(1 + m\rho) \sum_{k \geq 0} \left(\lambda\rho^2\right)^k]\sigma_S^2 \\ &= (1 - \lambda)(1 + m\rho)\frac{\sigma_u^2}{1 - \lambda\rho^2}\lambda \end{aligned}$$

The second term is:

$$\begin{aligned} Term_2 &= -\frac{(1-\lambda)^2}{\lambda}\rho\lambda cov(S_{t-1}, R_{t+1}) \\ &= -(1-\lambda)^2\rho(\sigma_u^2)(1+m\rho)\lambda^2 \end{aligned}$$

This term is clearly second order in λ, and so are all the subsequent terms in $cov(S_{t-j}, R_{t+1})$. So only $Term_1$ matters to the first order, i.e.

$$cov(Update_t, R_{t+1}) \approx (1+m\rho)\sigma_u^2\lambda$$

E. Absolute versus risk-adjusted performance

E.1. Definition

We define the risk-adjusted performance S_t^w as the expected PNL of the strategy per dollar of conditional volatility:

$$S_t^w = \frac{E_t R_{t+1}^w}{\sqrt{var_t R_{t+1}^w}}$$

which is the conditional Sharpe ratio of the portfolio w.

Given the formula for R_{t+1} previously shown, we have:

$$R_{t+1}^w - E_t R_{t+1}^w = m w_t' u_{t+1} + w_t' \epsilon_{t+1}$$

Thus, the conditional variance of such a portfolio is given by:

$$var_t R_{t+1}^w \approx N(m\sigma_u^2 + \sigma_\epsilon^2) var w_t$$

Thus, the risk-adjusted performance is:

$$S_t^w \approx \sqrt{\frac{N}{m\sigma_u^2 + \sigma_\epsilon^2}} \frac{cov(w_t, R_{t+1})}{\sqrt{var w_t}}$$

as $N \to \infty$.

The outcome of this analysis is that, in order to compute risk-adjusted performance, we just need to divide the covariances shown in Prediction 3 by the standard deviation of the weights.

E.2. Profitability

Here is how we can compute them. For profitability anomaly, $var w_t$ is simple to compute:

$$var \pi_t = \sigma_\epsilon^2 + \sigma_u^2/(1-\rho^2)$$

Hence:

$$
\begin{aligned}
S^P &= \sqrt{N}(1+m\rho)\frac{\rho\lambda^2}{1-\lambda\rho^2}\frac{\sigma_u^2}{\left(\sigma_\epsilon^2+\sigma_u^2/(1-\rho^2)\right)^{1/2}\left(\sigma_\epsilon^2+m^2\sigma_u^2\right)^{1/2}} \\
&\approx \sqrt{N}\frac{\rho\lambda^2}{1-\rho}\frac{\sigma_u^2}{\left(\sigma_\epsilon^2+\sigma_u^2/(1-\rho^2)\right)^{1/2}\left(\sigma_\epsilon^2+\frac{\sigma_u^2}{(1-\rho)^2}\right)^{1/2}}
\end{aligned}
$$

which can be rewritten as a function of the volatility of π, σ_π, the persistence of π, ρ_π and ρ, the actual persistence of the signal:

$$
S^P \approx \sqrt{N}\lambda^2\frac{(1+\rho)\rho_\pi}{\sqrt{1+2\rho_\pi/(1-\rho)}}
$$

E.3. Momentum

For the momentum anomaly, $varw_t$ is the steady state variance of returns, which is a bit more cumbersome. After some algebra, we get:

$$
\begin{aligned}
var(R_{t+1}) &= \left[m\left(m+\rho\lambda^2\right)+\lambda^2\left(1+m\rho\right)\right]\frac{\sigma_u^2}{1-\lambda\rho^2}+\sigma_\epsilon^2 \\
&\approx \left(\frac{1}{1-\rho}\right)^2\sigma_u^2+\sigma_\epsilon^2
\end{aligned}
$$

Clearly, risk-adjusted performance is not non-monotonically related to λ and ρ. Simulations will help us check that the model's properties are acceptable in the vicinity of reasonable parameters.

Assuming λ small and r small, one finds that:

$$
S^M \approx \sqrt{N}\lambda\frac{\frac{\sigma_u^2}{(1-\rho)^2}}{\frac{\sigma_u^2}{(1-\rho)^2}+\sigma_\epsilon^2}
$$

which can be rewritten as a function of the volatility of π, σ_π, the persistence of π, ρ_π and ρ, the actual persistence of the signal:

$$
S^M \approx \sqrt{N}\lambda\frac{1+\rho_\pi/(1-\rho)}{1+2\rho_\pi/(1-\rho)}
$$

D Comovement of strategies

Given the formula for R_{t+1} previously shown, we have:

$$
R^w_{t+1}-E_tR^w_{t+1} = mw_t'u_{t+1}+w_t'\epsilon_{t+1}
$$

Note $w_t = \pi_t$ for profitability and $w_t = R_t$ for momentum. Conditional variances write:

$$
\begin{aligned}
varR^P_{t+1} &\approx N(m^2\sigma_u^2 + \sigma_\epsilon^2)var\pi_t \\
varR^M_{t+1} &\approx N(m^2\sigma_u^2 + \sigma_\epsilon^2)varR_t
\end{aligned}
$$

The conditional covariance of momentum and profitability returns yields:

$$
\begin{aligned}
cov_t(R^M_{t+1}, R^P_{t+1}) &= N\left(\sigma_\epsilon^2 + m^2\sigma_u^2\right) cov(\pi_t, R_t) \\
&= N\left(\sigma_\epsilon^2 + m^2\sigma_u^2\right)\left[(1+m\rho)\frac{\lambda\sigma_u^2}{1-\lambda\rho^2} + \sigma_\epsilon^2\right]
\end{aligned}
$$

Again, the formula is a bit complicated, but we can make the small λ assumption and get the conditional correlation. In this case:

$$
corr_t(R^M_{t+1}, R^P_{t+1}) \approx \frac{\frac{\lambda}{1-\rho}\sigma_u^2 + \sigma_\epsilon^2}{\left(\frac{\sigma_u^2}{1-\rho^2} + \sigma_\epsilon^2\right)^{1/2}\left(\frac{\sigma_u^2}{(1-\rho)^2} + \sigma_\epsilon^2\right)^{1/2}}
$$

which can be rewritten as a function of the volatility of π, σ_π, the persistence of π, ρ_π and ρ, the actual persistence of the signal:

$$
corr \approx \frac{1 + ((1+\rho)\lambda - 1)\rho_\pi/\rho}{\sqrt{1 + 2\rho_\pi/(1-\rho)}}
$$