Final Report

STAT 697D

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NOTE TO ERINA: ALL CAPS ISN'T YELLING AT YOU. THAT'S HOW I MAKE NOTES TO MYSELF IN THESE DOCS SO THAT I SEE THEM. THEY ARE NOTES YOU CAN ADDRESS OR I CAN ADDRESS. SORRY BECAUSE THEY DO SOUND LIKE YELLING WHEN YOU READ THEM LOL

NOTE TO JENN: SOUNDS GOOD! WILL DO THE SAME. ALSO, I ADD "abc" WHEREVER THINGS NEED TO BE FILLED IN/WORKED ON LATER ON JUST FYI

Abstract

Recreate the paper, describe. Extend analysis through current year. Summarize findings.

The purpose of this project is to see what the differences between company fundamentals and share prices can tell us about economic recessions. We replacated the results from "Stock Market Market Crash of 2008: an empirical study of the deviation of share prices from company fundamentals" by Taisei Kaizoji and Michiko Miyano. We used the fundamental indicators of cash and short-term investments, dividends per share, and carrying value to fit out model and fit the individual fixed effects model. Then, we found the divergence rate from the actual share price. By looking at the divergence rates, we were able to see that there was a positive deviation between the company fundamentals and share prices right before a recession (i.e. overvalued during the years leading up to the recession in 2008) and a negative deviation during the recession (i.e. undervalued in 2008). Finally, we look at specific markets and market anomalies.

Data

Our data source is . Description of variables. Give relevant definitions, context, etc.

Our data is sourced from Factset. The quarterly fundamental indicators (i.e. cash and short-term investments, dividends per share, and carrying values) and share price from 2003 to 2019 were used. Time was treated as a discrete variable where share price was determined by taking the stocks' closing prices of the final day in the quarter to represent that quarter. It is important to note that 2019 contains data for only the first quarter. Additionally, we added a new binary variable to our data set based on dividends per share based on our initial data exploration. We noticed that many companies' quarterly data had dividends of 0. Therefore, dividends = 0 simply indicated whether that instance of company fundamental data had a dividend of 0 or not. Each row consisted of one company's fundamentals data for a specific quarter at a certain year, and any rows with any of the fundamental indicators of the share price missing were omitted, hich ultimately changed our total instances from 254,764 to 161,544. Our final data set included 5,727 U.S companies in 11 sectors (i.e. industrials, financials, IT, Utilities, Consumer Discretionary, Health Care, Energy, Materials, Real Estate, Consumer Staples and Telecommunications). 184 companies did not have a sector associated in the data.

The fundamental indicators give valuable information about stocks. Cash and short-term investments show the amount of liquid assets a company has. Liquid assets are important to consider because it shows how much the company has that can be quickly converted to cash in the event of something happening. Dividends per share is the amount in dividends that a firm pays out to shareholders. Finally, the carrying value, which is also known as the book value, shows the stock's market value and how much shareholders

would receive in the event that the company was liquidated. It is found by subtracting the company's total liabilities from its assets, and can be a good indicator for investors when making decisions; it gives a sense of whether a stock is being overvalued or undervalued. For example, comparing the price at which the stock is trading at and its carrying value may play a role in whether to buy or sell the stock. These 3 indicators are often used to evaluate company fundamentals.

JENN SHOULD WE ADD THIS QUOTE FROM THE PAPER?? "These three indicators are commonly used by financial professionals and investors in fundamental analysis as a tool for identifying the divergence of share price in the market from the intrinsic value of a company." A: SURE, IF WE WANT TO. I THINK IT BELONGS IN THE DATA SECTION.

NOTE ON DATA: NEED TO ADDRESS THE HANDLING OF TIME. WE USED IT AS A DISCRETE VARIABLE. COLLAPSED OVER FOUR QUARTERS INTO SINGLE POINT FOR EACH YEAR. ALSO NEED TO MENTION THAT 2019 ONLY CONTAINS 1 QUARTER AT THE TIME OF THE STUDY.

Models and Methodology

Our study focuses on the exploration of a number of linear regression models to predict stock price from company fundamentals. We started with the base model:

 $ln(price_{it}) = \beta_0 + \beta_1 ln(dividends_{it}) + \beta_2 \mathbb{I}(dividends = 0) + \beta_3 ln(bookvalue_{it}) + \beta_4 ln(cashflow_{it}) + \mu_i + \gamma_t + \epsilon_{it}$

In this model, μ_i indicates the company effects and τ_t indicates the discrete time effects. Then, we fit the models described in table one.

