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The Momentum Premium:
An Intermediary Asset Pricing Perspective

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Abstract

We attempt to explain the momentum premium using time-varying risk under the frictions of financial intermediation. Our conditional CAPM model reveals positive covariation between momentum's beta and the expected market risk premium. Consistent with observed time-varying risk-return trade-off, our periodic regressions reduce the alpha significantly. To capture the impact of financial intermediation we add two fund flow variables finding that consumer deposits and withdrawals into mutual funds affects momentum. Our paper offers a novel empirical finding that the momentum anomaly is at least in part driven by risk premium related to intermediaries' financing constraints.

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1. Introduction

A strategy based on purchasing past winners and selling past losers earns, on average, a positive and significant alpha against benchmark returns based on traditional risk factors. Momentum-type strategies were first discovered in 1993 by Jegadeesh & Titman (Jegadeesh & Titman, 1993) and made famous by Carhart in his 1997 paper (Carhart, 1997). Momentum is one of the most persistent financial anomalies within the academic literature with numerous studies documenting its existence across a variety of markets, asset-classes and time-periods (Okunev and White, 2003; Erb and Harvey, 2006; Chabot et al. 2009). While the premium and its persistence is well studied the literature has struggled to understand it. Given the documented high persistence it is even more puzzling that momentum strategies suffer from occasional crashes (Daniel & Moskowitz, 2016). To this end, we propose an empirical test of the momentum premium inspired by intermediary asset pricing.

Using return data from 2004 – 2016 we find that a momentum strategy using Swedish equities earned a mean monthly return of 1.4% ($t = 2.3$) with an alpha of 1.3% ($t = 11.1$) using the CAPM model with rolling regressions and a 24-month window for the beta. We split the time-period into three sub-periods to account for the momentum crash in 2009 and document significant variability in the returns with the alpha persisting over all periods. The inability of traditional factor models to capture the variability of momentum's returns has sparked wide debate. Academics have attempted to explain momentum using both efficient-market based asset pricing models with rational agents (e.g. Kothari & Shanken, 1992; Chordia & Shivakumar, 2002) as well as mispricing and behavioural explanations (e.g. Vayanos & Woolley, 2013).

In this paper we adopt a risk compensation perspective and emphasise time-varying risk using Petkova & Zhang's conditional CAPM methodology (Petkova & Zhang, 2005). We document a positive and significant beta premium sensitivity indicating a time-varying risk exposure for momentum with a smaller but significant alpha. Our results also suggest that we need to account for momentum's time-series based factor loadings, as documented by Grundy & Martin, and we therefore use periodic regressions (Grundy & Martin, 2001). We find that periodic regressions allow us to eliminate the alpha in all periods and document some variation in the conditional betas between the periods.

One of the most important innovations of our paper is the addition of two fund flow variables to our periodic conditional market regressions. Adding fund flows to the regressions allows us to arrive at the main empirical finding of the paper; mutual fund flows can help explain the momentum premium. We show that consumer deposits into mutual funds during the recovery period negatively affects the momentum portfolio with withdrawals having the opposite effect. Furthermore, mutual funds continue to have an effect on momentum in the post-recovery period during more normal market conditions. The R^2 for all regressions increases substantially by adding fund flows, with our model now able to explain 61% of the momentum portfolio's returns during the recovery period.

The key intuition behind the addition of fund flow variables is that intermediaries are marginal investors in risky assets and that their financing constraints affect the cross-section of asset returns (He & Krishnamurthy, 2013). In the literature, studies suggest various theoretical links between intermediaries and momentum (see e.g. Vayanos & Woolley, 2013). However, earlier empirical studies on the area establish only a weak link between momentum and intermediary asset pricing (Adrian et al., 2014; He et al., 2017). In contrast to the earlier studies this paper focuses on mutual funds which are empirically proven to trade momentum (Baltzer et al., 2019). Our significant fund flow coefficients indicate that the inability of earlier intermediary asset pricing studies to capture the momentum's portfolio returns may be due to their chosen intermediary of study.

Our findings are significant and economically relevant. For fund deposits during the recovery period we document a coefficient of -0.065 and for withdrawals a coefficient of 0.060 with both variables significant at the 5% level. The economic interpretation of the coefficient(s) is that SEK 1 billion in deposits (withdrawals) decreases (increases) the market exposure of the momentum portfolio by 0.065 (0.060). This effect is economically significant as the mean monthly deposits during the recovery period is 26 billion and the mean withdrawals is 23 billion. In the post recovery period the mutual fund deposits have a coefficient of 0.036 significant at the 5% level with withdrawals being insignificant. We connect the changing coefficients to our discussion around periodic regressions and suggest that the different coefficients between periods indicate different behaviour of intermediaries under different economic conditions. Inspired by our earlier discussion we see the significant coefficients and the increase in R^2 as evidence of the importance of accounting for intermediaries when studying momentum's time-varying risk exposure.

Our findings have broad implications for the asset pricing literature and investors in momentum-type strategies. We document the momentum portfolio's time-varying risk exposure and underline the importance of accounting for its shifting exposure suggesting periodic regressions. We also establish a link between intermediary asset pricing and momentum. We conclude that it is important to account for the correct intermediaries and suggest that further research should be conducted on different intermediaries and portfolios.

The rest of the paper is organized as follows: section 2 presents our literature review, section 3 introduces our data and empirical methodology, section 4 showcases our results, section 5 contains our discussion, and section 6 concludes the paper.

2. Literature Review

In the literature covering momentum multiple studies have focused on explaining the momentum premium using time-varying risk. One such paper is Chordia & Shivakumar who show that the momentum premium can be partially explained by a set of lagged macroeconomic variables (Chordia & Shivakumar, 2002). However, Chordia & Shivakumar's results are inconclusive with their tests having a low adjusted R^2. Our paper builds upon Chordia & Shivakumars' findings but uses Petkova & Zhang's methodology from their study of the value premium as well as the conditional CAPM framework laid out by Jagannathan & Wang (Petkova & Zhang, 2005; Jagannathan & Wang, 1996). In applying Petkova & Zhang's methodology we examine the portfolio's beta premium sensitivity finding a significant and positive value indicating a time-varying risk exposure for momentum in line with Chordia & Shivakumar's original theory. Studying momentum's time-varying risk exposure using this methodology contributes a new perspective to the literature by showcasing the theorized risk-return relationship in a direct manner.

In the momentum literature it is suggested that momentum may have a time-varying risk exposure as a natural consequence of the portfolio's time series construction (see e.g. Kothari & Shanken, 1992; Grundy & Martin, 2001). Grundy & Martin document that momentum has time-varying factor loadings depending on past factor realizations with positive loadings on factors with positive realizations and negative loadings on factors with negative realizations (Grundy & Martin, 2001). Daniel & Moskowitz build on Grundy & Martin and show that the momentum portfolio behaves as a short call option during bear markets (Daniel & Moskowitz, 2016). In this paper we suggest that it is important to account for momentum's time-varying risk-return trade-off due to its time-varying factor loadings. We distinguish between conditional market regressions which accounts for shifts in the predictive variables, i.e. a time-varying risk premium, and a shifting relationship (differing coefficients) to the predictive variables, i.e. different risk-return trade-off. In contrast to the earlier momentum literature we account for momentum's shifting relationship to the conditioning variables by running periodic regressions. Our results support the argument with the conditioning variables coefficients being highly variable between the periods.

Another growing part of the broader asset pricing literature and a key concept in our study of momentum's risk exposure is intermediary asset pricing. Intermediary asset pricing is a relatively new concept in the financial literature following the seminal paper written by He and Krishnamurthy (He & Krishnamurthy, 2013). He and Krishnamurthy build a model in which the marginal investor is a financial intermediary which faces an equity capital constraint. He et al. empirically test the theoretical model of He and Krishnamurthy by using the leverage ratio of primary dealers as a pricing kernel (He et al., 2017). The authors find that shocks to the intermediary capital ratio have a strong and consistent ability to explain cross-sectional differences in returns but cannot explain momentum. Adrian et al. use the leverage of securities broker-dealers as a candidate for a pricing kernel (Adrian et al., 2014). The author's single factor model is able to explain the most common factors with an R^2 of 77% and an average annual pricing error of 1% outperforming the standard multifactor benchmarks used to price these assets. For momentum Adrian et al. can price some of the portfolio deciles relatively successfully but they cannot explain the most important first and tenth decile (Adrian et al., 2014).

