Momentum, Reversal, and the Firm Fundamental Cycle*

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Momentum, Reversal, and the Firm
Fundamental Cycle*

Abstract

We link momentum and long-run return reversal to the cyclic behavior of firm fundamentals, which are represented by a fundamental index that summarizes succinctly and efficiently a broad range of business activities at firm level. In responding to repeated unanticipated positive (negative) shocks in fundamentals, investors continue to raise (lower) prices for winner (loser) firms, yielding momentum. However, due to the cyclicality of firm fundamentals, the unanticipated positive (negative) shocks decrease in magnitude overtime and eventually reverse, generating the reversal pattern. In addition, we find that firm fundamentals can explain stronger momentum in microcap stocks, and a long/short decile portfolio based on the firm fundamant index outperforms the popular momentum portfolio substantially by doubling the Sharpe ratio and does not suffer crashes.

JEL Classification: G11, G14

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“Clearly, I and my team are not satisfied with this level of performance and we see 2018 with the opportunity to prove to you that we can sharpen operational execution, dramatically improve the fitness we’re talking about and continue making the big decisions strategically on where to play, how to win and of course properly allocate capital.” - James Hackett, CEO, Ford, Q4 2017 Earnings Call Conference.

1 Introduction

Just as the whole economy goes through cycles, an individual firm typically exhibits cyclical behaviors in fundamentals. Firm fundamentals may initially increase (decrease) for a certain periods of time, then subsequently decrease (increase) over another period of time, and repeat it again. In this paper, we argue that the cyclical behavior of firm fundamentals drives return momentum and subsequent reversal.

Why do firms experience cycles in fundamentals? There are at least three reasons for this empirical fact. First, uptrend fundamentals may come from technological breakthroughs with new or better products, but this trend can slow down due to competitions from rivals with improved technologies or products. Second, a firm with poor performance may be due to mismanagement. As the case for the CEO of Ford, internal and external pressures can force the management team to turn the business around. Third, The cyclical nature of commodity prices, such as oil and iron ore, can drive the mining businesses and many other related businesses up and down, creating cyclical firm fundamentals.

How do firm fundamental cycles drive momentum and long-run reversal? Intuitively, as a business enters into an upward growth trend, the initial acceleration phrase is often accompanied by increasingly larger unanticipated positive changes in the fundamentals. Consequently, investors continue to raise the stock price in response to the repeated unanticipated positive shocks in firm fundamentals, and thus create winner momentum in price. As the
growth trend slows down, the unanticipated positive changes become smaller and smaller and eventually becomes negative, and the unanticipated negative changes become increasingly larger as the deterioration in fundamentals accelerates. Now, in response to these repeated unanticipated negative shocks in firm fundamentals, investors continue to lower the stock price, and thus winner momentum turns to reversal. Similarly, a loser momentum can reverse too. Although our paper is empirically oriented, we provide a simple theoretical model to justify the intuitive arguments. The model also helps understand why stock prices are not adjusted fully at the beginning of the cycles.

To find the relation between firm fundamentals and momentum and its reversal, we need to provide a measure that summarizes a wide range of business activities of a firm. We consider four major areas: the profitability, financial leverage and balance sheet strength, efficiency of asset management, and quality of earning and assets, on which there are available data on 13 different seasonally adjusted fundamental ratios. To capture unanticipated changes, we use the changes of the ratios between two adjacent quarters for each stock. Then we construct an index of the changes based on the partial least squares (PLS) method, as used by Kelly and Pruitt (2013, 2015), and Light, Maslov, and Rytchkov (2017) in other contexts. As an alternative, we also use the principal component analysis (PCA) to define an index of firm fundamentals. They will be referred below as PLS and PCA, respectively. Kelly and Pruitt (2013, 2015), and Light, Maslov, and Rytchkov (2017) show that the PLS is in general an efficient method for information aggregation, whereas the PCA extracts the maximum variation from the data.

Using quarterly future stock returns up to 10 quarters ahead, we document a strong momentum effect in the first two quarters and a strong and prolonged reversal effect in subsequent quarters with Fama-MacBeth regressions. The coefficient of the 12-month past returns is 1.993 with a $t$-stat of 4.29 and 0.938 with a $t$-stat of 2.08, respectively, for the first two quarters, representing the momentum effect. The coefficient becomes significantly negative starting from the fourth quarter. For example, it is $-0.691$ ($t$-stat=$-2.10$), $-0.963$
(t-stat=-2.85), -1.079 (t-stat=-3.04), and -0.946 (t-stat=-2.50), for quarter 4, 5, 6, and 7, respectively. Once we control for the revealed fundamental indexes (PLS or PCA indexes) of the concurrent quarter (with future returns) and the prior quarter, however, the momentum and subsequent reversal effects are no longer significant. Instead, both fundamental indexes are highly significant and positive. Further, the results are robust when we only include microcap stocks or during expansionary periods of the business cycle; in both cases, the momentums are documented stronger.

Novy-Marx (2015) provides a novel finding that the standardized unexpected earning surprise (SUE) drives momentum. In contrast to SUE, our fundamental index contains much more information about fundamentals that are not be reflected in SUE. The key difference between his finding and ours is that fundamental cycles explain both momentum and reversal, whereas SUE concerns about only momentum. Moreover, when running a horse race between SUE and our fundamental indices, we find that while the momentum effect is not be fully subdued by the earnings momentum at the quarterly frequency, the firm fundamental indexes can explain away both momentum and reversal with or without SUE. Our results suggest that firm fundamental indices replace SUE in explaining stock returns, and momentum and reversal.

Using an alternative portfolio sort approach and focusing on the first quarter momentum, we first estimate PLS implied returns constructed as the predicted returns from the cross-sectional regressions of regressing returns on both the first quarter and the previous quarter PLS indexes, and then conduct the dependent double sort with the PLS implied returns and the 12-month past returns. The momentum is not significant in all but the highest quintile of PLS implied returns. Alternatively, we take the component (residuals) of the 12-month past returns that is orthogonal to the PLS indexes via cross-sectional regressions and sort stocks by the residuals into deciles. Interestingly, the 10-1 spread portfolio does not have any significant returns. Lastly, in the spanning tests, the spread decile portfolio based on the PLS index subsumes the momentum factor, not vice versa, suggesting that momentum
is not independent of the PLS fundamental indexes.

Finally, we construct tradable strategies based on the previous quarter firm fundamental indexes. Compared to momentum, the spread decile portfolios deliver slightly lower average returns, but enjoy much smaller standard deviations, and therefore doubling the Sharp Ratio. In addition, the spread decile portfolios exhibit positive skewness, much lower maximum drawdown and much larger Calmar ratios, and more importantly, do not suffer from crashes.

In contrast to the explanations in the literature that are almost completely based on investor behavioral biases or market frictions (e.g. Hong and Stein (1999), Daniel, Hirshleifer, and Subrahmanyam (1998), and Chan, Jegadeesh, and Lakonishok (1996)), our explanation of the momentum and reversal effects is based on different phases of the firm fundamental cycle, during which investors rationally respond to unanticipated positive/negative shocks. In essence, the fundamentals news is continuously updated. While investors are rationally update their beliefs, there are unanticipated news each period. It is the rational response to these unanticipated news that creates initial momentum and subsequent reversal.

Our papers adds to the small literature on fundamental explanations based on rational-expectations models. Chordia and Shivakumar (2002) relate momentum profits to business cycle. They find that lagged macroeconomic variables related to the business cycles can explain the momentum profits to some extent. Andrei and Cujean (2017) provide a rational expectations model to explain both momentum and reversal, in which momentum to arise from the premise that information flows at an increasing rate. They argue that word-of-mouth communication spreads rumors and generates price run-ups and reversals.

The rest of the paper is organized as follows. Section 2 discusses the data. Section 3 discusses the construction of the fundamental index and its link to momentum and reversal. Section 4 provides empirical result. Section 5 examines robustness. Section 7 presents the fundamentally-based tradable strategies. Section 8 concludes.
2 Data Description

Monthly stock returns, prices, and other market attributes are from the Center for Research in Security Prices (CRSP). We include all domestic common stocks listed on the NYSE, AMEX, and Nasdaq stock markets, and exclude closed-end funds, real estate investment trusts (REITs), unit trusts, American depositary receipts (ADRs), and foreign stocks (or stocks that do not have a CRSP share code of 10 or 11). Following the vast literature on momentum, we use the 12-month past cumulative returns as the measure of momentum, and exclude any stocks whose prices are less then $1.

To capture firm fundamentals, we use a total of 13 firm fundamental ratios, namely profitability (ROA, ROE, Operating Profit Before Depreciation, EBITDA/TA, and Cash Flow Margin), financial leverage and strength (Debt Ratio, Cash Flow to Debt, Long-term Debt to Book Equity, and Free Cash Flow to Operating Cash Flow), efficiency of asset management (Inventory Turnover, Asset Turnover Ratio, Sales to Invested Capital); and quality of earning and assets (Accruals Ratio). The data is obtained from the Wharton Research Data Services (WRDS) financial ratio database and measured at quarterly frequency, and is available from January 1970 to December 2015.

To match with the quarterly fundamental ratios, we convert the monthly prices, market size, and 12-month momentum to quarterly frequency by taking the corresponding values at the quarter end, and compound the monthly stock returns to quarterly returns. We then merge the quarterly firm fundamental ratios with the quarterly stock returns to estimate the firm fundamental index described next. When merging the two datasets, we match the date of the quarterly return from CRSP with the publish date of the WRDS financial ratio database to minimize the possible looking forward bias. For example, if a company reports the first quarter result in April 2014, the ratios are matched with the information of the second quarter in 2014 in CRSP even if the ratios are actually realized fundamental numbers for the first quarter of 2014.
3 Firm Fundamental Indexes

In this section we first provide details on construction of the firm fundamental indexes, and then provide empirical evidence in support of the cyclical nature of firm fundamentals based on the PLS index and discuss how the firm fundamental cycles link to momentum and reversal. Finally, we provide a simple equilibrium model in which momentum and reversal are generated from the mean-reverting process of the fundamentals.

3.1 Construction of Firm Fundamental Indexes

As firm fundamental ratios typically exhibit strong seasonality, we first address the seasonality issue by taking the average of each ratio over the same quarter of the prior four years. We then subtract the average from the ratio of the current quarter. For example, we use the following to obtain the seasonally adjusted ROA,

\[ \text{ROA}_{i,qy}^{SA} = \text{ROA}_{i,qy} - \frac{\text{ROA}_{i,qy-1} + \text{ROA}_{i,qy-2} + \text{ROA}_{i,qy-3} + \text{ROA}_{i,qy-4}}{4}, \]

where \( \text{ROA}_{i,qy}^{SA} \) denotes the seasonally adjusted ROA for firm \( i \) in quarter \( q \) of year \( y \), and \( \text{ROA}_{i,qy-1}, \ldots, \text{ROA}_{i,qy-4} \) are the unadjusted ROA for firm \( i \) in quarter \( q \) for year \( y - 1 \) through \( y - 4 \). We do this for each of the 13 fundamental ratios. Except for three measures (Debt Ratio, Long-term Debt to Book Equity, and Accruals Ratio), a positive reading of the seasonally adjusted ratio implies that the firm performance is generally improved compared to the similar quarters before.

To capture the unanticipated shocks in the seasonally adjusted fundamental ratios, for each selected seasonally adjusted financial ratio, we calculate a change in the ratio between two adjacent quarters by taking the difference of the seasonally adjusted ratio for each stock.
Using ROA as an example again, we have

$$\Delta ROA_{i,t} = ROA_{i,t}^{SA} - ROA_{i,t-1}^{SA},$$

(2)

where $ROA_{i,t}^{SA}$ and $ROA_{i,t-1}^{SA}$ are the seasonally adjusted ROAs for firm $i$ in quarter $t$ and $t-1$ obtained from Eq. (1)\(^1\) and $\Delta ROA_{i,t}$ is the unanticipated change of ROA for firm $i$ in quarter $t$ to capture the nature of fundamental cycle — its sign indicates whether or not a business enters into a different stage of the fundamental cycle. For example, let’s assume that a business is in an upward trend of its fundamental cycle with both $ROA_{i,t}^{SA}$ and $ROA_{i,t-1}^{SA}$ positive. As the upward trend continues, $\Delta ROA_{i,t}$ would be positive, implying that the ROA of the business gets better due to the positive unanticipated shock in quarter $t$. On the other hand, if $\Delta ROA_{i,t}$ turns out to be negative, it suggests that the ROA of the business gets surprisingly worse due to the negative unanticipated shock in quarter $t$, even though $ROA_{i,t}^{SA}$ is still positive. The negative unanticipated shocks signal a turn in the trend from the upward one to a downward one.

