

CoAnomaly: Beyond Investment Opportunity and Volatility

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Abstract

I propose a new and unique risk measure, *CoAnomaly*, by calculating the correlations between 32 equity market anomalies. Using the benchmark test assets, I find evidence supporting that CoAnomaly is negatively priced and explains the cross-sectional return patterns of testing portfolios. I also study the time-variation of the CoAnomaly, and find that return premium in these equity anomalies is higher following high CoAnomaly; and arbitrageurs seem to be aware of this risk and behave accordingly. I estimate an intertemporal CAPM using VAR approach and find that the CoAnomaly gets risk premium beyond intertemporal hedging demand of time-varying investment opportunity and volatility. Finally, I provide evidence that links CoAnomaly, intermediary asset pricing, and endogenous risk.

JEL-Classification: G11, G23.

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Contents

1	Introduction	1
2	Related Literature	4
3	CoAnomaly	5
3.1	Data and Anomaly Construction	5
3.2	CoAnomaly Calculation	6
3.3	Time Variation of CoAnomaly	7
3.4	Relationship between CoAnomaly and Variance	9
3.5	Cross-Sectional Correlation Pattern of Different Anomalies	9
3.6	Preliminary Pricing Test of CoAnomaly Risk	10
4	Predicting Anomaly Returns: Time-series and Cross-sectional Evidence	11
4.1	Predictions	11
4.2	Testing with Anomalies' Returns	12
4.3	Robustness of the Results	17
4.4	Why CoAnomaly? But not CoVariance?	18
5	Intertemporal CAPM for Market-Neutral Investing	18
5.1	Stochastic Volatility Setting and VAR Approach	19
5.2	Market-Neutral Investment Universe and CoAnomaly	21
5.2.1	VAR specification	21
5.2.2	VAR Estimates and News Terms	22
5.2.3	Estimating the Anomaly ICAPM Using 32 Equity Market Anomalies	23
5.2.4	Interpretation of the Market-Neutral Investing ICAPM	25
5.3	CoAnomaly beyond the Aggregate Volatility in Anomaly Universe	25
6	Future Research Plan	26
7	Conclusion	27

1 Introduction

‘How should the risk of an asset be measured? And what economic forces determine the price of risk, the additional return an investor gets for bearing additional risk? These two questions are among the most fundamental in finance.’

Campbell (1996), *Understanding Risk and Return*.

These two questions still remain as the center of modern finance research. In this paper, I am exploring the same questions from a slightly different prospect: by considering the risk of trading equity market anomalies by an increasing body of market-neutral investors. As the largest financial market in the world, the US equity market shows evidence that a benchmark single market factor model like CAPM cannot fully price the cross-sectional variation of all the stocks. Since early 1990s and even before, there started huge competition both in academia and in industry to identify and explore assets and trading strategies generating abnormal returns beyond the benchmark market risk, which are normally called *equity market ‘anomalies’*. The asset management industry also increased a lot in the last few decades, and among them, hedge funds who are chasing market-neutral returns play an important role in terms of both holdings and tradings. Most recently, the Exchange-Traded Fund (ETF) industry also started issuing factor-based products and long-term investors are also investing in these assets, hoping to boost returns (see Cao, Hsu, Xiao, and Zhan (2018)).

Another recent puzzle discovered is the fact that high volatility is not accompanied by higher return as compensation. This counterintuitive effect shows up in the aggregate market (see Moreira and Muir (2017)), as well as for single anomaly portfolio (see Barroso and Santa-Clara (2015) and Barroso and Maio (2018)).

What are the risks of trading these equity market anomalies and how to quantify them? Are arbitrageurs facing time-varying investment opportunities as well? If yes, are arbitrageurs responding accordingly and what is their hedging demand? Then what is the implication to these anomaly assets and do these anomalies behave differently under specific circumstances?

In this paper, I propose a simple and straightforward measure of correlation risk faced directly by the sophisticated investors, which I name it *CoAnomaly*. I borrow the methodology developed by Lou and Polk (2013) and inspect deeper into the correlation between different equity market anomalies by, at each point of time, looking at the past degree of abnormal return correlations among these anomalies that arbitrageurs speculate on. Higher correlation between these anomaly assets corresponds to higher risks, since the portfolio variance also depends on the correlation between constituent assets. I would expect the anomaly return will be higher in a high correlation regime since arbitrageurs will demand a higher risk compensation. This logic goes back to the

portfolio theory of [Markowitz \(1952\)](#), since investors cannot diversify any more in a high asset-correlation environment and hence require higher future returns. I do not intend to explain the source of correlations between anomalies. I am taking the time-varying correlation structure as given, and studying the asset pricing implications for equity market neutral investors.

I first study the time-series variation of my CoAnomaly measure and find that it is priced in the equity market by examining benchmark portfolios. It carries a negative price of risk, which follows the intuition that investors would like to hedge a period with high CoAnomaly. In the meantime, it also shows strong explanation power for the cross-sectional return dispersion of size-value and momentum portfolios. I find that there is some level of persistence in CoAnomaly and it does not particularly correlate with any existing measure of risks. There is also a small upward trend over time, and I believe this echoes the increase of professional asset managers and their asset under management. I also explore the cross-sectional correlation patterns of different constituent anomalies. I find that there is a large dispersion in the unconditional pairwise partial correlations among anomalies. Next, I link the time-series pattern with the cross-sectional pattern, and find that the increase of CoAnomaly is not a parallel shift of the correlations of all anomalies, but more a monotonic pattern associated with the anomaly's unconditional partial correlations: if the anomaly has high unconditional partial correlations with other anomalies, its partial correlations will increase more in the time when CoAnomaly increases. This empirical fact enables me to do cross-sectional tests later.

I set out three predictions following a simple mean-variance trade-off: *Prediction 1* - on average, returns on these anomalies will be higher during high CoAnomaly periods; *Prediction 2* - if all arbitrageurs trade against these anomalies together, there will be a negative price impact when there is an anticipated increase in CoAnomaly; *Prediction 3* - the price impact in *Prediction 2* will be larger for the anomalies with higher increase in partial correlations with other anomalies. I use 32 equity market anomalies, studied in [Novy-Marx and Velikov \(2016\)](#) and [Cho \(2017\)](#), as my anomaly assets. I use Equity Market Neutral Index, HFRIEMNI, published by the Hedge Fund Research as part of their HFRI®Indices, as a proxy to the shocks to arbitrageurs who are mainly trading these equity market anomalies. I find strong empirical evidence consistent with all three predictions by observing returns and price impacts on anomaly assets. These findings also support the idea that arbitrageurs in real world are aware of this risk that they are exposed to, and they behave accordingly.

Since the future anomaly returns can be predicted by CoAnomaly and it also has a natural link with the volatility of the aggregate anomaly portfolio, I study the intertemporal hedging demand based on CoAnomaly. I follow [Campbell, Giglio, Polk, and Turley \(2017\)](#) and estimate an intertemporal CAPM with stochastic volatility for

market-neutral investing, which means that I am focusing on the anomaly returns orthogonal to the market. I find the CoAnomaly gets priced partially through intertemporal hedging demand for time-varying investment opportunity and volatility. Roughly another half of the CoAnomaly risk gets priced beyond the intertemporal hedging demand. Finally, I explore other possible mechanisms for the priced risk and find evidence that CoAnomaly is linked to intermediary asset pricing and endogenous risk in equity market anomalies.

My paper contributes to the literature in three aspects: first, I propose a straightforward and direct risk measure which is economically intuitive, computationally simple and robustly priced in the market. It can be computed with respect to different sets of portfolios, different time window and with either higher or lower frequency data. The last point is quite crucial to both in academic and in practice since most of existing (endogenous) risk measures are with very low frequency (e.g. [Adrian, Etula, and Muir \(2014\)](#) are using quarterly broker-dealer leverage data).

Second, this measure brings better understanding of the behaviors of the fast-growing sophisticated investors and the possible logic behind, by providing supportive evidence linking the two sets of literature: intermediary asset pricing and endogenous risk in financial market. Since the CoAnomaly risk does not fully transit through the hedging demand for investment opportunity and volatility shocks in the market-neutral investment universe, there must be other source of systematic risks which sustains the CoAnomaly risk price. In some preliminary test results of extending the test assets to non-equity markets, I still find that the CoAnomaly risk is robustly priced. This provides guidance to future theoretical work modelling the stochastic discount factor of the sophisticated institutional investors.

Third, my research also sheds light upon the understanding of the volatility-managed portfolios. Existing literature mainly focus on the volatility of a specific portfolio per se. However, I argue it is the comovement to the aggregate anomaly portfolio, or potentially to the marginal utility of arbitrageurs, that plays the right role. As argued in [Pollet and Wilson \(2010\)](#), if the [Roll \(1977\)](#)'s critique is important, variance in the stock market may be weakly correlated with the aggregate risk and subsequent stock market excess returns. The same logic applies to the sophisticated market-neutral investors, as the equity market anomalies consist a small *subset* of their investment universe.

The organization of my paper is as follows. Section 2 outlines the related literature concerning the correlation risk and endogenous risk in financial market. Section 3 describes the data and methods that I use to construct the CoAnomaly measure and studies the attributes of CoAnomaly. Section 4 sets up a simple framework to study the empirical facts between CoAnomaly and anomaly returns. Section 5 estimates an ICAPM and explores the mechanisms behind the CoAnomaly. Section 6 talks about

the future plan of my research and Section 7 concludes.

2 Related Literature

As assets comove togher, the magnitude of this correlation clearly affects how much investors can diversify and hence the future risk premium. **Correlation Risk** is studied pervasively: Pollet and Wilson (2010) show that the average correlation between daily stock returns predicts subsequent quarterly stock market excess returns, since market risk is determined by the *individual risks* and the *correlation* among them. Driessen, Maenhout, and Vilkov (2009) study the different exposures to correlation risk between index options and individual stock options and find that correlation risk exposure explains the cross-section of index and individual option returns well. Buraschi, Porchia, and Trojani (2010) provides a theoretical model in which the degree of correlation across industries, countries, or asset classes is stochastic. Buraschi, Kosowski, and Trojani (2013) find that the ability of hedge funds to create market-neutral returns is often associated with a significant exposure to correlation risk, which helps to explain the large abnormal returns found in previous models, and they also estimate a significant negative market price of correlation risk. Adrian and Brunnermeier (2016) propose a measure for systemic risk: CoVaR, the value at risk (VaR) of financial institutions conditional on other institutions being in distress.

In textbook asset pricing theory, arbitrage capital will respond quickly to any investment opportunity with excess returns after risk adjustment, thus eliminating those abnormal returns. However, what we observe in reality is that, with the rapid growth of sophisticated arbitrageurs such as hedge funds and also their asset under management, the abnormal returns of these anomalies have shrunk, but still not eliminated. A trending group of explanations to this is the limits to arbitrage, and among them, **endogenous risk story** is getting more popularity. Endogenous risk is a type of financial risk that is created by the interaction of market participants and can be amplified within the system. If these anomalies comove with the with the stochastic discount factor (SDF) of some specific sets of market participants, the endogenous risk behind the comovements can sustain the abnormal returns on anomaly assets. However, this endogenous risk does not have a clear definition or a clear measure. This first motivates me to find a better proxy for that.

Large and sophisticated agents in the financial market are aware of the endogenous systemic risk and will internalize the impact of their behavior: Kojien and Yogo (2015) find that most cross-sectional variation in stock returns is contributed to retail investors instead of large asset managers; Denbee, Julliard, Li, and Yuan (2016) find that most of the systemic risk is not necessarily generated by the obvious play-

ers. Meanwhile, there are also concerns about their roles and impacts, as Stein (2009) points out that *crowding* and *leverage* can impair market efficiency, and argue that capital regulation may be helpful in dealing with the latter problem. Both theoretical work and empirical evidence accumulate about this destabilizing effect of arbitrageurs, see Vayanos and Woolley (2013) and Lou and Polk (2013).

As the central part of financial market, financial intermediaries are crucial to asset pricing. Recently, there is a vast literature discussing the implication of them, and is referred as **intermediary asset pricing**. He and Krishnamurthy (2013) model the pricing kernel set by financial intermediaries, who are also the marginal traders of financial assets and facing an equity capital constraint, which leads to time-varying risk premia when constraints are binding. Adrian, Etula, and Muir (2014) use shocks to the leverage of securities broker-dealers to construct an intermediary SDF and their single-factor model prices size, book-to-market, momentum, and bond portfolios with an R^2 of 77% and an average annual pricing error of 1%-performing as well as standard multifactor benchmarks designed to price these assets. He, Kelly, and Manela (2017) also find that shocks to the equity capital ratio of financial intermediaries possess significant explanatory power for cross-sectional variation in expected returns across asset classes. Cho (2017) provides deeper insights of why intermediary balance sheet information can price many assets: sophisticated trading on anomalies (alpha) requires funding from intermediary, and hence creates an endogenous risk (beta). CoAnomaly directly measures the correlation risk faced by arbitrageurs, so it has a natural link to the endogenous risk, normally proxied by the SDF of a specific group of investors in the market.

3 CoAnomaly

3.1 Data and Anomaly Construction

To construct the equity market anomalies, I use the stock return data from the Center for Research in Security Prices (CRSP). Accounting data is from Compustat. I further obtain information of hedge funds from Morningstar CISDM Database. Short interest data is from Supplemental Short Interest File of Compustat - Capital IQ. Since I use quarterly accounting information to generate some anomalies, my sample period starts at 1973 and ends in 2017.

The hedge fund index data is from the Hedge Fund Research website. The HFRI® Indices are broadly constructed indices designed to capture the breadth of hedge fund performance trends across all strategies and regions. Here, I use the oldest and most popular HFRI Fund Weighted Composite Index (**HFRIFWI**), as well as Equity Market Neutral Index (**HFRIEMNI**), which both date back to the beginning of 1990.

Mispricing factors data is from Yuan’s website¹.

