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ARE INDIVIDUAL STOCK PRICES MORE EFFICIENT THAN MARKET-WIDE PRICES? EVIDENCE ON THE EVOLUTION OF SAMUELSON'S DICTUM

Authors: Jānis Reinis Beikmanis
Pauls Raimonds Sīlis

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Are individual stock prices more efficient than market-wide prices? Evidence on the evolution of Samuelson's Dictum

Jānis Reinis Beikmanis

and

Pauls Raimonds Sīlis

Supervisor: Tālis J. Putniņš

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Abstract

Paul Samuelson famously conjectured that while markets are efficient on a stock-relative-to-other-stocks basis (high "micro efficiency"), the overall market valuations are fairly inefficient (low "macro efficiency"). We empirically test this conjecture and examine how efficiency and informativeness of stock prices have evolved in US stock markets since the 1970s. Our measures of efficiency are based on how well stock returns can be predicted for individual companies and the market as a whole, while our measures of informativeness are based on how well stock prices predict future earnings of individual companies and the market as a whole. We have three major findings. First, we find support for Samuelson's Dictum in that stock prices appear significantly more efficient and informative in a relative sense (micro) than at the market-wide level (macro). Second, we show that the wedge between micro and macro efficiency/informativeness has become larger through time with micro efficiency and informativeness increasing while the opposite trend is observed at the macro level. Third, we find that the trends can largely be attributed to the increasing popularity of passive investing, consistent with recent theory, and a shift from direct participation of individuals in stock markets to delegated investment management by mutual funds. Our findings help understand puzzling recent phenomena in markets such as the inability of most active funds to generate alpha (micro efficiency), yet record high market-wide equity valuations (collapsing as we pen this thesis) despite the yield curve pointing to a recession (macro inefficiency).

Keywords: Samuelson's Dictum, information and market efficiency.

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1. Introduction

The morning of 14th August in 2019 came with a considerable reflection in the finance world as the US market observed the inverted yield curve for the first time since 2007: the 2-year Treasury bonds had higher yields than the 10-year Treasury bonds. An inverted yield curve is usually interpreted as an indicator of a looming recession. In fact, inverted yield curves have correctly predicted most of the economic recessions during the last century. Yet, at the same time, equity markets were trading at record stock valuation ratios, much higher than historical averages. Have the market-wide stock valuations become disconnected from fundamentals? Could markets, even large and liquid markets like the US stock markets, be inefficient at the market-wide level? And at the same time, given the evidence that sophisticated market participants such as active mutual funds and hedge funds struggle to "beat the market", could markets also be highly efficient but in a different way: at the micro level? In this thesis, we shed light on these issues.

Fama (1965, 1970) pioneers the Efficient Market Hypothesis and suggests that in strong form of efficient markets prices fully reflect all the available information. Hardly any predictors of individual stock returns (other than risk factors) that have been identified have remained reliable predictors following their discovery (McLean and Pontiff, 2016), suggesting that stocks have become more micro-efficient through time. Mutual and hedge funds have been underperforming the market compared to their historical levels, suggesting that it is harder to find mispriced assets in the cross-section (Chen, 2019). Investors have responded to the poor performance of active funds by shifting to passive investments such as ETFs at an alarming rate. Cheaper information costs, wider availability of data, and increased spending on price discovery make stocks more liquid that results in market participants quicker exploit any mispricing (French, 2008; Wermers, 2020). Individually stocks demonstrate that their relative valuations are accurate reflections of future stock-level cash flows and risks in companies demonstrating high micro efficiency.

However, the current situation at the macro or market-wide level casts considerable doubt as to whether such a high level of efficiency and informativeness holds at the market-wide level and, therefore, whether markets can be considered macro-efficient[1]. The market-wide valuations continue to present strong growth (until the recent collapse), while the inverted yield curve suggests a possible economic downturn. Benchmarks place additional pressure on mutual fund managers to reach the necessary returns and results in less usage of market timing strategies to correct mispricing on the macro level. Moreover, Garleanu and Pedersen (2019) argue that aggregation of stocks forms systematic factors that lead to the inefficiency of the portfolio when a number of assets are large. Therefore, the skepticism of macro efficiency arises, and the question should be asked, whether market-wide valuations can accurately reflect market-wide future cash flows and risk in companies?

The idea that the Efficient Market Hypothesis performs better for individual stocks than it does for the absolute levels of the whole stock market was put forth by Samuelson (1998). The theoretical framework of Samuelson's Dictum states that by aggregating stocks in an index, the signal from the future cash flows can become more ambiguous and create mispricing opportunities on a macro level. At the same time, stocks could be efficient relative to one another on the micro-level.

On the other hand, one can ask the question of what happens when stock prices do not tend to its fundamental values? The representative situation happened before the early 2000s recession when company valuation ratios were relatively high to their earnings, yet they continued to rise. Although investors on average were not able to predict stock return movement reflecting market efficiency, barely any information was available at that moment, so there was not much to be incorporated into; hence, the market was also uninformative. Informational efficiency shows what fraction of information is incorporated into prices from a given information set, while informativeness measures the total amount of information incorporated into prices.

The informativeness in prices is a crucial factor from the society's perspective as it is a question of allocating capital in stocks in an efficient manner (Bond, Edmans, and Goldstein, 2012). More uninformed traders deviate to passive investing and produce a relatively larger amount of noise factor in aggregate stock prices. According to Bennett, Stulz, and Wang (2019), when stock price informativeness is high, the companies make

[1] Paul A. Samuelson (1998) describes macro inefficiency as a situation when "aggregated indexes of security prices [are] below or above various definitions of fundamental values", thus making macro returns forecastable.

more efficient investment decisions. Thereby, the trend of informativeness is essential to efficient capital allocation for company managers.

Financial market efficiency is one of the most debated topics among finance practitioners, but rarely any paper discusses the differences and implications of micro and macro efficiency simultaneously. Moreover, as the example of an efficient, but uninformative market illustrates, it might be useful to consider both phenomena jointly - factors that do not explain efficiency might explain informativeness of stock prices and vice-versa. Efficiency and informativeness, micro versus macro – these are the main puzzles that lead us to the following research questions:

1. *What are the level differences between micro and macro efficiencies, individual and aggregate price informativeness?*
2. *How has the level of micro and macro efficiency/informativeness evolved through time?*
3. *What is driving the trends –which factors can explain the dynamic changes in efficiency and informativeness?*

This study is first of its kind to provide an empirical analysis of the comparison between levels of micro and macro efficiencies over time. By constructing proof of Samuelson's Dictum, we show that level of micro efficiency has been consistently larger than that of the macro. In fact, the trends of the efficiencies show that the wedge between two levels is growing. Secondly, we test informativeness of stock market alongside efficiency and obtain similar trends - increasing for micro but declining for macro. In addition, we explain these rising differences between micro and macro levels of efficiency and informativeness with increased passive investing activity and the deteriorating participation of direct investors. Our results of high micro efficiency help to interpret why many active mutual funds do not produce above-market returns. To add, the low efficiency on the macro level explains why market-wide equity valuations remained high regardless of the signals about a looming economic downturn.

This paper is structured as follows: Section 2 provides an extensive overview of related literature and describes hypotheses that are examined in our Thesis. Section 3 illustrates the data and methods used in this study. In section 4, we demonstrate empirical results and provide a discussion of primary analysis. Section 5 follows with robustness tests, Section 6 describes limitations and suggestions for further research, and Section 7 concludes.

2. Literature review

2.1 Efficient Market Hypothesis

The theory of the Efficient Market Hypothesis (EMH) is known to anyone related to the finance industry and has fundamentally shaped the field starting from the 1960s. Fama (1965) rooted the grounds of the theory that past behaviour of stock prices is of no use for predicting the future performance of prices. Fama (1965) points out that chart reading and pattern finding from historical stock prices do not give an investor any worthy information of future stock behaviour and is nothing more than just an exciting pastime activity. The author of EMH believes that stock price fluctuations in the market are random movements where stock prices converge to their fundamental values. Independently from Fama (1965), Samuelson (1965) argues that an efficient market is when there is perfect competition, no transaction costs, and fully available information for investors. However, Samuelson's idea is that this is a possible state of the market that is not reachable in reality.

Discussions of whether capital markets are “efficient” continue to this day, and many academics have come up with their definitions and explanations of the term “*efficient markets*”. Malkiel and Fama (1970) argue that an efficient market is one where “prices fully reflect all available information”, and the price changes happen only due to new information. Jensen (1978) indicates that the market is efficient when the person is not able to generate profits by trading based on previous information. Malkiel (2003) uses a simple analogy of finance professor advising the student not to bother with picking up a 100$ bill laying on the street, claiming that if it was a real one, someone else would have already picked it up. As observed in the stock market, if riskless opportunity to earn profits existed, it would be quickly arbitraged away by other market participants. Furthermore, Timmerman and Granger (2004) point out that in an efficient market, it should not be possible to predict future prices and returns as it would be possible to earn immense profits that could lead to an unstable economy. Therefore, one can conclude that the “efficiency” itself describes that investors cannot earn risk-less abnormal returns compared to other market participants.

2.2 Criticism on EMH

Some practitioners and academics awaited the idea of efficient markets with disbelief. Grossmann and Stiglitz (1980) argue that the theory itself does not make sense. The state of a perfectly efficient market gives no incentive for sophisticated investors to gather information and trade as there is no possibility to earn excess returns. However, if there are no sophisticated traders, there is no one to exploit the mispricing, making the market inefficient. Therefore, the market should find itself in some equilibrium model with both, active and passive, managers where there is no incentive to switch. Even though Grossman's and Stiglitz's (1980) comments were just a theoretical thought, there have been numerous practitioners who have tried to prove market inefficiency and active manager skills by using different analysis and gaining above-average returns with their strategies.

The frequent discussions of market efficiency and anomalies show quite exciting developments over time. Practitioners and financial economists implement strategies that prove inconsistencies with theoretical models of asset-pricing and allow investors to achieve additional profit possibilities. Lo and MacKinlay (2011) prove a momentary correlation between the past and today's returns. The relation supports the idea of short-term momentum. The behavioural finance supporters argue that investors are irrational, and often their behaviour in the stock market is predictable. The momentum can be explained by market participants seeing the stock price rise and immediately getting drawn to it in a “bandwagon effect” that makes the stock price increase even more (Malkiel, 2003).

The literature also provides evidence of profitability using other factor investing measures. Fama and French (1992) separate all stocks according to their market capitalization and see the relation between size and stock returns. The results indicate small stocks earning higher monthly returns compared to large stocks. Statisticians and economists use a similar methodology to find the *value* effect on stock returns. The findings of Basu (1977) and Rosenberg, Reid, and Lanstein (1985) demonstrate value stocks earning higher returns than growth stocks. The literature also suggests low volatility (Baker, Bradley and Wurgler, 2011), quality measures (Bender, Nielsen, 2013; Asness, Frazzini, and Pedersen, 2014), and yield factors (Litzenberger, Ramaswamy, 1979; Keim 1985) as possible variables to include in factor investing and earn above-average returns.

Another theory behind stock price predictiveness is mean reversion. Campbell, Shiller (2001) argue that stock prices relative to their fundamental value indicator should return to their mean levels in the future. Therefore, if the valuation metric has been drifted far from the historical mean value, it should predict the changes in the fundamentals in the future. The efficient market hypothesis declares that no valuation measure should predict the price changes in the future. The puzzle of the researchers is to understand which component – price or fundament - of the valuation ratios makes it revert. Campbell and Shiller (2001) prove that it is the price component that leads the valuation metric back to its normal levels for the dividend-price ratio and the price – smoothed earnings ratio. This relation allows to state that investors can predict price changes by looking at the fundamental values of the companies. Besides, Cochrane (2008) indicates that the proof that valuation metrics do not predict fundamental's change in the future is considered as more substantial evidence of market inefficiency than the argument that valuation metrics forecast future price changes.