In contrast to both He et al. and Adrian et al. we emphasize a specific type of intermediary which has been empirically shown to trade momentum (Baltzer et al, 2019). Baltzer et al. document that the key traders of momentum are intermediaries with consumers being contrarians. However, there is a large difference between intermediaries with mutual funds being the main traders with a trading size that is three times the economic magnitude of domestic banks (Baltzer et al, 2019). Accounting for the financing constraints of mutual funds, by adding two fund flow variables to our tests, we are able to explain more of the momentum premium showcasing the importance of selecting the most impactful intermediary depending on the area of study. We attribute the failure of He et al. and Adrian et al. in explaining momentum to their choice of intermediaries with them focusing on intermediaries more relevant for the broader equity market rather than the momentum portfolio (He et al, 2017; Adrian et al., 2014).

Overall, the most important contribution of our paper is strengthening the link between financial anomalies like momentum and intermediary asset pricing. We thereby further reinforce the importance of studying intermediaries as price-setters and their impact on the market.

3. Data and Methodology

3.1 Data

To examine the variability in the returns of a momentum-based portfolio we retrieve the Swedish monthly return data for the Fama-French-Carhart 4-factor model from the Swedish House of Finance's FINBAS database. The retrieved dataset is comprehensive for the period of 1983 - 2019 and covers firms listed on the different Swedish exchanges excluding the four smallest and most illiquid markets. The data is free from survivorship bias and is, to our knowledge, the most comprehensive dataset for the momentum factor for the Swedish market.

The Swedish House of Finance constructs the portfolio(s) by following the methodology of Asness et al. (Asness et al., 2013; Asness et al., 2019). The momentum portfolios are constructed with monthly rebalancing sorted on the last twelve months returns, skipping the most recent month. The breakpoint for the momentum portfolio returns is set at the 10th and 90th percentile with the size breakpoint set at the 80th percentile. In total four momentum portfolios are constructed called Small Winners (SW), Small Losers (SL), Big Winners (BW) and Big Losers (BL) sorted on size and past performance. Lastly, the momentum factor is constructed by the following Equation:

$$MOM = \frac{(SW + BW)}{2} - \frac{(SL + BL)}{2}$$

We use the same conditioning variables as Petkova & Zhang (Petkova & Zhang, 2005) and gather the Swedish equivalent variables from a variety of sources including the Swedish House of Finance, Bloomberg and Moody's. The short-term risk-free rate is retrieved via the same Swedish House of Finance FINBAS dataset. We retrieve the 10-year and 1-year Swedish treasury yields from Bloomberg and opt for the coupon-striped variant to avoid the effects of mismatched coupon rates. For the dividend yield we use the 12-month dividend yield of the SIXGX index, a value weighted index of all shares listed on the Stockholm Exchange, which we retrieve from Bloomberg. The European default spread (the spread between AAA and BAA3 bonds) is retrieved via Moody's. We are restricted to a time-span of 06/2004 – 12/2016 for the conditioning variables due to the lack of a longer-timespan in some of the underlying datasets.

To study the impact of intermediary financing constraints on the momentum premium we retrieve monthly Swedish fund-flow data from the Swedish Investment Fund Association

(*Sv. Fondbolagsföreningen*). The fund-flow dataset is composed based on information they retrieve from their member funds. The underlying data is expressed in millions of SEK and decomposed into inflows, outflows and assets under management per fund type. The broader dataset is made up of the following categories: Equity Funds (*Sv. Aktiefonder*), Mixed-Funds (*Sv. Blandfonder*), Long-Duration Fixed-Income (*Sv. Långa Räntefonder*), Short-Duration Fixed Income (*Sv. Korta Räntefonder*), and Hedge Funds/Other Funds (*Sv. Hedgefonder och Övriga Fonder*). We retrieve the equity fund dataset since it contains data on mutual funds and other saving vehicles like the Swedish pension fund AP7. Additionally, we confirm the comparability of the dataset across the years and our methodology of merging the fund-flow datasets into one file, ranging from 2004 to 2016, with the creators. Lastly, we convert the denominator from millions of SEK to billions of SEK to facilitate the interpretation of the coefficients.

3.2 Methodology

We begin our study by examining the size and variability of the momentum premium in our dataset. We do this both for the period of 01/2004 - 12/2016 but also with specific emphasis on three distinct time-periods: pre-recovery defined as 01/2004 - 01/2009, recovery defined as 02/2009 - 12/2012, and post-recovery defined as 01/2013 - 12/2016.

We motivate the selection of these specific periods through empirical literature including studies on the 2008 financial crisis, on broader disaster risk as well as specific studies on momentum's returns and crashes (Breeden, 1979; Lee et. al., 2014; Bai et. al., 2019; Daniel & Moskowitz, 2016; Barroso & Santa Clara 2015). When selecting the cut-off points for the sub-periods we follow Daniel & Moskowitz's methodology for classifying the momentum crash period and the broader recovery period. Consequently, 02/2009 is chosen as the start date for our recovery period as it is the bottom of the market following the subprime crisis. However, we deviate slightly from Daniel & Moskowitz's methodology by extending the recovery period to the end of 2012 to account for the recovery period of the euro crisis as well. The decision to deviate is driven by our usage of Swedish data with studies on momentum's behaviour generally utilising and/or emphasising American data. The emphasis on American data by prior papers limits the ability to study the impact of regional and/or smaller recessions and recoveries. The issue becomes especially relevant with the Euro crisis as the American market(s) did not see as a significant impact from the Euro crisis as their European equivalents.

To study the variability within the returns we use rolling Sharpe-Lintner CAPM regressions with a 24-month window for the beta. The rolling regressions should allow us to partially account for varying risk exposure in the traditional CAPM model. Our selection of a 24-month window is consistent with the current literature (Petkova & Zhang, 2005) and we do not note any significant difference in the results between a 12, 24 and 36 month window (results not reported). Furthermore, the smaller window size compared to Petkova & Zhang's 60 month window fits our overall shorter time-period.

In our return study we expect to see positive returns and, given the Sharpe-Lintner CAPM's documented failure to capture the momentum premium, likely also positive and significant alphas. We expect this both for the entire period but also for all of the sub-periods except for the recovery period. Our expectation stems from the literature on momentum crashes, with momentum crashing during the market recovery after a financial disaster, leading us to instead expect negative returns and an insignificant alpha (Daniel & Moskowitz, 2016).

Following our documentation of the momentum portfolio's returns and their variability we continue by examining the time-varying risk exposure of the momentum portfolio. The idea of momentum being exposed to time-varying risk has been discussed before in the literature (see e.g. Chordia & Shivakumar, 2002; Kothari & Shanken, 1992; Daniel & Moskowitz, 2016). To study the time-varying risk exposure of the momentum portfolio we apply Petkova & Zhang's methodology (Petkova & Zhang, 2005). While Petkova & Zhang's original intent was to examine the value premium's time-varying risk exposure using the conditional CAPM, we instead apply it when studying the time-varying risk exposure of the momentum portfolio.

To perform our study on the time-varying risk exposure of the momentum portfolio we begin by constructing a comprehensive dataset using the monthly return from the Swedish House of Finance FINBAS database and merging in the various conditioning variables as described in the data section. We begin by examining the expected market risk premium. As the expected market risk premium is an unobservable measure we fit the expected market risk premium from the conditioning variables. We elect to use the same conditioning variables as Petkova & Zhang's original paper and retrieve equivalent monthly data for the Swedish market as described in the data section: the dividend yield (DIV) of a value weighted index (SIXGX), the European default spread (DEF), the term spread between 1 and 10 year Swedish treasuries (TERM) and the short-term risk-free rate (TB). To fit the expected market risk premium we first regress the realized market excess return on the 1-month lagged conditioning variables to estimate the variables coefficients (Equation 1):

$$r_{mt+1} = \delta_0 + \delta_1 DIV_t + \delta_2 DEF_t + \delta_3 TERM_t + \delta_4 TB_t + e_{mt+1} \tag{1}$$

We use the results of Equation 1 to fit the expected market risk premium in Equation 2.

$$\widehat{\gamma_t} = \widehat{\delta_0} + \widehat{\delta_1} DIV_t + \widehat{\delta_2} DEF_t + \widehat{\delta_3} TERM_t + \widehat{\delta_4} TB_t \tag{2}$$

After having fitted and examined the expected market risk premium we move on to the conditional market regressions to study if time-varying risk can capture the momentum premium. We replicate Petkova & Zhang's conditional market regressions with momentum returns as the dependent variable:

$$r_{it+1} = \alpha_i + (b_{i0} + b_{i1} DIV_t + b_{i2} DEF_t + b_{i3} TERM_t + b_{i4} TB_t) * r_{mt+1} + \epsilon_{it+1} \tag{3}$$

If time-varying risk can capture the momentum premium the alpha should be insignificant and the R^2 should be higher than for our test with the Sharpe-Lintner CAPM. We run the conditional market regression (Equation 3) over the entire period to study if the model can accurately capture the portfolio's returns and eliminate the alpha.