I consider 32 equity asset anomalies. For each anomaly, I compute the time-series of monthly value-weighted (VW) returns on a long-short self-financed portfolio over the period. I use the NYSE breakpoints for the anomaly characteristics to sort all stocks trading on NYSE, AMEX, and NASDAQ. To make sure my results are not driven by micro-cap stocks and other microstructure issues, I exclude stocks with prices below \$5 per share or are in the bottom NYSE size decile. The full set of anomalies is shown in Table 4. I follow closely Novy-Marx and Velikov (2016) and Cho (2017) to construct anomalies, and please see the appendix of Novy-Marx and Velikov (2016) for the details of constructing anomalies.

3.2 CoAnomaly Calculation

I first construct value-weighted anomaly portfolios by sorting stocks into deciles based on their their anomaly characteristics available at the end of month $t-1$. Here, I follow the standard procedure in the literature by using the NYSE breakpoints for the sorting and the anomaly portfolio is longing the top decile and shorting the bottom decile². After getting all the anomaly portfolios, I then compute pairwise partial correlations using daily returns of these portfolios³, and then equal weighting these correlation coefficients across all pairs between two different anomalies. $CoAnomaly^{LS}$ is the average pairwise partial correlation for whole long-short portfolio. Short-leg CoAnomaly ($CoAnomaly^S$) is the average pairwise partial correlation for the bottom deciles of all anomalies, and Long-leg CoAnomaly ($CoAnomaly^L$) is the average pairwise partial correlation for the top deciles of all anomalies.

$$\begin{pmatrix} 1 & \rho_{1,2} & \rho_{1,3} & \cdots & \rho_{1,N} \\ \rho_{2,1} & 1 & \rho_{2,3} & \cdots & \rho_{2,N} \\ \rho_{3,1} & \rho_{3,2} & 1 & \cdots & \rho_{3,N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{N,1} & \rho_{N,2} & \rho_{N,3} & \cdots & 1 \end{pmatrix} \Rightarrow \begin{pmatrix} (\rho_{1,2} + \rho_{1,3} + \cdots + \rho_{1,N})/(N-1) = \rho_{1,-1} \\ (\rho_{2,1} + \rho_{2,3} + \cdots + \rho_{2,N})/(N-1) = \rho_{2,-2} \\ (\rho_{3,1} + \rho_{3,2} + \cdots + \rho_{3,N})/(N-1) = \rho_{3,-3} \\ \vdots \\ (\rho_{N,1} + \rho_{N,2} + \cdots + \rho_{N,N-1})/(N-1) = \rho_{N,-N} \end{pmatrix}$$

The correlation is partial in the sense that I control for the market factor when computing these partial correlations to purge out any comovement in anomaly returns induced by the market risk exposure. Two practical facts can justify this considera-

¹I thank Yu Yuan for providing the daily mispricing factors data.

²I adjust the anomaly characteristics so that the outperforming stocks are always on the top deciles (example: size and value stocks).

³There is some concern about the nonsynchronous trading as in Frazzini and Pedersen (2014), but the concern is mostly on stock level, but not on portfolio level.

tion: arbitrageurs (like hedge funds) who are the main traders and exploiters⁴ of these anomalies are chasing market neutrality, and in general, the market betas on portfolio level are fairly stable and can be predicted well. I use the look-back period for three months, which means the CoAnomaly measure at the end of June is constructed using daily returns in April, May and June. However, my main results are robust to other specifications.

$$CoAnomaly_t^{LS} = \frac{1}{N} \sum_{n=1}^N \underbrace{partialCorr_t(ret_n^{LS}, ret_{-n}^{LS} | MktRf)}_{\substack{\text{Average pairwise partial correlation} \\ \text{for anomaly } n \\ \text{with respect to all other anomalies } -n}} = \frac{1}{N} \sum_{n=1}^N \rho_{n,-n}^{LS},$$

$$CoAnomaly_t^S = \frac{1}{N} \sum_{n=1}^N partialCorr_t(ret_n^S, ret_{-n}^S | MktRf) = \frac{1}{N} \sum_{n=1}^N \rho_{n,-n}^S,$$

$$CoAnomaly_t^L = \frac{1}{N} \sum_{n=1}^N partialCorr_t(ret_n^L, ret_{-n}^L | MktRf) = \frac{1}{N} \sum_{n=1}^N \rho_{n,-n}^L,$$

where N is the number of total test anomalies, $ret_n^{LS(S/L)}$ is the daily return of the long-short(/short-leg/long-leg) portfolio for anomaly n , and $ret_{-n}^{LS(S/L)}$ is the equal-weight daily return of long-short(/short-leg/long-leg) portfolios for all test anomalies apart from anomaly n .

3.3 Time Variation of CoAnomaly

(Insert [Table 1](#))

I find that CoAnomaly for long-short anomaly portfolios is mainly driven by the shortleg. The CoAnomaly behaves quite differently for the long legs and the short legs, with a slightly negative correlation. In terms of magnitude, the shortleg CoAnomaly is larger than longleg CoAnomaly, which could be justified by 1) apart from size anomaly, most anomalies tend to have large firms on the longleg and small firms on the shortleg, so a larger price impact should be expected on the shortleg than on the longleg; and 2) arbitrageurs have a relatively higher trading presence on the short legs and they tend to trade all these assets simultaneously more comparing to other investors.

⁴Many anomalies did exist before the emergence of sophisticated asset managers, and there are other parties trading these anomalies before 1990s. However, this is a much smaller scale comparing to the situation right now.

I also check the contemporaneous correlation between different CoAnomaly measures and other market indices. None of the market excess returns, VIX, TED rate, and the market liquidity level has a particularly strong correlation with CoAnomaly measure. This pattern can be seen in [Figure 1](#) as well. The figure also shows a slightly increasing trend in the CoAnomaly, which may be linked to the growth of sophisticated investors in the last few decades. This phenomenon is also confirmed in the second panel of [Table 1](#), where I divide my full sample into half and focus on the second half of my sample. This is intended to check the consistency of the behaviors of the CoAnomaly measure, as well as that some time series measures are only available in the second half. I show that the average of magnitude of all three CoAnomaly measures increases slightly, however as for the correlations, roughly they remain the same compared with the full sample.

For the longshort CoAnomaly, I find it has the highest correlation with the volatility measure (positive, both realized vol and VIX) and equity neutral hedge fund index (negative). Finally, it is also highly correlated with the contemporaneous correlation of two mispricing factors as in [Stambaugh and Yuan \(2016\)](#), who argue most equity market anomalies can be explained by these two mispricing factors. From this point, unless explicitly addressed, when I talk about CoAnomaly, I refer to the long-short CoAnomaly⁵.

(Insert [Table 2](#))

In [Table 2](#), I conduct a predictive analysis of CoAnomaly. I find that all CoAnomaly measures are fairly persistent. Since I am focusing on the long-short CoAnomaly now, I run extra regressions of long-short CoAnomaly on various variables in the last quarter. The market excess return is the only robust predictor to CoAnomaly, and CoAnomaly tends to increase after market falls, which is consistent with a risk story since an increase in the risk of aggregate portfolio will induce a contemporaneous negative return shock and an increase in the correlation between assets. Apart from the market excess return, none of the coefficients for other predictors shows up significantly. While high arbitrage capital (lower TED rate, larger higher market and hedge fund return, lower volatility or higher liquidity) would induce more capital allocated in these anomalies, it is also possible that arbitrageurs trade more frequently when they are facing capital constraints. Both of these mechanisms may increase the comovement among assets. Given these effects are mixed, I do not overinterpret the signs at the moment. One final observation is that adding more predictors does not increase the forecastability of CoAnomaly significantly, as the R-squared shows.

⁵Empirical results remain qualitatively the same if I use the shortleg CoAnomaly.

3.4 Relationship between CoAnomaly and Variance

The variance of any portfolio, which serves a traditional measure of the risk, is determined by both the volatility of the constituent assets and the correlation between them. I focus on a naive portfolio by investing in these anomalies with equal amount, and I term its return as Equal-weighted Anomaly Return (E.A.R.), which is the simple equal-weight mean return of 32 equity market anomalies.

(Insert Table 3)

In Table 3, I first reports the correlation between CoAnomaly, Average Variance and Variance of E.A.R. Panel B reports the results of regressing the realized variance of the Equal-weighted Anomaly Returns (E.A.R.) on the contemporaneous CoAnomaly and the average realized variance of different single anomalies. Realized variance of the Equal-weighted Anomaly Returns (E.A.R.) is measured as the variance of daily returns within a given quarter. Average realized variance is equally averaging the realized daily variances for the 32 equity market anomalies in the same quarter. The results show that both the CoAnomaly and the average variance contribute to the variance of the Equal-weighted Anomaly Returns (E.A.R.), and these two components capture almost all of the time-series variation in the EAR variance (as the R-Squared goes to 100%).

3.5 Cross-Sectional Correlation Pattern of Different Anomalies

I also study the cross-sectional pattern of the average pairwise partial correlation $\rho_{n,-n}$ ⁶ for each anomaly. Two main findings are: first, there is some level of dispersion in the average pairwise partial correlations among these anomalies, and some of them have low or even negative partial correlation with the others; second, the time variation in CoAnomaly is not a parallel shift in the partial correlations across all anomalies, and instead, the change for each anomaly is proportional to the unconditional partial correlation of that anomaly.

(Insert Table 4)

The first column of Table 4 reports the unconditional mean of CoAnomaly and also the average pairwise partial correlation for each anomaly in increasing order. We can see the dispersion of anomaly correlations is quite large, with size being negative, and idiosyncratic volatility being positive and large. I also sort all quarters into low CoAnomaly, medium CoAnomaly and high CoAnomaly, and find that the in general,

⁶ $Partial_Correlation_n = \rho_{n,-n} = partialCorr(ret_n^S, ret_{-n} | MktRf)$, which equals the average pairwise partial correlation between strategy n and all other strategies.

the average pairwise partial correlation of most strategies is increasing over these three groups by construction. However, the pattern how they go up is not homogeneous for every strategy. Instead of increase in parallel, I find the change in correlation (column Diff 3-1) is increasing with the unconditional correlation for the anomalies. This relationship is also featured in [Figure 3](#) and [Figure 2](#).

(Insert [Figure 2](#) and [Figure 3](#))

I also run a plain regression to check this relationship. For all anomalies, I regress their changes in correlation (column Diff 3-1) on their average pairwise partial correlation (column Average). I report the results at the end of [Table 4](#). We can see the relationship is strong, even after I exclude the anomalies with negative average pairwise partial correlations. This cross-sectional pattern allows me to study the different dynamics for anomalies with different average pairwise partial correlation, because as we argue later, what matters is not the average pairwise partial correlation, but the change of it.

Finally, I want to note that the anomaly ranking in changes in partial correlation may not coincide the anomaly ranking in CoAnomaly beta, which I will study later. The reason is that, the anomaly, whose partial correlation increases a lot when the CoAnomaly is high, may not have a contemporaneous high return at the same period, which determines the CoAnomaly beta.

3.6 Preliminary Pricing Test of CoAnomaly Risk

Here I follow the procedure of [Fama and MacBeth \(1973\)](#) and [Adrian, Etula, and Muir \(2014\)](#) to conduct an asset pricing test of whether the CoAnomaly is priced in the market. I use the simple AR(1) innovation in CoAnomaly measure as the shock here. I first use the standard set of test portfolios, which includes 25 Fama-French size-value portfolios, 10 momentum portfolios, 5 industry portfolios and 6 treasury bond portfolios sorted by maturity⁷. I regress different portfolio returns on different time series based on different pricing models that I check, and then I regress the portfolio returns on the betas estimated in the first step. Here I assume constant betas on factors. By doing this, the prices of different risks are calculated.

(Insert [Table 5](#))

As shown in [Table 5](#), the cross-sectional test shows that the CoAnomaly risk is indeed priced among these test portfolios. The sign of CoAnomaly risk is negative, which is consistent with the intuition that higher loading on CoAnomaly will result in

⁷Portfolio returns are downloaded from French's website. Thank him for providing the data.

a lower return because high CoAnomaly-beta assets will do well in high CoAnomaly risk periods, which provide hedges against the CoAnomaly risk. This result echos the finding in [Driessen, Maenhout, and Vilkov \(2009\)](#). Notice that, the only specification that CoAnomaly risk does not has a significant risk premium is when it is combined with the momentum factor.

When I run a horse race with CoAnomaly against the size, value and momentum effect separately, as shown in the last three specification in panel A, I find that once I control the CoAnomaly risk, size, value and momentum risk premia are partially decreasing towards zero ⁸. Note that, the only specification that CoAnomaly risk does not has a significant risk premium is when it is combined with the momentum factor.

(Insert [Figure 4](#))

In the panel B of [Table 5](#), I exclude the 6 bond portfolios. The results show that market factor explains little of the cross-sectional variation of portfolio returns (and also comes with a wrong sign of risk premium). However, if I augment the CAPM model with my CoAnomaly, I find that one fourth of the total variations are explained. I plot this results in [Figure 4](#).

These results are strong evidence supporting that CoAnomaly is priced in the market, and the most well-known equity market anomalies (size, value and momentum) can be explained, at least partially, by the different loadings on the CoAnomaly risk.

4 Predicting Anomaly Returns: Time-series and Cross-sectional Evidence

4.1 Predictions

Let's start with a simple mean-variance optimization scenario. Suppose an investor is facing a bundle of risky assets. *Ceteris paribus*, the increase in the return correlation between all these assets will make the optimal portfolio riskier by increasing the variance. On the extensive margin, investors will allocate less capital to these risky assets. On the intensive margin, the change in the position to each asset will be negatively related

⁸In nontabulated results, I find that CoAnomaly risk price get subsumed to zero if I include all size, value and momentum factors together, which is not surprising since most test portfolios are based on the characteristics behind these factors and hence have a strong factor structure that can be explained by 'themselves'. [Cochrane \(2009\)](#) states this point, as he writes: '*Thus, it is probably not a good idea to evaluate economically interesting models with statistical horse races against models that use portfolio returns as factors. Economically interesting models, even if true and perfectly measured, will just equal the performance of their own factor-mimicking portfolios, even in large samples. Add any measurement error, and the economic model will underperform its own factor-mimicking portfolios. And both models will always lose in sample against ad hoc factor models that find nearly ex post efficient portfolios.*'

to the change in the partial correlation of that specific asset, since that asset comoves more strongly with the portfolio. These effects will be stronger when the investor is more risk-averse.