Yen and Lee (2008) comment that recently, EMH does not receive the strong support it gained right after the origination of the theory. Many behavioural finance supporters have tried to oppose it and introduce new fundamental value parameters and stock characteristics, predicting excess returns. Nevertheless, the relations of predicting excess returns and fundamental ratios often hold valid only for a specific period and data sets; thus, it can be a question of data manipulating and smoothening (Mclean and Pontiff, 2016; and Schwert, 2003).

The inconsistency of the efficient market literature has caused new theories and ideas around the topic. As papers examining efficient market hypothesis usually describe only the state of the market in a binary sense – efficient or inefficient, some of the academics have suggested that the market can change its state from efficient to inefficient and vice-versa. Lo (2004) put forth the Adaptive Market Hypothesis that supports dynamic changes in efficiency over time. Ito and Sugiyama (2009) use time-varying autocorrelation of stock returns and detect the market being most efficient in the late 1990s, but most inefficient during the 1980s. Also, Ito, Noda, and Wada (2016) find out that market efficiency has repetitive fluctuations every 30, 40 years. Many other academics have explored the perception of the adaptive behaviour of the US stock market (see, e.g., Lim, Lou, and Kim, 2013; Manahov and Hudsov, 2014; Urguhart and McGroarty, 2016).

2.3 Samuelson's Dictum

The overall market stability is always under the microscope for experts in the field. Paul A. Samuelson (1998), during the conference series of Federal Reserve Bank of Boston, introduced the spectators with a theory about the overall aggregate market and the efficiency of it. Samuelson's central idea of the theory is that stocks relative to each other show quite reasonable efficiency in the market. Nevertheless, when aggregated together, the market valuations earn the ability to predict market-wide returns. Jung and Shiller (2005) examine the theory with an emphasis on whether the D/P ratio predicts future changes in real dividends for both individual stocks and the aggregated stock market. Their results coincide with Samuelson's stated and prove that the D/P ratio predict dividend changes on a micro level, while on the macro level, they obtain insignificant results with the opposite sign. More recently, Garleanu and Pedersen (2019) evolve the theoretical framework of Samuelson's Dictum by showing how the condition appears with the asset amount increasing in the market. Garleanu and Pedersen's (2019) model considers changes in active and passive investment fees and how it affects market efficiency. There are not many other papers looking at micro and macro efficiencies together, but there is a significant amount of research done on each of the components separately.

2.3.1 Micro efficiency

One of the most popular theories to demonstrate a weak form of micro inefficiency is momentum. Jegadeesh, Titman (1993) prove that by buying stocks that earned high returns in the past and selling stocks that performed poorly, one can earn above-average returns in the short-term (3-12 month holding period). Many other experts in the field also advocate the short-run correlation of returns (see, e.g., Rouwenhorst, 1998; Lo, Mamaysky, and Wang, 2000; Lo, MacKinlay, 2011). On the other hand, DeBondt and Thaler (1985) advocate of long-run return reversals and justify that one can achieve abnormal profits by buying "losers" and selling "winners" for the 3-5-year horizon.

Many financial economists explore different fundamental value ratios predicting excess stock returns for individual companies (Kothari, 2001). Basu (1977, 1983) proves that companies with a high E/P ratio have higher risk-adjusted returns than companies with a low E/P ratio. Studies such as Fama and French (1992), Lakinonishok (1994), Pointiff and Schall (1998) introduce findings of high book-to-market ratio companies having higher risk-adjusted profits. Financial economists widely use dividend yield as a fundamental value measure to predict price changes. Numerous studies discuss the relation of high dividend-price ratio stocks earning higher returns (see, e.g., Blume, 1980; Naranjo, Nimalendran, and Ryngaert, 1998; Bansal, Dittmar, and Lundblad, 2005). Kelly and Pruitt (2013) use cross-sectional regressions with multiple valuations ratios to examine how well different measures can explain individual stock return variance. Paper provides evidence that forecasts using valuation ratios are similar to actual excess returns in- and out-of-sample. Contrary, Lewellen (2004) suggests that financial ratios, such as B/M, D/P, and E/P, have only weak power of predicting stock returns.

2.3.2 Macro efficiency

The literature about the aggregate stock market indicates many inefficiencies and opportunities to predict abnormal profits. Fama and French (1988, 1992), Goyal and Welch (2003), and Van Binsbergen, Koijen (2010) prove that aggregated dividend yield can predict excess returns for long-term horizon, while Lamont (1998) concludes the same relation, but for the short-term horizon. Campbell and Shiller (1988) argue that the CAPE ratio (cyclically-adjusted PE ratio uses a 10- year average of earnings) is a better predictor of excess returns than any other measurement. Ang and Bekaert (2007) contradict previous findings and show weak evidence of earnings yield predicting excess returns.

Fama and French (1988), Rapach and Wohar (2005) argue that the market shows macro inefficiency marks as the dividend-price ratio can forecast the stock market returns. Yung and Shiller (2005), Cochrane (2008) support the market inefficiency theory and add to the previous findings that the D/P ratio cannot predict aggregate dividend growth. However, Lettau and Ludvigson (2005) argue that contrary to the previous literature, the price-dividend ratio can predict dividend growth. Stambaugh (1999), Lettau and Ludvigson (2001), Goyal, Welch (2003), and Valkanov (2003) also defend market efficiency by confirming that log dividend-price ratio is not able to forecast the excess returns. Even though most of the academics are trying to prove which of the valuation ratio does explain the highest percentage of variance in returns, we are more interested in the overall efficiency measure of the market.

Multiple papers have used multivariate regressions combining valuation measures to predict excess market returns and find out about markets' aggregated inefficiency (see, e.g., Campbell and Shiller, 2001; Rangvid, 2006; Campbell and Yogo, 2006; Li, Ng, and Swaminathan, 2013). Every study finds a new contribution to the existing literature. Either it is a different time period or additional variables that predict the aggregated US stock markets' returns indicating inefficiency of the market.

The literature on stock market efficiency provides different views and results of individual stock return and market return predictability with fundamental ratios and past returns. A large part of this inconsistency is attributable to market efficiency varying over time. A similar observation can be detected by reading seminal surveys about the topic. While Malkiel and Fama (1970) in their survey of efficient capital markets indicate strong support of market efficiency, Fama (1991) in the updated version of the survey illustrates compelling evidence in the literature of inefficiencies in the market.

Overall, the theoretical frameworks suggest Samuelson's Dictum in time, but there is no one in the current literature to provide empirical evidence of differences between micro and macro efficiencies over time. The papers looking at cross-sectional regressions and individual stock return predictions use various methods, variables, and periods; therefore, every paper has a different scale of micro efficiency. The papers analysing time-series regressions for aggregate markets' efficiency do not replicate these methods and cannot compare them with micro efficiency. To add, financial economists that have delved into Samuelson's Dictum do not provide the time-series of this phenomenon. Our paper will try to fill the gap in the literature by answering the questions of whether stocks relative to each other have higher or lower efficiency compared to the aggregate market. Also, the divergence of the conclusions about whether markets are efficient encourages us to investigate differences of efficiency trends in time.

2.4 Informativeness measures

The efficiency measure provides the estimation of how a large fraction of total information has presented into stock prices. Nevertheless, the total information incorporated into prices is represented by price informativeness measures[2]. One of the ways to estimate price informativeness is by looking at R^2 measure of a regression where stock returns are being explained by industry-matched or market portfolios as, for example, in the seminal paper of Roll (1988). The rationale of the synchronicity measure is that individual stock will be less informative if its returns will be strongly correlated with market or industry returns. The numerous influential papers have been using price synchronicity as a measure of informativeness (see, e.g., Morck, Yeung, and

[2] For a more extensive explanation of price informativeness difference from informational efficiency look at section 3.2 (page 19.).

Yu, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; and Chen, Goldstein, and Jiang, 2007).

To continue, the paper of Easley, Kiefer, O'Hara, and Paperman (1996) measure price informativeness as the probability of informed traders (PIN measure) buying and selling stock. Transactions of the stock happen either by noise traders or informed traders. As informed traders will make their decision only when they believe that their information is not available to the public, the measure is sound to describe it as price informativeness.

Recent literature introduces price-based informativeness measures to determine information incorporated in stock prices. Bai, Phillipon, Savov (2016) observe how the company's prices predict future earnings to discover the trend of stock price informativeness over time. Bai, Phillion, Savov (2016) obtain price informativeness measure by calculating forecasting price efficiency as described in Bond, Edmans, and Goldstein (2012). Our approach is a simplified version of Bai, Phillipon, Savov (2016) measure. We look at explanatory power (R^2) of how current prices reflect the future cash flows of individual companies, as well as an aggregate market.

The vast majority of the current literature is comparing cross-country evidence on the price informativeness measures (King and Levine, 1993; Morck, Yeung, and Yu, 2000; Wurgler, 2000; Edmans, Jayaraman and Schneemeier, 2017). In comparison, studies about the price informativeness tendencies over time are rather new subject in the literature. Martineau (2017) documents improvement in time; the information (earning announcement) is being incorporated into stock prices much quicker. Interestingly, Broogard, Nguyen, Putnins, and Wu (2020) indicate an increase in individual stock co-movement with market returns in the period after the mid-1990's determining the reduction of individual stock price informativeness. Nevertheless, the study discredits price synchronicity measure and prove that noise component declines, observing an increase in price informativeness over time.

Using S&P 500 non-financial companies, Bai, Phillipon, and Savov (2016) conclude that the price informativeness grows steadily over time for 3- and 5-year horizons for the US 500 largest companies. Nevertheless, the work of Farboodi, Matray, and Veldkamp (2018) challenge the previous study and its discoveries pointing out that price informativeness increases only for large firms, wherein price informativeness for small firms deteriorates over time.

2.5 Factors explaining trends in informativeness and efficiency.

Many authors come up with theoretical frameworks or empirical evidence of what explains market efficiency. The costs associated with assets under management have shrunk significantly in time, and more individuals relocate their investment decisions to managers (French, 2008; Rydqvist, Spizman and Strebulaev, 2014). The decline in direct investor participation reduces uninformed traders involving in stock picking and leave the task to more experienced investors, thus making individual stocks more efficient (French, 2008; Bond, Garcia, 2019).

At the same time, the market participants switch from active investing to passive investing (Investment Company Institute, 2019). Stambaugh (2014) points out that passive investing is not only taking a share of total investments from active investing, but mutual funds are on average, making more “index-like” investments compared to the past. Benchmarks for fund managers do not allow them to deviate from their portfolios, limiting their usage of market timing strategies. The benchmarks incentivize fund managers to keep up with their benchmarks that lead the managers to follow *peer-effect* and miss opportunities to correct mispricing on a macro level (Bird, Woolley, 2003; Vayanos, Woolley, 2016). Compiling all of the effects together, change in the fees of passive investing increases micro efficiency, but have an opposite effect on macro efficiency. These relations are in line with the theoretical framework presented by Bond and Garcia (2019).

