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Restaurant Equities, the Economy and Pairs Trading

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Time Series Econometrics
Professor Bang
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Executive Summary

It is well studied that consumers tend to smooth consumption making consumer spending the least volatile element of economic output. Restaurant spending however, is commonly thought of as part of consumer discretionary spending and quite cyclical, in other words, when unemployment rises or the economy experiences a slowdown or recession most rational consumers will eat out less. During a general positive economic outlook spending at restaurants tends to go up (Bloomberg.com, 2019). This paper attempts to test this assumption and how low end, high end and mid range restaurants share prices are influenced by these different economic factors. By picking pairs of low, mid, and high end restaurants, analysis showed if and how those similar pairs of restaurants move together. Analysis showed how various factors impacted the pairs behavior differently and how cointegration analysis could show possibilities for pairs trading.

Specifically, this paper will contribute to the limited current literature by our comparison of low, mid and high end restaurants which is not a well studied topic. Additionally using the cointegration analysis on restaurant pairs filled a gap in pairs trading literature. Our paper uses more recent data from the past decade and subtleties such as using the U-6 rate to provide a holistic view of unemployment.

Our findings indicate significant impacts from macroeconomic factors on restaurant stock prices and found a pair of mid range restaurants that were cointegrated, providing a strong candidate for a pairs trade. Additionally we observed that middle and high end restaurant equity prices were positively correlated to the economy with high end restaurants significantly correlated with consumer sentiment while low end restaurants had no correlation. More detail and analysis will be provided in the empirical results section of this paper.

Research Questions and Testing Hypothesis

This paper tackles five questions: (1) the cyclical nature of the restaurant industry reflected in the data, (2) what economic factors affect the industry, (3) how these factors' roles differ at different price points within the industry, (4) how correlated are similar restaurants, and (5) could pairs trading be informed by applying our research to reduce risk and make a profit.

Based on these questions we hypothesised that (1) the restaurant industry was cyclical, (2) consumers sentiment, unemployment, and Personal Consumption Expenditures of food would have impacts on companies, (3) expensive restaurants would be more correlated to economic conditions than inexpensive restaurants, as they provided superior goods which would be substituted with inexpensive food, (4) similar restaurant equities move similarly, (5) these similar moves could be used in pairs trading to make money.

To prove these hypothesis we gathered similar pairs of restaurant equities for multiple reasons. The first was it allowed us to look at economic influences on segments of the restaurant industry across several companies, helping segregate idiosyncratic changes due to company specific events. The other reason we paired companies was to see if there was cointegration that could occur for our pairs trading hypothesis.

Theory and Literature Survey

The Bureau of Economic Analysis reported that consumer spending was $14.2 trillion in the fourth quarter of 2018 (U.S. Department of Commerce, 2018). Compared to the $20.9 trillion of the gross domestic product in that quarter, consumer spending made up for 68% of the United States' economy (U.S. Department of Commerce, 2018). Out of this $14.2 trillion, almost one-quarter is spent on non-durable goods, such as food (U.S. Department of Commerce, 2018). This shows that understanding how the restaurant industry works is highly pertinent. “Restaurant sales account for 4% of the United States’ economic output” (Barello). Furthermore, from 2007 to 2017, the Consumer Price Index (CPI) for all food (grocery store and restaurant food) rose by 24%, which was a larger increase than the 19% increase in the all-items CPI (Bureau of Labor Statistics, Feb. 2019), which is a goods basket comprised of everyday items, including food.

According to a previous study, overall real sales in restaurants have bared a large correlation to consumer sentiment with a coefficient of 0.87% since 2009 (Aaron Allen & Associates, 2017). Consumer sentiment has been on a rise over the last decade, with Americans feeling confident about the economy, which is good news for the industry, according to the findings of this study.

U.S. restaurant sales have been growing, even though it might be at the slowest rate over the last three years. Real growth decelerated by 37% between the first quarters of 2016 and 2017. Meanwhile, grocery sales grew about 2.8 times faster (Aaron Allen & Associates, 2017). This shows that consumers are thinking twice before dining out. This trend is likely to have negative effects on already weak same-store sales.

On average, chain restaurants have had negative same-store sales for more than a year, according to May data from Black Box. This is very interesting because there seems to be a lot of uncertainty surrounding the restaurant industry. Even when the restaurant industry is on a rise, aspects of it seem to be on a decline, and there do not seem to be concrete studies that clearly state or prove which factors affect the industry or how they influence it. This uncertainty and volatility, as can be seen on the graph below, gives us great opportunities when it comes to pairs trading.