In a second scenario, let’s assume that the business is in a challenging stage of its cycle with both $ROA_{i,t}^{SA}$ and $ROA_{i,t-1}^{SA}$ negative. If $\Delta ROA_{i,t}$ turns out to be negative, it indicates that the ROA of the business continues to deteriorate due to a negative unanticipated shock in quarter $t$ and the downward trend continues. On the other hand, if $\Delta ROA_{i,t}$ turns out to be positive, it implies that the business is turning around even through $ROA_{i,t}^{SA}$ is still negative. Again, the negative unanticipated shocks signal a turn in the trend from the downward one to an upward one.

All these 13 firm fundamental ratios may affect cross-sectional stock returns, however, not all ratios have the same impact and importance. The goal is to extract a common component from the 13 ratios such that it has the highest covariance with the expected stock returns or is the best in explaining the cross-section returns. Therefore, we follow

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\(^1\)To simplify the notation, we replace the combined subscripts $qy$ in Eq. (1) with a single subscript $t$. 

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Kelly and Pruitt (2015), Light, Maslov, and Rytchkov (2017) and Huang, Jiang, Tu, and Zhou (2015) and use the partial least square (PLS) approach to aggregate the relevant information contained in all 13 fundamental ratios. As pointed out by Huang, Jiang, Tu, and Zhou (2015), the difference between the PLS approach and the conventional principal component analysis (PCA) approach is that the PLS is to find the most relevant common components in explaining the returns, whereas the PCA approach is to maximize the common variations of all different fundamental ratios. Thus the common component obtained by PCA may contain large errors (variations or information that may not be relevant to returns).

We construct a PLS index for the level of the seasonally adjusted fundamental ratios as well as for the unanticipated changes of the seasonally adjusted fundamental ratios. Specifically, we conduct the following two-step regressions for each time period:

$$
\Delta RT_{i,t-1}^j = \delta_{i0}^j + \delta_{i}^j R_{i,t} + \epsilon_{i-1}^j, \quad \text{for } i = 1, \ldots, N, \tag{3}
$$

$$
\Delta RT_{i,t}^j = \theta_{i,t}^j + PLS_{i,t} \hat{\delta}_{i}^j + \mu_{i}^j, \quad \text{for } j = 1, \ldots, 13, \tag{4}
$$

where $\Delta RT_{i,t-1}^j$ denotes the unanticipated shock of the fundamental ratio $j$ for firm $i$ in quarter $t - 1$ obtained from Eq. (2) and further standardized cross-sectionally across firms, $R_{i,t}$ represents the quarterly returns on firm $i$ in quarter $t$, $\delta_{i}^j$ in Eq. (4) denotes the estimated slope coefficient obtained in the first-step regression in Eq. (3) for fundamental ratio $j$, and $PLS_{i,t}$ is the fundamental index estimated for firm $i$ in quarter $t$.

Using the future returns as a proxy for the latent common component, the first-step regression identifies the maximum correlation between a specific fundamental ratio and the common component each quarter. It is a cross-sectional regression in which the standardized unanticipated changes in fundamental ratio $j$ of firm $i$ in quarter $t - 1$ is regressed on firm $i$ return in quarter $t$ across firms. We run the regression each quarter for each of the fundamental ratios (13 regressions each quarter). After obtaining the estimates of the slope coefficient $\hat{\delta}_{i}^j$ from Eq. (3), in the second-step regression we regress the standardized
unanticipated changes in fundamental ratios in quarter $t$ on these slope coefficient estimates. Note that the second-step regression is also a cross-sectional regression not across firms but across the fundamental ratios. In other words, each quarter for each firm we run the regression with 13 observations (fundamental ratios). The estimated slope coefficient in the second-step regression is the estimate of the latent common component in quarter $t$, i.e., the PLS fundamental index for firm $i$ in quarter $t$, which should provide the best explanation of the cross-sectional returns. Following Light, Maslov, and Rytchkov (2017), we adopt a modified version of the second-step regression by replacing the slope coefficient estimate $\hat{\delta}_t^i$ with a time-series averages of $\hat{\delta}_t^i$ over the past 10 years. Using the average instead of a single estimate improves the stability of the estimated fundamental index, which is also used by Han, Zhou, and Zhu (2016).

### 3.2 Linkage between Firm Fundamental Cycles and Momentum and Reversal

At the end of each quarter, following the standard approaches in the momentum literature, we first sort stocks into deciles based on their prior 12-month cumulative returns (momentum). We then calculate the average PLS index for each decile. Results not reported show that PLS index monotonically increases as the past return increases during the formation period. We then examine the time-series behavior of the PLS indexes by tracking the decile portfolios up to 20 quarters before and after the formation quarter, which is illustrated in Panel A of Fig. 1. We denote the formation quarter as 0, the quarters before the formation quarter as negative quarters, and the quarters after the formation quarter as positive quarters. For example, quarter $-6$ denotes the sixth quarter before the formation quarter while quarter 6 denotes the sixth quarter after the formation quarter. For simplicity, we only plot the PLS index of the winner, loser, as well as winner-loser portfolios.

Panel A of Fig. 1 shows that the winner and loser PLS indexes are the same and equal
to zero from quarter \(-20\) to \(-6\) and then start to diverge approximately five quarters prior to the momentum formation period. The winner PLS index becomes positive and continues to increase until the formation quarter when the index reaches the highest, which suggests that the fundamentals of winner firms are not only getting better but also experiencing larger and larger positive unanticipated changes until the formation period. The loser PLS index behaves exactly the opposite — it becomes negative and continues to decrease until the formation quarter, which suggests that the fundamentals of the loser firms are not only getting worse but also experiencing larger and larger negative unanticipated changes (shocks). As a result, the difference between the winner and loser PLS indexes, which is represented by the PLS index of the winner-loser portfolio, becomes positive starting from quarter \(-4\) and continues to increase until the formation period. This indeed matches the timing of the 12-month past returns used to rank stocks.

After the formation period, the winner PLS index begins a downward trend. However, before quarter 3, the index is positive which means that winner firm fundamentals are still increasing before quarter 3 but the unanticipated increase becomes smaller and smaller.\(^2\) Eventually, winner firm fundamentals change from increase to decrease and the index becomes negative after quarter 3. The negative unanticipated change becomes larger and larger before quarter 6, then becomes smaller and smaller afterwards, and becomes completely zero around quarter 19. On the other hand, the loser PLS index behaves in the completely opposite way. After the formation period, it starts an upward trend meaning the fundamentals are getting better and better. Initially, there are still unanticipated negative changes but the negative shock becomes smaller and smaller and eventually negative unanticipated shocks become positive unanticipated shocks and become larger and larger until quarter 6. The positive unanticipated shocks then remain positive but are getting smaller and eventually become zero in quarter 19.

\(^2\)PLS index constructed from the seasonally adjusted fundamental ratios (not unanticipated changes) experiences slower cycles as one would expect. The PLS index for the fundamental level plateaus around quarter 3.
Consequently, the PLS index of the winner-loser portfolio, which is the difference in the PLS index between the winner and loser portfolios, is positive albeit decreasing after the formation period until quarter 3. It implies that the differences in fundamentals continue to widen up between the winner and loser firms but the widening process becomes slower and slower due to smaller and smaller unanticipated positive shocks in fundamentals for winner firms and smaller and smaller (in magnitude) negative shocks for loser firms in fundamentals, respectively. We argue that this widening process, once is revealed to the investors, calls for continued upward price adjustment following the initial formation period, and therefore leads to momentum profits, although the magnitude is decreasing.

Starting from quarter 3 after the formation period, however, this widening process in fundamentals apparently ceases and reverses; the differences in fundamentals between the winner and loser firms begin to shrink due to unanticipated negative shocks in fundamentals for winner firms and at the same time unanticipated positive shocks in fundamentals for loser firms. Furthermore, this shrinking process is first accelerating until quarter 6 and then slowing down to zero around quarter 19. Similarly, we argue that this shrinking process in fundamentals, once is revealed to the investors, calls for continued downward price adjustment, and therefore leads to return reversals.

As a robustness check, we also plot the fundamental index of the winner, loser and winner-loser portfolios using the PCA index. In Panel B Fig. 1, we observe the same cyclic behavior for the winner, loser and consequently the winner-loser portfolios. The PCA fundamental index of the winner-loser portfolio is positive between quarter $-4$ and 3 but turns to negative between quarter 3 and quarter 19, matching the initial momentum and subsequent reversal pattern observed.
3.3 Theoretic Support

Consider an infinite horizon pure exchange economy in which the randomness is generated by $(\Omega, \mathcal{F}_t, W)$, where $W = (W_Y, W_\theta, W_D, W_\mu)$ is a 4-dimensional generalized Brownian motion which will be explained shortly. There is one non-storable consumption good $Y$. The instantaneous aggregate endowment of $Y$ evolves according to the following process

$$\frac{dY_t}{Y_t} = \theta_t dt + \sigma_Y dW_Y \quad (5)$$

where $\theta$ follows the process

$$d\theta_t = \alpha(\bar{\theta} - \theta_t) dt + \sigma_{\theta} dW_\theta. \quad (6)$$

$\sigma_Y, \sigma_\theta, \alpha$ and $\bar{\theta}$ are positive constants.

Similar to Brennan and Xia (2001), the part of the endowment is in the form of a tradable stock which pays a continuous dividend at the rate, $D$. We assume that

$$\frac{dD}{D} = \mu_t dt + \sigma_D dW_D \quad (7)$$

and

$$d\mu_t = \kappa(\bar{\mu} - \mu_t) dt + \sigma_\mu dW_\mu \quad (8)$$

Here $\sigma_D, \sigma_\mu, \kappa$ and $\bar{\mu}$ are constants, each of $W_Y, W_\theta, W_D$ and $W_\mu$ is a one-dimensional Brownian motion and the correlation between these Brownian motions are constants and denoted by $\rho_{Y\theta}$ and so on.

The representative agent’s lifetime expected utility is of the form

$$\mathbb{E}_t \int_t^{\infty} U(s, c_s) ds, \quad (9)$$
and

\[ U(s, c_s) = e^{-\delta s \ln(c_s)}. \]  

We also assume that there are several traded contingent claims in addition to this stock such that the economy is a complete market. Therefore, the stochastic discount factor process \( M_t \) satisfies \( \lambda M_t = U_c(t, c_t^*) = U_c(t, Y_t) \) in equilibrium for a positive number \( \lambda \). Since

\[ \frac{dM_t}{M_t} = -r_t + \pi dW_Y, \]  

it is straightforward to derive that (see details in Duffie, 2001).

\[ r_t = \delta + \theta_t - \frac{3}{2} \sigma_Y^2 \]  

and the market price of risk \( \pi = -\gamma \sigma_Y \). Given the process of \( \theta_t \), the short-rate is consistent with Vasicek’s equilibrium term-structure model. We assume that these Brownian motions are either independent or positive correlated. That is, \( \rho_{YD} \geq 0, \cdots, \rho_{D\mu} \geq 0 \).

Among these parameters, the parameter \( \alpha \) and \( \kappa \) measure possible different trend of the market and the firm. To illustrate, we consider the expected aggregate growth rate \( \theta \). By its definition,

\[ d(\bar{\theta} - \theta_t) = -\alpha(\bar{\theta} - \theta_t)dt - \sigma_d dW_\theta. \]  

Let \( x_t \equiv \bar{\theta} - \theta_t \). Then,

\[ x_t = e^{-\alpha t} x_0 + \int_0^t e^{-\alpha(t-s)} \sigma_d dW_\theta. \]  

By the law of the large number, for \( t \to \infty \), \( \int_0^t e^{-\alpha(t-s)} \sigma_d dW_\theta \to 0 \), then \( x_t \to 0 \) and \( \theta_t \to \bar{\theta} \). Assume first \( \theta_0 < \bar{\theta} \), then for time \( t \), it is possible that \( x_t > 0 \), i.e., \( \theta_t > \bar{\theta} \), the probability of
the event occurred is \(^3\)

\[
N \left( -\frac{e^{-\alpha t} x_0}{\sigma \sqrt{\frac{1-e^{-2\alpha t}}{2\alpha}}} \right).
\]

The higher \(\alpha\) the larger the probability that \(x_t > 0\), and thus the more likely the trend of the process \(\theta_t\) is changed. The effect of \(\alpha\) to the probability that \(x_t < 0\) giving \(x_0 > 0\) is similar. Hence, the trend of the process \(x_t\) is essentially captured by the parameter \(\alpha\).

