Housing market forecasts via stock market indicators

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Abstract: Reliable forecasting of the housing market can provide salient insights into housing investments. Through the reinterpretation of housing data as candlesticks, we are able to utilize some of the most prominent technical indicators from the stock market to estimate future changes in the housing market. By providing an analysis of MACD, RSI, and Candlestick indicators (Bullish Engulfing, Bearish Engulfing, Hanging Man, and Hammer), we exhibit their statistical significance in making predictions for USA data sets (using Zillow Housing data), as well as for a stable housing market, a volatile housing market, and a saturated market by considering the data-sets of Germany, Japan, and Canada. Moreover, we show that bearish indicators have a much higher statistical significance then bullish indicators, and we further illustrate how in less stable or more populated countries, bearish trends are only slightly more statistically present compared to bullish trends. Finally, we show how the insights gained from our trend study can help consumers save significant amounts of money.

Keywords: Stock market indicators, housing market, trend study

I. INTRODUCTION

The mathematical study of housing markets dates back to the 1970s [1], and its been increasing in prominence, as consumers are increasingly looking at the right time to make a significant investment [2]. These studies have included complex models and economic examinations to varying levels of success [3]. However, after the housing market crashed in 2008, it's become clear that new models were necessary, and they became quickly established [4]. Yet, they aren't as robust or successful as they can potentially be [5]. Purchasing a house is never easy, and buying at the optimal time is a significant decision. We present new techniques to identify the optimal times to purchase or sell a house, using technical indicators that were originally designed for the stock market.

(a) A trend is considered **bullish** if it is corresponds to an increase in value for a time series.

(b) A trend is considered **bearish** if it corresponds to a decrease in value for a time series.

As a result of COVID, the housing market has become more volatile and has fluctuated significantly [6]. Therefore, we propose the utilization of technical indicators that are commonly applied in the stock market to the housing markets to identify both bearish and bullish trends in the housing market.

In the past, researchers have considered an increasing number of ways that stock market prices can be foretasted. These include, but are not limited to, speculating a stock's intrinsic value, employing complex algorithms, and speculating human behavior [7]. Some examples of complex algorithms include rolling window analysis and deep learning [8]. These methods were often not as successful as they were convoluted and couldn't account for some inherent randomness of the market, and it was often considered that blind predictions were often more robust and successful within the market [9].
However, recently, there has been more success around more simple but nuanced indicators, popularly candlestick analysis, MACD, and RSI [10]. Stock indicators are being used increasingly to identify trends in the stock market, as traders are looking to maximize their profits by trying to gain insight on the future of the market. There are a variety of techniques that traders use, but the most frequent one is utilizing technical indicators, that signify both bullish and bearish trends, to make timely decisions when selling or purchasing stock.
Inspired by COVID project [9] we consider Zillow's data set of the USA's housing market and study it through examining the usability of statistical indicators usually seen in the stock market. These include, but are not limited to, MACD Bearish, MACD Bullish, RSI Bearish, RSI Bullish, Hanging Man, and Hammer. These indicators can be used to identify trends (both bearish and bullish) that can be vital when it comes to house purchasing decisions. With the help of these indicators, trends (both bearish and bullish) can be detected and used when making purchasing decisions. Also, we calculated the statisical significance using the Wilcoxon test, where we ascertained that while both RSI indicators were statistically significant, only the bearish indicator is significant for MACD. We then spread this analysis to other countries, with the intent of being able to make insights in various types of markets. To be encompassing and robust, we considered all the different types of markets. For clarity, those definitions are provided below.

(a) A **saturated** housing market has a lot of activity and is usually correlational with a large population. These markets, with their large-scale activity, have high volume, and generate large numbers of transactions from both purchasers and sellers.

(b) A **volatile** housing market is one that changes quite frequently. For one period of time, it may be undergoing a bearish trend, but then it undergoes a sudden reversal in a short span of time and it is now growing in value. One purpose of our study is

being able to forecast these reversals with technical indicators typically found in the stock market.

(c) A **stable** housing market is one that has sustained trends and doesn't plunge or proliferate suddenly in value across a time period.

We chose Germany (a stable housing market), Canada (a volatile housing market), and Japan (a saturated housing market) to be representative countries, so analysis of these countries could yield powerful insights into not one but multiple different markets. To determine the statistical significance, we once again utilized the Wilcoxon test, and we came across some interesting results. For instance, we observed that across all countries, bearish indicators were much more statistically significant compared to bullish indicators. But that isn't all, as we also realized that this difference in the statistical significance of bullish and bearish trends isn't nearly as large in saturated and volatile housing markets. This is important because makes consumers aware which indicators are applicable based on the type of market they are a part of, which can help save huge amounts of money.

When using these methods to quantify trends within housing markets, one expects to observe certain behaviors. In particular:

(a) Prices are increasing at a larger rate then they are decreasing, resulting in a gradual yet continuous increase in housing prices. Figure 6 shows this phenomena.

(b) Bullish indicators are statistically less significant than bearish indicators for the vast majority of indicators.

To carry out our mathematical study, we have used RSI, MACD, and Candlestick Analysis conducted through R. To start we begin by parsing through our data and grouping individual data into Heikin Ashi candlesticks (See Section V C). After candlesticks values were made, we scanned the data for the four candlestick indicators mentioned above. After seeing the frequency of these indicators, we used the Wilcoxon test in R to determine the statisical significance of each indicator. Next, we proceeded to develop code that could produce RSI values. After obtaining RSI values, we then analyzed these values to gain some knowledge of reasonable thresholds that could be used for the indicators, as the RSI indicator is observed when the RSI crosses and upper threshold (bearish) or lower threshold (bullish). Section III details this in more specificity. Similarly, we looked at the frequency and used the Wilcox test to determine the statistical significance. For the MACD analysis, we developed code that determined MACD values, and then looking at the frequency of the indicator, we once again used the Wilcox test to outline statistical significance.

After introducing some background in Section III, we dedicate Section V and Section VI to the main findings of our work, which can be seen in two different directions in terms of the indicators themselves and their statistical significance in various markets.

We shall expand on the analysis and applications of the above findings in Section VII. Finally, we also attached our code for the project on Github [11].

II. NEW SECTION: HOUSING DATA VS ETF DATA

For our trend study, we considered housing market data for analysis. But another popular type of data we considered was **ETF Data**. ETFs, or Exchange-Trade Funds are a popular type of pooled investment security that can be purchased or sold on a stock exchange similar to a normal stock. We selected the Vanguard ETF because of its high AUM (Assests Under Management) and relative prominence in the market. Figure 1 depicts a candlestick chart of Vanguard's ETF over time.