Garleanu and Pedersen (2019) also put forward a theoretical model and prove that lower costs of passive management weaken efficiency, especially macro efficiency. Significant growth of passive investing in recent years strengthens the reduction of information incorporated in prices and intensify larger price inefficiency on macro-level (Sushko and Turner, 2018). On the other hand, the increase in hedge fund equity holdings increases the informational efficiency of individual stock prices as they are operating as arbitrageurs in the market (Cao, Liang, Lo and Petrasek, 2019). Chordia, Roll, and Subrahmanyam (2011) find evidence that a decrease in trading costs has significantly increased turnover in the US stock market. The rise in trading activity worsens individual stock return predictability suggesting higher micro efficiency.

Similarly, various academics explain which factors influence stock price informativeness. Several studies propose the evidence of how growth in passive investing declines individual stock price informativeness as the price of individual stock correlates more with market price (Cong, Xu, 2016; DeLisle, French, and Schutte, 2017;

Kacperczyk, Nosal and Sundaresen, 2018). The reduction in low precision information costs harms long-term price informativeness as it diminishes the benefit of active investors to learn high precision signals (Dugast and Foucault, 2018). Turley (2012) finds the short-term price informativeness increases when transaction fees reduce. The discoveries are in line with Weller (2018) and Gider, Schmickler, and Westheide (2019) findings, who look at the relation between individual stock price informativeness and the rise of algorithmic trading. Studies conclude that high-frequency trading reduces the information incorporated in prices as many active investing managers lose an incentive to determine full high precision information. Analogous findings discover Brunnermeier (2005), who says that informational leakage increase short-term price informativeness but have the opposite effect for long-term informativeness. French and Roll (1986) imply that higher stock liquidity goes in hand with greater stock price informativeness. The effect is substantially supported by Chordia, Roll, and Subrahmanyam (2008), as well as Bai, Phillipon, and Savov (2016). Davila and Parlatore (2018) identify that stocks with larger market capitalization and higher share turnover are associated with being more informative. Panousi and Papanikolau (2012) suggest a high uncertainty of firm-specific information influences individual stock price efficiency. The uncertainty leads risk-averse investors to underinvest in companies that result in micro inefficiencies. The literature also provides evidence that periods with high sentiment have lower micro price informativeness of the market (Baker, Wurgler, 2007). De Long, Shleifer, Summers, and Waldmann (1990) argue that the market consists of irrational investors who are devoted to external sentiment and informed arbitragers that are sentiment free. The high sentiment periods indicate many uninformed investors that integrate noise factor into prices.

Based on current literature and research conducted, we construct our hypotheses as follows:

Hypothesis 1: Samuelson's Dictum holds in US stock market; micro efficiency is higher than macro efficiency. Although informativeness is not strictly part of Samuelson's Dictum, it is likely to have a similar effect as an efficiency measure.

Hypothesis 2: Micro efficiency and informativeness increase over time, driven by (i) a shift of uninformed investors into index funds, (ii) a decrease in trading costs accompanied by an increase in stock turnover, (iii) a development of less uncertainty in stock markets.

Hypothesis 3: Macro efficiency and informativeness decrease over time, driven by (i) an increase in index investing, (ii) a shift from direct investor participation in markets to delegated investment management in mutual funds that have constraints on asset allocation decisions, (iii) systematic factors arising in the composite index when a number of assets is large.

Hypothesis 4: As a result of the expected trends described in Hypotheses 2-3, the wedge between micro and macro efficiency predicted by Samuelson's Dictum is increasing through time.

3. Research Design

Following the research design of measuring market efficiency and informativeness used by most practitioners in the field of finance, we conduct using only the secondary data collection method. Secondary data collection is used, mostly because estimating both measures requires gathering data from financial markets where investors trade and hope to earn some profits, thus, changing levels of efficiency and informativeness in the process. A study on these measures requires analysis of past data of prices and factors influencing the fluctuations in them, which is best achievable by secondary data analysis. Primary data collection would be time-consuming and unreliable, as information gathered during expert interviews or by other similar primary data collection methods, is subject to different behavioural biases.

3.1 Data description

For the following empiric analysis, we use data from several secondary sources. Firstly, we obtain monthly stock price, market capitalization, and traded volume of shares for the time frame from 1967-2018 for all companies listed on NYSE, Nasdaq, and AMEX stock exchanges from CRSP (Centre of the Research in Security Prices) database. Companies' book value of assets, earnings per share (EPS), and dividends are retrieved from Compustat database for the same time frame, but with quarterly frequency. Both data sets were provided by our supervisor, Prof. Tālis J. Putniņš, who has given us the approval to use the data for this research. Macroeconomic variables, like the US government's 3-month and 10-year bond yields, as well as Consumer Price Index (CPI), are taken from Thomson Reuters Database. For the last part of the analysis, different factors that might explain efficiency and informativeness trends are taken from various publicly available sources. We extract data on households' holdings of total US stocks from the Federal Reserve webpage, Financial uncertainty measure from Sydney C. Ludvigson's webpage, and Sentiment measure from Jeffrey Wurgler's webpage (more detailed description of factor variables can be seen in Appendix A). In the end, we merge all databases together with quarterly frequency.

Our main methods include explaining excess returns and earnings scaled by assets with different fundamentals (valuation measures) of the firms described in detail in the next sections of this paper. We calculate the excess returns by dividing future prices 1, 3, or 5 years ahead for the respective horizon by the current price, subtract one and then subtract the 3-months Treasury Bill. Similarly, we divide earnings 1, 3, or 5 years ahead by the current book value of assets of the company to get the scaled earnings measure for the three horizons. The logarithm of market capitalization divided by the book value of assets and logarithm of price divided by earnings are the valuation measures used in the base model for the following analysis. Besides, the logarithm of dividends divided by price and logarithm of price divided by the inflation-adjusted 10-year rolling mean of earnings (CAPE ratio) are added to the models for robustness tests later in the paper. All variables used to estimate efficiency and informativeness measures are summarized below.

Table 1. Summary statistics.

This table describes summary statistics for variables used in the final dataset of our regressions. All variables are winsorized at 1st and 99th percentiles and reported in fractions. Excess returns and earnings/assets are reported for 1, 3, and 5-year horizons. Sources: Compustat and CRSP.

Variable	Horizon	Obs	Mean	Median	Standard deviation	Min	Max
	1 year	814 355	0.060	-0.044	0.662	-0.890	3.614
Excess returns	*3 year*	669 972	0.248	-0.039	1.212	-0.979	7.162
	5 year	553 796	0.431	-0.022	1.658	-0.996	10.068
	1 year	731 977	-0.007	0.006	0.068	-0.389	0.113
Earnings/Assets	*3 year*	593 396	-0.004	0.008	0.085	-0.517	0.182
	5 year	484 026	0.000	0.009	0.105	-0.656	0.275
Log(MA)		812 850	-0.413	-0.352	1.200	-3.524	2.320
Log(PE)		855 866	1.956	3.671	3.502	-7.198	8.007
Log(DP)		229 751	-4.600	-4.467	1.227	-15.500	-2.486
Log(CAPE)		341 340	2.733	4.112	3.531	-6.953	7.156

3.2 Efficiency versus informativeness of stock market prices

Informational efficiency is the extent to which the available information is reflected in current prices such that it is not possible to reliably predict excess stock returns using available information. When a given piece of information is fully and accurately reflected in prices, it is not possible to use that information to predict future excess returns, and the market is said to be efficient with respect to that particular piece of information. Therefore, efficiency measures do not tell us the total amount of information in prices, but rather, the fraction of a given information set that is reflected in prices.

In contrast, price informativeness is how well current prices reflect the fundamental value or in simple terms: future cash flows. Informativeness is concerned with the total amount of information in prices, irrespective of whether that is a large or small fraction of the total available information.

One way to think about the difference is that informativeness is about the total amount of information reflected in prices, whereas efficiency is the measure of how accurately or to what extent an existing information set is reflected in prices, without regard for how rich is that information set. Given this distinction, the two measures can move in opposite directions. For example, the available information set could diminish in quantity or quality, which for a given level of efficiency would tend to decrease informativeness of prices. There could also be a contemporaneous increase in the efficiency with which the inferior information set is reflected in prices. Depending on the strength of the increase in efficiency compared to the deterioration of the information set, it is possible for the informativeness of prices to decline while efficiency increases. The opposite is also possible.

Another interpretation of the distinction between informativeness of prices and efficiency is informativeness links prices to fundamentals and asks how well prices reflect fundamentals. In contrast, most efficiency measures are concerned with the issue of can returns be predicted and thus, is there money to be made in markets by trading based on available information. Markets could be completely random in their price movements, rendering them “efficient” in the sense that the excess returns cannot be readily predicted and thus there is little or no money to be made in market timing or stock picking, yet if the random price movements are void of any relation with fundamentals then the prices could be completely uninformative. Thus, it is possible for a market to have efficient but uninformative prices. It is also possible, in informationally rich environments, for prices to be highly informative, yet not completely efficient.

Yet another way to consider the difference between efficiency and informativeness is more formally / mathematically[3]. Consider a stock with an uncertain future fundamental value v_T and a current market price of p_t that reflects some, all, or none of the current information set Ω_t. Price informativeness is given by

$$Informativeness = \frac{\mathrm{var}(v_T) - \mathrm{var}(v_T|p_t)}{\mathrm{var}(v_T)} = 1 - \frac{\mathrm{var}(v_T|p_t)}{\mathrm{var}(v_T)} \tag{1}$$

That is, price informativeness is about the absolute amount of information in prices, or how much of the uncertainty about the future fundamental value of the stock is reduced by observing the price (normalised by the unconditional uncertainty about future fundamental value). When the price contains no information about future fundamentals, the conditional variance $\mathrm{var}(v_T|p_t)$ is equal to the unconditional variance $\mathrm{var}(v_T)$, giving $Informativeness = 0$. At the other extreme, if the price is fully revealing and completely eliminates uncertainty about the future fundamental value, the conditional variance $\mathrm{var}(v_T|p_t) = 0$ and $Informativeness = 1$. More typically than these extreme cases, the price reveals some information about the future fundamentals and $0 < Informativeness < 1$.

In contrast, efficiency is given by

$$Efficiency = \frac{\mathrm{var}(v_T) - \mathrm{var}(v_T|p_\mathrm{t})}{\mathrm{var}(v_T) - \mathrm{var}(v_T|\Omega_\mathrm{t})} \tag{2}$$

The numerator is the amount of uncertainty about future value resolved by observing the price, i.e., the amount of information in prices. The denominator is the amount of uncertainty about future value resolved by observing all available information Ω_t, i.e., the amount of available information. Thus, efficiency is the fraction of available information that is reflected in prices. If the price were fully efficient and accurately reflected all available information Ω_t then $\mathrm{var}(v_T|p_t) = \mathrm{var}(v_T|\Omega_\mathrm{t})$ and $Efficiency = 1$. Yet if the price is completely inefficient and reflects none of the

[3] Our formal definitions of informativeness and efficiency are similar to those of Brunnermeier (2005).

available information Ω_t then $\mathrm{var}(v_T|p_t) = \mathrm{var}(v_T)$ and $Efficiency = 0$. More typically than these extreme cases, the price reflects some of the available information and $0 < Efficiency < 1$.

Following these theoretical definitions, informativeness can empirically be measured by asking what proportion of the variance in future fundamentals (e.g., future earnings) can be explained by current stock prices. A measure can be obtained by regressing future earnings of stocks on current market valuations of those stocks and extracting the regression $R^2 = Informativeness$. These regressions to measure the informativeness of prices can be estimated cross-sectionally to measure how informative are the valuations of individual stocks relative to other stocks about the future fundamentals of those stocks. These regressions can also be estimated from a time-series of market-wide valuations and future market-wide earnings, measuring how well time-series variation in market valuations explains future earnings of stocks overall. We refer to the cross-sectional and time-series measures of informativeness as micro-informativeness and macro-informativeness, respectively.