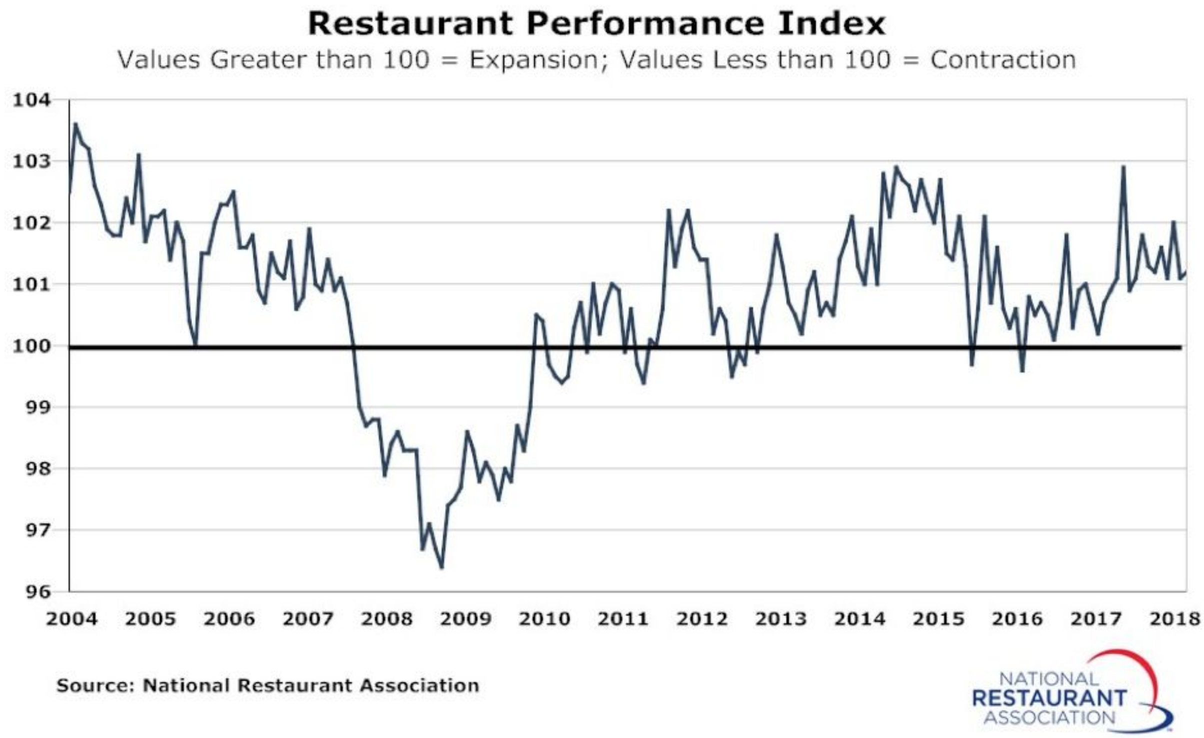

Figure. 1

Furthermore, over the past decade, the national employment rate has grown by 0.5% in the United States, and by 2% within the restaurant industry (Bureau of Labor Statistics, 2018). More than 14 million people are currently employed in the U.S. restaurant industry, which is about 10% of the working population. With rising issues surrounding topics like health care and minimum wage affecting labor costs, there is also an impacting need for restaurant operations to be more efficient.

The National Restaurant Association has recently reported that one of the key drivers for growth of the restaurant industry is the change in how people in the United States spend their money on food. In 1955, only 25% of American dollars spent on food was spent at restaurants, compared to the restaurant industry's share of the American food dollar in recent years, which has risen to over 47% and is still continuing to grow (National Restaurant Association, 2017). Over the past 60 years, restaurants have gained this significant increase in the food dollar share by adapting to the tastes and behaviors of their consumers. As more Americans, particularly women, joined the workforce, there was less time for people to prepare their meals at home. The heightened convenience of restaurants and higher disposable incomes was seen as more money became available to spend at restaurants. The restaurant industry is clearly an important and understudied component of the economy.

As noted above, there has been little amount of literature on this subject of the restaurant industry and the economic factors that affect it. One paper that does look in to this relationship is by Clayton W Barrows and Atsuyuki Naka, titled "Use of macroeconomic variables to evaluate selected hospitality stock returns in the U.S." (Barrows and Naka, 1994). Their paper investigates how selected macroeconomic variables, such as GDP, influence restaurant and hotel stock returns over a twenty-seven year period employing a regression analysis. The results suggest the direction of macroeconomic forces is consistent across the industrial, lodging and restaurant sectors although differences in significance do occur. Over the period studied, macroeconomic variables are able to explain the movement of restaurant stock returns to a greater extent than either the lodging or industrial sectors.

The literature discussing pairs trading is more extensive but does not look into the power of utilizing cointegration analysis. One paper by Yan-Xia Lin Michael McCrae and Chandra Gulati entitled "Loss protection in pairs trading through minimum profit bounds: A cointegration approach" does study cointegration uses for pair trading (Lin, McCrae and Gulati, 2006). The paper uses the cointegration principles to develop a procedure that embeds a minimum profit condition within a pairs trading strategy. The paper outlines a five step procedure of identifying eligible trades. Their results show that, at reasonable minimum profit levels, the protocol does not greatly reduce trade numbers or absolute profits relative to an unprotected trading strategy.

A study by Hossein Rad, Rand Kwong Yew Low and Robert Faff entitled “The profitability of pairs trading strategies: distance, cointegration and copula methods” compared the different pair trade approaches including cointegration. Their results found that “the cointegration method is the superior strategy during turbulent market conditions” (Rad, Low and Faff, 2015).

