Conditional Asset Pricing and Momentum

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Abstract

Winner stocks have higher risk exposure to Fama and French (1993) three factors (FF3F) than loser stocks during good economic times, and therefore should earn higher expected returns. Employing the conditional FF3F model to risk adjust returns on winner and loser stocks can reduce the average momentum alpha by 50% compared to the conventional portfolio-level estimate. We point out a bias in the existing methodology of component-level risk adjustment. After correcting for this bias, even though conditional asset pricing models still cannot completely explain momentum returns, the reduction in alpha remains strong.

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1. Introduction

The short-term momentum in monthly stock returns of Jegadeesh and Titman (1993) is a pervasive challenge to existing asset pricing models. The literature generally agrees that the unconditional capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) cannot explain the momentum effect. Jagannathan and Wang (1996) argue that the unconditional CAPM is not originally developed to describe a realistic multi-period economy, and therefore does not exhibit meaningful relationships between market betas and expected returns. They show that the conditional CAPM is powerful in explaining the cross-section of average returns. By allowing betas to be time-varying, Ferson and Harvey (1999) reject the conditional Fama and French's (1993) (FF3F) model in various asset pricing tests. Recently, Boguth, Carlson, Fisher, and Simutin (2011) find that when the CAPM is conditioned based on lagged realized betas of individual winner and loser stocks (components), the average momentum alpha declines by 20% to 40% relative to the unconditional measure.

This study is motivated to examine why the information of individual winner/loser stocks' lagged betas can enhance the explanatory power of the conditional CAPM in Boguth et al. (2011). We also study why the conditional FF3F model does not perform well on momentum effects. This issue is related to the curious finding about the incorrect prediction of FF3F model. Fama and French (1996) document that the unconditional loadings on their SMB and HML factors are higher on loser portfolios than winner counterparts, and hence falsely "predict" negative momentum returns (the reversal effect). There is little research on this special failure of the FF3F model in explaining momentum profits, even though this model can rationalize many other anomalies.[1]

In this study, we argue that the momentum effect is an artifact of the way stocks are selected in the portfolio such that their time-varying dynamics are concealed at the aggregate

[1]Fama and French (1996, p. 68) find that loser portfolios have higher loadings on SMB and HML factors than winner portfolios. Consequently, they conclude that "the three-factor model predicts reversal for the post-formation returns of short-term losers and winners, and so misses the observed continuation."

portfolio level. Our thinking is akin to Lo and MacKinlay (1990a) and Lewellen et al. (2010), who express skepticism about particular methods of sorting stocks that can significantly affect the final results.

We find that winner stocks on average load more on market risks during up markets whereas loser stocks have higher loadings in down markets. The time-series trends in market loadings of winner and loser stocks also move in opposite directions to each other over time. Interestingly, the aggregate *portfolio* return, however, does not exhibit these time-varying dynamics. Since Cooper et al. (2004) show that momentum returns are lower following market losses, we should expect to see the market beta of winner-minus-loser (WML) portfolios to be lower when the economy moves from the peak to the trough.[2] We do not find this behavior in the beta of aggregate portfolio returns. When the economy heads toward recessions, the WML beta computed using aggregate portfolio returns increases by 0.07, suggesting a rise, not a fall, in momentum returns. In stark contrast, the average WML beta computed using returns on individual stocks (components) shows the correct direction with a decrease in beta by 0.30 when the economy enters recessions. These findings indicate that Boguth et al.'s (2011) average component betas can improve the explanatory power of the conditional CAPM because they capture the large time variation of winner and loser stocks over time.[3]

Similar to the time-varying dynamics of the market beta, the SMB and HML factors of Fama and French (1993) also correctly rationalize returns on individual winner and loser stocks during good economic times. Winner stocks have higher exposure to the SMB and HML risk factors than do loser stocks. Therefore, winners should earn higher future average returns while losers should earn lower average returns, causing positive expected momentum profits during bull markets. The converse is true when risk loadings are estimated using

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[2] Grundy and Martin (2001) and Daniel and Moskowitz (2011) also document the lower momentum profitability in bear markets.

[3] Because the NBER business cycles are dated $ex-post$, there is a concern about the "look-ahead" bias if one is to use the dates. It should be noted that this study does not use NBER business cycles dates to form trading portfolios, nor does it rely on those dates in estimating conditional asset pricing models. Rather, we simply use those business cycle dates to demonstrate the time variation of momentum stocks' betas.

aggregate portfolio returns, consistent with the findings of Fama and French (1996). These observations suggest that the puzzle of Fama and French (1996) can be solved by looking at individual stock components. Consequently, we employ the conditional asset pricing model to risk adjust returns on individual stocks of the portfolio (this method is briefly called component-level risk adjustment).

Applying to CRSP monthly data, we find that when the conditional asset pricing model is used to risk adjust returns on individual winner and loser stocks, the reduction in average momentum alphas ranges from 14% (for the CAPM) to 50% (for the FF3F model) compared to the respective portfolio-level estimate. For the typical 6/1/6 momentum portfolio in which stocks are ranked by their continuously compounded returns over the past 6 months and then winner-loser portfolios are held over the next 6 months with one-month skipping period in between, the conditional FF3F model performs better than the conditional CAPM by reducing the average alpha by 30bps per month.[4] The average component-level alpha from the conditional FF3F model is reduced to 0.61% per month, representing a 50% decrease from the portfolio-level estimate. These findings confirm our conjecture that the component-level risk adjustment is able to capture the large time variation in betas (as we show in Section 4, this method accounts for the fact that the time variation in components' betas is much bigger than that of their portfolio counterparts). Consequently, asset pricing models have higher explanatory power when these facts are accounted for.

There are several reasons for the success of component-level risk adjustments. Boguth et al. (2011) argue that using the lagged component beta as a conditioning variable has the advantage of accounting for changing weights of individual stocks at the end of the ranking period; betas computed using aggregate portfolio returns, by contrast, miss out this information. Similarly, we argue that the success of the component-level risk adjustment comes from its ability to capture the change in weights of individual stock components. More

[4]This finding is interesting because, at the portfolio level, the CAPM performs better than the FF3F model in terms of reduction in alpha.

importantly, it accounts for the fact that the portfolio's composition changes frequently due to rebalancing and delisted stocks. Grundy and Martin (2001) document that 39.9% of winners and 36.2% of losers are dropped out of the portfolio at the end of the investment period. Eisdorfer (2008) notes that on average 10% of stocks in the winner and loser portfolios are delisted during the investment period, causing the portfolio's composition at both end points of the holding period to be different. Finally, the component-level risk adjustment has an advantage that tests on portfolio returns do not have, even if we use the component beta as an instrument; it can avoid the arbitrary method of stock selections of momentum strategies as argued in Lo and MacKinlay (1990a) and Lewellen et al. (2010).[5]

To demonstrate the mechanical way of sorting stocks into momentum portfolios that biases the unconditional alpha upwards, we conduct a small Monte Carlo simulation in which returns on 4000 stocks are generated by the CAPM (i.e., their returns are completely explained by the CAPM.) We follow the usual approach to form momentum portfolios whose average returns are risk-adjusted using the time-series market model regression. We find that the alpha is higher than the average raw momentum return and the null hypothesis of zero (portfolio) alpha is rejected 88% of the time at the five percent level. Though expected, these results are still striking because the CAPM holds exactly for every single stock, but the mechanical way of sorting stocks causes momentum alphas to be non-zero. The component-level risk adjustment is thus a natural way to "undo" the impact of portfolio construction on asset pricing tests while still maintaining the interpretation of risk-adjusted momentum returns.[6]

Our study is related to Chordia and Shivakumar (2002) who employ a macroeconomic

[5] Chordia, Goyal, and Shanken (2011) and Ang, Liu, and Schwarz (2010) also argue that applying asset pricing models on individual constituents of the portfolio can mitigate the critique of Lo and MacKinlay (1990a) about the arbitrary method of sorting stocks. In a study outside the momentum literature, Griffin et al. (2010) (page 3243), who test the efficiency of international exchanges, argue that "an advantage of using individual stocks is that one can allow correlations [between stocks] to switch sign".

[6] We repeat our simulations in which stocks' returns are now generated by the three risk factors of Fama and French (1993) downloaded from Ken French's website. We also simulate returns using the conditional version of these asset pricing models. Our conclusions do not change.

model to adjust returns on individual stock components of momentum portfolios. A more recently related paper is of Wang and Wu (2011) who use the unconditional FF3F model to risk adjust individual stock returns. In this study, we point out the 'sample selection bias'[7] in the existing methodology of component-level risk adjustments, which typically uses returns on individual stocks including the entire ranking period to run regressions.

We argue that using ranking period returns will bias the estimated beta because, *by construction*, the momentum strategy selects stocks with the most positive past returns for winner portfolios and those with the most negative past returns for loser portfolios. When the ranking period was a bull market, the WML beta would be positive, while the beta would be negative when the ranking period was a bear market.[8] Consequently, if betas are estimated using ranking period returns, the bias will be positive during bull markets while during bear markets, the bias will be negative. This bias serves to artificially amplify the dynamics of estimated betas, thereby causing all asset pricing models that account for time-varying risk to completely explain momentum returns.

We correct for this bias by simply excluding ranking period returns from the estimation and find that the magnitude of the bias is much bigger in down markets. For example, using CRSP data, we find that the bias causes the market beta of momentum portfolios to be 22% higher during economic expansions (as dated by the NBER), but 37% lower during contractions. Moreover, our Monte Carlo simulations also show that betas estimated using pre-ranking period returns are almost equal to the true beta that we use to simulate stock returns. By correcting for the bias, we find that the negative adjusted momentum returns documented in Chordia and Shivakumar (2002) are reversed. With the bias in place, we confirm their original results that their macroeconomic model yields the average adjusted

[7]This bias is not the survivorship or look-ahead bias. We acknowledge that the phrase "sample selection bias" is loose and subject to debate, but we use it as a convenient way to indicate the bias that is incurred by using ranking period returns, which are determined by the construction of momentum strategies, as the left-hand side of the regression. We explain this bias in detail in Section 4.

[8]The positive covariance between momentum returns and the market is also documented in Grundy and Martin (2001), Chordia and Shivakumar (2002), Daniel and Moskowitz (2011), and Boguth et al. (2011).

momentum return of -2.97% per month. After the bias correction, this average return reverses to positive 5.03% per month.[9]

2. Related Literature

Although the literature on time-varying risk premium has been well developed, applying the conditional models at individual stock levels is not frequently employed. In the momentum literature, Chordia and Shivakumar (2002) were among the first to use a set of macroeconomic variables to adjust returns on individual winner and loser stocks. In other words, their method is similar to ours, except that they do not have risk factors in the model. Chordia and Shivakumar (2002) find that momentum is strongly related to business cycles as dated by the NBER and consequently suggest that momentum can potentially be explained by time-varying expected returns. However, to be explained by rational theories, momentum payoffs must covary with risk factors. As also acknowledged by Chordia and Shivakumar (2002), the lack of common risk factors in their model constrains their claims to only the correlation between the predictive power of those variables and momentum payoffs.

Our study builds on their method to incorporate common risk factors. We also use a set of conditional asset pricing models that allow us to tackle the time-varying betas of individual stocks. The conclusions of this study are therefore more general, and the final momentum payoff can be interpreted as time-varying risk adjusted returns. More importantly, we find the problem of sample selection bias in the current component-level adjustment, which occurs because of the time-varying dynamics of winner and loser stocks over the ranking period. This run-up makes component-level regressions spurious when the

[9] Chordia and Shivakumar (2002) essentially employ two methods; the first is similar to ours and the second is a two-way dependent portfolio sort between raw and predicted returns. Using the second method, Griffin et al. (2003) show that the findings of Chordia and Shivakumar (2002) do not hold in 16 international markets. Similarly, Cooper et al. (2004) find that Chordia and Shivakumar's (2002) results from the two-way portfolio sorts are driven by the market microstructure bias of penny stocks. Our replications reported in this study suggest that the first method is still robust to the exclusion of penny stocks. Our contribution is to point out that, after excluding penny stocks, the component-level risk adjustment also needs to be corrected for 'sample selection bias'.

estimation window contains ranking period returns. After we correct for this problem, the average adjusted return from Chordia and Shivakumar's (2002) models reverses from -2.97% per month (t-statistic=-1.52) to 5.03% per month (t-statistic=2.34).

Boguth et al. (2011) compute a series of average lagged betas of individual stocks in the momentum portfolios and use them as another set of conditioning information to estimate conditional models at portfolio levels. They show that their conditional models help reduce momentum alphas by 20% to 40% compared to the unconditional versions. However, they do not investigate why the average betas of winner and loser stocks can be good conditioning variables.[10] We provide explanations for those curious results. In addition, Boguth et al. (2011) estimate the conditional CAPM and FF3F models at the portfolio levels, which is different from our method. There are several advantages in our simple risk adjustment at stock levels. Firstly, as we discuss in later sections, running conditional models at the individual stock level exploits (1) time-varying betas and the contrasting behavior of winner and loser stocks, and (2) the changing composition and weights of individual stocks over the investment period. These characteristics are not seen by looking at the aggregate portfolio return because the portfolio is rebalanced frequently. Secondly, since we apply the conditional model on returns of individual winner and loser stocks, we do not need to include the monthly beta series as another set of conditioning information, leading to the benefit of parsimony. The final difference is in terms of results. We find that applying the conditional FF3F on stock components' returns can result in stronger reduction in alpha. These findings shed light to explaining Fama and French (1996)'s puzzle of incorrect loadings on SMB and HML factors, which exist at portfolio levels.

