Two Essays in Empirical Finance

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Abstract

Revisiting Inflation and Individual Equities

This paper reexamines the inflation-hedging properties of individual equities. When determining inflation betas for individual equities we use multivariate regressions, which utilize all available data and account for equity market factor and reporting lags in inflation indices. We show how such an approach can even be used to create inflation-sensitive strategies for customized inflation indices. The facet of customization is necessary since different kinds of inflation impact different investors. For example, in retirement an investor is more concerned about medical expenses. We illustrate strategies for the US headline CPI, Forbes Cost of Living Extremely Well Index (CLEWI), and the US Medical Care Price Index. When constructing inflation-sensitive portfolios, besides using equal weighting scheme, we show how alternative weighting schemes can be used alongside the choice of inflation sensitive equities to accentuate inflation sensitivity, by using maximum beta optimization or to manage equity risk exposure—low volatility and low equity beta as result of using minimum volatility optimization.

The Cross-Sectional Dispersion and Volatility of Bond Returns and Manager Outperformance

This paper examines the link between fixed income manager outperformance and both longitudinal and cross-sectional volatility in the bond markets. By conditioning our analysis based on different market environments such as rising yield regimes and periods of increasing volatility, we show that opportunities in the bond markets and the effectiveness of manager skills are time-varying. Even after accounting for systematic manager style biases, both cross-sectional dispersion and time-series volatility measurably impact manager outperformance, thus providing bond managers with an opportunity for active management. Time-varying opportunity indicators can be utilized to successfully employ timing between active and passive strategies, thereby producing economically significant information ratios and demonstrating the benefits of time-varying active risk budget.

Revisiting Inflation and Individual Equities

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I. MOTIVATION AND PRIOR LITERATURE

Across the broad literature, equity markets, in aggregate, show poor inflation-hedging characteristics. Gultekin [1983] showed there is a consistent lack of positive relation between stock returns and inflation in most countries.[1] Geske and Roll [1983] suggested that stock returns signal a chain of events that leads to a higher rate of monetary expansion, and therefore, are negatively related to contemporaneous changes in expected inflation.

However, when using individual equities to hedge inflation, the literature is mixed. Bernard and Frecka [1983] demonstrated that no individual equities on their own have significant positive correlations to unexpected inflation. Most of the risk associated with individual stocks is non-inflation risk, making them ineffective candidates for hedging inflation. Sadorsky [2001] surprisingly found that the natural-resource equities are not good inflation hedges. Practitioners like Ma and Ellis [1989] show industries as inflation hedges.

Ang, Brière, and Signori [2012], on the other hand, found that equities with good inflation-hedging characteristics have, on average, earned higher nominal and real returns than other equities.

They found that the top quintile portfolio, sorted based on the realized inflation betas, yielded inflation beta of 1.65 over that sample period. Quintile portfolio tends to overweight oil/gas and technology sectors. The former sector benefits from rising

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[1] Other literature demonstrating common stocks on average a poor inflation hedge include Ang, Chua and Desai [1979], Jaffe and Mandelker [1976], Bodie [1976], Nelson [1976] and Fama and Schwert [1977].

commodity prices, a key component of headline inflation, whereas the latter sector commands technology premium due to innovation.

A shortcoming of the paper is that the authors concluded that trying to forecast inflation beta at an individual equity level is not easy, the premise being that the quintile portfolios constructed on an ex ante basis, using past inflation betas, show perverse inflation betas. They attribute poor outperformance to large time variation in inflation betas with 20% of realized beta changing signs in the course of a year.

Authors argued that inability to select companies that hedge CPI inflation on an ex ante basis points to the need for investors to consider other asset classes as better inflation hedges.

In our paper, we demonstrated how multiple regressions that recognize reporting lags in inflation indices and simultaneously account for equity market factor—along with inflation macro variable—lead to improved outcomes. By not accounting for market variables, inflation betas were overestimated. When constructing out of sample portfolios, we used betas using full sample data up to the prior month. Earlier authors used five-year rolling regressions, which materially impacted turnover and sign changes without any meaningful ex-post gains.

Similar to authors' suggestions on dissecting temporary and persistent components of inflation, we also considered different kinds of inflations, namely, actual, unexpected inflation and changes in expected inflation.[2,3]

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[2] Fama and Schwert [1977] reported negative relationship between commons stocks and expected and unexpected inflation. Balbach [1977] found that the adjustment of revised inflationary expectations causes shifts in both the nominal rate of interest and rate of return on real assets.

For hedging US CPI, alternatives like US Treasury Inflation Protected securities exist. However, this is not the case if an investor has a different bogey. A customized basket of equities that hedges the particular inflation seems all the more logical. Motivated by their suggestion to explore additional price indices, we explored inflation-hedging properties of equities where inflation was measured using Forbes' Cost of Living Extremely Well Index (*Source* Forbes) or by the US Medical Care Price Index (*Source* Bureau of Labor Statistics).

II. DATA AND METHODOLOGY

For our analysis, we used S&P 500 universe from January 1990-December 2013. In Section III, we first conducted an in sample analysis by first calculating beta to inflation for individual equities. Similar to Ang et al. [2012], we used the regression approach followed by Bekaert and Wang [2010]. However, for time-series regressions, we also used monthly equity market (S&P 500) factor along with monthly change in actual inflation (US CPI – All Urban All Items (CPI); we used subsequent month change to account for reporting lags – Nelson [1976]) as regressors and the individual equity returns as the dependent variable (Equation 1). Note Ang et al. [2012] used current month CPI and omitted using equity market factor as an additional regressor. [4]

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[3] Actual inflation is monthly change in the headline inflation. The surprises in forecast inflation (unexpected inflation) are measured as headline inflation in excess of expected inflation. The revisions in forecast inflation are calculated as change in expected inflation from prior forecast for the particular inflation horizon. We use Consensus Economics US CPI forecasts for the estimates.

[4] In Appendix B, we demonstrated necessity for including market factor when trying to determine inflation beta for individual equities. As an example, for Fama-French industries we showed that inflation beta varied significantly on whether regressors included market factor alongside inflation indices or not (actual inflation or first principal component factor (more details in Appendix A)). We also found that the inflation beta for individual equities vary significantly more than that for industries. For example we showed how Adobe inflation beta changes from 4 to 0.4 depending on whether market factor is excluded or included in the regressions. Note – Nelson [1976] mentions if inflation is measured by CPI; then a lead or lag of +1 to -1 month may convey some information which is in fact contemporaneous with R_{it}; also information

$$R_{it} = \alpha + \beta_1 INFL_t + \beta_2 SP500_t \quad (1)$$

We then performed portfolio sorts based on the derived inflation beta and came up with quintile portfolios. The individual equities within the quintile portfolios were equally weighted and rebalanced monthly back to equal weights. We then conducted a couple of multiple regression tests; the first model was similar to what was used in determining inflation beta (Equation 1), i.e., monthly quintile portfolio returns as dependent variable and S&P 500 monthly returns and changes in inflation (subsequent month CPI) as regressors. The second model was more comprehensive as we used monthly quintile portfolio returns as the dependent variable, and Fama-French [1993] and Carhart [1997] (FFC) and inflation (subsequent month CPI) as regressors, to measure inflation exposure (Equation 2).[5]

$$R_{pt} = \alpha_p + \beta_1 INFL_t + \beta_2 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t \quad (2)$$

In order to determine in sample inflation betas used for sorting quintile portfolios, we used a two factor model; later in Section V, we checked for robustness by alternatively using the five factor model to determine the in sample inflation betas. Having inflation beta for individual equities also allowed us to subsequently analyze average inflation beta across the industries and the distribution of inflation beta for the constituent universe. We repeated this in sample analysis with Forbes' Cost of Living Extremely Well Index (CLEWI) and the US Medical Care Price Index (MEDEXP) as alternatives to CPI.

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available to the markets may well exceed that contained in just past inflation history. In their regressions with lead coefficients, +1 month was important. These findings prompt us to use +1 month observations as inflation measure. Note – Ang et al. [2012] use current month CPI observations. They also tried equal weighting equities in portfolios, using 3 year and 7 year rolling regressions and also using S&P 500 returns in a 2 factor regression model. Since results are not reported it is unclear to what extent this was used altogether and if they were used in both in sample and out of sample analysis.

[5] Refer to Appendix C, where we showed how inflation factor can be used alongside with Fama-French Carhart factors to explain portfolio performance, particularly when the portfolio is designed to gain exposure to a specific factor, in this instance inflation factor.

CLEWI is an annual index tracked by Forbes since 1976 and includes categories like fashion, entertainment and toys, household, services, travel, and food and drink.[6]

Since CLEWI is only made available annually, we conducted temporal disaggregation in order to convert it to a monthly time-series, using the Chow and Lin [1971] approach. CLEWI is highly correlated (correlation of 0.78) with the US CPI – All Urban Food and Beverages on an annual basis, and so we used the latter index as the high frequency independent variable in the approach.

After validating in sample efficacy, in Section IV, we evaluated whether such equally weighted quintile portfolios—formed on an out of sample basis—had similar hedging properties or not. When sorting for quintile portfolios, we used inflation beta from the prior month. Results don't change materially when using beta from two months prior (not reported here). The quintile portfolios were sorted and rebalanced monthly. We conducted out of sample analyses for three different inflation indices, namely: CPI, CLEWI, and MEDEXP. Ang et al. [2012] used "Real" CPI unrevised vintages. Because we conduct full sample regressions using last available CPI time-series doesn't alter results materially (not reported here). Since CPI only addresses actual inflation, in order to address simultaneous impact on equities from changes in expected inflation, actual inflation, and unexpected inflation—measured as actual inflation in excess of expected inflation—we conducted principal component analysis.[7] We used the first principal component factor return along with S&P 500 equity returns to determine inflation betas. Using these prior month inflation betas, we additionally conducted fourth out of sample

[6] Detailed description on CLEWI is made available in Appendix D.
[7] Refer to Appendix A for further details.

quintile portfolio analysis. Since forecast inflation was not available for the custom indices like CLEWI and MEDEXP, we limited our differentiated analysis of using principal components to the consumer price index (CPI).

Ang et al. [2012] found perverse CPI inflation beta for the out of sample quintile portfolios. For their out of sample portfolio construction, they used inflation beta based on five-year rolling data; however, we used all sample data up to the prior month. Our approach significantly mitigated turnover and flip flopping of signs of inflation beta issues they reported. There is no economic explanation to this frequent flipping of sign of inflation beta for any given stock, other than five years is very short history. We validated out of sample quintile portfolio inflation sensitivity using both two factor (market and inflation) and five factor (FFC and inflation) multiple regression tests, compared the turnover to that from using five-year rolling approach, and also reviewed the difference in sector exposures between the two approaches.

In Ang et al. [2012], quintile portfolios were constructed using market value weighting schemes. However, since the universe is large cap equities (S&P 500), we equally weighted the stocks in each quintile portfolios. The equal weighting approach further mitigated relying on the beta of a few stocks in the quintile portfolios.[8] Checking for robustness, in Section V, we also constructed optimized quintile portfolios—both in sample and out of sample—using alternative weighting schemes such as minimum volatility and maximum inflation beta portfolio strategies.

[8] DeMiguel, Garlappi and Uppal [2009] showed 1/N portfolio to be just as effective any other portfolio optimization schemes.

In Section VI, using in sample inflation beta for various S&P 500 sectors, we showed that value-weighted sector-based strategies are an inferior way to access inflation exposure, and therefore, justifies an approach that utilizes individual equities instead.

III. INDIVIDUAL EQUITY FACTOR ANALYSIS – IN SAMPLE REGRESSIONS

CPI

We conducted the two factor (S&P 500 and actual inflation – CPI) and five factor (Fama-French, Carhart and actual inflation – CPI) regression tests on quintile portfolios, sorted based on in sample actual inflation – CPI beta, illustrated in Table 1 and Table 2, respectively.

Upon reviewing Table 2, we found that the in sample quintile 1 portfolio had significant and positive actual inflation beta. Similarly, the quintile 5 portfolio had significant negative inflation beta. The portfolio that was essentially long quintile 1 stocks and short quintile 5 stocks had significant and positive beta of 10.1. Both quintile 1 and quintile 5 portfolios had significant negative momentum. The quintile 5 portfolio, not surprisingly, had significant and positive exposure to risk free rate, implying a high dividend yielding portfolio. The long short portfolio had a significant negative high minus low (book-to-market) factor (hml), implying that the quintile 1 portfolio had less value exposure than the quintile 5 portfolio. Reviewing the small minus big (market cap) size factor (smb), we observed that the quintile 1 portfolio had small cap tilt since it had significant positive exposure to the factor. It is noteworthy that the intercept was significant and negative at -1% for the quintile 1 portfolio. The average monthly returns for the portfolios were very similar across all the quintile portfolios. Comparing the portfolio risk across the quintile portfolios, the portfolio risk is significantly higher for the quintile 1 portfolio.

Refer to Section V, where we alternatively used the 5 factor model to determine in sample inflation betas used for sorting quintile portfolios.

Table 3 demonstrates how average actual inflation betas across industries in metals and mining, energy, utilities, and technology sectors are significantly higher than the rest of the industries. Energy related industries— namely Oil Equipment & Services, Oil & Gas Producers, and Alternative Energy—rank top three with inflation beta for the industries being remarkably high.

Our in sample findings are similar to those reported in Ang et al. [2012]. Indeed the majority of consumer discretionary and consumer staples sectors—particularly the industries that are not producers—had, on average, negative actual inflation beta. The median inflation beta across all equities is close to 0.2. In Appendix E, we show how actual inflation betas of all the stocks are distributed.

CLEWI

Next, we conducted the aforementioned 2 factor and 5 factor regression tests, which included the CLEWI inflation factor, on quintile portfolios, sorted based on in sample CLEWI beta, illustrated in Table 4 and Table 5 respectively. Reviewing Table 5, we found consistent results as the quintile 1 portfolio had significant positive CLEWI exposure. The portfolio that was essentially long quintile 1 stocks and short quintile 5 stocks had significant and positive CLEWI beta of 4.1. Both quintile 1 and quintile 5 portfolios had significant negative momentum, and therefore, the long short portfolio had significant negative momentum exposure. The long short portfolio had a significant negative high minus low (book-to-market) factor (hml); this is due to large positive and significant hml exposure for the quintile 5 portfolio. Reviewing the small minus big market cap size factor (smb), we observed that the quintile 1 portfolio had higher significant and positive small cap tilt than the quintile 5 portfolio. The residual market beta was significant and positive. It is noteworthy that the intercept was significant and negative at -1% for the quintile 1 portfolio. The average monthly returns for the quintile portfolios were very similar across all the portfolios. Comparing the portfolio risk across the quintile portfolios, the portfolio risk is significantly higher for the quintile 1 portfolio. Appendix F shows how CLEWI betas of all the stocks are distributed.

Only few industries on average had positive CLEWI beta (Table 6). Knowing the composition of the CLEWI basket, it is rather surprising how industries like personal goods, travel & leisure, and leisure goods had negative CLEWI beta. This implies limited pricing power in such consumer-oriented industries. Industries belonging to the technology sector had large positive CLEWI beta on average.

Medical Care Expenses

Last, we conducted the regression tests (including Medical Care inflation factor) on quintile portfolios, sorted based on in sample MEDEXP beta, illustrated in Table 7 and Table 8, respectively. Reviewing Table 8, we found consistent results as the quintile 1 portfolio had significant positive MEDEXP exposure. The portfolio that was essentially long quintile 1 stocks and short quintile 5 stocks had significant and positive beta of 9.2. Both quintile 1 and quintile 5 portfolios had significant negative momentum. The quintile

5 portfolio had significant and positive exposure to risk-free rate, implying a high dividend yielding portfolio. The long short portfolio had a significant negative high minus low book-to-market factor (hml); quintile 5 portfolio had large positive and significant exposure. Reviewing the small minus big market cap size factor (smb), we observed that the quintile 1 portfolio had significant and positive small cap tilt. The residual market beta is significant and positive. It is noteworthy that the intercept is significant and negative at 2% for the quintile 1 portfolio. The average monthly returns for the portfolios vary across the quintiles. Returns increase as we move from quintile 1 to quintile 5 portfolio. Comparing the portfolio risk across the quintile portfolios, the portfolio risk is significantly higher for the quintile 1 portfolio. Appendix G shows how MEDEXP betas of all the stocks are distributed.

Refer to Section V, where we alternatively used the 5 factor model to determine in sample medical care inflation betas used for sorting the quintile portfolios.

From Table 9, we found food & drug retailers, health care equipment & services, and insurance industries to have positive MEDEXP beta on average. It is not surprising that the tobacco industry—which contributes to rising medical costs—had a large positive beta to MEDEXP on average, but it is surprising that the pharmaceutical & biotechnology industries had negative beta, implying limited pricing power with the industry.

IV. INDIVIDUAL EQUITIES FACTOR ANALYSIS – OUT OF SAMPLE REGRESSIONS

CPI

When conducting out of sample analysis, inflation beta for individual equities were determined by conducting regressions with equity returns as the dependent variable, and equity market returns and actual inflation as regressors. In order to calculate inflation betas, we used full sample data up to the prior month. We started the analysis beginning 12/31/1994 so that we had at least 5 years' history for the time series regressions. Out of sample portfolios were formed based on quintile sorts on inflation beta from the prior month. Results don't change materially when using beta from two months prior (not reported here). The individual equities in quintile portfolios were equally weighted; in Section V, we check for robustness by using alternative weighting schemes. The portfolios were rebalanced monthly.

Reviewing the regression tests—including actual inflation factor—we found that the inflation beta magnitude substantially decreased for out of sample quintile portfolios when compared with in sample quintile portfolios, illustrated in Table 10 and Table 11. However, the inflation betas were still significant and with signs as expected. As shown in Table 11, for the long short portfolio, similar to the in sample analysis, we found significant negative exposure to momentum and hml factor and significant positive exposure to smb factor. The out of sample regressions showed significant and negative intercept at 1% for quintile 1 portfolio.

The average characteristics again confirmed that the risk of the quintile 1 portfolio is significantly greater than that of other quintile portfolios. While the risk is greater, average returns are similar across all the quintiles.

In order to compute inflation beta for creating out of sample quintile portfolio sorts, if we alternatively used rolling 5-year samples and only inflation factor as regressor (Ang et al. [2012] approach), we found that not all inflation betas for the quintile portfolios were significant. With their approach, the quintile 5 portfolio inflation beta was not significant—even at 90% confidence interval (Appendix H, Table H1). Note we did not completely replicate their approach since the portfolio sorts here were equally weighted. In their paper, they used current month CPI and value-weighted portfolios, and therefore, their out of sample results were even more perverse. We also found the annual turnover for quintile 1 portfolio was cut in half as it came down to 48% from 95% by using our proposed changes. There was still overlap in constituents between the two approaches, as we found 65% of constituent overlap in the quintile 1 portfolio.

For our approach, when creating out of sample sorts, we also replaced actual inflation factor with first principal component factor as shown in Appendix A. By doing so, we found improved inflation betas with better t-statistics and improved R-squared (Appendix H, Table H2). The quintile 1 portfolio annual turnover was similar at 45%, and constituent overlap for quintile 1 portfolio was 89%.

Using Dimson beta estimates, we also contrast differences stemming from using subsequent month CPI in out of sample regressions to determine inflation beta versus using current month CPI. Ex-post evaluation reveals that by using current month CPI in out of sample regressions the ex-post inflation beta, even for quintile 1 portfolio, happens to be insignificant (Appendix H, Table H3).