Data Description

The data in our project focused on the biggest economic drivers for stock prices of restaurant equities. This data was organized by the first of every month from March 2009 to 2019. Monthly data was used in order to avoid the large amount of white noise that occurs when using daily data. We chose two low-tier equities (Dominos & Pizza Hut), two high-tier equities (Del Frisco’s & Ruth’s), and two mid-tier equities (Red Robin & Chili’s/Maggiano's) as our dependent variables. These restaurants were put into tiers based off the average dollar amount a consumer would spend in each restaurant determined by the money sign system on Yelp!. This was done in order to get a clearer picture of how the different priced restaurants react to different economic shocks. This was done to show the belief that the impact of different economic factors would have either a larger or smaller effect on the stock price based on the how expensive the restaurant may be. The independent variables were selected based off what we thought would have the most direct impact on these restaurant equities.

The first economic factor was the U-6 unemployment rate where we found complete monthly data from the Bureau of Labor Statistics. The U-6 rate includes people who are under employed for economic reasons, (e.g. working part time even but seeking full time employment) and people who have fallen out of the labor force because the have stopped looking for work, (e.g. they do not believe they could find a job even if they were looking for one). Due to this there are times when the U-3 rate (the official unemployment rate) can rise as a result of people believing that they can find work once again, this is actually a positive sign for the economy, but because the people once again searching for work rejoin the labor force the U-3 rate increases. The U-6 rate does not have this shortcoming and as a result can more accurately show unemployments effect on the restaurant equities.

The Consumer Sentiment Index from Michigan University was also used in our models. The index measures the average consumers confidence towards spending based on phone survey data collected from at least 500 households each month. This index was used to see how much of an impact an increase or decrease in consumer sentiment might affect the price of restaurant equities.

The next economic variable used was Personal Consumption Expenditures Index (PCE) of food. This data is recorded by the Bureau of Economic Analysis and is used to show household spending habits. In our analysis the PCE was used to show the elasticity of demand for restaurant spending and how this can be reflected in the stock price of the different restaurant equities.

We included the Restaurant Industry Index to find out how closely the restaurant equities selected perform with the restaurant industry as a whole. This data was collected from FactSet's industry tab. A shortcoming of using the Restaurant Industry Index is that it is highly concentrated by two very large companies, McDonald's and Starbucks, these companies make up for 62.55% of the industry, 38.62% & 23.93% respectively.

The final variable was the Russell 3000 Index, used as a benchmark for the US stock market, the Russell 3000 consists of 3000 securities representing small to ultra large cap companies. The Russell also has exposure to restaurant equities making it a reliable benchmark for how closely the equities move with the market. Monthly Russell 3000 data was collected from Yahoo finance.

Research Methodology

Unit root testing was performed with the Augmented Dickey Fuller on our original restaurant, industry and economic data. The data was non-stationary so we transformed it by taking the difference in logs to transform it into stationary return data which we then used for our analysis. The, now stationary data, was analyzed by running type twos of regressions, a least squares one lagged dependent variable, and an ARDL model using Akaike information criterion to determine the number of lags included in each model. Both of these models were created for each of the restaurants included as well as the industry as a whole as shown in our Appendix. This was done to discover which economic factors are shown to affect the price of the individual restaurant equities in a statistically significant way. All significant variables identified from the models were further analyzed with the Granger Causality tests.

To get a clearer picture of how these pairs worked together cointegration analysis were performed, with the original non stationary equity price data. This was done in order to discover whether or not our selected restaurant pairs were suitable for pairs trading analysis. The Error Correction analysis were also performed if cointegration was present.

Empirical Findings and Interpretation

EView Tests

Regressing the individual companies' stock returns against the economic indicators, Russell 3000 returns, and the returns of a restaurant industry index showed that there is generally no one factor that can be used as a common predictor across the restaurant industry.

Although, there were some commonalities in the regressions of stocks from a similar price range and each regression told a story of the individual stock returns with both information in the model and information that could be missing from the model.

Testing the restaurant industry returns against the economic indicators and the Russell returns showed that it is affected the Russell returns lagged by a month and the U-6 rate lagged two months. The significant Russell return lagged variable has a positive coefficient of 0.48 which says that an increase in the Russell returns by 1% increases the Restaurant industry returns by 0.48%. The U-6 variable lagged by 2 months has a negative coefficient of -0.32 which is barely not significant at the 5% level but is still worth considering. These variables are indicative of consumers feeling the effect of a change in their current income which changes their future spending habits. As consumers feel a drop in their current real income, they look toward ways to cut their spending and dining out at restaurants can amount to a significant cost leading to a decrease in their future consumption spending at restaurants. The Granger Causality test using these three variables showed that Russell returns Granger causes Industry returns with a highly significant test statistic supporting the claim of a lagged effect on future consumption but there was no Granger causality between Industry and the U-6 rate.

