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UNVEILING THE COVID-19 SHOCK: ITS INFLUENCE ON BETAS AND THE SECURITY MARKET LINE—A CAPM ANALYSIS of DOW JONES 30 IIS

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Abstract

The most well-known, broadly adopted, and frequently applied asset pricing model is the capital asset pricing model (CAPM). Sharpe (1964), Lintner (1965), and Mossin (1966) independently created the model. Prior to their discovery, there were no asset pricing models constructed from the ground up with unambiguous predictions that are testable about risk and return and the nature of preferences and investment opportunities. Additional improvements were suggested by Fama (1968), Black, Jensen, and Scholes (1972), Fama and Mac Beth (1973), Fama and French (1992), and others. The link between an asset's risk and expected return is precisely predicted by the CAPM. In applications including calculating a firm's cost of equity capital and assessing the managed portfolios' performance, the CAPM is still frequently employed even after 60 years. The wide use of CAPM is directly related to its clear logic and satisfying predictions on measuring the risk and about the risk and return trade-off. Although the model exhibits weak empirical results,it is employed in practical applications due to its simplicity. In this study, we tested if the CAPM works in practice to estimate the relationship between the expected return and the risk by using the monthly prices between 1/12/2016 and 1/12/2021 on the securities of Dow Jones Industrial Index (Dow-30). Also, it is tested whether Security Market Line (SML) holds for individual securities.

Anahtar Kelimeler: Asset Pricing Theory, CAPM, Alfa and Beta Estimation, Diversification, Risk.

COVID-19 ŞOKUNUN ORTAYA ÇIKARILMASI: BETALAR VE MENKUL KIYMET PİYASASI ÇİZGİSİ ÜZERİNDEKİ ETKİSİ - DOW JONES 30 IIS'NİN CAPM ANALİZİ

Öz

En iyi bilinen, geniş çapta benimsenen ve sıklıkla uygulanan varlık fiyatlandırma modeli sermaye varlıklarını fiyatlandırma modelidir (CAPM). Sharpe (1964), Lintner (1965) ve Mossin (1966) bağımsız olarak bu modeli oluşturmuşlardır. Onların keşfinden önce, risk ve getiri ile tercihlerin ve yatırım fırsatlarının doğası hakkında test edilebilir kesin tahminlere sahip, sıfırdan inşa edilmiş bir varlık fiyatlama modeli yoktu. Fama (1968), Black, Jensen ve Scholes (1972), Fama ve Mac Beth (1973), Fama ve French (1992) ve diğerleri tarafından ilave iyileştirmeler önerilmiştir. Bir varlığın riski ile beklenen getirisi arasındaki bağlantı CAPM tarafından tam olarak tahmin edilmektedir. Bir firmanın öz sermaye maliyetinin hesaplanması ve yönetilen portföylerin performansının değerlendirilmesi gibi uygulamalarda CAPM, 60 yıl sonra bile hala sıklıkla kullanılmaktadır. CAPM'in yaygın kullanımı, açık mantığı ve riskin ölçülmesi ile risk ve getiri ödünleşimine ilişkin tatmin edici öngörüleri ile doğrudan

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ilişkilidir. Modelin ampirik sonuçları zayıf olmasına rağmen, basitliği nedeniyle pratik uygulamalarda kullanılmaktadır. Bu çalışmada, Dow Jones Sanayi Endeksi (Dow-30) menkul kıymetlerinin 1/12/2016 ve 1/12/2021 tarihleri arasındaki aylık fiyatları kullanılarak CAPM'in beklenen getiri ve risk arasındaki ilişkiyi tahmin etmek için pratikte çalışıp çalışmadığı test edilmiştir. Ayrıca, Menkul Kıymet Piyasası Doğrusu'nun (SML) bireysel menkul kıymetler için geçerli olup olmadığı test edilmiştir.

Anahtar Kelimeler: Varlık Fiyatlama Teorisi, CAPM, Alfa ve Beta Tahmini, Çeşitlendirme, Risk.

Introduction

The Capital Asset Pricing Model (CAPM) aims to measure whether the current price of a stock is consistent with its potential return. Assessing the risk of an asset is the process of calculating its expected return. It is to evaluate whether a stock's risk and the time value of money are fairly evaluated when compared to its expected return. The expected return of the CAPM formula is used to discount the stock's expected dividends and capital gains over the expected holding period. Modern finance theory is based on two assumptions: The competitive stock market includes risk-averse investors who aim to maximize their returns from their investments. Eugene Fama and Kenneth French found that the betas of stock returns on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the Nasdaq are different. In other words, CAPM does not explain the performance of stocks. This study is focused on the theoretical model of CAPM which is developed for asset pricing in an efficient market. The model is seen as an extension of Markowitz Model, and it is a single-factor linear equilibrium pricing model that enables the financial analysts to price risky assets under market equilibrium. In the pricing of securities, the CAPM theory enables a risk-averse investor to focus on systematic risk or market risk with higher attention where the non-systematic or firm-specific risk can be diversified away.