In the setting of market-neutral investors trading equity market anomalies, I can identify these effects in a specific scenario where the whole set of arbitrageurs are experiencing a negative shock. During these periods, arbitrageurs tend to move in the same direction, and this will generate a market wide price impact, at least in the short-term period. This effect is also supported and strengthened by another empirical fact that, in general, hedge funds will experience an outflow of capital after poor performance, so the managers have to liquidate some positions to meet the redemption.

Putting these together in a real world setting, given empirically the CoAnomaly showing some persistence, there are several predictions I can test:

- *Prediction 1:* The return on equity market anomalies will be higher following high CoAnomaly periods, since arbitrageurs will require higher risk premium on these assets. This effect will be stronger when arbitrageurs are more risk-averse in aggregate.
- *Prediction 2:* With the increase of CoAnomaly from a low level to a higher level, arbitrageurs will decrease their position in equity anomalies. When all arbitrageurs tend to liquidate their positions together, it will create a short-term negative price impact on all equity anomaly assets.
- *Prediction 3:* The cross-sectional implication of *Prediction 2* - when CoAnomaly increases following a negative shock to all arbitrageurs, they will decrease the positions in high correlation strategies more than low correlation strategies. A short-term difference of the price impacts between these two sets of strategies will be capture by the next-period negative returns of a long-short portfolio which longs the high partial correlation anomaly strategies and shorts the low partial correlation anomaly strategies.

4.2 Testing with Anomalies' Returns

Here I split my full sample periods, from 1973Q1 to 2017Q4, into two halves: pre-1994, from 1973Q1 to 1994Q4, and post-1994, from 1995Q1 to 2017Q4. The results shown below is based on the second half of the total sample. I do not find any results significantly from zero in the first half. This fact is justified by the explosion of findind equity anomalies and emergency of sophisticated institutional investors since the early 90s.

Predictive Regression

(Insert Table 6)

In Table 6, I regress the Equal-weighted Anomaly Returns (E.A.R.) in the next quarter on the observables in current quarters. Column (1) shows that CoAnomaly is a strong forecaster of the EAR. Column (2) and (3) show that the predictive powers of the EAR variance and average variance of single equity anomalies are negligible. Column (4) and (5) include both CoAnomaly and the average variance and the realized variance of EAR, and they show that it is the average correlation component from the total variance that predicts future returns. In the last specification, I control for other alternative predictors and ensure the predictability of the CoAnomaly is not driven by other known predictors. They include the TED rate, market excess return, value spread and EAR return itself in the current quarters. I find that the predictive power is still significant, albeit with a smaller scale. Column (5) and (6) are effectively doing a horse race between the CoAnomaly, average variance and EAR variance since EAR variance can be decomposed into CoAnomaly and average variance as shown in Table 3. Note that most of these predictors are used in the intertemporal CAPM framework as state variables in the next section.

(Insert Table 7)

Table 7 reports predictive regression estimates of the Equal-weighted Anomaly Returns (E.A.R.) for return intervals of one and six months using overlapping data. The columns in each half are identical to the specification (1), (5) and (6) in Table 6. The regression results for 6-month EAR are stronger than 1-month EAR in terms of both coefficients and adjusted R-squared, which is not surprising considering that there are more noise within shorter window. However, we do find consistent results about the positive predictability of the CoAnomaly measure.

Pollet and Wilson (2010) presents a stylized model in which correlation between assets, but not the aggregate variance, is positively related to the aggregate risk premium. They show that the risk premium is given by

$$\mathbb{E}_t[r_{s,t+1}] - r_{f,t+1} + \frac{\bar{\rho}_t \bar{\sigma}_t^2}{2} = \frac{\gamma}{\beta_t(1 - \theta_t)} \bar{\rho}_t \bar{\sigma}_t^2 - \frac{\gamma}{\beta_t(1 - \theta_t)} \theta_t \bar{\sigma}_t^2, \quad (1)$$

where $r_{s,t+1}$ is the return on the stock market, $r_{f,t+1}$ is the risk-free rate, $\bar{\rho}_t$ and $\bar{\sigma}_t^2$ are the average correlation and the average variance of single stocks, β_t is the beta of stock market on the aggregate wealth portfolio, θ_t is the proportion that stock market risk component is to the total risk for a single stock.

As shown in the equation, the relationship between risk premium and average variance is not clear, however, the relationship between risk premium and average correlation is positive. This is due to the stock market is just part of the aggregate wealth

portfolio. In the market-neutral setting, for sophisticated arbitrageurs, the equity market anomalies are a small set of their investment strategy universe. Following the same logic, the variance on these anomalies provide little information about the risk of their aggregate portfolio. The intuition behind is that if the changes in the stock market variance is orthogonal to the risk in aggregate wealth portfolio, then such changes in stock market variance should be offset by changes in the covariance of the stock market with the rest of the aggregate wealth portfolio, holding the risk of aggregate wealth portfolio constant.

From another point of view, if single assets share common components from the aggregate portfolio, the increase of volatility of this common component will, first, drive up the volatility of single assets, and second and more importantly, induce stronger comovement among these single assets. When the aggregate portfolio cannot be measured perfectly, the volatility of an alternative pseudo-aggregate portfolio can be a bad proxy for the aggregate risk. However, the correlation effect between single assets remains robust.

In market-neutral investment setting, these equity market anomalies constitute a small subset of the whole investment universe of the sophisticated investors, which is a perfect scenario that fits Roll (1977)'s critique. In nontabulated results, I use non-equity hedge fund indices to proxy the non-equity investment universe of hedge funds and find that the CoAnomaly measure is highly correlated to the risk of trading other equity-neutral strategies.

Time-series Sorting

(Insert Table 8)

As shown in the Panel A of Table 8, I first simply sort all months based on the realized CoAnomaly within that month t . All time-series sortings are using 30% and 70% as breakpoints. First, I notice that high CoAnomaly does predict high future CoAnomaly. Apart from the persistence of CoAnomaly, there is also a mean-reversion pattern (see column CoAnomaly t and CoAnomaly $t+1$). So following a low CoAnomaly month, the CoAnomaly will increase but still stay relatively low. This allows me to test the last two predictions. I then check the returns of equal weighting the long-short returns of all anomalies from the next month $t+1$ to half of a year $t+6$. There is a monotonic and persistent pattern across groups: high CoAnomaly months are followed by high average returns on all equity anomalies. On average, the difference in returns between following a high CoAnomaly and following a low CoAnomaly (Diff 3-1) is more than 60 basis points in the following month, which is economically large and statistically significant. This difference in anomalies' returns is also persistent and significant up to half of a year. This result is in line with the *Prediction 1*.

I further check whether this pattern will hold under the different market conditions. Given the fact that hedge funds are the main players in trading these equity anomalies, I use the Hedge Fund Research Indices to proxy the level of capital constraint of these arbitrageurs. Among them, I choose the HFRI Equity Market Neutral Index, HFRIEMNI⁹, which is the average returns of all market-neutral quantitative equity funds in their database, to proxy the shocks to these arbitrageurs. So I first sort all months based on the HFRIEMNI in month t , and then within each group, I sort on the CoAnomaly level. As shown in the Panel A of Table 8, the two sorting variables, column HFRIEMNI t and column CoAnomaly t , do not show any increasing or decreasing relationship, so if I conduct the double sorting independently, the results shown below remain unchanged qualitatively.

The main advantage of using Equity Market Neutral Index is that HFRIEMNI is a direct measure of the shocks to the arbitrageurs who are mainly trading all equity market anomalies. I did not use the average returns on all anomalies as a proxy to the shocks to the arbitrageurs because I cannot assume that arbitrageurs are betting these anomalies consistently across time. There is a large literature documenting the timing ability of different anomalies (e.g. Cohen, Polk, and Vuolteenaho (2003) for timing value, Lou and Polk (2013) and Barroso and Santa-Clara (2015) for timing momentum, Moreira and Muir (2017) for timing an extensive sets of factors based on their realized volatility). Barroso, Edelen, and Karehnke (2017) directly test the behavior of institutional investors with 13F institutional holdings data, and find that these investors actually decrease their loading on momentum before momentum crash, which rejects the idea that momentum crashes relate to institutional crowding. In results not shown here, I also did the same test using the equal-weighted return on all anomalies as a proxy of shocks to arbitrageurs, and find similar pattern, but with less statistical significance.

The Panel B of Table 8 shows the results of this double sorting. The endogenous risk premium is much higher and more significant for the distress periods of hedge funds, which supports *Prediction 1*. This is consistent with the fact that hedge fund managers show higher risk aversion after poor returns due to many reasons, including the withdrawal of capital by investors. Another pattern is that there is a short-term negative return on anomalies following a bad shock to hedge funds in a low CoAnomaly periods. This is consistent with the intuition that hedge funds will take into account

⁹On their website, they state that ‘*Equity Market Neutral strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for **purchase** and **sale**. These can include both **Factor-based** and **Statistical Arbitrage/Trading strategies**. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and **leverage** is frequently employed to enhance the return profile of the positions identified.*’

the fact that CoAnomaly (risk) will go up in the future, so they tend to liquidate some positions in these anomaly assets. This empirical evidence aligns well with *Prediction 2*.

To test the *Prediction 3*, I consider a long-short portfolio on top of these anomalies. I am longing the high half of all anomalies in terms of A) high average pairwise partial correlation in month t , or B) high all sample period (unconditional) average pairwise partial correlation, or C) high changes in pairwise partial correlation from low CoAnomaly periods to high CoAnomaly periods. I study the behavior of this portfolio after a negative shock to the aggregate arbitrageurs group, but after different CoAnomaly level.

I use three different time-series to check the results, which turn out to be consistent across measures. This is not surprising consider the high correlation between the three measures, as shown in [Figure 3](#). For the first measure, average pairwise partial correlation in month t , with only information up to time t being used, so a tradable version of this pattern can be explored. Results are reported in [Table 9](#). After a negative shock to the whole arbitrageurs, if the current CoAnomaly is low, arbitrageurs will anticipate a high CoAnomaly and decrease positions in high correlation anomaly assets more than low correlation anomaly assets. I indirectly test this by looking at the (price impact) return difference between high partial correlation anomaly assets and low partial correlation anomaly assets, which is column Ret of (H.c.-L.c.) in [Figure 3](#). We can see that there is a negative shock to high correlation anomaly assets, which I argue is caused by the simultaneous selling by all arbitrageurs, consistent with *Prediction 3*.

(Insert [Table 9](#))

[Figure 5](#) shows the short-term patterns of the price impacts both in aggregate and cross-sectionally. Both figures are only considering the months with a shock to arbitrageurs as a whole. There is a short-term negative return right after after a low CoAnomaly month, which I argue that it is because arbitrageurs are seeing CoAnomaly increasing due to mean reversion, they are liquidating some positions in anomaly assets together. Decompose this effect into two sets of anomaly assets based on their average pairwise partial correlation in month t , we can see that high correlation anomalies are dominating this effect. This graphical illustration of empirical results is consistent with *Prediction 2* and *Prediction 3*. Note that the different behaviors of the high-correlation anomalies and the low-correlation anomalies disappear or even reverse in untabulated results when I focus on the periods with mild or high hedge fund returns.

(Insert [Figure 5](#))

Note that, the evidence supporting my predictions also requires that arbitrageurs are aware of the endogenous risk level. Given sophisticated nature of this type of investors, I believe this is not a strong assumption.

4.3 Robustness of the Results

(Insert [Table 10](#))

Too Many Anomalies and Lack of Dimension One concern about CoAnomaly is that among all these anomalies there are some large correlation between some of them, for example investment anomaly will mechanically be highly correlated with asset growth anomaly and net issuance anomaly. In the meantime, different strategy will have different size of trading capital in it. Following this two points, simple equal weighting different anomalies may overweight some anomalies and can not fully exploit all information from the correlation, hence containing quite some noise.

I fully acknowledge this concern, and conduct a simple robustness test, which produces results consistent with my findings. Instead of sorting months based on the CoAnomaly, I sort all months by the correlation between two mispricing factors as in [Stambaugh and Yuan \(2016\)](#). In their study, they group 11 anomalies, which have been studied in [Stambaugh, Yu, and Yuan \(2012\)](#) and [Stambaugh, Yu, and Yuan \(2015\)](#), into two sets based on either cross-sectional correlations of stocks rankings on the anomaly variables or time-series correlations of anomalies long-short return spreads. Both measures yield the same clusters of anomalies in their work. I believe this measure will not suffer the problem of incorrectly-overweighting some set of anomalies due to high correlation (low dimensionality). As reported in Panel A of [Table 10](#), there are two pieces of evidence supporting our results: first, the CoAnomaly measure in next period is also increasing across groups sorted by the correlation of two mispricing factors, which means that I am indeed catching up some component in the correlation among all these equity market strategies; second, the pattern of future returns for all anomalies is on the same level in both economic magnitude and statistical significance.

CoAnomaly Calculation Window As reported in Panel B of [Table 10](#), the results remain qualitatively unchanged if I use the CoAnomaly measure calculated within one previous month. My main goal is proposing a new measure. In practice, money managers are facing different beta constraints and concentration limits, and they also have different assets in hand. So they can certainly choose their optimal anomaly / strategy set, weights, frequency and sample window to calculate the endogenous risk measure tailored for and based on their portfolio composition and other concerns.

2008 Market Turmoil The market turmoil in 2008 has a large impact on broad financial markets and asset prices. As for the equity market anomalies, there has been some research about the different behaviors during these periods: [Daniel and Moskowitz \(2016\)](#) show that momentum strategy lost close to 50 percent following 2008. To make sure my results are not driven by these periods, I removed all months starting from 2008 in Panel C of [Table 10](#). The results are similar.

Market Risk Exposure I control the market risk exposure of the E.A.R. by subtracting the contemporaneous market returns times the in-sample beta of E.A.R.. The Panel D of [Table 10](#) shows that the results are not driven by the market risk.