Similarly, the theoretical concept of efficiency can be empirically measured by testing the extent to which future (abnormal) returns of stocks can be predicted with currently available information. When prices are fully efficient, all available information is already reflected in prices so current information will not be able to predict future price movements, which will be driven by new information emerging about v_T. Whereas if the available information is not fully or accurately incorporated into prices, it will have some ability to predict future stocks returns so long as stock prices are drawn towards v_T in the long run. Therefore, an empirical measure of efficiency can be obtained by regressing future stock returns on current available information and extracting the regression R^2 from which $Efficiency = 1 - R^2$. These regressions to measure the efficiency of prices can be estimated cross-sectionally to measure how efficient are the prices of individual stocks relative to other stocks. These regressions can also be estimated from a time-series of market-wide information and future market-wide returns, measuring how efficient are overall market-wide valuations. We refer to the cross-sectional and time-series measures of efficiency as micro-efficiency and macro- efficiency, respectively.

3.3 Measures of efficiency and informativeness

As put forward by Fama (1970), one of the drawbacks of measuring the efficiency of asset prices is the joint hypothesis problem, which states that the goodness of the asset pricing model itself is tested hand-in-hand with the market efficiency, which means that even if the test shows an inefficient market, the alternative explanation is that the asset pricing model is not precise. In reality, both of these explanations are somewhat true, but it is impossible to differentiate the error of the model, and actual inefficiency as no model brings a unique, true answer.

As in most of the studies, this issue remains unresolved, and considering all the endless factors of asset pricing and unlimited diversity and unpredictability of human behaviour; a joint hypothesis problem might never be resolved. To minimize the limitations of the research, we do not use any particular asset pricing model to determine the fundamental value of a stock or predicted level of returns, but, instead, we employ simple valuation measures as explanatory variables of changes in earnings and excess returns, to measure informativeness and efficiency, respectively.

3.3.1 Micro efficiency and informativeness

To further study the development of efficiency and informativeness of the US stock market, we establish a measurement technique. We obtain micro efficiency and informativeness measures by gathering R^2 from cross-sectional regressions. We use three different horizons for all of the following models – 4, 12 and 20 quarters similarly to Bai, Philippon, and Savov (2016), who pointed out that predicting short-horizon relations mostly lead to insignificant results, so, a diversity of horizons is useful to estimate the time frame when the explanatory power is the highest.

To explain individual stock excess returns by their past valuation ratios on a firm-level, we use cross-sectional regression in equation (3) as a base model:

$$\begin{gathered}\left(R_{i,t+h} - R_{f,t}\right) = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{i,t} + \beta_2 log\left(\frac{P}{E}\right)_{i,t} \\ +\beta_3\left(R_{i,t+h} - R_{f,t}\right)_{i,t-h} + \varepsilon_{i,t}\end{gathered} \tag{3}$$

, where i is a firm indicator, t is time indicator (in quarters), h is horizon indicator (4, 12 or 20 quarters), $R_{i,t+h}$ is the stock return for the respective horizon, $R_{f,t}$ is the 3-months Treasury Bill rate, $log\left(\frac{M}{A}\right)_{i,t}$ is the logarithm of market capitalization divided by the book value of assets, $log\left(\frac{P}{E}\right)_{i,t}$ is the logarithm of price divided by earnings per share, and $\left(R_{i,t+h} - R_{f,t}\right)_{i,t-h}$ is the past excess return.

We explain the individual stock earnings scaled by assets with their past valuation ratios as shown in equation (4) which is our base model for informativeness measure's estimation:

$$\left(\frac{E}{A}\right)_{i,t+h} = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{i,t} + \beta_2 log\left(\frac{P}{E}\right)_{i,t} + \left(\frac{E}{A}\right)_{i,t} + \varepsilon_{i,t} \tag{4}$$

, where $\left(\frac{E}{A}\right)_{i,t+h}$ is firm-level earnings divided by the book value of assets, $\left(\frac{E}{A}\right)_{i,t}$ is past firm-level earnings divided by book value of assets.

Efficiency measure $1 - R^2$ and informativeness measure R^2 are computed at each quarter, and the first observation at 1972 Q4 serves as the reference point of the efficiency and informativeness indices, respectively. It is important to note that the level of the efficiency and informativeness measures cannot be interpreted precisely in absolute terms but rather serves as indices that show the changes of both stock market phenomena in the time period from 1972 Q4 – 2017 Q4. To smoothen the measures, we apply one year rolling mean for firm-level measures of efficiency and informativeness.

3.3.2 Macro efficiency and informativeness

As manifested by Samuelson (1998), an aggregate stock market's efficiency can also deviate from that of individual stock efficiency or micro efficiency. We aim to test his hypothesis with a similar approach as used for micro efficiency to be able to compare those two. In addition, we test for both, micro and macro, informativeness to make a similar comparison to the one Samuelson made on efficiency. To answer the question of what the levels of efficiency and informativeness are for the aggregate stock market we use time-series regressions.

We aggregate valuation measures $log\left(\frac{M}{A}\right)_{m,t}$ and $log\left(\frac{P}{E}\right)_{m,t}$ for testing market-wide efficiency and informativeness as follows:

$$log\left(\frac{M}{A}\right)_{m,t} = log\left(\frac{\sum Market\ Capitalization_{i,t}}{\sum Book\ Value\ of\ Assets_{i,t}}\right)$$

(5)

$$log\left(\frac{P}{E}\right)_{m,t} = log\left(\frac{\sum Market\ Capitalization_{i,t}}{\sum Total\ Net\ Earnings_{i,t}}\right)$$

The excess returns for the market $(R_m - R_f)$ are obtained by value-weighted averages of individual stocks at each quarter, and market-wide earnings scaled by total assets $\left(\frac{E}{A}\right)_m$ are aggregated by summing earnings across all firms and dividing them by summed assets across all firms at each quarter:

$$(R_m - R_f) = \sum_{i=1} \left(w_{i,t} \times (R_{i,t} - R_{i,t})\right)$$

(6)

$$\left(\frac{E}{A}\right)_{m,t} = \left(\frac{\sum E_{i,t}}{\sum A_{i,t}}\right)$$

To keep the comparability between macro and micro efficiency and informativeness, we keep the independent variables the same as for micro regressions, but instead of firm-level data we use market-wide excess returns calculated in (5) and earnings scaled by assets calculated in (6) as inputs in time-series regression.

We explain market excess returns with the aggregated valuation measures and include the past market excess returns to match the model of micro efficiency:

$$\begin{gathered}(R_{m,t+h} - R_{f,t}) = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{m,t} + \beta_2 log\left(\frac{P}{E}\right)_{m,t} \\ +\beta_3 (R_{m,t+h} - R_{f,t})_{m,t-h} + \varepsilon_{m,t}\end{gathered} \tag{7}$$

Similarly to efficiency, for macro informativeness we use consistent model to micro informativeness, just with market-wide earnings and valuation measures:

$$\left(\frac{E}{A}\right)_{m,t+h} = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{m,t} + \beta_2 log\left(\frac{P}{E}\right)_{m,t} + \left(\frac{E}{A}\right)_{m,t} + \varepsilon_{m,t} \tag{8}$$

As there is only one data point at each quarter, a 10-year (40 quarters) window is used in regressions to approximate macro efficiency and informativeness in time-series regression. Values of both measures are recorded at the middle of the window for each of the consequent quarters *t* starting from (*t+20*), thus, losing the first 20 and last 20 quarters of the total sample (Figure 1):

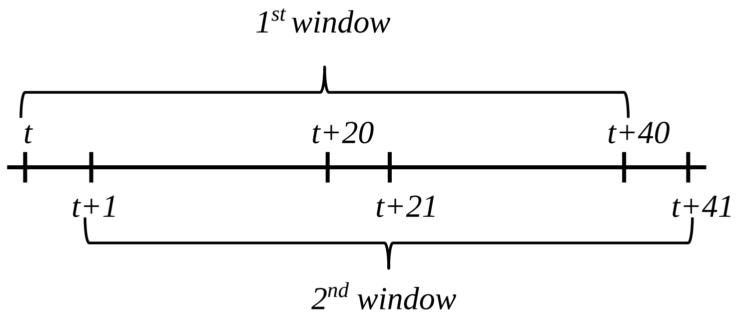

Figure 1. Illustration of recording macro efficiency and informativeness within the rolling window.

This figure depicts recording of efficiency and informativeness measures in the middle of each rolling window for macro level. Such procedure is done only for market-wide informativeness and efficiency, where time-series regressions are used. Figure created by authors.

4. Analysis and discussion of results

4.1 Differences in levels of micro and macro components.

In line with the techniques we demonstrate in the previous section, we look at the overall level of micro and macro efficiency/ informativeness. Our choice of using identical independent variables in micro and macro regressions allows us to compare individual stock versus aggregate stock market efficiency and informativeness.

The results of micro and macro efficiencies for the 5-year horizon are presented in Figure 2. The findings are in line with our expectations and indicate a strong presence of Samuelson's Dictum – US stock market has a higher level of micro efficiency compared to macro efficiency. The effect also holds for 1- and 3- year horizons, and graphical illustrations for these horizons are presented in Appendix B.

Our results support and complement Garleanu, Pedersen (2019), and Bond, Garcia (2019) papers by presenting an empirical analysis of their theory, as well as Jung and Shiller (2005) paper by introducing new independent variables and displaying the Samuelson's Dictum effect over time. The differences in levels of efficiency can also be thought of as follows. Garleanu, Pedersen (2019) argue that noise in individual stocks is purely idiosyncratic. Thus, when a number of securities is large (as it is in the US stock market), the variance of the composition tends to zero. However, because stocks are correlated by a common factor, the aggregation of securities in a composite index adds together all non-zero systematic factors, creating inefficiency on the macro-level.

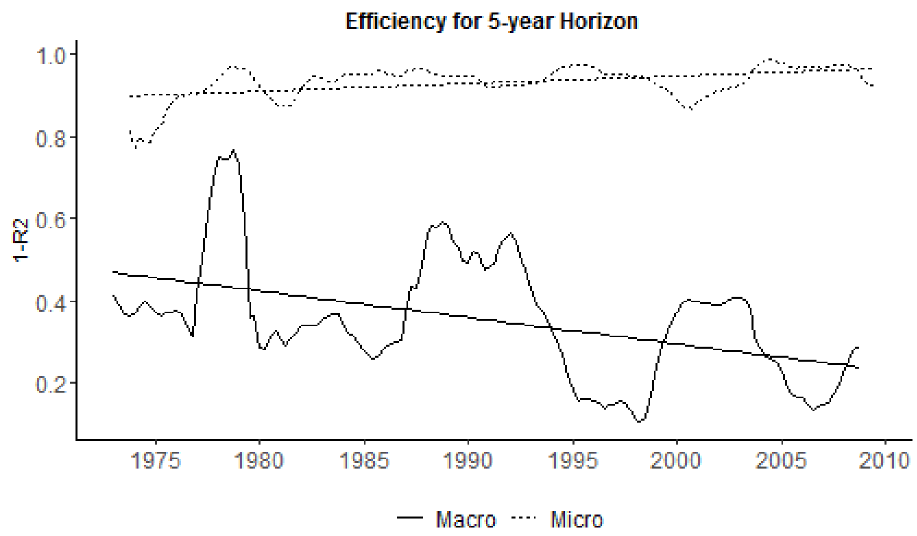

Figure 2. The comparison of macro and micro efficiencies for the 5-year horizon.