The basic structure of CAPM theory is constructed by Markowitz, Sharpe, Mossin and Lintner. The CAPM introduces the relationship between the expected return and market risk of the securities. The model is commonly used in finance in order to price the risky assets, for a given level of risk, and to produce expected return for those risky assets.

Literature Rewiev

The literature history of the classical CAPM is very new. The literature focuses on data from developed countries such as the US and the UK. Mostly, the ability of CAPM to adequately price financial securities has been examined. These studies are studies that fail to establish the relationship between stock beta and excess return. Michailidis et al. (2006) tested the model using Greek stock market data. According to the results of the research, they found that there is no linear relationship between beta and excess stock return. The same results were confirmed in a study on the Indian stock market. Choudhary and Choudary (2010). They worked on the Romanian stock market. In the tests conducted by Trifan (2009), it was found that stock returns did not have the suggested relationship. It is difficult for these data taken during crisis times to give healthy results. Perković (2011) tested CAPM on Croatian stock market data between 2000-2010. He stated that CAPM is not suitable for the Croatian stock market. Minović and Živković (2010) found that the LCAPM outperformed the standard CAPM in predicting stock returns during the period 2005-2009. Acheampong and Agalega (2013) investigated the CAPM in the Ghanaian stock market and examined the applicability of the CAPM in explaining the stock risk-return relationship. They found that the CAPM was not a suitable model in the Ghanaian stock market during the period January 2006 to December 2010, which coincided with the subprime mortgage crisis, indicating that it is not a valid model to explain stock returns. Setyowati (2010) examined whether the CAPM was suitable by analyzing 213 companies and using stock return data in the Indonesian stock market between 2004-2009. They concluded that the CAPM was not a valid model for explaining the stock returns of the Indonesian stock market. In Türkiye, Gursoy and Rejepova (2007) found no significant relationship between beta and stock return in the Turkish stock market during the period 1995-2004. Bilgin and Basti (2011) reported an insignificant beta-return relationship in the Istanbul Stock Exchange. Demircioglu (2015) examined data from 2012 to 2013 in the cement sector in Türkiye and found that the model yielded modest results in several developed markets. The same model failed in developing markets (Karakoc, 2016).

According to Shah (2015), an asset's required return has a direct or linear relation with the sensitivity coefficient (beta) of the asset. The CAPM assumes that the market is efficient and in equilibrium, and that for a given level of risk, the expected return of the security is equal to its required rate of return.

Sharpe (1964) ascribes that if the typical investor constructs a portfolio according to the basic principles of diversification ,where the security prices are adjusted, then the investor will be able to achieve any desirable point on Capital Market Line under equilibrium conditions. According to Mossin, market equilibrium requires prices to beat a level where each investor holds the identical weight of the total portfolio including all risky assets.

Rossi (2016) states that the CAPM is a practical instrument on forecasting the security cost of capitals and rate of returns when an investor decides to invest in the stocks of a firm. This model demonstrates the relationship between the risks and the returns of securities by measuring the covariance of the rate of returns with respect to the market's overall rate of returns as an indication of risk. The main prediction of CAPM indicates that the expected rate of return on two individual securities is linearly related with the covariance of the rate of returns with respect to market portfolio's rate of returns. The total risk of each security is decomposed into two components which are classified as firm-specific risk or non-systematic risk and market risk or systematic risk. Empirical studies from the 1970s show that most of the variation in returns predicted by the Black version of the CAPM cannot be attributed to market beta. Basu (1977) provided evidence that when common stocks are ranked by their earnings-to-price ratios, the future returns of high E/P stocks are higher than those predicted by the CAPM.

Banz (1981) finds that when stocks are ranked (price times shares outstanding), the average returns of small stocks are higher than those predicted by the CAPM. Bhandari (1988) finds that high debt-to-equity ratios are associated with very high returns relative to their market betas.

Statman (1980) and Rosenberg, Reid, and Lanstein (1985) document that stocks with high book-to-market ratios (B/M, the ratio of a common stock's book value to its market value) have high average returns that are not captured by their betas.