μ and μ for All Tested Models		
Model	μ	au
Pooled OLS	0	0
Individual Fixed Effects	Fixed Effect	0
Time Effects	0	Fixed Effect
Two-Way Fixed	0	Fixed Effect
Individual Random	Random	0
Time Random	0	Random
Two-Way Random	Random	Random

Table 1: μ and τ for All Tested Models

We used F-tests to assess the pooled ols and fixed effects model performance, likelihood ratio tests to compare the pooled ols and fixed effects models, and Hausman Tests to compare the fixed and random effects models. In all cases, we obtained p-values indicating that the fixed effects models out-performed the pooled ols model and the random effects model. The best model overall was the fixed effect model with time and company intercepts included. These results replicate the results obtained in our source paper, even though our models were built with many more years of data.

Divergence Rate

The overarching research question of the paper we replicate here is not about building the best model given the data (although that step is important). Instead, the research question is about using a model that accurately describes stock prices to notice anomalies in the stock market. For this reason, the authors of the paper chose to use the fixed effects model with only company effects. This works because we can assume that, in a perfect market, company fundamentals will always compose the stock price in an additive way with no

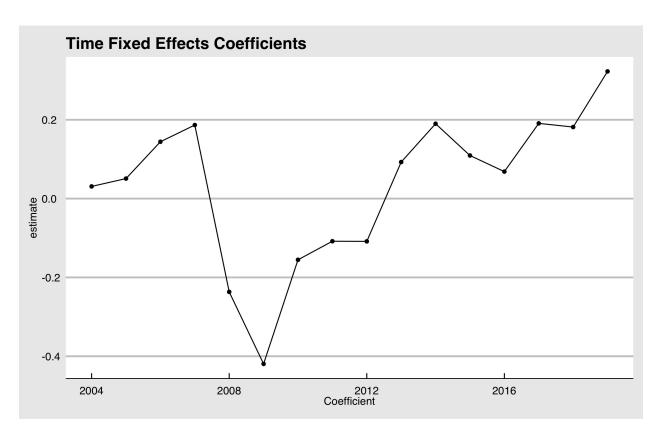


Figure 1: Figure #.

time effects. Then, we can use the predictions from our model to notice when stocks are over or under valued in the market. Our source paper proposes a metric for this purpose named divergence rate defined as follows:

$$D_{it} = ln(Y_{it}) - ln(\tilde{Y}_{it})$$

In this formula, Y_{it} is the observed stock price for company i at time t and Y_{it} is the model's prediction for the stock price of company i at time t. The divergence rate indicates how over or undervalued a company's stock is given that company's fundamental value.

The two figures below display the time effects coefficients from model and the mean divergence rate by year. We can see that, as expected, these two figures track each other. While it feels counterintuitive to leave an informative variable out of the model, in this case doing so gives us a powerful tool. Now, we can track in real time, how over or undervalued the market is as a whole. Our sample only contains one recession (2008-2009), so it is less powerful than a dataset that contains all known recessions. However, we can look here to seek potential recession indicating trends. In the years leading up to the recession, the market became overvalued. And then, in 2008, the recession led to an undervaluing of the market as a whole. Looking to the current year, we can see that 2019 the market appears more overvalued than at any other point in the dataset. Other recession indictors outside our model have also appeared recently, including the inversion of the bond yield curve, which has preceded every recent recession. (SOURCE: NEED TO CREATE CITATION: https://www.clevelandfed.org/en/our-research/indicators-and-data/yield-curve-and-gdp-growth.aspx) We interpret the overvaluing of 2019 by our indicated by our model cautiously, since we only have one quarter of 2019 in the data so far. But, this trend matches our assertion about the overvaluing of the market serving as a potential recession indicator.