This figure shows the times series trends and comparison of macro and micro efficiency. The micro efficiency is determined at every quarter using cross-sectional regressions of our base model and illustrated over time period. Macro efficiency is calculated at every quarter using 10-year rolling windows using aggregate values in our base model. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ from 1967 to 2018, and data is gathered from CRSP and Compustat databases.

Further on, analysis of our findings suggests markets being most macro inefficient in the years of 1998 and 2006. The reader could look with suspicion of our results remembering the major economic recession in the early 2000s and subprime mortgage crisis in 2007-2009 that indicated unambiguous inefficiencies of market prices. However, one should remember that our measure of macro efficiency has been calculated using 10-year rolling window and presented at the 5th year, the middle of the period (Figure 1). Recording the measure in the middle of the period is a reasonable assumption, and while recording the macro measures in a different year within the window shifts the graph $\pm$ 5 years, it does not influence our results or conclusions at all.

A different picture can be seen in the comparison of micro and macro informativeness (Figure 3). The total information of prices is higher on the macro-level compared to micro. However, the difference is converging, and in the new century the levels of informativeness are approximately similar. One of the causes of aggregate informativeness being higher than individual price informativeness in former times could come from the difficulty of gathering the data. It is a very challenging and time-consuming task to learn information from stock to stock, especially when technologies were not that advanced. Nonetheless, the continuous evolution of technology advancement has changed the industry and its practices. Computers are tracking all of the stock earning announcements and can immediately react to the new information, which also materializes into higher micro informativeness.

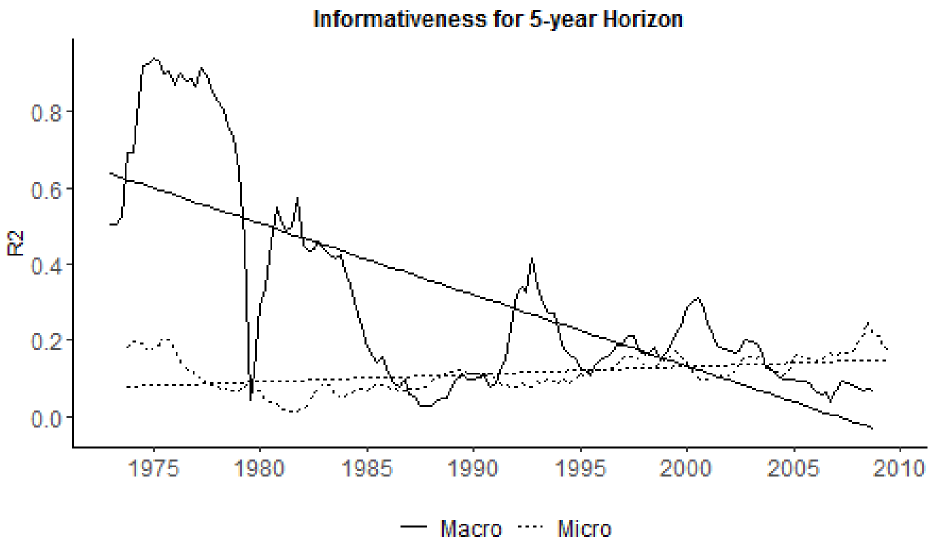

Figure 3. The comparison of macro and micro informativeness for the 5-year horizon.

This figure shows the times series trends and comparison of macro and micro informativeness. The micro informativeness is determined at every quarter using cross-sectional regressions of our base model and illustrated over time period. Macro informativeness is calculated at every quarter using 10-year rolling windows using aggregate values in our base model. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ from 1967 to 2018, and data is gathered from CRSP and Compustat database.

To formally test if there are differences between micro and macro levels of efficiency and informativeness, we construct simple t-statistics tests comparing the means of micro and macro components. The results are presented in Table 2.

Table 2.
Trends and levels comparison between macro, and micro efficiency, and informativeness.

This table documents mean, standard deviation, and trend for different efficiency and informativeness measures. The efficiency (1-R^2) and informativeness (R^2) measures are calculated using the base model. The trend is determined by regressing efficiency/informativeness measure on time variable. The last two columns report the difference between micro and macro means and the significance of the difference using a one-sided t-test. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

		Micro			**Macro**				
	Horizon	Mean	Standard deviation	Trend	Mean	Standard deviation	Trend	Mean difference	t-stat
Efficiency	1 year	0.97	0.03	-0.02	0.62	0.18	-0.36	0.35	(23.72) ***
	3 year	0.95	0.04	0.19 **	0.44	0.23	-1.87 **	0.51	(27.20) ***
	5 year	0.93	0.04	0.40 ***	0.35	0.15	-1.61 ***	0.58	(45.95) ***
Informativeness	1 year	0.28	0.06	0.40 ***	0.37	0.18	-0.76	-0.09	(-5.70) ***
	3 year	0.18	0.06	0.78 ***	0.30	0.20	-2.66 ***	-0.13	(-7.50) ***
	5 year	0.13	0.06	0.76 ***	0.30	0.27	-4.68 ***	-0.18	(-7.80) ***

4.2 What factors drive the trends of efficiency and informativeness?

In the last part of this paper, we examine the trends of measures of interest and factors explaining them. By regressing efficiency measure (1-R^2) and informativeness (R^2) on time variable, we obtain the overall trend of efficiency and informativeness. The statistical results of time trends are consistent with our hypotheses and are presented in Table 2.

We observe an upwards sloping trend for micro efficiency and informativeness. On the other hand, the macro efficiency and informativeness deteriorate over time, revealing evidence of the market becoming more macro inefficient. Our findings indicate that wedge between levels of micro and macro efficiency is enlarging through time. This finding supports the existence of Samuelson's Dictum even more, and the question of what drives the trends apart from each other is of high importance.

We now turn our attention to the relation between different factors and trends of efficiency and informativeness. We construct a time-series regression with Newey-West standard errors (Newey and West, 1987) to account for serial autocorrelation. Equation (9) illustrates the model used to explain efficiency and informativeness with several factors.

$$\begin{aligned} Efficiency_t / \, Informativeness_{\,t} \\ &= \alpha + \beta_1 PIM_{\,t-1} + \beta_2 \Delta Turnover_{t-1} \\ &+ \beta_3 Households\ Share_{\,t-1} + \beta_4 Financial\ Uncertainty_{\,t-1} \\ &+ \beta_5 Sentiment_{\,t-1} + \beta_6 \Delta Number\ of\ Firms_{\,t-1} + \varepsilon_t \end{aligned} \tag{9}$$

, where $Efficiency = 1 - R^2$ (gathered from a model in equation (3)), Informativeness $= R^2$ (gathered from a model in equation (4)).

Separate regressions are run for efficiency and informativeness, so essentially equation (10) depicts two regression models. In addition, both measures include micro and macro level data to explore differences of drivers between firm-level changes in efficiency and informativeness, as well as market-wide fluctuations. The descriptive statistics, more explanations, and data sources of factors are presented in Appendix A.

We conduct five different specifications to see how the model responds to a different set of independent variables. We are mostly interested in the signs and significance of coefficients for PIM, growth of turnover, households share, financial uncertainty measures, and sentiment measures, while the growth of companies is set as a control variable. The results of factors explaining efficiency measures are reported in Table 3.

Table 3.

Relations between factors and micro, macro efficiency.

This table show how factors explain the efficiency measure and coefficients calculated from the regression*:*

$$Efficiency = \alpha + \beta_1 PIM_{t-1} + \beta_2 \Delta Turnover_{t-1} + \beta_3 Households\ Share_{t-1} + \beta_4 Financial\ Uncertainty_{t-1} + \beta_5 Sentiment_{t-1} + \beta_6 \Delta Number\ of\ Firms_t + \varepsilon_t.$$

Efficiency measure is calculated from our base model as $1\text{-}R^2$. PIM is a measure of passive investing, as explained by Bhattacharya and Galpin (2011). $\Delta Turnover$ measure is a quarterly change in stock market turnover. Households Share is a proxy of direct investor participation. Financial uncertainty is a proxy of expected volatility. Sentiment is a proxy of irrational investors participating in the market. Growth in a number of companies is a quarterly change in a number of listed companies in the US stock market. All variables are normalized. The numeration (1) – (5) resembles differences in specifications. Specifications differ by a set of factors used as independent variables. T-statistics are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1)		(2)		(3)		(4)		(5)	
Factor	Micro	Macro	Micro	Macro	Micro	Macro	Micro	Macro	Micro	Macro
PIM	0.181 **	0.085	0.149 *	0.108	0.163 *	0.054	0.066	0.108	0.146 *	0.085
	(2.13)	(0.61)	(1.84)	(0.79)	(1.85)	(0.39)	(0.51)	(0.71)	(1.80)	(0.63)
Growth in turnover	0.071 *	-0.072	0.068 *	-0.066	0.075 *	-0.066	0.008	-0.055	0.072 *	-0.050
	(1.70)	(-1.16)	(1.66)	(-1.04)	(1.85)	(-1.05)	(0.16)	(-0.95)	(1.78)	(-0.76)
Households share	-0.535 ***	0.308 *	-0.579 ***	0.376 **	-0.570 ***	0.232	-0.585 ***	0.347 **	-0.591 ***	0.331 **
	(-4.13)	(1.87)	(-4.05)	(2.14)	(-4.79)	(1.57)	(-3.31)	(2.05)	(-4.48)	(2.02)
Financial uncertainty	-0.567 ***	0.164	-0.564 ***	0.155	-0.555 ***	0.192			-0.557 ***	0.187
	(-5.68)	(1.24)	(-5.72)	(1.19)	(-5.61)	(1.47)			(-5.62)	(1.50)
Sentiment	0.079	-0.097			0.048	-0.165	0.054	-0.074		
	(0.85)	(-0.83)			(0.52)	(-1.33)	(0.35)	(-0.59)		
Growth in number of companies	-0.066	-0.131 *	-0.037	-0.166 **			0.049	-0.166 **		
	(-1.23)	(-1.90)	(-0.60)	(-2.14)			(0.37)	(-2.06)		

Our results indicate that PIM measure has statistically significant effect on micro efficiency but, contrary to our hypothesis, has no significance explaining macro efficiency. According to our first specification, the increase of one standard deviation of PIM rises micro efficiency by 0.181 standard deviations. Our findings partially confirm Garleanu, Pedersen (2019), and Bond, Garcia (2019) theoretical frameworks who argue that passive investing also negatively affect macro efficiency. Nevertheless, we can conclude why passive investing does impact micro efficiency. The decrease in fees for passive investing increases the popularity of passive investing and encourage the switch from active to passive investing. Bond and Garcia (2019) argue that market participants that shift from active to passive are relatively uninformed as informed traders have no incentive to switch. This change leaves relatively more informed traders in active investing who do not produce noise and quickly correct mispricing in individual stocks. The theory is in line with our findings and explains why passive investing positively impact micro efficiency.

The results of Growth in turnover variable are in line with Chordia, Roll, and Subrahmanyam's (2011) findings and our hypotheses. New technologies and wider availability of data have definitely decreased costs associated with investing that leads to more people involving in market actions. Our results state that the shock of one standard deviation in turnover growth contributes to 0.071 standard deviation rise in micro efficiency. The measure does not have a statistically significant effect on macro efficiency.