4.4 Why CoAnomaly? But not CoVariance?

The risk of a single asset evaluated with respect to a portfolio is measured by the covariance between the asset and the portfolio, which is the standard portfolio theory or CAPM conclusion. However, in the case of equity market anomalies, I argue CoAnomaly, which is a measure based on correlations, is better than the covariance to proxy the risk: To access the covariance, a benchmark portfolio is needed, which is particularly difficult in the case of sophisticated institutional investors. Unlike the standard macrofinance models assuming that longterm investors hold the aggregate market, the investment universe of institutional investors go way beyond the equity market, to fixed-income, derivatives, and even to real estate and antiques. On the other hand, even if the exact composition of the portfolio is known, the exact weight on each asset (strategy) is still unknown. So in this case, a benchmark portfolio like the aggregate market portfolio does not exist, hence the covariance measure lacks a clear definition to measure the risk.

However, as I argue before, if single assets share common components from the aggregate portfolio, the increase of volatility of this common component will induce stronger comovement among these single assets. This effect on comovement justifies my choice of using the correlations to calculate the CoAnomaly measure.

5 Intertemporal CAPM for Market-Neutral Investing

I have shown evidence that CoAnomaly is a strong predictor of the Anomaly returns, and it also has a mechanical link to the volatility of trading these anomalies as a portfolio. The next step follows naturally to study the intertemporal hedging demand of the market-neutral investors.

As ? argued, the ICAPM places restrictions on the behavior of the state variable: if a state variable forecasts positive changes in the investment opportunities, its innovation should carry a positive price of risk. On the other hand, if the state variable forecasts the increase in the volatility, its price of risk should be negative. Given the empirical fact that CoAnomaly forecast both higher aggregate anomaly returns and high aggregate anomaly risks, and it also carries a negative price of risk, I explore the composition of the priced risks through the ICAPM setting.

Based on the results I get, in the intertemporal CAPM setting for market-neutral investing, the cash-flow news and volatility news maintain significant risk prices, but the discount-rate news does not get a robust and consistent risk with the model prediction. This finding is in line with the findings in the aggregate equity market. The CoAnomaly risk price is halved once I control the time-varying investment opportunity and volatility. However, the remaining half of risk still shows up robustly and I provide evidence it is linked to the intermediate asset pricing.

5.1 Stochastic Volatility Setting and VAR Approach

Campbell, Giglio, Polk, and Turley (2017) consider a investor with Epstein and Zin (1991) Recursive utility and can write the investor's value function as

$$U_t = \left\{ (1 - \delta)C_t^{\frac{1-\gamma}{\theta}} + \delta E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}}$$

where γ is the relative risk aversion RRA parameter, $\theta = \frac{1-\gamma}{1-1/\psi}$ and ψ is the intertemporal elasticity of substitution IES. RRA measures the willingness to substitute consumption across states of nature, and IES measures willingness to substitute over time.

Epstein and Zin (1991) show that this utility specification leads to the Euler equation

$$E_t \left[\delta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{\frac{\theta}{\psi}} \left(\frac{1}{R_{W,t+1}} \right)^{1-\theta} R_{t+1} \right] = 1,$$

where $R_{W,t+1} = W_{t+1}/(W_t - C_t)$ is the return on a claim to the wealth, Epstein and Zin use stock market index return as a proxy. The corresponding stochastic discount factor can be written as

$$M_{t+1} = \delta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{\frac{\theta}{\psi}} \left(\frac{W_t - C_t}{W_{t+1}} \right)^{1-\theta} \quad (2)$$

Campbell and Vuolteenaho (2004) assumes homoscedasticity of market returns, so they cannot generate time-varying risk premium and all discount rate shocks are coming from shocks to the risk-free rate. Campbell, Giglio, Polk, and Turley (2017) expand this

to heteroscedasticity by considering time-varying volatility. They rewrite the innovation in the log SDF as

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = \frac{\theta}{\phi}(h_{t+1} - \mathbb{E}_t[h_{t+1}]) - \gamma(r_{t+1} - \mathbb{E}_t[r_{t+1}]) \quad (3)$$

where $h_{t+1} = \ln(W_{t+1}/C_{t+1})$. Solving forward, they get

$$\begin{aligned} h_{t+1} - \mathbb{E}_t[h_{t+1}] &= (\phi - 1)(\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &\quad + \frac{1}{2} \frac{\phi}{\theta} (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j \text{Var}_{t+j}[m_{t+1+j} + r_{t+1+j}] \\ &= (\phi - 1)N_{DR,t+1} + \frac{1}{2} \frac{\phi}{\theta} N_{RISK,t+1}. \end{aligned} \quad (4)$$

Rearrange the two equations, they get

$$\begin{aligned} m_{t+1} - \mathbb{E}_t[m_{t+1}] &= -\gamma[r_{t+1} - \mathbb{E}_t[r_{t+1}]] - (\gamma - 1)N_{DR,t+1} + \frac{1}{2}N_{RISK,t+1} \\ &= -\gamma N_{CF,t+1} - (-N_{DR,t+1}) + \frac{1}{2}N_{RISK,t+1}. \end{aligned} \quad (5)$$

To implement their model, they assume that the economy can be described by a first-order VAR

$$\mathbf{x}_{t+1} = \bar{\mathbf{x}} + \Gamma(\mathbf{x}_t - \bar{\mathbf{x}}) + \sigma_t \mathbf{u}_{t+1} \quad (6)$$

where \mathbf{x}_{t+1} is an $n \times 1$ vector of state variables that has r_{t+1} as the first element, σ_{t+1} as its second, and $n - 2$ other variables that can contribute to the prediction of the first and second moments of the aggregate returns.

Given this structure, news about discount rates can be written as

$$N_{DR,t+1} = e'_1 \rho \Gamma (I - \rho \Gamma)^{-1} \sigma_t \mathbf{u}_t, \quad (7)$$

while news about cash flow follows

$$N_{CF,t+1} = (e'_1 + e'_1 \rho \Gamma (I - \rho \Gamma)^{-1}) \sigma_t \mathbf{u}_t. \quad (8)$$

Campbell, Giglio, Polk, and Turley (2017) show that the log-linear assumption about the economy will imply that the news about risk $N_{RISK,t+1}$ can be written as the news about the return volatility $N_{V,t+1}$ times a constant ω .

$$N_{RISK,t+1} = \omega \rho e'_2 \Gamma (I - \rho \Gamma)^{-1} \sigma_t \mathbf{u}_t = \omega N_{V,t+1} \quad (9)$$

Following the moment condition that the SDF prices all assets $\mathbb{E}_t[M_{t+1}R_{i,t+1}]$, the

pricing equation can be written as

$$\begin{aligned}\mathbb{E}_t[R_{i,t+1} - R_{f,t+1}] &= \gamma Cov_t[r_{i,t+1} - r_{f,t+1}, N_{CF,t+1}] \\ &\quad + Cov_t[r_{i,t+1} - r_{f,t+1}, -N_{DR,t+1}] - \frac{1}{2}\omega Cov_t[r_{i,t+1} - r_{f,t+1}, -N_{V,t+1}],\end{aligned}\tag{10}$$

where the ω solves

$$\omega\sigma_t^2 = (1 - \gamma)^2 Var_t[N_{CF,t+1}] + \omega(1 - \gamma)Cov_t[N_{CF,t+1}, N_{V,t+1}] + \frac{1}{4}\omega^2 Var_t[N_{V,t+1}].\tag{11}$$

5.2 Market-Neutral Investment Universe and CoAnomaly

5.2.1 VAR specification

Here I borrow the same framework to study the market-neutral investment universe. I estimate a first-order VAR as in Equation 6, where \mathbf{x}_{t+1} is a 5×1 vector of state variables with the following order:

$$\mathbf{x}_{t+1} = [\quad r_{EAR,t+1} \quad EVol_{EAR,t+1} \quad CoAnomaly_{t+1} \quad TED_{t+1} \quad VS_{t+1} \quad]'. \tag{12}$$

Instead of the real market return $r_{M,t+1}$ in Campbell, Giglio, Polk, and Turley (2017), I put $r_{EAR,t+1}$ as the first element, which is the equal-weighted return of the equity market anomalies (equal-weighted anomaly return, E.A.R.) that I have introduced before. Since the trading size / capacity of different anomalies has no clear definition like market cap for different stocks and is difficult to measure precisely, here I remain agnostic about the relative composition of the 'market portfolio' in this market-neutral investment universe. Recently there has been some literature studying this topic: Novy-Marx and Velikov (2016) find strategies based on size, value, and profitability have the greatest capacities to support new capital. The results remain qualitatively similar in some different specification I have explored.

The second variable is the expected volatility of equal-weighted anomaly return $EVol_{EAR,t+1}$. This variable is meant to capture the conditional volatility of the EAR, so the innovation to this variable naturally links to the N_V term above. To estimate the $EVol_{EAR,t+1}$, I follow Campbell, Giglio, Polk, and Turley (2017) by first running a regression of the realized variance $RVol_{EAR,t+1}$ on $RVol_{EAR,t}$ as well as other state variables at time t , and then using the predicted value for $\widehat{RVol}_{EAR,t+1}$ as the $EVol_{EAR,t}$, which only depends on information available at time t . $RVol_{EAR,t+1}$ is measured by the daily variance of the EAR in a given quarter $t + 1$, and I multiply this number by

the average trading days in a quarter, 64, to get the quarterly variance.

The third variable is the CoAnomaly measure. This measure has a natural connect with the volatility of the EAR, since the volatility of the anomaly portfolio will increase with the correlation between these anomalies, given the volatility of single anomaly staying constant. I also have also shown that this measure predicts future equal-weighted anomaly return, so it contains information about the hedging incentive of the sophisticated investors chasing market-neutral performance.

The fourth variable is TED spread (TED), which is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). This interest spread is known to proxy the funding cost of the arbitrageurs in broad financial markets. Data is downloaded from the Federal Reserve Bank of St. Louis, and it starts from 1986, so it limits our VAR sample period from 1986 to 2017.

The fifth variable is small-stock value spread (VS), which is adapted from previous literature (see [Campbell and Vuolteenaho \(2004\)](#) and [Campbell, Giglio, Polk, and Turley \(2017\)](#)). The value spread is a strong predictor for the value premium, which can explain some part of the premia for many anomalies, since many of them are somehow 'value-ish'.

5.2.2 VAR Estimates and News Terms

Two-Stage VAR regression - The estimation procedure follows [Campbell, Giglio, Polk, and Turley \(2017\)](#) closely by using a two-stage VAR regression with quarterly data. In the first stage of estimating the expected volatility, I deviate from the standard OLS in three ways: first, given the heteroskedasticity is modeled directly, I estimate this regression using Weighted Least Square (WLS), where the weight of each observation pair is based on the realized volatility in the previous quarter; second, I make sure the predicted value (expected volatility) is positive by winsorizing the fitted values which are negative or positive but close to zero; third, I shrink the weight towards to the equal weight by choosing a shrinking ratio 0.9, which means the 90% of the weight is based on the past volatility. The last step is to make sure my results are not driven by the observations in the low volatility environment. In the second stage, I use the inverse of expected volatility in time t to weight the regression with dependent variables in time $t+1$, as in [Equation 6](#).

(Insert [Table 11](#))

[Table 11](#) report the estimates of the two-stage VAR. Consistent with literature, past realized volatility strongly predicts future realized volatility. As for other variables, the predictive power is not statistically significant.

In panel B, I present the VAR estimation. Unlike the aggregate market returns, there is some level of persistency in the equal-weight anomaly return, and lower volatility, higher TED spread and higher value spread implies higher future returns. Expected volatility is highly persistent, and past returns can help to positively predict it.

News Terms

(Insert Table 12)

Table 12 shows that CoAnomaly shock is negatively correlated with the discount-rate news. However, the correlation is positive for the contemporaneous EAR shocks and CoAnomaly shocks, which does not contradict the negative correlation between CoAnomaly shocks and discount-rate news since EAR shocks equals the cashflow news minus the discount-rate news. The fact that CoAnomaly shocks is negatively correlated with discount-rate news is also not contradicting the findings that higher CoAnomaly (not CoAnomaly shock) is associated with higher average anomaly returns as in Table 8.

(Insert Figure 6)

Figure 6 plots the cash-flow news, the discount-rate news, and the volatility news. The shocks in 2001 and 2008 are mainly picked up through the volatility channel. The post-crisis period after 2008 is characterized by a negative news about the future returns which is consistent with the anecdotal evidence about of the ‘*slow death of active investment*’ in the last decades due to the low return in this period.

5.2.3 Estimating the Anomaly ICAPM Using 32 Equity Market Anomalies

Test Assets I use the 32 equity market anomalies, separating their longlegs and shortlegs, as the test assets to estimate the ICAPM model. Since I am studying the market-neutral investment universe, I removed the market component for each test asset by subtracting its in-sample beta times the contemporaneous market return in each period.

Beta Estimation Following Campbell and Vuolteenaho (2004) and Campbell, Giglio, Polk, and Turley (2017), I divide all three covariances by the sample variance of the EAR returns to compare to previous research:

$$\begin{aligned}
\beta_{i,CF_{EAR}} &\equiv \frac{Cov(r_{i,t}, N_{CF_{EAR},t})}{Var(r_{EAR,t} - \mathbb{E}_{t-1}[r_{EAR,t}])} \\
\beta_{i,DR_{EAR}} &\equiv \frac{Cov(r_{i,t}, -N_{DR_{EAR},t})}{Var(r_{EAR,t} - \mathbb{E}_{t-1}[r_{EAR,t}])} \\
\beta_{i,V_{EAR}} &\equiv \frac{Cov(r_{i,t}, N_{V_{EAR},t})}{Var(r_{EAR,t} - \mathbb{E}_{t-1}[r_{EAR,t}])}.
\end{aligned} \tag{13}$$

(Insert Table 13)

As shown in Table 13, the beta spreads between longlegs and shortlegs are large and positive in statistical sense for the EAR shocks, CoAnomaly shocks, cash-flow news, and the volatility news. The betas on CoAnomaly shocks for most test portfolios are negative, which means that they are all risky in the sense that they pay badly when CoAnomaly goes up.

Model Estimation

$$\bar{R}_i = g_1\hat{\beta}_{i,CF_{EAR}} + g_2\hat{\beta}_{i,DR_{EAR}} + g_3\hat{\beta}_{i,V_{EAR}} \quad (+g_4\hat{\beta}_{i,News_{CoAnomaly}}) \quad + e_i \quad (14)$$

(Insert Table 14 and Table 15)

By using GMM to estimate, I evaluate the pricing performance of the following asset pricing models. I find that the ‘vanilla CAPM’ in the market-neutral investment universe works much better than in the aggregate equity market, with a significantly positive price of risk which is close to the unconditional EAR. This is not surprising considering the sophisticated nature of the investors in this special setting.