After running the conditional market regression we study momentum's conditional beta and, later on, its beta premium sensitivity. If the strong returns of the momentum portfolio acts as risk compensation we would expect a positive conditional beta throughout most of the period as well as a positive beta premium sensitivity. With that said, given the short call option behaviour during bear markets documented by Daniel & Moskowitz (Daniel & Moskowitz, 2016), we would not be surprised to see that the conditional beta turns negative during the recovery period. We fit the conditional beta in Equation 4 from the results of the conditional market regression (Equation 3).

$$\hat{\beta}_{it} = \hat{b}_{i0} + \hat{b}_{i1} DIV_t + \hat{b}_{i2} DEF_t + \hat{b}_{i3} TERM_t + \hat{b}_{i4} TB_t \tag{4}$$

To study the beta premium sensitivities we continue to follow Petkova & Zhang's methodology. Firstly, the conditional beta is defined as:

$$\beta_{it} = Cov_t[r_{it+1}, r_{mt+1}]/Var[r_{mt+1}] \tag{5}$$

Secondly, using the definition in Equation 5 and the conditional CAPM, following Jagannathan and Wang (Jagannathan & Wang, 1996), we take unconditional expectations on both sides of the conditional CAPM and obtain Equation 6:

$$E[r_{it+1}] = \bar{\gamma}\bar{\beta_i} + Cov[\gamma_t, \beta_{it}] = \bar{\gamma}\bar{\beta_i} + Var[\gamma_t]\varphi_i \tag{6}$$

Where γ_t is the expected market risk premium, $\bar{\beta_i}$ is the average beta and φ_i is the beta premium sensitivity defined as $\varphi_i = Cov[\beta_{it}, \gamma_t]/Var[\gamma_t]$. Jagannathan and Wang highlight that the beta premium sensitivity is unique to the conditional CAPM and measures the degree of instability in an asset's beta. To estimate φ_i we regress the conditional beta of momentum on the expected market risk premium (Equation 7).

$$\beta_{ity} = c_i + \varphi_i\hat{\gamma}_t + \epsilon_{it} \tag{7}$$

Given the risk compensation hypothesis we are interested in the beta premium sensitivities as it allows us to examine if the portfolio's exposure increases or decreases in conjunction with the expected market risk premium. In other words, we study the conditional beta's covariance with the expected market risk premium. A positive beta premium sensitivity would indicate a significant risk exposure and support the risk compensation hypothesis as the portfolio's beta increases when the price of risk increases. A negative beta premium sensitivity, meanwhile, would imply the opposite relationship.

Following our application of Petkova & Zhang's methodology we extend our study by accounting for potential shifts in the risk-return trade-off over the time-period. As mentioned in the literature review, both Grundy & Martin and Kothari & Shanken argue that a past-return sorted portfolio mechanically has a significant and varying exposure to systematic factors given the portfolio's construction (Grundy & Martin, 2001; Kothari & Shanken, 1992). If momentum's exposure to the conditioning variables changes throughout the period, for example due to shifting market conditions, we would need to account for that. Since our sample contains both the run-up to a crisis, the crisis as well as the recovery period after we believe it is likely that the risk-return trade-off is affected.

One method to account for potential shifts in the risk-return trade-off would be to utilise rolling regressions, but given our dataset length and the emphasis on periods in the momentum crash literature (Daniel & Moskowitz, 2016) we instead turn to a periodic framework. Furthermore, the variability in the conditional beta(s) when using 24-month rolling regression(s) within the conditional CAPM framework is too large to provide meaningful results (results not reported).

Running the beta fittings and the conditional market regressions in a periodic setting allows us to account for the shifting exposure to the conditioning variables. We broadly use the same three periods as in our return study and consequently split the broader period into three parts: pre-recovery (06/2004 - 01/2009), recovery (02/2009 - 12/2012) and post-recovery (01/2013 - 12/2016).

Having studied the Conditional CAPM's ability to capture the returns in a periodic setting we attempt to improve the model by accounting for additional risk factors. A relatively new theory in the literature which may help explain the momentum premium is intermediary asset pricing. The core concept of intermediary asset pricing is that intermediaries are marginal investors in risky assets instead of consumers. As mentioned in the literature section, He and Krishnamurthy's framework for intermediary asset pricing has been tested empirically with several papers finding strong explanatory power over expected returns but varied results for financial anomalies such as momentum (He & Krishnamurthy, 2013; Adrian et al., 2014; He et al., 2017). We attribute the inability of the literature in capturing the momentum returns to the specific intermediaries being emphasised in the different papers. Research has shown that the main intermediaries trading momentum is mutual funds (Baltzer et al., 2019) and not traditional financial intermediaries such as financial institutions which has been the main focus of the intermediary asset pricing literature thus far. We therefore focus on mutual funds effects on momentum.

Mutual funds are special financial intermediaries in the sense that they do not have a balance sheet like traditional financial institutions (Boguth & Simutin, 2018). Consequently, when accounting for their constraints we are not able to apply the traditional measures used in the intermediary asset pricing literature. Mutual funds are instead constrained by their fund flows and ability to take up leverage with the constraints affecting their behaviour (Boguth & Simutin, 2018; Pollet & Wilson, 2008). We add two fund flow variables, Swedish equity fund inflows and withdrawals, to our periodic conditional market regressions to capture the impact of intermediary behaviour on momentum (Equation 8). We use equity fund inflows and withdrawals as they are the variables in the underlying Swedish fund flow dataset that contains data for mutual funds and other saving vehicles like the Swedish pension fund AP7.

$$r_{it+1} = \alpha_i + (b_{i0} + b_{i1}DIV_t + b_{i2}DEF_t + b_{i3}TERM_t + b_{i4}TB_t + b_{i5}FundDep_t + b_{i6}FundWith_t) * r_{mt+1} + \epsilon_{it+1} \quad (8)$$

After having run the periodic conditional market regressions with fund flows we subsequently refit the conditional beta for each of the periods using Equation 9.

$$\hat{\beta}_{it} = \hat{b}_{i0} + \hat{b}_{i1}DIV_t + \hat{b}_{i2}DEF_t + \hat{b}_{i3}TERM_t + \hat{b}_{i4}TB_t + \hat{b}_{i5}FundDep_t + \hat{b}_{i6}FundWith_t \quad (9)$$

We calculate the beta premium sensitivities for the respective periods based on the conditional beta fitted using Equation 9 by regressing them on the fitted expected market risk premium as in Equation 7.

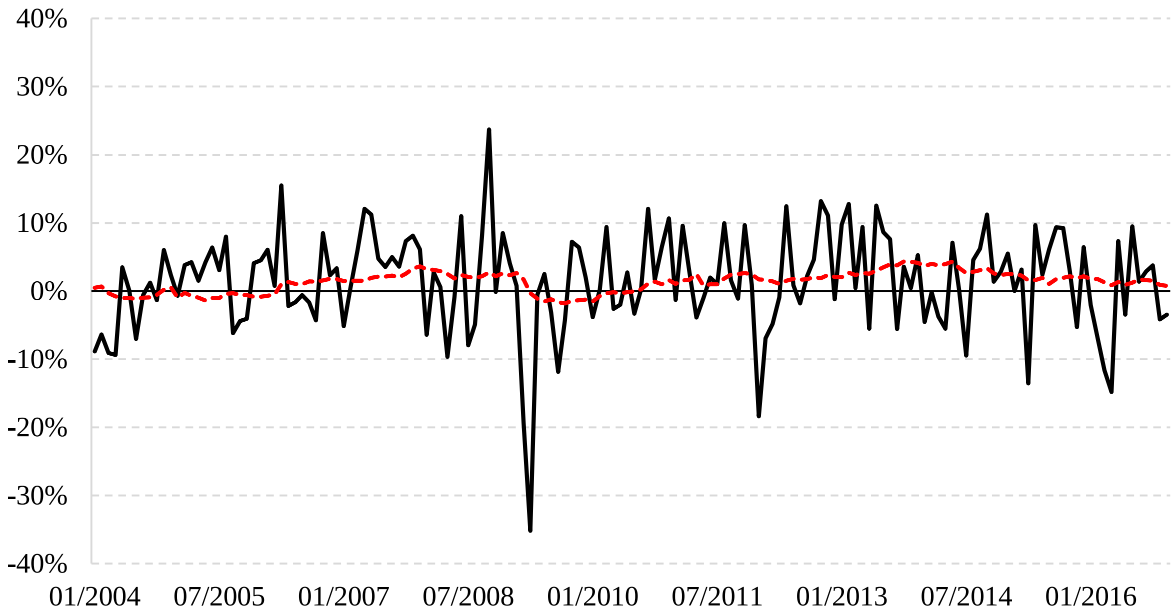
We do not refit the expected market risk premium with our intermediary risk components since the academic literature show that predictive variables of the expected market risk premium are strongly correlated with mutual funds flows (Jank, 2012). Given the high correlation, adding fund flows to our expected market risk premium fitting would not add any new information and would thus not alter our conclusion about the risk premium in any way. As a reference, we test Jank’s findings by refitting the expected market risk premium with fund flows and the correlation with the original fitting is 92%. The only minor difference is that the seasonality in the flows adds more noise to the fitting.