Our study can also be seen as a robust extension of Wang and Wu (2011) who employ the unconditional FF3F to adjust for the risk of individual winner and loser stocks. They find that average momentum alphas are reduced by approximately 40%. Although they run

[10]Boguth et al. (2011) show that conditional alphas are lower than unconditional because unconditional alphas are biased due to volatility timing. They then suggest that lagged component betas, as conditioning information, can mitigate the problem.

rolling regressions at individual stock levels, Wang and Wu (2011) do not estimate the FF3F model under conditioning information and hence do not account for the time variation in the parameters. Ignoring conditioning information may also lead to problematic inferences as pointed out by Boguth et al. (2011). Boguth et al. (2011) show that running rolling regressions without conditioning variables will incur "overconditioning" bias to the average momentum alpha. This overconditioning bias incurs because the nonlinearity in payoffs of winners and losers. In fact, we show that even at the firm level, individual winner and loser stocks are exposed to the market risk differently in different economic states, causing the payoffs to be nonlinear. Consistent with Boguth et al. (2011), we find that conditioning betas on a set of state variables can significantly improve the explanatory power of asset pricing models. Wang and Wu (2011) also do not discuss how errors in variables may affect their results. Similar to the problem of Chordia and Shivakumar (2002), accounting for the sample selection bias increases the risk-adjusted return in Wang and Wu (2011) by approximately 20%.

3. Data and Empirical Methodology

This study employs monthly returns from every stock in the Center for Research in Security Prices (CRSP) database from January 1963 to December 2009. Consistent with the literature, we examine stocks with share codes of 10 or 11 and thus exclude closed-end funds, Real Estate Investment Trusts (REITs), trusts, American Depository Receipts (ADRs), and foreign stocks from the sample. Computed returns also take into account distribution events such as stock splits or right issues. To ensure that we do not incur any look-ahead bias, we do not apply any filters to this raw data set until the construction of momentum portfolios.

As we are interested in testing conditional asset pricing models, we employ instrumental variables. Ghysels (1998) shows that selecting instruments is not a trivial task and researchers typically have to make a choice. Our motivation for selecting instruments is to maintain the parsimony of our models, and thus we limit the set to only the most common conditioning variables that are also examined in Fama and French (1989). We include a constant; the dividend yield ratio (DY) computed as the cumulative 12-month dividends divided by the current price index level; the term spread (TERM) calculated as the difference in yields between ten-year and three-month yield spread in the Treasury market; and the default spread (DEF) which is the difference in yields between Baa- and Aaa-rated bonds.[11] Data on these state variables, which are obtained from Amit Goyal's website[12], are also comprehensively examined in Goyal and Welch (2008). Finally, we obtain the Fama and French (1993) three factors, namely excess market returns (R_M), SMB, and HML, from Ken French's website.[13]

< INSERT TABLE 1 AROUND HERE >

Table 1 reports summary statistics for three instrumental variables. The mean value of DEF is the lowest and it also has the lowest standard deviation. The three variables are also not highly correlated, with the highest correlation of 0.46 between DY and DEF. These low correlations mean that we do not employ duplicating state variables.

3.1. Constructing Momentum Portfolios

We follow Jegadeesh and Titman (1993) to construct momentum portfolios. In order to aid comparisons with other conditional models in the momentum literature (for example, Lewellen and Nagel (2006) and Boguth et al. (2011)), we consider 6/1/6 strategies where stocks are ranked over the past 6 months. Specifically, at the end of each month, continuously compounded returns on each stock are computed as a criterion to rank stocks over the past 6 months (formation period). To be eligible for ranking, stocks must have a return history of 6 months and be actively traded from the beginning to the end of the formation

[11]Including another conditioning variable of three-month T-Bill does not change our conclusions. In our replication of Chordia and Shivakumar (2002), we also include T-Bill to make the results comparable with theirs.

[12]Amit Goyal's research data, `http://www.hec.unil.ch/agoyal/`, accessed 08/06/2011. We thank Amit Goyal for publicizing the data.

[13]We also thank Kenneth French for making the data available on `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

period. This restriction is necessary because stocks with invalid returns at both endpoints of ranking period cannot be computed. Moreover, if the stocks are not traded at the end of the formation period, they cannot be purchased or sold, and thus cannot be included in the relative-strength portfolio.

Following Jegadeesh and Titman (2002), stocks must also be priced above \$5 at the end of each ranking period $t-1$ in order to be included in either winner or loser portfolios.[14] Stocks with market capitalizations in the bottom decile (using NYSE breakpoints) at time $t-1$ are also excluded from the examination. Because we are interested in testing asset pricing models on individual stock returns, we ensure meaningful regression estimates by requiring that stocks must also have 24 valid returns over the past 60 months to be ranked at time $t-1$. These requirements do not induce look-ahead bias as all historical information is known prior to the holding period. If a stock is delisted from the exchange, we will use CRSP's corresponding delisting return in the last month of returns in the holding period.[15]

Stocks are then grouped into deciles where the top decile consists of best performers (winners) and the bottom decile contains worst performers during the ranking period (losers). In the next 6 months (referred to as holding or investment period), the momentum strategy enters a long position in an equally-weighted portfolio of winners and a short position in an equally-weighted loser portfolio. In order to avoid bid-ask bounce and price pressure, we follow the literature to introduce one-month skipping period between formation and holding periods (Jegadeesh (1990), Lo and MacKinlay (1990b), Boudoukh et al. (1994) and Grinblatt and Moskowitz (2004)).[16] The strategies are followed each month, and thus overlapping calendar-time portfolios are constructed.

[14]In order to unify the time reference, we denote t as the skipping month (the month before the holding period). Thus, the formation period is from $t-6$ to $t-1$ and the holding period is from $t+1$ to $t+6$.

[15]This practice follows the existing literature (e.g. Eisdorfer (2008)). Beaver et al. (2007) document that the majority of delisting distribution payments are made in the month of the delisting. Therefore, they suggest that assuming delisting returns are realized immediately after the delisting month is usually reasonable.

[16]Lo and MacKinlay (1990b) show that bid-ask bounces may cause short-term reversals in which losers may become winners and vice versa.

4. Portfolio- versus Component-Level Risk Adjustment

In this section, we first compliment the literature that portfolio-level risk adjustments using the conditional CAPM and FF3F models cannot explain the momentum effect. We then proceed to applying those models on returns of individual winner and loser stocks (components) that comprise momentum portfolios.

4.1. Portfolio-Level Risk Adjustment

Panel A of Table 2 reports raw returns on the 6/1/6 momentum strategy. The strategy yields the average return of 1.01% per month with an associated t-statistic of 4.87, which is statistically significant at the 1% level. This magnitude of return is comparable to that of the existing studies (e.g. Jegadeesh and Titman (2001)). Panel B shows the alpha from the following unconditional time-series regression:

$$r_{WML,t} = \alpha_{WML} + \boldsymbol{\beta}_{WML}^{\top} \boldsymbol{f}_{j,t} + \epsilon \tag{1}$$

where $r_{WML,t}$ is the return on winner-minus-loser portfolio, $\boldsymbol{f}_{jt}$ represents common risk factors namely the excess market return (r_m) or the Fama and French (1993) three factors (FF3F). α_{WML} is reported as the unconditional risk-adjusted return at portfolio levels.

Panel B of Table 2 confirms previous research that unconditional asset pricing models cannot explain the momentum effect. The unconditional CAPM alpha is 1.04% per month, which is slightly higher than the average raw return in panel A. Of note is the failure of the FF3F model, whose WML alpha is much higher than that of the CAPM. Consistent with Fama and French (1996), the intercept on the loser portfolio is strongly negative (-0.74%), thereby inflating the average WML alpha to 1.23% per month (t-statistic = 5.90), which is higher than both the CAPM alpha and the average raw momentum return of 1.01% per month.

Panel C reports the alpha from conditional multi-factor models:

$$r_{WML,t} = \alpha_{WML} + \sum_{j=1}^{K} (\boldsymbol{\beta}_{WML,j}^{\top} \boldsymbol{Z}_{t-1}) \boldsymbol{f}_{jt} + \varepsilon_t \tag{2}$$

where $r_{WML,t}$ is the return on the winner-minus-loser portfolio and $\boldsymbol{f}_{jt}$ represents common risk factors. $\boldsymbol{Z}_{t-1}$ is the row vector of lagged instrumental variables including a constant. α_{WML} and $\boldsymbol{\beta}_{\boldsymbol{WML}}$ are the constant loadings to be estimated. $\boldsymbol{Z}_{t-1}\boldsymbol{\beta}_{WML,t-1}$ are the additional conditional risk loadings on the factor. The main advantage of this econometric specification, which is also used in Ferson and Schadt (1996) and Boguth et al. (2011), is the ease of interpretation.[17] Specification (2) says that the conditional model is expressed as an unconditional multi-factor model consisting of common risk factors and their corresponding interactions with state variables. If the model is correctly specified, α_{WML} is expected to be equal to zero.

Panel C shows that conditional models offer no improvements in pricing errors. The conditional CAPM alpha is 1.04% per month with the associated t-statistic of 4.67, which is equal to that of the unconditional model. Similarly, the conditional FF3F alpha is 1.19% per month (t-statistic = 5.55) – only 4 bps lower than the unconditional estimate.

In unreported tables, we compute Gibbons-Ross-Shanken (GRS) F-tests of intercepts on 10 momentum portfolios, which show that conditional models perform slightly better in explaining momentum profits than their unconditional counterparts. The GRS test shows that the conditional FF3F model produces the lowest F-statistic of 5.23, compared with 5.81 for the conditional CAPM. Nevertheless, consistent with the literature (Grundy and Martin, 2001), conditional models that are applied at the portfolio level still do not fully rationalize the momentum effect. We therefore turn to the component-level risk adjustment of Chordia and Shivakumar (2002) in which the focus is now on the individual constituent of winner

[17] Shanken (1990) and Ferson and Harvey (1999) also allow the alpha to be time-varying with the conditioning information.

and loser portfolios.

< INSERT TABLE 2 AROUND HERE >

4.2. Component-Level Versus Portfolio-Level Betas

In this subsection, we examine the difference in dynamics of betas between individual stocks and aggregate portfolio returns. We point out that the time variation of average betas of individual winner and loser stocks is much higher than that of aggregate portfolios. These time-varying dynamics cannot be seen at the portfolio level because momentum portfolios re-balance frequently, causing their compositions and individual stocks' market capitalizations to change on a monthly basis. Without loss of generality, the following market model regression is run for each stock i belonging to winner or loser portfolios using 120 months of its returns prior to the ranking period.[18]

$$r_{i,t} = \alpha + \beta_i r_{m,t} + \epsilon_i \tag{3}$$

where $r_{i,t}$ is the excess return on stock i; $r_{m,t}$ is the excess returns on the market. Beta loadings for individual stocks are preserved in each month and the monthly value-weighted average of betas across the winner and loser stocks are computed, taking into account the market capitalization of each stock at the end of ranking periods. For easy comparison across betas at different levels, we use value weights by market capitalization of stocks at the end of ranking period when reporting average betas and their graphs. In order to avoid losing too much data, we use 60-month window in the first 120 months of a stock's life, and then employ the full 120-month window afterward. Nevertheless, earlier versions of the paper also

[18]Consistent with the vast majority of the momentum literature, we estimate betas using monthly returns. Although it is increasingly popular to use daily data to estimate betas, Gilbert et al. (2014) show that, contrary to the conventional belief, betas estimated at daily frequency are not better or more precise. In fact, Gilbert et al. (2014) find that, in the presence of the opacity of small firms and risk-averse investors, betas estimated at daily frequency are poor measures of systematic risk and tests using daily returns can be confounded by the effect of opacity. Monthly returns, however, do not suffer from this problem.

report results for fixed 60-month windows, and the conclusion does not qualitatively change. As argued by Boguth et al. (2011), the advantage of computing betas in this way is that we do not leave out the information in the weight (i.e. market capitalization) of the individual components. We plot the time series of component-level betas in the first graph of Figure 1. Since we wish to capture more economic contractions and expansions, the sample period in this analysis is extended between January 1936 and December 2009.