We determine the negative and significant effect between direct investor participation and micro efficiency. The first specification in our results indicates that the change of one standard deviation in Household share has an -0.535 standard deviation impact on micro efficiency. However, we observe the opposite effect of macro efficiency. Our results conclude that when informed traders relocate their financial assets to asset managers (Household share goes down), the macro efficiency declines. These results are supportive to Vayanos and Wooley (2016), who highlight the importance of constraints that benchmarks and huge competition set to funds. The limitations for funds to deviate from their portfolios leaves a significant impact on macro efficiency as mispricing cannot be corrected in a timely fashion.

To continue, financial uncertainty harms micro efficiency. Our finding supports the claim of Panousi and Papanikolau (2012), who argue that high uncertainty leads to underinvestment and inefficiency on the micro-level. When market participants expect volatile markets, the risk of investing escalates, and more inefficiency arises. We do not find any significant relation between the sentiment of the stock market and efficiency.

We proceed with our analysis of how factors influence micro and macro informativeness. The results are seen in Table 4. Similarly to tests with efficiency, we have five specifications, and each differs by a set of variables used in regressions.

We conclude an inconsistent relation between PIM measure and micro informativeness for different specifications. Nonetheless, two of the specifications show that micro informativeness has a positive and significant response when passive investing increases. The explanation is similar to one of the efficiencies. When uninformed investors switch to indexing, relatively more informed investors trade on a micro level that decreases noise factor in prices. The reduction in noise factor indeed

Table 4.

Relations between factors and micro, macro informativeness.

This table shows how factors explain the informativeness measure and coefficients calculated from the regression*:*

$$Informativeness = \alpha + \beta_1 PIM_{t-1} + \beta_2 \Delta Turnover_{t-1} + \beta_3 Households\ Share_{t-1} + \beta_4 Financial\ Uncertainty_{t-1} + \beta_5 Sentiment_{t-1} + \beta_6 \Delta Number\ of\ Firms_t + \varepsilon_t.$$

Informativeness measure is calculated from our base model as R2. PIM is a measure of passive investing, as explained by Bhattacharya and Galpin (2011). $\Delta Turnover$ measure is a quarterly change in stock market turnover. Households Share is a proxy of direct investor participation. Financial uncertainty is a proxy of expected volatility. Sentiment is a proxy of irrational investors participating in the market. Growth in a number of companies is a quarterly change in a number of listed companies in the US stock market. The numeration (1) – (5) resembles differences in specifications. Specifications differ by a set of factors used as independent variables. T-statistics are reported in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1)		(2)		(3)		(4)		(5)	
Factor	Micro	Macro	Micro	Macro	Micro	Macro	Micro	Macro	Micro	Macro
PIM	0.028	-0.043	0.247 **	0.021	0.000	-0.038	0.038	-0.027	0.217 *	0.011
	(0.27)	(-0.61)	(2.18)	(0.26)	(0.00)	(-0.53)	(0.41)	(-0.35)	(1.81)	(0.13)
Growth in turnover	-0.013	0.009	0.003	0.025	-0.006	0.008	-0.008	0.021	0.033	0.032
	(-0.32)	(0.28)	(0.07)	(0.72)	(-0.16)	(0.25)	(-0.19)	(0.67)	(0.64)	(0.91)
Households share	-0.744 ***	0.675 ***	-0.432 **	0.861 ***	-0.799 ***	0.688 ***	-0.740 ***	0.703 ***	-0.532 ***	0.842 ***
	(-4.64)	(5.80)	(-2.35)	(6.88)	(-5.32)	(7.03)	(-4.43)	(6.12)	(-2.83)	(7.09)
Financial uncertainty	0.049	0.118	0.033	0.092	0.067	0.113			0.092	0.107
	(0.51)	(1.53)	(0.30)	(1.11)	(0.68)	(1.47)			(0.76)	(1.31)
Sentiment	-0.561 ***	-0.266 **			-0.610 ***	-0.255 ***	-0.559 ***	-0.250 **		
	(-5.53)	(-2.58)			(-6.06)	(-2.86)	(-5.38)	(-2.20)		
Growth in number of companies	-0.103 *	0.022	-0.310 ***	-0.074			-0.113 *	-0.003		
	(-1.76)	(0.40)	(-3.05)	(-1.25)			(-1.69)	(-0.05)		

reveal the rise in price informativeness, as discussed in Broogard, Nguyen, Putnins, and Wu (2020).

The growth in turnover and financial uncertainty of the stock market does not have any significant relation between informativeness measures. However, analogous to efficiency measures, the household share variables have a positive effect on macro informativeness and adverse effect on micro informativeness. The transfer of financial assets from direct investors to fund managers reduces the noise factor on micro-level and increase micro informativeness.

At last, the sentiment of the stock market negatively influences micro and macro informativeness. As argued by Baker and Wurgler (2007), more sentiment in financial markets is associated with less informed arbitrageurs participating in the market. Thus, the negative relation between the variables assumes smaller informativeness in the presence of uninformed and irrational investors in the market.

Overall, our results conclude the opposite effects for micro and macro components that create a rising wedge through time. As argued in Garleanu, Pedersen (2019), the investors have a higher utility gain of learning information in more inefficient markets. Our findings show the evidence of higher macro inefficiency that potentially should incentivize mutual funds managers to quit stock picking and do market-timing strategies on a macro level. Stambaugh (2014) already provide evidence of mutual funds making more index-like investments than in the past. However, we observe that shift to indexing negatively impacts macro efficiency that should lead to even more investors shifting to passive investing. We believe that deviation from active to passive investing should also continue in the future.

Moreover, Bond and Garcia (2019) suggest that the effect of macro efficiency decreasing and micro efficiency increasing is self-reinforcing. The statement coincides with our results. Declining costs of passive investing incentivize uninformed investors to switch to indexing. This outcome results in lower macro efficiency but higher micro efficiency. However, as there are more opportunities to earn profit in less efficient markets, the uninformed traders that still are in active investing will be better off by switching to passive (Bond, Garcia, 2019). As uninformed investors shift to passive investing, the effect iterates itself repeatedly, and the wedge between two efficiencies continue to increase.

4.2 Small vs Large stocks

Now we turn our attention to observe the distinction of trends and levels between large and all stocks on the micro-level. We define large stocks as those constituents of the S&P 500 index that are available in our dataset at every quarter. The graphical presentation of large and all stock efficiency can be seen in Figure 4.

The efficiency of both series experiences upwards sloping trends over time. The micro efficiency of large stocks experiences drops during periods of global recessions. Interestingly, large stocks have larger inefficiencies in comparison with all stocks. This result is against the conventional idea found in most of the literature on efficiency, that large stocks are more efficient. A possible explanation for this anomaly is that small stock returns are much noisier, so it is harder to predict their returns, making small stocks artificially efficient.

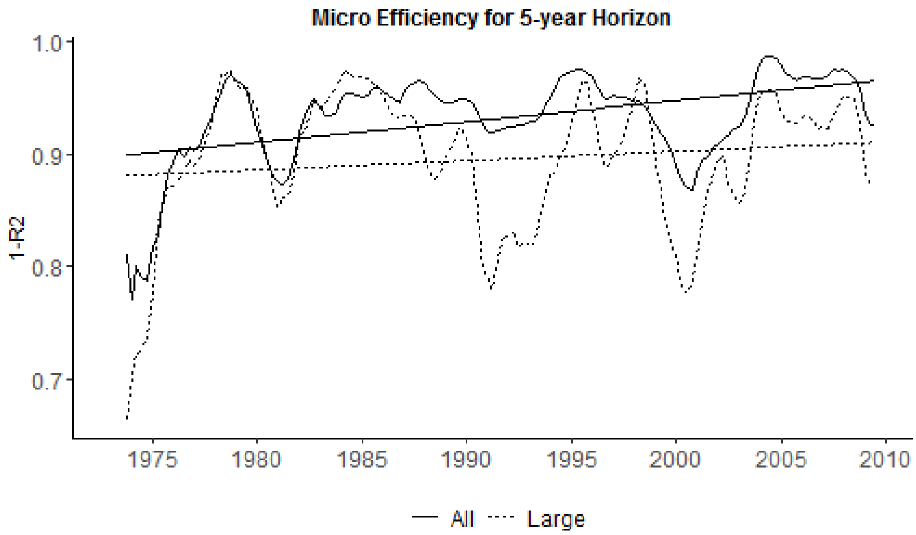

Figure 4. The comparison of large and all stock micro efficiency for the 5-year horizon.

This figure shows the times series trends and comparison of micro efficiency for a series of large (constituents of S&P 500) and all stocks. The micro efficiency is determined at every quarter using cross-sectional regressions of our base model and illustrated over time. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ from 1967 to 2018, and data is gathered from CRSP and Compustat databases.

Besides, the test of micro efficiency of large stocks illustrates a limitation that occurs in efficiency measures – the noisy returns lead to a conclusion that the market is efficient, but at the same time very small amount of information is being impounded into prices and the market is uninformative. According to Griffin, Kelly, and Nardari (2010), this limitation applies to weak-form efficiency measures (such as the one we have constructed) interpreted separately from informativeness. This particular weak-form efficiency measures' drawback emphasizes the importance of testing efficiency and informativeness jointly because separate tests might show an incomplete image of the market's microstructure.

We present the results of large and all stock informativeness in Figure 5. Large stocks show higher informativeness compared to all stock market in terms of level; nevertheless, the wedge between informativeness of large stocks and all stocks has been converging in our sample. The large companies see a decline over time while all stock market experiences rise in micro informativeness. The results do not coincide with studies investigating this topic (see, e.g., Bai, Phillipon, and Savov, 2016; Farboodi, Matray, and Veldkamp, 2018). The differences in trends might be explained by differences in data samples. Our study has a smaller data sample that does not include years from 1960-1972. When we look at the trends of Bai et al. (2016) and Farboodi et al. (2018) for the same time period as ours, we observe similar tendencies. The subsample of 1980-2013 shows that price informativeness for large firms has risen over time, which is in line with current literature.

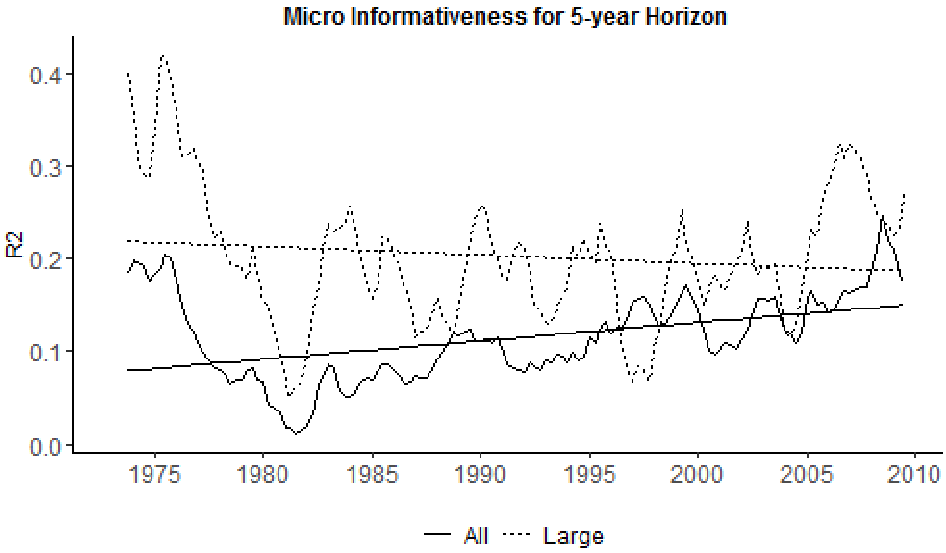

Figure 5. The comparison of large and all stock micro informativeness for the 5-year horizon.