We perform robustness tests to verify the integrity of our results. Firstly, in all regressions we control for heteroskedasticity in the data using robust standard errors. Secondly, we examine the degree of multicollinearity in the underlying conditioning variables by studying the variance inflation factors. We report the findings of our robustness test(s) in the appendix.

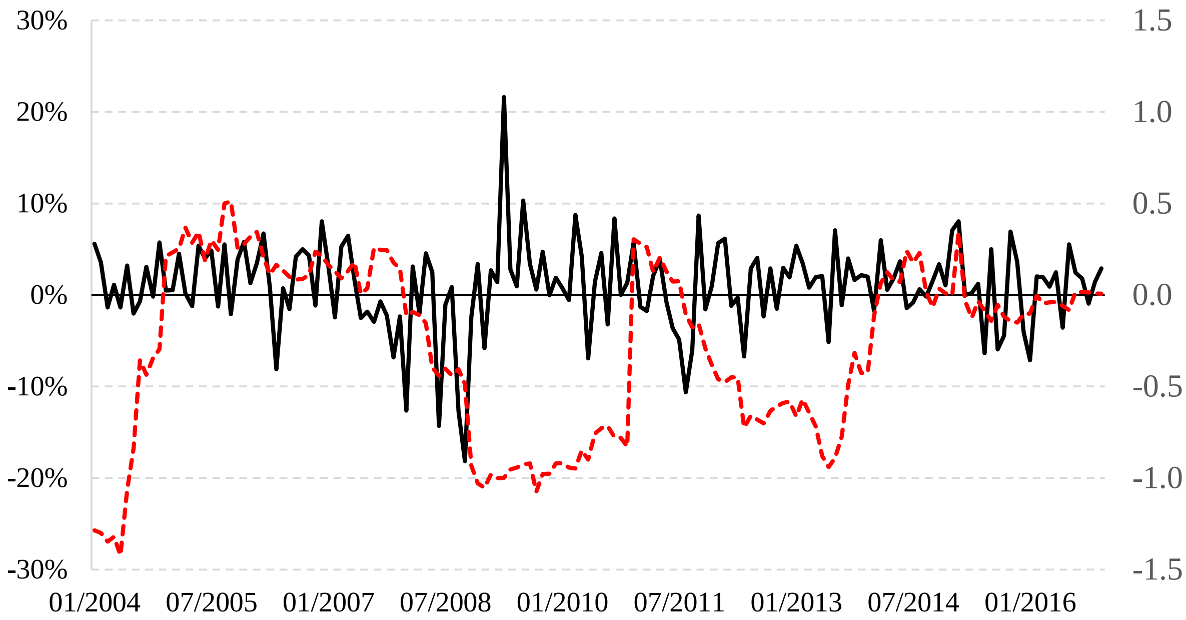
4. Results

4.1 Momentum Premium

For the time-period of 01/2004 - 12/2016 we find a mean monthly return of 1.4% ($t = 2.3$) with a 1.3% ($t = 11.1$) alpha. The mean beta for the period is -0.3 ($t = -7.8$) and the mean R^2 is 14%. The positive return coupled with the positive and significant alpha confirms the existence of the momentum premium in Swedish data. The large and significant alpha and the low R^2 indicates that a rolling Sharpe-Lintner CAPM model with a 24-month beta cannot explain the portfolio returns. Since the data contains a large financial disaster, and momentum has been shown to crash in the subsequent recovery period, we divide the entire time-period into the three sub-periods to study the variability within the returns and the beta. In **Graph 1** below we present the momentum returns and alpha for the entire period and in **Graph 2** below we present the excess market returns and the beta for the entire period.



Graph 1: Depicts the momentum portfolio returns (solid black) and alpha (dashed red) estimated from a rolling Sharpe-Lintner CAPM model with a 24 month beta.



Graph 2: Depicts the excess market return (solid black) on the left-hand axis and beta (dashed red) on right-hand axis estimated from a rolling Sharpe-Lintner CAPM model using a 24 month window.

4.1.1 Pre-Recovery Period (01/2004 – 01/2009)

The first sub-period is the pre-recovery period defined as 01/2004 to 01/2009. The pre-recovery period is chosen to study momentum's behaviour leading up to the crash and throughout the financial crisis. In the pre-recovery period momentum's mean monthly return is 1.9% ($t = 2.2$) with a 0.9% ($t = 4.7$) alpha. The mean beta for the pre-recovery period is -0.2 ($t = -2.4$) and the mean R^2 is 13%. The positive and significant return as well as the positive and significant alpha confirm earlier research that momentum does not crash during financial disasters as visible in **Graph 1** and **Graph 2** above. We note that the mean beta is close to zero per the Sharpe-Lintner CAPM indicating low market exposure. Similar to our findings for the entire time-period the R^2 for the pre-recovery period is low.

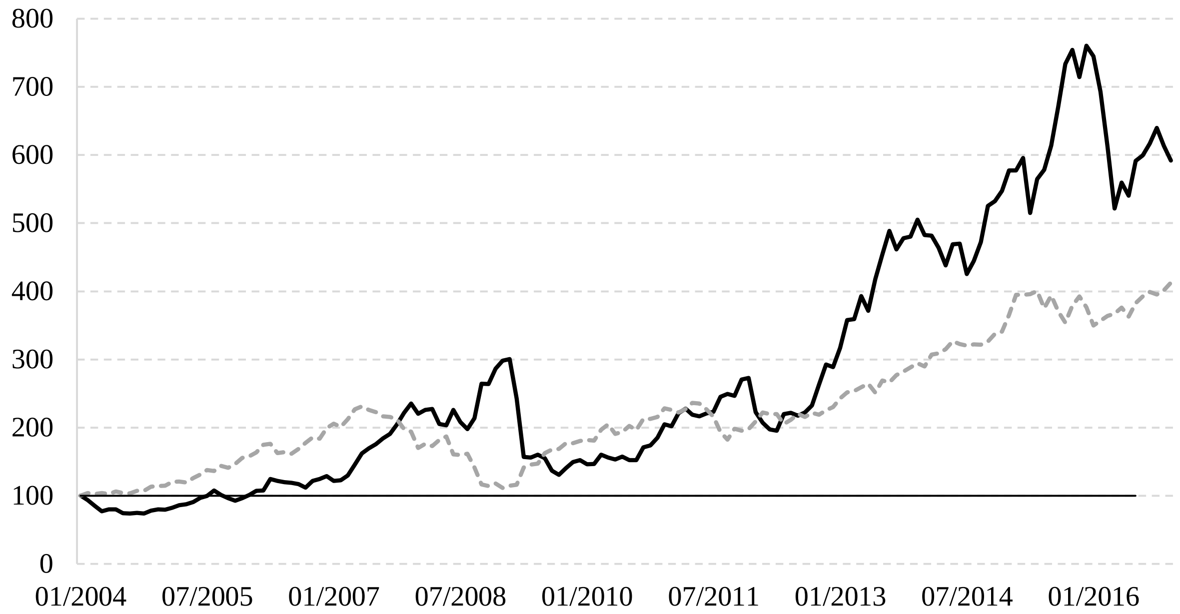
4.1.2 Recovery Period (02/2009 – 12/2012)

The second sub-period is the recovery period defined as 02/2009 to 12/2012. In the recovery period momentum has a mean monthly return of 0.4% ($t = 0.3$) with a 0.8% ($t = 3.9$) alpha. The mean beta for the recovery period is -0.6 ($t = -9.2$) and the mean R^2 is 25%. We note that for the recovery period the return is insignificantly different from zero in line with the empirical literature. We also document a significant alpha once again showcasing the CAPM's failure to accurately capture the returns. In line with Daniel & Moskowitz's empirical findings we document a considerably more negative beta during the recovery period when the market rebounds, shown graphically in **Graph 2**, and also a higher R^2 for the period. One interpretation of the higher R^2 is that momentum's correlation with the market becomes more pronounced during the market recovery when momentum crashes.