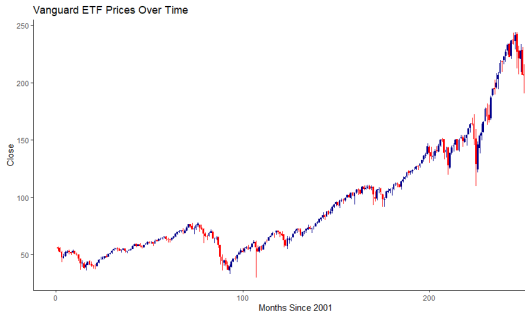

FIG. 1: A visualization showing a candelstick chart of ETFs from 2001 onward. Similar to housing prices, this real estate ETF has increased over time.

Since ETFs are easier to analyze and study, some may saying that studying ETFs alone (without considering housing prices as our study did) would be sufficient. But as shown in figure 2 that would be impractical and yield an incomplete study.

ETF	Indicator	P-Value
Vanguard	MACD Bearish	$2.5564 \cdot 10^{-88}$
Vanguard	MACD Bullish	0.9999
Vanguard	RSI Bearish	$3.2399 \cdot 10^{-6}$
Vanguard	RSI Bullish	0.9080
Vanguard	Bearish Engulfing	0.9997
Vanguard	Bullish Engulfing	$1.8713 \cdot 10^{-13}$
Vanguard	Hanging Man	0.3937
Vanguard	Dark Cloud Over	0.0022

FIG. 2: A visualization showing a candelstick chart of ETFs from 2001 onward. Similar to housing prices, this real estate ETF has increased over time

Figure 2 is a table of the statistical significance

measured across each indicator for the ETF in our study. This was calculated with the Wilcoxon test in R, after we scanned the code for each of these indicators (MACD, RSI, and Candlestick Indicators which included Bearish and Bullish Engulfing, Hanging Man, and Dark Cloud Over) and technical definition of these indicators is provided in Section III. The **P-Value** is defined as the probability of the **null hypothesis** occurring. This is the probability that a external factors caused the reversal we are studying, and not the indicator, and more on this test measuring statistical significance is provided in Section V.

Thus, high statistical significance is associated with a low p-value for any indicator, since we want to observe the efficacy of indicators. As shown in figure 2, the indicator, all of the bearish indicators have low p-values (signifying high statistical significance) while all of the bullish indicators have high p-values (signifying low statistical significance). As a result, studying ETFs alone wouldn't give us enough insight into predicting housing market trends since bullish trends couldn't be foreseen with the usage of technical indicators.

Therefore, we expanded our study to include actual housing market data for countries across the globe within varying housing markets, including saturated, volatile, and stable housing markets. Our full results, summarized in Section V, can be seen with Figure 10. Observe how some bullish indicators have low p-values (correlating to a high statistical significance), for example MACD Bullish in Canada has a p-value of 0.11. This means that more insights could be made with bullish indicators through the consideration of housing data rather then ETF prices, and it also allowed for diversification in our study as we were able to analyze different types of market to make these insights applicable to any market in the world.

III. BACKGROUND: STOCK MARKET INDICATORS

The current research is inspired by the previous work, and thus we shall dedicate this section to reviewing some of the main results which shall prove useful for our research and for comparison with our results. Their research proposes that there are statistical indicators that could be of use during the COVID-19 pandemic to identify trends in the number of cases [12]. The indicators they proposed included candlestick analysis, in addition to RSI and MACD indicators.An indicator is described as **bullish** if that indicator predicts a future decrease while an indicator is described as **bearish** if it describes a future increase in prices. After observing these indicators, they measured the statisical significance of all of these indicators. As described above, this was done by first considering the null hypothesis, the probability that an external circumstance was the cause of a bearish or bullish trend, not an indicator. This probability was denoted as a p-value, and it was then ascertained that lower p-values translated to higher statistical significances as that meant the probability of a trend being forecasted by an indicator was higher in comparison to a random external event. After considering this hypothesis, they used the Wilcoxon test for R to determine these p-values across all of the indicators. This allowed them to make conclusions about the applicability of indicators.

A. Candlestick Analysis

The first type of indicators considered were candlestick indicators, which included Hammer, Dark Cloud Over, Hanging Man, Bearish Engulfing, and Bullish Engulfing. To begin, weekly candlesticks were constructed with the real body constituting the region marked by the endpoints of the opening and closing values (covid cases), and the upper and lower limits being the maximum and minimum cases over the time interval respectively. Then, R code was developed to identify candlestick patterns (Bearish Engulfing, Bullish Engulfing, Dark Cloud Over, Hanging Man, and Hammer) within the dataset to identify the frequencies at which these patterns occurred.

B. RSI

The RSI (Relative Strength Index), is a popular indicator that is similar to considering the recent "momentum" of a time series through average rate of increases and decreases in a market, in this case the market in consideration (housing, COVID, or stock). The indicator is constructed by dividing the closing values C_t over some period into two sets:

- The set G_t in which the series increased: $G_t = \frac{C_t - C_{t-1}}{C_t}$, $C_t > C_{t-1}$
- The set D_t in which the series decreased: $D_t = \frac{C_{t-1} - C_t}{C_t}$ $C_t < C_{t-1}$

From the above sets one can compute the averages A_t and B_t using the EMA V_n over n periods with a smoothing factor of $\frac{1}{n}$ leading to

$$A_t = V_n[G_t] \text{ and } D_t = V_n[D_t]$$

Then, the RSI_t indicator at time t is defined as follows

$$RSI_t = 100 - \frac{100}{1 + \frac{G'_t}{D_t}}$$

The indicator occurs when this RSI value exceeds a lower and upper threshold, as that is when the stock in consideration becomes overbought or oversold. If the RSI value falls below the lower threshold, that signifies a stock being oversold, which signals a bullish trend as stock prices will soon increase in price. Conversely, if the RSI value exceeds an upper threshold, that signifies

a stock being overbought, signaling a bearish trend as stock prices will fall. Figure 4 shows the RSI indicator in action with stock market data.