In Table 12, we contrast between the sector exposure changes when we used our approach versus that used by Ang et al. [2012]. We found that the sector weights varied a lot in the rolling five-year approach; the energy exposure dipped as low as 4%, and technology was as high as 50%, whereas, with our approach, the quintile 1 portfolio at least maintained 20% exposure to the energy sector.

In Table 13, reviewing individual equities ranked by inflation beta as of 12/31/2013, we found that—with an exception of General Growth Properties (financial sector, REIT)—all the rest of top 20 stock belonged to energy or the basic materials sector. However, using out of sample portfolios derived using the rolling five-year sample and only inflation factor as regressors, we found significant exposure to finance and insurance companies as well. This is unintuitive to us and likely is explained by the great recession led by the finance sector and subsequent financial recovery— inflation plummeted simultaneously with the crash in oil prices during the recession and later recovered after the end of the recession.

CLEWI

Reviewing the monthly regression test—including the CLEWI inflation factor—we find that the CLEWI inflation beta magnitude substantially decreases for out of sample quintile portfolios when compared with in sample quintile portfolios, illustrated in Table 14 and Table 15. However, the quintile 1 portfolio CLEWI inflation beta is still positive and significant albeit at 90% confidence interval (Table 15). Again, similar to the in sample results, we find that the long short portfolio has significant positive exposure to CLEWI and smb factor and significant negative exposure to momentum and hml factors.

The average characteristics again confirm that the risk of the quintile 1 portfolio is significantly greater than that of other quintile portfolios. While the risk is greater, average returns are similar across all quintiles.

In order to compute CLEWI beta for creating out of sample quintile portfolio sorts, if we alternatively used rolling 5-year sample and only CLEWI inflation factor as regressor (Ang et al. [2012] approach), we found that even inflation beta for quintile 1 portfolio was not significant and the r-squared for the long short (Q1 – Q5) portfolio using the 2 factor regression test was zero (not reported here). The annual turnover for the quintile 1 portfolio was cut more than half as it came down to 41% from 108% by using our proposed changes. The overlap in constituents of the quintile 1 portfolio between the two approaches was only 47%.

Using our approach for out of sample analysis, quintile 1 portfolio has large allocation to technology, industrials, and consumer cyclical industries. Individual equity names such as Netflix, First Solar, and Broadcom rank in the top three with the largest CLEWI beta.

Medical Expenses

Reviewing monthly regression tests (including MEDEXP inflation factor); we found perverse results for out of sample quintile portfolios (not reported here). So to construct out of quintile portfolios we only used stocks that had in sample MEDEXP inflation beta—either greater than 2.5 or less than 2.5—from quintile 1 and quintile 5 portfolio sorts, respectively. In Table 18 and Table 19, we report regression tests for the newly formed portfolios. MEDEXP inflation beta magnitude substantially decreases for out of sample quintile portfolios when compared with in sample quintile portfolios. The quintile 1 portfolio MEDEXP inflation beta is positive and significant. Similar to other regressions, we found that the long short portfolio had significant negative exposure to momentum and hml factors and significant positive exposure to smb factors. The long short portfolio (Q1 – Q5) had significant and negative intercept of 2%.

The average characteristics again confirm that the risk of the quintile 1 portfolio is significantly greater than that of the quintile 5 portfolio. While the risk is greater, average returns are similar across the quintiles. The annual turnover for the quintile 1 portfolio is 60.1%.

V. CHECK FOR ROBUSTNESS

Portfolio sorts using individual equity inflation beta calculated using 5 factors (in sample)

CPI

Not surprising, we find the results in Table 20 are very stable and similar to Table 2, confirming after accounting for equity market factor, inflation betas are very stable regardless of the model choice. In Appendix I, we additionally show in sample regression tests for CLEWI and Medical Expense inflation.

Optimized quintile portfolios formed using alternative weighting schemes, such as minimum volatility and maximum beta optimization[9]

CPI

For in sample portfolio optimization, we used full sample covariance matrix. For out of sample portfolio optimization, we used sample data till prior month to calculate covariance matrix. However, we accounted for estimation errors by shrinking the covariance matrix to constant correlation.[10] Optimization constraints included long only portfolio, no leverage, and maximum equity weight of 5%. For maximum beta optimization, we appropriately used either in sample inflation beta or out of sample—beta derived using regression up to the prior month. Regressors included monthly S&P

[9] Amenc, Goltz, Lodh and Martellini [2012] used efficient frontier portfolios such as maximum sharp ratio portfolio and global minimum variance portfolios

[10] Ledoit and Wolf [2014] showed approach to shrink correlation matrix to constant correlations in order to account for estimation error.

500 returns and CPI changes. The quintile 1 portfolio maximized inflation beta and quintile 5 portfolio minimized the inflation beta.

In Table 21, we found the volatility of the minimum volatility portfolio was lower than other constructs and that too with low equity beta. We also observed the performance of the minimum volatility portfolio was greater than that of equally weighted or maximum beta portfolios. The maximum beta portfolio had very high volatility; however, for quintile 1 portfolio it came along with expected objective of large inflation beta. This portfolio also had equity beta greater than 1. Depending on investor preference indeed alternative weighting schemes can be used alongside the choice of inflation sensitive equities to accentuate inflation sensitivity, by using maximum beta optimization or managing equity risk exposure—low volatility and equity beta as result of using minimum volatility optimization.

CLEWI AND MEDICAL EXPENSES

We also conducted portfolio optimization for CLEWI and medical expense portfolio sorts. We found while in sample optimized quintile portfolios regression results showed significant inflation betas, out of sample optimized quintile portfolios regression results showed inflation betas were not significant (not shown here).

For out of sample CLEWI optimized quintile portfolios, we only included stocks with in sample inflation beta greater than 1 from quintile 1 portfolio sort, and we only included stocks with beta less than -1 from quintile 5 portfolio sort. Similarly, for out of sample medical expense optimized quintile portfolios, we only included stocks with in sample inflation beta greater than 2.5 from quintile 1 portfolio sort, and we only included stocks with beta less than -2.5 from quintile 5 portfolio sort. The choice of betas is arbitrary based on beta distribution illustrated in Appendix F and G. We report regression test results for newly formed portfolios in Appendix J.

Reviewing regression test results for CLEWI optimized portfolios (out of sample) we found CLEWI inflation betas were significant and positive for both quintile 1 portfolios—one constructed using minimum volatility optimization and the other using maximum beta optimization. However, only quintile 5 portfolio constructed using minimum volatility optimization had significant and negative CLEWI inflation beta.

Reviewing regression test results for medical expense optimized portfolios (out of sample) we found MEDEXP inflation betas were significant and positive for quintile 1 portfolio constructed using minimum volatility optimization. Similarly, quintile 5 portfolio constructed using minimum volatility optimization had significant and negative MEDEXP inflation beta.

VI. SECTORS IN LIEU OF INDIVIDUAL EQUITIES DO NOT ALWAYS WORK

One might argue that rather than addressing inflation hedging using individual equities, equity sectors may be used instead. Of course, a definite advantage is no monthly rebalancing, no high turnovers, and therefore, limited transaction costs. In Table 22, reviewing sector performance from 1995 – 2013, we found energy, utilities, and materials sectors to have significant (at 99%, 95%, and 90% confidence interval respectively) positive betas to actual inflation. Consumer discretionary and telecom services sector had significant (99% confidence interval) negative betas to actual inflation. However, the in sample maximum beta optimized quintile 1 portfolio, sorted based on the actual inflation betas of individual equities as illustrated in section V, had ex-post inflation beta of 10.5; this is a lot larger than the energy sector actual inflation beta of 5.9.

There exists no more than one sector that could be used reliably when inflation in question is more specific, for example, CLEWI or medical expenses. Only information technology had positive significant beta (90% confidence interval) to CLEWI. Industrial and consumer staples sectors had negative significant beta (90% confidence interval) to CLEWI. For medical care inflation, the only sector with significant and positive beta is materials. Remaining sectors had inflation betas that are insignificant. Surprisingly, the health care sector has negative beta to the medical care inflation factor.

VII. CONCLUSION

We demonstrated a methodology for using individual equities for hedging inflation. We used multivariate regression, which utilized all available data and accounted for equity market factor and reporting lags in measures of inflation, when determining inflation betas for individual equities. We showed how such an approach can be used to create inflation-sensitive strategies for customized inflation indices. Not only did we show the approach works in sample but also out of sample for all the inflation indices. We illustrated strategies for the US headline CPI, Forbes' Cost of Living Extremely Well Index, and the US Medical Care Price Index.

The facet of customization is necessary since different kinds of inflation impact investors differently. For example, in retirement an investor is more concerned about medical expenses. For an investor with an affluent life style, the inflation bogey may be different; here, we used Forbes' CLEWI to define that.

We showed how alternative weighting schemes can be used alongside the choice of inflation sensitive equities to accentuate inflation sensitivity—by using maximum beta optimization—or managing risk, low volatility and equity beta as a result of using minimum volatility optimization. An investor can also simply opt for naïve diversification by equally weighting the equities in the portfolios without sacrificing inflation sensitivity; however, the portfolio has a higher risk than the minimum volatility portfolio.

There exists no directly investable asset class if investors' inflation bogeys are different. Our approach allows investors to align their investment portfolio closer to their investment goals.

Determining merits of the proposed portfolios—as part of investor's performance-seeking portfolio in presence of such bespoke liabilities—can serve as a next step to further this research.

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Appendix A

Widely-used inflation indicators include actual inflation, unexpected inflation (SURPRISE), and changes to expected inflation (REVISION). We propose principal component analysis and using first principal component factor returns to determine inflation beta. Using first principal component factor returns, which explains 76% of the variance, allows us to simultaneously address various effects and pick stock that are sensitive to all the three indicators.

Table A1

Principal Component Analysis, Eigen Values, and Eigen Vectors, for Actual Inflation, Unexpected Inflation, and Changes to Expected Inflation.

Eigen Values

Number	**Value**	**Difference**	**Proportion**	**Cum. Value**	**Cum. Proportion**
1	2.29	1.61	0.76	2.29	0.76
2	0.68	0.64	0.23	2.97	0.99
3	0.03	---	0.01	3	1

Eigen Vectors

Variables	**PCOMP1**	**PCOMP2**	**PCOMP3**
SURPRISE	0.63	-0.35	0.7
REVISION	0.45	0.89	0.05
CPI	0.64	-0.28	-0.72

The first principal component factor return has correlation 0.71 with S&P GSCI for the period from 10/31/1989 – 12/31/2013. For the same period, correlation to US equity markets is 0.18 and to a combination of long inflation portfolio and short deflation portfolio (formation described in Appendix C) is 0.49.

Appendix B

Table 1 displays inflation beta for handful of Fama-French industries with significant inflation betas. The inflation betas are obtained from in sample regression from 12/31/1994 – 12/31/2013. We also show inflation beta for a representative stock Adobe since it was featured in Ang et al. [2012]. We find inflation betas are overestimated if market factor is not used in regressions. Particularly note how Retail industry sign flips and has significant negative beta in reality. Similarly, inflation beta magnitude is definitely magnified for individual equities, as illustrated here for Adobe. Switching to principal component factor return, we find for most industries, improvement in t-statistics for inflation beta.

Table B1

In Sample Regression, Full Sample, Regressors: Inflation Factor (CPI/Principal Component), Dependent Variable: Industry/Adobe Returns

			Multiple Regression				**Multiple Regression**	
	CPI BETA	**CPI Beta T-Stat**	**CPI Beta (with S&P 500)**	**CPI Beta T-Stat (with S&P 500)**	**PCOMP Beta**	**PCOMP T-Stat**	**PCOMP Beta (with S&P 500)**	**PCOMP Beta T-Stat (with S&P 500)**
Oil	7.97	7.45	6.17	6.98	1.47	7.85	1.14	7.35
Coal	16.26	6.71	13.62	5.97	3.12	7.41	2.65	6.66
Mines	8.15	4.94	5.29	3.95	1.58	5.49	1.06	4.52
Mach	6.59	4.56	3.17	3.76	1.28	5.04	0.65	4.39
Steel	8.54	4.79	4.56	3.95	1.59	5.08	0.86	4.23
Gold	8.81	3.76	8.08	3.42	1.42	3.44	1.29	3.07
Whlsl	4.16	4.11	1.90	2.90	0.76	4.29	0.35	3.02
Chems	4.26	3.48	1.48	1.91	0.88	4.12	0.38	2.77
Util	3.31	3.81	2.18	2.77	0.59	3.83	0.38	2.72
MedEq	4.47	4.19	2.32	2.98	0.76	4.03	0.36	2.63
Agric	4.22	3.08	2.43	1.95	0.82	3.38	0.49	2.23
LabEq	5.38	3.56	2.03	2.06	0.98	3.67	0.36	2.07
Adobe	*4.49*	*1.42*	*0.43*	*0.15*	*0.95*	*1.71*	*0.21*	*0.41*
Trans	0.68	0.57	-2.01	-2.70	0.18	0.89	-0.31	-2.35
Telcm	0.95	0.82	-1.75	-2.52	0.19	0.91	-0.31	-2.55
Banks	0.26	0.18	-2.97	-3.36	0.10	0.42	-0.49	-3.13
Rtail	0.07	0.06	-2.47	-3.48	0.05	0.24	-0.42	-3.36
Meals	-0.41	-0.37	-2.72	-3.49	-0.05	-0.24	-0.47	-3.42

Instead of in sample analysis, we now look at average beta and t-statistics if regressions were performed every month using full sample up to that month (Table 2). With this out of sample approach, the number of industries with significant inflation beta—on average throughout the time period—decreases significantly.

Table B2

Out of Sample Regression, Full Sample, Regressors: Inflation Factor (CPI/Principal Component), Dependent Variable: Industry/Adobe Returns

			Multiple Regression				Multiple Regression	
	CPI BETA	**CPI Beta T-Stat**	**CPI Beta (with S&P 500)**	**CPI Beta T-Stat (with S&P 500)**	**PCOMP Beta**	**PCOMP T-Stat**	**PCOMP Beta (with S&P 500)**	**PCOMP Beta T-Stat (with S&P 500)**
Oil	6.70	4.26	6.95	4.95	1.32	4.52	1.50	5.68
Coal	10.19	3.17	10.46	3.31	2.04	3.48	2.26	3.83
Steel	3.17	1.58	3.37	2.10	0.53	1.54	0.80	2.57
Gold	7.70	2.05	7.83	2.02	1.39	1.95	1.48	1.98
Mines	1.96	1.32	2.00	1.40	0.38	1.48	0.53	1.89
Adobe	*-1.93*	*0.08*	*-1.38*	*-0.05*	*-0.43*	*0.11*	*-0.05*	*0.17*
Txtls	-4.33	-1.35	-4.14	-1.79	-1.05	-1.72	-0.86	-1.87
Clths	-4.56	-1.37	-4.08	-2.09	-1.07	-1.66	-0.77	-2.00
Insur	-2.78	-1.00	-2.34	-1.66	-0.83	-1.63	-0.57	-2.07
Rtail	-3.31	-1.34	-2.80	-2.31	-0.82	-1.73	-0.54	-2.31
Banks	-4.11	-1.38	-3.51	-2.42	-1.03	-1.82	-0.69	-2.47
Meals	-4.58	-1.90	-4.04	-2.85	-1.08	-2.32	-0.80	-2.92

We now look at average beta and t-statistics if regressions were performed every month using last five-year sample up to that month (Table 3). With this out of sample approach, number of industries with significant inflation beta—on average throughout the time period—whittles down to only two industries: namely Oil and Coal.

Table B3

Out of Sample Regression, 5 Year Rolling Sample, Regressors: Inflation Factor (CPI/Principal Component), Dependent Variable: Industry/Adobe Returns

			Multiple Regression				**Multiple Regression**	
	CPI BETA	**CPI Beta T-Stat**	**CPI Beta (with S&P 500)**	**CPI Beta T-Stat (with S&P 500)**	**PCOMP Beta**	**PCOMP T-Stat**	**PCOMP Beta (with S&P 500)**	**PCOMP Beta T-Stat (with S&P 500)**
Oil	9.02	3.25	7.74	3.02	1.75	3.4	1.58	3.24
Coal	16.73	3.19	14.92	2.82	3.15	3.34	2.93	2.99
Adobe	*9.61*	*1.13*	*7.14*	*0.47*	*2.21*	*1.38*	*1.89*	*0.75*

Appendix C

Using in sample inflation betas—regressors include first principal component factor returns and S&P 500—for Fama-French industries, we create two portfolios: one with positive inflation betas and the other with negative inflation betas. Each industry within the portfolio is proportionally weighted according to the magnitude of the inflation beta. Industry weights are illustrated in Table 1 of this section.

Table C1

Table Shows the Industry Weights in the Two Portfolios. Weights Are Determined Proportional to In Sample Inflation Beta of the Industries.

	Inflation		Deflation
Coal	20.70%	Banks	11.90%
Gold	10.10%	Meals	11.50%
Oil	8.90%	Rtail	10.30%
Mines	8.30%	PerSv	8.00%
Steel	6.70%	Telcm	7.60%
Mach	5.10%	Trans	7.50%
Agric	3.80%	Clths	5.90%
RlEst	3.30%	Beer	5.50%
FabPr	3.20%	Hshld	5.50%
Util	3.00%	Comps	5.30%
Chems	2.90%	Paper	3.50%
MedEq	2.80%	Food	3.30%
LabEq	2.80%	Rubbr	2.80%
Whlsl	2.70%	Insur	2.70%
Ships	2.70%	Drugs	2.40%
Smoke	2.30%	Toys	1.70%
Boxes	1.70%	Other	1.40%
Cnstr	1.60%	BusSv	1.10%
Hlth	1.30%	Autos	0.80%
ElcEq	1.20%	Fin	0.70%
Guns	1.20%	Soda	0.50%
Fun	1.10%		
Books	1.10%		
Aero	0.70%		
Chips	0.40%		
Txtls	0.20%		
BldMt	0.10%		

Upon reviewing the portfolio performance in Figure 1, no one portfolio outperformed over the full sample; however, in periods of very high inflation, we see the inflation portfolio outperforming the deflation portfolio.[11] The portfolio subsequently outperformed in better half of the commodity super cycle, from beginning of 2000 leading up to the financial crisis.[12]

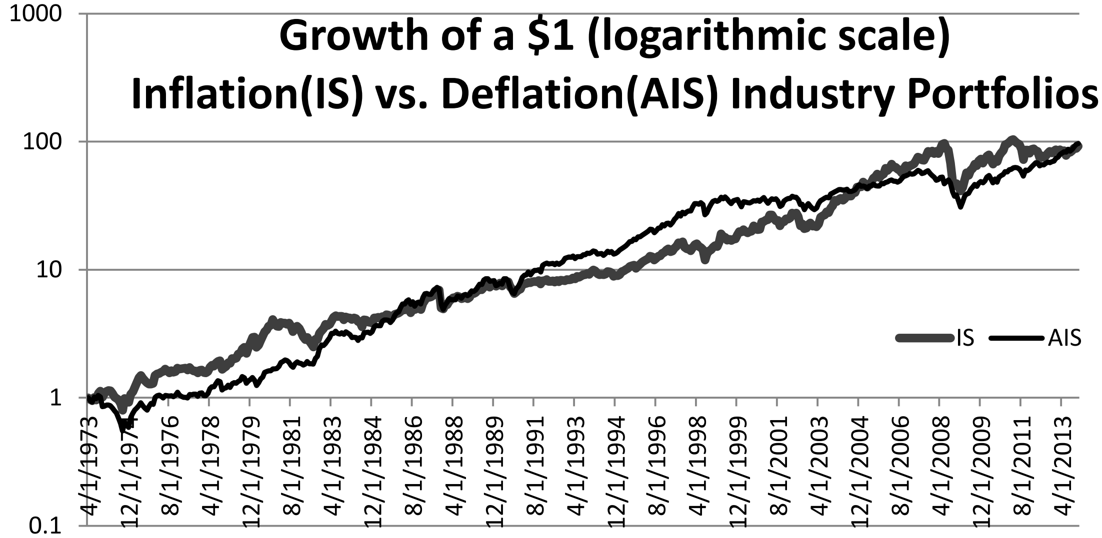

Figure C1

We evaluate the portfolio performance using Fama-French and Carhart Factors (Table 2). We also include inflation factor which is the first principal component factor returns. Monthly analysis period is from 10/31/1989 - 12/31/2013.