**Proposition 1** The equilibrium stock price \(S_t\) at time \(t\) is

\[
\frac{dS_t}{S_t} = \alpha_{S,t} dt + \sigma_{S,t} dW_S.
\] (15)

The cumulative excess returns accruing to the holder of a unit investment in the stock, \(CER_t\), is

\[
dCER_t = \frac{dS_t}{S_t} - r_t dt + \frac{D_t}{S_t} dt.
\] (16)

The instantaneous expected excess return of the stock in the time period \([t, t+dt]\) is

\[
EER_t = \alpha_{S,t} - r_t + \frac{D_t}{S_t}.
\] (17)

**Momentum:** Assume that \(\alpha\) and \(\kappa\) are close enough, then for a positive number \(l\)

\[
\mathbb{E}_t [(EER_{t+l} - \mathbb{E}_t[EER_{t+l}]) (CER_{t+l} - \mathbb{E}_t[CER_{t+l}])] > 0 \quad (18)
\]

**Long-Term Reversal:** When \(\alpha\) and \(\kappa\) are significantly different from each other, then under certain condition on parameters (which is stated in the proof), the conditional covariance, \(\text{Cov}_t (EER_{t+l}, CER_{t+l})\) is negative, even though \(\text{Cov}_t (EER_{t+l}, EER_{t+l})\) is positive when \(l_2\) is sufficiently close to \(l_1\) and \(l_2 > l_1\) (short-term momentum).

\(^3\)It is known that \(x_t\) has a normal distribution with mean \(e^{-\alpha t} x_0\) and variance \(\int_0^t e^{-2\alpha(t-s)} \sigma^2 ds\).
Proof: See the Appendix.

When $\theta_t$ is a constant, this model is the same as the model studied in Brennan and Xia (2001) with observable expected return. Johnson (2002) demonstrates a short-term momentum in this model. We show that robust momentum of the stock returns holds when $\theta_t$ displays a mean-reversion process and the firm displays a similar cycle as the market, in the sense of close parameters $\alpha$ and $\kappa$. If $\alpha$ is significantly different from $\kappa$, however, a long-term reversal might be generated.

The intuition of short-term momentum and long-term reversal in this simple model is as follows. Thinking about the mean-reversion cycle of the growth rate of the firm and the cycle of the market trend. In a short-term, since both the trends move along the same direction, a higher (smaller) stock price leads to a likely higher (smaller) stock price in the future time. On the other hand, in the long-term, the stock price will change to adjust the effect of the market trend on the firm’s growth rate. In particular, the mean-reversion feature of the market trend strongly push the firm’s stock price to be consistent with its expected stock price. Therefore, the long-term reversal of the stock price is generated under certain conditions.

The model is different from those behavioral models in Daniel, Hirshleifer, and Subrahmanyan (1998), Hong and Stein (1999) in which the investors’ overconfidence or limited attention drive the asset prices depart from the fundamental values, yielding momentum or reversal. By contrast, the investors are rational in our model. On the other hand, our model is different from recent rational model of reversal such as in Johnson (2016), Andrei and Cujean (2017). In these models, asset prices are driven by the heterogeneity among investors instead of the firm characteristics.
4 Fama-MacBeth Regressions

4.1 The Main Results

We thus far use the PLS fundamental index to graphically illustrate that: (1) firm level fundamentals are cyclical on average; (2) intuitively, the PLS fundamental index matches well with the timing of momentum and reversal. In this section, we use the Fama-MacBeth regression method to conduct more formal statistical tests. Specifically, we first identify the momentum and reversal effect based on Fama-MacBeth regressions. We then add the corresponding PLS fundamental index as control variables to test whether the momentum and reversal effect would disappear.

To conduct the regression tests of both momentum and reversal, we adopt an approach similar to the portfolio sort approach of testing momentum and reversal. Specifically, for each quarter we estimate the 12-month past returns up to the end of the quarter, and we fix the quarter as quarter 0; it is similar to the formation period in the portfolio sort approach.\(^4\) We then match the 12-month past returns at quarter 0 with returns and PLS fundamental indexes in future quarters up to 10 quarters ahead. This is similar to holding longer period in portfolio sort, however, it is worth noting that we use each future quarterly returns and do not use cumulative returns as in Cooper, Gutierrez, Jr., and Hameed (2004).

For the \(n^{th}\) future quarter, we conduct the following Fama-MacBeth cross-section regressions:

\[
R_{i,t+n} = \beta_0 + \beta_1 \log(SZ_{i,t}) + \beta_2 \log(BM_{i,t}) + \beta_3 Rt12_{i,t} + \beta_4 PLS_{i,t+n} + \beta_5 PLS_{i,t+n-1} + \epsilon_{i,t+n},
\]

\[(19)\]

where \(Rt12_{i,t}\) denotes the 12-month past returns estimated in quarter \(t\), \(\log(SZ_{i,t})\) and \(\log(BM_{i,t})\) denote, respectively, the natural log of firm size and the book-to-market ratio

\(^4\)Since we use quarterly returns, we do not skip one month as is normally done with monthly returns. However, we consider skipping one month as a robustness check later.
measured in quarter $t$, and $R_{i,t+n}$ denotes the quarterly return in quarter $t+n$, i.e., the $n^{th}$ future quarter, for firm $i$. Depending on which future quarterly returns used, the coefficient $\beta_3$ of $R_{t12,i,t}$ could represent either the momentum effect (if positively significant) or reversal effect (if negatively significant). $PLS_{i,t+n}$ and $PLS_{i,t+n-1}$ represent firm PLS fundamental index for firm $i$ in quarter $t+n$ and $t+n-1$. We include the PLS index of prior quarter as an additional explanatory variable to capture its lagging effect on the cross-sectional stock returns. Our hypothesis is that after adding the contemporaneous (to future return) and prior quarter PLS fundamental indexes, the coefficient $\beta_3$ would lose its significance in Eq. (19) as the cross-sectional variations in the quarterly returns should be captured by the variations in the concurrent PLS indexes.

At this point, it is worth emphasizing that we use the regression model specified in Eq. (19) to explain the momentum and reversal effect on the cross-sectional variation of future returns with the *concurrent* PLS index, and therefore this model cannot be used to forecast future returns or forming tradable strategies.\textsuperscript{5} We will discuss how to use the fundamental index to form tradable strategies and compare them with the momentum strategies in the last section.

The regression results are reported in Table 1. First, Panel A shows that there is a significant momentum effect for the first quarter. For example, the coefficient of $R_{t12,i,t}$ is 1.933 with a $t$-stat of 4.29. The coefficient becomes smaller (0.938) although still significant ($t$-stat of 2.08) in the second quarter. The downward trend in the coefficient continues; the coefficient becomes insignificant in the third quarter and significantly negative afterwards. In other words, beginning from the fourth quarter, there are significant reversal effect, which lasts to the tenth quarter. The reversal effect gets stronger, becomes the strongest in the sixth quarter, and then declines gradually all the way to the tenth quarter.\textsuperscript{6}

\textsuperscript{5}Since we match the published date of firm fundamentals with returns of the same quarter, the fundamental information actually corresponds to the previous quarter.

\textsuperscript{6}Our result of significant momentum profit up to two quarters is consistent with Conrad and Deniz Yavuz (2017). It is also likely due to the fact that we use individual quarterly returns instead of cumulative returns often used in the literature.
the coefficient of $Rt12_{i,t}$ is $-0.691$ ($t$-stat of $-2.10$) in quarter 4, $-1.079$ ($t$-stat of $-3.04$) in quarter 6, and still $-0.762$ ($t$-stat of $-2.51$) in quarter 10.

It is striking that the timing, magnitude, and significance of momentum and reversal effects match well with the cyclical dynamics of the PLS index plotted in Fig. 1. When the difference in the PLS fundamental index is positive between the winner and loser firms in the first two quarters, i.e., when winner (loser) firms are experiencing repeated unanticipated positive (negative) shocks in fundamentals, there are significant momentum effects. On the other hand, when the difference in the PLS fundamental is negative from the fourth quarter and on, i.e., when winner (loser) firms are experiencing repeated unanticipated negative (positive) shocks in fundamentals, there are significant reversal effects. In addition, from quarter 1 to quarter 3, the difference in the PLS index is widening at a reduced speed and thus the momentum becomes weaker; from quarter 4 to quarter 6, the difference is shrinking at an increased speed and thus the reversal becomes stronger; from quarter 7 to quarter 10, the difference is shrinking at a slower speed and thus the reversal becomes weaker.

Turning to Panel B where we add the two PLS index variables, $PLS_{i,t+n-1}$ and $PLS_{i,t+n}$, it paints a completely different picture. The coefficient of $Rt12_{i,t}$ is no longer significant for all future quarterly returns, indicating that the momentum and reversal effects observed in Panel A can be explained entirely by the firm-level fundamental index. In addition, the coefficients of both PLS index variables are highly significant and positive, indicating that these two variables indeed play important roles in explaining the cross-sectional stock returns. For example, the coefficients of $PLS_{i,t+n}$ is $0.262$ with a $t$-stat of $6.62$ for the first quarter, and remain similar for the other quarters. Finally, it also makes intuitively sense that the coefficients of the prior quarter PLS index, $PLS_{i,t+n-1}$, are smaller than those for $PLS_{i,t+n}$. This pattern implies that the lagging effect, although significant, is not as important as the impact of the revealed fundamentals in the contemporaneous period on the cross-sectional stock returns.
4.2 Microcap Stocks

Microcap stocks defined as stocks whose market cap falls into the bottom quintile ranked by NYSE stocks only, make up on average only about 3% of the market cap of the NYSE-AMEX-NASDAQ universe, but account for 60% of the number of stocks and tend to display the strongest anomalies including momentum and reversal (see, e.g., Fama and French, 2008, 2015; Hou, Xue, and Zhang, 2017) The literature often attributes the stronger anomalies of the microcap stocks to stronger investor’s behavior bias, market friction, and limits to arbitrage. For instance, Daniel, Hirshleifer, and Subrahmanyam (1998) attribute momentum and reversal to investors overconfidence and biased self-attribute. Their influence on small-size companies is found to be more profound since individual investors hold a greater proportion of shares (Statman, Thorley, and Vorkink, 2006).

In this section, we test whether the firm fundamental index can explain momentum and reversal effects even for microcap stocks. After all, if momentum and reversal are largely attributable to behavior bias, market friction, and limits to arbitrage, we should not expect that our fundamental index explains away momentum and reversal for the microcap stocks.

The results are reported in Table 2. Similarly, Panel A reports the Fama-MacBeth regression results without the fundamental indexes, which are weakly stronger than those reported in Table 1. For example, the coefficient of $R_{t12,i,t}^j$ is 1.033 ($t$-stat of 2.31) for the microcap stocks versus 0.938 ($t$-stat of 2.08) for all stocks in the second quarter, and is $-1.351$ ($t$-stat of $-3.64$) for the microcap versus $-1.079$ ($t$-stat of $-3.04$) for all stocks in the sixth quarter.

Nevertheless, Panel B of Table 2 reports the results after controlling for the PLS indexes, $PLS_{i,t+n-1}$ and $PLS_{i,t+n}$. Against, we found that both the momentum and reversal effects are explained away by the concurrent and prior PLS fundamental indexes, and consequently

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7 The weaker performance of the microcap is likely due to the fact that many of the microcap stocks who have fundamentals reported tend to be larger.
none of the coefficients of $R_{t12,i,t}$ are statistically significant.

### 4.3 Business Cycles

Chordia and Shivakumar (2002) find that the momentum profit depends on business cycles. Specifically, the momentum profit is only positive and significant in the economic expansionary periods, but negative and insignificant in the recessionary periods. This finding is also consistent with several other studies, such as Cooper, Gutierrez, Jr., and Hameed (2004), Daniel and Moskowitz (2016), Antoniou, Doukas, and Subrahmanyam (2013), which document stronger momentum profits following up market states or high sentiment and no or negative profits following down states or low sentiment. As business cycles could affect firm-level fundamental cycles, it is of interest to test whether or not the firm PLS fundamental index could still explain both the momentum and reversal effects during the economic expansionary periods. Following Chordia and Shivakumar (2002), we define the economic expansionary periods based on the NBER definition.

Table 4 reports the results of the Fama-MacBeth regressions only for the economic expansionary periods. Panel A reports the coefficients of $R_{t12,i,t}$ without adding the PLS indexes. Comparing to Table 1, the momentum effect is indeed stronger as the second quarter is still highly significant with a $t$ value of 3.53. Meanwhile, the reversal effect is weaker but still noticeable as most of the coefficients are significantly negative after quarter 5. On the other hand, Panel B shows that all of the coefficients of $R_{t12,i,t}$ are no longer statistically significant once the PLS indexes are included in the regressions, suggesting that the PLS fundamental indexes, $PLS_{i,t+n-1}$ and $PLS_{i,t+n}$, are still able to explain away the momentum and reversal effects during the economic expansionary periods when the momentum profits are concentrated.
4.4 Earnings Momentum

Novy-Marx (2015) argues that the standardized unexpected earning surprise (SUE) drives price momentum. Specifically, he shows that the earning surprise measured by SUE and cumulative three-day abnormal returns (CAR3) subsume the power of momentum to predict cross-sectional variations in expected returns based on the results obtained from the Fama-MacBeth regression. In the subsequent spanning test, He shows that the earnings momentum strategy fully captures the alpha of the price momentum strategy. Therefore, Novy-Marx (2015) concludes that the price momentum is not an independent anomaly from the earnings momentum. Our PLS index could well be related to SUE as both are unexpected shocks to fundamentals, however, our PLS index clearly contains a lot more information about fundamentals that may not be reflected in SUE. There are two other important differences as well. First, Novy-Marx (2015) argues that the predictive power of past SUEs subsume the predictive power of momentum or past returns, whereas we argue that the predictive power of momentum on future stock returns is captured by the PLS fundamental indexes that are concurrent to the future returns. Second, we argue that there is a firm-level fundamental cycles that explains both momentum and reversal.