C. MACD

MACD (Moving Average Convergence Divergence) centralizes around a moving average and a signal line. For the MACD (Moving Average Convergence Divergence) indicators, R code was developed to calculate MACD and signal line values for the weekly candlesticks. Next, code was developed to identify when the MACD values crossed the signal values from above (bearish trend) and when the MACD values crossed the signal lines from below (bullish trend), and the statistical significance of both of these indicators. The MACD is calculated using two exponential moving averages (EMAs), calculated over two periods of differing length n. Specifically, for a given dataset of length n, usually the closing values $C_1, C_2, \ldots, C_3$, the EMA V_n is calculated recursively via

$$\begin{aligned} V_i[C_i] &= C_1 && \text{if } i = 1 \\ &= sC_i + (1-s)V_{i-1} && \text{if } i > 1 \end{aligned}$$

where S $= \frac{2}{n+1}$ is a smoothing factor. Thus, V_n can be seen as the exponential average over n intervals, which by substitutions can be expressed

$$V_n = R[C_n + (1-R)C_{n-1} \ldots (1-R)^{n-1}C_1]$$

Observe that the coefficient of each term decreases exponentially for earlier values in the time series, thus giving greater weighting to more recent data, hence the name. Given the EMA, the MACD is defined by the difference between a longer period average n_2 and a shorter period average n_1 thus by convention $(n_1 < n_2)$ as follows

$\text{MACD}_{(n_1,n_2)} = V_{n_1}$ - V_{n_2}

Figure 3 shows the MACD indicators in action. As depicted in the graphs a bullish trend with MACD occurs when the MACD line crosses the signal line from below, and a bearish trend within MACD occurs when the MACD line crosses the signal line from above.

D. Statistical Significance

As mentioned above statistical significance values were calculated using the Wilcoxon test for R, after consideration of the null hypothesis. This was considered a robust test to measure the significance, due its non-reliability on normalization and it is a non-parametric method.

E. Results

The results were fascinating, as it was determined that both bearish and bullish indicators were significant in consideration of COVID cases. However, their study highlighted that specifically, 3 bullish trends (Hammer, Bullish Engulfing, and Bullish MACD) and 1 bearish trend (Bearish MACD) were statistically significant. All other indicators, with high p-values, were determined to be statistically insignificant in forecasting COVID cases.

Another indicator they considered was MACD (Moving Average Convergence Divergence), which looked at the exponential moving average of the dataset in comparison to a signal, or trend line. These indicators would be the cornerstones of our trend study on housing markets.

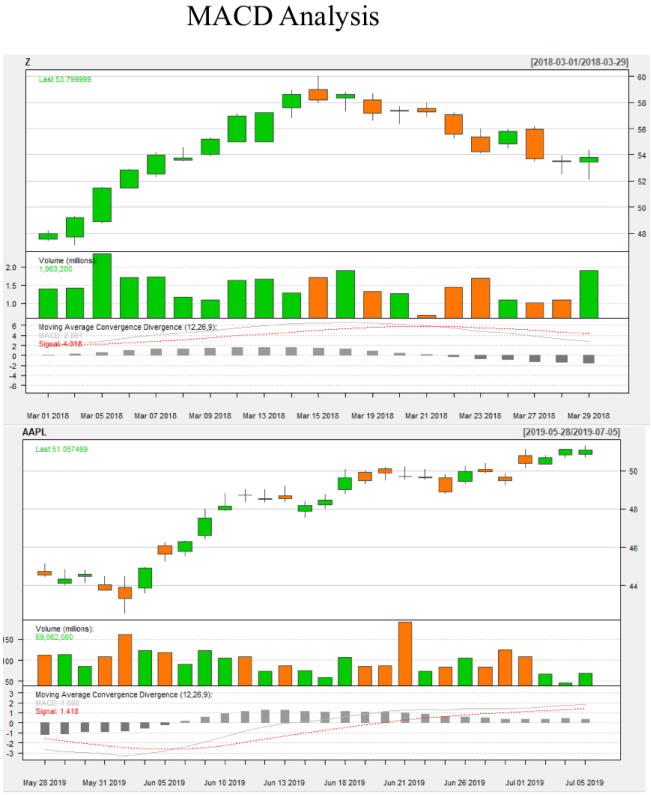

FIG. 3: Two visualizations demonstrating the use of the MACD indicator on Zillow and Apple Stock respectively.

IV. AN OVERVIEW OF HEIKIN ASHI

While we were conducting our trend study, we recognized that there were individual data points that were altering the statistical significance levels of our indicators quite noticeably. This was also posing a problem with the identification of indicators, because trends were often not noticeable or fluctuative. To solve this problem, we utilized Heikin Ashi candlesticks. Heikin Ashi is similar to normal candlestick analysis, except there is a difference in how the individual bars

are calculated. These bars are calculated differently as shown below:

(a) $\text{Close}_n = 1/4[\text{Open}_n + \text{High}_n + \text{Low}_n + \text{Close}_n]$

(b) $\text{Open}_n = 1/2[\text{Close}_{n-1} + \text{Open}_{n-1}]$

(c) $\text{High}_n = \text{Max}[\text{High}_n, \text{Open}_n, \text{Close}_n]$

(d) $\text{Close}_n = \text{Min}[\text{High}_n, \text{Low}_n, \text{Close}_n]$

It is important to notice how the terms for the calculating the open values are recursively taking the mean

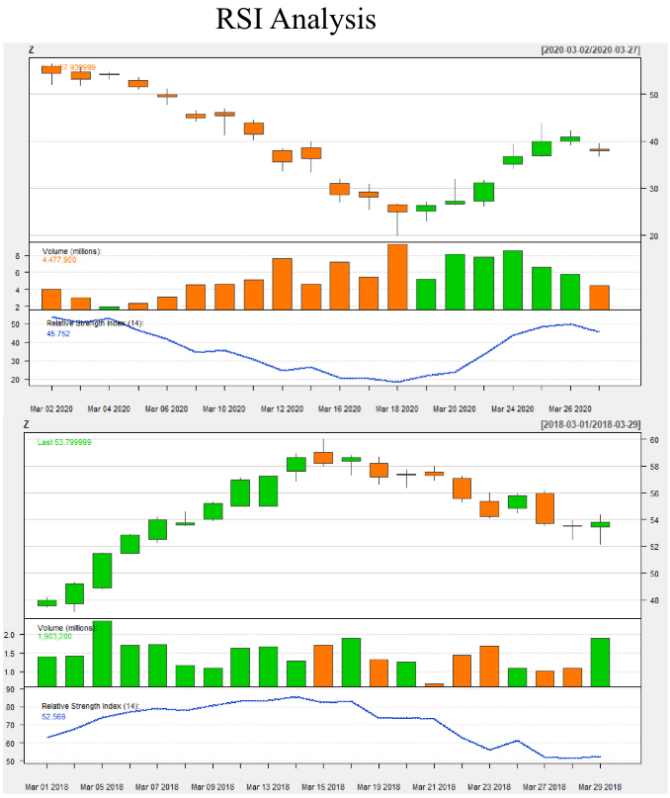

FIG. 4: Two visualizations demonstrating the use of the RSI indicator on Zillow Stock. .

of the previous open and close values. This lends itself to better forecasting because it signifies a continuity within a trend. For example, with a normal candlestick analysis, there can be certain days that contradict the trend, which makes analyzing and identification of trends difficult. However, since these values are being recursively calculated, it has the effect of smoothing values over time, such that trends will persist and be more apparent for analysis. This solved our problem of the contradictory points, and can also be compared to the smoothing factor in the [12] in the mathematical expression of the RSI indicator.