[11] The period of 1965 to 1982 is regarded as the great inflation era. http://www.federalreservehistory.org/Period/Essay/13

[12] After 2002 and before the last quarter of 2008 commodity prices rose beyond their historic trend, Kaplinsky [2010].

Table C2

	In Sample Inflation Beta Weighted Portfolios								
	Inflation	**Inflation**	**Deflation**	**Deflation**	**Inflation less Deflation**	**Inflation less Deflation**	**GSCI**	**GSCI**	**S&P500**
Intercept	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mkt-RF	**1.01**	**0.94**	**0.95**	**0.97**	0.07	-0.03	**0.34**	**0.13**	**0.99**
SMB	**0.27**	**0.25**	-0.01	-0.01	**0.28**	**0.25**	0.15	0.10	**-0.18**
HML	**0.43**	**0.38**	**0.24**	**0.25**	**0.19**	0.13	**0.29**	0.16	**0.03**
RF	1.31	0.46	0.67	**0.98**	0.64	-0.52	2.27	-0.13	**1.17**
MOM	0.04	0.02	**-0.07**	**-0.06**	**0.11**	0.08	**0.18**	**0.13**	**-0.02**
Inflation		**0.99**		**-0.35**		**1.34**		**2.78**	-0.02
R-Squared	0.63	0.69	0.9	0.92	0.07	0.29	0.07	0.52	0.99

Referring to the Table 2 results, we illustrate merits of using macro factors such as the inflation factor. We see how—for long short equity portfolio (Inflation less Deflation), when only using the FFC factors—the R-squared is 0.07. However, including inflation factor remarkably improves the R-squared to 0.29. We see that the inflation factor beta for Inflation portfolio is 0.99 and significant (bold implying significant at 95% confidence interval). For the Deflation portfolio, inflation beta is -0.35 and significant. Inflation less Deflation portfolio has significant small cap bias with SMB beta of 0.25. The inflation beta for this long short portfolio is 1.34 and significant. This is half the magnitude of inflation beta for S&P Goldman Sachs Commodity Index (GSCI).

Appendix D

FORBES' Exclusive Cost of Living Extremely Well Index (CLEWI) That Tracks the Prices of Forty Ultraluxury Goods. Index, Created in 1976, Tracks Prices of Items That Are Affordable Only to Those With Very Substantial Means.

Compositions of Forbes Cost of Living Extremely Well Index

http://b-i.forbesimg.com/scottdecarlo/files/2013/09/2013_Clewi_table-9-17-13_III.png

Item	Price 2013	Price change from 2012
Airplane/Learjet 70, standard equipment, certified, 7 passengers/Bombardier, Canada	$11,296,000	NA
Automobile/Phantom Drophead Coupe/Rolls-Royce Motor Cars, U.K.	$470,000	NA
Catered dinner/serving 40 people/Ridgewells, Md.	$7,600	3%
Caviar/Tsar Imperial Sevruga, one kilo/Petrossian, Calif. & N.Y.	$13,600	0%
Champagne/Dom Perignon Magnum 2003, case/Sherry-Lehmann, N.Y.	$2,879	NA
Chateaubriand/seven pounds/Lobel's, N.Y.	$595	13%
Cigars/Aniversario No. 1, Dominican Republic, 25 cigars/Davidoff, N.Y.	$900	0%
Coat/natural Russian sable/Maximilian at Bloomingdale's, N.Y.	$295,000	11%
Dinner/Grand Menu, estimated per person (including wine and tip)/La Tour d'Argent Paris, France	$353	9%
Face-lift/well-recognized and experienced Facial Plastic Surgeon, N.Y.	$18,500	0%
Flowers in season/arrangements for 6 rooms per month, changed weekly/Jerome Florists, N.Y.	$8,175	0%
Handbag/"Jypsière", clemence bull calf leather, 28 cm/Hermès, France	$7,300	0%
Helicopter/Deluxe Executive VIP S-76D/Sikorsky Aircraft, Conn.	$16,250,000	5%
Hospital/one-day VIP, concierge, security, gourmet meals, supplies, specialized nursing care/MedStar Washington Hospital Center, Wash. D.C.	$3,096	14%
Hotel/average rate for one night, Manhattan One-Bedroom Suite/Four Seasons, N.Y.	$4,550	-5%
Lawyer/average hourly fee for estate planning by partner/Schlesinger, Gannon & Lazetera LLP, N.Y.	$950	0%
Loafers/horsebit in leather/Gucci, Italy	$545	10%
Magazine/one-year subscription/Forbes, N.Y.	$60	0%
Motor yacht/80 MY (with 1,600hp Caterpillar C-32 engines)/Hatteras Yachts, N.C.	$5,336,000	4%
Opera/two tickets, six Saturday night performances, Center Parterre Premuim seats/Metropolitan Opera, N.Y.	$4,570	-2%
Perfume/1000 Parfum, 0.5 oz./Jean Patou, France	$350	0%
Piano/concert grand, Model D, ebonized/Steinway & Sons, N.Y.	$142,300	4%
Psychiatrist/45 minutes, standard fee/Upper East Side, N.Y.	$350	0%
Sailing yacht/Oyster 625/Oyster Yachts, U.K.	$3,400,000	-4%
Sauna/8-by-10-by-7 feet, eight-person, Nordic Spruce, Abachi/Finnleo Sauna, Minn.	$16,860	2%
School/preparatory, one-year tuition, room & board/Groton School, Mass.	$53,870	4%
Sheets/set of king-size Italian linen, "Paris Opera Pizzo"/Frette, Italy	$2,940	NA
Shirts/one dozen cotton, bespoke/Turnbull & Asser, U.K.	$4,860	5%
Shoes/men's black calf wing tip, custom-made/John Lobb, U.K.	$5,446	8%
Shotgun/pair of James Purdey & Sons (12 gauge side-by-sides)/Griffin & Howe, N.J. &	$225,395	2%
Silk Dress/classic/Bill Blass Fashions, LLC, N.Y.	$1,900	-5%
Spa/Co-ed weekly rate/Golden Door, Calif.	$7,850	1%
Sterling Silver Flatware/Francis I pattern, 5-piece dinner set for 12/Reed & Barton, Mass.	$9,927	NA
Swimming pool/Olympic-size (50 meters)/Mission Pools, Calif.	$1,442,000	3%
Tennis court/clay court/Putnam Tennis and Recreation, Conn.	$55,000	0%
Thoroughbred/yearling, average price, Saratoga Summer Select Sale/Fasig-Tipton, Ky.	$295,093	-1%
Train set/Pennsylvania Flyer Freight Train, Lionel/FAO Schwartz, N.Y.	$230	0%
Travel Bag/Keepall Bandouliere 60 with strap/Louis Vuitton, France	$1,620	3%
University/one-year tuition, room & board, insurance/Harvard University, Mass.	$56,407	4%
Watch/Calatrava,classic men's in yellow gold with alligator strap/Patek Philippe, Switzerland	$20,800	0%
NA: Not available or applicable.		

Appendix E

Distribution of actual inflation beta for the S&P 500 individual equities from 12/31/1994 – 12/31/2013.

***Bin* (Inflation Beta)**	***Frequency***	***Cumulative %***
-10	16	1.7%
-5	89	11.0%
-2.5	126	24.2%
-1	128	37.6%
0	100	48.1%
1	106	59.2%
2.5	123	72.1%
5	128	85.5%
10	73	93.2%
15	51	98.5%
More	14	100.0%

Appendix F

Distribution of inflation beta (to CLEWI) for the S&P 500 individual equities from 12/31/1994 – 12/31/2013.

Bin (Inflation Beta)	***Frequency***	***Cumulative %***
-7.5	3	0.3%
-5	6	0.9%
-2.5	50	6.2%
-1	180	25.1%
0	296	56.1%
1	214	78.5%
2.5	121	91.2%
5	75	99.1%
7.5	5	99.6%
10	2	99.8%
More	2	100.0%

Appendix G

Distribution of inflation beta (to medical care price index) for the S&P 500 individual equities from 12/31/1994 – 12/31/2013.

Bin (Inflation Beta)	*Frequency*	*Cumulative %*
-15	10	1.1%
-10	11	2.2%
-7.5	16	3.9%
-5	32	7.2%
-2.5	79	15.5%
-1	108	26.8%
0	126	40.0%
1	105	51.1%
2.5	142	65.9%
5	162	82.9%
7.5	68	90.0%
10	46	94.9%
15	34	98.4%
More	15	100.0%

Appendix H

Table H1

ROLLING 5 YEAR, REGRESSOR: ACTUAL INFLATION, OUT OF SAMPLE REGRESSION ANALYSIS

Table H1 shows the regression betas for the quintile portfolios for the monthly sample from 12/31/1994 – 12/31/2013. As mentioned before, the equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas are derived for individual equities using rolling five-year sample and changes in actual inflation (CPI) as regressor. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

	CPI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	3.10***	-0.31***	0.65	0.12**	0.29***	1.19***	0.00	0.86
quintile 5	-0.77	-0.07***	1.59**	0.41***	-0.07*	0.96***	0.00	0.84
quintile 1 minus quintile 5	3.87***	-0.23***	-0.94	-0.29***	0.36***	0.23***	0.00	0.40

Table H2

FULL SAMPLE, REGRESSORS: EQUITY MARKET & 1ST PRINCIPAL COMPONENT OF INFLATIONS (OUT OF SAMPLE REGRESSION ANALYSIS)

Table H2 shows the regression betas for the quintile portfolios for the monthly sample from 12/31/1994 – 12/31/2013. As mentioned before, the equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas are derived for individual equities using full sample, equity market factor and first principal component (Appendix A) as regressors. ***, **, and * denote 99%, 95%, and 90% confidence interval, respectively.

	CPI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	3.52***	-0.25***	0.69	0.12*	0.22***	1.10***	0.00	0.83
quintile 5	-1.43***	-0.14***	1.36**	0.43***	0.02	1.11***	0.00	0.90
quintile 1 minus quintile 5	4.95***	-0.11**	-0.66	-0.32***	0.20***	-0.01	-0.01	0.26

Table H3

FULL SAMPLE, REGRESSORS: EQUITY MARKET & ALFRED VINTAGE CPI (OUT OF SAMPLE REGRESSION DIMSON BETA COMPARISON: OOS_RealCPI_Curr vs. OOS_RealCPI_Lead FOR QUINTILE 1 PORTFOLIOS)

Table H3 shows the regression betas for the quintile 1 portfolios for the monthly sample from 12/31/1994 – 12/31/2013. As mentioned before, the equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas are derived for individual equities using full sample, equity market factor and unrevised “real” actual inflation collected from vintage CPI data provided by St. Louis Fed ALFRED as regressors. However, the CPI from current month is used in case of first strategy (OOS_RealCPI_Curr) whereas next month CPI is used in case of later strategy (OOS_RealCPI_Lead). We find Dimson inflation beta has significant F-statistic (different from zero) when quintile 1 portfolio is constructed using next month CPI. ***, **, and * denote 99%, 95%, and 90% confidence interval, respectively.

beta	**OOS_RealCPI_Curr**		**OOS_RealCPI_Lead**	
alpha	0.00	0.00	0.00	0.00
CPI(-1)		-1.16*		-0.80
CPI	0.38	0.34	1.07	0.08
CPI(+1)		1.28*		3.35***
S&P 500	1.28***	1.26***	1.25***	1.20***
r-squared	0.82	0.82	0.73	0.75
CPI(Dimson)		0.46		2.62**

Appendix I

<u>*CLEWI*</u>

Table I1

IN SAMPLE REGRESSION TEST (5 FACTORS – FAMA-FRENCH, CARHART AND CLEWI)

Table I1 shows the 5 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, were derived using Fama-French, Carhart factors, and changes in CLEWI as regressors. Also reported are average inflation betas, monthly returns, and risk for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	**CLEWI**	**mom**	**rf**	**hml**	**smb**	**mkt-rf**	**alpha**	**r-squared**
quintile 1	2.07***	-0.24***	1.00	-0.03	0.18***	1.22***	-0.01***	0.90
quintile 5	-1.85***	-0.22***	0.72	0.55***	0.08**	1.07***	0.01***	0.90
quintile 1 minus quintile 5	3.92***	-0.01	0.27	-0.57***	0.11*	0.15***	-0.02***	0.52

average	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
beta	1.8	0.3	-0.3	-0.8	-2.1	3.9
returns	1.00%	1.05%	1.16%	1.07%	1.08%	-0.07%
risk	6.52%	5.01%	4.27%	4.38%	5.82%	3.85%

Table I2

IN SAMPLE REGRESSION TEST (5 FACTORS: FAMA-FRENCH, CARHART, AND MEDICAL EXPENSES)

Table I2 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). Equally weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using Fama-French, Carhart factors, and changes in medical care expense as regressors. Also reported are average inflation betas for each of the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval, respectively.

beta	MEDEXP	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	5.99***	-0.22***	-0.66	0.43***	0.21***	1.14***	-0.02***	0.92
quintile 5	-3.91***	-0.19***	2.46***	0.13***	0.07*	1.05***	0.01***	0.89
quintile 1 minus quintile 5	9.90***	-0.03	-3.12***	0.29***	0.14***	0.09**	-0.03***	0.32

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	5.8	2.3	0.9	-0.5	-4.5	10.3
returns	0.93%	1.02%	1.08%	1.18%	1.15%	-0.21%
risk	6.01%	4.97%	4.76%	4.39%	5.54%	2.81%

Appendix J

Table J1

REGRESSION TEST RESULTS FOR OUT OF SAMPLE QUINTILE PORTFOLIOS (BASED ON CLEWI BETA SORTS)

		2 Factor			5 Factor						
Q1		**CLEWI**	**SP500**	**alpha**	**CLEWI**	**mom**	**rf**	**hml**	**smb**	**mkt-rf**	**alpha**
min. vol	**beta**	0.80	1.01	0.00	0.90	-0.16	0.91	0.27	0.03	0.96	0.00
	t-statistics	1.98	27.26	-1.28	2.42	-5.30	1.10	5.45	0.74	26.34	-1.10
max. beta	**beta**	1.25	1.56	0.00	1.13	-0.37	2.48	-0.28	0.26	1.34	0.00
	t-statistics	1.65	22.63	-1.18	1.78	-7.28	1.76	-3.31	3.27	21.60	-0.81
Q5		**CLEWI**	**SP500**	**alpha**	**CLEWI**	**mom**	**rf**	**hml**	**smb**	**mkt-rf**	**alpha**
min. vol	**beta**	-0.73	0.74	0.01	-0.59	-0.05	0.55	0.46	-0.16	0.78	0.01
	t-statistics	-1.75	19.50	3.04	-1.72	-1.89	0.71	10.00	-3.78	23.11	2.47
max. beta	**beta**	-0.24	1.03	0.01	-0.02	-0.10	0.75	0.51	0.03	1.04	0.00
	t-statistics	-0.48	22.55	1.86	-0.05	-2.94	0.79	9.07	0.61	25.06	1.26
		Q1	**Q5**								
min. vol	**return**	0.87%	1.06%								
	risk	5.07%	4.21%								
max. beta	**return**	1.31%	1.31%								
	risk	8.27%	5.52%								

Table J2

REGRESSION TEST RESULTS FOR OUT OF SAMPLE QUINTILE PORTFOLIOS (BASED ON MEDICAL EXPENSE BETA SORTS)

		2 Factor			5 Factor						
Q1		**MEDEXP**	**SP500**	**alpha**	**MEDEXP**	**mom**	**rf**	**hml**	**smb**	**mkt-rf**	**alpha**
min. vol	**beta**	1.83	0.87	0.00	2.45	-0.10	0.28	0.50	-0.05	0.88	0.00
	t-statistics	1.17	20.17	-0.58	1.82	-2.95	0.31	9.11	-0.95	22.22	-0.96
max. beta	**beta**	1.99	1.37	-0.01	1.08	-0.28	0.31	0.17	0.32	1.24	0.00
	t-statistics	0.99	24.46	-0.91	0.65	-6.85	0.27	2.55	5.03	25.16	-0.02
Q5		**MEDEXP**	**SP500**	**alpha**	**MEDEXP**	**mom**	**rf**	**hml**	**smb**	**mkt-rf**	**alpha**
min. vol	**beta**	-3.55	0.82	0.02	-3.15	-0.03	1.21	0.34	-0.11	0.84	0.01
	t-statistics	-2.71	22.38	3.59	-2.57	-1.16	1.45	6.77	-2.28	23.25	3.00
max. beta	**beta**	-0.87	1.09	0.00	-1.21	-0.16	1.42	0.25	-0.02	1.04	0.00
	t-statistics	-0.55	24.99	0.84	-0.82	-4.51	1.41	4.15	-0.36	23.87	0.96
		Q1	**Q5**								
min. vol	**return**	1.00%	1.18%								
	risk	4.86%	4.41%								
max. beta	**return**	1.18%	1.11%								
	risk	7.15%	5.66%								

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Table 1

IN SAMPLE REGRESSION TEST (2 FACTORS – S&P500 AND CPI)

Table 1 shows the 2 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, were derived using equity market (S&P 500) returns and changes in actual inflation (CPI) as regressors. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CPI	S&P500	alpha	r-squared
quintile 1	6.27***	1.14***	-0.01***	0.78
quintile 5	-3.95***	1.11***	0.01***	0.81
quintile 1 minus quintile 5	10.22***	0.03	-0.02***	0.41

Table 2

IN SAMPLE REGRESSION TEST (5 FACTORS – FAMA-FRENCH, CARHART, AND CPI)

Table 2 shows the 5 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, were derived using equity market (S&P 500) returns and changes in actual inflation (CPI) as regressors. Also reported are average inflation betas, monthly returns, and risk for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CPI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	5.85***	-0.19***	0.87	0.28***	0.22***	1.07***	-0.01***	0.85
quintile 5	-4.22***	-0.16***	1.30**	0.51***	0.01	1.09***	0.01***	0.91
quintile 1 minus quintile 5	10.06***	-0.03	-0.43	-0.24***	0.21***	-0.02	-0.02***	0.48

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	6.9	1.6	0	-1.6	-4.9	11.8
returns	1.03%	1.10%	1.09%	1.19%	0.95%	0.08%
risk	6.49%	4.77%	4.90%	4.68%	5.37%	4.56%

Table 3
ACTUAL INFLATION BETAS BY INDUSTRIES (IN SAMPLE)

Table 3 shows average regression betas across all equities grouped by industries (monthly sample from 12/31/1994 – 12/31/2013). Inflation betas are derived for individual equities using equity market (S&P 500) returns and changes in actual inflation (CPI) as regressors.