Consistent with the ICPAM finding in aggregate equity market, I also find the much larger and more robust risk premium on cash-flow beta (bad beta), and the risk prices on discount-rate beta (good beta) is statistically nondistinguishable from zero. Moreover, volatility betas carry a significantly negative price of risk, implying that arbitrageurs in this market-neutral investing universe do care about the volatility.

In Table 15, I augment the ICAPM models with the CoAnomaly shocks, and find it negatively priced, consistent with the aforementioned preliminary results in Table 5. In the CAPM with CoAnomaly case, I find the CoAnomaly risk is very large and negative. Once I expand the CAPM to the three-beta ICAPM, the CoAnomaly risk price shrink about 20%, however, it is still significant. Since the CoAnomaly shocks are correlated with other news shocks, I orthogonalize CoAnomaly shocks with respect to cash-flow news, discount-rate news and volatility news, and then use the orthogonalized CoAnomaly shocks in the computation of betas. The negative price still shows up as in the last column. However, once the CoAnomaly betas are controlled, the volatility risk does not gain a significant price any more.

In a nutshell, this is strong evidence that the CoAnomaly risk can be partially attributed to the cash-flow risk and volatility risk. However, there is still more than half of the original risk price left that cannot be explained by the three-beta ICAPM. Note that the CoAnomaly risk also drives the zero-beta rate in this market-neutral investment universe to zero.

5.2.4 Interpretation of the Market-Neutral Investing ICAPM

In the special setting of market-neutral investment, there is no value-weighted portfolio of different asset anomalies. And arbitrageurs as a whole are not always holding these anomalies with fixed composition or weight. This is the intrinsic difference with the aggregate stock market, which by definition, the investors as a whole will hold the market portfolio. Even though there is an implied risk-aversion coefficient from the estimated risk prices, it cannot be interpreted as the risk-aversion coefficient of a representative arbitrageur, as interpreting the risk-aversion coefficient of a representative long-term investor in [Campbell, Giglio, Polk, and Turley \(2017\)](#). The result can only be understood as: if there is an arbitrageur chasing market neutrality by holding these anomalies, how does her SDF look like given the behavior of these anomaly assets.

5.3 CoAnomaly beyond the Aggregate Volatility in Anomaly Universe

(Insert [Table 16](#))

Since I find that CoAnomaly does not get fully priced in through the most straightforward portfolio volatility mechanism, I explore other possible source of the remaining significantly negative risk price of CoAnomaly. I link the CoAnomaly to the intermediary asset pricing literature that catches a lot of attention recently. Both [Adrian, Etula, and Muir \(2014\)](#) and [He, Kelly, and Manela \(2017\)](#) find that the shocks to financial intermediaries' balance sheet can have strong asset pricing power, however their results are somehow contradictory about the sign of the price of risk¹⁰. [Cho \(2017\)](#) directly models that the intermediary-originated funding shocks to arbitrageurs will induce excess comovement (beyond fundamentals) in anomaly returns and hence generate endogenous risk¹¹. This research directly link my CoAnomaly measure to the time-series variation of intermediary balance sheet.

[Table 16](#) reports the regression results of CoAnomaly and its shocks on these financial intermediary time series. I find that CoAnomaly shock has a negative loading on both leverage shock and the capital ration shock, which is consistent with the opposite signs in risk prices between the CoAnomaly (negative) and the leverage shock (positive as in [Adrian, Etula, and Muir \(2014\)](#)) / the capital ration shock (positive as in [He, Kelly, and](#)

¹⁰[Adrian, Etula, and Muir \(2014\)](#) use leverage of securities broker-dealers and [He, Kelly, and Manela \(2017\)](#) use equity capital ratio of primary dealers, which is the reciprocal of the leverage. However, both of them find positive risk price for the shocks.

¹¹Of course to infer the endogenous risk partially induced by the trading of sophisticated investors, ideally researchers would like to observe their trading behaviors directly. However, the trading data and holding data are both notoriously difficult to obtain in practice. Given the size of the institutional investors, their trading behaviors will pose substantial price impact on any assets, hence generating comovements and price impacts across assets. This also motivates my study in the previous sections.

Manela (2017)). However, I do not find any relationship with the term structure noise from Hu, Pan, and Wang (2013), which measures the illiquidity in the arbitrage of the treasuries across maturities. I also checked if CoAnomaly shocks are correlated with real economy risk variables, but I find no strong relationships with financial uncertainty and macro uncertainty from Jurado, Ludvigson, and Ng (2015), *cay* variable from Lettau and Ludvigson (2001).

The evidence is consistent with that the CoAnomaly measure is partially linked to the intermediary asset pricing, and the endogenous risk generated by the arbitrageurs trading these anomalies. It is also a support for Cho (2017)’s argument that the funding shocks from the financial intermediaries will induce comovement in anomaly assets through affecting the trading behavior of arbitrageurs.

6 Future Research Plan

A step forward, a natural question follows: what is the mechanism between the comovement and the endogenous risk? Is it really endogenous to the sense that because arbitrageurs are trading anomaly assets so they comove together? Or it is because they comove together for some ‘exogenous’¹² reason and all arbitrageurs are subject to this common source of risk, so it shows up as an endogenous risk to the arbitrageurs? Several papers support that the trading behavior of arbitrageurs is generating the comovement in asset prices, hence endogenous risk, which is a plausible story especially in the context of real world. However, I cannot fully rule out another possibility that there is another reason these assets comove together and arbitrageurs happen to hold them, so the correlation becomes a ‘endogenous’ risk to arbitrageurs. To answer this, I would like to have exogenous shock to the trading behavior of hedge funds.

I would also like to explore the implications on the arbitrageurs side and use fund level data to study the effect of CoAnomaly: implication for cross-sectional dispersion of hedge fund returns? How (different) hedge funds react to this effect? Are fund investors also behave accordingly like hedge fund managers by using fund flow data. From the anomaly asset side, I plan to borrow the short interest as a proxy to the arbitrage capital allocated to different anomalies by Hanson and Sunderam (2013). If it cannot help me to identify the mechanism between the comovement and the endogenous risk, at least it will tell us more about how capital is allocated across assets over time.

In the meantime, I plan to explore the other mechanisms which may affect my CoAnomaly measure. I will design a methodology to rule out that CoAnomaly increases simply because anomalies are sharing more the same mispriced stocks. I also need to distinct my market-neutral CoAnomaly measure from the correlation risk related to the

¹²Exogenous to the sense that it is beyond the scope of direct arbitraging activities.

aggregate equity market risk, see Pollet and Wilson (2010) and Driessen, Maenhout, and Vilkov (2009).

7 Conclusion

I propose a measure *CoAnomaly* based on averaging the daily correlation between equity market anomalies to proxy one dimension of risk faced by arbitrageurs, who are the main traders of these anomalies. CoAnomaly measure is robust, convenient to calculate and flexible with respect to different settings. I find this measure is not particularly correlated with existing risk measures, but robustly priced in the equity market. It also subsumes the explanatory power of size, value and momentum factors. I study the time-series pattern of CoAnomaly and find it to be time-varying but still quite persistent. However, different anomaly assets contribute differently to the time-variation of CoAnomaly.

Instead of using the return correlation to proxy the crowdedness of arbitrage capital, I find arbitrageurs are actually quite smart and are careful about this risk. Under my simple mean-variance setting, I observe both time-series and cross-sectional return patterns which are consistent the idea that arbitrageurs take into this CoAnomaly risk into account and behave accordingly.

I further study the potential mechanisms through which the CoAnomaly risk gets priced in by considering an intertemporal CAPM with stochastic volatility. Surprisingly, I find evidence against that the CoAnomaly gets priced in through either time-varying investment opportunity or the mechanical volatility channel. Finally, I find the evidence that links the CoAnomaly, intermediary asset pricing and endogenous risk of trading equity market anomalies.

The fact that CoAnomaly is robustly priced across different assets has a strong asset pricing implication: the impact of professional asset managers is substantial since the risk matters to them is incorporated into prices of many assets. There is policy implications for the CoAnomaly measure as well: regulators can use it to value how likely it is that the equity market arbitrageurs destabilize the market if there is a market-wise fire-sale. Based on this measure, future research can explore the mechanisms and rationales behind the behaviors of the arbitrageurs with substantial size, which may in turn lead to a better understanding of asset markets.

Table 1: Correlation

This table reports summary statistics of CoAnomaly measures and the correlation between the CoAnomaly for the long-short portfolios, longleg only and shortleg only. Correlation between CoAnomaly measures and other contemporaneous market variables. MktRf is the market excess return from French's website. Realized Vol is the quarterly realized variance in the market, calculated from the daily returns. CBOE VIX is the key measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices. TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). Avg_Liq_Level is the market liquidity measure of by [Pastor and Stambaugh \(2003\)](#). HFRIEMNI is the Equity Market Neutral Index from Hedge Fund Research. Mispricing Factors Correlation is the quarterly correlation of two mispricing factors from [Stambaugh and Yuan \(2016\)](#)

	Panel A: Full Sample			Panel B: Post-1994		
	CoAnomaly_LS	CoAnomaly_S	CoAnomaly_L	CoAnomaly_LS	CoAnomaly_S	CoAnomaly_L
Mean	0.16	0.30	0.15	0.18	0.33	0.17
St.D.	0.08	0.08	0.08	0.09	0.07	0.08
No. Observ.	180	180	180	84	84	84
Correlation						
CoAnomaly_LS	1	0.69	-0.24	1	0.63	-0.17
CoAnomaly_S	0.69	1	-0.23	0.63	1	-0.18
CoAnomaly_L	-0.24	-0.23	1	-0.17	-0.18	1
MktRF	0.01	-0.04	0.02	-0.09	-0.17	0.12
Realized Vol	0.30	0.15	-0.04	0.31	0.10	-0.12
VIX				0.31	0.09	-0.03
TED rate				-0.11	-0.24	0.04
Liquidity Level				-0.01	0.05	-0.06
HFRIEMNI				-0.27	-0.08	0.20
Mispricing Factors Corr.				0.50	0.43	-0.04

Table 2: Determinants of CoAnomaly

This table reports the regression results of regressing CoAnomaly measures on the lag of the same CoAnomaly measure and other state variables in the last quarter. The coefficient on VIX is multiplied by 100. T-stats, shown in parentheses, are computed with [Newey and West \(1987\)](#) correction for 4 lags.

Dep. Var.	CoAnomaly_LS [1]	CoAnomaly_L [2]	CoAnomaly_S [3]	CoAnomaly_LS [4] [5] [6]		
lag(Dep. Var.)	0.49 (5.63)	0.48 (6.58)	0.56 (8.70)	0.51 (5.74)	0.40 (4.50)	0.48 (5.43)
MktRf t-1				-0.22 (-2.86)		-0.21 (-2.69)
TEDRate t-1				1.35 (1.42)		1.30 (1.18)
HFRIEMNI t-1				-0.05 (-0.13)		0.22 (0.61)
VIX t-1					0.33 (3.36)	0.17 (1.54)
Avg.Liquidity t-1					0.18 (1.93)	0.17 (1.78)
Trend Var.	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	45%	37%	34%	48%	47%	49%

Table 3: Decomposing the Variance of the Equal-weighted Anomaly Returns (E.A.R.)

Sample periods covers from 1973Q1 to 2017Q4. In panel A, I report the correlation between CoAnomaly, Average Variance and Variance of E.A.R. In panel B, the dependent variable is realized variance of the Equal-weighted Anomaly Returns (E.A.R.), measured as the variance of daily returns within a given quarter. CoAnomaly is the average pairwise partial correlation for whole long-short portfolio of 32 equity market anomalies. Average realized variance is equally averaging the realized daily variances for the 32 equity market anomalies. All of them are measured in the same quarter. T-stats, shown in parentheses, are computed with [Newey and West \(1987\)](#) correction for 4 lags.

Panel A: Correlation between CoAnomaly, Average Variance and Variance of E.A.R.						
	CoAnomaly_LS	CoAnomaly_S	CoAnomaly_L	Average Var.	Variance EAR	
Average Var.	0.29	0.16	-0.01	1	0.88	
Variance EAR	0.47	0.25	0.04	0.88	1	
Panel B: Dependent Variable: Variance of Equal-weighted Anomaly Returns (E.A.R.) estimated at t						
	(1)		(2)		(3)	(4)
Constant	-0.0007 (-3.54)		-0.0002 (-4.46)		-0.0008 (-6.41)	-0.0001 (-3.80)
CoAnomaly	0.0072 (4.03)				0.0035 (4.14)	
Average Var.			0.16 (7.85)		0.15 (8.04)	
CoAnomaly*(Avg.Var.)						0.66 (20.90)
Adj. R square	20.7%		79.8%		83.7%	96.3%
N	180		180		180	180

Table 4: CoAnomaly and Anomalies Partial Correlation

This table reports the CoAnomaly and average pairwise partial correlation for every anomaly, for all sample periods and also for periods with different CoAnomaly levels. **Diff 3-1** is the difference between the high CoAnomaly periods (**3**) and the low CoAnomaly periods (**1**). T-stats of the differences are also reported.