The differences in Figure 5 and Figure 7 exhibit the above-mentioned reasons further. Normal candlesticks can fluctuate more within a certain trend, however, since Heiken Ashi relies on averages, trends are more continuous and observable for analysis. This lends itself better to analysis and heightens the statistically significance of indicators, since it makes it more clear that indicators were more likely the sole thing connected to a change, rather then a random external factor. The statisical significance is assisted because it centralizes around

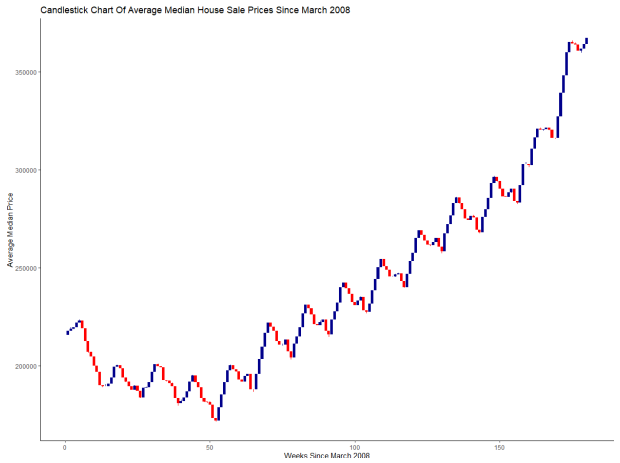

FIG. 5: Housing Prices Over Time Candlesticks

a p-value, or the probability that a random external event is the cause of a trend occurring. Therefore, by eliminating small contradictory points, the potential of the p-value being large is made smaller as it isolates the trend as causing the change.

V. PREDICTING HOUSING MARKET TRENDS

To start we calculated the statistical significance of all of our indicators. In order to accomplish this, we utilized the Wilcoxon test to measure the statistical significance of this and the other indicators we were considering. We did this by considering the null hypothesis, that a trend occurred randomly rather then an indicator inducing it. We called this probability the p-value, so the larger the p-value, the less statistically significant our indicator is. However, the closer the p-value was to 0, the more statistically significant our indicator is, since there is less of an inherent random event changing the housing prices compared to the indicator taking effect.

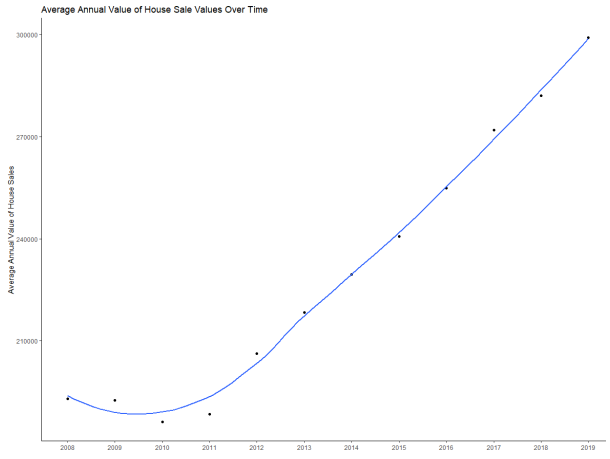

FIG. 6: Housing Prices Over Time (original data graph)

As mentioned before, the data we shall use in the

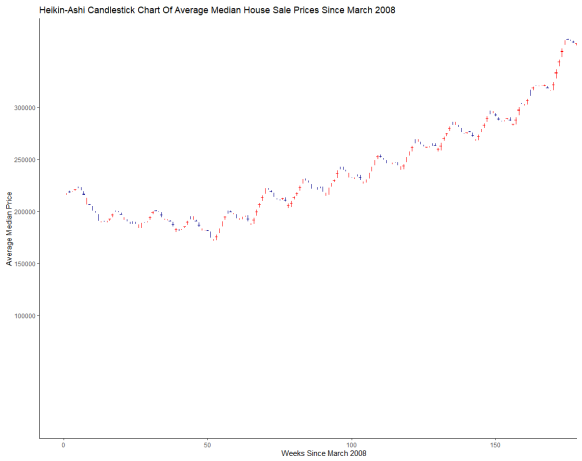

FIG. 7: Housing Prices Over Time Heikin Ashi Candlesticks

present manuscript consists of Zillow Data [13] that had information on average median housing sales per week in a region. We also utilized historical housing data from Germany, Canada, and Japan [14]. Although housing prices are increasing over a large period of time we shall consider the following indicators: MACD, RSI, and candlestick patterns via Heikin Ashi candlesticks to investigate short-term trends that will help potential buyers. We grouped our data in the form of monthly Heikin Ashi candlesticks for the Zillow (USA) data, and then yearly candlesticks for the various countries and utilized these datasets to substantiate and support our claims.

A. Predictions via RSI

As mentioned above, the RSI indicator centralizes around the "momentum" of a stock. We apply this indicator to the Zillow Data Set as a way to forecast trends, both bearish and bullish. We developed R code to produce RSI values of monthly candlesticks, and observed viable lower and upper thresholds respectively. We then produced code that would identify the frequency of both RSI Bearish and Bearish indicators, noticing two interesting trends.

- All RSI Bearish indicators weren't statistically insignificant, with p-values larger then 0.9 This is the case except when we analyzed the US housing market with Zillow Data.
- RSI is the only non-candlestick indicator across all 4 countries in examination that had a statistically significant bearish indicator. It seemed that across MACD, more on MACD in the next section, and RSI, bullish indicators were much more statistically significant than bearish trends. Figure 9 shows RSI in action with Zillow data, as a bearish trend is indicated by the RSI value crossing an upper threshold (as in the top visualization), and a bullish trend is indicated by the RSI value crossing a lower threshold (as in the bottom image).