Average Actual Inflation Betas by Industries			
Negative Beta		**Positive Beta**	
Travel & Leisure	-3.67	Support Services	0.39
Banks	-3.52	Food Producers	0.39
Nonlife Insurance	-2.7	Chemicals	0.41
Fixed Line Telecommunications	-2.6	Construction & Materials	0.63
Household Goods & Home Construction	-2.11	Electronic & Electrical Equipment	0.69
Food & Drug Retailers	-2.09	Aerospace & Defense	0.81
Financial Services (Sector)	-1.98	Tobacco	1.03
Automobiles & Parts	-1.89	Life Insurance	1.07
Leisure Goods	-1.81	Health Care Equipment & Services	1.08
Forestry & Paper	-1.61	Electricity	1.51
General Retailers	-1.37	Technology Hardware & Equipment	1.57
Real Estate Investment & Services	-1.19	Pharmaceuticals & Biotechnology	1.82
General Industrials	-0.93	Software & Computer Services	2.06
Industrial Transportation	-0.63	Gas, Water & Multiutilities	2.19
Beverages	-0.53	Real Estate Investment Trusts	2.59
Media	-0.51	Industrial Metals & Mining	3.65
Industrial Engineering	-0.35	Equity Investment Instruments	4.36
Mobile Telecommunications	-0.23	Mining	7.07
Personal Goods	-0.01	Alternative Energy	9.31
		Oil & Gas Producers	9.64
		Oil Equipment & Services	11.52

Table 4

IN SAMPLE REGRESSION TEST (2 FACTORS – S&P500 AND CLEWI)

Table 4 shows the 2 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). Equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in CLEWI as regressors. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CLEWI	S&P500	alpha	r-squared
quintile 1	2.11***	1.41***	-0.01***	0.81
quintile 5	-2.25***	1.05***	0.01***	0.75
quintile 1 minus quintile 5	4.36***	0.36***	-0.02***	0.24

Table 5

IN SAMPLE REGRESSION TEST (5 FACTORS – FAMA-FRENCH, CARHART, AND CLEWI)

Table 5 shows the 5 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). Equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in CLEWI as regressors. Also reported are average inflation betas for each of the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CLEWI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	2.09***	-0.29***	1.56*	-0.12**	0.21***	1.24***	-0.01***	0.89
quintile 5	-2.00***	-0.20***	0.73	0.62***	0.10**	1.03***	0.01***	0.90
quintile 1 minus quintile 5	4.09***	-0.10**	0.83	-0.74***	0.12*	0.21***	-0.02***	0.57

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	2.1	0.4	-0.3	-0.8	-2.1	4.2
returns	1.01%	1.12%	1.04%	1.08%	1.10%	-0.09%
risk	6.92%	4.99%	4.38%	4.29%	5.66%	4.53%

Table 6

CLEWI INFLATION BETAS BY INDUSTRIES (IN SAMPLE)

Table 6 shows average regression betas across all equities grouped by industries (monthly sample from 12/31/1994 – 12/31/2013). Inflation betas are derived for individual equities using equity market (S&P 500) returns and changes in CLEWI as regressors.

Average Inflation Betas (to CLEWI) by Industries			
Negative Beta		**Positive Beta**	
Real Estate Investment & Services	-3.36	Industrial Metals & Mining	0.08
Life Insurance	-1.22	Real Estate Investment Trusts	0.09
Nonlife Insurance	-1.03	Household Goods & Home Constr.	0.11
Oil & Gas Producers	-0.95	Industrial Engineering	0.16
Beverages	-0.90	Financial Services (Sector)	0.19
Mobile Telecommunications	-0.87	Forestry & Paper	0.40
Oil Equipment & Services	-0.80	Mining	0.49
Gas, Water & Multiutilities	-0.77	Construction & Materials	0.74
Banks	-0.77	Industrial Transportation	0.85
Food Producers	-0.74	Electronic & Electrical Equipment	0.87
Personal Goods	-0.63	Software & Computer Services	1.47
Travel & Leisure	-0.60	Technology Hardware & Equipment	2.00
Tobacco	-0.57	Alternative Energy	6.86
Chemicals	-0.47		
Food & Drug Retailers	-0.44		
Aerospace & Defense	-0.42		
Equity Investment Instruments	-0.39		
Media	-0.39		
Automobiles & Parts	-0.34		
General Retailers	-0.32		
Fixed Line Telecommunications	-0.26		
Leisure Goods	-0.22		
Health Care Equipment & Services	-0.20		
Pharmaceuticals & Biotechnology	-0.11		
Support Services	-0.08		
Electricity	-0.06		
General Industrials	-0.03		

Table 7

IN SAMPLE REGRESSION TEST (2 FACTOR – S&P500 AND MEDICAL EXPENSE)

Table 7 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). Equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in medical care expenses as regressors. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	MEDEXP	S&P500	alpha	r-squared
quintile 1	6.57***	1.36***	-0.02***	0.83
quintile 5	-3.61***	0.99***	0.02***	0.80
quintile 1 minus quintile 5	10.18***	0.37***	-0.04***	0.33

Table 8

IN SAMPLE REGRESSION TEST (5 FACTOR – FAMA-FRENCH, CARHART, AND MEDICAL EXPENSE)

Table 8 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). Equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and change in medical care expense as regressors. Also reported are average inflation betas for each of the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	MEDEXP	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	5.37***	-0.30***	0.52	0.07*	0.25***	1.21***	-0.02***	0.92
quintile 5	-3.79***	-0.13***	2.02***	0.35***	0.00	0.97***	0.01***	0.86
quintile 1 minus quintile 5	9.16***	-0.18***	-1.50*	-0.28***	0.25***	0.24***	-0.03***	0.56

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	7.3	2.5	0.8	-0.6	-3.6	10.8
returns	0.82%	1.04%	1.10%	1.12%	1.28%	-0.46%
risk	6.69%	4.95%	4.64%	4.65%	4.97%	3.59%

Table 9

MEDEXP (MEDICAL CARE) INFLATION BETAS BY INDUSTRIES (IN SAMPLE)

Table 9 shows average regression betas across all equities grouped by industries (monthly sample from 12/31/1994 – 12/31/2013). Inflation betas are derived for individual equities using equity market (S&P 500) returns and changes in medical care expense index as regressors.

Average Inflation Betas (to Medical Expense) by Industries			
Negative Beta		**Positive Beta**	
Travel & Leisure	-3.67	Support Services	0.39
Alternative Energy	-10.89	Food Producers	0.29
Fixed Line Telecommunications	-2.17	Equity Investment Instruments	0.58
Gas, Water & Multiutilities	-1.69	Industrial Transportation	0.73
Oil & Gas Producers	-1.2	Beverages	0.77
Pharmaceuticals & Biotechnology	-0.89	Financial Services (Sector)	1
Electricity	-0.85	Food & Drug Retailers	1.01
Media	-0.52	Household Goods & Home	1.07
Automobiles & Parts	-0.49	Nonlife Insurance	1.12
Banks	-0.46	Support Services	1.14
Forestry & Paper	-0.28	Personal Goods	1.4
Mining	-0.21	Construction & Materials	1.61
Oil Equipment & Services	-0.21	Real Estate Investment & Services	1.69
Aerospace & Defense	-0.08	Life Insurance	1.92
Industrial Engineering	0	Leisure Goods	1.96
		Health Care Equipment & Services	2.05
		Chemicals	2.23
		General Industrials	2.37
		Travel & Leisure	2.5
		General Retailers	2.68
		Real Estate Investment Trusts	2.86
		Industrial Metals & Mining	4.04
		Electronic & Electrical Equipment	4.08
		Tobacco	4.28
		Software & Computer Services	4.41
		Technology Hardware & Equipment	4.93
		Mobile Telecommunications	5.64

Table 10

OUT OF SAMPLE REGRESSION TEST (2 FACTOR – S&P500 AND CPI)

Table 10 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in actual inflation (CPI) as regressors—regressions use full sample data up to prior month. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CPI	S&P500	alpha	r-squared
quintile 1	3.63***	1.19***	-0.01**	0.76
quintile 5	-0.84	1.14***	0.00	0.83
quintile 1 minus quintile 5	4.47***	0.05	-0.01***	0.11

Table 11

OUT OF SAMPLE REGRESSION TEST (FIVE FACTORS – FAMA-FRENCH, CARHART AND CPI)

Table 11 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in actual inflation (CPI) as regressors—regressions use full sample data up to prior month. Also reported are average inflation betas for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CPI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	3.34***	-0.24***	0.89	0.14**	0.19***	1.09***	0.00	0.83
quintile 5	-1.22***	-0.14***	1.46**	0.44***	0.07*	1.12***	0.00	0.91
quintile 1 minus quintile 5	4.56***	-0.11**	-0.57	-0.30***	0.13*	-0.03	-0.01	0.21

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	8.9	1.9	-0.6	-2.7	-6.6	15.5
returns	1.10%	1.12%	1.07%	1.04%	1.02%	0.07%
risk	6.44%	4.80%	4.57%	4.76%	5.51%	3.93%

Table 12

SECTOR WEIGHTS FOR SORTS BASED ON ACTUAL INFLATION BETA (OUT OF SAMPLE REGRESSION)

Table 12 shows average, minimum, and maximum sector weights, during the analysis period, for quintile 1 portfolios. Our approach uses full sample data and equity market (S&P 500) factor as regressor along with actual inflation factor. The other approach similar to Ang et al. [2012] uses rolling five-year sample data and only actual inflation factor as regressor. Note both quintile portfolios are equally weighted.

	Quintile 1 (Full Sample)			Quintile 1 (5 Year Rolling)		
Sectors	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**
Basic Materials	7.60%	2.10%	18.00%	7.40%	3.10%	14.50%
Consumer Cyclicals	4.60%	0.00%	14.80%	8.80%	0.00%	26.40%
Consumer Non-Cyclicals	3.70%	0.00%	10.40%	4.00%	0.00%	13.60%
Energy	30.20%	20.10%	41.60%	26.20%	4.10%	41.20%
Financials	6.80%	1.00%	15.70%	8.50%	0.00%	28.10%
Healthcare	11.10%	4.20%	16.60%	8.40%	3.10%	16.60%
Industrials	6.20%	2.10%	14.60%	9.00%	2.10%	22.00%
Technology	19.00%	3.10%	41.20%	20.50%	2.10%	49.50%
Telecommunications Services	1.30%	0.00%	6.20%	1.20%	0.00%	6.20%
Utilities	9.10%	3.10%	16.90%	5.60%	0.00%	18.70%

Table 13

TOP 20 STOCKS SORTS BASED ON ACTUAL INFLATION BETA (OUT OF SAMPLE REGRESSION)

Table 13 shows top 20 stocks for 12/31/2013 for quintile 1 portfolios. Our approach uses full sample data and equity market (S&P 500) factor as regressor along with actual inflation factor. The other approach similar to Ang et al. [2012] uses rolling five-year sample data and only actual inflation factor as regressor. Note both quintile portfolios are equally weighted.

Rank	Quintile 1 (Full Sample)	Quintile 1 (Five Year Rolling)
1	CHESAPEAKE ENERGY	GENERAL GW.PROPS.
2	GENERAL GW.PROPS.	GENWORTH FINANCIAL CL.A
3	PIONEER NTRL.RES.	TESORO
4	CONSOL EN.	LINCOLN NATIONAL
5	NATIONAL OILWELL VARCO	NATIONAL OILWELL VARCO
6	DENBURY RES.	NOBLE
7	VALERO ENERGY	VALERO ENERGY
8	NABORS INDUSTRIES	TENET HEALTHCARE
9	NOBLE	CAMERON INTERNATIONAL
10	PEABODY ENERGY	ENSCO CLASS A
11	RANGE RES.	HARTFORD FINL.SVS.GP.
12	HELMERICH & PAYNE	TRANSOCEAN
13	CAMERON INTERNATIONAL	HESS
14	NEWFIELD EXPLORATION	MORGAN STANLEY
15	ROWAN COMPANIES CL.A	CLIFFS NATURAL RESOURCES
16	CABOT OIL & GAS 'A'	PRUDENTIAL FINL.
17	ENSCO CLASS A	PRINCIPAL FINL.GP.
18	TRANSOCEAN	GANNETT
19	HESS	HALLIBURTON
20	MOSAIC	LSI

Table 14

OUT OF SAMPLE REGRESSION TEST (2 FACTORS – S&P500 AND CLEWI)

Table 14 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using full sample and equity market (S&P 500) returns and changes in CLEWI as regressors (regressions use full sample data up to prior month). ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CLEWI	S&P500	alpha	r-squared
quintile 1	0.67	1.36***	0.00	0.81
quintile 5	-0.25	1.08***	0.00*	0.82
quintile 1 minus quintile 5	0.91*	0.28***	-0.01***	0.15

Table 15

OUT OF SAMPLE REGRESSION TEST (5 FACTORS – FAMA-FRENCH, CARHART, AND CLEWI)

Table 15 shows the regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using full sample and equity market (S&P 500) returns and changes in CLEWI as regressors—regressions use full sample data up to prior month. Also reported are average inflation betas for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CLEWI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	0.70*	-0.31***	1.38*	0.05	0.21***	1.20***	0.00	0.89
quintile 5	-0.08	-0.16***	1.01*	0.42***	0.05	1.05***	0.00	0.91
quintile 1 minus quintile 5	0.78*	-0.15***	0.37	-0.38***	0.16***	0.15***	-0.02***	0.39

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	2.4	0.4	-0.3	-0.9	-2.3	4.7
returns	1.00%	1.00%	1.04%	1.14%	1.18%	-0.18%
risk	6.68%	5.04%	4.40%	4.34%	5.32%	3.22%

Table 16
SECTOR WEIGHTS FOR SORTS BASED ON CLEWI BETA (OUT OF SAMPLE REGRESSION)

Table 16 shows average, minimum and maximum sector weights, during the analysis period, for quintile 1 portfolios. Our approach uses full sample data and equity market (S&P 500) factor as regressor along with CLEWI inflation factor. Note quintile portfolio is equally weighted.

	Quintile 1 (Full Sample)		
Sectors	**Average**	**Min**	**Max**
Basic Materials	6.30%	1.00%	15.90%
Consumer Cyclicals	13.20%	5.20%	20.80%
Consumer Non-Cyclicals	2.50%	0.00%	6.20%
Energy	2.10%	0.00%	6.30%
Financials	10.90%	2.10%	21.10%
Healthcare	8.00%	4.10%	15.70%
Industrials	17.60%	8.30%	40.40%
Technology	34.80%	17.60%	46.30%
Telecommunications Services	1.10%	0.00%	4.20%
Utilities	2.90%	0.00%	7.20%

Table 17

TOP 20 STOCKS FOR SORTS BASED ON CLEWI BETA (OUT OF SAMPLE REGRESSION)

Table 17 shows top 20 stocks for 12/31/2013 for quintile 1 portfolios. Our approach uses full sample data and equity market (S&P 500) factor as regressor along with CLEWI inflation factor. Note the quintile portfolio is equally weighted.

Rank	Quintile 1 (Full Sample)
1	NETFLIX
2	FIRST SOLAR
3	BROADCOM 'A'
4	QUANTA SERVICES
5	EMC
6	CF INDUSTRIES HDG.
7	LSI
8	COVIDIEN
9	BEST BUY
10	HUDSON CITY BANC.
11	E*TRADE FINANCIAL
12	RED HAT
13	XILINX
14	NETAPP
15	PERKINELMER
16	JUNIPER NETWORKS
17	VERTEX PHARMS.
18	YAHOO
19	INTEL
20	DELTA AIR LINES

Table 18

OUT OF SAMPLE REGRESSION TEST (2 FACTORS – S&P 500 AND MEDICAL EXPENSES)

Table 18 shows the regression test results for the quintile portfolios (or the monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in medical care price index as regressors—regressions use full sample data up to prior month. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively. Note we only include stocks with in sample inflation beta greater than or less than 2.5 from each of the quintile portfolios.

beta	MEDEXP	S&P500	alpha	r-squared
quintile 1	3.53**	1.31***	-0.01*	0.81
quintile 5	-3.61**	1.09***	0.01***	0.77
quintile 1 minus quintile 5	7.15***	0.23***	-0.02***	0.17

Table 19

OUT OF SAMPLE REGRESSION TEST (5 FACTORS – FAMA-FRENCH, CARHART AND MEDICAL EXPENSE)

Table 19 shows the regression test results for the quintile portfolios (or the monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, are derived using equity market (S&P 500) returns and changes in medical care price index as regressors—regressions use full sample data up to prior month. Also reported are average inflation betas for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively. Note we only include stocks with in sample inflation beta greater than or less than 2.5 from each of the quintile portfolios.

beta	MEDEXP	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	2.28**	-0.31***	1.18	0.15***	0.25***	1.16***	0.00	0.91
quintile 5	-3.99***	-0.16***	1.44	0.25***	0.00	1.04***	0.01***	0.81
quintile 1 minus quintile 5	6.27***	-0.15***	-0.26	-0.10*	0.25***	0.13***	-0.02***	0.31

average	Q1	Q5	Q1-Q5
beta	9.1	-6.9	16
returns	1.22%	1.22%	0.01%
risk	6.50%	5.55%	3.23%

Table 20

IN SAMPLE REGRESSION TEST (5 FACTOR – FAMA-FRENCH, CARHART, AND CPI)

Table 20 shows the 5 factor regression test results for the quintile portfolios (monthly sample from 12/31/1994 – 12/31/2013). The equally-weighted quintile portfolios are formed by conducting inflation beta sorts on individual equities. Inflation betas for individual equities, used for sorting, were derived using Fama-French, Carhart factors, and changes in actual inflation (CPI) as regressors. Also reported are average inflation betas, monthly returns and risk for the quintile portfolios. ***, **, and * denote 99%, 95%, and 90% confidence interval respectively.

beta	CPI	mom	rf	hml	smb	mkt-rf	alpha	r-squared
quintile 1	5.64***	-0.17***	-0.05	0.45***	0.17***	1.03***	-0.01***	0.85
quintile 5	-4.37***	-0.16***	1.89***	0.40***	0.02	1.14***	0.01***	0.92
quintile 1 minus quintile 5	10.01***	0.00	-1.94*	0.06	0.15**	-0.11**	-0.01***	0.45

average	Q1	Q2	Q3	Q4	Q5	Q1-Q5
beta	5.3	0.9	-0.6	-1.9	-4.8	10.1
returns	1.01%	1.06%	1.15%	1.15%	0.99%	0.02%
risk	6.15%	4.84%	4.78%	4.75%	5.54%	4.21%

Table 21

IN SAMPLE AND OUT SAMPLE REGRESSION TEST (2 FACTOR S&P AND CPI AND 5 FACTOR – FAMA-FRENCH, CARHART, AND CPI)

We conduct minimum volatility portfolio and maximum beta portfolio optimization for both in sample and out of sample quintile portfolio sorts.