Nevertheless, we run a horse race between the PLS fundamental indexes and SUEs plus CAR3 to see which explains momentum and reversal. Following Livnat and Mendenhall (2006), we obtain SUEs based on a rolling seasonal random walk model and CAR3 from day −1 to 1 window around earnings announcement dates. Panel A of Table 3 shows that, similarly to Novy-Marx (2015), SUEs (CAR3) positively predict stock returns up to the second (third) quarter. For instance, the coefficients of SUE and CAR3 are 4.152 (t-stat of 4.04) and 7.500 (t-stat of 4.11), respectively, in the first quarter. However, the coefficients of \( R_{t12_i,t} \) are still positively significant coefficients for quarter 1 and 2, and the magnitude and significance are only slightly smaller than what are reported in Table 1. For example, the coefficient of \( R_{t12_i,t} \) in the first quarter is 1.707 with a \( t \)-value of 3.30 versus 1.933 with
$t$-stat of 4.29 in Table 1. Therefore, our results suggest that the momentum effect may not be fully subdued by the earnings momentum at least at the quarterly frequency. Panel A also illustrates that SUE and CAR3 do not predict future returns in the longer horizons as most of the coefficients of SUE and CAR3 do not exhibit significance after quarter 3. In contrast, the reversal effect is still observable as the coefficients of $Rt12_{i,t}$ are statistically significant and negative for most of quarters after quarter 3.

Panel B of Table 3 reports the results of adding the PLS fundamental indexes. Similar to previous results, the momentum effects in the first two quarters and the reversal effect after quarter 3 disappear once the PLS indexes are added to the regressions as none of the coefficients of $Rt12_{i,t}$ are significant. Similarly, all the coefficients of $PLS_{i,t+n-1}$ and $PLS_{i,t+n}$ are positive and statistically highly significant, and hardly differ from what are reported in Table 1. Interestingly, the coefficients and their $t$-stats of SUE and CAR3 barely change from what reported in the panel A, too. These results suggest that the firm fundamental index proposed in this paper is independent of the earnings surprise in explaining stock returns and it’s ability to explain the momentum and reversal effects.

5 Portfolio Sorting and the Spanning Tests

In the previous sections, we use the Fama-MacBeth regression method to show that the contemporaneous PLS index, combing with its prior quarter PLS index can explain both the momentum and reversal effects. Using the Fama-MacBeth regression approach allows us to easily test the relation between the past 12-month cumulative returns and the future quarterly returns in multiple periods, and illustrate the cyclic change in returns. Nevertheless, tests based on portfolio sorting method are also popular in the literature. In this section, we focus on using the portfolio sorting method to show that the momentum effect can be captured by the firm PLS index.
5.1 PLS Index Implied Returns in Explaining Momentum

As shown in the previous regressions, the momentum effect in the first quarter is attributable to the revealed PLS index, \( PLS_{i,t+1} \), in the same quarter and the prior quarter PLS index, \( PLS_{i,t} \). To show that the momentum effect can be captured by the PLS indexes using the portfolio sorting approach, we first combine the information in the two PLS indexes into one variable, which we refer to as the PLS index implied return, and then conduct a dependent double sort on the implied return and the 12-month past return.

To combine the information in the PLS indexes from two quarters, we run the following two-step procedure,

\[
R_{i,t} = a_0 + a_1 PLS_{i,t} + a_2 PLS_{i,t-1} + \epsilon_{i,t}, \tag{20}
\]

\[
\hat{R}_{i,t+1} = \hat{a}_0 + \hat{a}_1 PLS_{i,t+1} + \hat{a}_2 PLS_{i,t},
\]

where \( \hat{R}_{i,t+1} \) is the PLS implied return for firm \( i \) for quarter \( t+1 \). It is worth noting that the implied return is not forecasted return at \( t+1 \) because the contemporaneous information is used, which is consistent with the regression in Eq. (19). In essence, we first regress the quarter \( t \) returns on the concurrent PLS index and prior-quarter PLS index and use the estimated coefficients to construct the implied returns for the next quarter, \( t+1 \). We emphasize that it is different from the usual approach to construct a forecasted return and the strategy itself is not tradable and is only used to test the relation between momentum and PLS fundamental index.

To control for the PLS indexes in portfolio sorting, we first sort the stocks into quintiles based on the PLS implied returns from Eq. (20), and then within each quintile we further sort stocks into quintiles by their 12-month past returns. Finally we form 25 quintile portfolios and report their average quarterly excess returns in Panel A of Table 5. Except for the highest quintile of the PLS implied return, none of the remaining four momentum strategies
can generate significantly positive returns.

As an alternative approach, we decompose the 12-month past returns into a component that is related to the PLS indexes and an orthogonal component that is unrelated to the PLS indexes and sort stocks using the orthogonal component. Specifically, we conduct the following cross-sectional regressions each quarter to extract the orthogonal component.

\[
R_{t12,i,t} = a_0 + a_1 PLS_{i,t+1} + a_2 PLS_{i,t} + \epsilon_{i,t}.
\] (21)

We take the residuals from Eq. (21) and sort stocks on the residuals into decile portfolios. The average quarterly excess returns of the residual decile portfolios are reported in Panel B of Table 5, and we also report those of the momentum decile portfolios as the benchmark. First, the average returns of the momentum decile portfolios increase monotonically from the loser to the winner, whereas those of the residual decile portfolios fail to display a monotonic pattern, indicating information related to future returns in the 12-month past returns is lost in the residuals. A more definite evidence is the winner-loser portfolio, which yields an average quarterly return of 3.071% with a \(t\)-stat of 3.28 for the momentum deciles, whereas it only yields an average quarterly return of 0.908%, which is statistically insignificant, for the residual deciles. Therefore, both Panel A and B of Table 5 provide evidence that the significant momentum profits could be explained away by the firm PLS fundamental index.

### 5.2 Spanning Tests

Results in Table 5 suggest that momentum profits are largely explained by the firm PLS fundamental index in the portfolio sorting approach. In this subsection we further demonstrate that the abnormal returns of the momentum is fully captured by the PLS implied returns in time-series regressions. To this end, We first sort stocks into deciles by the PLS implied returns and form the high-low spread portfolio for the PLS implied returns, which
Table 6 reports the results of the spanning tests. Panel A reports the regression results of the winner-loser momentum decile portfolio. Under CAPM, the abnormal return is about 3.192% per quarter, comparable to the momentum literature on the monthly basis. However, once the PLS implied factor is added, the abnormal return is reduced to a negative −0.364% with a $t$-stat of −0.27 that is insignificant. Clearly, adding the PLS implied factor completely removes the significant abnormal return of the momentum factor. Similar results are obtained for the Fama-French three- and five-factor models. For example, the abnormal return of the momentum factor remains significant at 4.188% with a $t$-stat of 5.35 under the Fama-French three-factor model, but is reduced to merely 0.544% and insignificant ($t$-stat of 0.48). In addition, the momentum factor shows significant and negative loadings on SMB and HML, but significant and positive loading on the PLS implied factor. Essentially the same results for the five-factor model are observed as the momentum factor do not significantly load on the other two new factors.

Panel B reports the regression results of the PLS implied factor. Under CAPM, the abnormal return of the PLS implied factor is high at 5.040% per quarter, which is likely due to the looking forward bias. Similar to the momentum factor, adding the Fama-French three or five factors hardly diminishes the abnormal return. In contrast to the momentum factor, however, the abnormal return of the PLS implied factor is only slightly reduced, even though the PLS implied factor significantly loads on the momentum factor. For example, the abnormal return is 4.591% (4.572%) in the present of the momentum factor under the Fama-French three (five)-factor model. Therefore, Table 6 presents clear and strong evidence that adding the momentum factor to the PLS implied factor fails to provide any additional information but adding the PLS implied factor to the momentum provides additional useful
information for portfolio returns.

6 Robustness

In this section, we examine the robustness of the results along several dimensions. First, we use the alternative Principal Component Analysis (PCA) approach to extract the common fundamental factor. Second, we skip one month when matching the past returns and other quarterly variables. Third, we focus on the period before the financial crisis as momentum appears much weakened after the crisis. Although not reported in the paper, we also add other control variables such as various liquidity measures such as Amihud measure and proportional spread, and idiosyncratic volatility, and obtain similar results. Finally, we use 6-month past returns instead of 12-month past returns to measure momentum and reversal, and obtain similar results (not reported in the paper).

6.1 Principal Component Analysis

In addition to using the PLS method to obtain the most relevant common component based on fundamental ratios to explain cross-sectional returns, we also use the first principal component obtained through the principal component analysis (PCA) approach as a proxy for the aggregate firm-level fundamental. This is similar to Baker and Wurgler (2006, 2007) who use the same method to obtain a proxy for the market sentiment index. As pointed out by Huang, Jiang, Tu, and Zhou (2015), the difference between the PLS approach and the PCA approach is that the PLS is to find the most relevant common components in explaining the returns, whereas the PCA approach is to maximize the common variations of all different fundamental ratios. They show that the measure obtained by PCA may contain large errors (variation or information) which may not be relevant to returns. Nevertheless, as a robustness check, we also use the fundamental index obtained through the first principal
component following the PCA approach. Statistically, the first principal component is a linear combination of all the fundamental ratios, with the coefficients (eigenvalues) chosen to capture as much joint variations across those ratios as possible. Since higher debt and accrual ratio imply weaker fundamentals, we switch the sign for both measures to maintain consistency with other measures while conducting the first principal component analysis. For convenient purposes, we refer to the obtained index as the PCA index.

We conduct the similar regression using the PCA fundamental indexes and report the results in Table 7. Compared to what reported in Table 1, these results are similar. For example, all the coefficients of $PCA_{i,t+n-1}$ and $PCA_{i,t+n}$, are positive and statistically strongly significant. In addition, none of the coefficients of $Rt12_{i,t}$ are statistically significant once $PCA_{i,t+n-1}$ and $PCA_{i,t+n}$ are included as the additional explanatory variables. It implies that the momentum and reversal effects are fully explained by the dynamics of the firm fundamental index captured by PCA method.

### 6.2 Skipping One Month

So far, we use the 12-month cumulative returns estimated to the last month of each quarter. The momentum literature often add one month between the month when the past returns are estimated and the testing month in regression or skip one month between portfolio formation month and portfolio holding period. This is primarily to avoid the short-term reversal and bid-ask bounce to a less degree. This concern is unlikely to be important in our analysis as we conduct all the tests at the quarterly frequency. Nevertheless, it is interesting to test whether our results hold when we skip one month in the regression tests. To this end, we match the 12-month past returns to the month before the last month of a quarter. For example, we would match the 12-month past cumulative returns estimated up to August to the quarter ending in September. The results are reported in the Table 8. Again, the results are almost identical to Table 1 and the proposed PLS fundamental indexes subsume both
the momentum and reversal effects.

6.3 Before Financial Crisis Period

Recently, the crash risk of the momentum strategy has drawn considerable attention. Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) both show that momentum crashed during the most recent financial crisis. For example, the Fama-French momentum factor experienced a loss of $-34.7\%$ in April, 2009. Momentum has been substantially weakened during and after the financial crisis - the Fama-French momentum factor lost 1.319\% a month on average during the crisis, and only gained 0.367\% a month on average after the crisis. Therefore, it is of interest to check whether our results are driven by the weakening of momentum profits after the financial crisis. To rule out that possibility, we conduct the regressions by using the data up to the third quarter of 2007. The results are reported in Table 9. Comparing to the baseline results in Table 1, the momentum results in Panel A are indeed stronger, however, Panel B shows that all of the coefficients of $R_{12,t}$ become insignificant after controlling for the PLS indexes.

7 Tradable Portfolio Strategies

In the previous sections, we show that the concurrent firm fundamental index could explain the crosssectional momentum and reversal effects. In Section 5 we construct decile portfolios based on the PLS implied returns. We emphasize there that because of looking forward bias, the decile portfolios do not represent a tradable strategy. Although it is not our focus in this paper, one natural question worth of investigating is to study whether or not we can use the fundamental index to forecast future returns in real time and form profitable trading strategies.