We also plot average WML betas on 'hypothetical' portfolios, which are equivalent to the average component beta. At the end of each ranking period $t-1$, we compute value-weighted average returns on the WML portfolio over the past 120 months prior to the six-month ranking period (from $t-126$ to $t-7$). We then regress these 120 months of WML portfolio returns on the excess market return and obtain the beta. We repeat this 'portfolio-level regression' as we form a new portfolio in the following month. Because the portfolio beta should be equal to the value-weighted average of individual stocks' betas, the betas of these hypothetical portfolios should be similar to those computed at the individual component levels in the first graph. In fact, the correlation coefficient between the average firm-level betas and hypothetical portfolios' betas is 0.98 (not tabulated).

Hypothetical portfolio betas are plotted in the second graph of Figure 1. We call these portfolio betas hypothetical because they are different from those computed using returns on actual Jegadeesh and Titman's (1993) momentum portfolios, which do not take into account changes in stock compositions and weights at the end of each ranking period. The purpose of constructing these hypothetical portfolios is to show that firm-level risk adjustment is similar to portfolio-level risk adjustment as long as changes in the portfolio composition are properly accounted for.

In order to compare component-level betas with the contemporaneous portfolio betas, we also plot their portfolio betas of the actual value-weighted WML portfolio in the third graph (to make betas comparable across graphs, the momentum portfolio in the third graph is value-weighted.). These market betas are computed by running 120-month rolling regressions of average monthly WML returns on the market risk (again, we use only 60 months of returns in the first 120 months). Lewellen and Nagel (2006) argue that this method can capture the effect of time-varying betas as long as betas are fixed within the window.

The first two graphs of Figure 1 show that the average component-level WML beta varies dramatically over time. They are even more volatile during crisis periods such as the early 2000s market crash and the recent Global Financial Crisis between 2007 and early 2009. These time-varying dynamics of WML portfolio beta computed using returns on individual stocks indicate that if we treat the aggregate momentum portfolio as a test asset and run model (3) as one-shot regression to obtain a single estimate, we will miss out the important time variation in the beta of individual momentum stocks at the end of the ranking period. This problem still exists even when we estimate betas using rolling-window regressions on the monthly portfolio return.[19]

The first three rows of Panel B of Table 1 report the average market beta of individual winner and loser stocks (components) computed at the end of each ranking period. Winner stocks load more on the market than losers during economic expansions (1.23 versus 1.12), suggesting that WML portfolios should earn higher expected return in the holding period. Loser stocks on the other hand have the average market loading of 1.26 during contractions, which is higher than 0.96 of winner stocks, indicating that the WML portfolio should earn lower average return in the holding period. The last two columns of Table 1 show the movements of betas from the peak to the trough of the economy and vice versa. Consistently, winner betas on average decrease by 0.26 when the market moves from the peak to the trough while they increase by 0.13 during recovery periods. The movement of loser betas is just the opposite. When the economy falls into recessions, the average beta of loser stocks increases by 0.05. But their betas decrease by 0.13 when the economy heads toward the next peak. These contrasting dynamics of winners and losers suggest that (1) the betas of winner and loser

[19] Boguth et al. (2011) show that the methods to estimate conditional models in these studies give problematic inferences, as they suffer from "over-conditioning bias" in which the conditioning information was not observed by investors at time $t-1$.

stocks (components) are time-varying with the market states, and (2) a closer examination of the risk exposure of individual stocks may give us a better understanding of the underlying risk of momentum portfolios.

The third graph of Figure 1 shows the contemporaneous market beta on the aggregate value-weighted momentum portfolio. Compared with the first two graphs, there is much less time variation at the portfolio level, consistent with Lewellen and Nagel (2006). Moreover, the time-series trend also moves in the opposite direction to that at component levels, especially during crisis periods. For instance, the contemporaneous portfolio-level beta trended downwards during the early 2000s market crash whereas the average component-level beta trended upward. In fact, the correlation coefficient (not reported) between component-level betas and portfolio-level betas is -0.14.

Panel B of Table 1 quantifies the trend of portfolio-level betas (three middle rows). In contrast to average component-level betas, the average portfolio-level winner beta is lower than that of loser's during economic expansions (1.30 versus 1.37), suggesting that the momentum portfolio should earn low (or negative) expected return. We also see similar trends during economic contractions, which cause the aggregate WML portfolio beta to be similar in both states of the economy (with -0.08 in expansions and -0.07 in contractions). These results show that the contemporaneous portfolio-level beta computed using monthly portfolio returns does not vary over time, and therefore the contrasting dynamics in the betas of winner and loser stocks (components) do not appear in the portfolio-level beta.

Our view is that the movement of market betas computed on aggregate monthly portfolio returns is counter-intuitive to what we know from the momentum literature. Given that Cooper et al. (2004) show that momentum returns are lower following market losses, we should expect to see the beta on WML portfolios to decrease when the economy moves from the peak to the trough. This is not the case for portfolio-level betas. The last two columns of Panel B of Table 1 shows that when the economy moves from the peak to the trough, the portfolio-level WML beta increases by 0.07, indicating a rise, not a fall, in momentum returns. On the other hand, the average component-level WML beta shows the correct direction with a decrease in beta by 0.30 when the market heads toward the trough. This is another support for the use of component-level risk adjustments.

The variance of component-level betas, hypothetical betas, and portfolio-level betas are 0.159, 0.146, and 0.044, respectively (not tabulated). We test the hypothesis that the variance of betas is statistically equal to zero using the delta method corrected for autocorrelations of betas as described in Cochrane (2005). The t-statistics of the variance in the first, second, and third series of betas are 7.42, 5.85, and 2.88, respectively. The variance of portfolio-level betas has the lowest t-statistic, indicating that it is not volatile enough to describe the time-varying dynamics of momentum stocks' betas. We also compute average conditional betas from the Ferson and Schadt's (1996) conditional market model (in which model (3) has the market return and its interactions with state variables); our conclusions in this section do not change.

The fact that the time variation of components' betas cannot be seen on the aggregate portfolio return indicates that applying conditional asset pricing models on aggregate portfolio returns will miss out the important dynamics of individual stocks. Even though we use 120 months of returns to estimate betas, the behavior of portfolio-level betas in the third graph is consistent with the finding of Lewellen and Nagel (2006, p. 291) that portfolio betas "do vary considerably over time – just not enough to explain large unconditional pricing errors". However, looking at component-level betas we can see a large variation in the average WML betas, which suggests that a potential source of alpha can be detected at this level. Our findings compliment Boguth et al. (2011) who argue that the component beta uses the important information of the weights of individual stocks at the end of ranking period whereas portfolio-level betas do not account for changing portfolio weights, though they do not make the above points about the dynamics of component-level betas. We provide a more formal theoretical argument for the component-level risk adjustment in Subsection 4.4.

< INSERT FIRGURE 1 AROUND HERE >

4.3. Component-Level Risk Adjustment and Sample Selection Bias

In this subsection, we employ unconditional and conditional asset pricing models (Models (1) and (2), respectively) to adjust for the risk of individual stocks (components) in momentum portfolios. The method is first used by Chordia and Shivakumar (2002) and later adopted by Wang and Wu (2011). Our methodology differs from theirs in three distinct ways. First and foremost, for reasons explained below, we use estimation windows *prior* to the ranking period. Second, we employ full conditional models in which betas are explicitly allowed to be time-varying. Third, in order to maintain some variations in returns on risk factors and conditioning variables, we employ 120-month windows instead of 60-month windows to estimating asset pricing models.[20]

Our component-level risk adjustment proceeds as follows. Momentum portfolios are formed normally and the constituents (components) of the portfolio are exactly the same as those in Table 2. But during the six-month holding period from $t+1$ to $t+6$, returns on each individual stock i belonging to winner or loser portfolios are risk-adjusted using the following general model. The process of computing portfolio returns then proceeds normally just as we form the raw Jegadeesh and Titman (1993) portfolio.

$$r_{i,t}^{adj} = r_{i,t} - r_f - \sum_{j=1}^{K} (\hat{\boldsymbol{\beta}}_{ij}^{\top} \boldsymbol{Z}_{t-1}) \boldsymbol{f}_{jt} \tag{4}$$

where $\boldsymbol{\beta}_{ij}^{\top}$ is estimated using the past 120-month returns prior to the ranking period (i.e., individual stock returns from $t-120-6$ to $t-7$. The reason for this exclusion of six-month ranking period returns will be explained shortly). Stocks are required to have at least 24 valid observations in the estimation period. (To ensure results are comparable between tables, this constraint was also in place when we formed the raw momentum portfolio.) In order to avoid losing too much data, we use 60-month windows of returns in the first 120

[20] Again, in the earlier version of our paper, we also use fixed 60-month windows of stock returns and our conclusions do not qualitatively change. Subsection 4.7 also employs extending-window estimations to which our conclusions remain robust.

months and then use the full 120-month window afterwards. Risk factors, $\boldsymbol{f}_{jt}$, are excess returns on the market (r_m) or the Fama and French three factors (FF3F). State variables, $\boldsymbol{Z}_{t-1}$, are dividend yield, term spread, and the default spread. Before we discuss the main results of this risk adjustment in Table 5, we should first note the differences between our methodology and that of Chordia and Shivakumar (2002), which is mainly the exclusion of ranking period returns from the estimation.

Measurement Errors

The estimation of conditional models at individual stock levels may raise concerns about errors-in-variable (EIV) biases. We note that although the firm-level risk adjustment has been used in a few momentum studies, EIV is not extensively discussed. First of all, there is an EIV bias in usual standard errors. Cochrane (2005) shows that the correct standard error can be calculated in a GMM framework. Assuming that the errors are i.i.d., the variance of estimated alphas can be computed by the following formula:

$$var(\hat{\alpha}) = \frac{1}{T}(1 + \boldsymbol{\mu}_f^\top \boldsymbol{\Omega}_f^{-1} \boldsymbol{\mu}_f)\boldsymbol{\Sigma} \tag{5}$$

where $\boldsymbol{\mu}_f$ is $K \times 1$ mean vector of the risk factors; $\boldsymbol{\Omega}_f$ is the variance-covariance matrix of the risk factors and $\boldsymbol{\Sigma}$ is the residual covariance matrix.[21] We find that EIV causes standard errors to be slightly higher, and hence making the t-statistic slightly smaller. Consistent with the literature (see Chordia, Goyal, and Shanken (2011) for a discussion), employing corrected standard errors does not affect any of the conclusions. Nevertheless, all standard errors of risk-adjusted returns in this paper are calculated using Equation (5).

Using individual stocks as test assets is often thought to incur more estimation errors than portfolios. However, this argument is not really true as pointed out by Ang, Liu, and Schwarz (2010), who show that standard errors from component-level cross-sectional regressions are

[21] If the alpha is estimated using conditional models, $\boldsymbol{f}$ will include the risk factors and their interactions with the state variables.

not higher, and sometimes are even lower, than those from portfolios. Recently, Chordia, Goyal, and Shanken (2011) also endorse the use of cross-sectional regressions on individual stocks. Both studies focus on the econometrics sides of tests rather than the explanatory power (on momentum anomaly) of asset pricing models. It should also be noted that we do not employ cross-sectional but simple time-series regressions. As noted in the discussion of Chordia et al. (2011), since estimated betas do not serve as explanatory variables in our tests there is no EIV in the coefficients.

Readers not familiar with how momentum strategies rebalance may raise concerns about the difference between component-level betas and portfolio-level betas. Theoretically, portfolio betas should be equal to value-weighted averages of individual stocks' betas. However, due to the fact that individual stocks' weights and composition of momentum portfolios change frequently, the beta computed on aggregate portfolio returns will be different from that computed at the end of each ranking period. The portfolio's composition can change not only because the momentum strategy is rebalanced monthly (Grundy and Martin (2001) document that 39.9% of winner portfolio's composition change each month and this statistic for loser portfolios is 36.2% due to rebalancing), but also because of stocks being delisted during the holding period. Eisdorfer (2008) notes that 10% of stocks in the winner and loser portfolios are delisted between 1975 to 2005, causing the portfolio's composition at the end of formation period to be different from that during the investment period. Our hypothetical portfolios (see the second graph of Figure 1) show that if we could compute portfolio-level betas at the end of each ranking period (before we form the next overlapping portfolio), there would be virtually no difference between component-level betas and portfolio-level betas.