	In Sample			
	Minimum Volatility		**Maximum Beta**	
beta	**Quintile 1**	**Quintile 5**	**Quintile 1**	**Quintile 5**
2 factor				
CPI	4.02***	-3.83***	11.10***	-6.52***
S&P 500	0.61***	0.65***	1.11***	1.07***
alpha	0.00	0.01***	-0.02***	0.01***
r-squared	0.69	0.68	0.61	0.68
5 factor				
CPI	3.76***	-3.95***	10.50****	-6.77***
mom	-0.02	-0.05*	-0.14**	-0.16***
rf	1.44*	2.02***	0.97	1.74*
hml	0.23***	0.23***	0.17	0.47***
smb	-0.04	-0.14***	0.30***	-0.01
mkt-rf	0.63***	0.65***	1.05***	1.05***
alpha	0.00	0.01***	-0.02***	0.01***
r-squared	0.73	0.73	0.66	0.77
returns	1.21%	1.17%	1.14%	0.84%
risk	3.82%	3.47%	8.16%	5.72%
	Out Sample			
	Minimum Volatility		**Maximum Beta**	
beta	**Quintile 1**	**Quintile 5**	**Quintile 1**	**Quintile 5**
2 factor				
CPI	3.77***	-1.61***	7.51***	-0.92
S&P 500	0.65***	0.79***	1.30***	1.17***
alpha	0.00	0.00**	-0.01***	0.00
r-squared	0.54	0.68	0.60	0.73
5 factor				
CPI	3.52***	-1.70***	7.21***	-1.57**
mom	0.01	0.00	-0.26***	-0.09**
rf	0.48	1.09	1.57	2.34**
hml	0.49***	0.39***	-0.08	0.46***
smb	-0.08	-0.25***	0.16	0.15***
mkt-rf	0.71***	0.84***	1.18***	1.17***
alpha	0.00	0.00	-0.01**	0.00
r-squared	0.66	0.77	0.65	0.80
returns	1.19%	0.83%	1.08%	1.06%
risk	4.43%	4.22%	8.50%	6.05%

Table 22

S&P SECTOR PERFORMANCE INFLATION BETA (IN SAMPLE)

Monthly regressions are conducted with dependent variable as sector performance and S&P 500 as regressor. Also included as regressors are the respective inflation indices (CPI, Medical Care or CLEWI).

	CPI		**MEDEXP**		**CLEWI**	
	beta	**t-Stat.**	**beta**	**t-Stat.**	**beta**	**t-Stat.**
Energy	5.93	6.25	-0.24	-0.10	-1.03	-1.46
Industrials	-0.61	-1.18	1.67	1.45	-0.61	-1.74
Health care	0.65	0.85	-1.91	-1.12	0.06	0.12
Financials	-1.59	-2.50	0.82	0.57	0.07	0.16
Utilities	2.16	2.29	-0.46	-0.21	0.71	1.10
Materials	1.56	1.78	4.42	2.27	-0.81	-1.35
Consumer discretionary	-1.81	-3.34	-1.08	-0.87	-0.18	-0.48
Consumer staples	-0.48	-0.71	0.14	0.09	-0.81	-1.77
Telecom services	-3.51	-3.27	1.54	0.63	-0.11	-0.15
Info technology	-0.72	-0.90	-1.23	-0.69	0.92	1.69

The Cross-Sectional Dispersion and Volatility of Bond Returns and Manager Outperformance

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I. MOTIVATION AND PRIOR LITERATURE

Most academic literature associated with active management finds that the active managers in aggregate underperform relative to their benchmarks. Carhart [1997] finds that the average actively managed U.S. mutual fund underperforms its benchmark by over 1% per year on a net return basis.

Nonetheless, Fischer and Wermers [2012, p. 287] note that the proponents of active management argue its benefits are most pronounced in periods of heightened volatility and economic stress. Kacperczyk, Nieuwerburgh, and Veldkemp [2013] show that the effectiveness of manager skills is time-varying and also market-environment-dependent. They find that the same fund managers who pick stocks well in expansion periods also time the market well in recession. These fund managers significantly outperform other funds and their respective passive benchmarks.

One of the conclusions in McEnally and Todd [1992] is that cross-sectional volatility in common stock returns is time-varying, revealing implications on the value of diversification, the potential rewards from security selection, and the risk of being wrong in favorable market environments. Later, Ankrim and Ding [2002] show that measures of volatility and dispersion, which quantify the variability in stock or sector returns in a market within any given period, are related. Thus, changes in longitudinal or cross-sectional volatility of returns are of interest to investors, as they suggest a changing active management environment.

However, there is limited literature showing the impact of market environment on security alpha or on manager outperformance.[13] Gorman, Sapra, and Weigand [2010b] show how the dispersion of stock level alpha in U.S. equity markets changes with both longitudinal and cross-sectional market volatility. The authors cite that this relationship is becoming part of conventional wisdom in investing.[14]

De Silva, Sapra, and Thorley [2001] provide a unique treatment of this subject by extending the performance measurement literature. To resolve the performance noise issue, they recommend a weighted least squares procedure by dividing excess fund and market returns by period-specific dispersion. Accounting for time-varying dispersion impact helps in estimating the true alpha for the fund; however, it ignores the question of what is the impact of the dispersion on manager outperformance. After all, the managers should be able to systematically exploit the opportunity, and the impact should not dissipate due to portfolio construction constraints and other related issues.[15]

Gorman et al. [2010b] further show that the cross-sectional dispersion of U.S. equity returns provides accurate forecasts of the dispersion of alpha over both three-month and one-year horizons. Again, very limited literature has exploited dispersion to scale active risk budget. Reibnitz [2015] shows active strategies have the greatest impact on returns during periods of high dispersion, when alpha produced by the most active funds

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[13]This relationship is primarily established using the theoretical framework employed in Yu and Sharaiha [2007] and Gorman, Sapra, and Weigand [2010a]. Empirically, literature such as Ankrim and Ding [2002] and Bouchey, et al. [2011], which use stylized facts or correlation studies, only show relationship of cross-sectional volatility with equity manager returns dispersion.

[14]In the *Financial Times*, Rosanne Pane of Standard & Poors cited lower cross-sectional dispersion as a major reason why fixed income managers have a harder time than equity managers outperforming their benchmarks [Grene, 2008].

[15] Clarke, de Silva, and Thorley [2002] term the portfolio efficiency measure as the “transfer coefficient.”

significantly exceeds that produced in the other months. Deciding when to invest in active funds, therefore, can be as important as deciding which funds to invest in. She shows that switching between highly active and passive funds based on dispersion produces significant alpha of over 2.7% p.a., after fees.

We find that various threads of active management literature cited above have been more focused on equity markets. We contribute to academic literature by addressing these several questions using the active fixed income manager universe.

We concur with broad literature by showing that the average outperformance of fixed income managers is insignificant.[16] We review both longitudinal and cross-sectional volatility in the bond markets and demonstrate that they are related and that both are time-varying [McEnally & Todd, 1992; Ankrim & Ding, 2002]. We establish and empirically quantify the impact of the volatility and dispersion on fixed income manager outperformance [Gorman et al., 2010a,b; De Silva et al., 2001].[17] To check for robustness, we quantify the impact for equity universe as well, where the relationship is already shown to exist. We further the time-varying skills literature [Kacperczyk, 2013] as we demonstrate that fixed income manager skills are more effective in periods of rising yield and periods of rising volatility. Finally, we add to timing active passive literature [Reibnitz, 2015] by demonstrating how the dispersion in fixed income sector returns can be used as an indicator to time when to go active versus passive for fixed

[16]Other widely cited studies include Elton, et al. [1993], Brown and Goetzmann [1995], and Bogle [1998]. Barras, Scalliet, and Wermers [2010] estimate 75% of funds generate zero-alpha (net of expenses), which is consistent with the Berk and Green [2004] equilibrium. More recently, Busse, Goyal, and Wahal [2010] conclude that there is little evidence of superior performance even before fees. Blake, Elton, and Gruber [1993] show how overall and for subcategories of bond funds underperform relevant indices post-expenses.

[17]De Silva et al. [2001] recommend that the alpha estimation can be made more robust by accounting for different fund betas and style biases. In our paper we correct for style biases.

income investments, alternatively implying the active risk budget should be scaled commensurate with the opportunity.[18]

The rest of the paper is organized as follows: in section II we discuss the data and the methodology used in this paper. In section III, by reviewing manager outperformance conditional on yield regimes and conditional on changes in volatility, we show that the opportunity and effectiveness of skills are time-varying. In the section, we empirically establish and quantify the relationship of manager outperformance with dispersion (cross-sectional volatility) and volatility (longitudinal). Finally, in the section we conduct several robustness checks to ensure the validity of our findings by similarly assessing volatility impact on equity manager outperformance and by conducting extensive factor analysis on fixed income manager outperformance (using principal component factors). Lastly, in section IV we demonstrate the way cross-sectional dispersion indicators can be used for timing between active versus passive strategies in fixed income.

II. DATA AND METHODOLOGY

Besides the cross-section dispersion in U.S. equity returns Gorman et al. [2010b] used VIX to show the linkage between opportunity and dispersion in equity alpha. In order to define opportunity in fixed income, for our study we use MOVE (Merrill Option Volatility Estimate, a bond-implied volatility measure similar to VIX for stocks) and the cross-sectional volatility – standard deviation of fixed income sector returns[19] (CSV) as a

[18]Raubenheimer [2011] cites that ex ante, cross-sectional volatility must be considered hand in hand with risk limits and active risk targets when setting and monitoring investment mandates. The higher the cross-sectional volatility, the greater is the opportunity for active risk-taking, all other things being equal. Conversely, to remain efficient, active risk taking should be reduced during periods of low cross-sectional dispersion.
[19]Refer to Appendix A for list of indices.

measure of dispersion. Instead of firm or equity alpha, we directly use the manager outperformance. Similar to Gorman et al. [2010a], our analysis assumes constant skills; thus, we evaluate the 25th percentile manager outperformance and the median manager outperformance, which proxy for superior and mediocre skills, respectively. Figure 1 shows these monthly variables historically from 12/31/1988–9/30/2013.

We use eVestment U.S. core plus fixed income universe for the manager performance, gross of fees.[20] Iwanowski [1996] conducted the U.S. Fixed Income sector allocation research to demonstrate systematic sector risk premia. Hence, for a benchmark proxy we use an equal weighted fixed income sector benchmark; this choice of using average performance aligns with using CSV a as dispersion indicator.[21]

Longitudinal and cross-sectional volatility in the bond markets are interrelated. We conducted a Granger Causality test which reveals endogeneity between these variables, namely implied volatility (MOVE), cross-sectional volatility in fixed income sector returns (CSV), and the 25th percentile manager outperformance (TOPA). The results can be found in Table 1. MOVE and CSV Granger Cause each other and are endogenous. Similarly, both CSV and TOPA Granger Cause each other and are endogenous. TOPA and MOVE do not Granger Cause each other, implying that the real transmission mechanism is via CSV from MOVE to TOPA. As such, Gorman et al. [2010a] theory suggests these variables to be endogenous.

None of the variables Granger Cause changes in yield, implying that these variables do not precede the changes in 10-year U.S. government yield (*Source:* Datastream). This

[20] Additional details on eVestment database are provided in Appendix A.
[21] Refer to Appendix A for list of indices.

and other exogeneity test imply treating D(YIELD) as exogenous variable in our subsequent framework.

In order to evaluate the impact of opportunity on outperformance, we used a monthly vector autoregressive model of order 1 (VAR(1)). The model allows us to understand the interdependencies of these three endogenous variables: implied volatility (MOVE), cross-sectional volatility in fixed income sector returns (CSV), and the 25th percentile manager outperformance (TOPA).[22] We account for the style biases, since our dependent variable is manager outperformance, as measured by manager returns in excess of benchmark returns. Change in the U.S. 10-year government yield D(YIELD) is the exogenous variable in the model. Augmented Dickey Fuller tests show variables in the model are stationary.

Additionally, for robustness analysis we use the VAR(1) model for U.S. large cap core equity manager universe, and we assess the impact of equity volatility both longitudinally and cross-sectionally on manager outperformance. Similar to Gorman et al. [2010b], we use VIX as an indicator for inter-temporal volatility. We calculate the cross-sectional equity volatility using 30 Fama French industries.

While the suggested VAR framework is parsimonious, it confirms the linkage between opportunities, namely volatility and cross-sectional dispersion, and the manager outperformance. There are some additional concerns that ought to be addressed, such as the manager style biases beyond just duration bets, multicollinearity in the endogenous

[22] We conduct VAR stability and VAR Lag Order Selection Criteria tests, as shown in Appendix B.

variables, and an incomplete specification from some endogenous variables being omitted.

To address the omitted variables issue and to assess the lagged level impact, we also include the 10-year Constant Maturity Treasury yield and the spread between Moody's BAA Corporate Bond yield and the 10-year Constant Maturity Treasury yield as endogenous (lagged level) variables, along with MOVE and cross-sectional volatility in fixed income spread sector returns (CSVSPRD).[23]

We address the style bias issue by expanding the exogenous (change) variables set to include all four fixed income specific factors as in Fung and Hsieh [1997] and Martellini, Priaulet, and Priaulet [2005, p. 308].[24] Besides the four exogenous factors above, we propose using two more exogenous variables: monthly change in cross-sectional volatility in spread sectors D(CSVSPRD) and monthly change in MOVE denoted as D(MOVE). These two independent variables additionally qualify the outperformance. While the four fixed income specific factors help explain the skills, the latter two that we proposed help quantify the impact of breadth on outperformance.

To address multicollinearity, we create principal component factor returns from these exogenous and endogenous independent variables separately before conducting

[23]Simulating active management performance in fixed income has been addressed in literature for several regions including the U.S., Japan, and Euroland. The two key drivers essentially are rate anticipation spread trades and inter-market spread trades [Boyd & Mercer, 2010; Fabozzi, 2010].

[24]Location factors (typically approximated by payoffs from buy-and-hold policy), i.e., Sharpe's traditional factors include D(H15Yield) and D(H15BAAYield), and trading strategy factors (typically approximated with option based payoffs) include return of primitive trend following strategy with bond look-back straddle (FHBONDTREND) and return of primitive trend following strategy with short-term interest rate look-back straddle (FHSIRTREND).

robustness regressions using lag one autoregressive models. To demonstrate how multicollinearity distorts some findings, we contrast the regressions with and without using the principal component factor returns.

Lastly, similar to Reibnitz [2015], we propose a timing strategy between active and passive. To our knowledge, we are the first to propose this in fixed income asset class.

For the portfolio formation at time t, we allocate to an active strategy for three months when the average cross-sectional volatility for last three months is greater by half standard deviation than the long-term average.[25] The timing strategy formula:

$$\frac{\sum_{t-1}^{t-3} CSV}{3} \geq \left(\frac{\sum_{t-1}^{t-n} CSV}{n} + 0.5 * \sigma\ CSV_{t-1}^{t-n}\right)$$

We allocate to the passive strategy in remainder instances, i.e., zero manager outperformance.

The active strategy is proxied with the outperformance of median manager and alternatively with the median outperformance of top quartile manager universe sorted by activeness.

[25]To separate signal from noise, we use half standard deviation threshold similar to other timing literature such as Schizas, Thomakos, and Wang [2011]. For robustness, instead of 0.5 we tried various other thresholds like 0.4, 0.6, and 1.0, and they produced similar information ratios. The timing strategy, similar to short-term momentum trading strategy, is 3-month/3-month construct.

III. CROSS-SECTIONAL DISPERSION, VOLATILITY, AND IMPACT ON OUTPERFORMANCE

A. Time-varying opportunity and the effectiveness of skills

As can be seen from Table 2, both median and the 25th percentile manager performances imply a shorter duration and longer spread duration than the two illustrated benchmarks. While both outperform the benchmarks, the median manager outperformed only slightly when compared with the equal weighted fixed income sector benchmark. Both duration and spread duration are calculated using multivariate regression of monthly performance as the dependent variable and monthly change in 10-year yield and change in BAA spreads as the independent variables.

We observed that the change in yields Granger Causes both MOVE and CSV. From a cursory style analysis, we note that the manager performance has shorter duration. These findings prod us to review the manager outperformance conditionally on the market environment, which in this instance is during rising yield and falling yield episodes. We later evaluate the outperformance based on volatility changes.

Outperformance of the managers conditional on the yield regimes

Investors have experienced a trend of falling yields for multiple decades. In our analysis period from 12/31/1988 to 9/30/2013, as shown in Table 3, we have 10 episodes when yield rose by 1% or more. The median episode duration is 11 months, and the median increase in U.S. 10-year yield is 124 bps.

As shown in Table 4, during such episodes, yields rose on an average by 15 bps every month, whereas in the remaining periods, yields fell on average by 11 bps. During the entire period, yields have been trending downward and have fallen on average by 2 bps each month. We looked at the median manager outperformance and the 25th percentile manager outperformance during this period. We find that the median manager outperformance on average has been 2 bps per month; however, during the episodes of rising yield, the median manager outperformance rose to an average of 25 bps per month. It is noteworthy that in the remaining periods, the median manager outperformance was -10 bps on average. In comparison, the 25th percentile manager outperformance was 26 bps per month on average. In episodes of rising yield, this outperformance is notably higher (50 bps per month on average), while the outperformance is lower in the remaining periods (14 bps per month on average). The differences in outperformance, in both rising yield and remaining periods, from the historical average are statistically significant, at the 99% confidence interval. With only 2 bps monthly outperformance gross of fees for the median manager, we concur, with Busse et al. [2010] and several other publications, that there is little evidence of superior performance even before fees.

We confirm that this stylized fact, i.e., significant difference in outperformance observed in rising yield periods from that in the remainder periods, is not an artifact of our database or benchmark selection The difference in means of the rising yield and the remainder period average outperformance across the major fixed income Lipper categories are significant at the 99% confidence interval. Not surprisingly, this trend is true for the spread-sensitive Lipper categories as well.[26]

Secondly, we slice the universe based on activeness quartiles. Activeness is measured by the in sample ex-post tracking error of the manager. As shown in Table 4, we find that the outperformance of the most active versus least active managers is concentrated during the rising yield periods. This conclusion is similar to Reibnitz's [2015] findings that the outperformance of more active funds is concentrated in the months of high dispersion compared with more benchmark-hugging funds. Reviewing the universe characteristics reveals that the last 12-month turnover for the most active 25th percentile is 83%, which is twice as much for the least active universe (44%).

Kacperczyk et al. [2013] show that the effectiveness of skills is time-varying and market-environment-dependent. We confirm this result for our analysis by demonstrating that the manager skill deteriorates in the remainder (falling yield) periods and significantly improves in the rising yield periods.

Our stylized facts are contrary to Gorman et al. [2010a], wherein they claim that the manager's information ratio is expected to remain unchanged as realized tracking error is expected to be proportional to the manager's active returns. Our analysis finds that the tracking error remains the same in the rising yield periods, and therefore the information ratio improves significantly. The information ratio of the most active manager is significantly higher than that of the least active manager in rising yield periods, pointing to the fact that the most active managers benefit significantly from improved dispersion

[26]Refer to Appendix C

environment. While this outperformance may be attributed to skill, there is no reason to believe that the median most active manager is more skillful than the median least active manager in a rising yield environment. Hence, the most active managers are able to exploit and benefit from the leverage effect due to the dispersion.

Outperformance of the managers conditional on the changes in volatility

Up until now, we have reviewed conditional manager performance across the rising and the falling yield environments. Similarly, as demonstrated in Table 5, we look at the manager outperformance conditional on months when MOVE moved up versus when it moved down. We find that the overall median manager information ratio is not significantly different from zero. However, it is positive and significant in the rising MOVE periods. The fact that the median manager IR is negative in falling MOVE periods also implies time-varying skills.