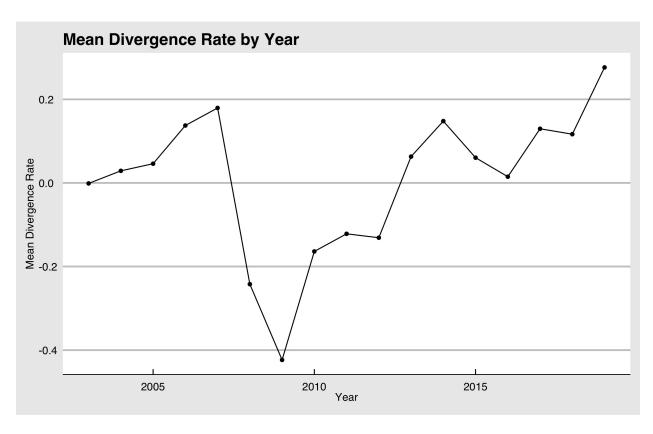


Figure 2: Figure #.

Findings Summary? (Do we need this section? Unclear at this point.)

Which model is most significant? Did we replicate what the paper reported? What did we learn from our extension of the model to more recent data? Of the models we tested, we found that the Two-Way Fixed Effects had the best R-squared of abc. We can see in Figure abc. that there is time effect. However, we decided to use the Individual Fixed Effects, which had a R-squared of abc, 0.2 less than the former model instead of including the time effects as well, because we are interested in the company fundamental indicators alone showing the time effect. Therefore, the Individual Fixed Effect is more suited for our goals. This is the same decision as the authors of the paper, and we

JUST SAW YOUR NOTE IN PARENTHESIS (WAS WORKING ON THIS BEFORE I PULLED). WE MIGHT NEED TO SWITCH THE ORDER

RESPONSE: I LITERALLY EXPLAIN THIS EXACT PARAGRAPH YOU WROTE IN THE MODELS SECTION.

Applications NOT SURE IF GOOD TITLE

We look at the divergence distributions for the years from 2003 to 2019. Figure abc. is a graph with all years. Figure abc. and Figure abc. shows the distributions for the periods of 2006 to 2008, 2009 to 2013 and 2015 to 2019, since the graph with all years can be too much at once. Between 2006 and 2008, we can see that the 2006 and 2007's distributions are centered above 0; in other words, the stock prices are being overvalued. On the other hand, in 2008 the distribution is centered below 0; in other words, the stock prices are being

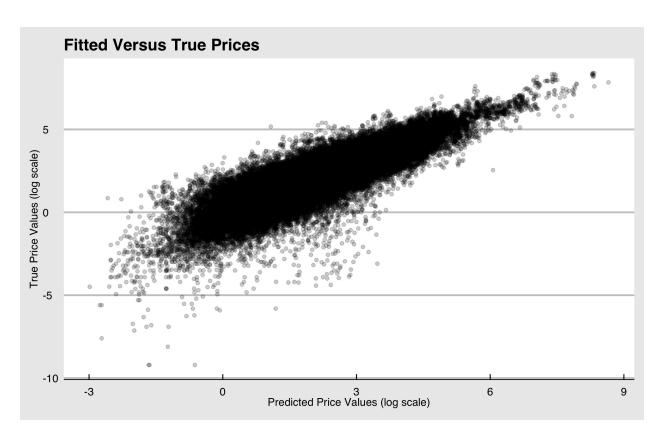


Figure 3: Figure #.

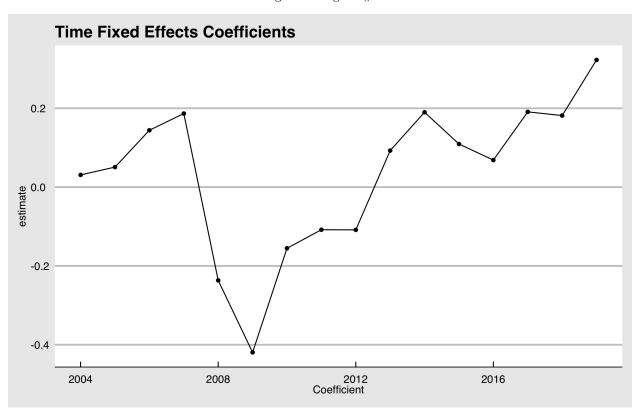


Figure 4: Figure #.