Sample Selection Bias

In the momentum context, betas from time-series regressions may be biased, not because of being estimated at component levels, but due to the inclusion of ranking period returns in the regression. The momentum strategy mechanically selects stocks with the most positive returns over the ranking period into winner portfolios and those with the most negative returns over the same period into loser portfolios. Consequently, if we include ranking period returns as the left-hand side of regressions, the variable is no longer randomly selected, thereby causing the regression assumptions to be violated. Because winner and loser betas vary through time as shown in Figure 1 and the Panel B of Table 1, the magnitude of this bias is dependent on the market states. In order to see this, without loss of generality to multifactor models, we can resort to the fundamental representation of measurement error in the estimated CAPM $\hat{\beta}_{it}$ for each component of the WML portfolio as follows:

$$\hat{\beta}_{it|t-1} - \beta_{it} = \frac{\sum_{s=t-S-T_0}^{t-S-1}(r_{m,s} - \bar{r}_{mt}) \cdot \varepsilon_{it}}{\sum_{s=t-S-T_0}^{t-S-1}(r_{m,s} - \bar{r}_{mt})^2} \tag{6}$$

where T_0 is the estimation window (e.g., 120 months); S is the finishing month of the estimation window (e.g., if $S = 0$, we include ranking period returns in the estimation whereas if $S = 6$, we exclude ranking period returns); $\bar{r}_{mt} = T_0^{-1} \sum_{s=t-S-T_0}^{t-S-1} r_{m,s}$ is the mean of the market return over the estimation period; β_{it} is the true beta; and ε_{it} is the idiosyncratic component of the market model regression. Grundy and Martin (2001) show that the idiosyncratic return of a stock is the driving force for it to be a winner or loser stock. Because we are classifying stocks as either "winners" or "losers" on the basis of their returns over the ranking period, we can appeal to the theory of order statistics[22] to assert

[22] When we have a sample of N observations from some distribution $f_X(x)$ and we order the observations from smallest to largest, $X_1 = \min\{X_1, X_2, \ldots, X_N\}$ and $X_N = \max\{X_1, X_2, \ldots, X_N\}$ then the density of the k-th order statistic is given by:

$$f_{X_{(k)}}(x) = i\binom{n}{k}[F_X(x)]^{k-1}[1 - F_X(x)]^{N-k} f_X(x)$$

where, for example, the density of the minimum return $X_{(1)}$ equals

$$f_{X_{(1)}} = f_X(x) \cdot [1 - F_X(x)]^{N-1} \cdot \frac{n!}{1!(n-1)!}$$

which is the unconditional density evaluated at x multiplied by the probability that all of the other $N - 1$ outcomes are greater than that x, and the number of ways this can be achieved, and where $F_X(x)$ denotes the cumulative distribution function of X. As the number of draws increases the density of the first order statistic shifts to the left, while the density of the highest order statistic shifts to the right. If the mean of X is zero, as in the case of the regression residual, this means that the lower order statistics (corresponding to loser stocks) have a negative mean, while the higher order stocks (corresponding to winner stocks) have positive means.

that for winner stocks, ε_W will be positive while for loser stocks, ε_L will be negative.

As is usual for showing the unbiased estimator of OLS, if we assume that $\varepsilon_{i,t}$ is independent of the regressor $r_{m,t}$, which is a common assumption when dealing with stochastic regressors (see Section 8.2, p. 207-208 of Hamilton (1994)), we establish the typical result that the OLS beta is unbiased (in Equation (6), $E(\hat{\beta}_{it|t-1}) = \beta_{it}$).

However, in the momentum context, the assumption that $r_{m,t}$ is independent of ε_{it} is clearly indefensible when ranking period returns are included in the estimation. To see this note that because we are selecting extreme winners and losers, $\varepsilon_{W,t}$ and $\varepsilon_{L,t}$ will be positive and negative, respectively. If the ranking period was a bull market (formally, let the discrete state indicator $S_s = 0$ correspond to a month that is a bull market) then $E((r_{m.s} - \bar{r}_{mt})\varepsilon_{W,s}|S_s = 0) > 0$ and $E((r_{m.s} - \bar{r}_{mt})\varepsilon_{L,s}|S_s = 0) < 0$ (for $s = t - S + 1, \ldots, t - 1$), while for bear markets (i.e., $S_s = 1$) $E((r_{m.s} - \bar{r}_{mt})\varepsilon_{W,s}|S_s = 1) < 0$ and $E((r_{m.s} - \bar{r}_{ms})\varepsilon_{L,s}|S_t = 0) > 0$. This will bias the results, and we summarize the direction of bias in the table below.[23]

Direction of sample selction bias		
Market	Portfolios	β Bias
	Winner	+
Bull	Loser	−
	WML	+
	Winner	−
Bear	Loser	+
	WML	−

Note: this table summarizes the direction of bias on component betas when they are estimated using ranking period returns. "+" denotes upward trends while "−" denotes downward trends.

The bias will cause winner betas to be biased upwards while loser betas are biased downwards during economic expansions, and vice versa for contracting periods in which winner betas are biased downwards and loser betas are biased upwards. Because the direction of bias in WML betas is positively related to the market states, any asset pricing model that

[23]The positive covariance between $\varepsilon_{i,t}$ for momentum portfolios and the market is also documented in Grundy and Martin (2001), Chordia and Shivakumar (2002), Cooper et al. (2004), Boguth et al. (2011), and Daniel and Moskowitz (2011).

accounts for time-varying risks can completely explain momentum returns (if ranking period returns are included in the estimation). In order to avoid this problem, we estimate betas in Equation (4) using 120 months of returns on individual stocks *prior* to the ranking period ($S = 6$). Holding period returns from $t+1$ to $t+6$ will then be risk-adjusted using Equation (4) (i.e., we skip the six-month ranking period before predicting returns in the holding period).[24]

To study the size of the bias and how it can be corrected by excluding ranking period returns from the estimation, we undertake a small Monte Carlo experiment. We fit a regime switching model to the market returns in which the conditional distribution of the market depends on the state variable S_t, which varies between periods of bull markets when returns have high mean and low variance, and bear markets when returns have high variance and a slightly negative mean.[25] In this model, the state $S_t = 0$ corresponds to the low volatility, typically bullish state; and the state $S_t = 1$ corresponds to the high volatility, typically bearish state. The state evolves as a Markov Chain with transition probabilities $P(S_t = 0|S_{t-1} = 0) = 0.9784$ and $P(S_t = 1|S_{t-1} = 1) = 0.8916$ and the market return is given by:[26]

$$r_{m,t} \sim \begin{cases} N(1.0045, 3.6753) & \text{if } S_t = 0 \\ N(-2.2022, 10.1701) & \text{if } S_t = 1 \end{cases}$$

We then simulate the returns on 4000 stocks assuming that the CAPM prices returns exactly

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[24]We thank Jeffrey Wooldridge for a discussion on this issue. Excluding six-month ranking period returns from the estimation does not contradict the idea of time-varying betas because a business cycle is typically longer than six months. In the early version of this paper, we also employed the beta adjustment of Vasicek (1973) to which our results again remain robust.

[25]In particular we use the model of Hamilton (1989), which has been applied in a number of studies to stock returns, including Turner et al. (1989). This model has also been applied to studying long-run mean reversion by Kim et al. (2001) and portfolio selection by Ang and Bekaert (2002).

[26]The model's parameters were estimated using monthly stock returns on the value-weighted CRSP index by maximum likelihood subject to the usual constraints to ensure non-degenerate solutions.

(i.e., each stock's alpha is zero):

$$r_{i,t} = \beta_i \cdot r_{m,t} + e_{i,t}$$

where $\beta_i \sim N(1, 0.3)$, and $e_{i,t} \sim N(0, 8)$. We generate a total of 1000 returns, and follow Jegadeesh and Titman (1993) to form 6/1/6 (decile) momentum portfolios. We follow the convention of skipping a month between ranking and holding periods, even though we obviously do not have any microsctructural effects to be concerned about in this simulation.

When we construct a simple test for a zero intercept in the usual market model using the time series of returns on the WML portfolio, we reject the null hypothesis of zero alpha 88% of the time at the five percent level. This is striking because the unconditional CAPM holds for every single stock, but the mechanics of selecting winners and losers in bull and bear markets ensures that the WML portfolio has high betas during good times and negative betas during down times. This produces a positive correlation between the conditional beta and market returns, that biases the unconditional alpha upwards.

When we estimate betas using either the component-level beta or the hypothetical portfolio return that include the ranking period return (with the sample selection bias), we find a statistically significant but *negative* momentum effect. In fact, we reject the null hypothesis in 83% of the samples at the five percent level, but of course with the negative average momentum return. The negative return is consistent with the findings of Chordia and Shivakumar (2002).

However, when we construct the test using component-level betas (or equivalently based on hypothetical portfolio returns) but we only use pre-ranking period returns, we only reject the null hypothesis 5.36% of the samples at the five percent level. These findings provide strong support to our recommendation to estimate beta using component-level returns, but to include only pre-ranking period returns – anything else would lead to substantial bias in the test statistic.

To further investigate how excluding ranking period returns helps avoid the bias, Table 3 reports the summary statistics, based on the Monte Carlo simulation, for betas estimated using 120 months of pre-ranking period returns (correcting for the sample selection bias) and betas estimated using 120 months of pre-holding period returns (including ranking period returns, and hence incurring the sample selection bias), and then see how these betas are close to the true beta.

< INSERT TABLE 3 HERE >

Table 3 shows that betas estimated using pre-ranking period returns (the third column) are almost equal to the true beta whereas betas estimated with ranking period returns (the second column) are biased (we know the true beta because it is what we use to simulate stock returns from the CAPM). Table 3 also reaffirms our analysis of the direction of bias in betas. During a bull (bear) market, the average return over the ranking period will generally be higher (lower) than in the distant past (and recall that we use estimation windows between 5 and 10 years of monthly returns), and for winner (loser) stocks we will have positive (negative) residuals. This means that the bias in estimated pre-holding betas will be positive for winner stocks and negative for loser stocks during up markets, while it will be negative for winner stocks and positive for loser stocks during down markets. This bias will serve to artificially amplify the dynamics of estimated betas relative to the true beta dynamics.

Note that the positive unconditional alpha is driven by the positive covariance between subsequent betas and the market returns (as shown in Subsection 4.4): during bull markets the WML portfolio will have high betas, while during bear markets the WML portfolio will typically have negative betas. Because of the (deliberate) stock selection of momentum strategies over the ranking period, during bull markets the estimated WML portfolio beta will be even higher than the true WML beta on average, and during bear markets the estimated WML beta will be more negative than the true WML beta. Consequently, the estimated alpha adjusting for time-varying risks will be too low or even negative, suggesting that the dynamics of beta artificially account for more of the estimated unconditional alpha than the conditional CAPM can actually explain.

Empirically, Table 4 uses CRSP data and shows the magnitude of sample selection bias in different NBER business cycles by comparing the difference between pre-holding period betas (with the bias) and pre-ranking period betas (without the bias).[27] Consistent with our conjecture, the pre-holding period betas are on average higher than their pre-ranking counterparts during expansions. During contractions, pre-holding betas are biased downwards and much lower than the pre-ranking-period estimates. For example, the difference in market beta of momentum portfolios between the pre-holding period and pre-ranking period is 0.02 (or approximately 22% higher) during expansions, but it is -0.11 during contractions. The latter estimate represents an average decrease of 37% – economically large magnitude that is sufficient to affect the risk-adjusted return.

As the bias correction reduces the exposure of momentum stocks to risk factors, we expect that the bias-corrected alpha be higher. Surely, in order to explain the momentum anomaly through beta risk exposure, one would need more exposure, rather than less. Admittedly, this method of bias correction is not perfect, but it is consistent and not subject to the sample selection through portfolio constructions. One of the objectives of this study is to show that one needs a consistent and unbiased estimate of beta exposure rather than an 'artificially' increased exposure when betas are estimated using ranking period returns.

Readers may also be concerned that excluding the ranking period may miss out valuable information. We argue that the trade-off is not large for momentum strategies with ranking period up to one year. We test the sensitivity of this bias correction on 11/1/1 strategies that rank stocks on the basis of 11 months of historical returns and then hold the WML portfolio for one month. The bias-corrected alpha from the conditional FF3F model is 0.38% per month with an insignificant t-statistic of 0.77. The good performance of this bias

[27] Although the NBER business cycle dates are determined ex-post, we only use those dates to demonstrate the bias and the time-varying dynamics of betas. We do not employ them in any of our estimations or portfolio formations, and therefore there is no "look-ahead" bias.

correction and the conditional FF3F model suggests that the loss of information is minimal for momentum strategies with a short ranking period.

< INSERT TABLE 4 HERE >

The Main Results: Component-Level Risk Adjusted Returns Using CRSP Data

Table 5 reports the average component-level risk-adjusted return on momentum portfolios, corrected for the sample selection bias. Panel A reports average risk-adjusted returns from unconditional models where $\boldsymbol{Z_{t-1}}$ do not appear in the model 4 (no interaction terms). The average unconditional CAPM alpha is 0.96% per month with the associated t-statistic of 4.75, statistically significant at the 1% level. Comparing with the portfolio-level CAPM alpha from panel B of Table 2, the component-level risk adjustment can only reduce the average alpha by 8bps per month, which is economically small. Of note is the better performance of the unconditional FF3F model with the average firm-level alpha of 0.78% per month (t-statistic = 4.46), a reduction of 45bps per month compared with the portfolio-level alpha in Table 2.[28]

However, this risk adjustment method with no conditioning variables may suffer from overconditioning biases as argued by Boguth et al. (2011). Boguth et al. (2011) show that running rolling regressions without conditioning variables will bias the average momentum alpha due to the nonlinearity in payoffs of winners and losers. Indeed, we have shown above that even at the firm level, individual winner and loser stocks are exposed to the market risk differently in different economic states, causing payoffs to be nonlinear. We therefore modify this model by allowing betas to be time-varying with the state variables, Z_{t-1}, as in Equation (4).