To forecast future returns in real time, we modify Eq. (20) to eliminate looking forward
bias. Specifically, we run the following two-step procedure:

\[
R_{i,t} = a_0 + a_1 PLS_{i,t-1} + a_2 PLS_{i,t-2} + \epsilon_{i,t},
\]

\[
\hat{R}_{i,t+1} = \hat{a}_0 + \hat{a}_1 PLS_{i,t} + \hat{a}_2 PLS_{i,t-1},
\]

where \( \hat{R}_{i,t+1} \) is the forecasted returns in quarter \( t+1 \) using information from only up to quarter \( t \), which is different from Eq. (20). In essence, we replace \( PLS_{i,t} \) and \( PLS_{i,t-1} \) in the regression step of Eq. (20) with \( PLS_{i,t-1} \) and \( PLS_{i,t-2} \), and \( PLS_{i,t+1} \) and \( PLS_{i,t} \) in the second step of Eq. (20) with \( PLS_{i,t} \) and \( PLS_{i,t-1} \). We then sort the stocks into decile based on the forecasted stock returns \( \hat{R}_{i,t+1} \) and form a tradable strategy by longing stocks in the highest decile and shorting those in the lowest decile.

Following Haugen and Baker (1996), Han, Zhou, and Zhu (2016), Green, Hand, and Zhang (2017), and Han, He, Rapach, and Zhou (2018), instead of using the estimated coefficients, \( \hat{a}_0, \hat{a}_1, \) and \( \hat{a}_2 \), directly in the second step of Eq (22), we use the time-series averages of the estimated coefficients over the past 10 and 20 quarters, respectively, to reduce the unnecessary volatility introduced by quarter-to-quarter fluctuation. We then form trading strategies using the forecasted returns. We denote the first strategy as PLS trading strategy, and the latter two using average of coefficients as FPLS10 and FPLS20 trading strategies, respectively. We follow the same procedure to construct trading strategies using the PCA fundamental index, and denote them as PCA, FPCA10, and FPCA20 trading strategies.

The average excess returns and other summary statistics of these strategies are reported in Table 10. We also report those of the momentum decile strategy as the benchmark. Compared to the momentum strategy, the strategies based on either the PLS or PCA fundamental indexes deliver lower average excess returns. For example, the average quarterly excess return of momentum strategy is 3.07%, whereas the PLS, FPLS10, and FPLS20 strategy generate 2.26%, 2.13%, and 2.00% per quarter, respectively. Those of the PCA strategies are even smaller, 1.55%, 1.54%, and 1.70%, respectively, for PCA, FPCA10, and FPCA20.
However, the advantage of momentum strategy stops there. Strategies based on the PLS and PCA fundamental indexes show more desirable characteristics in many other aspects. First, these strategies generate less volatile returns as the standard deviations are much smaller than that of the momentum strategy. For example, the volatilities of the PLS trading strategies are 3.82%, 3.41%, and 3.63% per quarter while that of the momentum is 11.22% per quarter. As a result, the Sharpe ratio of the momentum strategy, 0.274, is much lower than those of PLS strategies, which are 0.590, 0.625, and 0.551 for the PLS strategies and 0.413, 0.405, and 0.431 for the PCA strategies.

Second, the momentum strategy generates large negative skewness (-0.831) and positive kurtosis (6.68), which indicate very large losses. Indeed, the biggest quarterly loss for the momentum strategy is \(-47.32\%\). In contrast, except for PLS strategy, which has a smaller negative skewness, FPLS10 and FPLS20 strategies both yield positive skewness, at 0.1166 and 0.2199, respectively. As a result, the biggest losses of these trading strategies are much smaller. For example, the FPLS10 strategy only has a maximum loss of \(-8.22\%\) per quarter.

Finally, it is of no surprise that the momentum strategy has huge downside risks as highlighted by the crash risk literature (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015). The maximum drawdown (MDD), a popular metric of actively managed funds in practice, is defined as the largest percentage drop in price from a peak to a bottom. The MDD measures the maximum loss of an investor who invests in the asset at the worst time. Table 10 shows that MDD is 74.53% for the momentum strategy, which is much higher than those of the PLS or PCA strategies. For example, the MDD of the PLS10 strategy is 21.41%. Another related downside risk measure, the Calmar ratio, which is the ratio of the average annualized return and the maximum drawdown. The lower the Calmar ratio, the worse the performed on a risk-adjusted basis. Clearly, the momentum strategy has the lowest Calmar ratio at 4.07%. For example, PLS10 strategy has a Calmar ratio of 9.30%.

Table 10 demonstrates that the PLS or PCA strategies clearly outperform the momentum
strategy on the risk-adjusted basis, and has more desirable properties than the momentum strategy. In particular, the FPLS10 trading strategy seems to deliver the highest Sharpe ratio and lowest volatility.

8 Conclusion

Momentum and reversal are the two most profound and robust anomalies identified in the financial markets. Previous literature often attribute the source of the anomalies to investor behavioral bias such as underreaction or overconfidence. This paper argues that momentum and reversal are generated by the cyclical nature of firm fundamentals and investor rational reaction to unanticipated changes of firm fundamentals. When the environment is good (bad) for the business, firm fundamentals are in an upward (downward) trajectory characterized by continued unanticipated positive (negative) changes. When these unanticipated shocks are revealed, investors keep to raise (lower) the stock prices as they continue to update their believes given the new information, and thus create winner (loser) stocks and momentum in returns. As the environment becomes more and more challenging (accommodating) for the winner (loser) firms, business is slowing down (picking up) and the unanticipated positive (negative) changes become smaller and smaller and eventually become negative (positive). Once the unanticipated shocks switch sign, winners become losers and losers become winners and return reversal occurs.

We approximate the unanticipated changes in fundamentals using the differences between two adjacent quarters, and use PLS to aggregate the useful information from 14 fundamental ratios. In a series of Fama-MacBeth regressions, we show that momentum loses its predictability after controlling for the portion of the cross-section variation which is explained by the current and most recent prior quarter revealed firm fundamental index. The results are robust in many aspects, such as limiting stocks to micro-cap only, controlling for earnings momentum, limiting testa to expansionary periods, and using measures defined by
the PCA method, etc.

In addition to tests based on the Fama-MacBeth regression, we also conduct dependent double sorts or residual sort as ways to control for the information carried by the PLS fundamental index. The resulting momentum strategies subsequently do not show significant profitability under most circumstances. A related spanning test also shows that the momentum factor is fully captured by the PLS index factor.

Finally, comparing to momentum tradable strategy, the fundamental index proposed by this paper could potentially serve as a better price indicator to fund managers to form tradable strategy. The subsequent risk-return profile based on the fundamental index is superior to that of momentum strategy from the perspective of the minimum return, Sharpe ratio, MDD, Calmar ratio, Skewness, and Kurtosis.

Appendix

In this Appendix, we first state Proposition 1 in more details and then provide the proof.

**Proposition 1** The equilibrium stock price $S_t$ at time $t$ is

$$S_t = D_t U(\mu_t, \theta_t),$$

(23)

where

$$U(\mu, \theta) = \int_0^\infty \exp \left\{ -\delta s + A(s) + \frac{1 - e^{-\alpha s}}{\alpha} \theta + \frac{1 - e^{-\kappa s}}{\kappa} \mu \right\} ds,$$

(24)

and $A(s)$ is a deterministic function that is specified in the proof. Write

$$\frac{dS_t}{S_t} = \alpha_{S,t} dt + \sigma_{S,t} dW_S.$$

(25)

The cumulative excess returns accruing to the holder of a unit investment in the stock, $CER_t$,
The instantaneous expected excess return of the stock in the time period \([t, t+dt]\) is

\[
EER_t = \alpha S_t - r_t + \frac{D_t}{S_t}.
\]  

(27)

Assume that \(\alpha\) and \(\kappa\) are close enough, then for a positive number \(l\) (momentum)

\[
\mathbb{E}_t \left[(EER_{t+l} - \mathbb{E}_t[EER_{t+l}]) (CER_{t+l} - \mathbb{E}_t[CER_{t+l}])\right] > 0
\]  

(28)

On the other hand, when \(\alpha\) and \(\kappa\) are significantly different from each other, then under certain condition on parameters (which is stated in the proof), the conditional covariance, \(\text{Cov}_t(EER_{t+l}, CER_{t+l})\) is negative (long-term reversal), even though \(\text{Cov}_t(EER_{t+l_1}, EER_{t+l_2})\) is positive when \(l_2\) is sufficiently close to \(l_1\) and \(l_2 > l_1\) (short-term momentum).

**Proof:** Given the stochastic discount factor process \(\{M_t\}\), the equilibrium stock price is

\[
S_t = \mathbb{E}_t \int_t^\infty \frac{M_s}{M_t} D_s ds
\]

\[
= \mathbb{E}_t \left[e^{-\delta(s-t)} \frac{Y_t^{-1}}{Y_t^{-2}} D_s ds\right]
\]

\[
= \int_t^\infty e^{-\delta(s-t)} Y_t \mathbb{E}_t [Y_t^{-1} D_s] ds.
\]

We show that

\[
S_t = D_t U(\mu_t, \theta_t)
\]  

(29)

where

\[
U(\mu, \theta) = \int_0^\infty \exp \left\{ -\delta s + A(s) + \frac{1 - e^{-\alpha s}}{\alpha} \theta + \frac{1 - e^{-\kappa s}}{\kappa} \mu \right\} ds,
\]
where the deterministic function $\alpha(t)$ satisfying that $A(0) = 0$ and

$$
\frac{dA(t)}{dt} = -\sigma_Y D + (\alpha \theta - \sigma_Y \theta + \sigma_D \theta) \beta_3(t) \\
+ (\kappa \mu - \sigma_Y \mu + \sigma_D \mu) \beta_4(t) \\
+ \frac{1}{2} \sigma_D^2 \beta_3(t)^2 + \frac{1}{2} \sigma_\mu^2 \beta_4(t)^2 + \sigma_\theta \mu \beta_3(t) \beta_4(t),
$$

and $\beta_3(t) = \frac{1}{\alpha} (1 - e^{-\alpha t})$, $\beta_4(t) = \frac{1}{\kappa} (1 - e^{-\kappa t})$, $t \geq 0$.

To prove it, we define a 4-dimensional Gaussian process $X(t) = (X_1(t), X_2(t), X_3(t), X_4(t))$ where $X_1(t) = \ln(Y_t)$, $X_2(t) = \ln(D_t)$, $X_3(t) = \theta(t)$, $X_4(t) = \mu(t)$. Then by the Kolmogorov backward equation, the function $f(t, X_1(t), X_2(t), X_3(t), X_4(t)) = \mathbb{E}_t \left[ e^{-X_1(s)+X_2(s)} \right]$ satisfies

$$
f_t + \mathcal{D}f = 0, \quad (30)
$$

where $\mathcal{D}$ is the Dynkin operator of the Gaussian process $X$ and $f(s, X_1, X_2, X_3, X_4) = e^{-\gamma X_1 + X_2}$. Given its affine feature, following from Duffie, Pan, and Singleton (2000), we obtain

$$
f(t, X_1(t), X_2(t), X_3(t), X_4(t)) = \exp \left\{ A(s-t) + \sum_{i=1}^{4} \beta_i(s-t) X_i(t) \right\} \quad (31)
$$

with the boundary conditions $\alpha(0) = 0$, $\beta_1(0) = -\gamma$, $\beta_2(0) = 1$ and $\beta_3(0) = \beta_4(0) = 0$. By plugging the above specification function into the partial differential equation (30), it is easy to derive $\beta_1 = -\gamma$, $\beta_2 = 1$ and

$$
\beta_3(t) = \frac{1 - e^{-\alpha t}}{\alpha}, \beta_4(t) = \frac{1 - e^{-\kappa t}}{\kappa}, t \geq 0. \quad (32)
$$

Finally, the function $A(t)$ can be determined as explained above. The equilibrium stock price is derived.