Examining the low-range priced pair, Dominos and Papa Johns, there is a significant lagged effect of PCE-food by one month on the returns of Papa Johns and a significant non-lagged variable of Industry Returns. The lagged PCE-food is -3.82 showing that a 1% increase in PCE-food lowers Papa John's estimated return by 3.82% which seems relatively large. An explanation for this is Papa John's business model which focuses on its ingredients and spending a premium to avoid the use of artificial ingredients. The PCE-food captures overall inflation in the cost of their inputs better than CPI as it is chain-linked averages. Although the regressions on the stocks showed a significant effect of the restaurant industry returns, they did not exhibit any Granger Causality between them and the restaurant industry nor with PCE-food. Domino's exhibited extreme returns of between 2,000-3,000% during the 2009-2018 time period that was studied. This is due to factors such as a change in CEO and push for a new recipe, causing difficulty using these economic indicators to predict its returns.

The regressions of the mid-range priced companies, Red Robin and Chili's & Maggiano's, revealed a highly statistically significant, positive effect of the Russell 3000 returns but there is no lag effect there. Running a Granger Causality test confirmed that Russell returns did not Granger Cause the returns of the individual companies or vice versa. Red Robin's ARDL model also showed that there is a significant, negative effect of the U-6 rate but there was no significant lagged effect and the Granger Causality test did not show any either. This shows that the mid-range priced companies tend to follow the business cycle in that they will do well when the market is performing well and give worse returns when the market is performing poorly. For Red Robin's, it would be estimated to perform worse when there is observed rising unemployment.

The high-range priced companies, Del-Frisco's and Ruth's Chris Steak House, showed the most sensitivity to the effect of the economic factors that were studied. Granger Causality tests showed that the Russell returns Granger caused both Del Frisco's and Ruth's Chris which is reflected in Ruth's Chris ARDL model but not in Del Frisco's meaning that there must be some interference or noise in the output of Del Frisco's ARDL. Checking a regression of just Del Frisco's versus Russell returns showed a significant, positive coefficient for Russell returns lagged by one month. Consumer sentiment was found to Granger Cause Ruth's returns and Ruth's returns Granger Causes PCE-food. This reflects Ruth's sensitivity to how the consumer feels about their future spending habits and how a high end restaurant would probably be sacrificed in the average consumer's budget. Del-Frisco's ARDL model showed a significant

(10% level), positive effect of Consumer Sentiment but no Granger Causality. The better the consumer feels about the economy at the moment, the more likely they'd be willing to patronize Del-Frisco's. These restaurants would be expected to suffer the most among the price ranges in the event of an economic downturn.

Generally, the models all had a R^2 of less than 0.33 which speaks to the difficulty in estimating stock prices or stock returns. There was no economic factor that was a significant variable for all companies but similar stories were found for restaurants from the same price range. The results affirm the idea of the importance of researching company specific data along with general economic factors to properly assess the value of investing in a company.

Application

Traditional investment strategy dictates that consumer discretionary companies, such as restaurants, underperform in a downturn or slowdown in the economy. Additionally economics dictates that consumers will switch to inferior substitutes for superior goods when wages fall and incomes contract. These two sentiments led us to intuitively believe restaurants as a whole were cyclical and that more expensive restaurants would be more impacted by these economic factors which we confirmed through our tests. We found that the more expensive Ruth's and Del Frisco's steak houses were correlated with consumer sentiment with 0.58 and 0.62 coefficients respectively. This indicates that when consumer sentiment begins to fall so do these companies' share prices. This situation is during an economic downturn. We also looked to see if this relation existed in the inexpensive restaurants, Domino's and Papa John's. We found that neither consumer sentiment nor any of our economic variables had a statistically significant relation with the two restaurants as predicted.

Pairs trading is based on the concept that similar companies share prices change in similar directions over the long run. When viewing non stationary data, such as share price, occasionally datasets are highly related through cointegration, indicating that over time their values move in a long run equilibrium. This is the premise of pairs trading, indicating that pairs of equities whos share prices are cointegrated are strong candidates. We tested all three pairs of restaurant equities for cointegration and found our middle end restaurant stocks, EAT and RRGB, were cointegrated from March of 2009 to June of 2018 at a 1% significance level, only breaking after RRGB was influenced by a company specific event in late 2018 bringing their t-Statistic to -2.25. We also found their error correction term to be -0.17. Since we are using monthly data this implies correction over period of slightly less than 6 months. Del Frisco's and Ruth's as well as Papa John's and Domino's both saw differences in share price changes that were noticeably driven by company specific events as shown in Figures 5 and 6. This led us to believe they were not cointegrated which we confirmed by testing the residuals of their regressions returning t-Statistics of -0.54 and -0.82 for the pizza chains and steak houses respectively. EAT and RRGB's cointegration, over a almost decade presented multiple opportunities to walk through a trade as seen below.

In Figure. 2. we see the ratio of EAT's price to RRGB's price over this time which trades around an average of 0.83. Occasionally we see this ratio drift out of its equilibrium before returning, presenting opportunities to enter a trade that will take advantage of a temporary disequilibrium like the two we see from September of 2016 to May of 2018 which we break down in Figure 3.