Lipson *et al*. (2011) refute Fama and French's (2008) conclusion that the investment effect exists only in small firms. Fama and French's investment measure excludes the part of asset growth related to equity issues, which is a major source of financing for large firms. Also, the investment effect is stronger in firms with high idiosyncratic volatility and is concentrated around earnings announcement dates.

Titman *et al*. (2004) study the investment effect in international markets and find that it is stronger in countries with more developed markets than in countries with less developed markets. This evidence lends support to the investment CAPM because financial market development aligns managers' incentives with shareholders', and the investment effect arises from maximising the shareholder value.

The model introduces a methodology to quantify the risk and express it into expected return estimates. The CAPM's main advantage is that it provides an objective nature for the security's estimated costs that can be yielded by the model. It is widely used by the financial analysts as a supplement for other methods and enables them in developing rationale, useful and realistic calculations on cost of the security.

According to Adeyeye (2009), the CAPM theory is based on the following underlying principles:

i. Investors are risk-averse and attempt to maximize the expected utility at the end of their wealth period. This premise implicitly tells us that the model is established as a one-period model.
ii. Investors are price takers, and they expect the returns of securities to be normally distributed.
iii. Investors can lend or borrow unlimited amounts of risk-free asset at a risk-free rate.
iv. The number of the securities are constant, and all these securities are accepted as perfectly divisible and marketable.
v. There are some restrictions on investments which can be neglected. The data is available and costless for all investors.
vi. There is not any investor capable of affecting the market price of a security since the market is highly efficient.

Hou et al. (2016) compare the q-factor model with the Fama-French five-factor model on empirical grounds. To make the sample comparable to Fama and French (2015), who start their sample in July 1963, Hou et al. extend the sample for the q-factors backward to January 1967.

Investors always need to be compensated for risks and the money' time value. Hodnett (2012) presents that CAPM theory is established on the concept that non-systematic or firm-specific risk can be diversified away, and the only expectation of the investors is to be compensated against the impacts of systematic or market risk.

Black (1972) states that the traditional form of CAPM tells us that the expected excess return of a security is equal to its systematic risk level, beta, times the market portfolio's expected excess return. The following formula is used in calculations of the expected return of a risky asset for a given level of risk:

$$E(R_i) = \beta_i \left(ER_m - R_f\right) \qquad \textbf{(1)}$$

where;

$E(R_i)$ = expected return of security

R_f = risk-free rate

β_i = beta of the security

$(ER_m - R_f)$ = market risk premium

In CAPM, the risk-free rate used in the formula stands for money' time value. The other parameters in the formula considered as an additional risk-taking of the investor. The beta shows us the sensitivity of the security to the movements in the market. If the security is riskier with respect to the market trend, then it will have a beta (sensitivity coefficient) that is greater than one. When the beta is less than one for a stock, the risk of a portfolio will decline according to the formula. Then beta of security is multiplied by the risk premium of the market and risk-free rate is added in order to find the expected return of the security. The objective of the formula of the CAPM is to evaluate if a particular security is fairly valued with respect to its time value of money and risk, compared with its expected return.

According to Blume and Friend (1973), the CAPM is an *ex-ante* model which is introduced solely in terms of investor expectations and a transition into an *ex-post* model should be conducted in order to test it by specifying process on return generation. Early tests performed in CAPM theory presented that higher rate of returns on stocks were usually associated with higher beta values of the stocks. These empirical results were accepted as evidence to support the CAPM, while other results contradicted the model for not being a fully adequate asset pricing model as these have not people's confidence and will for CAPM in the theoretical level.

According to Hawadar (2011), after performing the aggregation of demands and market clearing, the relationships between the securities' expected returns derived under the equilibrium shown that, as a contradiction to the classical CAPM theory, the expected returns on risky securities may vary from the risk-free rate where there is no systematic or market risk.

A recent qualitative study by Bannerjee, Pillai, Tabash, and Al-Absy (2025) highlights the limitations of expert-driven sampling and the need for diversified methodologies—such as longitudinal designs and machine learning-based volatility modeling—to better capture asset behavior under macroeconomic shocks and geopolitical uncertainty. Their findings also emphasize the evolving role of gold and bitcoin in dynamic portfolio strategies, especially in high-volatility regimes.

O'Donnell, Shannon, Sheehan, and Ashraf (2024) demonstrate that the Fama–French Five-Factor Model retains explanatory power even under pandemic-induced volatility, with notable shifts in SMB and HML dynamics across sectors. Their findings suggest that multi-factor frameworks offer greater resilience than single-factor models like CAPM, especially when markets face systemic disruptions and investor preferences pivot toward value and quality.