All Months		Sorting on CoAnom			Difference between 3 and 1	
	Average	1 (<30%)	2	3 (>70%)	Diff 3-1	t-stat Diff 3-1
N. Observ.	180	54	72	54		
CoAnomaly	0.16	0.07	0.16	0.25	0.18	(21.07)
Partial Correlation for Anomalies						
Anomalies	Average	1 (<30%)	2	3 (>70%)	Diff 3-1	t-stat Diff 3-1
size	-0.28	-0.20	-0.34	-0.28	-0.08	(-1.50)
rev1m	-0.25	-0.20	-0.23	-0.32	-0.12	(-2.35)
relrev1m	-0.09	-0.04	-0.07	-0.19	-0.15	(-3.16)
value	-0.07	-0.11	-0.07	-0.04	0.07	(1.28)
rev60m	-0.04	-0.01	-0.08	-0.01	0.00	(0.01)
relrev1m_low	-0.01	-0.01	0.00	-0.04	-0.03	(-0.92)
seasonal	0.05	-0.01	0.09	0.07	0.08	(1.57)
gm	0.08	0.01	0.09	0.12	0.10	(1.94)
acc	0.08	0.05	0.16	0.00	-0.05	(-0.84)
ato	0.09	0.00	0.02	0.25	0.25	(4.86)
peadcar3	0.12	0.06	0.13	0.16	0.09	(2.25)
indmom1m	0.14	0.05	0.16	0.19	0.14	(2.66)
atgrowth	0.13	0.05	0.10	0.24	0.19	(3.29)
profit	0.14	0.06	0.13	0.24	0.18	(3.45)
beta	0.16	-0.02	0.07	0.47	0.49	(8.36)
invest	0.17	0.12	0.15	0.23	0.11	(2.19)
hfcombo1	0.20	0.13	0.25	0.22	0.09	(1.98)
hfcombo2	0.23	0.16	0.26	0.25	0.09	(2.15)
piotroski	0.24	0.17	0.22	0.33	0.16	(3.11)
ohlson	0.24	0.10	0.26	0.37	0.27	(5.34)
valprof	0.25	0.18	0.19	0.39	0.21	(4.20)
peadsue	0.26	0.15	0.27	0.36	0.21	(4.75)
netissue_m	0.26	0.11	0.28	0.40	0.28	(4.65)
idiovol	0.27	0.04	0.25	0.52	0.48	(9.68)
netissue_a	0.27	0.10	0.30	0.41	0.31	(5.52)
valmom	0.28	0.11	0.26	0.45	0.34	(6.96)
rome	0.32	0.21	0.29	0.47	0.26	(5.83)
mom12m	0.34	0.16	0.30	0.56	0.40	(8.51)
roa	0.39	0.25	0.38	0.53	0.28	(5.70)
valmomprof	0.41	0.25	0.40	0.58	0.33	(7.20)
roe	0.41	0.25	0.38	0.59	0.34	(8.06)
failprob	0.41	0.18	0.41	0.63	0.45	(11.49)
Regressing Anomalies' Diff 3-1 on their unconditional Partial Correlation						
	No. of Anomalies	adj. R-Square	coefficient	t-stat		
All Anomalies	32	61%	0.74	(7.00)		
Excluding Anomalies with Negative Correlation	26	35%	0.77	(3.77)		

Table 5: Preliminary Pricing Test of CoAnomaly Risk

$$\mathbb{E}[R^e] = \lambda_0 + \widehat{\beta_{fac}} \lambda_{fac}$$

This table reports pricing results for 25 size and book-to-market portfolios, 10 momentum portfolios, 5 industry portfolios and 6 treasury bond portfolios sorted by maturity. All these test portfolios are downloaded from French Data Library. In each row, I estimate the risk prices of each factor in every the pricing model by regressing the factor returns on estimated betas from time-series regression. The estimated risk premia, along with [Fama and MacBeth \(1973\)](#) t-stats and [Shanken \(1992\)](#) t-stats, are reported. Cross-sectional R^2 statistics are also reported for each pricing model of explaining the average return variation of the test portfolios. In panel B, I exclude the 6 bond portfolios.

Pricing Models	Intercept	MktRf	CoAnomaly	SMB	HML	UMD	Adj. R-squared
Panel A: Equity Portfolios and Bond Portfolios							
CAPM	1.10	1.13					24.9%
t-FM	(3.92)	(1.57)					
t-Shanken	(2.96)	(1.25)					
CoAnomaly	2.04		-1.19				30.0%
t-FM	(3.57)		(-2.61)				
t-Shanken	(2.49)		(-1.97)				
CAPM + CoAnomaly	1.62	0.48	-0.88				33.1%
t-FM	(5.37)	(0.66)	(-3.75)				
t-Shanken	(3.54)	(0.33)	(-2.97)				
CAPM + Size	1.24	0.41		0.66			25.7%
t-FM	(4.28)	(0.55)		(1.70)			
t-Shanken	(3.01)	(0.44)		(1.02)			
CAPM + Value	0.88	1.67			1.29		47.0%
t-FM	(3.19)	(2.16)			(2.52)		
t-Shanken	(2.53)	(1.80)			(2.33)		
CAPM + Momentum	0.95	1.78				2.06	42.3%
t-FM	(3.34)	(2.42)				(3.28)	
t-Shanken	(2.62)	(1.94)				(2.64)	
CAPM + Size + CoAnomaly	1.61	0.11	-0.71	0.45			34.3%
t-FM	(5.12)	(0.15)	(-3.34)	(1.15)			
t-Shanken	(3.44)	(0.07)	(-2.70)	(0.76)			
CAPM + Value + CoAnomaly	1.30	1.12	-0.66		1.16		53.7%
t-FM	(4.38)	(1.40)	(-2.74)		(2.22)		
t-Shanken	(2.96)	(0.99)	(-2.38)		(2.20)		
CAPM + Momentum + CoAnomaly	1.16	1.47	-0.32			1.83	45.1%
t-FM	(3.71)	(1.99)	(-1.41)			(2.71)	
t-Shanken	(2.68)	(1.63)	(-0.88)			(2.32)	
Panel B: Only Equity Portfolios							
CAPM	3.31	-0.90					3.5%
t-FM	(3.82)	(-0.84)					
t-Shanken	(2.42)	(1.25)					
CAPM + CoAnomaly	3.91	-1.66	-1.02				26.4%
t-FM	(4.49)	(-1.54)	(-4.03)				
t-Shanken	(3.14)	(-1.33)	(-3.14)				

Table 6: Predictive Regression at Quarterly Level

The dependent variable is the Equal-weighted Anomaly Returns (E.A.R.) for the next quarter $t + 1$. All independent variables are measured in the quarter t . CoAnomaly is the average pairwise partial correlation for whole long-short portfolio of 32 equity market anomalies. Average realized variance is equally averaging the realized daily variances for the 32 equity market anomalies. Realized variance of the Equal-weighted Anomaly Returns (E.A.R.) is measured as the variance of daily returns. TED spread (TED) is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). MktRf is the excess return on the aggregate stock market, downloaded from French website. E.A.R. is Equal-weighted Anomaly Returns and Value Spread is small-stock value spread. T-stats, shown in parentheses, are computed with [Newey and West \(1987\)](#) correction for 4 lags.

Dependent Variable: Quarterly Equal-weighted Anomaly Returns (E.A.R.) at t+1						
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.023 (-1.43)	0.013 (2.83)	0.014 (3.55)	-0.024 (-1.45)	-0.036 (-1.95)	-0.113 (-3.14)
CoAnomaly	0.12 (2.34)			0.12 (2.31)	0.15 (2.70)	0.11 (2.08)
Average Var.		0.15 (0.35)		0.13 (0.29)	1.28 (1.40)	0.81 (0.84)
Realized Var.			0.21 (0.10)		-6.20 (-1.43)	-5.25 (-1.25)
TED rate						0.01 (0.71)
MktRf						0.14 (3.16)
E.A.R.						0.21 (1.48)
Value Spread						0.11 (2.35)
Adj. R square	6.2%	-1.3%	-1.5%	4.9%	6.4%	24.8%
N	84	84	84	84	84	84

Table 7: Predictive Regression at Monthly Level for Different Horizons

The dependent variable is the Equal-weighted Anomaly Returns (E.A.R.) for the next 1 month or 6 months. All independent variables are measured in the quarter t , so there is overlapping data. CoAnomaly is the average pairwise partial correlation for whole long-short portfolio of 32 equity market anomalies. Average realized variance is equally averaging the realized daily variances for the 32 equity market anomalies. Realized variance of the Equal-weighted Anomaly Returns (E.A.R.) is measured as the variance of daily returns. TED spread (TED) is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). MktRf is the excess return on the aggregate stock market, downloaded from French website. E.A.R. is Equal-weighted Anomaly Returns and Value Spread is small-stock value spread. The coefficients in the first half are multiplied by six, so it can be compared with the second half. T-stats, shown in parentheses, are computed with [Newey and West \(1987\)](#) correction for 4 lags.

Dependent Variable: Equal-weighted Anomaly Returns (E.A.R.) in the future						
	E.A.R. in next 1 month			E.A.R. in next 6 months		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.033 (-1.04)	-0.033 (-1.04)	-0.235 (-3.09)	-0.027 (-1.81)	-0.028 (-1.90)	-0.201 (-6.37)
CoAnomaly	0.19 (1.98)	0.19 (1.96)	0.16 (1.38)	0.18 (3.86)	0.17 (3.67)	0.14 (2.92)
Average Var.		0.00 (0.01)	-0.48 (-0.26)		0.55 (1.52)	0.56 (0.73)
Realized Var.			-2.26 (-0.26)			-5.26 (-1.48)
TED rate			0.02 (0.90)			-5.26 (-1.48)
MktRf			0.13 (1.43)			0.03 (3.25)
E.A.R.			0.04 (0.14)			0.12 (3.19)
Value Spread			0.29 (2.96)			0.28 (2.45)
Adj. R square	1.4%	0.9%	4.8%	6.4%	7.0%	30.3%
N	332	332	332	332	332	332

Table 8: Monthly Sorting

This table reports the mean of different measures after sorting all months into different groups based on A) single-sort by CoAnomaly measure; or B) double-sort by returns of quantitative equity hedge funds, and then by CoAnomaly measure. T-stats are shown in parentheses.

HFRIEMNI Group	CoAnomaly Group	No. Months	HFRIEMNI t	CoAnomaly t	CoAnomaly t+1	E.A.R. t+1	E.A.R. t+3	E.A.R. t+6
Panel A: Sort all months based on CoAnomaly								
	1	110	1.54%	0.09	0.12	-0.0%	0.2%	1.1%
			(6.91)	(9.76)	(11.19)	(-0.28)	(0.73)	(2.29)
	2	148	1.49%	0.16	0.17	0.3%	1.1%	1.9%
			(8.36)	(18.23)	(16.68)	(2.06)	(3.79)	(4.06)
	3	110	1.43%	0.26	0.22	0.8%	2.0%	4.0%
			(8.33)	(26.35)	(16.60)	(3.42)	(4.85)	(6.46)
	Diff 3-1		-0.11%	0.17	0.10	0.9%	1.8%	2.9%
			(-0.39)	(12.68)	(5.61)	(3.13)	(3.49)	(3.71)
Panel B: First sort all months based on HFRIEMNI, and then sort on CoAnomaly								
1	1	32	-0.72%	0.12	0.21	-1.0%	-1.5%	-2.0%
	2	44	-0.37%	0.17	0.18	0.6%	0.8%	1.0%
	3	32	-0.10%	0.27	0.22	0.8%	1.6%	2.0%
	Diff 3-1					1.77%	3.03%	3.93%
						(3.06)	(2.51)	(2.65)
2	1	44	1.62%	0.08	0.10	0.2%	0.7%	1.3%
	2	60	1.42%	0.18	0.17	0.4%	1.0%	1.8%
	3	44	1.34%	0.27	0.22	0.5%	1.6%	3.3%
	Diff 3-1					0.25%	0.89%	1.97%
						(0.62)	(1.26)	(1.90)
3	1	32	3.47%	0.09	0.09	0.2%	0.9%	3.1%
	2	44	3.48%	0.11	0.15	0.5%	2.3%	4.1%
	3	32	3.28%	0.23	0.20	1.1%	2.2%	5.9%
	Diff 3-1					0.80%	1.30%	2.87%
						(1.51)	(1.82)	(1.93)

Table 9: High Corr - Low Corr

This table reports the monthly return of a portfolio which are longing high partial correlation anomalies and shorting low partial correlation anomalies, following a negative shock to arbitrageurs (HFRIEMNI Group 1) but under different CoAnomaly states (CoAnomaly Group 1, 2 and 3).

HFRIEMNI Group	CoAnomaly Group	No. Months	Ret of (H.c.-L.c.)	t-stat
Panel A: Using Anomalies' Partial Correlations from month t				
1	1	21	-2.1%	(-2.94)
	2	30	-0.3%	(-0.56)
	3	22	0.9%	(2.01)
Panel B: Using Anomalies' Partial Correlations of all sample				
1	1	21	-0.9%	(-1.69)
	2	30	-0.1%	(-0.26)
	3	22	1.3%	(2.10)
Panel C: Using the changes of Anomalies' Partial Correlations from Low to High CoAnomaly				
1	1	21	-1.2%	(-2.77)
	2	30	-0.5%	(-0.88)
	3	22	1.6%	(2.01)

Table 10: Robustness

This table reports the robustness check results for Table 8. Instead of using CoAnomaly measure, I use the correlation between two mispricing factors in [Stambaugh and Yuan \(2016\)](#).