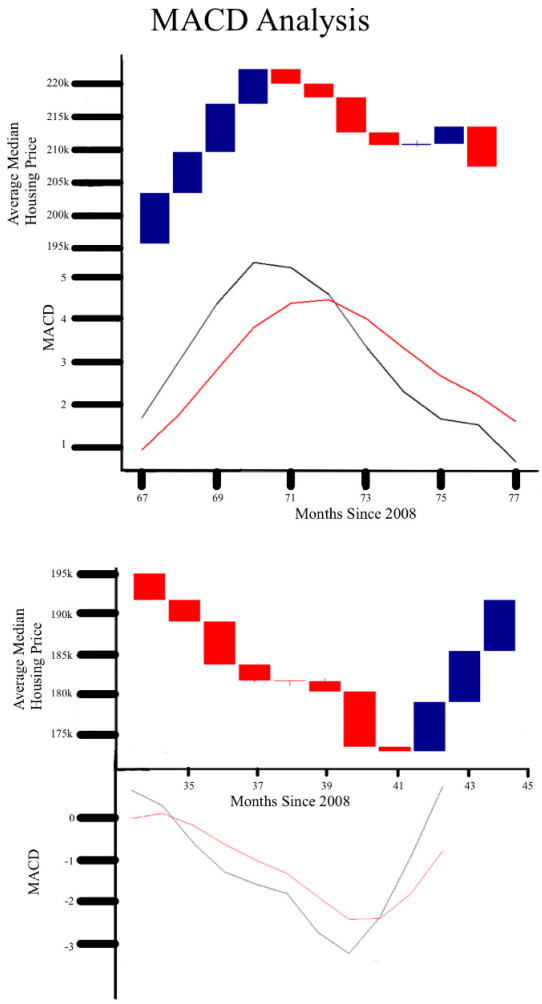

FIG. 8: A visual demonstrating successful predictions for the MACD indicator with Zillow (USA) housing market data.

B. Predictions via MACD

As explained in the Background section, the MACD indicator centralizes around the idea of a moving average and the signal line. Therefore, we developed R code that could produce MACD and signal lines for the data that we had in the form of monthly candlesticks. We then

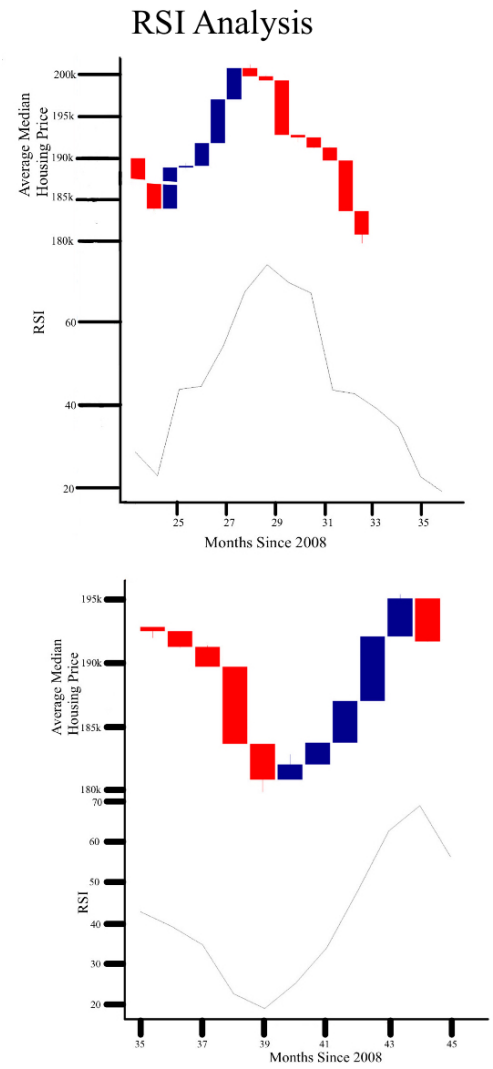

FIG. 9: A visual demonstrating how RSI values work. In the top visualization, observe as the RSI value crosses an upper threshold, corresponding to a bearish trend, or a decrease in housing prices. Conversely, observe that in the bottom visualization, the RSI value crosses a lower threshold, corresponding to a bullish trend, or an increase in housing prices.

used our R code to scan for when the MACD crossed the signal line from above (which would signify a bearish reversal) and from below (which would signify a bullish reversal). Figure 8 shows MACD indicators successfully working with Zillow data, as a bearish trend occurs when the MACD line crosses the signal line from above (as in the top visualization), and a bullish trend occurs when the MACD line crosses the signal line from below (as in the bottom visualization). Once again, p-values were calculated for each indicator using the Wilcoxon test over monthly intervals as described above. From our study we see different levels of accuracy obtained in our predictions, allowing us to make the following key observations.

- MACD is the most frequently occurring indicator that our R code detected when we did our analysis. This is salient since it might be the most ubiquitous for consumers to utilize for their benefit.

- While MACD is the most popular indicator, it is also striking the differences in the statistical significance between the MACD Bearish and MACD Bullish indicator. While MACD Bullish had a low p-value with high statistical significance ($7.384 * 10^{-15}$), MACD Bearish had a high p-value with low statistical significance (0.99). This followed the norm with the RSI values, with the exception being the US housing market.

C. Predictions via Heikin Ashi

We examined the dataset with respect to 4 different candlestick patterns via Heikin Ashi candlesticks, Hammer, Hanging Man, Bearish Engulfing, and Bullish Engulfing. We then scanned the data with R code for these indicators, and then used the Wilcoxon test reiterated above to determine the statistical significance. From our study we saw different levels of accuracy obtained in our predictions, allowing us to infer certain candlestick pattern indicators were more viable with respect to others. Some key observations:

- The norm across the US and other housing markets is that bearish trends were less statistically significant compared to bullish trends.

- Within the US candlestick patterns detected followed the norm in that the Bearish signal (Hanging Man) is determined to be statistically insignificant with a p-value of 0.97, but the Bullish signal is determined to be a viable indicator and statistically significant indicator with a p-value of 0.05.

- However, in other countries examined the converse is true in that p-values for bearish indicators were lower (high statistical significance) and the p-values for bullish indicators were higher (low statistical significance). A table of statistical significance for all of the indicators is provided, and will be the focus of our analysis.