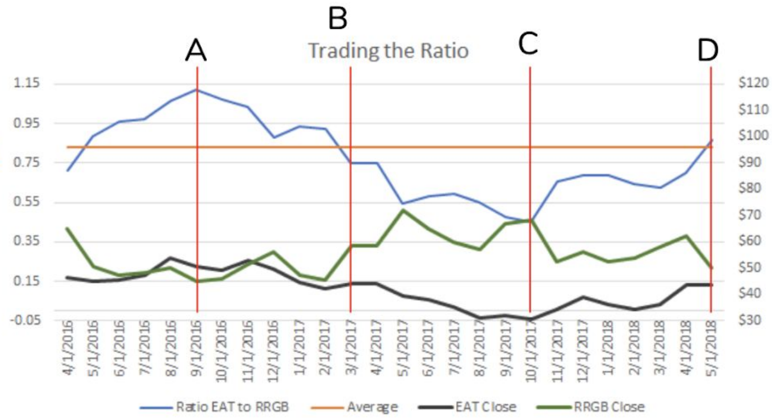

Figure. 2

Figure. 3

We see at point A that this ratio is higher than its equilibrium, implying that EAT is overvalued or RRGB is undervalued. We assume that we don't know which is true but by shorting EAT and buying RRGB we are guaranteed to make money, this is the pairs trade. We then enter the positions requiring an investment of $44.94 to enter the long and a 25% collateral for our naked short adding up to a total of $57.55. We then sell when the ratio is back in equilibrium at point B. We assume it would take approximately 6 months for this to happen as that is what our error correction term predicts and this holds true. As we see this ratio drop below its equilibrium we can also take advantage of that by entering the reverse trade as before as shown in Figure 4 which outlines all of our trades and profits.

The Trade								
Date	**Ratio (Avg: 0.83)**	**EAT**	**Buy or Short**	**EAT Profit**	**RRGB**	**Buy or Short**	**RRGB Profit**	**Holding Period**
9/1/2016	1.12	$50.43	Enter Short	$ -	$ 44.94	Enter Long	$ -	
3/1/2017	0.75	$43.96	Exit Short	$ 6.47	$ 58.45	Sell Long	$ 13.51	6 Months
10/1/2017	0.45	$30.72	Enter Long	$ -	$ 68.40	Enter Short	$ -	7 Months
5/1/2018	0.87	$43.73	Sell Long	$ 13.01	$ 50.35	End Short	$ 18.05	7 Months
Total				$ 19.48			$ 31.56	20 Months

Profits	
Initial Capital	$ 57.55
End Capital	$ 108.59
Total Return	88.69%
Annualized Return	53.22%

Figure. 4

After exiting this reversed trade 7 months later, close to the predicted correction period, we have again made a profit on the trade. Over these two pairs trades an individual would have made a 88.69% return on our initial capital both showing that money can be made and illustrating that the error correction term is a strong approximate for the length of the trades.

Conclusion

Our research indicates there are statistically significant impacts on restaurant equities associated with specific factors of the economy. Additionally we saw cointegration among one of the equity pairs, indicating a potential candidate for pairs trading. Both these observations present opportunities to either inform or structure investment decisions, allowing us to better allocate capital and produce alpha return in a portfolio.

We saw that middle and high end restaurant equity prices were positively correlated to the economy while low end restaurants had no correlation. From this we can infer that during economic slowdowns it is better to hold low end restaurants as part of a stock portfolio as they will not suffer as much as these high end restaurants, mitigating your downside. Alternatively during periods of economic growth we would recommend holding these more sensitive companies over the inexpensive restaurants to capitalize on the upturn. Specifically a high end company which has a the largest impact from the change in economic conditions, such as Del Frisco’s or Ruth’s. If held over these respective periods you would see outperformance relative to a portfolio that doesn’t change allocation or which simply held the industry index.

When examining cointegration we found that companies who are similar can have long run equilibrium which indicate strong candidates for pairs trading. Examining the ratio of the companies share prices that often trade in a similar range we can take advantage of over and under valuations, such as those in Figure. 3, when that ratio rises or falls an abnormal amount. We can also approximate the length of this trade based on the error correction term as a proxy for the length of time it would take to return to its expected ratio. This can be seen in a hypothetical trade set up using our middle end restaurant equities EAT and RRGB shown in the results section which produced a 88.69% return. Cointegration tests can be run on other pairs of companies who are similar to find candidates for pairs trading that we would structure in the same way as described above. That being said the majority of pairs trading is done algorithmically on a much shorter basis. Our trades took several months based on the error correction term as we only used monthly data. Many computers go through this same process but with data on a seconds or minutes interval to try and arbitrage daily inefficiencies. To structure these trades we would run these cointegration tests on a higher frequency of data to mitigate the probability of company specific events arising over the correction period. This would allow us to construct shorter less risky trades.

It is important to note that although both pairs trading and portfolio allocation based on these tests works in many applications there are also many situations that these strategies do not lend themselves to. Primarily these are situations where prices are being influenced by company specific events that have large effects and do not affect pair companies the same way. This mutes the effect of economic factors making the weighting scenario less relevant for individual holdings and more relevant if holding a grouping of similar companies. Additionally this would change the expected ratio for pairs as this change in share could be more permanent or indicate the beginning of a random walk trend that breaks cointegration between the two stocks. These methods of investing work much better when the companies are not in the midst of strategic initiatives and when the companies are mature established companies who see a more predictable impact from the macroeconomic environment.