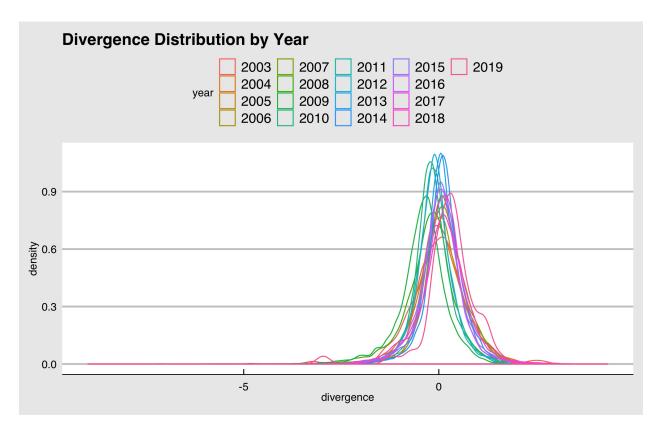


Figure 5: Figure #.

undervalued. This trend of a shift in distribution centers can be seen in the other two graphs as well. In Figure abc., it is important to note that 2019 only has data for 1 quarter; therefore, the distributions may shift as more data is included from the remaining quarters. However, there seems to be a shift of stocks being overvalued, which may be an indication of another recession.

We also look at divergence rates by sector to see if there are differences in the trends between them. We can see in Figure abc. as well that there is a positive mean divergence rate before the years leading up to the Great Recession and then the graph goes deeply below 0 once it hits. The trend seems to be rising again as we approach 2019 and again, while we must be weary of the fact that we only have 1 quarter's worth of data so far, we seem to be headed towards positive divergence rate again as well.

JENN PLEASE CHECK THIS PART + ADD THE PART ON OIL + HOUSING

Limitations & Future Work

The data we used is not the same as the one used in the paper, which had 7,796 international companies between the years 2004 to 2013 from the OSIRIS database. Our data was filtered for companies that showed share price in USD, and was filtered out for rows that were not missing in any of the fundamental indicators and response variable. However, as shown earlier, the results we had were similar to that of the paper and the graphs were reproducible as well. Our model performance was also high.

INCLUDE LIMITATION

In the future, we would like to try several other models to determine if we can have better performance and accuracy in company fundamentals. NOTE: WE HAVE GREAT PERFORMANCE SO I THINK WE SHOULD LEAVE THIS FIRST SENTENCE OUT. ALSO, WE MAKE AN ASSERTION THAT THESE

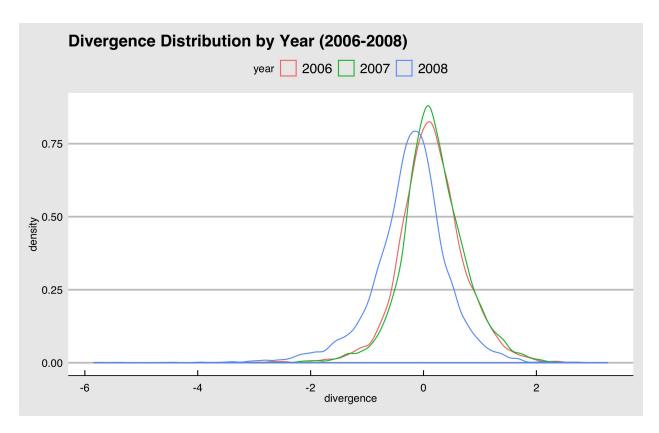


Figure 6: Figure #.

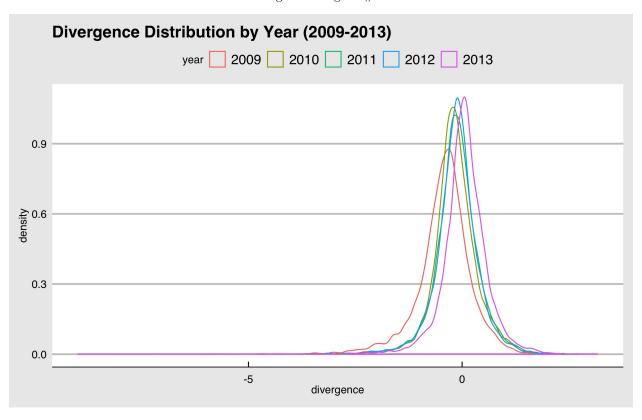


Figure 7: Figure #.