VI. AN ANALYSIS VIA STOCK MARKET INDICATORS

Indicator	Country	Type of Market	P-Value
Bearish Engulfing	Germany	Stable	0.17
Bullish Engulfing	Germany	Stable	0.99
Hammer	Germany	Stable	0.94
MACD Bearish	Germany	Stable	0.97
MACD Bullish	Germany	Stable	0.24
RSI Bullish	Germany	Stable	0.96
RSI Bearish	Germany	Stable	$2.2 * 10^{-16}$
Hanging Man	Germany	Stable	0.000545
Bullish Engulfing	Canada	Volatile	0.82
Hammer	Canada	Volatile	0.78
MACD Bearish	Canada	Volatile	0.93
MACD Bullish	Canada	Volatile	0.11
RSI Bullish	Canada	Volatile	0.99
RSI Bearish	Canada	Volatile	$2.1 * 10^{-15}$
Bearish Engulfing	Canada	Volatile	0.14
Hanging Man	Canada	Volatile	0.22
Bullish Engulfing	Japan	Saturated	0.95
Hammer	Japan	Saturated	0.70
MACD Bearish	Japan	Saturated	0.97
MACD Bullish	Japan	Saturated	0.35
RSI Bullish	Japan	Saturated	0.99
RSI Bearish	Japan	Saturated	0.000015
Bearish Engulfing	Japan	Saturated	0.95
Hanging Man	Japan	Saturated	0.70

FIG. 10: A table of all of the determined p-values, broken down by country and market that underwent analysis.

After determining all of the p-values and the statisical significance values, we noticed some interesting trends that provide some insight. For context, we selected and analyzed the US housing market, the German housing market (representative of a stable economy), the Canadian housing market (representative of a volatile economy), and the Japanese housing market (representative of a populated/saturated market). Here are some powerful things we noticed, broken down by section.

A. MACD

With the MACD indicator, and in accordance with Figure 10, we were able to make some key observations right away.

- This indicator followed the pattern that is emerging within our analysis that exhibited high statistical significance for bullish trends and low statistical significance for bearish trend, but only for the United States.
- For other countries, the converse of the norm is true, that bearish MACD indicators were more statistically significant compared to bullish trends.
- While MACD Bullish can be used by both consumers and sellers in the housing market, people who are looking to forecast bearish reversals in the housing market shouldn't look to utilize this indicator.

But the most important thing to realize is the difference in the statistical significance between the MACD Bearish and Bullish. In more populated, saturated, and volatile markets, the difference in statistical significance is smaller, as exemplified by Japan. In Japan, the difference between MACD Bearish and Bullish is 0.62, but in Germany is significantly larger, hovering around 0.73. This variance in difference is a salient insight because it exhibits that indicators, both statistically significant and insignificant, can be evaluated differently. In a market with a large difference, the failures and effectiveness of indicators can be more established (due to the higher polarization of p-values), but this won't be the case with more inherent randomness with a smaller difference and decreased polarization. But what's noteworthy is that this trend is persisting when the significance of the MACD is at a constantly low value (p-value > 0.9). This signifies that MACD Bearish trends are less statistically significant in more crowded and volatile housing markets, which is important information for consumers in that region looking to save money.

B. RSI

The RSI is also an intriguing area of study since it proved to uphold the trends we observed throughout our examination. This trend, as reiterated above, is that bullish indicators were less statistically significant in comparison to bearish indicators, across all 3 countries except for the United States. In the United States, as exhibited by the table, RSI is very significant statistically in terms of both bullish and bearish. The United States case is interesting because the US can be justified both as a populated yet stable market, so further research into the US housing market can lend itself to even more intriguing analysis. But the following main takeaways are important.

- For the United States, RSI is the only statistically significant and viable indicator for bearish trends. This is important for buyers who are looking to purchase at the optimal price.
- The p-values for RSI were mostly similar across the 3 countries, which signifies that the circumstances of a market may not dictate RSI's efficacy. This makes sense considering RSI's emphasis on recency over long term processes.

Given this last takeaway, it seems almost contradictory that the RSI indicators can have a low statistical significance. After all, RSI's focus on recency and its practicality when identifying trends should lend itself to higher statistical significance. However, this is where we need to remind ourselves that external circumstances still must be considered, as not all markets are conducive to high statistical significance (low p-values).

C. Heikin Ashi Candlestick Indicators

However, the most appealing analysis is the one that can be done Heikin Ashi candlesticks. Similar to

RSI and MACD and as exemplified in the table, the bearish indicators (Hanging Man, Bearish Engulfing) were more statistically significant then the bullish indicators (Hammer, Bullish Engulfing). However, this trend didn't continue in the housing markets for Japan and the US, which constituted our saturated/popular housing markets in our study. In the US and Japan, both bearish and bullish indicators had low statisical significance, compared to the bearish being of high statistical significance and the bullish being of low statistical significance. This is interesting because it provides insight into the applicability of these indicators in more populated markets. This could help consumers to know which indicators not to use, as that is just as important as knowing which ones to use. The main takeaways can be summarized as follows for Heikin Ashi Candlesticks indicators

- The bearish indicators were more significant compared to the bullish ones, which is consistent with our other results.

- However, for more populated housing markets such as the US and Japan, neither bullish nor bearish candlestick indicators were significant statistically. An insight to be made here is that these indicators are less likely to be significant with more volume in the market, as that proliferates any inherent randomness.

VII. CONCLUDING REMARKS

In the present paper we have analyzed datasets provided by Zillow [**?**] and FRED [14] for Japan, Germany, and Canada's historical housing prices. We then used technical indicators typically utilized in the Stock Market to identify trends with respect to our data. To determine the usability and frequency of technical indicators, we analyzed 4 candlestick patterns, we used the Wilcoxon test, developed in R code to calculate a p-value that signified statistical significance. The p-value is centralized around the probability of the null hypothesis being true, which in our study is that the indicator isn't the cause of a trend occurring. Since the p-value is the probability that the null hypothesis is true, a high p-value would signify a trend occurring randomly, thus decreasing the significance. Conversely, if a p-value is low, then the probability of the null hypothesis is low, meaning the statistical significance of the trend is high since no other event except for the indicator is responsible for the trend.

An application of this research study is being able to reliably forecast future trends using these stock market indicators. Figure 11 and Figure 12 demonstrate the capacity of forecasting and its usability to save immense amounts of money.