These are two different ways in which econometrics can be used to inform investment decisions and enhance income. This is done through stronger portfolio allocation based on economic factors and diversifying return strategies to increase expected return and remove economic correlation from a portfolio. Although these tests focused on restaurant equities they could also be applied to other industries to inform portfolio allocation as well as test other pairs of equities for cointegration. If we were to continue research we would focus on finding several other cointegrated pairs using more incremental, such as hourly, data and watching to see what portions of the trades played out as expected.

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Appendix

Team Work

Team Member	Responsibilities
Charles Sproul	● Presentation 1 ○ Non-Stationary to Stationary (Slides 5&6) ○ Data (Slide 11) ● Presentation 2 ○ Cointegration Analysis/Explanation of the Trade (Slides 17-19) ● Paper ○ Findings and Interpretation (Application) ○ Conclusion
Piper Montesi	● Presentation 1 ○ Analysis of Ruth Chris's ○ Literature ● Presentation 2 ○ Recap of Part 1 ○ Data Description ● Paper ○ Methodology ○ Literature ○ Introduction
Thomas Nguyen	● Presentation 1 ○ Methodology ○ Domino's analysis ● Presentation 2 ○ Pairs Trading explanation ○ Red Robin's analysis ● Paper ○ Findings and Interpretation (Eviews Tests)
Abdullah Omer	● Presentation 1 ○ Data Description ○ Papa John's Analysis ● Presentation 2

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Literature
Paper
Literature
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<tr><td>Sean Moran</td><td>

Presentation 1
Del Frisco's Analysis
Eviews
Conclusion
Presentation 2
Chili's/Maggiano's Analysis
Eviews
Conclusion
Paper
Description of Data

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Regressions and Charts:

Dependent Variable: DOMINOSR
Method: ARDL
Date: 03/17/19 Time: 11:20
Sample (adjusted): 2009M06 2018M12
Included observations: 115 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR INDUSTRYR
Fixed regressors: C
Number of models evalulated: 12500
Selected Model: ARDL(1, 0, 0, 2, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DOMINOSR(-1)	-0.044223	0.082220	-0.537866	0.5918
CSENTR	0.116808	0.156187	0.747872	0.4562
PCER	2.024100	1.614329	1.253833	0.2127
U6R	0.039275	0.412943	0.095109	0.9244
U6R(-1)	-0.296456	0.399744	-0.741615	0.4600
U6R(-2)	0.509399	0.399323	1.275655	0.2049
RUSSELLR	-0.055204	0.190081	-0.290423	0.7721
INDUSTRYR	0.962376	0.203013	4.740457	0.0000
C	0.013984	0.010259	1.363143	0.1757

R-squared	0.219163	Mean dependent var	0.029347
Adjusted R-squared	0.160232	S.D. dependent var	0.080941
S.E. of regression	0.074174	Akaike info criterion	-2.289781
Sum squared resid	0.583187	Schwarz criterion	-2.074961
Log likelihood	140.6624	Hannan-Quinn criter.	-2.202587
F-statistic	3.718969	Durbin-Watson stat	1.796036
Prob(F-statistic)	0.000723		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: PAPAR
Method: ARDL
Date: 03/17/19 Time: 11:18
Sample (adjusted): 2009M07 2018M12
Included observations: 114 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR INDUSTRYR
Fixed regressors: C
Number of models evalulated: 12500
Selected Model: ARDL(3, 0, 1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
PAPAR(-1)	-0.038586	0.093611	-0.412189	0.6810
PAPAR(-2)	0.151811	0.092585	1.639691	0.1041
PAPAR(-3)	-0.171216	0.096640	-1.771685	0.0794
CSENTR	0.108576	0.166518	0.652039	0.5158
PCER	-2.852941	1.855560	-1.537510	0.1272
PCER(-1)	-3.815774	1.851821	-2.060552	0.0418
U6R	-0.319066	0.450691	-0.707950	0.4806
RUSSELLR	0.211831	0.201631	1.050586	0.2959
INDUSTRYR	0.595337	0.216922	2.744471	0.0071
C	0.014964	0.011575	1.292755	0.1990

R-squared	0.149480	Mean dependent var	0.010741
Adjusted R-squared	0.075877	S.D. dependent var	0.081434
S.E. of regression	0.078283	Akaike info criterion	-2.173337
Sum squared resid	0.637339	Schwarz criterion	-1.933319
Log likelihood	133.8802	Hannan-Quinn criter.	-2.075927
F-statistic	2.030901	Durbin-Watson stat	1.873765
Prob(F-statistic)	0.042912		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: EATR
Method: ARDL
Date: 03/17/19 Time: 11:30
Sample (adjusted): 2009M07 2018M12
Included observations: 114 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR INDUSTRYR
Fixed regressors: C
Number of models evaluated: 12500
Selected Model: ARDL(3, 0, 0, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
EATR(-1)	0.002262	0.098125	0.023050	0.9817
EATR(-2)	0.146608	0.092388	1.586875	0.1155
EATR(-3)	-0.190036	0.091779	-2.070575	0.0409
CSENTR	-0.077605	0.155347	-0.499559	0.6184
PCER	2.445601	1.565503	1.562182	0.1213
U6R	-0.651883	0.403746	-1.614585	0.1094
RUSSELLR	0.628886	0.187195	3.359518	0.0011
INDUSTRYR	0.028697	0.211023	0.135991	0.8921
C	-0.007055	0.008989	-0.784859	0.4343