Raubenheimer [2011] argues that the active risk should be commensurate with the cross-sectional dispersion. While we acknowledge Raubenheimer’s point, we argue that the active risk should also be commensurate with the market environments when the manager skills are effective; for example, during the rising yield and the rising MOVE periods.

These stylized facts prompt us to further investigate whether or not conditional outperformance simply stems from the style bets.

Relationship of manager outperformance with dispersion and volatility

As a reminder, we used lag one vector autoregression (VAR(1)) model to understand the interdependencies of three endogenous variables: implied volatility (MOVE), cross-sectional volatility in fixed income sector returns (CSV), and the 25th percentile manager outperformance (TOPA). The results, which are shown in Table 6, are based on monthly data from 12/31/1988 to 9/30/2013.

Impact of the yield changes (D(YIELD)) on the outperformance

The results in Table 6 show that the rising interest rates are associated with rising volatility and with outperformance of the 25th percentile manager (TOPA). The coefficients for change in yield (D(YIELD)) of both MOVE and TOPA are positive and statistically significant. For every 100 bps change in yield, there is simultaneous 7 bps move in the MOVE index that month. The contemporaneous relationship of D(YIELD) to the 25th percentile manager outperformance (TOPA) denotes that for every 100 bps change in yield, TOPA rises by 115 bps. As mentioned earlier, the yield has come down 2 bps per month, implying a 2.3 bps monthly drag on the 25th percentile manager outperformance. Looking at the median manager and the 25th percentile manager outperformance, our analysis shows that the active managers maintain a relatively shorter duration exposure. This relatively shorter duration bias is because of active manager's preference for liquidity, a perception of better opportunities in the shorter duration spread products, or because of their belief in eventual reversion of yields to fair value.

The data do not show a statistically significant independent relationship between D(YIELD) and the cross-sectional volatility in sector returns (CSV).

Impact of the changes in the volatility environment on the outperformance

Focusing on the relative performance of the 25th percentile manager (TOPA), we see that the outperformance is higher when the cross-sectional volatility (CSV) is high, and that the coefficient is statistically significant. The coefficient for CSV(-1) of TOPA tells us that for every 100 bps rise in cross-sectional volatility (CSV) at a one-month lag, the 25th percentile manager outperformance (TOPA) rises by 9 bps for the month.

The rows labeled MOVE(-1), CSV(-1), and TOPA(-1) show the impact of lagged variables on themselves and the other variables. Not surprisingly, MOVE and CSV show a statistically significant serial correlation. For example, if the MOVE index is high this month, it is likely to be high next month as well. We also see persistence in cross-sectional volatility (CSV).

Although insignificant, a good portion of cross-sectional volatility (CSV) is explained by the lagged implied volatility index (MOVE(-1)). The coefficient for MOVE(-1) of CSV implies that if MOVE(-1) is 100 bps then 20 bps of the next month CSV is explained by it.

In addition to benefitting from changes in yields, our analysis (Figure 2) shows that there is persistent outperformance added from increases in implied volatility and increases in cross-sectional volatility. The generalized impulse response of cross-sectional volatility in fixed income sector returns (CSV) to a one standard deviation shock to MOVE index accumulates to 81 bps over 12 months. To illustrate, mean CSV is 98 bps in the sample, i.e., CSV would increase by almost 80% with the shock in MOVE. The response of the 25th percentile manager outperformance (TOPA) to a one standard deviation shock to cross-sectional volatility in fixed income sector returns (CSV) accumulates to 21 bps over 12 months. To illustrate, mean TOPA is 26 bps in the sample, i.e., TOPA would increase by almost 80% with the shock in CSV.[27]

B. On the robustness of the results

Volatility impact on the equity manager outperformance

For robustness analysis, we validate our framework with equities where the link between dispersion, volatility, and manager outperformance is already established. Similar to our approach for fixed income analysis, we used a lag one vector autoregression model (VAR(1)) to understand the interdependencies of these three endogenous variables: implied volatility (VIX), cross-sectional volatility in equity industry returns (CSV), and the 25th percentile manager outperformance from U.S. large cap core universe (LCC_25A).[28] We account for the style biases, since our dependent variable is manager outperformance, as measured by manager returns in excess of S&P 500 benchmark returns. The three Fama-French factors: Market, High minus Low, and Small minus Big excess returns facilitate controlling for systematic style bias and are exogenous variables in the regression.

---

[27]Additional impulse response shocks are illustrated in Appendix D. The variance decomposition analysis in Appendix D shows that more than 8% variation in the 25th percentile alpha is due to cross-sectional volatility.

[28]Just as bond volatility (MOVE) and cross-sectional volatility of fixed income sector returns are interrelated, we find equity volatility (VIX) and cross-sectional volatility of equity industry returns are interrelated. Granger causality test shows that VIX Granger Causes CSV at 99% confidence interval. Both, CSV and VIX, Granger Cause LCC_25A at 99% and 90% confidence interval respectively. Granger causality results are shown in Appendix E.

As shown in Table 7, focusing on the outperformance, which is LCC_25A, we find positive and significant loading to CSV. The beta implies 9 bps of monthly outperformance is contributed from every 1% in cross-sectional volatility. While VIX does not directly impact LCC_25A, its loading for CSV is significant. From the regression results, similar to what we observed for fixed income regressions, we find a transmission via CSV from VIX to LCC_25A.

Generalized impulse response one standard deviation shock to CSV results in 52 bps accumulated impact at the end of twelve months on the 25th percentile outperformance. Similarly, one standard deviation shock to VIX results in 35 bps of accumulated impact at the end of twelve months on the 25th percentile outperformance.[29]

Correcting for multicollinearity and accounting for style biases

Aforementioned fixed income VAR analysis was a concise and parsimonious model with only three endogenous and one exogenous variables. However, we acknowledge that multicollinearity and omitted variables may potentially cause concern.

As mentioned earlier in the 'Data and Methodology' section, we include 10 Yr CMT Yield and Moody's BAA Yield – 10 Yr CMT Yield (BAA spreads), along with cross-sectional volatility in spread sectors, MOVE, and the dependent variable at lag one as endogenous variables, allowing us to evaluate impact of lagged levels on outperformance.

[29]Generalized impulse response results are shown in Appendix E.

We also recognize existence of style biases beyond duration and hence in exogenous variables (change variables). Besides monthly change in 10-year constant maturity Treasury yield D(H15Yield), we additionally include credit spread factor, which is the monthly change in the Moody's BAA yield less 10- year constant maturity Treasury yield, denoted as D(H15BAAYield), return of primitive trend following strategy with bond look-back straddle (FHBONDTREND), return of primitive trend following strategy with short-term interest rate look-back straddle (FHSIRTREND), monthly change in cross-sectional volatility in spread sectors D(CSVSPRD), and monthly change in MOVE denoted as D(MOVE).

We also contrast the regressions with and without employing principal component analysis in order to stress the fact of how multicollinearity distorts some findings.

We not only conduct lagged auto regression of order one analysis for the 25^{th} percentile outperformance as dependent variable but also conduct regressions for the median manager outperformance, the most active quartile median manager outperformance, the timing strategy between most active quartile median outperformance and passive (using CSV timing signal, illustrated in subsequent section), the timing strategy between high yield and long duration (using CSV timing signal, illustrated in subsequent section), the high yield outperformance (in order to verify if our framework invalidates systematic style bias based outperformance), and for the same reason the long duration treasury outperformance.

Lag one auto regressive analysis without using PCA

In Table 8 we combine outcomes from all independent lag one auto regressions so that we can compare the results side by side for the outperformance variables. Looking at the coefficients for exogenous variables, we note that the 25th percentile and the timing strategies have significant and positive exposure to monthly change in cross-sectional volatility, illustrating them benefiting from increase in cross-sectional volatility. It is noteworthy that the two timing strategies, namely switching between most active quartile and benchmark and switching between high yield and government index, which were created using cross-sectional volatility as the switching signal, have more than double and ten times exposure respectively to the change in cross-sectional volatility variable when compared with the exposure for 25th percentile manager outperformance. Both median and 25th percentile outperformance also has positive and significant exposure to monthly change in MOVE. We thereby demonstrate and quantify positive impact of uncertainty, both longitudinal and cross-sectional volatility, on the fixed income manager outperformance.

We note that the median, 25th percentile, 25th percentile most active, and the 25th percentile most active timing strategy have shorter duration and have longer spread duration. This is because the coefficient for D(H15YIELD) is positive and that for D(H15BAA_YIELD) is negative. We also find significant exposure to FHBONDTREND factor for all strategies except for the high yield versus government timing strategy. Indeed it is justified using additional style factors to account for systematic style biases.

Comparing the most active quartile timing strategy with the most active quartile average outperformance, we observe reduced systematic exposure to the exogenous variables such as D(H15YIELD), D(H15BAA_YIELD), and FHBONDTREND. This reduction comes with the benefit of intended increase in exposure to change in cross-sectional volatility.

Upon reviewing coefficient to endogenous lagged variables, we find that the timing strategies have significant exposure to lagged cross-sectional volatility, suggesting timing strategies benefiting from persistent dispersion environment. The median, 25th percentile, and the most active quartile outperformance have significant exposure to lagged spreads, suggesting outperformance from higher income instruments or from manager capturing value opportunities.

Lag one auto regressive analysis using PCA

Table 9 shows regressions results for all outperformance strategies with independent variables as principal component factor returns, except for its own lag (i.e., Dependent(-1) in regression results).[30] Looking at coefficients to exogenous variables related principal component factor returns, we note that the median, 25th percentile, 25th percentile most active, and the timing strategies have positive and significant exposure to change in cross-sectional volatility related principal component, i.e. (PCOMP3s). These

[30]In order to understand principal component factor returns, we first perform correlation analysis with actual variables. Correlations of the principal component factors derived from exogenous variables are shown in Appendix F. The first principal component explains 35% of the variance and is related to spreads. The second principal component explains 20% of variance and is related to 10-year Treasury rates. The third principal component explains close to 16% of variance and is related to dispersion. The fourth and fifth principal components explain close to 22% of variance and are related to trading strategy factors. Refer to Appendix F for details on eigenvectors and eigenvalues.

Similarly, correlations of endogenous variables to its principal component factor returns are shown in Appendix G. We find that the first principal component explains 56% of variance and is related to spreads. The second principal component explains close to 29% of variance and is related to 10-year Treasury yields. The third principal component explains 12% of variance and is related to dispersion in spread sectors. Refer to Appendix G for details on eigenvectors and eigenvalues.

significant exposures to change in cross-sectional volatility related principal component factor return allows us to empirically validate our earlier argument of improved outperformance due to change in cross-sectional volatility. We also note that the median, 25th percentile, 25th percentile most active, and the 25th percentile most active timing strategy have shorter duration and longer spread duration. We determine this given negative loading on first principal component (PCOMP1s) and positive loading on second principal component (PCOMP2s). Both median and the 25th percentile outperformance have significant exposure to trading strategy-related principal component (PCOMP4s). This justifies our use of Fung and Hsieh factors for active management style analysis. Upon reviewing the intercepts, only the outperformances for the 25th percentile outperformance and for the suggested timing strategies are significant. It is noteworthy that the intercepts for these strategies were not significant when we conducted regressions without using principal component factors. We cannot stress enough the requirement to use principal component factors, which is not so common in the literature.

Up on reviewing the endogenous lagged variable related principal component factors, we find that the timing strategies have significant exposure to lagged cross-sectional volatility. This can be confirmed from positive and significant loadings to lag one third principal component, i.e. PCOMP301(-1). This suggests momentum in cross-sectional volatility and validates the timing strategy, which is utilizing cross-sectional volatility as an indicator. We also find that the 25th percentile and the timing strategies have significant exposure to lagged spreads (PCOMP101(-1)), suggesting outperformance from higher income instruments or from manager capturing value opportunities.

For additional robustness check, we regressed outperformance of all the managers using this approach and reviewed median beta to all the regressors. We found very similar results to what we had for median outperformance (results not reported here).

IV. TIMING ACTIVENESS USING CROSS-SECTIONAL DISPERSION

Raubenheimer [2011] remarks that ex-ante, cross-sectional volatility must be considered hand in hand with risk limits and active risk targets when the mandates are both set and monitored. The higher the cross-sectional volatility, the greater the opportunity for active risk-taking, all other things equal. Conversely, to remain efficient, active risk-taking should be reduced during the periods of low cross-sectional dispersion.

Reibnitz [2015] shows that active strategies have the greatest impact on returns during periods of high dispersion, when alpha produced by the most active funds significantly exceeds that produced in other months. Therefore, deciding when to invest in the active funds can be just as important as deciding which funds to invest in. She shows that switching between the highly active and passive funds based on dispersion produces significant alpha of over 2% p.a., after fees.

We propose a timing strategy between active and passive strategies in fixed income asset class.

For the portfolio formation at time t, we allocate to an active strategy (proxied by the median or the median of 25th percentile by activeness outperformance) for three months when the average cross-sectional volatility for last three months is greater by half standard deviation than the long-term average.[31]

$$\frac{\sum_{t-1}^{t-3} CSV}{3} \geq \left(\frac{\sum_{t-1}^{t-n} CSV}{n} + 0.5 * \sigma\ CSV_{t-1}^{t-n}\right)$$

We allocate to the passive strategy in the remaining instances, i.e., zero outperformance. As shown in Figure 3, periods coinciding with number one are months when the timing strategy is employing active manager, and periods coinciding with number zero are when the timing strategy allocates to the equal weighted fixed income sector benchmark.

As shown in Table 10, while the median active strategies improve IR, it is insignificant even after employing timing. The IR becomes significant when we use most active median outperformance. This improvement comes both from improved outperformance and reduced tracking error.

Earlier, we showed the efficacy of the timing strategy using cross-sectional volatility across all fixed income sectors as an indicator. Instead, using cross-sectional volatility in spread sectors as an indicator improves the timing strategy significantly. This finding makes sense, since the inter-market spread trades are on one of the key components of active management [Boyd and Mercer, 2010; Fabozzi, 2010]. Comparing the results of Table 11 with Table 10, the IR of the most active median manager strategy improved from 0.41 to 0.65 when new timing indicator is employed. Throughout the evaluation period, the strategy is active 40% of the time and passive 60% of the time.

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[31]To separate signal from noise, we use half standard deviation threshold similar to other timing literature such as Schizas, Thomakos, and Wang [2011]. For robustness, instead of 0.5 we tried various other thresholds like 0.4, 0.6, and 1.0, and they produced similar information ratios. The timing strategy, similar to short-term momentum trading strategy, is 3 month/3 month construct.

We know ex-post that the high yield sector outperformed all other sectors when yields rose and that the long duration treasury sector outperformed the rest when yields fell. If cross-sectional volatility is any indication of timing, it should also effectively time between long duration treasuries and the high yield sectors. As we show in Appendix H, the timing strategy information ratio is 0.8 for the analysis period. The strategy employs the same spread sector cross-sectional volatility indicator for timing. On average, strategy remains in the high yield sector 40% of the time and in the long duration treasury sector 60% of the time. Nevertheless, the demonstration of the timing strategy does not imply full economic benefits. For a large institutional client, the transition management costs are overwhelming. With the trend of no-transaction-fee platforms and proliferation of actively managed ETFs, this is a viable strategy for retail investors. The merits of the strategy are more for the active managers to scale their active risk budget commensurate with the opportunity or by market timing between various risk premia strategies, as illustrated here between rates and spreads.

V. CONCLUSION

Rising interest rate environments tend to be associated with uncertainty in bond yield; for example, higher implied volatilities and increased cross-sectional dispersion of returns across sectors. Our analysis shows that active managers have relatively shorter duration, longer spread duration exposure, and benefit from rising rates. We also attribute outperformance to the increased cross-sectional volatility, since it presents larger than normal opportunities, and skilled managers have ability to capitalize on these opportunities.

Not only do we demonstrate that the active strategies benefit from uncertainty, both longitudinal and cross-sectional volatility even after accounting for style biases, but also we quantify this impact on the outperformance.

It becomes extremely important when allocating active strategies to take into account time-varying effectiveness of skills and time-varying dispersion. We also notice increased outperformance as measured by the information ratio for most active managers particularly during times of increased uncertainty and dispersion. As illustrated with timing strategies, investors can also benefit from persistence of dispersion by scaling the active risk budget.

While we only explored the cross-sectional dispersion and inter temporal volatility channels, an additional channel to impact information ratio and outperformance is inter-temporal correlations. We proxied inter-temporal volatility with implied volatility, since it is observable; however, no such model free estimates exist for correlation.[32]

[32]This research can be advanced to include analyzing impact on outperformance due to correlations. For estimating correlations, technique of realized covariance as introduced by Andersen et al. [2003] may be utilized.

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Appendix A

Monthly Total Return Indices
BARCLAYS US CORP HIGH YIELD
BARCLAYS US AGG CORP AA INTERMEDIATE
BARCLAYS US AGG CORP AA LONG
BARCLAYS US CORP : INVESTMENT GRADE
BARCLAYS MUNICIPAL BOND
BARCLAYS US AGENCY INTERMEDIATE
BARCLAYS US AGENCY LONG
BARCLAYS US AGG SUPRANATIONAL
BARCLAYS US AGG SPNAT. LONG
BARCLAYS US SOVEIGN: LONG
BARCLAYS US AGG SOVERIGN
BARCLAYS US TREASURY LONG
BARCLAYS US TREASURY INTERMEDIATE
BARCLAYS FHLMC 15Y
BARCLAYS GOVT NAT MTGE ASSN (GNMA)
BARCLAYS FNMA 15Y
BARCLAYS US MORTGAGE BACKED SECS

Manager Database

We used data from eVestment Alliance to address these research questions. eVestment Alliance collects monthly data about performance and portfolio characteristics on active money managers who self-report the data. It classifies managers as core-plus, and it relies both on self-reporting and its own analysis. The database was launched in mid-2000, but data is available as far back as 1980s. The database is widely used in manager search and performance measurement by consultants and institutional investors. There is no survivorship bias in the database after 2000, but there is a back-filling bias (managers might back-fill historical data once they start reporting) and a self-reporting bias. However there is no reason to believe that these biases impact the conditional analysis, and the relative performance in different market environment is likely to be bias-free. As of 9/30/2013, there are 149 managers.