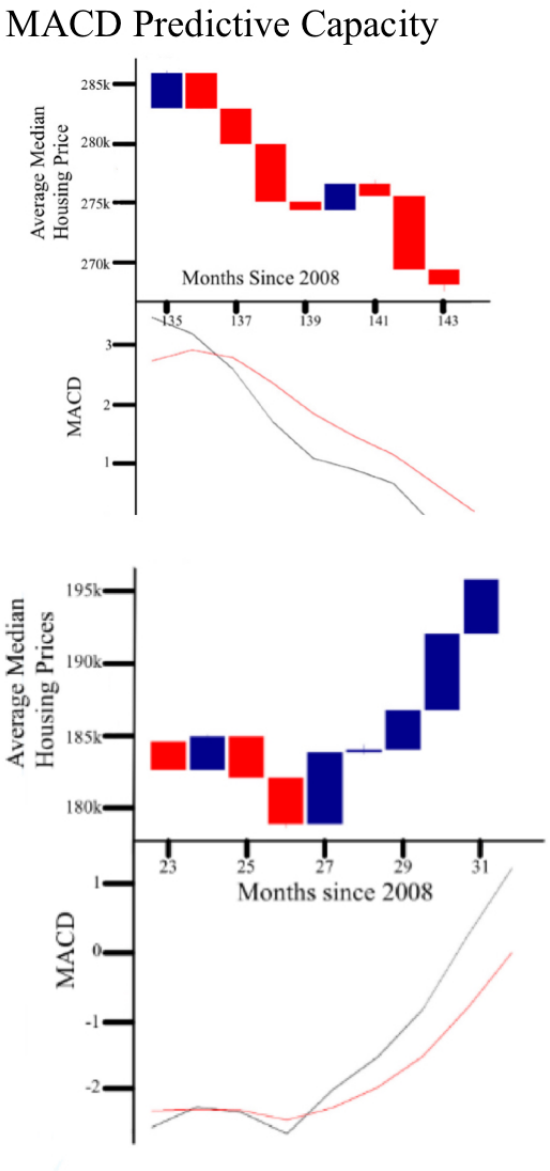

FIG. 11: A visual demonstrating the predictive capacity of the MACD indicator, for both bearish and bullish trends.

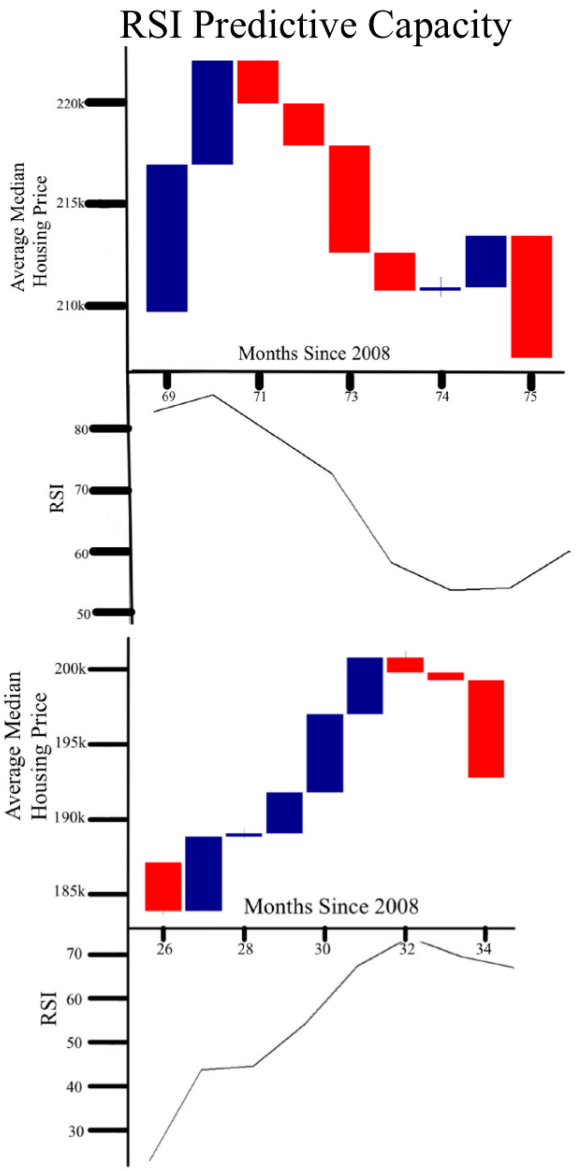

FIG. 12: A visual demonstrating the predictive capacity of the RSI indicator, for both bearish and bullish trends.

A. Summary of results

In total we looked at 4 candlestick indicators via Heiken Ashi (Hammer, Hanging Man, Bearish Engulfing, Bullish Engulfing). In particular, we find that:

(I) Populated/Saturated housing markets have low statisical significance values due to more randomness present in a more active market.

(II) For the US housing market in particular, we found that bearish trends were less statistically significant compared to bullish trends.

(III) The converse of this is true when we examined the data for other countries, with bearish trends being less statistically significant compared to other countries.

(IV) Another interesting insight is the difference in the significance of bearish and bullish trends. In more volatile and saturated housing markets such as the US, Canada, and Japan, this difference is smaller as there is more randomness to decrease polarization, but in a stable market such as Germany this isn't the case.

For nearly all of our analysis, RSI remained fairly strong in terms of its applicability. We conjecture this is the case because While most indicators analyze over a large period of time, RSI places its emphasis on recent trends. This is because RSI is synonymous with the "momentum" of a time series. A strong RSI lends itself to a bullish trends, and a weak RSI signifies a bearish trend. Therefore, when an RSI crosses a threshold, it becomes overbought or oversold, signifying a reversal. However, all of the other indicators such as MACD, Hanging Man, and Bullish Engulfing, an emphasis on later trends accounts for the decrease in statisical significance since there is a larger probability of external factors playing a role.

Using the Wilcoxon test in R, we were able to determine the p-value of all of our indicators. The p-values were correlational to the statisical significance because the p-value is the probability that the null hypothesis is true. The null hypothesis is the probability an event occurred randomly. Therefore, a low p-value is indicative that a technical indicator is statistically significant since it suggests that a trend didn't happen randomly but more so as a result of the indicator. On the other hand, a low p-value shows statistical insignificance because it exemplifies that an event occurred randomly, thus weakening the usability of the indicator.

Type of Market	Viable Indicators
Stable (Germany)	RSI Bearish Hanging Man
Volatile (Canada)	MACD Bullish RSI Bearish and Bearish Engulfing
Saturated (Japan)	RSI Bearish

FIG. 13: A table detailing the most usable indicators for the markets and countries that we analyzed in our study. We determined this by parsing through our p-values in Figure **??** and determining the lowest p-values per market and country, as these would yield the most statistically significant indicators for each case.