The first row of panel B reports the average time-varying risk-adjusted return at the individual stock level using the conditional CAPM. The conditional CAPM further reduces

[28] This unconditional model is employed in Wang and Wu (2011), but they do not compare the performance between the CAPM and FF3F model.

the average alpha to 0.90% per month with the t-statistic of 4.12, still statistically significant at the 1% level. The conditional FF3F model performs exceptionally well with the average alpha of 0.61% per month (t-statistic = 2.13), statistically significant at the 5% level. This represents a reduction of approximately 50% from the portfolio-level estimate. The better performance of the conditional FF3F model is contrasted with Grundy and Martin (2001) who estimate this model on aggregate portfolio returns.

Panel C shows average adjusted returns from the macroeconomic model of Chordia and Shivakumar (2002):

$$r_{i,t}^{adj} = r_{i,t} - r_f - \hat{\beta}_{DIV} DIV_{t-1} - \hat{\beta}_{TERM} TERM_{t-1} - \hat{\beta}_{DEF} DEF_{t-1} - \hat{\beta}_{YLD} YLD_{t-1} \quad (7)$$

where DIV, TERM, DEF and YLD are the dividend yield, term spread, default spread, and the yield on three-month T-Bill, respectively. Chordia and Shivakumar (2002) also add another January dummy variable in the model. They show that their models can completely explain momentum returns by making the average adjusted return negative. Panel C shows that with the bias correction, the average adjusted return from the macroeconomic model is positive and statistically significant. The average adjusted return from Model (7) is 5.03% per month with the associated t-statistic of 2.33, statistically significant at the 5% level. Adding the January dummy variable to the model reduces the average adjusted return to 4.04% per month (t=1.80), statistically significant at the 10% level. Although the statistical significance is not impressive, the economic magnitude of these returns is much higher than the raw average momentum return of 1.01% per month, suggesting that Chordia and Shivakumar (2002) model cannot explain momentum profits. The difference between our methodology and theirs is exclusion of ranking period returns from the estimation. As we will present our replication of Chordia and Shivakumar's (2002) results in Subsection 4.6, the fact that the average return changes from economically negative return to economically positive return suggests the high sensitivity of including ranking period returns in the estimation.

< INSERT TABLE 5 AROUND HERE >

4.4. Alpha Decomposition

In this subsection, we employ the well-known theoretical framework of Jagannathan and Wang (1996) to understand why allowing betas to be time-varying at component levels can enhance the explanatory power of conditional models. Jagannathan and Wang (1996) show that when the conditional CAPM holds exactly, the unconditional alpha can be expressed as follows:

$$\alpha_{WML} = cov(\beta_t, r_{m,t}) - \frac{\bar{r}_m}{\sigma_m^2}\text{cov}(\beta_t, \sigma_t^2) \tag{8}$$

The Appendix generalizes this alpha decomposition to multifactor models. In particular, when the right-hand side is the Fama and French's (1993) three risk factors, the unconditional alpha can be represented as:

$$\alpha_{WML} = E(\boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}) - \boldsymbol{\mu}'_f \boldsymbol{\Sigma}_f^{-1} \text{cov}(\boldsymbol{f}_t, \boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}) \tag{9}$$

where $E(\boldsymbol{\eta}_{it}) = \mathbf{0}$ from the relation: $\boldsymbol{\beta}_{it} = \bar{\boldsymbol{\beta}}_i + \boldsymbol{\eta}_{it}$; $\boldsymbol{\Sigma}_f^{-1}$ is the variance-covariance matrix of risk factors; $E(\boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}) = \text{plim}\frac{1}{T}\sum_{t=1}^{T} \boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}$ and $E(\boldsymbol{f}_t \boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}) = \text{plim}\frac{1}{T}\sum_{t=1}^{T} \boldsymbol{f}_t \boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}$ are consistent estimators of the relevant expectations. Equation (9) nests Equation (8) such that with $f_t = r_{mt}$, $E(\boldsymbol{f}'_t \boldsymbol{\eta}_{i,t}) = \text{cov}(r_{mt}, \eta_{it})$. It shows that when the conditional alpha is equal to zero, the unconditional alpha can be high due to the market timining (the first term) and volatility timing (the second term) components.

Lewellen and Nagel (2006) employ the aggregate return on momentum portfolios to estimate short-horizon betas and find that the second term of Equation (9) is empirically so small that it does not help improve the performance of the conditional CAPM. They also find that the first term is approximately equal to -0.04. This small and wrong-signed covariance leads Lewellen and Nagel (2006, p. 291) to conclude "no evidence that betas covary with the market risk premium in a way that might explain the portfolio's unconditional alphas. Indeed, the covariances often have the wrong sign."

Boguth et al. (2011) find that volatility timing has a significant contribution to the alpha, ranging from -0.22% to -0.17% per month. They show that running short-window rolling regressions without instrumentation can incur "overconditioning" bias in which the contemporaneous realized beta contains estimation errors that are not known by the investors. This overconditioning bias can be reduced by using longer estimation windows, but they show that this reduction comes with the tradeoff of losing the time variation in betas. Boguth et al. (2011, p. 375) suggest the use of value-weighted average betas estimated using individual winner and loser stock's (components) returns as a conditioning variable, which exploits the "portfolio weights of individual stocks at the beginning of the investment period".

As argued in the Introduction, our study builds on the intuition of Boguth et al. (2011) to take advantage of the time variation in individual components' betas. We do so by applying conditional asset pricing models directly on individual stock returns, thereby uncovering not only the portfolio weights of individual stocks but also undoing the mechanical way of sorting stocks that may conceal the valuable information (Lo and MacKinlay, 1990a). It is important to note that the conventional method of employing Ferson and Schadt (1996) conditional models on portfolio returns has its disadvantage in the momentum context because it requires researchers to correctly identify a conditioning variable that can capture the large variation in portfolio compositions and weights. Using the component betas of Boguth et al. (2011) as a conditioning variable is one way to mitigate the problem, but it does not account for the arbitrary method of sorting stocks. Consequently, the component-level risk adjustment is a straightforward candidate to tackle this problem.

We estimate Equation (9) using both portfolio and average component betas and report results in Table 6. The first panel shows results from the unconditional betas at firm and portfolio levels. Using contemporaneous portfolio-level betas (those betas in the third graph of Figure 1), our estimates of the first and second terms of Equation (8) are -0.01% and 0.00%, respectively, thereby causing the theoretical alpha to be -0.01%. The contemporaneous portfolio-level beta from the unconditional FF3F model also yield the negative theoretical alpha of -0.02% per month. These small and wrong-signed alphas are consistent with Lewellen and Nagel (2006), suggesting that contemporaneous portfolio betas are not volatile enough to intuitively predict the positive momentum alpha. The unconditional component-level betas provide some improvements by correctly predicting the positive empirical alpha. The unconditional alpha from the FF3F model is also economically large with 0.32% per month, but this mainly comes from the market timing component rather than the volatility bias (the latter is important to account for as suggested by Boguth et al. (2011)).

Our main results are supported by the estimate from conditional component-level betas (second panel). The alpha from the conditional FF3F model has the market timing and volatility timing estimates of 0.57% and -0.21% per month, respectively, causing the final alpha to be highly positive (0.78% per month). The high volatility timing estimate is also consistent with the findings of Boguth et al. (2011), supporting our argument that the component-level risk adjustment is consistent with their intuition of using lagged stocks' betas as a conditioning variable.

The economically large alpha of 0.78% per month, which is much closer to the positive average momentum return, is interesting because it says that we can find a significant time variation in the component's beta that is volatile enough to explain the observed momentum return. Unlike Boguth et al. (2011) however, we find that the conditional FF3F model is more powerful than the conditional CAPM. The second panel also shows that running rolling-window regressions of conditional models on aggregate portfolio returns can also improve the explanatory power of the conditional FF3F model, but the conditional beta is still not as volatile as that at the component level.

In short, this subsection has provided a theoretical justification for the use of component-level risk adjustment. We find that the average component-level beta is much more volatile than the portfolio-level estimate, and this large time variation causes high momentum alphas.

4.5. Risk Loadings at Individual Stock (Component) Levels

Fama and French (1996) show that their three-factor model cannot explain returns on momentum strategies. The main puzzle they raise is that loser portfolios load more on SMB and HML factors than winner portfolios. Thus, the FF3F model incorrectly predicts that loser portfolios should have higher returns than their winner counterparts. Looking at individual stocks' risks, we find that their conditional model can explain 50% of the portfolio-level alpha. In order to understand how the component-level risk adjustment can solve their puzzle, we follow their approach (which they use to show that their model cannot predict the continuation in returns) to examine the risk loading of individual stocks (components) on each of the factors.

Panel A of Table 7 reports the average raw (unadjusted for risks) WML returns of 0.93% and 0.51% per month during economic expansions and contractions as dated by the NBER business cycles, respectively. Thus, momentum portfolios are much more profitable during expansions than contractions. Panels B and C show the mean and standard deviation of value-weighted average betas, which are estimated as in the first graph (components' returns with the correction of sample selection bias) and third graph (portfolio's returns) of Figure 1, respectively. To correctly predict momentum returns in panel A especially during economic expansions, winners' risk loadings should be higher than those of losers, and hence the average WML beta should be positive.

The first row of Panel B show the value-weighted average of component-level market betas. These betas are equivalent to those in Panel B of Table 1, except that betas here are corrected for the bias by excluding ranking period returns from the estimation window. Comparing betas in two tables, we can see that correcting for the bias slightly reduces the magnitude of betas, but the contrasting market loadings of winner and loser stocks still remain. Winner stocks have higher market loadings than losers during economic expansions, causing the average WML beta to be positive (correctly predicting positive momentum profits). This trend is reversed during economic contractions, suggesting that betas are time-varying.

The loadings on SMB and HML are more interesting here. The general picture is that the SMB and HML loadings of WML portfolios have the right positive sign during economic expansions. Winners behave like small distressed stocks, and therefore the FF3F model correctly predicts that they will earn higher average returns than loser firms. This model however does not perform as well during economic contractions, with the loading of WML portfolio on SMB and HML factors are -0.08 and 0.00. Although these betas are negative and close to zero, the fact that their magnitude is much lower than that estimated during economic expansions correctly predicts that momentum portfolios are more profitable in up markets. Another point is that all betas exhibit time variations as evidenced by the contrasting changes in loadings of winner and loser stocks when the economy switches from expansions to contractions. In short, applying the FF3F model on individual stock returns can shed light on solving the puzzle of Fama and French (1996).

Again, these results, which have not been documented before, are concealed when asset pricing models are estimated on aggregate portfolio returns. Panel C reports the average of contemporaneous betas of winner/loser portfolios that are estimated by running 120-month rolling window regressions of monthly WML returns on the risk factors. In general, the picture in panel B is reversed here. The high (favorable) loading on the market risk of WML portfolios during economic expansions now disappears. Average betas on SMB and HML also incorrectly predict negative momentum profits in both states of the economy. Similar to Fama and French (1996), loser portfolios load more on SMB and HML factors than winner portfolios, counter-intuitively suggesting that losers should earn higher average returns than winners. In other words, the puzzle of Fama and French (1996) is still unsolved when the test is conducted on aggregate portfolio returns. Panel C also shows that although both the CAPM and the FF3F model cannot predict momentum returns, the former model has a less negative market beta in both economic states, indicating that Boguth et al. (2011) find evidence in favor of the conditional CAPM because they estimate their models at portfolio levels.

These findings suggest that momentum may be an artifact of the way stocks are selected in the portfolio. When stocks are grouped into portfolios the time variation and the asymmetric behavior of winner and loser stocks are hidden. Winner/loser portfolios' betas, when estimated using monthly portfolio returns, become less time-varying and act differently to those estimated using returns on individual stocks. This leads us to suspect that momentum is a puzzle not because we lack an asset pricing model to explain it, but because the myth of momentum is obscured by the mechanical way of stock selections. The asset pricing model is therefore more powerful when being examined on individual stock components.

< INSERT TABLE 7 AROUND HERE >

4.6. The Sensitivity of Sample Selection Bias

As described earlier, the primary difference between our methodology of component-level risk adjustments and previous research is that we correct for the sample selection bias by excluding ranking period returns from the estimation window. In order to demonstrate the sensitivity of this bias, we now replicate Chordia and Shivakumar (2002) and Wang and Wu (2011) whose results are reported in Table 8. The methodology of this Table is similar to that of Table 5, except that the estimation window is now the past 120 months of stock returns from $t-120$ to the end of the ranking period $t-1$ (i.e., including the six-month ranking period). Again, to avoid losing too much data, we employ 60-month window in the first 120 months of a stock's life and the full 120-month window afterward.