R-squared	0.181971	Mean dependent var	0.008322
Adjusted R-squared	0.119645	S.D. dependent var	0.077475
S.E. of regression	0.072692	Akaike info criterion	-2.329501
Sum squared resid	0.554841	Schwarz criterion	-2.113485
Log likelihood	141.7815	Hannan-Quinn criter.	-2.241832
F-statistic	2.919661	Durbin-Watson stat	2.037783
Prob(F-statistic)	0.005549		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RRGBR
Method: ARDL
Date: 03/17/19 Time: 11:28
Sample (adjusted): 2009M06 2018M12
Included observations: 115 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR INDUSTRYR
Fixed regressors: C
Number of models evaluated: 12500
Selected Model: ARDL(1, 0, 0, 0, 0, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
RRGBR(-1)	-0.020638	0.086685	-0.238083	0.8123
CSENTR	-0.009026	0.212375	-0.042502	0.9662
PCER	-0.295511	2.129575	-0.138765	0.8899
U6R	-1.768230	0.552026	-3.203161	0.0018
RUSSELLR	1.293771	0.258022	5.014190	0.0000
INDUSTRYR	0.666003	0.280160	2.377226	0.0192
INDUSTRYR(-1)	-0.345430	0.274502	-1.258388	0.2110
INDUSTRYR(-2)	0.476301	0.270553	1.760473	0.0812
C	-0.030418	0.013967	-2.177873	0.0316

R-squared	0.302772	Mean dependent var	0.003780
Adjusted R-squared	0.250151	S.D. dependent var	0.114971
S.E. of regression	0.099558	Akaike info criterion	-1.701133
Sum squared resid	1.050641	Schwarz criterion	-1.486313
Log likelihood	106.8152	Hannan-Quinn criter.	-1.613939
F-statistic	5.753830	Durbin-Watson stat	2.061134
Prob(F-statistic)	0.000004		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: RUTHR
Method: Least Squares
Date: 03/17/19 Time: 13:01
Sample (adjusted): 2009M07 2018M12
Included observations: 114 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RUTHR(-1)	0.230342	0.086113	2.674884	0.0087
RUTHR(-2)	0.006535	0.062183	0.105097	0.9165
RUTHR(-3)	-0.104397	0.063711	-1.638602	0.1044
CSENTR	-0.180975	0.198083	-0.913634	0.3631
CSENTR(-1)	0.359976	0.193536	1.859997	0.0658
PCER	0.580332	2.274705	0.255124	0.7991
PCER(-1)	4.195975	2.267594	1.850408	0.0671
U6R	-0.320883	0.518256	-0.619160	0.5372
RUSSELLR	0.219834	0.238283	0.922575	0.3584
RUSSELLR(-1)	0.735291	0.288957	2.544633	0.0124
INDUSTRYR	0.566602	0.299045	1.894704	0.0610
C	-0.015815	0.014944	-1.058316	0.2924

R-squared	0.294337	Mean dependent var	0.016154
Adjusted R-squared	0.218236	S.D. dependent var	0.104442
S.E. of regression	0.092345	Akaike info criterion	-1.827275
Sum squared resid	0.869810	Schwarz criterion	-1.539254
Log likelihood	116.1547	Hannan-Quinn criter.	-1.710384
F-statistic	3.867718	Durbin-Watson stat	2.072285
Prob(F-statistic)	0.000112		

Dependent Variable: DFRGR
Method: ARDL
Date: 03/17/19 Time: 11:41
Sample (adjusted): 2012M11 2018M12
Included observations: 74 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR INDUSTRYR
Fixed regressors: C
Number of models evaluated: 12500
Selected Model: ARDL(2, 1, 0, 0, 2, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
DFRGR(-1)	-0.145638	0.112412	-1.295570	0.1999
DFRGR(-2)	0.338070	0.110979	3.046261	0.0034
CSENTR	0.688314	0.323191	2.129744	0.0371
CSENTR(-1)	0.484020	0.315856	1.532408	0.1304
PCER	-4.398976	3.169736	-1.387805	0.1701
U6R	0.073076	0.635849	0.114927	0.9089
RUSSELLR	-0.159776	0.374903	-0.426179	0.6714
RUSSELLR(-1)	0.579815	0.446307	1.299141	0.1986
RUSSELLR(-2)	0.655970	0.474023	1.383834	0.1713
INDUSTRYR	0.995622	0.417227	2.386284	0.0200
C	-0.023360	0.015873	-1.471636	0.1461