4.1.3 Post-Recovery Period (01/2013 – 12/2016)

The third and final sub-period is the post-recovery period defined as 01/2013 to 12/2016. In the post-recovery period momentum's mean monthly return is 1.7% ($\text{t} = 1.8$) with a 2.5% ($\text{t} = 16.3$) alpha. The mean beta for the post-recovery period is -0.2 ($\text{t} = -4.7$) and the mean R^2 is 5%. The positive return with a positive and significant alpha is in line with our expectations and the existing literature on the momentum premium. The beta for the period is, similar to the pre-recovery period, close to zero once again indicating a relatively low correlation with the broader market. To our surprise the R^2 for the period is quite low at 5%.

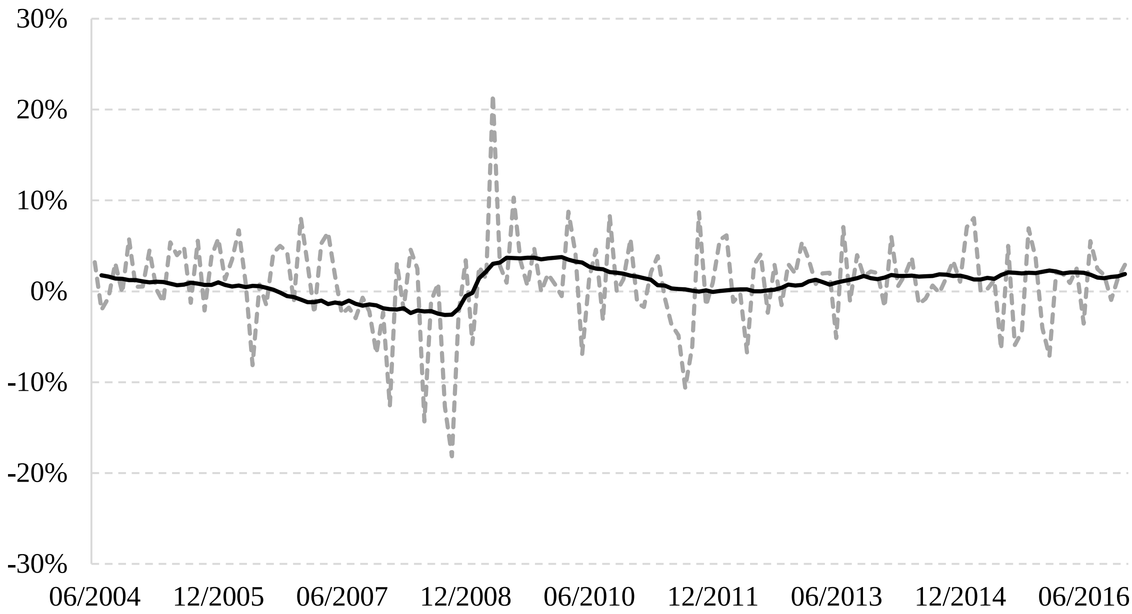
Overall, the momentum premium is positive and significant for the entire period but loses some significance when we divide it into sub-periods. Furthermore, we document a positive and significant alpha in all periods with the largest alpha in the post-recovery period. We confirm the existence of the momentum premium in Swedish data, the inability of a CAPM model in capturing it, and its tendency to crash during times of economic recovery (visually illustrated in **Graph 1** and **Graph 2** above as well as **Graph 3** below). Having concluded our return study we turn to Petkova & Zhang's methodology to examine the momentum portfolio's time-varying risk exposure.



Graph 3: Depicts cumulative indexed returns of the momentum portfolio (solid black) and the market (dashed grey) (100 = 01/2004).

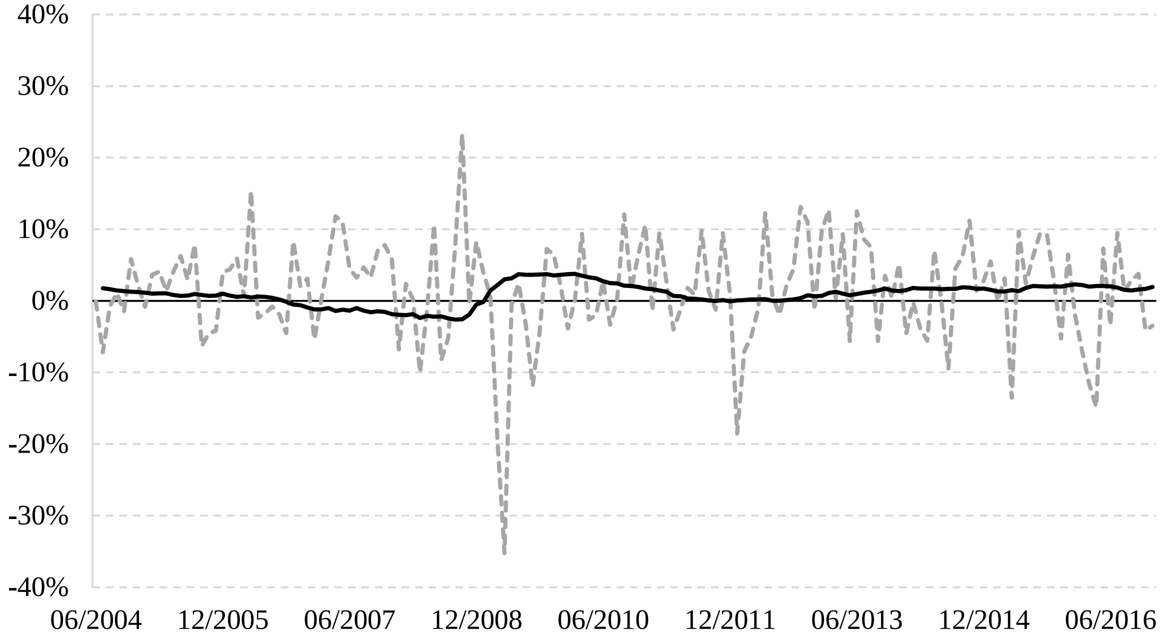
4.2 Expected Market Risk Premium

To study momentum's time-varying risk exposure we need a measure of the expected market risk premium. One of the key advantages of using Petkova & Zhang's methodology is that it uses conditioning variables (dividend yield, term-spread, default spread and short-term interest rate) to predict the expected market risk premium. The fitted expected market risk premium is a less noisy measure of the overall economic conditions compared to the standard in the literature, the realized market excess return (Petkova & Zhang, 2005). We note that the variance of the realized market excess return is about ten times larger than that of our fitted expected market risk premium illustrating the difference in noise. In **Graph 4** below we plot the result from fitting the expected market risk premium together with the excess market return for the entire period.



Graph 4: Depicts the fitted expected market risk premium (solid black) and the realized market excess return (dashed grey).

Upon a visual inspection one can see the lower volatility of the fitted expected market risk premium compared to the realized excess market return. The expected market risk premium behaves in line with our expectations and the broader financial literature (Campbell & Cochrane, 1999; Constantinides & Duffie, 1996). It is counter-cyclical with lower risk compensation in good times when volatility is lower and people are willing to take on risk, such as the period leading up to the financial crisis, and increases in bad times such as during and after the 2008 financial crisis. In **Graph 5** we switch the market excess return with the momentum portfolio excess returns and plot it with the expected market risk premium. We note, as visible in **Graph 5** below, that the risk premium peaks in 2009 during the recovery when momentum crashes.



Graph 5: Depicts the fitted expected market risk premium (solid black) and realized excess momentum returns (dashed grey).

4.3 Conditional Market Regressions

After having fitted the expected market risk premium we turn to study momentum's time-varying risk exposure using conditional market regressions. We run Equation 3 (the conditional market regression) for the entire time-period of our dataset (06/2004 - 12/2016) controlling for heteroskedasticity and present the output in **Table 1** below.