This figure shows the times series trends and comparison of micro informativeness for a series of large and all stocks. The micro informativeness is determined at every quarter using cross-sectional regressions of our base model and illustrated over time. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ from 1972 to 2018, and data is gathered from CRSP and Compustat databases.

5. Robustness tests

To check the robustness of our results, we apply additional independent variables and different specifications of our base model. We execute three various model specifications for all regressions. The equations (10) and (11) add two additional variables to our base model for efficiency and informativeness, respectively. Both equations compose a model (2) in our regressions.

$$\left(R_{i,t+h} - R_{f,t}\right) = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{i,t} + \beta_2 log\left(\frac{P}{E}\right)_{i,t} + \beta_3 log\left(\frac{D}{P}\right)_{i,t} + \beta_4 log(CAPE)_{i,t} + \beta_5\left(R_{i,t+h} - R_{f,t}\right)_{i,t-h} + \varepsilon_{i,t} \quad (10)$$

$$\left(\frac{E}{A}\right)_{i,t+h} = \alpha + \beta_1 log\left(\frac{M}{A}\right)_{i,t} + \beta_2 log\left(\frac{P}{E}\right)_{i,t} + \beta_3 log\left(\frac{D}{P}\right)_{i,t} + \beta_4 log(CAPE)_{i,t} + \beta_5\left(\frac{E}{A}\right)_{i,t} + \varepsilon_{i,t} \quad (11)$$

, where $logCAPE_{i,t}$ is price divided by the inflation-adjusted 10-year rolling mean of earnings, and $log\left(\frac{D}{P}\right)_{i,t}$ is logarithm of total dividends/number of share outstanding divided by price.

Due to the unavailability of valid data for the new variables in the first years of the sample, we run regressions from 1984 to 2018 for a model (2).

The model (3) is identical to our base model; however, for measuring efficiency, we extract and plot Adjusted R^2 of the regression instead of simple R^2. We look at the Adjusted R^2 measure to account for the number of predictors in our model that can increase the R^2 by chance. We do the same procedure for a model (4), which is identical to model (2), but illustrate Adjusted R^2 values. The graphs of efficiency and informativeness measures are presented in Appendix C.

Persistent with our main findings, we discover the existence of Samuelson's Dictum in all additional robustness tests. We construct simple t-statistics tests to obtain statistical proof of differences in levels Appendix D. The relation of micro efficiency being larger than macro efficiency holds for all horizons and all significance levels. Model (2) and (3) illustrate macro informativeness being larger compared to micro informativeness. However, model (4) show no significant differences in levels for micro and macro informativeness. The robustness test suggests that macro informativeness is larger in the years before the 1990s, however, after that, there is no statistical evidence that it would be larger than micro informativeness.

We obtain similar outcomes, with small corrections, for interpretation of efficiency and informativeness trends over time (Appendix E). The informativeness measure shows consistent trends through all of the models. The macro informativeness is decreasing, while micro informativeness experiences a rise in all our models. For efficiency, we acquire a positive trend for 1-year horizon macro efficiency at a 5% significance level at (2) and (4) model, but still a negative and strong downward trend for a 5-year horizon. The micro efficiency trend becomes insignificant in a model (2) and (4). Our finding indicates that micro efficiency does not have any statistically significant trend effect and can be considered quite steady in the period after the 1980s.

6. Limitations and further research

There are several limitations to this study that should be mentioned. First, we use only one of the weak-form measures to determine efficiency and informativeness. The literature suggests many other potential measures (variance ratio, delay measure, unit root test, and others) to discover the informational efficiency of the market and every one of them might indicate different results. Besides, considering our current measure, many other valuation ratios could be used to explain returns and earnings, which is worth trying in future research. However, there no one generally accepted measure to define weak form of efficiency and every paper has its interpretation of it.

Second, we use a 10-year rolling window and record the efficiency and informativeness measure in the middle of the window. This construction helps us create a proxy of the market-wide measures, but it does not give us the precise efficiency for every quarter. We use 10 years of quarterly observations to produce a measure for a single quarter, which implies that the macro measures are more imprecise than micro, because for micro regressions we had thousands of firms at every quarter. Nevertheless, this limitation does not significantly influence our results, nor the conclusions drawn from them.

Trends of efficiency in our measure suggest that wedge between micro and macro efficiency will continue to increase in case of development of passive investing and delegated investment management. What is more, the decline in macro efficiency is like a trigger for investors to switch to passive, which leads to even more inefficiency on a macro level. This self-reinforcing process opens the discussion of possible negative effects of the economy, when the inefficiency of stock prices on macro-level is continuing to increase, as well as the effect on firm manager governance when a number of investors on the micro-level decline.

7. Conclusions

This research examines how efficiency and informativeness change over time in the US stock market. We explore whether there exists the phenomenon of Samuelson's Dictum that states individual stocks relative to each other are efficient, but when aggregated together, become inefficient. We determine factors that influence efficiency and informativeness on both, macro and micro level. To our knowledge, this study is the first of its kind and complements financial theories and theoretical frameworks of efficiency and informativeness.

We find statistically significant evidence that the level of micro efficiency is larger than that of macro. The effect holds for all sample period and robustness tests and validates the presence of Samuelson's Dictum. Our analysis shows that micro efficiency and informativeness improves, while macro efficiency and informativeness deteriorates over time. These trends indicate that the wedge between levels of micro and macro efficiencies are increasing over time. Previous research and theoretical models suggest trends of micro and macro components can be described by active versus passive investing activities. Our results confirm that the shift from active to passive investing positively affects micro efficiency. We also conclude that decreasing trading costs improve stock market liquidity, which consequently improves micro efficiency. Moreover, a shift from direct investor participation to delegated investment management has a negative effect on macro efficiency and informativeness.

Although the research was conducted on the US equity market for years 1972-2017, the results present much broader conclusions and are attributable to all times when functioning financial markets are present. Our results of a relatively high level of micro efficiency help to understand why even sophisticated investors struggle to find significant alphas on the individual stock level these days. At the same time, we illustrate that macro efficiency has shrunk over time, which explains the puzzle of record-high valuations during times of an inverted yield curve.

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9. Appendices

Appendix A. The efficiency and informativeness for 1- and 3- year horizons.

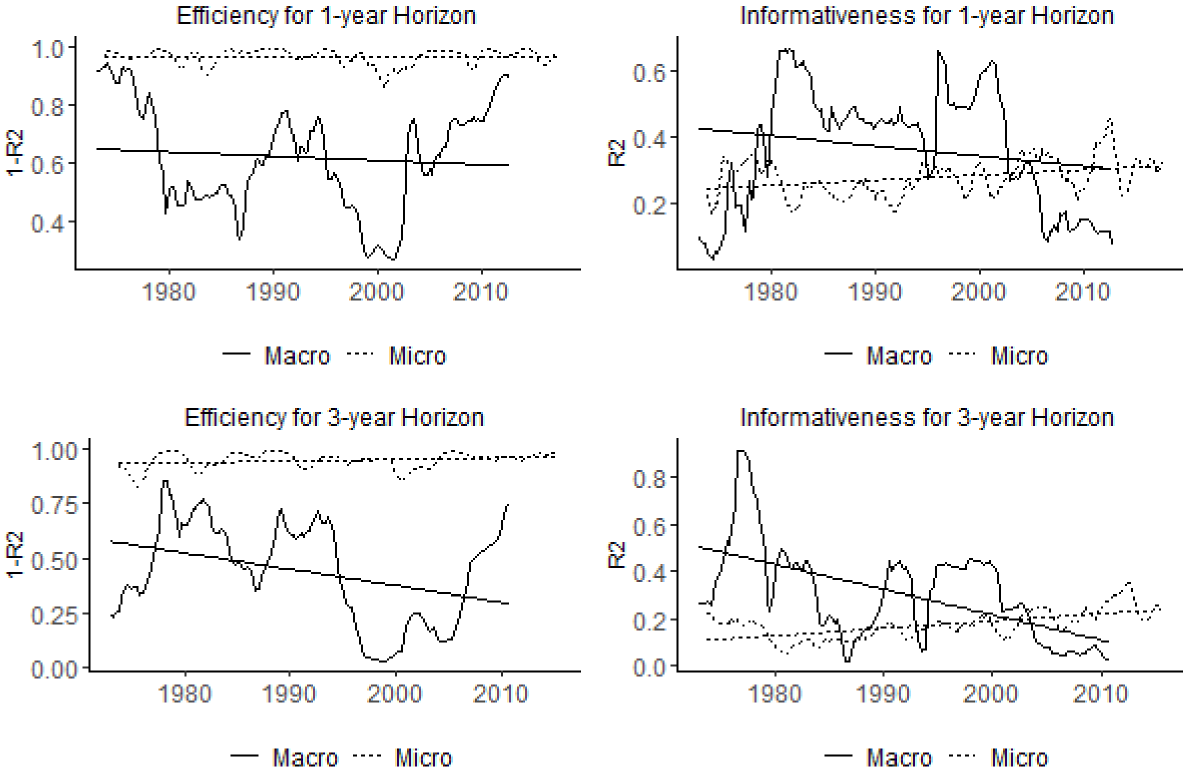


Figure 6. The efficiency and informativeness for 1- and 3- year horizons.

This figure shows the times series trends and comparison of macro and micro efficiency, as well as micro and macro informativeness. The efficiency and informativeness measures are gathered from our base model. The micro efficiency and informativeness is determined at every quarter using cross-sectional regressions of our base model and illustrated over time. Macro efficiency and informativeness is calculated at every quarter using 10-year rolling windows using aggregate values in our base model. The sample consists of stocks listed on NYSE, AMEX and NASDAQ from 1967 to 2018 and data is gathered from CRSP and Compustat databases.

Appendix B. Description of factors used to explain efficiency and informativeness

Table 5.
Description of factors used to explain efficiency and informativeness.

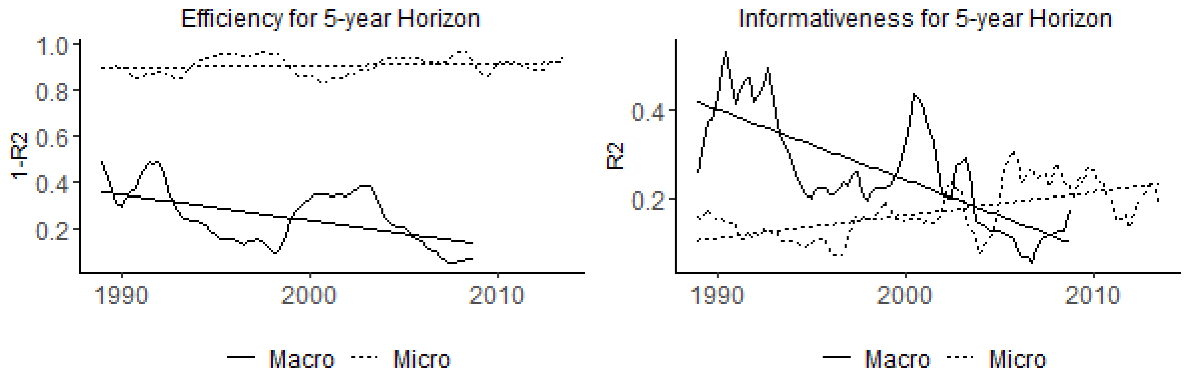
Financial uncertainty	Financial uncertainty for h=12 months ahead is a proxy of investor expectations about stock market volatility. Data is taken from the study "Measuring Uncertainty" (Jurado, Ludvigson, and Ng, 2013). The proxy consists of indicators measuring both, cross section and aggregate market, returns.
Growth in number of companies	Growth of number of companies listed in the US stock market. Data is taken from CRSP and Compustat databases.
Growth in turnover	Growth in Turnover ratio. Turnover is expressed as: $Turnover_t = \frac{\sum(Price_{i,t} \times Number\ of\ shares\ traded\ per\ quarter_{i,t})}{\sum(Market\ Capitalization_{i,t})}$ Data gathered from the CRSP database.
Households share	Variable is a proxy of direct investor participation in the market. Calculated as household investments in corporate equity divided by all sector investments in corporate equities. Data are extracted from the Federal Reserve Board database.
PIM	The passive investing measure is calculated as explained in Bhattacharya and Galpin (2011). Calculated as $PIM = e^{-\sum_t \left(w_{i,t} \times \left(ln(Turnover_{i,t}) - \sum_t \left(w_{i,t} \times ln(Turnover_{i,t})\right)\right)^2\right)}$ Data acquired from the CRSP database.
Sentiment	Sentiment index is a proxy of a share of irrational traders participating in market activities. Data is taken from Baker and Wurgler (2007) and based on the first principal component of five (standardized) sentiment proxies.