Panel A of Table 8 reports results from unconditional models where $\boldsymbol{Z_{t-1}}$ do not appear in the model (4) (no interaction terms). The unconditional firm-level adjustment is employed in Wang and Wu (2011). Comparing with average unconditional CAPM alpha of Table 5, we can see that the sample selection bias does not affect the average alpha, which remains at 0.96% per month (t-statistic = 4.96). The average alpha from the unconditional FF3F model however is badly affected. The unconditional average FF3F alpha is 0.65% per month (t-statistic = 3.63), which is a 13bps reduction from that in Table 5. Thus, having the sample selection bias in place can reduce the average risk-adjusted returns even when betas are not allowed to be time-varying.

Panel B reports risk-adjusted returns from the full conditional model (4). The first row of panel B reports the average time-varying risk-adjusted return at the individual stock level using the conditional CAPM. The conditional CAPM performs exceptionally well by reducing the average alpha to 0.61% per month with the t-statistic of 2.46, statistically significant at the 5% level. The conditional FF3F model is even more aggressive in reversing the momentum effect, with the average alpha being -0.29% per month (t-statistic = -0.86), statistically insignificant even at the 10% level. These findings indicate that the bias causes the conditional risk adjustment at component levels to explain all momentum returns.

Panel C shows the average adjusted returns from the macroeconomic model of Chordia and Shivakumar (2002). Consistent with their study, panel C shows that their models can also make momentum returns disappear. The average adjusted momentum return using Equation (7) is -2.97% per month, which is economically significant although the t-statistic is only -1.52. Adding the January dummy makes the adjusted return even more negative with -3.45% per month (t-statistic = -1.63).

< INSERT TABLE 8 AROUND HERE >

In short, results in Table 8 are too good to be true because the sample selection bias "forces" the asset pricing model to always "work".

4.7. Sensitivity Analysis: Expanding-window Estimation

This subsection provides a robustness test on whether the component-level risk adjustment is sensitive to expanding-window estimations. Specifically, we estimate the conditional models using each component i's returns over an extending window, starting from the first month of stock's returns to the month prior to the ranking period. This sensitivity test is motivated by Fama and French (1992), Ferson and Harvey (1999), Lettau and Ludvigson (2001), and Liu and Zhang (2008) who endorse the use of extending windows, which arguably produces more accurate estimations due to having more data.

Table 9 shows the average component-level alpha estimated similar to Table 5, but with extending windows. Our conclusions do not change. Panel A reports the average alpha from unconditional models. These alphas are not economically different from those of Table 5. The average alpha from the unconditional FF3F is 0.80% per month (t-statistic = 4.55), compared with the 0.78% per month (t-statistic = 4.46) of 120-month windows in Table 5. Similarly, Panel B shows that the conditional FF3F model also performs well in terms of reducing the average alpha, with 0.65% per month and the t-statistic of 2.35, statistically significant at the 5% level. This represents a 45% reduction over the corresponding portfolio-level estimate (Table 2). Finally, the average adjusted return from Chordia and Shivakumar's (2002) macroeconomic models is still highly positive, suggesting that this model is sensitive to the correction of sample selection bias.

In short, this subsection has shown that our findings still hold under the expanding-window estimation. It reconfirms that the correction for sample selection bias is crucial and that the conditional FF3F model performs much better when being applied on the individual component of momentum portfolios.

4.8. Sensitivity Analysis: Fama and French's (1996) Momentum Portfolios

This subsection tests whether our main results still hold under a different construction of momentum portfolios. In particular, we examine the momentum portfolio of Fama and French (1996) in which stocks are ranked based on their continuously compounded returns over the past year, and the portfolio is held for one month with one-month skipping period in between. Although we can confirm the robustness of our findings in other strategy formations of Jegadeesh and Titman (1993), we report the results for Fama and French's (1996) portfolios to be consistent with Fama and French (1996) and many subsequent papers (e.g., Grundy and Martin (2001) and Asness et al. (2013)). Because these strategies have one-month holding period, they are rebalanced more frequently and therefore we expect that conditional asset pricing models are more powerful when being applied on individual components' returns. Again, this high explanatory power comes from its ability to account for the frequent change in portfolio compositions and weights of the portfolio's components.

Table 10 reports average risk-adjusted returns, which are computed similarly as in Table 5. Panel A shows the results from unconditional models in which state variables are not included in the regression. We can see that both the unconditional CAPM and FF3F model cannot explain momentum returns. The average alpha from the CAPM is 1.19% per month (t-statistic = 4.85) while the FF3F model has the average alpha of 0.95% per month (t-statistic=4.37); both of them are statistically significant at the 1% level.

Panel B shows average alphas from conditional models. We see a better picture here where the conditional CAPM yields the average risk-adjusted return of 0.96% per month (t-statistic = 3.10), statistically significant at the 1% level. The conditional FF3F model performs exceptionally well by reducing the average alpha to only 0.38% per month (t-statistic = 0.77), statistically insignificant even at the 10% level. This reduction is also economically large with 60% down from the conditional CAPM. These findings confirm our conjecture that, as the Fama and French's (1996) momentum portfolios involve frequent rebalancing and changes in the weight of individual stocks, the component-level risk adjustment from the FF3F model can correctly account for the time variation of individual components' betas, which are not seen on the aggregate portfolio return. Finally, panel C shows average returns from Chordia and Shivakumar's (2002) macroeconomic model. Consistent with the earlier findings that, once we correct for the sample selection bias, the average WML return becomes economically positive, ranging from 3.76% per month to 5.03% per month although they are still statistically insignificant.

In short, our findings also hold for the popular momentum portfolio of Fama and French (1996). Fama and French (1996) find that their FF3F model inflates the momentum alpha rather than reducing it when being applied on aggregate portfolio returns. Using the same momentum portfolio construction, we find empirical support for their multifactor model. The conditional FF3F model performs well by reducing the average alpha to 0.38% per month, representing a 60% reduction from the conditional CAPM estimate.

5. Conclusion

We argue that the momentum effect is an artifact of the way stocks are selected into portfolios. Particularly, stocks are picked in such a way that their time-varying dynamics are concealed on aggregate portfolio returns. The conventional method of employing conditional models on portfolio returns has its disadvantage in the momentum context because it requires researchers to correctly identify a conditioning variable that can (a) capture the true variation in portfolio compositions and weights and (b) uncover the mechanical selection of stocks by momentum strategies (Lo and MacKinlay, 1990a). Consequently, the component-level risk adjustment is a straightforward way to tackle these problems. Motivated by this observation, we find that the puzzle of Fama and French (1996) can be solved by looking at returns on individual winner and loser stocks (components). Winner stocks load more on the SMB and HML factors than do losers. Therefore, winners should earn higher future average returns and losers should earn lower average returns, causing positive expected momentum profits.

We pick two of the most popular momentum portfolios in the literature to report our results. The first one is the 6/1/6 momentum portfolio of Jegadeesh and Titman (1993). We find that the conditional FF3F, when being used to risk adjust returns on individual stocks (components) of the portfolio, reduces the average alpha to 0.61% per month (t-statistic = 2.13), representing a 50% decrease from the portfolio-level estimate. The second portfolio is consistent with Fama and French (1996), which has only one-month holding period. Because the component-level risk adjustment can correctly account for the frequent change in weights and portfolio's compositions, the conditional FF3F model performs exceptionally well with the average alpha of 0.38% (t-statistic = 0.77), statistically insignificant even at the 10% level.

Another important contribution of this study is to point out the bias in the existing component-level risk adjustment in which winner and loser betas are biased due to the inclusion of ranking period returns in the estimation. Because of this bias, asset pricing models that account for time-varying risks can completely explain momentum returns. We propose a simple correction by excluding the ranking period returns from the estimation. Our simulations confirm that this exclusion of ranking period returns in fact provides an estimated beta nearly identical to the true beta. Using CRSP data, we find that the negative adjusted momentum returns (ranging from -2.97% to -3.45% per month) in Chordia and Shivakumar (2002) become economically positive ranging from 3.76% to 5.03% per month after the bias correction. For the conditional FF3F model and CAPM, although the bias-corrected risk adjustment still cannot fully explain momentum returns, the average alpha is still significantly (50%) lower than the corresponding portfolio-level estimate.

We acknowledge that our method of bias correction is not perfect. To the extent that the information of ranking period is missed out, some of our conclusions need to be verified by using more complex econometrics methods, which would have to accomplish at least two goals: (1) correctly identifying an instrumental variable that correctly captures the time variation and frequent changes in the composition of momentum portfolios, and (2) fixing the 'sample selection' bias incurred through the process of portfolio construction. Nevertheless, we do not wish to imply that this method will also work for other portfolios with ranking periods of more than one year. Our results show that, for conventional momentum strategies that employ ranking periods of up to 11 months, our simple straightforward method produces consistent and unbiased estimate of betas. Recall that the bias correction still works well on the 11/1/1 strategy – suggesting that the loss of information is not excessively large and the time variation of stock components is still maintained. This is not surprising because an economic cycle typically lasts for much more than one year.

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Table 1: Descriptive Statistics, January 1963 to December 2009

Panel A reports the summary statistics of the three instrumental variables, namely the dividend yield (DY), the default spread (DEF), and the term spread (TERM). The sample period is from January 1963 to December 2009. SD is the standard deviation. AC(1) and AC(12) are the autocorrelation with lag 1 and lag 12, respectively. The two right-most columns present the correlation between the variables. Panel B shows the statistics of the same variables as well as the cross-sectional average of winner and loser betas during expansions and contractions, as dated by the NBER business cycles. The last two columns of panel B reports the average change in beta loadings from peak to trough and trough to peak, respectively. The sample period in panel B is intentionally lengthened from January 1936 to December 2009 since we want to capture more expansions and contractions of the economy. The firm-level average loading on the market risk are constructed as follows. At the end of each ranking period $t-1$, the CAPM is run on each winner and loser stock using returns from $t-120$ to $t-1$ (as we will show in later section, this window includes ranking period returns and hence biases the estimated beta. For the purpose of comparing between biased beta and non-biased beta (reported in Table 7), we present the biased beta in this Table). Betas are preserved each month and the value-weighted average across winner and loser stocks is computed to get the monthly time-series of average betas whose descriptive statistics are reported in the first three rows of Panel B. We also compute contemporaneous betas on the momentum portfolios by running 120-month rolling window regressions of portfolio returns on the market risk. We report these portfolio-level betas in rows four to six of Panel B.

Panel A: Descriptive Statistics (January 1963 to December 2009)

					Correlation	
	Mean (%)	SD (%)	AC(1)	AC(12)	DEF	TERM
DY	3.12	1.18	0.99	0.89	0.46	−0.16
DEF	1.04	0.48	0.97	0.56		0.25
TERM	1.69	1.52	0.95	0.51		

Panel B: Business Cycle Dependence (January 1936 to December 2009)

	Expansion		Contraction		Average Change	
	Mean	SD (%)	Mean	SD (%)	Peak-Trough	Trough-Peak
Component-level Winner Betas	1.23	0.26	0.96	0.28	−0.26	0.13
Component-level Loser Betas	1.12	0.25	1.26	0.23	0.05	−0.13
Component-level WML Betas	0.11	0.43	−0.30	0.45	−0.30	0.26
Portfolio-level Winner Betas	1.30	0.11	1.34	0.11	−0.06	−0.05
Portfolio-level Loser Betas	1.38	0.20	1.41	0.21	−0.13	−0.01
Portfolio-level WML Betas	−0.08	0.22	−0.07	0.17	0.07	−0.04
DY	3.71%	1.54	4.38%	1.57	0.70%	−0.87%
DEF	0.97%	0.45	1.29%	0.72	0.52%	−0.48%
TERM	1.71%	1.25	1.30%	1.31	1.85%	−1.85%

Table 2: Portfolio-Level Risk Adjustment

This table reports risk-adjusted returns on momentum portfolios using unconditional models (panel B) and conditional models (panel C) between January 1963 and December 2009. All returns (reported in percentages) are risk-adjusted (i.e. estimated intercepts) by regressing excess raw returns on the risk factors (Equation (1)) and their interactions with the state variables (Equation 2). The factors are excess returns on the market (R_M) or the Fama and French's (1993) three factors (FF3F). Three state variables are dividend yield, term spread and the default spread. WML is the return on $winner - loser$ portfolios. Stocks are required to have at least 24 months of valid returns over the past 60 months to be ranked. $t - statistics$ calculated using Newey and West (1987) standard errors with six lags are reported in parentheses. $*, **, ***$ represent the significance levels at 10%, 5% and 1%, respectively.

Models	Winners	Losers	WML
Panel A: Raw returns			
Raw Returns	1.57	0.56	1.01
	(6.71)***	(2.52)**	(4.87)***
Panel B: Unconditional risk adjustment			
CAPM	0.53	−0.52	1.04
	(3.22)***	(−3.18)***	(5.23)***
FF3F	0.49	−0.74	1.23
	(4.09)***	(−5.61)***	(5.90)***
Panel C: Conditional risk adjustment			
CAPM	0.58	−0.46	1.04
	(3.30)***	(−2.54)***	(4.67)***
FF3F	0.52	−0.68	1.19
	(4.55)***	(−4.73)***	(5.55)***

Table 3: Bias in Estimated Betas: Monte Carlo Simulation

This table reports summary statistics for CAPM betas estimated from Monte Carlo simulations, which are described in the text. True-β denotes the beta used to simulate stock returns. Pre-Holding-β denotes the average beta estimated using 120 months of returns on individual stocks (components) that include the ranking period. Pre-Ranking-β denotes the average beta estimated using 120 months of returns on individual stocks, but the estimation window does not include the ranking period.