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	2.002	0.721	2.78	0.006
RM DEF	4.879	26.030	0.19	0.852
RM DIV	-62.040	29.463	-2.11	0.037
RM TB	-82.617	131.324	-0.63	0.530
RM Term	-3.951	19.495	-0.20	0.840
Constant	0.014	0.005	2.67	0.008
n = 150	**Prob > F = 0.000**	$\mathbf{R^2 = 0.277}$		

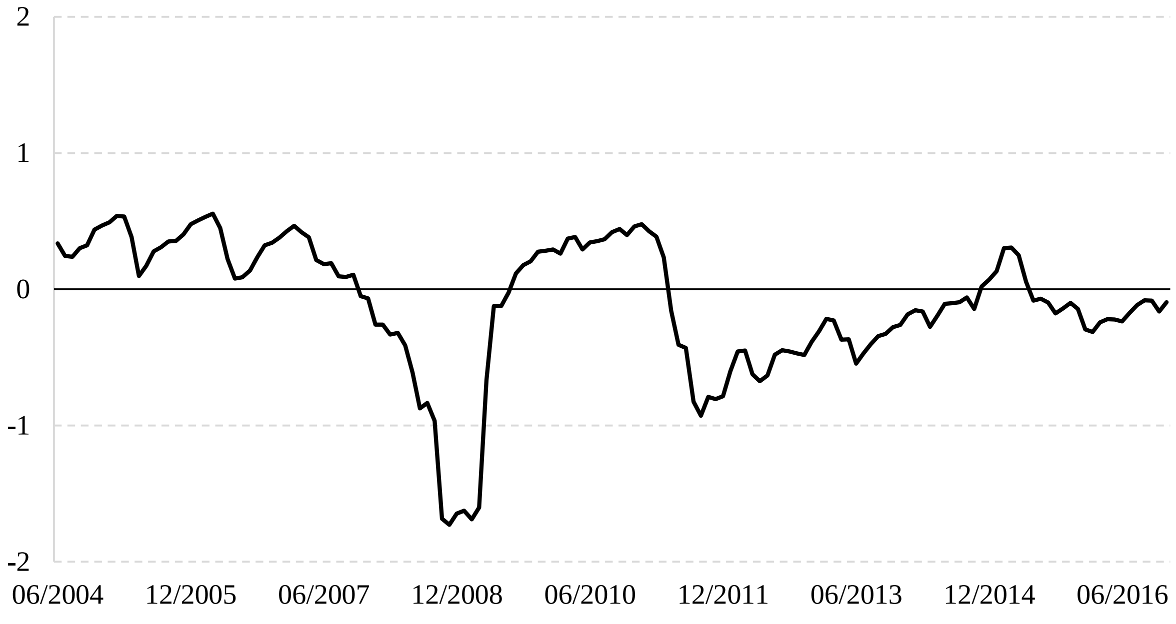
Table 1: The output from the conditional market regression (Equation 3) is presented above. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread.

The main result from the conditional market regression is that the intercept (alpha) is positive at 1.4% (per month) and significant at the 1% level ($t = 2.7$). The market excess return is also significant at the 1% level ($t = 2.8$) with the dividend yield being significant at the 5% level ($t = -2.1$). We argue that the lack of significance for the other conditioning variables is not a cause for concern given their rigorous empirical background as predictors of the market risk premium (Petkova & Zhang, 2005; Fama & French, 1988; Keim & Stambaugh, 1986; Campbell, 1987; Fama & French, 1989; Fama & Schwert, 1977; Fama, 1981). Furthermore, we note that the R^2 of the regression is double that of our earlier tests, at 28%, which is a step in the right direction.

At a first glance, the significant alpha seemingly indicates that time-varying risk cannot explain the momentum premium. The model's inability to capture the returns provides significant incentives for further study. As discussed by Petkova & Zhang the model's ability to capture the alpha of a portfolio is only part of the risk compensation explanation (Petkova & Zhang, 2005). To better understand the relationship between the expected market risk premium and the momentum premium we proceed to study its conditional beta and its beta premium sensitivity.

4.4 Conditional Beta and Beta Premium Sensitivity

To calculate the momentum portfolio's conditional beta we run Equation 4 fitting the conditional beta by using the conditioning variables. The result from the regression is presented in **Graph 6** below.



Graph 6: Depicts the conditional beta (solid black) fitted from Equation 4.

We find that the mean conditional beta is -0.1 ($t = -2.4$). A conditional beta around zero is in line with our expectations of a long-short portfolio. However, upon a visual inspection of **Graph 6** one can see that the conditional beta varies considerably over the period with a sharp dip during the end of the sub-prime crisis and the start of the recovery period. The sharp dip around 2009 is in line with what we would expect given Daniel & Moskowitz's findings of momentum's time-varying beta (Daniel & Moskowitz, 2016). A similar pattern can be seen during the Euro crisis but with a slower beta recovery.

We proceed to study the portfolio's beta premium sensitivity to better understand the covariance between the portfolio's beta and the expected market risk premium. Using Equation 7 we find a beta premium sensitivity of 9.7 ($t = 3.6$), controlling for heteroskedasticity. The positive and significant beta premium sensitivity implies that momentum's exposure to the market increases when the risk premium increases. Similar to Petkova & Zhang's findings for the value premium we see this as evidence of momentum bearing time-varying risk with our results going in the right direction in explaining the premium.

In line with the literature surrounding momentum's shifting factor loadings (Daniel & Moskowitz; Grundy & Martin, 2002; Kothari & Shanken, 1992) we believe the significant alpha may be an effect of the static fitting procedure of our model. To capture momentum's shifting risk-return trade-off, due to the shifting relationship to the conditioning variables, we run the conditional market regressions in a periodic setting.

4.5 Periodic Framework

To perform the periodic regressions we run the conditional market regression (Equation 3), fit the conditional betas (Equation 4), and calculate the beta premium sensitivities (Equation 7) for the three time periods: pre-recovery (06/2004 - 01/2009), recovery (02/2009 - 12/2012), and post-recovery (01/2013 - 12/2016). In all periodic regressions we control for heteroskedasticity in the data.

4.5.1 Pre-Recovery Period (06/2004 - 01/2009)

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	0.312	1.522	0.21	0.838
RM DEF	43.622	38.382	1.14	0.261
RM DIV	-97.172	58.548	-1.66	0.103
RM TB	546.770	442.047	1.24	0.222
RM Term	74.276	40.676	1.83	0.074
Constant	0.016	0.008	1.91	0.062
n = 55	**Prob > F = 0.000**	$\mathbf{R^2 = 0.292}$		

Table 2: The output from the conditional market regression (Equation 3) for the pre-recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread.

The results from the conditional market regression for the pre-recovery period are presented in **Table 2** above. Compared to our one period test the alpha has lost some significance and is now only significant at the 10% level $(t = 1.9)$. The weaker significance indicates that we are able to more accurately capture the returns in a periodic setting. The conditional beta for the period is more positive with a mean of 0.1 $(t = 1.2)$. Accounting for shifting sensitivities to the conditioning variables seems to provide a better model fit in explaining the returns and the portfolio's overall behaviour.

We note that the coefficients and significance for the conditioning variables differ from our regression over the entire period in line with the literature around shifting factor loadings. We see that the dividend yield is no longer significant at the 5% level with the term spread now being significant at the 10% level. The R^2 has also increased slightly compared to the conditional market regression ran over the entire period.

For the period we find a positive beta premium sensitivity with a value of 25.1 significant at the 1% level $(t = 6.2)$. We are cautious to draw any conclusion from the shifting results in one period but we are optimistic that the periodic regressions are helping us better capture the returns of the momentum portfolio as implied by the lower significance of the alpha. We move on to study the next period(s) to more accurately examine the results before any conclusions are made.

4.5.2 Recovery Period (02/2009 - 12/2012)

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	3.065	1.336	2.29	0.027
RM DEF	-30.208	45.001	-0.67	0.506
RM DIV	-25.120	46.124	-0.54	0.589
RM TB	-1212.141	676.304	-1.79	0.080
RM Term	-30.235	41.880	-0.72	0.474
Constant	0.013	0.010	1.25	0.218
n = 47	**Prob > F = 0.000**	$\mathbf{R^2 = 0.528}$		

Table 3: The output from the conditional market regression (Equation 3) for the recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread.

The results from the conditional market regression for the recovery period are presented in **Table 3** above. The alpha is insignificant $(t = 1.3)$ further indicating that we are able to more accurately capture the returns in a periodic setting. The conditional beta for the period is negative at -0.2 $(t = -2.3)$. We are not surprised by the negative conditional beta for the period given Daniel & Moskowitz's observation of momentum's negative beta during economic recoveries (which can be seen visually in **Graph 6**) (Daniel & Moskowitz, 2016).

We see the high R^2 of 53% as an indication that our method of accounting for the shifting sensitivities to the conditioning variables allows for a better model fit in explaining the returns and the portfolios overall behaviour. We observe once again, that the R^2 for the recovery period is twice as high as for the other period(s) similar to our return study providing further evidence of momentum's increased correlation with the market during this time.