Given the equilibrium stock price $S_t$, we next calculate $\alpha_{S,t}$, $EER_t$ and $CER_t$. By Ito’s
\[ dU = U_\mu d\mu + U_\theta d\theta \]
\[ + \frac{1}{2} U_{\mu \mu} (d\mu)^2 + \frac{1}{2} U_{\theta \theta} (d\theta)^2 + U_{\mu \theta} d\mu d\theta \]
\[ = \left\{ U_\mu \kappa (\overline{\mu} - \mu) + U_\theta \alpha (\overline{\theta} - \theta) + \frac{1}{2} U_{\mu \mu} \sigma_\mu^2 \right. \]
\[ + \frac{1}{2} U_{\theta \theta} \sigma_\theta^2 + \frac{1}{2} U_{\mu \theta} \sigma_\mu \sigma_\theta \left\} dt \]
\[ + U_\mu \sigma_\mu dW_\mu + U_\theta \sigma_\theta dW_\theta \]

Then
\[ \frac{dD \cdot dU}{D \cdot U} = \frac{U_\mu}{U} \sigma_\mu D + \frac{U_\theta}{U} \sigma_\theta D. \quad (33) \]

As
\[ \frac{dS_t}{S_t} = \frac{dD}{D} + \frac{dU}{U} + \frac{dD \cdot dU}{D \cdot U}, \quad (34) \]

we obtain
\[ \alpha_{S,t} = \mu + \frac{U_\mu}{U} (\sigma_\mu D + \kappa (\overline{\mu} - \mu)) \]
\[ + \frac{U_\theta}{U} (\sigma_\theta D + \alpha (\overline{\theta} - \theta)) \]
\[ + \frac{1}{2} \frac{U_{\mu \mu}}{U} \sigma_\mu^2 + \frac{1}{2} \frac{U_{\theta \theta}}{U} \sigma_\theta^2 + \frac{U_{\mu \theta}}{U} \sigma_\mu \sigma_\theta, \]

and the diffusion term of \( \frac{dS_t}{S_t} \) is
\[ \sigma_D dW_D + \frac{U_\mu}{U} \sigma_\mu dW_\mu + \frac{U_\theta}{U} \sigma_\theta dW_\theta. \quad (35) \]

In equilibrium, it is well known that
\[ EER_t = \alpha_{S,t} - r_t + \frac{D_t}{S_t} = Cov_t \left( \frac{dY}{Y}, \frac{dS}{S} \right). \quad (36) \]
Then, by using equation (35),

\[ EER_t = \sigma_{DY} + \frac{U_\mu}{U} \sigma_{\mu Y} + \frac{U_\theta}{U} \sigma_{\theta Y}, \]  

\hspace{1cm} \text{(37)}

and

\[ \alpha_{S,t} = r_t + \sigma_{DY} + \frac{U_\mu}{U} \sigma_{\mu Y} + \frac{U_\theta}{U} \sigma_{\theta Y} - \frac{1}{U}. \]  

\hspace{1cm} \text{(38)}

By Ito’s Lemma, the diffusion term of \( EER_t \) is

\[ \frac{\partial}{\partial \mu} \left( \frac{U_\mu}{U} \right) \sigma_{\mu Y} dW_\mu + \frac{\partial}{\partial \theta} \left( \frac{U_\theta}{U} \right) \sigma_{\theta Y} dW_\theta + \frac{\partial}{\partial \mu} \left( \frac{U_\mu}{U} \right) \sigma_{\mu Y} dW_\mu + \frac{\partial}{\partial \theta} \left( \frac{U_\theta}{U} \right) \sigma_{\theta Y} dW_\theta. \]  

\hspace{1cm} \text{(39)}

Moreover,

\[ dCER_t = EER_t dt + \sigma_D dW_D + \frac{U_\mu}{U} \sigma_{\mu Y} dW_\mu + \frac{U_\theta}{U} \sigma_{\theta Y} dW_\theta. \]  

\hspace{1cm} \text{(40)}

Before proceeding, we show the following facts by following similar arguments in Lemma 1 in Johnson (2002),

- \( U \) is positive, \( U \) is increasing with respect to \( \theta \) and \( \mu \).

- \( V = \ln(U) \) is convex with respect to \( \theta \) and \( \mu \). That is, \( \frac{\partial^2}{\partial \mu^2} (V) > 0, \frac{\partial^2}{\partial \theta^2} (V) > 0 \). But the sign of \( \frac{\partial^2}{\partial \theta \partial \mu} (V) \) is a crucial issue in the discussion.

We let \( h(s; \mu, \theta) \) to represent the integrand inside the definition of \( U(\cdot) \). Then clearly, \( U \) is increasing with respect to \( \theta \) and \( \mu \), as \( \frac{\partial U}{\partial \mu} = \int_0^\infty h(s) \frac{1}{\pi} (1 - e^{-\kappa s}) ds > 0 \). Similarly, the second order-derivatives of \( U \) are positive. For the second part, it suffices to show that

\[ U_{\mu \mu} U \geq U_{\mu}^2, U_{\theta \theta} U \geq U_{\theta}^2 \]  

\hspace{1cm} \text{(41)}
By Cauchy-Schwartz inequality,

\[
U_\mu^2 = \left( \int_0^\infty h(s) \frac{1}{\kappa} (1 - e^{-\kappa s}) ds \right)^2 < \left( \int_0^\infty h(s) \left( \frac{1}{\kappa} (1 - e^{-\kappa s}) \right)^2 ds \right) \times \int_0^\infty h(s) ds,
\]

then \( U_\mu U > U_\mu^2 \). Similarly, \( U_\theta U > U_\theta^2 \). Moreover, \( U_\mu U_\theta < UU_\mu U_\theta \) when \( \alpha = \kappa \). By the continuity argument, \( U_\mu U_\theta \leq UU_\mu U_\theta \) if \( \alpha \) and \( \kappa \) are close enough.

By equation (37), the diffusion term of \( EER_t \) is

\[
\frac{\partial}{\partial \mu} \left( \frac{U_\mu}{U} \right) \sigma_\mu \sigma_\mu Y dW_\mu + \frac{\partial}{\partial \theta} \left( \frac{U_\mu}{U} \right) \sigma_\theta \sigma_\mu Y dW_\theta + \frac{\partial}{\partial \mu} \left( \frac{U_\theta}{U} \right) \sigma_\mu \sigma_\theta Y dW_\mu + \frac{\partial}{\partial \theta} \left( \frac{U_\theta}{U} \right) \sigma_\theta \sigma_\theta Y dW_\theta. \quad (42)
\]

Similar to the proof of Johnson (2002), Proposition 2, the conditional covariance, from time \( t \)'s perspective, between \( EER_{t+l} \) and \( CER_{t+l} \) is the same as the conditional covariance between \( EER_t - E_t[EER_{t+l}] \) and \( CER_t - E_t[CER_{t+l}] \), and is the integrated expected instantaneous cross-variance of the process \( EER_t \) and \( CER_t \). Since

\[
\frac{\partial}{\partial i} \left( \frac{U_i}{U} \right) > 0, i, j \in \{\mu, \theta\}, \quad (43)
\]

the above diffusion terms in (42) and (40) is positive, then the cross variation is positive. Hence, its integrated expected value from \( t \) to \( t + l \) is positive.

On the other hand, when the parameters \( \alpha \) and \( \kappa \) are not close enough such that \( U_\mu U_\theta < U_\mu U_\theta \), then

\[
\frac{\partial}{\partial \theta} \left( \frac{U_\mu}{U} \right) = \frac{\partial}{\partial \mu} \left( \frac{U_\theta}{U} \right) < 0. \quad (44)
\]

Therefore, the instantaneous expected instantaneous cross-variance of the process \( EER_t \) and
\( CER_t \) is written as

\[
\begin{align*}
Cov_t & \left( \sigma_D dW_D + \frac{U_\mu \sigma_\mu}{U} dW_\mu + \frac{U_\theta \sigma_\theta}{U} dW_\theta, \frac{\partial}{\partial \mu} \left( \frac{U_\mu}{U} \right) \sigma_\mu \sigma_\mu Y dW_\mu + \frac{\partial}{\partial \theta} \left( \frac{U_\theta}{U} \right) \sigma_\theta \sigma_\theta Y dW_\theta \right) \\
+ Cov_t & \left( \sigma_D dW_D + \frac{U_\mu \sigma_\mu}{U} dW_\mu + \frac{U_\theta \sigma_\theta}{U} dW_\theta, \sigma_\theta \sigma_\mu Y dW_\theta + \sigma_\mu \sigma_\theta Y dW_\mu \right) \times \frac{\partial}{\partial \theta} \left( \frac{U_\mu}{U} \right),
\end{align*}
\]

where first term is positive while the second term is negative. Under certain conditions on the model parameters, the second term in average dominates the first term, yielding a negative conditional covariance between \( EER_t - \mathbb{E}_t[EER_{t+t}] \) and \( CER_t - \mathbb{E}_t[CER_{t+t}] \). That is, a long-term reversal.

Finally, when \( l_2 - l_1 \to 0 \) and \( l_1 \) is fixed, we see that

\[
Cov_t(EER_{t+l_1}, EER_{t+l_2}) \to Var_t(EER_{t+l_1}) > 0. \quad (45)
\]

Then, by a continuity argument, \( Cov_t(EER_{t+l_1}, EER_{t+l_2}) \) is positive when \( l_2 \) is close enough to \( l_1 \). Therefore, the conditional covariance between the instantaneous expected excess return at time \( t + l_1 \) and the next time \( t + l_2 \) is positive. \( \Box \)
References


Figure 1. Firm Fundamental Cycles, Momentum, and Reversal
We first sort stocks into deciles based on their prior 12-month cumulative returns (momentum). We then calculate the average PLS index (PCA index) for each decile. The time-series behavior of the PLS (PCA) indexes of the winner, loser, as well as Winner-Loser portfolio up to 20 quarters before and after the formation quarter (0) are then exhibited in Figures 1a and 1b, respectively.
Table 1: Fama-MacBeth Regression of Momentum and Reversal Effects

The table reports results of Fama-MacBeth regressions of individual future quarterly stock returns, $n^{th}$ quarter after the quarter (quarter 0) when the 12-month past cumulative returns are estimated, on the 12-month past cumulative returns $R_t^{12}$ and PLS fundamental indexes. Additional control variables are LSZ and LBM representing the natural log of firm size and the book-to-market ratio estimated at the end of quarter 0, respectively. $PLS_{n-1}$ and $PLS_n$ represent the PLS firm fundamental index for firm $i$, the $n-1^{th}$ and $n^{th}$ quarter after quarter 0. A stock is eliminated if its price falls below $1.00 threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>$n^{th}$ Quarter Future Return (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
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<tr>
<td><strong>Panel A: Momentum and Reversal Effects</strong></td>
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<td>Intercept</td>
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<td>4.930</td>
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<td>(-1.72)</td>
<td>(-1.71)</td>
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<td>0.564</td>
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<td>(3.96)</td>
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<td>(2.82)</td>
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<td>(2.23)</td>
<td>(2.04)</td>
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<td>(0.86)</td>
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<td>0.231</td>
<td>0.222</td>
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<td>(5.43)</td>
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Table 2: Microcap Stocks

The table reports results of the same Fama-MacBeth regressions of individual future quarterly stock returns as Table 1, but applied to microcap stocks only. The microcap stocks are stocks whose market sizes fall below the 20% of NYSE breakpoints. For simplicity, we only report the coefficients of $R_{t12}$, the 12-month past cumulative returns, and the $n-1$th and $n$th quarter PLS fundamental indexes, $PLS_{n-1}$ and $PLS_n$. A stock is eliminated if its price falls below $1.00$ threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

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<th>$n$th Quarter Future Return (%)</th>
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<td>$R_{t12}$</td>
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<td>0.277</td>
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</tr>
<tr>
<td></td>
<td>(7.49)</td>
<td>(8.50)</td>
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<td>(12.23)</td>
<td>(13.36)</td>
<td>(14.03)</td>
<td>(12.49)</td>
<td>(12.32)</td>
<td>(10.90)</td>
<td>(10.85)</td>
</tr>
<tr>
<td>$PLS_{n-1}$</td>
<td>0.129</td>
<td>0.131</td>
<td>0.123</td>
<td>0.112</td>
<td>0.109</td>
<td>0.132</td>
<td>0.122</td>
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<td>0.121</td>
</tr>
<tr>
<td></td>
<td>(5.08)</td>
<td>(5.81)</td>
<td>(5.79)</td>
<td>(5.66)</td>
<td>(5.49)</td>
<td>(6.56)</td>
<td>(5.93)</td>
<td>(5.56)</td>
<td>(5.12)</td>
<td>(5.37)</td>
</tr>
</tbody>
</table>
Table 3: Earnings Surprise versus Fundamental Index