HFRIEMNI Group	Corr. Group	No. Months	HFRIEMNI t	CoAnomaly t	CoAnomaly t+1	E.A.R. t+1	E.A.R. t+3	E.A.R. t+6
Panel A1: sorting on Correlation of two Mispricing Factors								
	1	110	0.49% (4.26)	0.11 (9.09)	0.13 (11.65)	0.18% (1.17)	0.67% (2.26)	1.93% (4.35)
	2	148	0.62% (6.67)	0.16 (17.77)	0.16 (16.15)	0.30% (1.83)	0.81% (2.44)	1.68% (3.10)
	3	110	0.41% (3.67)	0.22 (16.53)	0.20 (13.25)	0.64% (2.39)	1.84% (4.05)	3.46% (4.84)
	Diff 3-1		-0.08% (-0.51)	0.11 (6.43)	0.07 (3.87)	0.46% (1.48)	1.17% (2.14)	1.54% (1.82)
	Panel A2: First sort all months based on HFRIEMNI, and then sort on Correlation of two Mispricing Factors							
1	1	32	-0.54%	0.15	0.16	0.03%	-0.22%	0.28%
	2	44	-0.40%	0.19	0.18	-0.28%	-0.12%	-0.62%
	3	32	-0.38%	0.24	0.19	0.90%	2.03%	4.12%
	Diff 3-1					0.88% (1.45)	2.25% (1.70)	3.84% (2.04)
Panel B1: sorting on the 1-month CoAnomaly								
	1	110	0.58% (5.21)	0.09 (9.45)	0.12 (9.92)	-0.01% (-0.07)	0.21% (0.64)	0.98% (1.88)
	2	148	0.48% (4.84)	0.15 (16.73)	0.17 (15.83)	0.29% (1.78)	1.15% (3.62)	1.87% (3.63)
	3	110	0.51% (4.74)	0.23 (19.49)	0.19 (15.08)	0.84% (3.19)	1.83% (4.14)	4.14% (6.24)
	Diff 3-1		-0.07% (-0.39)	0.14 (9.01)	0.08 (4.32)	0.85% (2.79)	1.62% (2.93)	3.16% (3.75)
	Panel B2: First sort all months based on HFRIEMNI, and then sort on 1-month CoAnomaly							
1	1	32	-0.50%	0.13	0.16	-0.81%	-1.17%	-0.92%
	2	44	-0.40%	0.17	0.16	0.31%	0.83%	0.46%
	3	32	-0.41%	0.29	0.21	0.95%	1.75%	3.90%
	Diff 3-1					1.76% (2.47)	2.92% (2.08)	4.82% (2.34)
Panel C1: sorting on the CoAnomaly, excluding 2008								
	1	107	1.54% (6.58)	0.09 (9.41)	0.12 (10.71)	-0.02% (-0.17)	0.24% (0.78)	1.07% (2.13)
	2	142	1.34% (7.52)	0.16 (17.68)	0.17 (15.57)	0.30% (1.90)	1.10% (3.58)	1.81% (3.71)
	3	107	1.68% (8.77)	0.24 (20.72)	0.20 (15.39)	0.82% (3.28)	1.83% (4.39)	3.90% (6.12)
	Diff 3-1		0.14% (0.45)	0.15 (10.07)	0.08 (4.58)	0.85% (2.93)	1.58% (3.03)	2.83% (3.47)
	Panel C2: First sort all months based on HFRIEMNI, and then sort on CoAnomaly, excluding 2008							
1	1	31	-0.79%	0.12	0.21	-1.09%	-1.61%	-2.02%
	2	42	-0.41%	0.17	0.18	0.59%	0.84%	0.98%
	3	31	-0.14%	0.26	0.21	0.59%	1.19%	1.20%
	Diff 3-1					1.68% (2.79)	2.80% (2.20)	3.22% (2.17)
Panel D1: sorting on the CoAnomaly, returns control for market exposure								
	1	110	1.56% (6.26)	0.09 (9.45)	0.12 (9.92)	0.10% (0.73)	0.55% (1.90)	1.52% (3.34)
	2	148	1.30% (7.24)	0.15 (16.73)	0.17 (15.83)	0.40% (2.66)	1.44% (4.97)	2.48% (5.44)
	3	110	1.84% (8.94)	0.23 (19.49)	0.19 (15.08)	0.89% (3.99)	2.06% (5.49)	4.60% (8.04)
	Diff 3-1		0.28% (0.85)	0.14 (9.01)	0.08 (4.32)	0.79% (2.98)	1.51% (3.20)	3.08% (4.20)
	Panel D2: First sort all months based on HFRIEMNI, and then sort on CoAnomaly, returns control for market exposure							
1	1	32	-0.76%	0.11	0.20	-0.42%	-0.37%	-0.31%
	2	44	-0.43%	0.17	0.18	0.33%	0.61%	0.93%
	3	32	-0.26%	0.23	0.17	0.54%	1.27%	1.86%
	Diff 3-1					0.97% (1.92)	1.64% (1.50)	2.17% (1.84)

Table 11: VAR Estimation

This table reports the WLS parameter estimates of the first-order VAR model. State variables include the equal-weight anomaly return, the realized volatility and expected volatility calculated from the first stage, CoAnomaly, default yield spread, and value spread between small-value stocks and small-growth stocks. R^2 is reported in percentage. T-stats, reported in parentheses, are calculated with bootstraps to accommodate the estimation errors in the first stage. The sample period for the dependent variables is 1974:1-2017:12.

Panel A: Forecasting Quarterly Realized Volatility (RVol t+1)							
First Stage	Constant	EAR t	RVol t	CoAnomaly t	TED t	VS t	R-square
RVol t+1	-0.019 (-0.47)	0.261 (1.42)	0.877 (8.39)	-0.049 (-1.06)	0.010 (1.24)	0.048 (0.90)	34.9%
Panel B: VAR Estimates							
Second Stage	Constant	EAR t	EVol t	CoAnomaly t	TED t	VS t	R-square
EAR t+1	-0.070 (-2.87)	0.212 (2.32)	-5.007 (-1.93)	-0.025 (-0.87)	0.012 (2.06)	0.119 (3.68)	13.7%
EVol t+1	-0.026 (-0.53)	0.790 (4.25)	0.687 (13.02)	-0.044 (-0.75)	0.000 (0.38)	0.060 (0.94)	62.3%
CoAnomaly t+1	0.110 (1.46)	-0.154 (-0.55)	2.158 (0.27)	0.527 (5.96)	-0.015 (-0.85)	0.078 (0.78)	53.7%
TED t+1	0.540 (2.28)	0.103 (0.12)	-40.098 (-1.60)	-0.271 (-0.97)	0.860 (15.21)	-0.493 (-1.57)	74.6%
VS t+1	0.104 (3.09)	-0.213 (-1.69)	13.102 (3.66)	-0.001 (-0.03)	0.001 (0.10)	0.843 (18.84)	81.7%

Table 12: Cash-Flow, Discount-Rate, and Volatility News for the Equal-weighted Anomaly Portfolio

This table reports different news implied by the first-order VAR model. The upper panel reports the functions that map state-variable shocks to cash-flow, discount-rate, and volatility news. The lower panel shows the correlation between these shocks and news.

	EAR shock	N_CF	N_DR	N_Vol
Functions				
EAR shock	1	1.07	0.07	0.03
EVOL shock	0	-12.56	-12.56	2.82
CoAnomaly shock	0	-0.10	-0.10	-0.01
TED shock	0	0.09	0.09	0.00
VS shock	0	0.39	0.39	0.02
Correlations				
EAR shock	1	0.64	0.00	0.46
EVOL shock	0.32	0.19	-0.02	0.89
CoAnomaly shock	0.25	-0.02	-0.23	0.03
TED shock	0.15	0.71	0.81	0.68
VS shock	-0.11	0.32	0.51	0.09
N_CF	0.64	1	0.76	0.60
N_DR	0.00	0.76	1	0.40
N_Vol	0.46	0.60	0.40	1

Table 13: Betas on Different News for the Longleg and Shortleg of 32 Equity Market Anomalies

This table reports the betas estimated on different Shocks and News from the VAR. Here I assume constant betas for all portfolios. The Volatility betas are multiplied by 100 for readability. At the end, I take the simple average of the betas across all anomalies.

	EAR Shocks		CoAnomaly Shocks		CF News		DR News		Vol News	
	longleg	shortleg	longleg	shortleg	longleg	shortleg	longleg	shortleg	longleg	shortleg
acc	-0.64	-0.33	-1.10	-0.67	-0.69	-0.49	0.05	0.16	-4.94	-2.07
atgrowth	0.20	-0.50	-0.24	-0.72	0.15	-0.60	0.05	0.10	1.86	-3.43
ato	0.63	-0.83	-0.02	-0.34	0.46	-0.69	0.18	-0.15	6.12	-7.91
beta	0.68	-0.81	-0.39	-0.57	1.27	-0.59	-0.59	-0.23	6.70	-2.56
failprob	0.56	-1.77	-0.10	-0.55	0.40	-1.16	0.16	-0.63	-0.38	-6.92
gm	-0.09	-0.10	-0.08	-0.66	0.12	-0.18	-0.21	0.08	-1.47	-1.10
hfcombo1	0.35	-0.76	-0.56	-0.80	0.71	-0.84	-0.36	0.08	1.83	-1.38
hfcombo2	0.45	-0.69	-0.30	-0.34	0.72	-0.79	-0.26	0.10	1.26	0.60
idiovol	0.48	-1.22	0.91	-1.35	0.58	-1.39	-0.10	0.16	3.76	-10.03
indmom1m	0.53	-0.56	-0.08	0.31	0.45	-0.38	0.08	-0.18	1.13	-0.76
invest	0.43	-0.02	-0.11	-0.42	0.43	-0.19	0.01	0.17	1.89	-1.17
mom12m	0.20	-1.82	-1.06	-0.16	0.09	-2.10	0.11	0.27	-4.18	-8.64
netissue_a	0.55	-0.46	0.22	-0.54	0.56	-0.61	0.00	0.14	5.35	-5.27
netissue_m	0.50	-0.65	0.45	-0.28	0.43	-0.69	0.07	0.03	4.25	-7.52
ohlson	0.04	-0.73	-0.11	-1.41	0.07	-0.51	-0.03	-0.22	-0.73	0.51
peadcar3	-0.35	-0.52	-0.70	0.07	-0.28	-0.55	-0.08	0.03	-0.81	-2.69
peadsue	0.31	-0.67	-0.33	0.04	0.28	-0.48	0.03	-0.20	-0.63	-1.01
piotroski	0.16	-1.36	0.29	-1.89	0.10	-1.04	0.07	-0.33	0.24	-6.17
profit	0.48	-0.48	0.01	-0.81	0.57	-0.30	-0.09	-0.19	3.53	-2.31
relrev1m	-0.86	-0.48	-0.95	-1.01	-0.83	-0.90	-0.03	0.42	-6.14	-4.00
relrev1mlow	0.36	0.44	0.58	0.31	1.03	-0.19	-0.66	0.64	7.76	2.92
rev1m	-0.99	-0.25	-0.36	-0.65	-0.92	-0.53	-0.07	0.28	-4.88	-3.49
rev60m	0.09	-0.18	-0.30	-1.10	0.15	-0.26	-0.05	0.07	4.02	-4.11
roa	0.57	-1.12	0.23	-1.42	0.51	-0.67	0.07	-0.45	0.89	-4.25
roe	0.43	-1.29	0.62	-1.00	0.51	-0.88	-0.08	-0.42	4.04	-6.97
rome	0.37	-1.23	0.47	-1.00	-0.07	-0.90	0.44	-0.33	1.54	-6.57
seasonal	0.13	-0.19	-0.69	-0.34	0.27	-0.77	-0.14	0.57	-1.14	1.60
size	-0.04	0.10	-0.63	0.38	0.11	0.18	-0.15	-0.08	5.24	-0.09
valmom	0.59	-0.27	-0.29	0.13	0.49	-0.06	0.10	-0.21	1.39	2.39
valmomprof	0.40	-0.72	-0.68	0.06	0.30	-0.50	0.11	-0.23	0.12	-0.74
valprof	0.45	-0.36	-0.11	-0.20	0.48	-0.32	-0.03	-0.05	7.71	-3.84
value	0.49	0.00	0.26	-0.17	0.54	0.16	-0.05	-0.16	3.69	-1.74
	0.23	-0.62	-0.16	-0.53	0.28	-0.60	-0.04	-0.02	1.53	-3.08
	(2.84)	(-6.04)	(-1.66)	(-4.88)	(3.04)	(-6.84)	(-1.09)	(-0.42)	(2.16)	(-4.76)

Table 14: Market-Neutral Asset Pricing Tests

$$\bar{R}_i = g_0 + g_1\hat{\beta}_{i,CF_{EAR}} + g_2\hat{\beta}_{i,DR_{EAR}} + g_3\hat{\beta}_{i,V_{EAR}} + e_i$$

Risk price estimates for different factors in four different asset pricing models are reported. All models are estimated in the market-neutral universe. CAPM is constraining the cash-flow news and discount-rate news having the same price of risk. 2-beta ICAPM and 3-beta ICAPM is constraining the risk price of discount-rate news to be the variance of the equal-weighted anomaly return, while other risk prices are freely estimated. Unconstrained allows full freedom of estimation of all risk prices. T-stats, reported in parentheses, are calculated with bootstraps to accommodate the estimation errors in previous steps.

Market-Neutral Asset Pricing Test				
	CAPM	2-beta ICAPM	3-beta ICAPM	Unconstrained
r_zerobeta	0.09 (2.08)	0.07 (1.48)	0.07 (1.55)	0.08 (1.76)
g_cf	1.34 (19.66)	1.42 (20.92)	1.65 (13.86)	1.69 (13.70)
g_dr	1.34 (19.66)	0.07 -	0.07 -	0.30 (1.64)
g_vol			-4.20 (-2.30)	-4.70 (-2.52)

Table 15: Market-Neutral Asset Pricing Test augmented with CoAnomaly

$$\bar{R}_i = g_0 + g_1\hat{\beta}_{i,CF_{EAR}} + g_2\hat{\beta}_{i,DR_{EAR}} + g_3\hat{\beta}_{i,V_{EAR}} + g_4\hat{\beta}_{i,News_{CoAnomaly}} + e_i$$

Risk price estimates for different factors in four different asset pricing models are reported. In the first two rows, I estimate the risk prices for the 3-beta ICAPM and Unconstrained models, both augmented with raw CoAnomaly shocks. In the last two rows, I estimate the risk prices for the 3-beta ICAPM and Unconstrained models, both augmented with CoAnomaly shocks orthogonalized with respect to cash-flow news, discount-rate news and volatility news. T-stats, reported in parentheses, are calculated with bootstraps to accommodate the estimation errors in previous steps.