Furthermore, we note that the coefficients and significance for the conditioning variables differ from both the pre-recovery period and the entire period. For example, we see that all four conditioning variables now have negative coefficients although with varying significance.

Lastly, we document that the beta premium sensitivity is positive at 27.1 and significant at the 1% level $(t = 5.5)$ indicating increased exposure as the risk premium increases in line with the time-varying risk explanation.

4.5.3 Post-Recovery Period (01/2013 - 12/2016)

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	1.145	3.296	0.35	0.730
RM DEF	-93.615	162.981	-0.57	0.569
RM DIV	22.588	156.165	0.14	0.886
RM TB	561.745	1055.198	0.53	0.597
RM Term	-14.292	84.387	-0.17	0.866
Constant	0.014	0.013	1.10	0.278
n = 48	**Prob > F = 0.958**	$\mathbf{R^2 = 0.0266}$		

Table 4: The output from the conditional market regression (Equation 3) for the post-recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread.

The results from the conditional market regression for the post-recovery period are presented in **Table 4** above. The alpha is insignificant $(t = 1.1)$ further indicating that we are able to more accurately capture the returns in a periodic setting. The conditional beta for the period is positive at 0.1 $(t = 2.7)$.

To our surprise we document an R^2 of only 2.7% indicating low explanatory power for the model during the post-recovery period. Consequently, we also note that none of the conditioning variables are significant. The low explanatory power of the model, in contrast to the earlier periods, is a reminder that conditional market regressions are not perfect in capturing the returns. We view our models inability in capturing the returns as indication of the need to complement the traditional state variables.

The beta premium sensitivity for the period is negative at -52.9 and significant at the 1% level $(t = -6.4)$ contrary to what we would expect from the time-varying risk explanation. However, given the low R^2 for the period we do not put too much emphasis on the results.

Overall, the results from the periodic regressions are going in the right direction of a time-varying risk explanation for momentum with less significant alphas in all periods and positive beta premium sensitivities in two out of the three periods. The large variance in the coefficients of the conditioning variables (and their varying significance) coupled with the varying R^2 is evidence of momentum's shifting risk-return trade-off and indicates that a periodic framework is an important innovation. We document some variation in the conditional betas between the periods with the lowest value being recorded during the recovery period in accordance with what we would expect from Daniel & Moskowitz's findings (Daniel & Moskowitz, 2016).

However, the low R^2 for the post recovery period is concerning and indicates that our periodic model still needs improvement. Inspired by He & Krishnamurthy's intermediary asset pricing framework and Baltzer et al.'s empirical documentation of mutual funds as momentum traders we add two fund flow variables as state variables into our conditional market regressions (He & Krishnamurthy, 2013; Baltzer et al., 2019).

4.6 Periodic Regressions and Intermediary Asset Pricing

To perform the periodic regressions with our added fund flow variables we run the conditional market regression (Equation 8), fit the conditional betas (Equation 9), and calculate the beta premium sensitivities (Equation 7) for the three time periods: pre-recovery (06/2004 - 01/2009), recovery (02/2009 - 12/2012), and post-recovery (01/2013 - 12/2016). In all periodic regressions we control for heteroskedasticity in the data.

4.6.1 Pre-Recovery Period (06/2004 - 01/2009)

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	-1.362	2.412	-0.56	0.575
RM DEF	-1.469	59.863	-0.02	0.981
RM DIV	-23.822	91.416	-0.26	0.796
RM TB	380.890	434.206	0.88	0.385
RM Term	85.310	52.034	1.64	0.108
RM FundDep	0.024	0.020	1.17	0.247
RM FundWith	0.002	0.028	0.08	0.940
Constant	0.018	0.008	2.19	0.034
n = 55	**Prob > F = 0.000**	$\mathbf{R^2 = 0.315}$		

Table 5: The output from the conditional market regression with fund flows (Equation 8) for the pre-recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread, FundDep = Equity Fund Deposits, FundWith = Equity Fund Withdrawals.

The results from regression 8 for the pre-recovery period are presented in **Table 5** above. The alpha for the regression is positive at 1.8% and significant at the 5% level ($t = 2.2$). The mean conditional beta for the period is 0.0 ($t = 0.5$). The R^2 for the period increases by about 2 percentage points to 31.5% compared to the model without fund flows. The coefficients for the fund flow variables are insignificant and we note that the conditioning variables now have different coefficients compared to our model without fund flows. We view this as an indication that our fund flow variables are capturing some of the conditioning variables explanatory power. However, we do not see any issues with multicollinearity in our data as indicated by our VIF test (Appendix 1).

The beta premium sensitivity is positive at 25.0 and significant at the 1% level ($t = 7.6$). The t-stat of 7.6 is slightly higher than for the model without fund flows. We are hesitant to draw any final conclusions from the pre-recovery period given the conflicting results with weak significance for our fund flow variables but large changes to the coefficients of the conditioning variables.

4.6.2 Recovery Period (02/2009 - 12/2012)

$\mathbf{r_{Momentum} - r_f}$	**Coefficient**	**Robust Standard Error**	**t-stat**	**P > | t |**
$\mathbf{r_m - r_f}$	3.717	1.219	3.05	0.004
RM DEF	28.764	40.054	0.72	0.477
RM DIV	-76.245	42.449	-1.80	0.080
RM TB	-1338.830	627.169	-2.13	0.039
RM Term	-46.987	37.922	-1.24	0.223
RM FundDep	-0.065	0.030	-2.17	0.036
RM FundWith	0.060	0.025	2.44	0.019
Constant	0.013	0.010	1.31	0.198
n = 47	**Prob > F = 0.000**	$\mathbf{R^2 = 0.6070}$		

Table 6: The output from the conditional market regression with fund flows (Equation 8) for the recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread, FundDep = Equity Fund Deposits, FundWith = Equity Fund Withdrawals.

The results from regression 8 for the recovery period are presented in **Table 6** above. Similar to our regression without the fund flow variables, we note that the alpha for the recovery period is insignificant. The conditional beta is negative with a mean of -0.4 ($t = -2.9$). Compared to the prior recovery period, without our fund flow variables, the conditional beta is slightly more negative.

Most conditioning variable coefficients have changed with both the significance levels and the magnitude of the coefficients increasing. The R^2 for the regression also increases substantially from 53% to 61%. The changes in the coefficients of the conditioning variables indicates that our former regression was effected by the conditioning variables correlation to the added fund flow variables. By adding these variables to the regression we are able to remove that effect and single out the impact of the conditioning variables on momentum.

Examining the individual fund flow coefficients we note that the fund deposits variable is negative and significant at the 5% level $(\mathrm{t} = -2.2)$. The economic interpretation of the coefficient is that SEK 1 billion more in monthly deposits decreases the momentum portfolio's market exposure (measured as the beta) by 0.065. The effect is economically significant as the average monthly deposits during the recovery period is SEK 26 billion.

We also note a positive coefficient on the fund withdrawals variable significant at the 5% level. The economic interpretation of the significant fund withdrawals coefficient is, as for the deposit coefficient above, that SEK 1 billion more in outflows increases the momentum portfolio’s market exposure (measured as the beta) by 0.060. We find it interesting that the fund flow variables have opposite coefficients.

We document a beta premium sensitivity of 28.0 significant at the 1% level $(\mathrm{t} = 3.5)$. Incorporating a variable for intermediary financing constraints into our model slightly increases the beta premium sensitivity even though the conditional beta decreases. As mentioned earlier, the positive beta premium sensitivity is expected from the time-varying risk explanation.

4.6.3 Post-Recovery Period (01/2013 - 12/2016)

$r_{Momentum} - r_f$	Coefficient	Robust Standard Error	t-stat	P > | t |
$r_m - r_f$	-3.852	4.243	-0.91	0.369
RM DEF	-161.273	162.933	-0.99	0.328
RM DIV	160.094	173.305	0.92	0.361
RM TB	279.673	1053.892	0.27	0.792
RM Term	-5.534	73.525	-0.08	0.940
RM FundDep	0.036	0.014	2.58	0.014
RM FundWith	0.010	0.032	0.30	0.765
Constant	0.016	0.013	1.21	0.232
n = 48	**Prob > F = 0.130**	**$R^2 = 0.0712$**		

Table 7: The output from the conditional market regression with fund flows (Equation 8) for the post-recovery period. All conditioning variables denoted with RM are lagged 1 month and multiplied with the excess market return. Variables are denoted as $r_{Momentum} - r_f$ = Excess Momentum Returns, $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-Free Rate, TERM = Term Spread, FundDep = Equity Fund Deposits, FundWith = Equity Fund Withdrawals.