	Winner			Loser		
	True-β	Pre-Holding-β	Pre-Ranking-β	True-β	Pre-Holding-β	Pre-Ranking-β
Bull Market	1.0370	1.0539	1.0370	0.9636	0.9470	0.9634
Bear Market	0.9427	0.8166	0.9425	1.0584	1.1860	1.0583
Unconditional	1.0211	1.0143	1.0210	0.9796	0.9869	0.9794

Table 4: Empirical Magnitude of Bias in Estimated Betas

This table reports the empirical magnitude of sample selection bias estimated using CRSP data over business cycles as dated by the NBER between January 1936 and December 2009 (the sample period is extended to 1936 to capture more economic expansions and contractions). Betas are estimated using 120-month returns on individual stocks (components) of the momentum portfolio at the end of the ranking period (similar to the first graph of Figure 1). Reported numbers are the average difference between betas estimated with sample selection bias (including ranking period returns in the estimation) and betas without the bias (excluding ranking period returns from the estimation).

	Expansion			Contraction		
	Winners	Losers	WML	Winners	Losers	WML
R_M	0.01	−0.01	0.02	−0.05	0.06	−0.11
	(0.06)	(0.04)	(0.09)	(0.06)	(0.08)	(0.12)
SMB	0.02	0.01	0.01	−0.01	0.03	−0.04
	(0.09)	(0.07)	(0.15)	(0.07)	(0.07)	(0.14)
HML	0.01	0.02	−0.01	−0.01	0.04	−0.05
	(0.11)	(0.09)	(0.19)	(0.10)	(0.13)	(0.22)

Figure 1: Time-Series Betas of Momentum Portfolios

The figure plots the time-series market beta on 6/1/6 winner-minus-loser (WML) portfolios from January 1936 to December 2009 (the sample period is extended to 1936 to capture more economic expansions and contractions). The first graph plots the value-weighted average loadings of individual stocks (components) in the WML portfolio, corrected for sample selection bias. At the end of each ranking period, 120 months (from $t - 120 - 6$ to $t - 6$) of excess returns on each stock i in the winner and loser portfolios is regressed against the excess returns on the market. The betas are preserved each month and the value-weighted average of betas across winner and loser stocks are computed taking into account the market capitalization of each stock at the end of ranking periods. The second graph plots the average betas on the value-weighted hypothetical portfolios. At the end of each ranking period, we compute the weighted average returns on winner and loser stocks over the past 120 months ($t-120-6$ to $t-6$). This gives us 120 months of portfolio returns, which are then regressed on the excess market return to obtain portfolio-level beta at the end of the ranking period. We repeat this portfolio formation and the regression test as we form a new overlapping momentum portfolio in the following month. Since the portfolio beta should be equal to the weighted average of individual stocks' betas, we expect hypothetical portfolio betas and firm-level betas to be highly correlated. In fact, the correlation between these two time-series of betas is 0.98. The third graph plots the contemporaneous betas, which are computed by running 120-month rolling window regressions of monthly value-weighted WML portfolio returns on the market (to make betas comparable, the momentum portfolio in the third graph is also value-weighted). In order to use all data, we employ windows of 60 months in the first 120 months and then the full 120 months afterward. Vertical lines represent the peaks and troughs of business cycles as dated by the NBER.

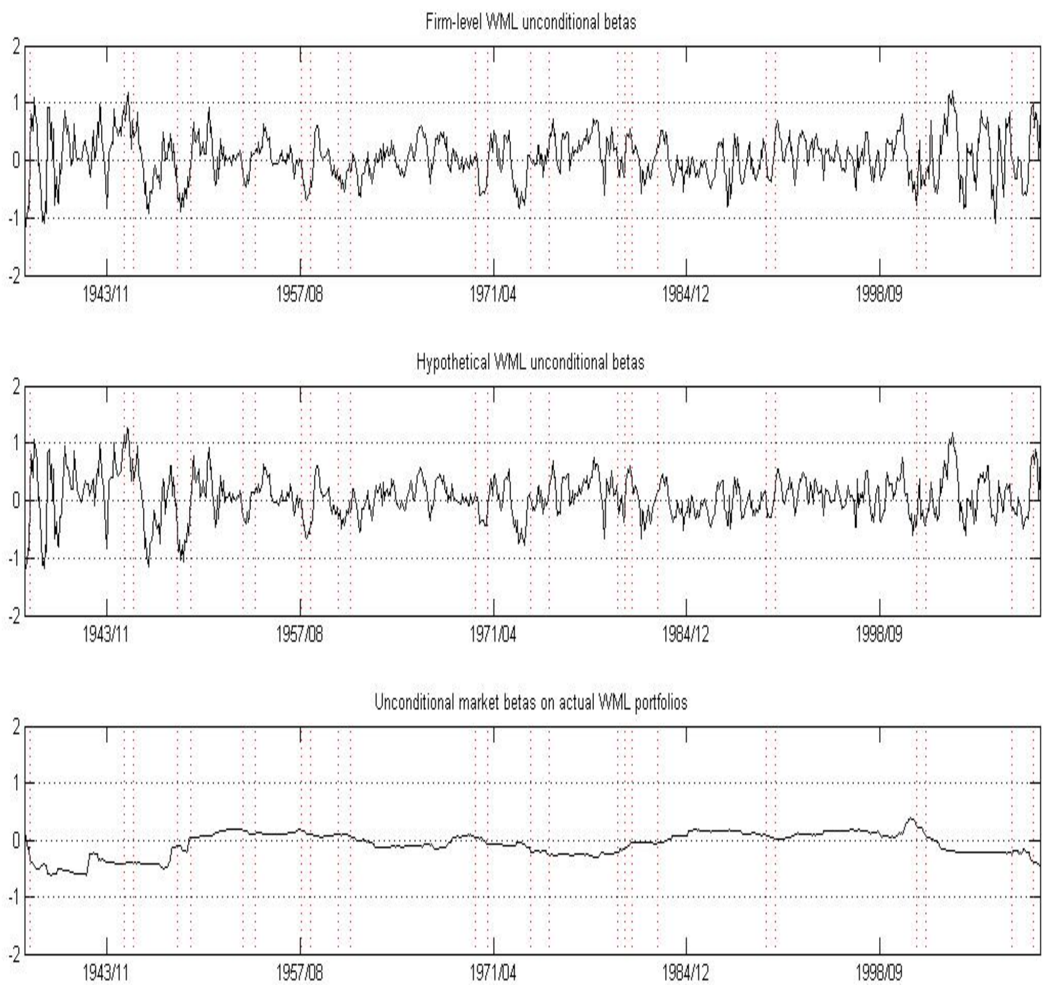

Table 5: Component-Level Risk-Adjusted Momentum Returns

This table reports average risk-adjusted returns on 6/1/6 momentum portfolios from January 1963 to December 2009. 6/1/6 overlapping portfolios are constructed by ranking returns over the past 6 months and then skip one month before holding stocks for the next 6 months. The strategy is followed every month. In panel B, returns on each individual stock in the winner and loser portfolios are risk-adjusted using the following model:

$$r_{i,t}^{adj} = r_{i,t} - r_f - \sum_{j=1}^{K} (\hat{\boldsymbol{\beta}}_{ij}^{\top} \boldsymbol{Z}_{t-1}) \boldsymbol{f}_{jt}$$

where $\boldsymbol{\beta}_{ij}^{\top}$ is estimated using 120-month returns prior to the ranking period (i.e, ranking period returns are not included in the estimation). In order to avoid losing too much data, we use 60-month windows of returns in the first 120 months and then use the full 120-month window after that. Risk factors, $\boldsymbol{f}_{jt}$, are excess returns on the market (R_M) or Fama and French three factors (FF3F). State variables, $\boldsymbol{Z}_{t-1}$, are dividend yield, term spread, and the default spread. Panel A reports average risk-adjusted returns that are similarly computed as in panel B, except that the unconditional model does not have interaction terms between risk factors and state variables (without $\boldsymbol{Z}_{t-1}$). Returns are reported in percentages. WML is the return on *winner* $-$ *loser* portfolios. Panel C shows average adjusted returns from macroeconomic model of Chordia and Shivakumar (2002), which includes the three state variables in this study, the yield on three-month T-bills, and a January dummy (without risk factors, $\boldsymbol{f}_{jt}$). t-statistics from the method outlined in Cochrane (2005) are reported in parentheses; the adjustment factor is calculated using formula (5). $*, **, ***$ represent the significance levels at 10%, 5% and 1%, respectively.

Models	Winners	Losers	WML
Panel A: Unconditional risk adjustment			
CAPM	0.55	−0.41	0.96
	(3.58)***	(−2.43)***	(4.75)***
FF3F	0.27	−0.51	0.78
	(2.83)***	(−3.85)***	(4.46)***
Panel B: Time-varying risk adjustment			
CAPM	0.67	−0.23	0.90
	(3.86)***	(−1.22)	(4.12)***
FF3F	0.17	−0.44	0.61
	(0.82)	(−2.74)**	(2.13)**
Panel C: Chordia and Shivakumar's (2002) conditional macroeconomic adjustment			
Macro variables	−4.52	−9.55	5.03
	(−1.73)*	(−3.30)****	(2.34)**
Macro and Jan	−7.1991	−11.24	4.04
	(−2.75)***	(−3.98)***	(1.79)*

Table 6: Alpha Bias Decomposition

This table reports the theoretical unconditional alpha from Equation (9), which are estimated either at the component level or at the portfolio level between 1963 and 2009. The unconditional alpha is decomposed into two components namely market timing and volatility timing. The component-level beta is estimated in a similar way to that in Table 5, which corrects for the sample selection bias while the contemporaneous portfolio-level beta is estimated by running 120-month rolling regressions of portfolio returns on conditional/unconditional models.

Models	Alpha (%) =	Market Timing (%) −	Volatility Timing (%)
Unconditional component-level betas			
CAPM	0.07	0.04	−0.03
FF3F	0.32	0.26	−0.06
Unconditional portfolio-level betas			
CAPM	−0.01	−0.01	0.00
FF3F	−0.02	−0.10	−0.07
Conditional component-level betas			
CAPM	0.32	0.27	−0.05
FF3F	0.78	0.57	−0.21
Conditional portfolio-level betas			
CAPM	−0.04	−0.09	−0.05
FF3F	0.15	−0.03	−0.18

Table 7: Business Cycle Dependence of Momentum

This table reports means and standard deviations (reported in parentheses) for the series of value-weighted average winner and loser betas (corrected for sample selection bias) during economic expansions and contractions as dated by the NBER business cycles between January 1936 and December 2009. The sample period is lengthened to capture more economic expansions and contractions. Panel A reports average raw (unadjusted for risks or returns on the conventional momentum strategies) profits on winner and loser portfolios. Panel B shows average component-level betas of winner and loser stocks while panel C presents average betas for winner and loser portfolios. To compute the average component-level beta in panel B, we run time-series market regressions using 120 months of returns (prior to the ranking period) of individual winner and loser stocks and preserve the betas (the stock constituents are the same across all tables). After skipping six-month ranking period to avoid the sample selection bias, value-weighted average of stock's betas are computed taking into account the market capitalization of stocks at the end of each ranking period. The process is repeated every month as we form a new overlapping portfolio. To avoid losing too much data, the estimation window is 60 months in the first 120 months of a stock's life. To compute average betas at portfolio levels (panel C), we form 6/1/6 value-weighted momentum portfolios as normal to get time series of monthly returns (to make betas comparable, the momentum portfolio in the third graph is value-weighted). We then run 120-month rolling regressions across the monthly return series to obtain contemporaneous portfolio betas. Risk factors are market returns (R_M), SMB, and HML. "WML" column shows the average beta on the winner-minus-loser portfolio.