The table reports results of Fama-MacBeth regressions of individual future quarterly stock returns, \( n^{th} \) quarter after the quarter (quarter 0) when the 12-month past cumulative returns are estimated. The future quarterly returns are regressed on \( R_{t12} \), the 12-month past cumulative returns, SUE and CAR3, the standardized earning surprise and the cumulative three-day abnormal returns from day -1 to 1 around the earnings announcement dates, as well as the \( n - 1^{th} \) and \( n^{th} \) quarter PLS fundamental indexes, \( \text{PLS}_{n-1} \) and \( \text{PLS}_n \). A stock is eliminated if its price falls below $1.00 threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. \( t \)-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>( n^{th} ) Quarter Future Return (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Momentum and Reversal Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Rt12</td>
<td>1.707</td>
<td>0.907</td>
<td>0.216</td>
<td>-0.617</td>
<td>-0.858</td>
<td>-1.017</td>
<td>-0.857</td>
<td>-1.070</td>
<td>-0.701</td>
<td>-0.522</td>
</tr>
<tr>
<td></td>
<td>(3.30)</td>
<td>(1.65)</td>
<td>(0.49)</td>
<td>(-1.64)</td>
<td>(-2.42)</td>
<td>(-2.49)</td>
<td>(-2.03)</td>
<td>(-2.42)</td>
<td>(-1.84)</td>
<td>(-1.35)</td>
</tr>
<tr>
<td>SUE</td>
<td>4.152</td>
<td>4.538</td>
<td>1.553</td>
<td>0.907</td>
<td>0.446</td>
<td>-0.064</td>
<td>2.059</td>
<td>4.628</td>
<td>-2.595</td>
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</tr>
<tr>
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<td>(4.04)</td>
<td>(2.31)</td>
<td>(1.50)</td>
<td>(0.41)</td>
<td>(0.33)</td>
<td>(-0.04)</td>
<td>(1.89)</td>
<td>(3.69)</td>
<td>(-1.34)</td>
<td>(-0.91)</td>
</tr>
<tr>
<td>CAR3</td>
<td>7.500</td>
<td>6.205</td>
<td>3.311</td>
<td>-0.042</td>
<td>1.982</td>
<td>-0.546</td>
<td>-0.268</td>
<td>-0.094</td>
<td>-1.030</td>
<td>2.299</td>
</tr>
<tr>
<td></td>
<td>(4.11)</td>
<td>(2.99)</td>
<td>(2.00)</td>
<td>(-0.03)</td>
<td>(1.28)</td>
<td>(-0.41)</td>
<td>(-0.19)</td>
<td>(-0.05)</td>
<td>(-0.69)</td>
<td>(0.93)</td>
</tr>
<tr>
<td><strong>Panel B: Controlling for the PLS Index</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Rt12</td>
<td>0.713</td>
<td>0.347</td>
<td>-0.026</td>
<td>-0.256</td>
<td>-0.555</td>
<td>-0.089</td>
<td>0.303</td>
<td>0.299</td>
<td>0.292</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>(1.18)</td>
<td>(0.49)</td>
<td>(-0.05)</td>
<td>(-0.57)</td>
<td>(-1.28)</td>
<td>(-0.21)</td>
<td>(0.78)</td>
<td>(0.75)</td>
<td>(0.73)</td>
<td>(0.77)</td>
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<tr>
<td>SUE</td>
<td>4.083</td>
<td>2.518</td>
<td>0.586</td>
<td>-1.852</td>
<td>4.045</td>
<td>2.820</td>
<td>2.543</td>
<td>2.221</td>
<td>0.443</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>(4.19)</td>
<td>(2.62)</td>
<td>(0.57)</td>
<td>(-1.09)</td>
<td>(3.07)</td>
<td>(2.18)</td>
<td>(1.67)</td>
<td>(1.27)</td>
<td>(0.30)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>CAR3</td>
<td>5.487</td>
<td>3.306</td>
<td>3.711</td>
<td>2.088</td>
<td>1.314</td>
<td>1.066</td>
<td>-0.145</td>
<td>-1.836</td>
<td>-1.744</td>
<td>1.917</td>
</tr>
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<td></td>
<td>(3.25)</td>
<td>(1.96)</td>
<td>(2.60)</td>
<td>(1.36)</td>
<td>(0.79)</td>
<td>(0.80)</td>
<td>(-0.07)</td>
<td>(-0.76)</td>
<td>(-0.89)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>( \text{PLS}_n )</td>
<td>0.254</td>
<td>0.243</td>
<td>0.221</td>
<td>0.226</td>
<td>0.225</td>
<td>0.217</td>
<td>0.223</td>
<td>0.234</td>
<td>0.227</td>
<td>0.223</td>
</tr>
<tr>
<td></td>
<td>(6.47)</td>
<td>(7.48)</td>
<td>(10.49)</td>
<td>(12.69)</td>
<td>(10.98)</td>
<td>(11.58)</td>
<td>(11.61)</td>
<td>(10.55)</td>
<td>(10.94)</td>
<td>(10.83)</td>
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<tr>
<td>( \text{PLS}_{n-1} )</td>
<td>0.078</td>
<td>0.098</td>
<td>0.085</td>
<td>0.089</td>
<td>0.077</td>
<td>0.084</td>
<td>0.086</td>
<td>0.092</td>
<td>0.069</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td>(4.57)</td>
<td>(4.68)</td>
<td>(4.94)</td>
<td>(5.20)</td>
<td>(4.29)</td>
<td>(4.61)</td>
<td>(4.80)</td>
<td>(5.40)</td>
<td>(4.17)</td>
<td>(5.30)</td>
</tr>
</tbody>
</table>
Table 4: Economic Expansionary Periods

The table reports results of the same Fama-MacBeth regressions of individual future quarterly stock returns as Table 1, but only applied to the economic expansionary periods identified by the National Bureau of Economic Research (NBER). For simplicity, we only reports the coefficients of $R_{t12}$, the 12-month past cumulative returns, and the $(n - 1)^{th}$ and $n^{th}$ quarter PLS fundamental indexes, $PLS_{n-1}$ and $PLS_n$. A stock is eliminated if its price falls below $1.00$ threshold at the end of quarter $0$. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>$n^{th}$ Quarter Future Return (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Momentum and Reversal Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$R_{t12}$</td>
<td>2.188</td>
<td>1.340</td>
<td>0.443</td>
<td>-0.539</td>
<td>-0.560</td>
<td>-0.854</td>
<td>-0.772</td>
<td>-0.816</td>
<td>-0.655</td>
<td>-0.912</td>
</tr>
<tr>
<td></td>
<td>(5.51)</td>
<td>(3.53)</td>
<td>(1.20)</td>
<td>(-1.52)</td>
<td>(-1.66)</td>
<td>(-2.15)</td>
<td>(-1.82)</td>
<td>(-2.05)</td>
<td>(-2.07)</td>
<td>(-3.06)</td>
</tr>
<tr>
<td>Panel B: Controlling for the PLS Index</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{t12}$</td>
<td>0.819</td>
<td>0.720</td>
<td>0.405</td>
<td>-0.107</td>
<td>-0.151</td>
<td>0.189</td>
<td>0.548</td>
<td>0.427</td>
<td>0.383</td>
<td>0.247</td>
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<tr>
<td></td>
<td>(1.64)</td>
<td>(1.32)</td>
<td>(0.74)</td>
<td>(-0.22)</td>
<td>(-0.36)</td>
<td>(0.47)</td>
<td>(1.39)</td>
<td>(1.08)</td>
<td>(1.14)</td>
<td>(0.61)</td>
</tr>
<tr>
<td>$PLS_n$</td>
<td>0.212</td>
<td>0.215</td>
<td>0.212</td>
<td>0.213</td>
<td>0.213</td>
<td>0.225</td>
<td>0.227</td>
<td>0.233</td>
<td>0.236</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(12.76)</td>
<td>(11.25)</td>
<td>(11.96)</td>
<td>(11.87)</td>
<td>(11.75)</td>
<td>(11.40)</td>
<td>(11.59)</td>
<td>(11.43)</td>
<td>(10.98)</td>
<td>(10.72)</td>
</tr>
<tr>
<td>$PLS_{n-1}$</td>
<td>0.088</td>
<td>0.097</td>
<td>0.090</td>
<td>0.085</td>
<td>0.089</td>
<td>0.098</td>
<td>0.085</td>
<td>0.090</td>
<td>0.080</td>
<td>0.096</td>
</tr>
<tr>
<td></td>
<td>(6.13)</td>
<td>(6.17)</td>
<td>(6.72)</td>
<td>(5.98)</td>
<td>(6.01)</td>
<td>(6.38)</td>
<td>(5.19)</td>
<td>(5.09)</td>
<td>(4.75)</td>
<td>(5.23)</td>
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</table>
Table 5: Conditionally Sorted Momentum Portfolios

In Panel A, we first sort the stocks into quintiles based on the PLS implied returns from Eq. (20), and then within each quintile we further sort stocks into quintiles by their 12-month past returns. Finally we form 25 quintile portfolios and report their average quarterly excess returns. In Panel B, we take the residuals from Eq. (21) and sort stocks on the residuals into decile portfolios, and report the average quarterly excess returns of the residual decile portfolios. We also report the average quarterly excess returns of the momentum decile portfolios as the benchmark. A stock is eliminated if its price falls below $1.00 threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. *t*-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>Panel A: Double Dependent Sort on PLS Implied Return and Momentum</th>
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<tbody>
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<tr>
<td></td>
</tr>
<tr>
<td>Mom Rank</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>-</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>5 − 1</td>
</tr>
<tr>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Panel B: Decile Portfolios Sorted on Momentum or Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rt12</td>
</tr>
<tr>
<td>(0.47)</td>
</tr>
<tr>
<td>(3.16)</td>
</tr>
</tbody>
</table>
Table 6: Spanning Tests

The table reports results of spanning tests of the momentum spread portfolio (Panel A) and the spread portfolio based on the PLS implied returns (Panel B), respectively, under CAPM, Fama-French three-factor, and Fama-French five-factor models. For the Fama-French quarterly three-factor model, we first convert the monthly returns to quarterly returns for the $2 \times 3$ size and book-to-market sorted portfolios obtained from Ken French’s online data library, and then construct the factors SMB and HML according to Fama and French (1996). Similarly, for the Fama-French quarterly five-factor model, we first obtain the quarterly returns from the monthly returns for the $2 \times 3$ size and operating profitability sorted portfolios and size and investment sorted portfolios, respectively, and then construct the quarterly returns for the other two factors (RMW and CMA). In addition, we reconstruct the size factor by taking the average across the three size factors obtained along with the other three factors according to Fama and French (2015) as shown on French’s website. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Momentum Spread Portfolio</th>
<th>Panel B: PLS Implied Spread Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha (%)$</td>
<td>3.192 -0.364 4.188 0.544 3.757 0.575</td>
<td>5.040 4.704 5.105 4.591 4.970 4.572</td>
</tr>
<tr>
<td></td>
<td>(4.15) (-0.27) (5.35) (0.48) (3.37) (0.50)</td>
<td>(11.13) (10.70) (11.12) (11.57) (10.06) (11.11)</td>
</tr>
<tr>
<td>$\beta_{mkt}$</td>
<td>-0.0583 -0.103 -0.0459 -0.0559 0.00692 -0.00237</td>
<td>0.0591 0.0653 0.0163 0.0216 0.0340 0.0319</td>
</tr>
<tr>
<td></td>
<td>(-0.34) (-0.66) (-0.43) (-0.55) (0.07) (-0.02)</td>
<td>(1.39) (1.65) (0.36) (0.49) (0.74) (0.71)</td>
</tr>
<tr>
<td>$\beta_{smb}$</td>
<td>-0.485 -0.579 -0.480 -0.561</td>
<td>0.115 0.175 0.113 0.164</td>
</tr>
<tr>
<td></td>
<td>(-2.25) (-2.74) (-2.61) (-2.93)</td>
<td>(1.67) (2.23) (1.81) (2.21)</td>
</tr>
<tr>
<td>$\beta_{hml}$</td>
<td>-0.590 -0.523 -0.965 -0.827</td>
<td>-0.0827 -0.0126 -0.247 -0.143</td>
</tr>
<tr>
<td></td>
<td>(-2.71) (-2.78) (-3.40) (-3.31)</td>
<td>(-1.00) (-0.16) (-2.46) (-1.58)</td>
</tr>
<tr>
<td>$\beta_{rmw}$</td>
<td>-0.0313 0.0407</td>
<td>-0.0510 -0.0518</td>
</tr>
<tr>
<td></td>
<td>(-0.08) (0.11)</td>
<td>(-0.46) (-0.56)</td>
</tr>
<tr>
<td>$\beta_{cma}$</td>
<td>-0.816 -0.641</td>
<td>-0.361 -0.269</td>
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<tr>
<td></td>
<td>(-1.77) (-1.40)</td>
<td>(-2.67) (-2.11)</td>
</tr>
<tr>
<td>PLS</td>
<td>0.724 0.731 0.645</td>
<td>0.102 0.120 0.105</td>
</tr>
<tr>
<td></td>
<td>(2.73) (3.08) (2.75)</td>
<td>(2.52) (2.73) (2.50)</td>
</tr>
</tbody>
</table>
Table 7: PCA Fundamental Index