R-squared	0.332760	Mean dependent var	-0.010633
Adjusted R-squared	0.226849	S.D. dependent var	0.106611
S.E. of regression	0.093742	Akaike info criterion	-1.760178
Sum squared resid	0.553614	Schwarz criterion	-1.417682
Log likelihood	76.12659	Hannan-Quinn criter.	-1.623552
F-statistic	3.141883	Durbin-Watson stat	2.029444
Prob(F-statistic)	0.002576		

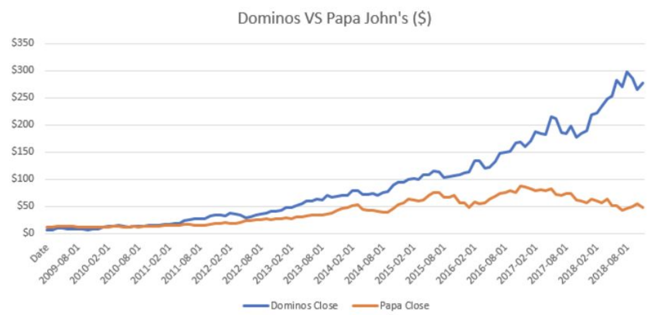
*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: INDUSTRYR
Method: ARDL
Date: 03/17/19 Time: 11:14
Sample (adjusted): 2009M06 2018M12
Included observations: 115 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): CSENTR PCER U6R RUSSELLR
Fixed regressors: C
Number of models evalulated: 2500
Selected Model: ARDL(1, 0, 0, 2, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
INDUSTRYR(-1)	0.016755	0.097016	0.172699	0.8632
CSENTR	0.080813	0.067528	1.196745	0.2341
PCER	0.401027	0.661363	0.606365	0.5456
U6R	0.161065	0.170412	0.945151	0.3468
U6R(-1)	0.087684	0.165336	0.530341	0.5970
U6R(-2)	-0.319605	0.163995	-1.948875	0.0540
RUSSELLR	-0.069482	0.079650	-0.872347	0.3850
RUSSELLR(-1)	0.482432	0.083488	5.778434	0.0000
RUSSELLR(-2)	-0.120401	0.095488	-1.260898	0.2101
C	0.009500	0.004304	2.207161	0.0295

R-squared	0.315572	Mean dependent var	0.014318
Adjusted R-squared	0.256907	S.D. dependent var	0.035697
S.E. of regression	0.030772	Akaike info criterion	-4.041507
Sum squared resid	0.099424	Schwarz criterion	-3.802818
Log likelihood	242.3867	Hannan-Quinn criter.	-3.944624
F-statistic	5.379194	Durbin-Watson stat	1.849716
Prob(F-statistic)	0.000005		

*Note: p-values and any subsequent tests do not account for model selection.



		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.542810	0.8776
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

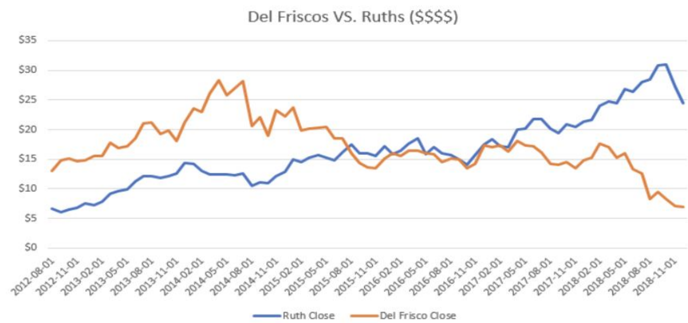
*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CHEAP_RESID)
Method: Least Squares
Date: 03/09/19 Time: 11:06
Sample (adjusted): 2009M04 2018M12
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CHEAP_RESID(-1)	-0.014049	0.025882	-0.542810	0.5883
C	-0.219161	0.376040	-0.582812	0.5612

R-squared	0.002556	Mean dependent var	-0.223492
Adjusted R-squared	-0.006118	S.D. dependent var	4.054197
S.E. of regression	4.066579	Akaike info criterion	5.660428
Sum squared resid	1901.763	Schwarz criterion	5.707644
Log likelihood	-329.1350	Hannan-Quinn criter.	5.679597
F-statistic	0.294642	Durbin-Watson stat	1.825827
Prob(F-statistic)	0.588311		

Figure. 5



Null Hypothesis: EXPENSIVE_RESID has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.826937	0.8074
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EXPENSIVE_RESID)
Method: Least Squares
Date: 03/09/19 Time: 11:10
Sample (adjusted): 2009M04 2018M12
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EXPENSIVE_RESID(-1)	-0.019403	0.023464	-0.826937	0.4100
C	-0.077310	0.169922	-0.454973	0.6500

R-squared	0.005911	Mean dependent var	-0.079431
Adjusted R-squared	-0.002733	S.D. dependent var	1.835272
S.E. of regression	1.837779	Akaike info criterion	4.071938
Sum squared resid	388.4045	Schwarz criterion	4.119155
Log likelihood	-236.2084	Hannan-Quinn criter.	4.091108
F-statistic	0.683824	Durbin-Watson stat	1.877700
Prob(F-statistic)	0.409985		

Figure. 6