Table 6.
Descriptive statistics of the factors explaining efficiency and informativeness.
This table depicts statistics of the factors used to explain the drivers of efficiency and informativeness. Financial uncertainty and Sentiment are indexes, Growth of companies and growth of turnover are the quarterly changes in percentages of the respective variables, Households share is the share of direct investors among all investors and PIM is the proxy for passive investing. For a more detailed explanation, see Table 5.

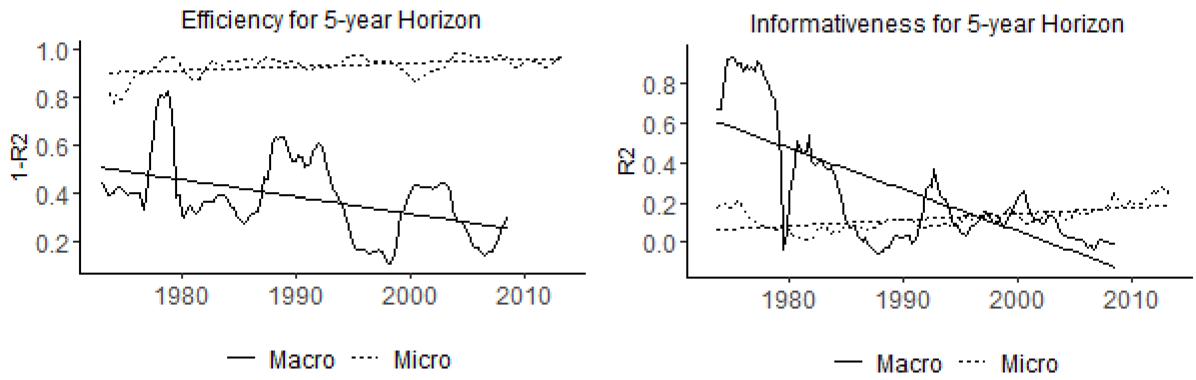
Factor	**Mean**	**Median**	**Standard deviation**	**Min**	**Max**
Financial uncertainty	0.985	0.981	0.048	0.905	1.123
Growth of companies	0.002	-0.002	0.028	-0.036	0.266
Growth of turnover	0.020	0.001	0.146	-0.548	0.804
Households share	0.461	0.444	0.096	0.348	0.726
PIM	0.576	0.592	0.074	0.387	0.709
Sentiment	0.022	0.073	0.901	-2.287	2.932

Appendix C. Graphical illustration of micro versus macro efficiency and informativeness.

Model (2)



Model (3)



Model (4)

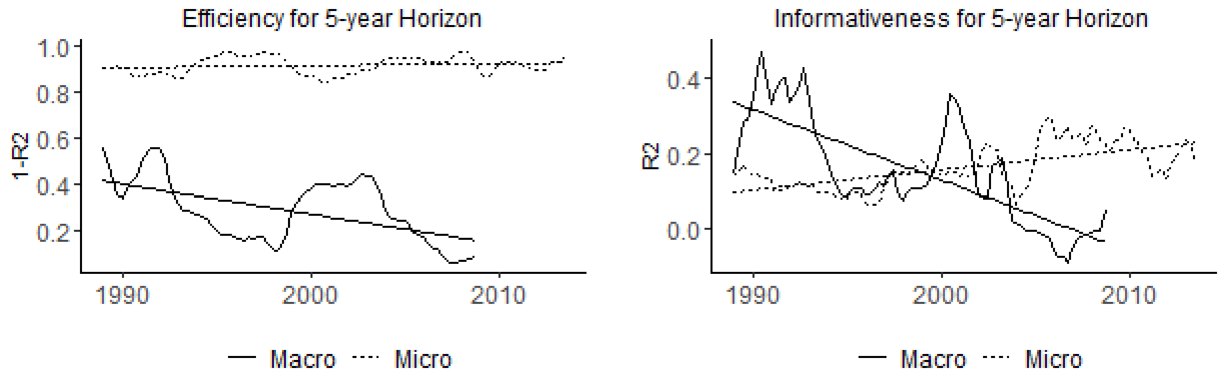


Figure 7. Comparison of micro versus macro efficiency and informativeness for 5-year horizon.

This figure shows the times series trends and comparison of macro and micro efficiency, as well as micro and macro informativeness. The efficiency and informativeness measures are gathered from our robustness models. Model (2) adds two additional independent variables (log(CAPE) and log(DP) ratios) to base model regressions. The data sample of model (2) is from 1984-2018. Model (3) is identical to the base model, but reports Adjusted R^2 instead of simple R^2. Model (4) is identical to model (2) but reports Adjusted R^2 instead of simple R^2. The micro efficiency and informativeness is determined at every quarter using cross-sectional regressions in the particular model. Macro efficiency and informativeness is calculated at every quarter using 10-year rolling windows using aggregate values in particular model. The sample consists of stocks listed on NYSE, AMEX and NASDAQ from 1967 to 2018 and data is gathered from CRSP and Compustat databases.

Appendix D. Statistical tests for comparison of micro versus macro efficiency and informativeness.

Table 7.
Levels comparison of macro versus micro efficiency, and informativeness.

This table documents mean, median, and standard deviation for different samples of efficiency and informativeness measures. The numeration (1)-(4) resembles differences in models obtaining efficiency and informativeness measure. The model (1) is our base model and is included for comparison reasons. Model (2) adds two additional independent variables (log(CAPE) and log(DP) ratios) to base model regressions. The data sample of model (2) is from 1984-2018. Model (3) is identical to the base model, but reports Adjusted R^2 instead of simple R^2. Model (4) is identical to model (2) but reports Adjusted R^2 instead of simple R^2. The last two columns report the difference between micro and macro means and the significance of the difference using a one-sided t-test. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

		Micro			**Macro**				
	Horizon	Mean	Median	Standard deviation	Mean	Median	Standard deviation	Difference	t-stat
Model (1)									
	1 year	0.97	0.98	0.03	0.62	0.62	0.18	0.35	(23.72) ***
Efficiency	3 year	0.95	0.96	0.04	0.44	0.47	0.23	0.51	(27.20) ***
	5 year	0.93	0.95	0.04	0.35	0.36	0.15	0.58	(45.95) ***
	1 year	0.28	0.28	0.06	0.37	0.43	0.18	-0.09	(-5.70) ***
Informativeness	3 year	0.18	0.18	0.06	0.30	0.27	0.20	-0.13	(-7.50) ***
	5 year	0.13	0.12	0.06	0.30	0.19	0.27	-0.18	(-7.80) ***
Model (2)									
	1 year	0.95	0.95	0.03	0.49	0.47	0.15	0.46	(30.32) ***
Efficiency	3 year	0.93	0.94	0.03	0.21	0.20	0.13	0.72	(49.71) ***
	5 year	0.92	0.92	0.04	0.25	0.24	0.12	0.66	(46.42) ***
	1 year	0.32	0.30	0.08	0.40	0.46	0.15	-0.08	(-4.47) ***
Informativeness	3 year	0.21	0.20	0.07	0.33	0.35	0.15	-0.12	(-7.04) ***
	5 year	0.16	0.15	0.06	0.26	0.23	0.12	-0.10	(-5.20) ***
Model (3)									
	1 year	0.97	0.98	0.03	0.67	0.67	0.20	0.29	(18.70) ***
Efficiency	3 year	0.95	0.96	0.04	0.47	0.51	0.25	0.48	(23.43) ***
	5 year	0.94	0.95	0.04	0.38	0.38	0.16	0.55	(40.62) ***
	1 year	0.28	0.28	0.06	0.32	0.39	0.20	-0.04	(-2.43) ***
Informativeness	3 year	0.17	0.18	0.06	0.25	0.23	0.22	-0.07	(-3.85) ***
	5 year	0.13	0.12	0.06	0.24	0.11	0.29	-0.11	(-4.62) ***
Model (4)									
	1 year	0.95	0.96	0.03	0.56	0.54	0.17	0.39	(22.68) ***
Efficiency	3 year	0.94	0.94	0.03	0.24	0.23	0.15	0.70	(41.99) ***
	5 year	0.92	0.93	0.04	0.29	0.27	0.14	0.63	(38.81) ***
	1 year	0.32	0.29	0.08	0.31	0.38	0.18	0.01	(0.44)
Informativeness	3 year	0.21	0.19	0.07	0.23	0.25	0.17	-0.02	(-1.23)
	5 year	0.16	0.14	0.06	0.15	0.11	0.14	0.01	(0.41)

Appendix E. Trends of efficiency and informativeness measures

Table 8.
Trends of efficiency and informativeness measures.

This table shows the coefficients calculated from the regression*:*

$$Measure = \alpha + \beta_1 \; TimeTrend + \varepsilon_t \; .$$

The numeration (1)-(4) resembles differences in models obtaining efficiency and informativeness measure. The model (1) is our base model and is included for comparison reasons. Model (2) adds two additional independent variables (log(CAPE) and log(DP) ratios) to base model regressions. The data sample of model (2) is from 1984-2018. Model (3) is identical to the base model but reports Adjusted R^2 instead of simple R^2. Model (4) is identical to model (2) but reports Adjusted R^2 instead of simple R^2. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Measure	***Horizon***	***(1)***		***(2)***		***(3)***		***(4)***	
Macro Efficiency	*1 year*	-0.3640		1.6592	**	-0.3943		1.9032	*
	3 year	-1.8700	**	-1.1547		-2.0258	**	-1.3245	
	5 year	-1.6147	***	-2.9393	***	-1.7492	***	-3.3715	***
Micro Efficiency	*1 year*	-0.0188		-0.0452		-0.0257		-0.0604	
	3 year	0.1949	**	0.0375		0.1842	*	0.0208	
	5 year	0.4002	***	-0.0312		0.3858	***	-0.0486	
Macro informativeness	*1 year*	-0.7619		-3.9324	***	-1.0963		-4.5107	***
	3 year	-2.6555	***	-4.4264	***	-3.0858	***	-5.0773	***
	5 year	-4.6764	***	-3.8254	***	-5.1879	***	-4.3880	***
Micro informativeness	*1 year*	0.3952	***	1.1549	***	0.4002	***	1.1715	***
	3 year	0.7836	***	1.0843	***	0.7900	***	1.1045	***
	5 year	0.7602	***	1.0246	***	0.7680	***	1.0463	***