The table reports results of Fama-MacBeth regressions of individual future quarterly stock returns, $n^{th}$ quarter after the quarter (quarter 0) when the 12-month past cumulative returns are estimated, on the 12-month past cumulative returns $Rt_{12}$ and PCA fundamental indexes. Additional control variables are LSZ and LBM representing the natural log of firm size and the book-to-market ratio estimated at the end of quarter 0, respectively. $PCA_{n-1}$ and $PCA_n$ represent the PCA firm fundamental index for firm $i$, the $n-1^{th}$ and $n^{th}$ quarter after quarter 0. A stock is eliminated if its price falls below $1.00 threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>$n^{th}$ Quarter Future Return (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.940</td>
<td>4.907</td>
<td>5.291</td>
<td>5.743</td>
<td>5.321</td>
<td>5.107</td>
<td>5.032</td>
<td>5.221</td>
<td>5.196</td>
<td>4.918</td>
</tr>
<tr>
<td></td>
<td>(4.31)</td>
<td>(4.41)</td>
<td>(4.70)</td>
<td>(4.87)</td>
<td>(4.76)</td>
<td>(5.03)</td>
<td>(4.89)</td>
<td>(5.01)</td>
<td>(4.86)</td>
<td>(4.69)</td>
</tr>
<tr>
<td>LSZ</td>
<td>-0.217</td>
<td>-0.219</td>
<td>-0.232</td>
<td>-0.273</td>
<td>-0.217</td>
<td>-0.191</td>
<td>-0.203</td>
<td>-0.207</td>
<td>-0.211</td>
<td>-0.178</td>
</tr>
<tr>
<td></td>
<td>(-1.84)</td>
<td>(-1.97)</td>
<td>(-2.03)</td>
<td>(-2.26)</td>
<td>(-1.81)</td>
<td>(-1.75)</td>
<td>(-1.83)</td>
<td>(-1.85)</td>
<td>(-1.83)</td>
<td>(-1.56)</td>
</tr>
<tr>
<td>LBM</td>
<td>0.460</td>
<td>0.452</td>
<td>0.474</td>
<td>0.214</td>
<td>0.404</td>
<td>0.476</td>
<td>0.454</td>
<td>0.462</td>
<td>0.482</td>
<td>0.475</td>
</tr>
<tr>
<td></td>
<td>(1.78)</td>
<td>(1.83)</td>
<td>(1.88)</td>
<td>(0.89)</td>
<td>(1.67)</td>
<td>(1.96)</td>
<td>(1.84)</td>
<td>(1.88)</td>
<td>(2.03)</td>
<td>(1.91)</td>
</tr>
<tr>
<td>$Rt_{12}$</td>
<td>0.279</td>
<td>0.353</td>
<td>0.252</td>
<td>-0.016</td>
<td>-0.294</td>
<td>0.133</td>
<td>0.391</td>
<td>0.307</td>
<td>0.452</td>
<td>0.519</td>
</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(0.54)</td>
<td>(0.45)</td>
<td>(-0.04)</td>
<td>(-0.67)</td>
<td>(0.35)</td>
<td>(1.01)</td>
<td>(0.74)</td>
<td>(1.16)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>$PCA_n$</td>
<td>0.020</td>
<td>0.020</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
<td>0.020</td>
<td>0.019</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(14.99)</td>
<td>(15.46)</td>
<td>(15.99)</td>
<td>(16.11)</td>
<td>(16.38)</td>
<td>(15.63)</td>
<td>(15.21)</td>
<td>(15.75)</td>
<td>(16.06)</td>
<td>(15.56)</td>
</tr>
<tr>
<td>$PCA_{n-1}$</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.016</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(17.70)</td>
<td>(18.63)</td>
<td>(19.08)</td>
<td>(17.95)</td>
<td>(17.25)</td>
<td>(17.63)</td>
<td>(17.99)</td>
<td>(17.85)</td>
<td>(16.75)</td>
<td>(17.02)</td>
</tr>
</tbody>
</table>


Table 8: Skip One Month

The table reports results of the same Fama-MacBeth regressions of individual future quarterly stock returns as Table 1, except that the 12-month past cumulative returns are matched to the second month instead of the third month of quarter 0, i.e. to skip one month. For simplicity, we only reports the coefficients of $R_{t12}^s$, the 12-month past cumulative returns with one-month skipped, and the $n^{th}$ and $n^{-1}$ quarter PLS fundamental indexes, $PLS_{n-1}$ and $PLS_n$. A stock is eliminated if its price falls below $1.00$ threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>$n^{th}$ Quarter Future Return (%)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Momentum and Reversal Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{t12}$</td>
<td>2.118</td>
<td>1.281</td>
<td>0.479</td>
<td>-0.698</td>
<td>-1.002</td>
<td>-1.064</td>
<td>-0.940</td>
<td>-0.962</td>
<td>-0.814</td>
<td>-0.990</td>
</tr>
<tr>
<td></td>
<td>(4.30)</td>
<td>(2.90)</td>
<td>(1.25)</td>
<td>(-2.10)</td>
<td>(-2.74)</td>
<td>(-2.61)</td>
<td>(-2.16)</td>
<td>(-2.15)</td>
<td>(-2.24)</td>
<td>(-3.13)</td>
</tr>
<tr>
<td><strong>Panel B: Controlling for the PLS Index</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{t12}$</td>
<td>0.766</td>
<td>0.542</td>
<td>0.038</td>
<td>-0.438</td>
<td>-0.516</td>
<td>-0.160</td>
<td>0.326</td>
<td>0.333</td>
<td>0.118</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(1.31)</td>
<td>(0.83)</td>
<td>(0.06)</td>
<td>(-0.94)</td>
<td>(-1.14)</td>
<td>(-0.36)</td>
<td>(0.76)</td>
<td>(0.74)</td>
<td>(0.28)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>$PLS_n$</td>
<td>0.274</td>
<td>0.261</td>
<td>0.238</td>
<td>0.237</td>
<td>0.225</td>
<td>0.222</td>
<td>0.231</td>
<td>0.237</td>
<td>0.234</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(5.61)</td>
<td>(6.64)</td>
<td>(10.18)</td>
<td>(10.93)</td>
<td>(11.15)</td>
<td>(10.83)</td>
<td>(10.53)</td>
<td>(10.87)</td>
<td>(10.01)</td>
<td>(9.94)</td>
</tr>
<tr>
<td>$PLS_{n-1}$</td>
<td>0.114</td>
<td>0.120</td>
<td>0.112</td>
<td>0.108</td>
<td>0.105</td>
<td>0.114</td>
<td>0.106</td>
<td>0.099</td>
<td>0.090</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>(6.26)</td>
<td>(6.76)</td>
<td>(7.17)</td>
<td>(7.69)</td>
<td>(7.22)</td>
<td>(7.32)</td>
<td>(6.70)</td>
<td>(5.86)</td>
<td>(5.33)</td>
<td>(5.79)</td>
</tr>
</tbody>
</table>
Table 9: Before Financial Crisis

The table reports results of the same Fama-MacBeth regressions of individual future quarterly stock returns as Table 1, but only applied to the periods before the most recent financial crisis (before the fourth quarter of 2007). For simplicity, we only report the coefficients of $R_{t12}$, the 12-month past cumulative returns with one-month skipped, and the $n-1$ and $n$th quarter PLS fundamental indexes, $PLS_{n-1}$ and $PLS_n$. A stock is eliminated if its price falls below $1.00$ threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. $t$-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>$n$th Quarter Future Return (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2 3 4 5 6 7 8 9 10</td>
</tr>
</tbody>
</table>

Panel A: Momentum and Reversal Effects

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{t12}$</td>
<td>2.118</td>
<td>1.281</td>
<td>0.479</td>
<td>-0.698</td>
<td>-1.002</td>
<td>-1.064</td>
<td>-0.940</td>
<td>-0.962</td>
<td>-0.814</td>
<td>-0.990</td>
</tr>
<tr>
<td></td>
<td>(4.30)</td>
<td>(2.90)</td>
<td>(1.25)</td>
<td>(-2.10)</td>
<td>(-2.74)</td>
<td>(-2.61)</td>
<td>(-2.16)</td>
<td>(-2.15)</td>
<td>(-2.24)</td>
<td>(-3.13)</td>
</tr>
</tbody>
</table>

Panel B: Controlling for the PLS Index

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{t12}$</td>
<td>0.766</td>
<td>0.542</td>
<td>0.038</td>
<td>-0.438</td>
<td>-0.516</td>
<td>-0.160</td>
<td>0.326</td>
<td>0.333</td>
<td>0.118</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(1.31)</td>
<td>(0.83)</td>
<td>(0.06)</td>
<td>(-0.94)</td>
<td>(-1.14)</td>
<td>(-0.36)</td>
<td>(0.76)</td>
<td>(0.74)</td>
<td>(0.28)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>$PLS_n$</td>
<td>0.274</td>
<td>0.261</td>
<td>0.238</td>
<td>0.237</td>
<td>0.225</td>
<td>0.222</td>
<td>0.231</td>
<td>0.237</td>
<td>0.234</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(5.61)</td>
<td>(6.64)</td>
<td>(10.18)</td>
<td>(10.93)</td>
<td>(11.15)</td>
<td>(10.83)</td>
<td>(10.53)</td>
<td>(10.87)</td>
<td>(10.01)</td>
<td>(9.94)</td>
</tr>
<tr>
<td>$PLS_{n-1}$</td>
<td>0.114</td>
<td>0.120</td>
<td>0.112</td>
<td>0.108</td>
<td>0.105</td>
<td>0.114</td>
<td>0.106</td>
<td>0.099</td>
<td>0.090</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>(6.26)</td>
<td>(6.76)</td>
<td>(7.17)</td>
<td>(7.69)</td>
<td>(7.22)</td>
<td>(7.32)</td>
<td>(6.70)</td>
<td>(5.86)</td>
<td>(5.33)</td>
<td>(5.79)</td>
</tr>
</tbody>
</table>
Table 10: Tradable Fundamental Index Strategies

We form tradable strategies using the firm fundamental index. PLS (PCA): Each quarter we sort stocks into deciles using their PLS (PCA) index at the previous quarter and form a spread portfolio longing the 10th decile and shorting the first decile. FPLS10 (FPLS20): Each quarter we estimate the PLS forecasted returns from Eq. (22) using their PLS indexes in the previous two quarters, and then form time-series averages using the forecasted returns of the previous 10 (20) quarters. We then sort the stocks into deciles based on average forecasted returns and form the long/short spread portfolio. The spread portfolios FPCA10 (FPCA20) are constructed similarly. We also report the summary statistics of the momentum decile portfolios as the benchmark. A stock is eliminated if its price falls below $1.00 threshold at the end of quarter 0. The sample covers January, 1970 through December, 2015. t-statistics in parentheses are Newey-West adjusted.

<table>
<thead>
<tr>
<th>Strategies</th>
<th>N</th>
<th>Mean(%)</th>
<th>Std Dev(%)</th>
<th>Sharp Ratio</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Minimum(%)</th>
<th>Maximum(%)</th>
<th>MDD(%)</th>
<th>Calmar(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOM</td>
<td>165</td>
<td>3.071</td>
<td>11.22</td>
<td>0.274</td>
<td>-0.831</td>
<td>6.682</td>
<td>-47.35</td>
<td>54.85</td>
<td>74.53</td>
<td>4.07</td>
</tr>
<tr>
<td>PLS</td>
<td>167</td>
<td>2.256</td>
<td>3.82</td>
<td>0.591</td>
<td>-0.628</td>
<td>3.087</td>
<td>-15.19</td>
<td>11.05</td>
<td>15.19</td>
<td>14.85</td>
</tr>
<tr>
<td>FPLS10</td>
<td>156</td>
<td>2.132</td>
<td>3.41</td>
<td>0.625</td>
<td>0.117</td>
<td>0.611</td>
<td>-8.22</td>
<td>12.16</td>
<td>21.41</td>
<td>9.30</td>
</tr>
<tr>
<td>FPLS20</td>
<td>146</td>
<td>2.000</td>
<td>3.63</td>
<td>0.551</td>
<td>0.220</td>
<td>0.110</td>
<td>-6.32</td>
<td>12.39</td>
<td>30.63</td>
<td>5.71</td>
</tr>
<tr>
<td>PCA</td>
<td>165</td>
<td>1.552</td>
<td>3.76</td>
<td>0.413</td>
<td>-0.227</td>
<td>3.006</td>
<td>-14.12</td>
<td>16.62</td>
<td>16.37</td>
<td>9.37</td>
</tr>
<tr>
<td>FPCA10</td>
<td>157</td>
<td>1.540</td>
<td>3.80</td>
<td>0.405</td>
<td>0.071</td>
<td>2.363</td>
<td>-14.47</td>
<td>16.39</td>
<td>27.13</td>
<td>5.34</td>
</tr>
<tr>
<td>FPCA20</td>
<td>147</td>
<td>1.700</td>
<td>3.94</td>
<td>0.431</td>
<td>0.011</td>
<td>2.933</td>
<td>-15.09</td>
<td>17.39</td>
<td>23.62</td>
<td>6.33</td>
</tr>
</tbody>
</table>