The results from regression 8 for the post-recovery period are presented in **Table 7** above. Similar to our regression without our fund flow variables, we note that the alpha for the post-recovery period is insignificant. The conditional beta for the period has a mean of 0.0 ($t = 0.4$).

We document an R^2 of 7.1% for the post-recovery period. Although the R^2 has more than doubled by the inclusion of our fund flow variables, highlighting their strong explanatory power, we still find the periods noticeably lower R^2 interesting.

Examining the fund flow coefficients we note that the fund deposits variable is positive and significant at the 5% level ($t = 2.6$). The economic interpretation of the coefficient is the same as for the recovery period but with the opposite effect. SEK 1 billion more in monthly deposits increases the momentum portfolio's market exposure (measured as the beta) by 0.036. The effect is economically significant as the average monthly deposits during the recovery period is SEK 30 billion. Furthermore, we note that the withdrawals coefficients is insignificant.

Contrary to our expectation we document a negative beta premium sensitivity at -38.8 significant at the 5% level ($t = -2.4$). However, we note that accounting for intermediary financing constraints lowers the significance and size of the negative beta premium sensitivity coefficient.

As mentioned before the weak R^2 for the period make an economic interpretation difficult but our ability to eliminate the alpha, increase the R^2, and decrease the significance of the negative beta premium sensitivity indicates that incorporating intermediary financing constraints are a step in the right direction.

5. Discussion

While our findings around intermediary asset pricing suggest a clear impact of intermediaries and their financing constraints on momentum the varying coefficients and significance provide cause for further thought.

We find it curious that neither fund flow variable are significant in the pre-recovery period, see section 4.6.1, and speculate on why this is the case. One possible explanation is increased regulatory requirements for the financial sector leading to financing constraints becoming more binding after the crisis. To be more specific, prior to the crisis it was easier for fund managers to off-set temporary liquidity fluctuations from disproportionate fund flows via alternative means like taking up leverage or using derivatives. Following the 2008 sub-prime crisis the European Union and Swedish Financial Supervisory Authority undertook sweeping regulatory changes which may impact fund managers ability to do so. The aforementioned theory is consistent with the intermediary asset pricing framework as well as the increasing significance of our fund flow variables in the later periods and we believe it warrants further study.

In the results section, see sections 4.6.2 and 4.6.3, we note that the deposit coefficient changes signs between the recovery and post recovery period while the withdrawals coefficient loses its significance between the periods. The changing deposit coefficient between the periods indicate that the relationship between intermediaries and momentum varies over time. We view this as an interesting discovery and speculate whether the time-variation is due to shifting asset allocations as a consequence of varying economic conditions. There are multiple studies on the impact of financing conditions on asset allocations with investors and financial intermediaries allocating towards high-beta assets when financially constrained (Frazzini & Pedersen, 2014; Boguth & Simutin, 2018). Momentum can also be linked to high-beta assets as shown by Daniel & Moskowitz with them finding that momentum is short high beta stocks following periods of financial distress (Daniel & Moskowitz, 2016). The exact mechanisms are hard to distinguish but we believe the link between momentum and intermediary demand for high-beta stocks has potential as a future research area.

Furthermore, the shifting significance for the withdrawals coefficient in the post-recovery period may be an effect of less binding financing constraints throughout the period. As the market has normalized following the recovery period intermediaries might be able to partially make up any shortfalls from withdrawals using other means such as leverage (Boguth & Simutin, 2018).

Another interesting area to discuss is the large drop in explanatory power between the recovery period and the post-recovery period both with and without our fund flow variables, see sections 4.5 and 4.6. One possible explanation for our results in the post-recovery period is the documented weaker significance of certain financial anomalies (see e.g. Cotter & McGeever, 2018). We see signs of the documented weaker significance in our return study with a lower t-value for the period ($\mathrm{t} = 1.8$). The aforementioned effect can also be observed visually in **Graph 1** as more volatility. A weaker momentum premium would imply noise in the regressions and consequently a lower R^2. However we believe the low value of 7% for the sub-period cannot be solely explained by weakening anomalies instead also indicating that our model fails to fully capture the portfolio's exposure in the post-recovery period.

Our findings have implications for future momentum studies but also for the broader intermediary asset pricing literature. In particular, we show the large impact from selecting what intermediary to study illustrated by our different findings from earlier empirical tests of intermediary asset pricing (Adrian et al., 2014; He et al., 2017). Our significant coefficients support the theory behind He & Krishnamurthy's original framework and provide incentives for further study around the link between intermediaries and other anomalies.

6. Conclusion

In this paper we show empirically the link between intermediary asset pricing and momentum. We find that a conditional CAPM model with two fund flow variables can capture the returns of the momentum portfolio with our added variables increasing the explanatory power considerably. Our overall results indicate that intermediary financing constraints play an important role in understanding the momentum premium.

We show that fund inflows during the recovery period negatively affects the market exposure of the momentum portfolio with outflows having the opposite effect. The effect of fund inflows persists into the post-recovery period during more normal market conditions but with the opposite sign. The economic interpretation of our coefficient(s) during the recovery period is that SEK 1 billion in deposits (withdrawals) decreases (increases) the market exposure of the momentum portfolio by 0.065 (0.060). The same interpretation applies to the deposits variable in the post-recovery period but with a coefficient of 0.036 instead.

Our findings suggest that momentum's risk-return trade-off varies over time and we therefore propose a periodic framework. We document substantial variability in the coefficients and significance of the conditioning variables between the sub-periods with our conditional market regressions now being able to eliminate the alpha for all periods. We see the large variation in the conditioning variable's coefficients as evidence of the shifting risk-return trade-off and the variable factor loadings as documented by Grundy & Martin (Grundy & Martin, 2001).

We document a significant time-varying risk exposure evidenced by insignificant alphas along with positive and significant beta premium sensitivities. We also find significant variability in the conditional beta in line with the momentum crash literature.

The explanatory power of our model varies between the periods with our model explaining 61% of the variation in the returns in the recovery period but only 7% in the post-recovery period. We speculate that the low explanatory power in the post-recovery period could be due to weakening significance of financial anomalies as documented by Cotter & McGeever (Cotter & McGeever, 2018).

Our documentation of the impact of intermediaries on momentum is consistent with the intermediary asset pricing framework but the changing signs and significance of the fund flow coefficients provide cause for further though. We speculate that the shifting significance might be due to regulatory changes following the financial crisis and that the shifting signs between the recovery and post-recovery period can be attributed to changing investor preferences depending on how binding the financing constraints become.

Our paper contributes to the literature by strengthening the link between the momentum premium and intermediary asset pricing and by showing the time-varying risk exposure of the momentum portfolio. Our results are consistent with the original intermediary asset pricing framework by He & Krishnamurthy with our measure of financing constraints having significant explanatory power over momentum in contrast to earlier empirical tests of the framework (He & Krishnamurthy, 2013; Adrian et al., 2014; He et al., 2017). As discussed previously, we attribute this to our chosen intermediary of study highlighting the importance of this choice. Furthermore, our findings of momentum's time-varying risk exposure are a step in the right direction in explaining the momentum premium and indicate that the returns are compensation for bearing risk.

We propose several areas for further study: Firstly, we suggest that studies should be conducted on the intersection of intermediary asset pricing and financial anomalies emphasising intermediaries which has been shown to trade the underlying factor portfolios. Secondly, we propose that studies should be conducted on the impact of regulatory changes on intermediary financing constraints. Finally, we recommend that future papers study the channels and mechanisms through which intermediary asset pricing affects momentum.

7. References

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8. Appendix

Appendix 1: Testing for Multicollinearity using Variance Inflation Factors (VIF)

Variable	VIF	1/VIF
DIV	6.37	0.157
DEF	6.14	0.163
TERM	3.80	0.263
RF	3.06	0.327
FundWith	2.24	0.446
FundDep	1.85	0.541
$\mathbf{r_m - r_f}$	1.72	0.580
Mean VIF	3.60	

Table 8: The variance inflation factors for the conditioning variables over momentum for the entire time period. Variables are denoted as $r_m - r_f$ = Excess Market Return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk–Free Rate, TERM = Term Spread, FundDep = Equity Fund Deposits, FundWith = Equity Fund Withdrawals.

We find that none of the variance inflation factors are above 10 with most factors being below 4. Overall we see no reason to believe multicollinearity impacts the results of our paper.