Appendix B

Roots of Characteristic Polynomial
Endogenous variables: MOVE CSV TOPA
Exogenous variables: C D(YIELD)
Lag specification: 1 1
Date: 11/08/13 Time: 14:06

Root	Modulus
0.816926	0.816926
0.445812	0.445812
0.144367	0.144367

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR Lag Order Selection Criteria
Endogenous variables: MOVE CSV TOPA
Exogenous variables: C D(YIELD)
Date: 11/08/13 Time: 14:06
Sample: 1988M12 2013M09
Included observations: 286

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1719.960	NA	35.02348	12.06965	12.14635	12.10039
1	-1497.257	437.6182	7.858579	10.57523	10.76697*	10.65208
2	-1483.430	26.88198	7.597948	10.54147	10.84826	10.66444
3	-1460.281	44.51729	6.882654	10.44252	10.86437	10.61161
4	-1437.617	43.10771	6.256233	10.34697	10.88387	10.56218*
5	-1429.973	14.38079	6.316979	10.35645	11.00839	10.61777
6	-1416.483	25.09277	6.123351*	10.32505*	11.09205	10.63249
7	-1408.751	14.21965	6.180120	10.33392	11.21596	10.68747
8	-1405.853	5.269513	6.452537	10.37659	11.37368	10.77626
9	-1396.291	17.18445*	6.431018	10.37267	11.48480	10.81844
10	-1392.835	6.139115	6.690073	10.41143	11.63862	10.90333
11	-1384.568	14.51015	6.730359	10.41656	11.75880	10.95457
12	-1381.759	4.872300	7.035452	10.45985	11.91714	11.04397

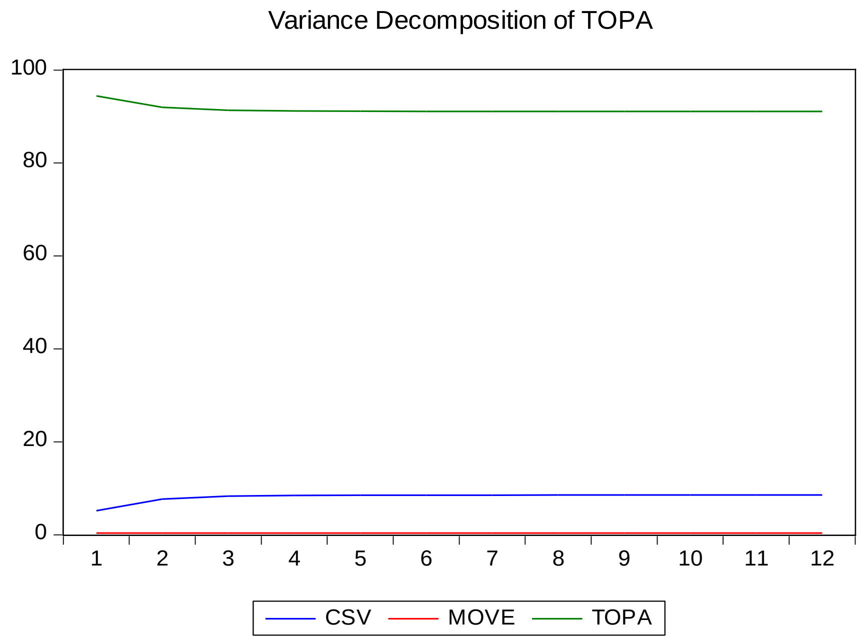
* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix C

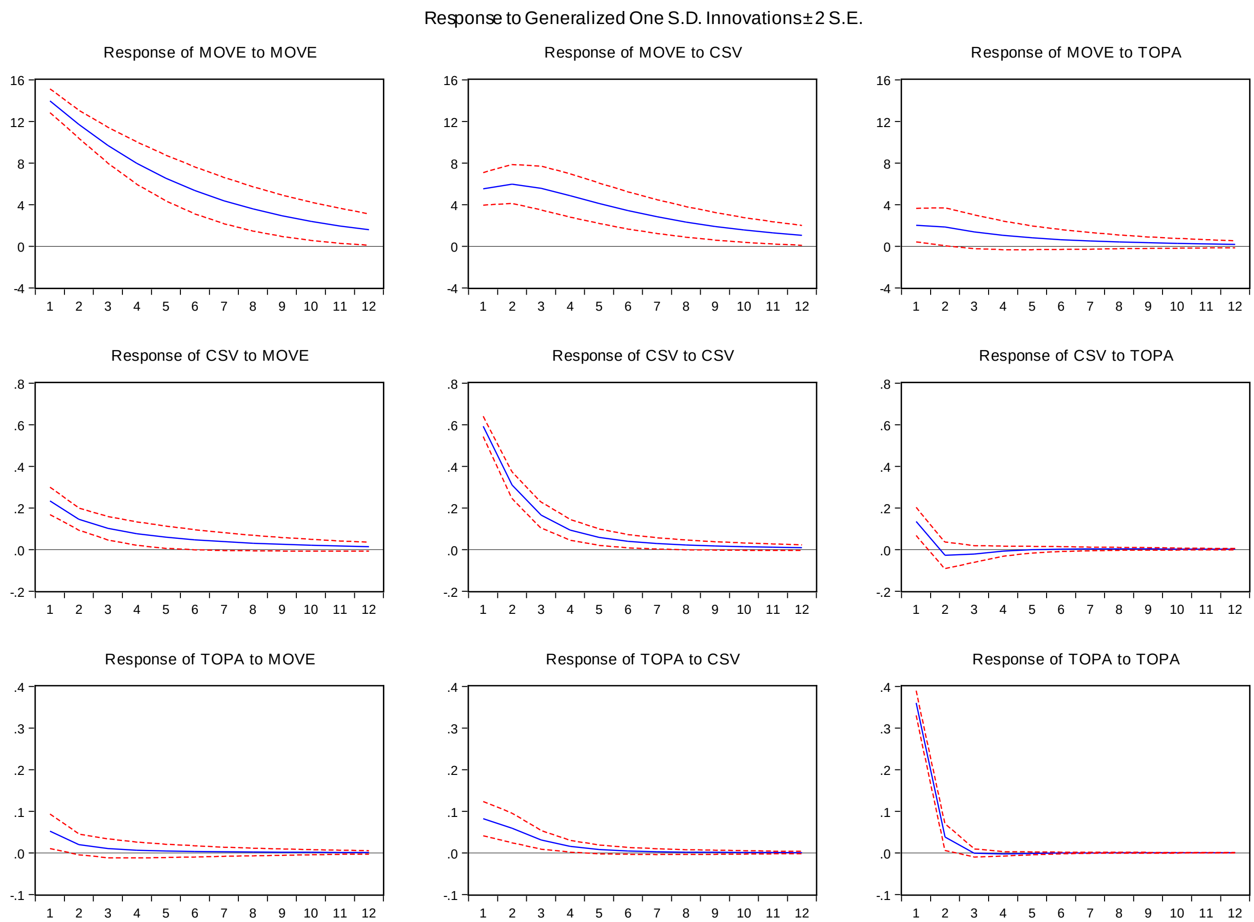
The table shows monthly average for various Lipper categories. The table shows monthly average for regimes when yield rose by 100 bps and also for remainder periods. The average outperformances are different at 99% confidence interval. *** imply significance at 99% confidence interval.

	Lipper Categories - Primary Share Class						
Average Monthly Outperformance	**General Bond**	**Multi-Sector Income**	**Corporate Debt A**	**Corporate Debt BBB**	**Intermediate Investment Grade**	**High Yield**	**U.S. Mortgage**
Rising Yield	0.29	0.65	0.12	0.24	0.29	1.18	0.22
Remainder	-0.29	-0.37	-0.18	-0.17	-0.39	-0.5	-0.33
Total	-0.08	0	-0.07	-0.02	-0.15	0.1	-0.13
Rising Yield - Remainder	0.58***	1.01***	0.3***	0.41***	0.67***	1.68***	0.54***

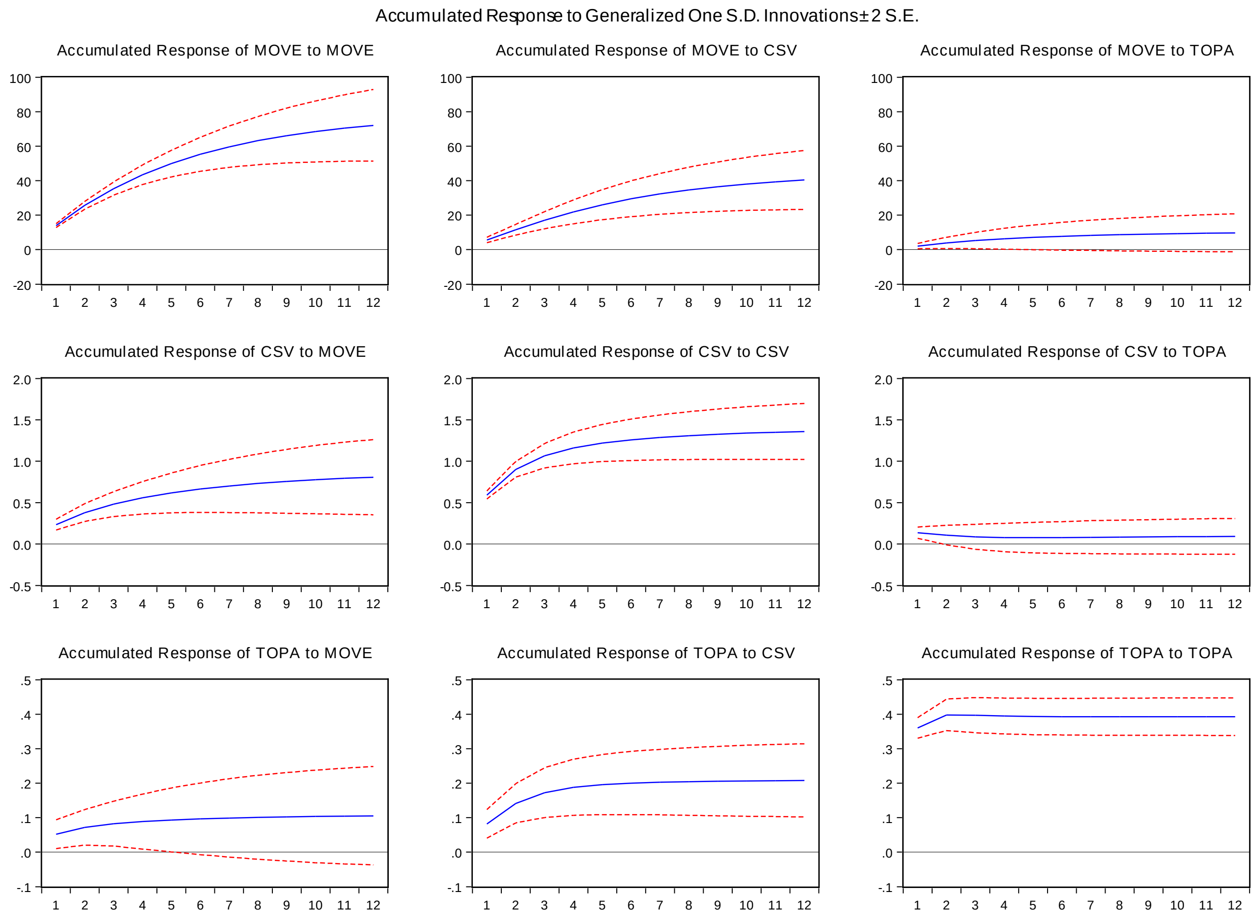
Appendix D



Variance Decomposition of TOPA
100
80
60
40
20
0
1
2
3
4
5
6
7
8
9
10
11
12
CSV
MOVE
TOPA



Response to Generalized One S.D. Innovations ± 2 S.E.
Response of MOVE to MOVE
Response of MOVE to CSV
Response of MOVE to TOPA
Response of CSV to MOVE
Response of CSV to CSV
Response of CSV to TOPA
Response of TOPA to MOVE
Response of TOPA to CSV
Response of TOPA to TOPA


Accumulated Response to Generalized One S.D. Innovations ± 2 S.E.
Accumulated Response of MOVE to MOVE
Accumulated Response of MOVE to CSV
Accumulated Response of MOVE to TOPA
Accumulated Response of CSV to MOVE
Accumulated Response of CSV to CSV
Accumulated Response of CSV to TOPA
Accumulated Response of TOPA to MOVE
Accumulated Response of TOPA to CSV
Accumulated Response of TOPA to TOPA

Appendix E

Pairwise Granger Causality Tests

Date: 03/28/16   Time: 15:54

Sample: 1991M08 2013M12

Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
VIX does not Granger Cause LCC_25A	268	3.670	0.057
LCC_25A does not Granger Cause VIX		1.499	0.222
CSV does not Granger Cause LCC_25A	268	35.226	0.000
LCC_25A does not Granger Cause CSV		5.811	0.017
CSV does not Granger Cause VIX	268	0.771	0.381
VIX does not Granger Cause CSV		32.636	0.000

Roots of Characteristic Polynomial

Endogenous variables: LCC_25A VIX CSV

Exogenous variables: C MKT_RF HML SMB

Lag specification: 1 1

Date: 03/28/16   Time: 15:56

Root	Modulus
0.849	0.849
0.449	0.449
0.047	0.047

No root lies outside the unit circle.

VAR satisfies the stability condition.

VAR Lag Order Selection Criteria

Endogenous variables: LCC_25A VIX CSV

Exogenous variables: C MKT_RF HML SMB

Date: 03/28/16 Time: 15:55

Sample: 1991M08 2013M12

Included observations: 261

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1519.91	NA	25.15711	11.73876	11.90265	11.80464
1	-1233.61	557.2364	3.005048	9.613886	9.900687*	9.729171
2	-1217.47	31.0417	2.845279	9.55918	9.968895	9.723872
3	-1199.21	34.70924	2.650650	9.488189	10.02082	9.702288*
4	-1189.11	18.9534	2.629053	9.479793	10.13534	9.743301
5	-1176.17	23.99746	2.551646*	9.449596*	10.22805	9.762511
6	-1168.59	13.8815	2.580676	9.46048	10.36185	9.822802
7	-1158.73	17.83851*	2.565092	9.453858	10.47815	9.865589
8	-1151.46	12.97928	2.601203	9.467119	10.61432	9.928257

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

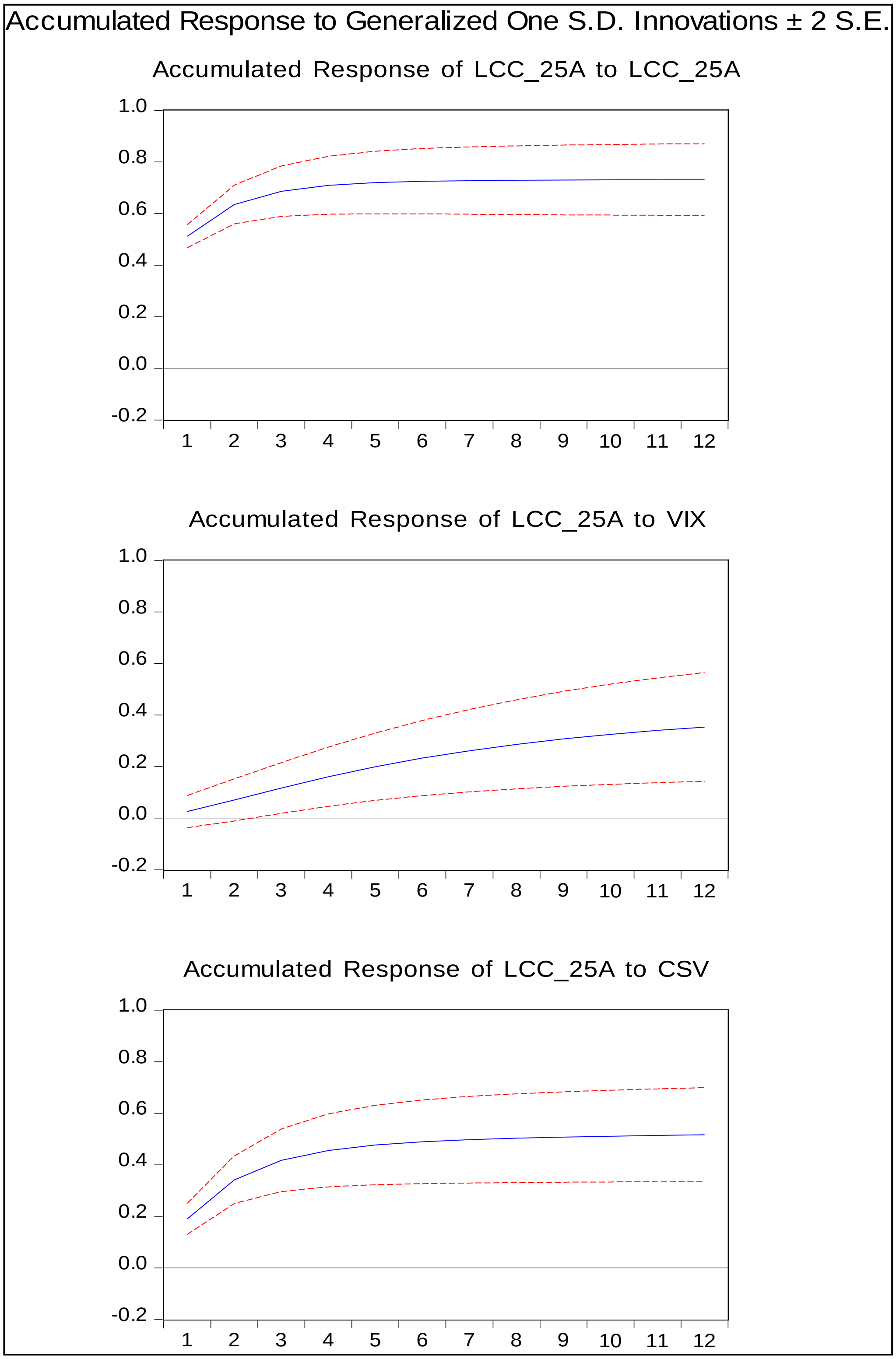
FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Generalized Impulse Response Function



Appendix F

Correlations of Principal Component Factors with Exogenous Variables						
	PCOMP1S	**PCOMP2S**	**PCOMP3S**	**PCOMP4S**	**PCOMP5S**	**PCOMP6S**
DH15YIELD	-0.57	0.57	0.37	0.19	0.30	0.25
DH15BAA_YIELD	0.77	-0.46	0.05	0.01	0.07	0.52
FHBONDTREND	0.54	0.44	-0.45	-0.35	0.39	-0.03
FHSIRTREND	0.66	0.09	0.10	0.68	0.14	-0.16
DMOVE	0.50	0.71	0.00	-0.01	-0.52	0.14
DCSVSPRD	0.45	0.01	0.79	-0.38	0.06	-0.14

Exogenous Variables - Eigenvectors						
	PCOMP1S	**PCOMP2S**	**PCOMP3S**	**PCOMP4S**	**PCOMP5S**	**PCOMP6S**
ZFHSIRTREND	0.46	0.09	0.10	0.78	0.21	-0.33
ZFHBONDTREND	0.38	0.40	-0.46	-0.40	0.57	-0.08
ZDMOVE	0.34	0.64	0.00	-0.01	-0.66	0.19
ZDH15BAA_YIELD	0.52	-0.40	0.05	0.02	0.10	0.74
ZDH15YIELD	-0.39	0.51	0.37	0.22	0.42	0.47
ZDCSVSPRD	0.31	0.01	0.80	-0.42	0.09	-0.27

Exogenous Variables - Eigenvalues					
				Cumulative	
	Value	**Difference**	**Proportion**	**Value**	**Proportion**
PCOMP1S	2.10	0.86	0.35	2.10	0.35
PCOMP2S	1.24	0.27	0.21	3.34	0.56
PCOMP3S	0.97	0.21	0.16	4.31	0.72
PCOMP4S	0.76	0.22	0.13	5.07	0.85
PCOMP5S	0.54	0.15	0.09	5.61	0.94
PCOMP6S	0.39---		0.06	6.00	1.00

Appendix G

Correlations of Principal Component Factors with Endogenous Variables				
	PCOMP101	**PCOMP201**	**PCOMP301**	**PCOMP401**
H15YIELD	-0.62	0.74	0.14	0.22
H15BAA_YIELD	0.93	-0.17	-0.13	0.30
MOVE	0.58	0.71	-0.38	-0.13
CSVSPRD	0.80	0.26	0.54	-0.08

Endogenous Variables - Eigenvectors				
	PCOMP101	**PCOMP201**	**PCOMP301**	**PCOMP401**
STDH15YIELD	-0.41	0.69	0.21	0.55
STDH15BAA_YIELD	0.62	-0.16	-0.19	0.74
STDCSVSPRD	0.54	0.24	0.78	-0.20
STDMOVE	0.39	0.66	-0.55	-0.32

Endogenous Variables – Eigenvalues					
Number	**Value**	**Difference**	**Proportion**	**Cumulative Value**	**Cumulative Proportion**
PCOMP101	2.23	1.09	0.56	2.23	0.56
PCOMP201	1.14	0.67	0.29	3.37	0.84
PCOMP301	0.47	0.30	0.12	3.84	0.96
PCOMP401	0.16	---	0.04	4.00	1.00

Appendix H

Risk Premia Timing Strategy

Allocating between long duration treasuries and high yields based on dispersion in spread sector returns.