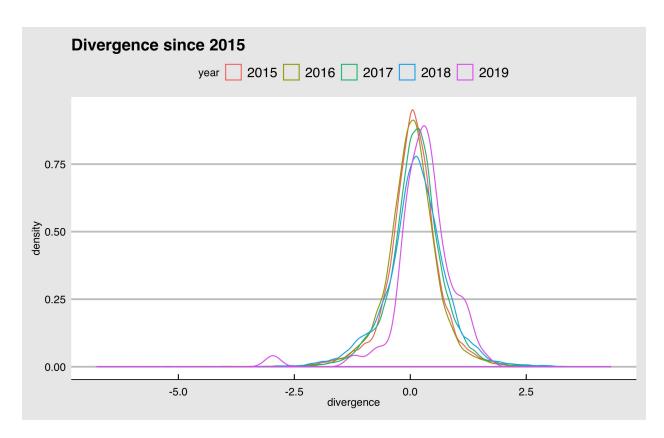


Figure 8: Figure #.

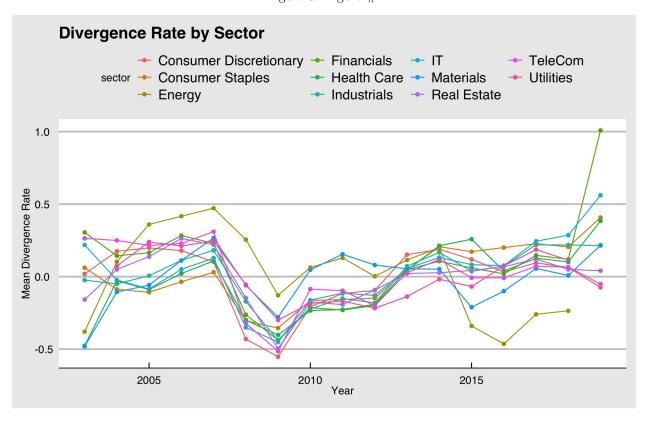


Figure 9: Figure #.

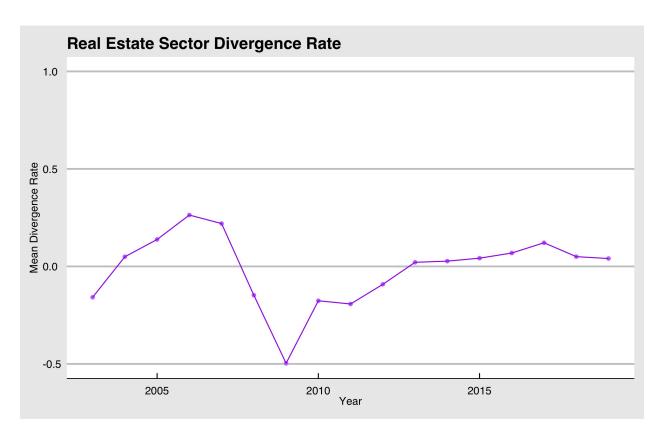


Figure 10: Figure #.

VARIABLES SHOULD PREDICT MARKET VALUE PERFECTLY IN A PERFECT MARKET, SO THIS UNDERMINES OUR POINT.

Looking forward, we could add to this work in several ways. First, our model only contains data from U.S. companies, since comparisions across currencies would have made the work of building this model more difficult. Normalizing across global currencies and including companies from markets outside the United States would likely improve the ability of this model to forecast recessions. Second, due to computational limitations, we did not include the entire history of the United States stock market. However, since the sample size of recessions is so small, including as many of them as possible in the model is important before drawing overarching conclusions about the validity of this model as a recession indicator. As of this work, the model only demonstrates that a high divergence rate may be related to an oncoming recession. Adding more recession samples might allow us to say that a high divergence rate is a likely recession indicator.

Conclusion

Plots

Reproduce the plots in the paper. Note differences and extend to new years. Explore new plots, see if we can come up with anything more descriptive.

Resources

Kaizoji, Taisei, and Michiko Miyano. "Stock Market Market Crash of 2008: an empirical study of the deviation of share prices from company fundamentals." arXiv preprint arXiv:1607.03205 (2016).

Appendix

This project has an extensive codebase, which may be accessed on github. (https://github.com/elegant-chaos/recession_indicators) Please note: the database we sourced our data from has usage restrictions, so the repository does not include our dataset.