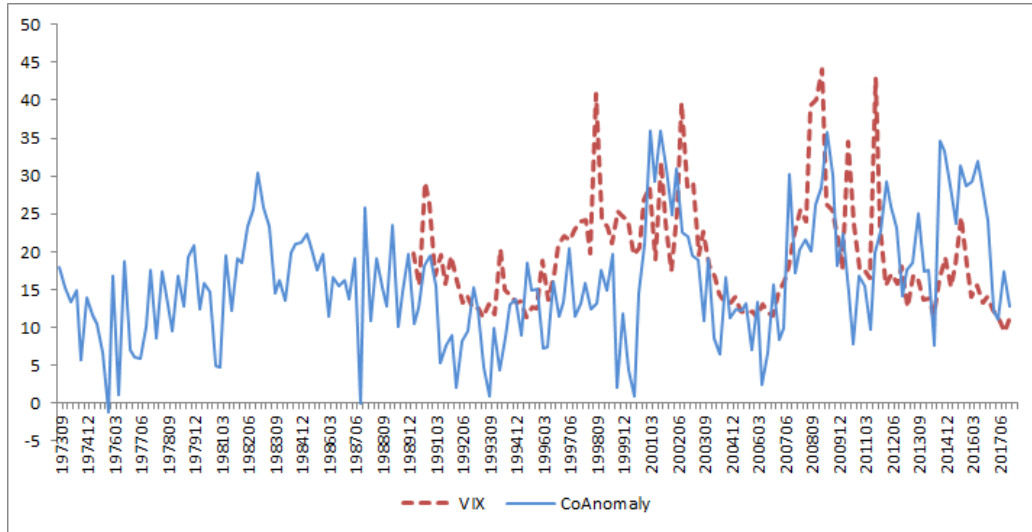
Market-Neutral Asset Pricing Test augmented with CoAnomaly				
	Shocks of CoAnomaly			Shocks of CoAnomaly Otho
	CAPM	3-beta ICAPM	Unconstrained	3-beta ICAPM
r_zerobeta	0.00 (0.01)	-0.02 (-0.28)	-0.01 (-0.16)	-0.01 (-0.16)
g_cf	1.52 (18.51)	1.68 (14.06)	1.74 (14.02)	1.55 (11.91)
g_dr	1.52 (18.51)	0.07 -	0.41 (2.24)	0.06 (0.29)
g_vol		-2.21 (-1.14)	-2.73 (-1.39)	-2.88 (-1.48)
g_CoAnomaly	-0.37 (-3.90)	-0.30 (-3.07)	-0.33 (-3.37)	-0.33 (-3.37)

Table 16: Regressing the CoAnomaly Shocks and CoAnomaly Levels on Financial Intermediary Balance Sheet Levels and Shocks

This table reports the contemporaneous quarterly regression estimates. Financial Intermediary Leverage and Leverage shock are constructed as in [Adrian, Etula, and Muir \(2014\)](#) and [Cho \(2017\)](#). Capital Ratios and Shocks follow [He, Kelly, and Manela \(2017\)](#). Term structure noise is from [Hu, Pan, and Wang \(2013\)](#), financial uncertainty and macro uncertainty from [Jurado, Ludvigson, and Ng \(2015\)](#), *cay* variable from [Lettau and Ludvigson \(2001\)](#). I also control for time trend and seasonality. T-stats, shown in parentheses, are computed with [Newey and West \(1987\)](#) correction for 4 lags.

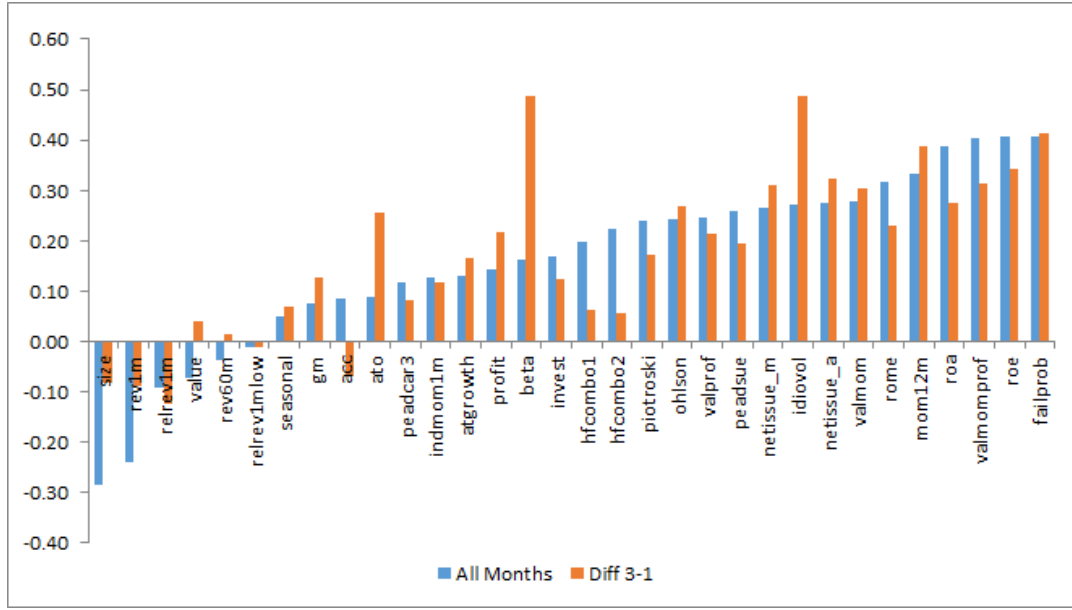
Dependent Variable: CoAnomaly Shock						
	[1]	[2]	[3]	[4]	[5]	[6]
Leverage	0.001 (1.69)	0.001 (0.98)				
Leverage Shock	-0.012 (-2.11)	-0.010 (-1.62)				
Capit.Ratio			-0.060 (-0.24)	-0.034 (-0.14)		
Capit.Ratio Shock			-0.105 (-2.14)	-0.109 (-2.25)		
Term Structure Noise					0.000 (0.07)	0.004 (0.75)
Financial Uncertainty					0.022 (0.39)	0.013 (0.23)
Macro Uncertainty					0.022 (0.21)	-0.057 (-0.43)
Cay					-0.195 (-0.59)	-0.059 (-0.17)
Trend and Season	No	Yes	No	Yes	No	Yes
Adj. R-Squared	3.2%	4.9%	2.7%	7.2%	-2.7%	1.6%

List of Figures



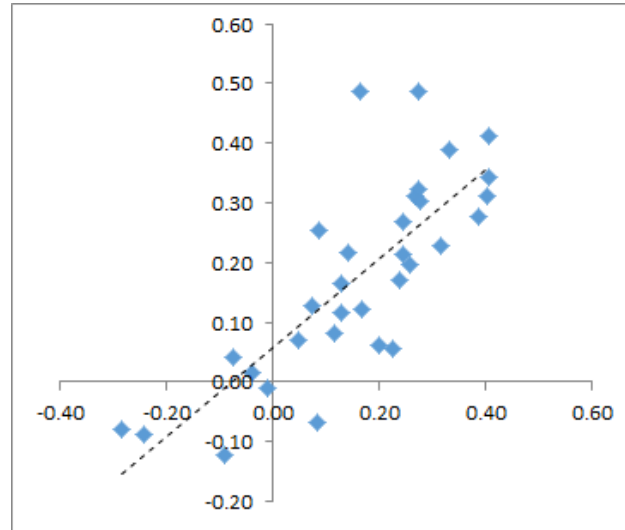
This figure plots the time-series of CoAnomaly measure of the equity market anomalies. The blue line is the CoAnomaly measure, and the red dashed line is the CBOE VIX measure.

Figure 1: Time-Series of the CoAnomaly.



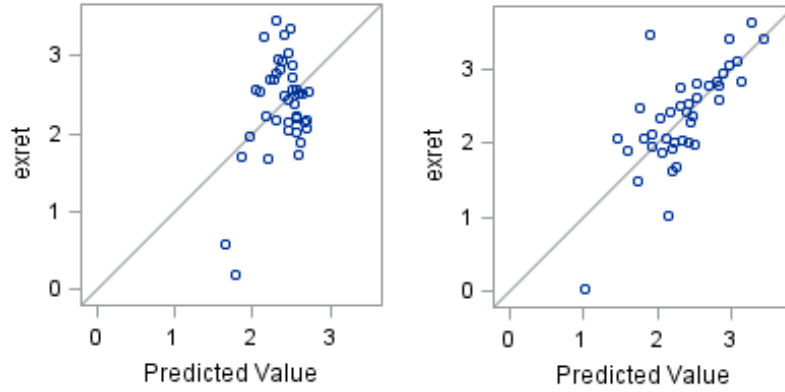
This figure reports the full-sample unconditional average pairwise partial correlations and the changes of partial correlations (from CoAnomaly states to high CoAnomaly states) for all equity market anomalies. Blue bars are the unconditional average pairwise partial correlations and red bars are the changes of partial correlations.

Figure 2: Unconditional Average Pairwise Partial Correlations and the Changes



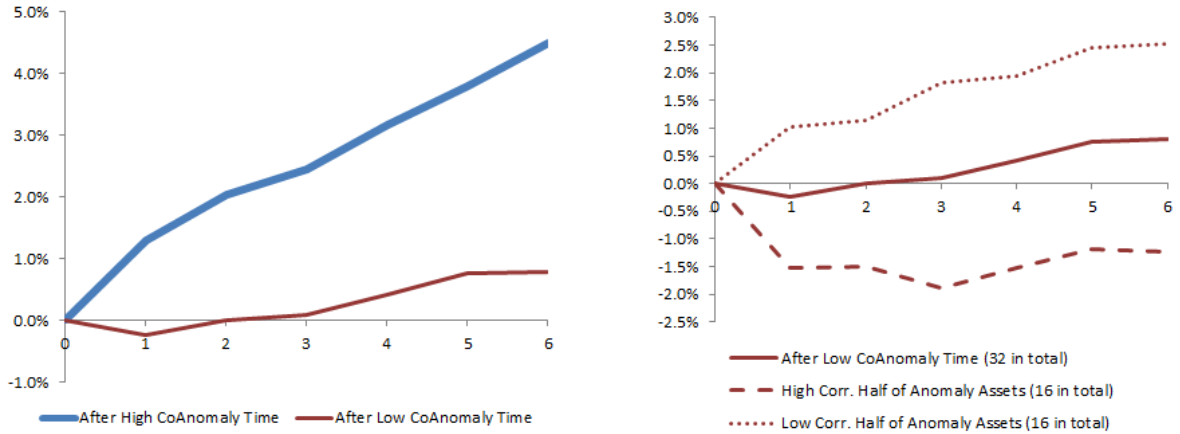
This figure plots the relationship between the full-sample unconditional average pairwise partial correlations and the changes of partial correlations for all equity market anomalies. On the x-axis, I have the full-sample unconditional average pairwise partial correlations, and on the y-axis, I have the changes of partial correlations. A linear fitting is also plotted.

Figure 3: Relation of Unconditional Average Pairwise Partial Correlations and the Changes



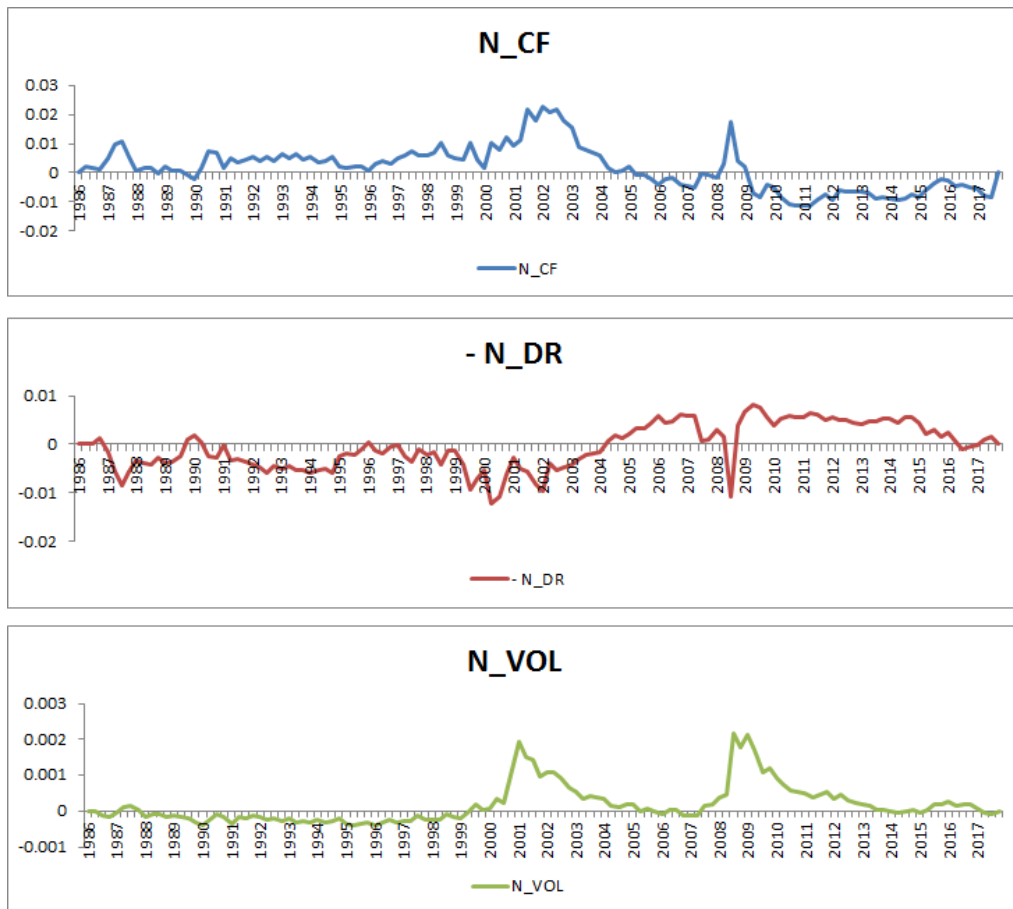
This figure plots the realized mean excess returns of 40 equity portfolios (25 size- and book-to-market-sorted portfolios, 10 momentum-sorted portfolios and 5 industry portfolios) against the predicted mean excess returns. In the left figure, I use CAPM to predict portfolio returns, and in the right figure, I use CAPM + CoAnomaly.

Figure 4: Realized versus predicted mean returns: Comparing CAPM versus CAPM + CoAnomaly.



These two figures plot the average cumulative returns of equity market anomalies up to six months after high CoAnomaly time or low CoAnomaly time, both following a negative shock to quantitative equity hedge funds. The second plot splits the anomalies into high partial correlation anomalies and low partial correlation anomalies. Note that the solid red lines in both figures are the same.

Figure 5: Average Returns of Anomalies after a negative shock to quantitative equity hedge funds.



These three figures plot the Smoothed News of Cash-flow, Discount-rate and Volatility.

Figure 6: Smoothed News of Cash-flow, Discount-rate and Volatility.

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