	Expansion			Contraction		
	Winners	Losers	WML	Winners	Losers	WML
Panel A: Raw momentum returns						
	1.90%	0.97%	0.93%	−0.39%	−0.91%	0.51%
	(0.08)	(0.07)	(0.05)	(0.08)	(0.11)	(0.06)
Panel B: Component-level rolling betas						
R_M	1.22	1.13	0.09	1.00	1.21	−0.21
	(0.24)	(0.24)	(0.38)	(0.25)	(0.23)	(0.42)
SMB	0.38	0.19	0.19	0.15	0.23	−0.08
	(0.36)	(0.27)	(0.54)	(0.23)	(0.29)	(0.42)
HML	0.16	0.03	0.13	0.15	0.15	0.00
	(0.32)	(0.27)	(0.43)	(0.30)	(0.34)	(0.57)
Panel C: Portfolio-level rolling betas						
R_M	1.30	1.38	−0.08	1.34	1.41	−0.07
	(0.11)	(0.20)	(0.22)	(0.11)	(0.21)	(0.17)
SMB	0.70	0.87	−0.16	0.65	0.84	−0.18
	(0.25)	(0.21)	(0.39)	(0.27)	(0.22)	(0.43)
HML	−0.04	0.20	−0.24	−0.00	0.20	−0.20
	(0.18)	(0.17)	(0.24)	(0.16)	(0.10)	(0.17)

Table 8: Component-Level Risk Adjusted Momentum Returns, with Sample Selection Bias

This table reports average risk-adjusted returns on 6/1/6 momentum portfolios between January 1963 and December 2009. 6/1/6 overlapping portfolios are constructed by ranking returns over the past 6 months and skip one month before holding stocks for the next 6 months. The strategy is followed every month. In panel B, returns on each individual stock in the winner and loser portfolios are risk-adjusted using the following model:

$$r_{i,t}^{adj} = r_{i,t} - r_f - \sum_{j=1}^{K} (\hat{\boldsymbol{\beta}}_{ij}^{\top} \boldsymbol{Z}_{t-1}) \boldsymbol{f}_{jt}$$

where $\boldsymbol{\beta}_{ij}^{\top}$ is estimated using the past 120-month returns from t-120 to t-1 (i.e. 120 months prior to the holding period). Risk factors, $\boldsymbol{f}_{jt}$, are the excess return on the market (R_M) or Fama and French three factors (FF3F). State variables, $\boldsymbol{Z}_{t-1}$, are dividend yield, term spread, and the default spread. Panel A reports risk-adjusted returns that are similarly computed as in panel B, except that the model does not have interaction terms between risk factors and state variables. Returns are reported in percentages. WML is the returns on $winner - loser$ portfolios. Panel C shows the adjusted returns from macroeconomic model of Chordia and Shivakumar (2002), which includes three state variables, the yield on three-month T-bills, and a January dummy (without risk factors, $\boldsymbol{f}_{jt}$). t-statistics from the method outlined in Cochrane (2005) are reported in parentheses; the adjustment factor is calculated using formula (5). $*, **, ***$ represent the significance levels at 10%, 5% and 1%, respectively. Stocks are required to have at least 24 months of valid returns over the past 60 months to be ranked. The estimation window is 60 months in the first 120 months of a stock's life, afterward the window is extended to 120 months.

Models	Winners	Losers	WML
Panel A: Unconditional risk adjustment			
CAPM	0.54	−0.42	0.96
	(3.58)***	(−2.51)*	(4.96)***
FF3F	0.1986	−0.45	0.65
	(1.70)*	(−3.70)***	(3.63)***
Panel B: Time-varying risk adjustment			
CAPM	0.42	−0.19	0.61
	(2.24)**	(−1.03)	(2.46)**
FF3F	−0.29	0.01	−0.29
	(−1.45)	(0.01)	(−0.87)
Panel C: Chordia and Shivakumar's (2002) conditional macroeconomic adjustment			
Macro variables	−10.79	−7.82	−2.97
	(−7.91)***	(−6.79)***	(−1.52)
Macro and Jan	−12.79	−9.34	−3.45
	(−2.42)**	(−2.07)**	(−1.63)

Table 9: Component-Level Risk-Adjusted Momentum Returns, Expanding-Window Estimation

This table reports average risk-adjusted returns on 6/1/6 momentum portfolios between January 1963 and December 2009. 6/1/6 overlapping portfolios are constructed by ranking returns over the past 6 months and then skip one month before holding stocks for the next 6 months. The strategy is followed every month. In panel B, returns on each individual stock in the winner and loser portfolios are risk-adjusted using the following model:

$$r_{i,t}^{adj} = r_{i,t} - r_f - \sum_{j=1}^{K}(\hat{\boldsymbol{\beta}}_{ij}^{\top}\boldsymbol{Z}_{t-1})\boldsymbol{f}_{jt}$$

where $\boldsymbol{\beta}_{ij}^{T}$ is estimated using returns over an extending window, starting from the first month to the month prior to the ranking period (i.e, ranking period returns are not included in the estimation). Risk factors, $\boldsymbol{f}_{jt}$, are excess returns on the market (R_M) or Fama and French three factors (FF3F). State variables, $\boldsymbol{Z}_{t-1}$, are dividend yield, term spread, and default spread. Panel A reports risk-adjusted returns that are similarly computed as in panel B, except that the unconditional model does not have interaction terms (without $\boldsymbol{Z}_{t-1}$). Returns are reported in percentages. WML is the return on *winner* − *loser* portfolios. Panel C shows average adjusted returns from macroeconomic model of Chordia and Shivakumar (2002), which includes the three IVs in this study and the yield on three-month T-bills and a January dummy (without risk factors, $\boldsymbol{f}_{jt}$). t-statistics from the method outlined in Cochrane (2005) are reported in parentheses; the adjustment factor is calculated using formula (5). $*, **, ***$ represent the significance levels at 10%, 5% and 1%, respectively.

Models	Winners	Losers	WML
Panel A: Unconditional risk adjustment			
CAPM	0.53	−0.44	0.97
	(3.47)***	(−2.62)	(4.79)***
FF3F	0.30	−0.50	0.80
	(3.13)*	(−3.76)	(4.55)**
Panel B: Time-varying risk adjustment			
CAPM	0.66	−0.25	0.91
	(3.85)*	(−1.34)	(4.13)***
FF3F	0.20	−0.45	0.65
	(0.96)*	(−2.87)	(2.35)**
Panel C: Chordia and Shivakumar's (2002) conditional macroeconomic adjustment			
Macro variables	−4.91	−9.52	4.61
	(−1.96)*	(−3.41)	(2.23)**
Macro and Jan	−7.41	−11.09	3.68
	(−3.01)*	(−4.08)	(1.69)*

Table 10: Component-Level Risk-Adjusted Returns on Fama and French (1996) Momentum Portfolios

This table reports average risk-adjusted returns on Fama and French's (1996) momentum portfolios from January 1963 to December 2009. Momentum portfolios are constructed by ranking stock returns over the past 11 months and then skip one month before holding stocks for the next one month. The strategy is followed every month. In panel B, returns on each individual stock in the winner and loser portfolios are risk-adjusted using the following model:

$$r_{i,t}^{adj} = r_{i,t} - r_f - \sum_{j=1}^{K} (\hat{\boldsymbol{\beta}}_{ij}^{\top} \boldsymbol{Z}_{t-1}) \boldsymbol{f}_{jt}$$

where $\boldsymbol{\beta}_{ij}^{\top}$ is estimated using 120-month returns prior to the ranking period (i.e, ranking period returns are not included in the estimation). In order to avoid losing too much data, we use 60-month windows of returns in the first 120 months and then use the full 120-month window after that. Risk factors, $\boldsymbol{f_{jt}}$, are excess returns on the market (R_M) or Fama and French three factors (FF3F). State variables, $\boldsymbol{Z_{t-1}}$, are dividend yield, term spread, and default spread. Panel A reports average risk-adjusted returns that are similarly computed as in panel B, except that the unconditional model does not have interaction terms (without $\boldsymbol{Z_{t-1}}$). Returns are reported in percentages. WML is the return on *winner − loser* portfolios. Panel C shows average adjusted returns from macroeconomic model of Chordia and Shivakumar (2002), which includes the three IVs in this study and the yield on three-month T-bills and a January dummy (without risk factors, $\boldsymbol{f_{jt}}$). t-statistics from the method outlined in Cochrane (2005) are reported in parentheses; the adjustment factor is calculated using formula (5). $*, **, ***$ represent the significance levels at 10%, 5% and 1%, respectively.

Models	Winners	Losers	WML
Panel A: Unconditional risk adjustment			
CAPM	0.70	−0.49	1.19
	(4.04)***	(−2.73)***	(4.85)***
FF3F	0.40	−0.55	0.95
	(3.43)***	(−3.86)***	(4.37)***
Panel B: Time-varying risk adjustment			
CAPM	0.78	−0.18	0.96
	(3.65)***	(−0.83)	(3.10)***
FF3F	0.12	−0.26	0.38
	(0.40)	(−1.02)	(0.77)
Panel C: Chordia and Shivakumar's (2002) conditional macroeconomic adjustment			
Macro variables	−4.35	−9.38	5.03
	(−1.47)	(−3.12)****	(1.75)*
Macro and Jan	−7.31	−11.07	3.76
	(−2.47)**	(−3.73)***	(1.26)

Appendices

A. Derivations of Alpha Decomposition in Multifactor Models

Consider a multi-factor pricing model

$$r_{it} = \boldsymbol{f}_t' \cdot \boldsymbol{\beta}_{it} + e_{it}$$

where $\boldsymbol{f}_t = \boldsymbol{\mu}_t + \boldsymbol{u}_t$ and $\boldsymbol{\beta}_{it} = \bar{\boldsymbol{\beta}}_i + \boldsymbol{\eta}_{it}$ and $E(\boldsymbol{\eta}_{it}) = \boldsymbol{0}$ and is likely to be positively serially correlated. Consider estimating the unconditional version of the CAPM, with

$$\hat{\boldsymbol{\theta}}_T = \left(\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t\boldsymbol{X}_t'\right)^{-1}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t r_{it}$$

where

$$\hat{\boldsymbol{\theta}} = \begin{pmatrix} \hat{\alpha}^U \\ \hat{\boldsymbol{\beta}}^U \end{pmatrix}$$

and $\boldsymbol{X}_t = (1, \boldsymbol{f}_t')'$. Under quite general regulatory conditions we have

$$\text{plim}\hat{\boldsymbol{\theta}}_T = \boldsymbol{Q}^{-1}\text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t r_{it}$$

where

$$\boldsymbol{Q} = \text{plim}\frac{1}{T}\sum_{i=1}^{T}\boldsymbol{X}_t\boldsymbol{X}_t' = \begin{pmatrix} 1 & \boldsymbol{\mu}_f' \\ \boldsymbol{\mu}_f & \boldsymbol{\Sigma}_f + \boldsymbol{\mu}_f\boldsymbol{\mu}_f' \end{pmatrix}$$

and using the partitioned matrix inverse formula we have

$$\boldsymbol{Q}^{-1} = \begin{pmatrix} 1 + \boldsymbol{\mu}_f'\boldsymbol{\Sigma}_f^{-1}\boldsymbol{\mu}_f & -\boldsymbol{\mu}_f'\boldsymbol{\Sigma}_f^{-1} \\ -\boldsymbol{\Sigma}_f^{-1}\boldsymbol{\mu}_f & \boldsymbol{\Sigma}_f^{-1} \end{pmatrix}.$$

We note that

$$
\begin{aligned}
\text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t r_{it} &= \text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t(\boldsymbol{f}'_t\beta_i + \boldsymbol{f}'_t\boldsymbol{\eta}_{i,t} + \varepsilon_{i,t}) \\
&= \underbrace{\text{plim}\frac{1}{T}\sum_{t=1}^{T}\begin{pmatrix}\boldsymbol{f}'_t \\ \boldsymbol{f}_t\boldsymbol{f}'_t\end{pmatrix}}_{=\begin{pmatrix}\boldsymbol{\mu}'_f \\ \boldsymbol{\Sigma}_f + \boldsymbol{\mu}_f\boldsymbol{\mu}'_f\end{pmatrix}}\beta_i + \text{plim}\frac{1}{T}\sum_{t=1}^{T}\begin{pmatrix}\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t} \\ \boldsymbol{f}_t\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}\end{pmatrix} + \underbrace{\text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_t\varepsilon_{i,t}}_{=\boldsymbol{0}}
\end{aligned}
$$

So we then have

$$
\text{plim}\hat{\boldsymbol{\theta}}_T - \begin{pmatrix}0 \\ \bar{\boldsymbol{\beta}}_i\end{pmatrix} = \boldsymbol{Q}^{-1}\text{plim}\frac{1}{T}\sum_{t=1}^{T}\begin{pmatrix}\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t} \\ \boldsymbol{f}_t\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}\end{pmatrix}
$$

and in particular

$$
\begin{aligned}
\text{plim}\hat{\alpha}_T &= (1 + \boldsymbol{\mu}'_f\boldsymbol{\Sigma}_f^{-1}\boldsymbol{\mu}_f)E(\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) - \boldsymbol{\mu}'_f\boldsymbol{\Sigma}_f^{-1}E(\boldsymbol{f}_t\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) \\
&= E(\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) - \boldsymbol{\mu}'_f\boldsymbol{\Sigma}_f^{-1}\text{cov}(\boldsymbol{f}_t, \boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) \qquad (10)
\end{aligned}
$$

where $E(\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) = \text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}$ and $E(\boldsymbol{f}_t\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}) = \text{plim}\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{f}_t\boldsymbol{f}'_t\boldsymbol{\eta}_{i,t}$ are consistent estimators of the relevant expectations.