In Figure 13 we present which indicators would be viable for various markets. This comes to embody the final results of our study, where we present the most effective indicators. However, there are some things that we would like to draw attention to. Firstly, notice how

RSI Bearish was statistically significant across all markets, signaling that is an indicator that can be used in practically any case study. Further, as depicted in Figure **??**, the difference in statistical significance between bearish and bullish indicators is smaller, as exemplified by Japan. In Japan, the difference between MACD Bearish and Bullish is 0.62, but in Germany is significantly larger, is 0.73. This means that in more crowded and volatile markets it can be more confusing and inherently variable about not only the success of statistically significant indicators but the failures of statistically insignificant indicators, whereas this notion is minimized as the difference gets larger in stable markets. This is because lower and higher p-values dictate a more concrete sense of failure and success for statistically insignificant and significant indicators respectively. This knowledge of not only which indicators are significant or insignificant but the reliability of certain indicators is vital information for consumers looking to save money. Visuals showing 6-month forecasts through the usage of MACD and RSI are shown in Figure 11 and Figure 12, depict how consumers can forecast prices with these indicators to their benefit. Within the MACD analysis, observe that for the top visualization, consumers can deduce that for this period of 6 months (in this case Months 135-143 from 2008, so February to July 2020, prices will decrease, due to the fact the black MACD line crossed the red signal line from above. Similarly, for the bottom visualization consumers can deduce that for this period of 6 months (in this case Months 23-31 from 2008, so November 2009 to April 2010, prices will increase, due to the fact the black MACD line crossed the red signal line from below. This can be similarly extended to the RSI analysis, where observe that for the top visualization, consumers can deduce that for this period of 6 months (in this case Months 69-75 from 2008, so August 2013 to March 2014, prices will decrease, due to the fact the RSI values crosses an upper threshold. Similarly, for the bottom visualization consumers can deduce that for this period of 6 months (in this case Months 26-34 from 2008, so April 2011 to September 2011, prices will increase, due to the fact the black MACD line crossed the red signal line from below. More applications of these benefits can be seen in the following section.

B. Future work

In our study, we did an extensive analysis on utilizing stock market indicators upon housing data from a variety of housing markets, ranging from volatile to stable housing markets in Canada, Germany, Japan, and the US. However, an interesting future application is rentals/apartments. These could be of immense interest with the application of indicators because the renting market is even more volatile then the housing market [15]. This is because there a plethora of other external factors being inherently present due to the rental being a temporary residence. These external factors could include season, weather, etc. For example, a number of college students take rentals when doing internships at a company headquartered at a city. This would certainly being an appealing continuation of our present study.

In the last decade, there has been significant innovation in stock market analysis and the evolution of the housing market. In the past, the stock market has been analyzed with less nuanced techniques such as intrinsic value and speculating human behavior [7]. However, this changed drastically with the rise of candlestick analysis, as well as the emergence of the MACD and RSI indicators [16]. Moreover, the onset of the COVID-19 pandemic has meant that the housing market has transformed significantly [17]. This inspired us to present the application of stock market indicators on the housing market with data from a variety of housing markets, so people, no matter what type of market they are in, can know which indicators are significant and how trends can be forecasted, which is salient in saving millions of dollars within the housing market [18].

Finally, it is noteworthy to realize that bearish trends were less statistically significant in the US but more significant in other countries. A appealing continuation of our research could be to analyze whether this would be true across other time series, such as the rental market described earlier. But in the meantime, it is significant to realize that there are certain stock market indicators that can forecast future trends in housing prices, with the potential to save significant amounts of money for people. For instance, buyers can have the capacity to forecast bearish trends and avoid spending money that didn't need be spent. Conversely, sellers can obtain the most values for their homes through the forecasting of bullish trends and circumvent losing potential money.

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[1] A. M. Kirby, Transactions of the Institute of British Geographers **1**, 2 (1976), ISSN 00202754, 14755661, URL http://www.jstor.org/stable/621308.

[2] C. M. Gong, C. Lizieri, and H. X. Bao, Journal of Business Research **97**, 51 (2019), ISSN 0148-2963, URL https://www.sciencedirect.com/science/article/pii/S0148296318306465.

[3] D. T. Carruthers, Urban Studies **26**, 214 (1989), https://doi.org/10.1080/00420988920080181, URL https://doi.org/10.1080/00420988920080181.

[4] A. Khalafallah, Tsinghua Science and Technology **13**, 325 (2008).

[5] R. M. Kirwan and D. B. Martin, Environment and Planning A: Economy and Space **3**, 243 (1971), https://doi.org/10.1068/a030243, URL https://doi.org/10.1068/a030243.

[6] S. Liu and Y. Su, Economics Letters **207**, 110010 (2021), ISSN 0165-1765, URL https://www.sciencedirect.com/science/article/pii/S0165176521002871.

[7] M. Chauvet and S. Potter, Journal of Empirical Finance **7**, 87 (2000), ISSN 0927-5398, URL https://www.sciencedirect.com/science/article/pii/S0927539899000158.

[8] D. Matsunaga, T. Suzumura, and T. Takahashi, *Exploring graph neural networks for stock market predictions with rolling window analysis* (2019), URL https://arxiv.org/abs/1909.10660.

[9] Competitiveness Review: An International Business Journal **23**, 426 (2013), ISSN 1059-5422, URL https://doi.org/10.1108/CR-02-2013-0010.

[10] T. T.-L. Chong, W.-K. Ng, and V. K.-S. Liew, Journal of Risk and Financial Management **7**, 1 (2014), ISSN 1911-8074, URL https://www.mdpi.com/1911-8074/7/1/1.

[11] Varun121322, *Varun121322/housing-market-forecasts-via-stock-market-indicators: An analysis of housing market forecasts with popular stock market indicators, including macd, rsi, and candlestick indicators.* (2022), URL https://github.com/Varun121322/Housing-Market-Forecasts-Via-Stock-Market-Indicators.

[12] Y. Liang and J. Unwin, *Covid-19 forecasts via stock market indicators* (2021), URL https://arxiv.org/abs/2112.06393.

[13] *Zillow data* (2021), URL https://www.zillow.com/research/data/.

[14] *Housing*, URL https://fred.stlouisfed.org/categories/97.

[15] K.-H. Kim, C.-M. Lee, and Y.-M. Lee, *Chapter 12: Rental housing system and housing market volatility: Monthly rent-based vs. asset-based systems* (2014), URL https://www.elgaronline.com/view/edcoll/9781783472871/9781783472871.00020.xml.

[16] R. Bhansali and L. P. Schaposnik, Proceedings of the Royal Society A **476**, 20190826 (2020).

[17] K. S. Cheung, C. Y. Yiu, and C. Xiong, Journal of Risk and Financial Management **14** (2021), ISSN 1911-8074, URL https://www.mdpi.com/1911-8074/14/3/108.

[18] G. V. Engelhardt and C. J. Mayer, Journal of Urban Economics **44**, 135 (1998), ISSN 0094-1190, URL https://www.sciencedirect.com/science/article/pii/S0094119097920647.