Annualized Performance %	Timing HYLD vs LD TSY	40% HYLD 60% LD TSY	Outperformance
	1/99-9/30		
Returns	13.37	7.14	6.23
Risk	10.51	6.92	7.83
Returns/Risk (IR)	1.27	1.03	0.80
	10 Year		
Returns	14.53	7.58	6.95
Risk	11.29	7.05	8.08
Returns/Risk (IR)	1.29	1.08	0.86

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Table 1

TEST FOR ENDOGENEITY

Using Pairwise Granger Causality Tests at lag 1, using monthly data from 12/31/1988 to 9/30/2013, we show that three variables, implied volatility (MOVE), cross-sectional volatility in fixed income sector returns (CSV), and the 25^{th} percentile manager outperformance (TOPA) are endogenous, whereas change in 10-year bond yield D(YIELD) Granger Causes both MOVE and CSV and hence is exogenous.

Null Hypothesis	Observations	F-Statitic	Probability
MOVE does not Granger Cause D(YIELD)	296	0.99	0.32
D(YIELD) does not Granger Cause MOVE		3.56	0.06
CSV does not Granger Cause D(YIELD)	296	0.18	0.67
D(YIELD) does not Granger Cause CSV		11.04	0.00
TOPA does not Granger Cause D(YIELD)	296	0.02	0.89
D(YIELD) does not Granger Cause TOPA		0.84	0.36
CSV does not Granger Cause MOVE	297	4.52	0.03
MOVE does not Granger Cause CSV		1.81	0.18
TOPA does not Granger Cause MOVE	297	0.05	0.82
MOVE does not Granger Cause TOPA		0.00	0.99
TOPA does not Granger Cause CSV	297	16.07	0.00
CSV does not Granger Cause TOPA		3.23	0.07

Table 2
PERFORMANCE METRICS

Table shows returns and risk for median and 25th percentile manager performance along with that for average fixed income sector returns and Barclays U.S. aggregate. A multivariate regression, using data from 12/31/1988 to 9/30/2013, with change in 10-year government yield and change in BAA spreads as regressors additionally provide sensitivities similar to duration and spread duration.

	Returns	Risk	Slope D(H15Yield) Duration	Slope D(H15BAAYield) Spread Duration
Median	7.8%	3.9%	3.8	2.2
25th Percentile	10.9%	3.9%	3.8	2.0
Average Sector	7.5%	4.7%	4.9	1.9
U.S. Aggregate	6.9%	3.8%	4.0	1.1

Table 3
RISING YIELD REGIMES

In aggregate, we record 10 episodes when Datastream U.S. 10-year government yields rose by 100 bps from trough to peak.

Episode	Period		Yield (%)		Change
Months	**Begin**	**End**	**Begin**	**End**	**bps**
9	7/31/1989	4/30/1990	7.80	9.03	123
14	9/30/1993	11/30/1994	5.39	7.92	253
8	12/29/1995	8/30/1996	5.58	6.94	137
16	9/30/1998	1/31/2000	4.41	6.67	225
5	10/31/2001	3/29/2002	4.27	5.41	114
2	5/30/2003	7/30/2003	3.34	4.48	114
12	6/30/2005	6/30/2006	3.94	5.14	119
12	12/31/2008	12/31/2009	2.25	3.84	158
7	8/31/2010	3/31/2011	2.47	3.45	98
13	7/31/2012	8/20/2013	1.49	2.75	126

Table 4

MANAGER OUTPERFORMANCE BY YIELD REGIMES

The table shows monthly average for both median and 25th percentile manager outperformance. We also show monthly averages for average performance of most active and least active manager quartiles. The table shows monthly average for regimes when yield rose by 100 bps and also for remainder periods. The average outperformances are different at 99% confidence interval. *** imply significance at 99% confidence interval.

Monthly Average	Change in Yield (bps)	Median Manager Out-performance %	25th Percentile Manager Out-performance %	Most Active Quartile Median Out-performance %	Least Active Quartile Median Out-performance %
Rising Yield Periods	15	0.25	0.50	0.43	0.16
Remainder Periods	-11	-0.10	0.14	-0.13	-0.09
Total Period	-2	0.02	0.26	0.05	-0.01
Rising Yield Less Remainder		0.35***	0.37***	0.56***	0.25***
Rising Yield Information Ratio		1.96	3.10	2.05	1.41
Total Period Information Ratio		0.12	1.84	0.24	-0.05

Table 5

MANAGER OUTPERFORMANCE BY MONTHLY CHANGES IN MOVE

The table shows annualized monthly average for both median and 25th percentile manager outperformance for months when MOVE moved higher and when MOVE fell for the month. Similarly, we conditionally show tracking errors and information ratios for these periods. Tracking error is calculated as annualized standard deviation of monthly outperformance.

Annualized Monthly Average	CSV%	Outperformance %		Tracking Error %		Information Ratio	
	Average	Median Manager	25th Percentile	Median Manager	25th Percentile	Median Manager	25th Percentile
All Periods	3.38	0.19	3.09	1.60	1.67	0.12	1.84
Falling MOVE	3.02	-0.16	2.46	1.41	1.54	-0.11	1.60
Rising MOVE	3.79	0.58	3.79	1.78	1.80	0.33	2.10

Table 6

VAR ANALYSIS WITH MOVE, CSV, and 25^{TH} PERCENTILE MANAGER OUTPERFORMANCE

Table shows vector autoregression for MOVE, Cross-sectional volatility (CSV), and 25^{th} percentile manager outperformance (TOPA); ***, **, and * imply significance at 99%, 95%, and 90% respectively.

Coefficients	MOVE	CSV	TOPA
MOVE(-1)	0.794***	0.002	0.000
CSV(-1)	2.745**	0.541***	0.094***
TOPA(-1)	-0.329	-0.294***	0.072
C	18.229***	0.274*	0.213**
D(YIELD)	6.454**	-0.040	1.153***
Adj. R-squared	0.69	0.33	0.45

Table 7

VAR ANALYSIS WITH VIX, CSV and 25TH PERCENTILE MANAGER OUTPERFORMANCE

This table shows vector autoregressive model results for VIX, cross-sectional volatility in 30 Fama French industries (CSV), and 25th percentile manager outperformance of U.S. equity large cap core universe (LCC_25A); ***, **, and * imply significance at 99%, 95%, and 90% respectively. Monthly regression uses monthly sample from 9/30/1991–12/31/2013. The Market, High minus Low, and Small minus Big excess returns facilitate controlling for systematic style bias and are exogenous variables in the regression.

Coefficients	**LCC_25A**	**VIX**	**CSV**
LCC_25A(-1)	0.152***	0.031	0.342***
VIX(-1)	0.004	0.861***	0.081***
CSV(-1)	0.091***	-0.073	0.331***
C	0.257***	3.574***	0.926***
MKT-RF	-0.057***	-0.693***	-0.019
HML	0.035***	-0.135**	0.051*
SMB	0.090***	-0.050	0.021
Adj. R-squared	0.438	0.878	0.457

Table 8

REGRESSION ANALYSIS FOR SEVERAL OUTPERFORMANCE STRATEGIES

We present regression output for seven different lag one auto regressions conducted for various outperformance strategies. Monthly regression conducted using sample from 1/31/1994–9/30/1993. Regressions controlled for various style biases and additional lagged level variables included; ***, **, and * imply significance at 99%, 95%, and 90% respectively.

	MEDIAN	TOPA	MOST ACTIVE	HYLD OUT-PERFORM	TSYLD OUT-PERFORM	TIMING MOST ACTIVE	TIMING SPREAD GOVT
H15YIELD(-1)	0.015	0.024	0.036	-0.122	-0.158	0.024	-0.001
H15BAA_YIELD(-1)	0.131*	0.179**	0.204*	0.292	-0.555**	0.103	0.032
CSVSPRD(-1)	-0.080	0.066	-0.065	-0.210	0.148	0.198***	0.924***
MOVE(-1)	-0.003*	-0.001	-0.006**	-0.005	0.005	-0.002	-0.003
DEPENDENT(-1)	-0.190***	-0.122**	-0.075	-0.169**	-0.314***	0.137**	0.148**
C	0.002	-0.210	0.042	0.674	1.497**	-0.256	-0.288
D(H15YIELD)	1.147***	1.054***	0.640***	0.490	-4.278***	0.317**	-1.070
D(H15BAA_YIELD)	-0.401**	-0.478**	-2.162***	-7.686***	1.820***	-0.867***	-2.743***
FHBONDTREND	-0.767***	-0.837***	-1.362***	-3.215***	3.808***	-0.666***	1.372
FHSIRTREND	0.149	0.210*	-0.006	-0.009	-0.446	0.082	0.138
D(CSVSPRD)	-0.012	0.123***	0.023	0.008	0.036	0.281***	1.209***
D(MOVE)	0.005***	0.007***	-0.001	-0.011	-0.013*	-0.004	-0.029***
Adj. R-squared	0.431	0.434	0.441	0.375	0.433	0.318	0.225

Table 9

REGRESSION ANALYSIS FOR SEVERAL OUTPERFORMANCE STRATEGIES (WITH PRINCIPAL COMPONENTS FACTOR RETURS AS REGRESSORS)

We present regression output for seven different lag one auto regressions conducted for various outperformance strategies. Monthly regression conducted using sample from 1/31/1994–9/30/1993. Regressors are first transformed to principal component factor returns before conducting regressions. Regressions controlled for various style biases and additional lagged level variables included; ***, **, and * imply significance at 99%, 95%, and 90% respectively.

	MEDIAN	TOPA	MOST ACTIVE	HYLD OUT-PERFORM	TSYLD OUT-PERFORM	TIMING MOST ACTIVE	TIMING SPREAD GOVT
PCOMP101(-1)	-0.013	0.092***	-0.014	0.092	-0.030	0.106***	0.436***
PCOMP201(-1)	-0.062**	0.003	-0.090*	-0.315**	-0.011	0.022	0.143
PCOMP301(-1)	-0.031	0.045	0.017	-0.178	0.052	0.167***	0.696***
PCOMP401(-1)	0.130*	0.127	0.216	0.123	-0.560*	0.068	-0.125
DEPENDENT(-1)	-0.190***	-0.122**	-0.075	-0.169**	-0.314***	0.137*	0.146**
C	0.001	0.270***	0.053	0.040	0.119	0.077**	0.415***
EXOGENOUS							
PCOMP1s	-0.146***	-0.093***	-0.342***	-1.017***	0.672***	-0.081***	0.122
PCOMP2s	0.168***	0.182***	0.141***	0.317**	-0.534***	0.028	-0.101
PCOMP3s	0.144***	0.238***	0.149**	0.212	-0.608***	0.269***	0.653***
PCOMP4s	0.138***	0.099***	0.099*	0.194	-0.550***	-0.035	-0.571***
PCOMP5s	-0.006	-0.031	-0.086	-0.262	0.060	0.022	0.363*
PCOMP6s	0.086**	0.035	-0.210***	-0.971***	-0.279*	-0.158***	-0.886***
Adj. R-squared	0.43	0.43	0.44	0.38	0.43	0.32	0.22

Table 10
OUTPERFORMANCE IMPROVEMENT WITH TIMING STRATEGY

This table shows annualized monthly average for both median and most active quartile median outperformance with and without employing aforementioned timing strategy.

Annualized Monthly Average Outperformance %	Median	Timing Strategy	Most Active Quartile Median	Timing Strategy
		1/99-9/13		
Outperformance	0.10	0.41	0.60	1.22
Tracking Error	1.94	1.63	3.40	2.95
Information Ratio	0.05	0.25	0.18	0.41
		10 Year		
Outperformance	0.20	0.62	0.80	1.31
Tracking Error	2.23	1.87	3.95	3.44
Information Ratio	0.09	0.33	0.20	0.38

Table 11

TIMING STRATEGY USING SPREAD SECTOR BASED INDICATOR

This table shows annualized monthly average for both median and most active quartile median outperformance with and without employing aforementioned timing strategy. Timing is based on cross-sectional volatility in spread sectors.

Annualized Monthly Average Outperformance %	**Median**	**Timing Strategy**	**Most Active Quartile Median**	**Timing Strategy**
		1/99-9/13		
Outperformance	0.10	0.50	0.60	1.47
Tracking Error	1.94	1.38	3.40	2.27
Information Ratio	0.05	0.36	0.18	0.65
		10 Year		
Outperformance	0.20	0.81	0.80	1.95
Tracking Error	2.23	1.51	3.95	2.50
Information Ratio	0.09	0.54	0.20	0.78

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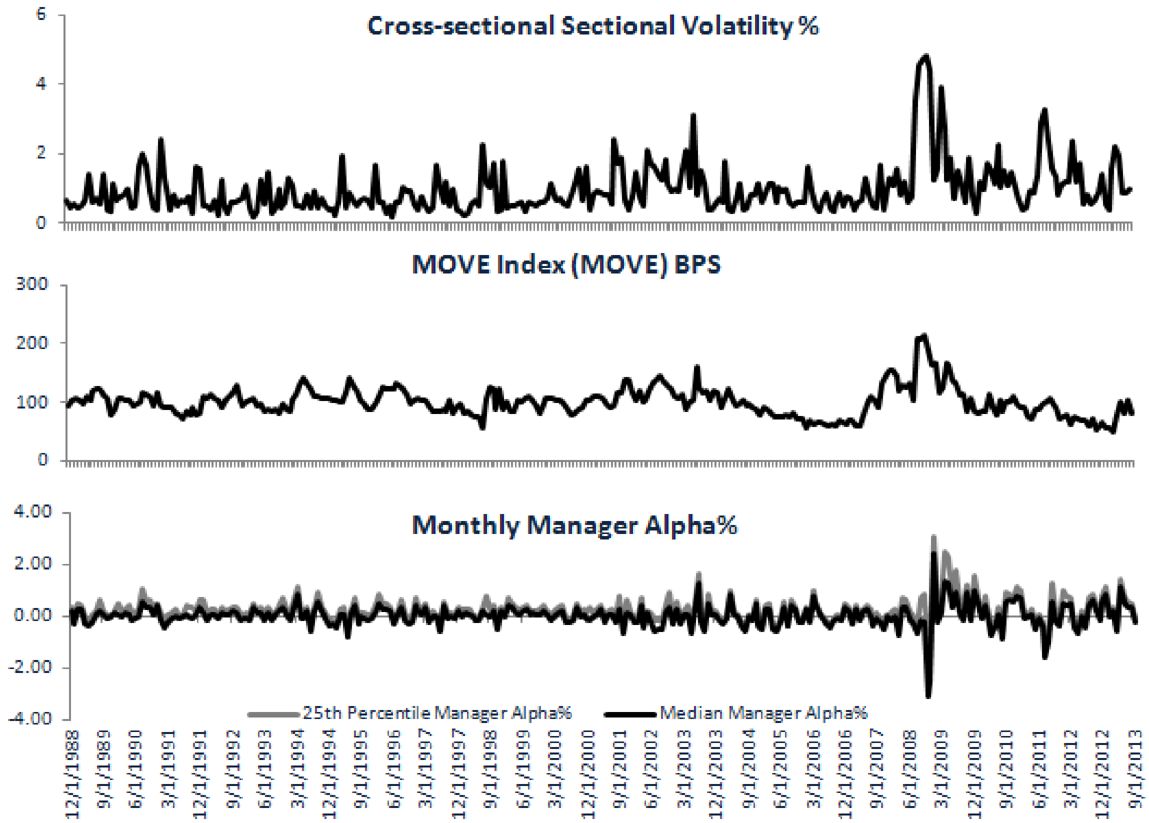
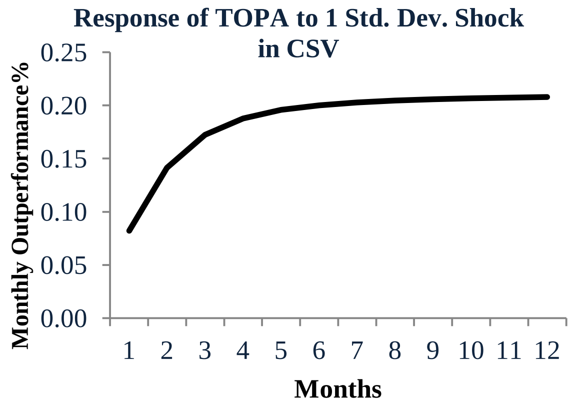


Figure 1. ***CROSS-SECTIONAL VOLATILITY, MOVE, AND MANAGER OUTPERFORMANCE***



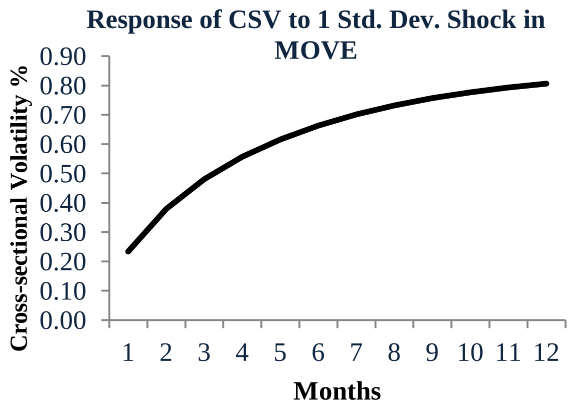
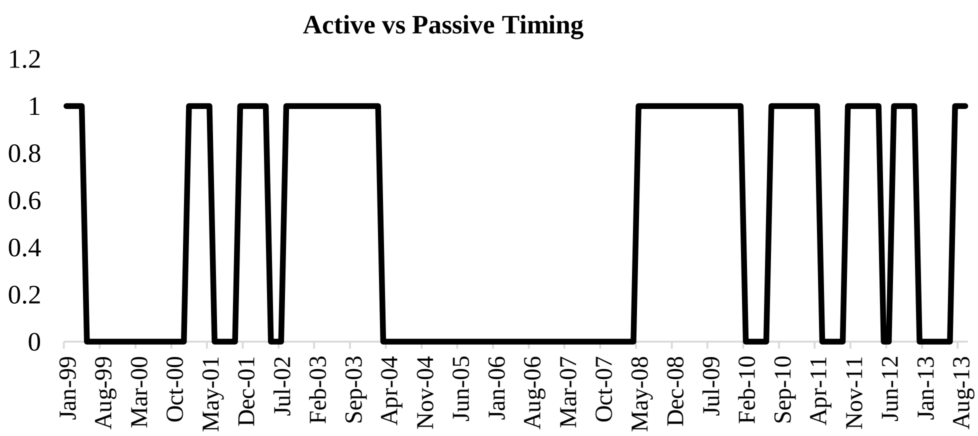


Figure 2. ***CUMULATIVE GENERALIZED IMPULSE RESPONSE FUNCTION ANALYSIS***



Active months marked one and passive months marked zero

Figure 3. ***ACTIVE VS. PASSIVE TIMING***