Shahzad, Si Mohammed, and Karimi (2025) reveal that dynamic connectedness between corporate bonds, oil prices, and uncertainty indices such as VIX and GPR intensifies during periods of geopolitical tension and economic stress. Their findings underscore the asymmetric nature of shock transmission and highlight the need for adaptive modeling frameworks—especially when traditional asset pricing models like CAPM fall short in capturing systemic interdependencies under crisis conditions.

Lebdaoui, Kiyadi, Bendriouch, Chetioui, Lebdaoui, and Alhayki (2025) provide compelling evidence that stock market volatility in the MENA region during the COVID-19 crisis was significantly shaped by the interplay between government stringency measures, economic resilience, and corporate governance structures. Their integrated framework highlights how institutional strength and policy calibration can mitigate the destabilizing effects of pandemic-induced uncertainty—an insight that complements critiques of CAPM's limited explanatory power under systemic stress.

Rubbaniy, Khalid, Syriopoulos, and Polyzos (2025) demonstrate that asset contagion and volatility spillovers intensify during health and geopolitical crises, with soft commodities and cryptocurrencies emerging as effective hedging tools. Their findings challenge traditional portfolio construction logic and highlight the need for adaptive strategies—especially when single-factor models like CAPM fail to capture dynamic interdependencies across asset classes.

Ben Dor, Florig, Guan, and Zeng (2021) argue that the COVID-19 crisis fundamentally reshaped the beta landscape, rendering historical calibrations unreliable and exposing the limitations of static risk models like CAPM. Their findings emphasize the need for dynamic beta management and sector-aware portfolio optimization, especially during systemic shocks when traditional low-volatility assets may paradoxically become high-risk exposures.

Louraoui (2023) demonstrates that equity factor volatility during the COVID-19 crisis exhibited clustering patterns best captured by GARCH(1,1) models, with Minimum Volatility showing resilience and Momentum and Value factors experiencing heightened instability. His findings reinforce the need for dynamic volatility modeling and real-time portfolio adaptation—especially when traditional frameworks like CAPM fail to reflect the nuanced behavior of style-based returns under macroeconomic shocks.

Jain (2022) finds that beta coefficients surged during the first wave of COVID-19, particularly in consumer goods, infrastructure, insurance, and IT sectors, while energy industries remained relatively stable. Her results also reveal positive abnormal residual returns across both waves, suggesting that CAPM may understate sector-specific risk dynamics during pandemic-induced volatility.

Yaqub (2022) identifies a long-run equilibrium relationship between the DJIA index and key U.S. macroeconomic variables—such as money supply, interest rate, inflation, and unemployment—using Johansen cointegration and VECM analysis. His findings underscore the importance of monetary policy calibration during crises like COVID-19, and highlight the limitations of static asset pricing models like CAPM in capturing macroeconomic sensitivities.

Boru İpek (2023) demonstrates that hybrid modeling techniques significantly enhance stock price prediction accuracy across pre- and post-COVID-19 periods, achieving mean absolute percent errors below 0.131 even under volatile conditions. Their findings highlight the limitations of traditional models like CAPM in forecasting during systemic disruptions and underscore the value of adaptive, data-driven approaches.

Soltani and Boujelbène Abbes (2022) show that financial stress regimes—bullish, bearish, and calm—exert distinct influences on stock market returns in the MENA region, with turbulent events like COVID-19 and the Arab Spring amplifying volatility across all states. Their Hidden Markov Model analysis reveals that regime persistence and transition probabilities vary significantly by country, challenging the static assumptions of CAPM and underscoring the need for regime-sensitive investment strategies.

Methodology

The standard testing method in the CAPM model is two-pass regression, where the portfolio has been built, based on the betas of the stocks. The goal of the first-pass regression was to estimate each security's beta by using the Ordinary Least Squares Methods. The securities have been sorted accordingly into portfolios based on their betas. Hypotheses tests and other econometrical tests were used in the second-pass regression because it was a cross-sectional regression.

On the first pass regression, β_i = cov (r_i, r_m)/ var(r_m) equation was used for calculation of the stock betas for the 29 companies. In order to formulate the regression equation, the expected return of each stock has been calculated corresponding to the stock beta at the same time. The expected return of each stock was calculated by taking the average of the stock's 60-month return.

Since it has been ranked the beta and average monthly returns in the first pass regression, cross-sectional regression was executed by using the CAPM model equation to observe and analyze the statistical properties resulted.

The selected time frame of 2016–2021 offers a coherent and analytically sound window that captures both pre-pandemic market behavior and the systemic shock induced by COVID-19. This period was deliberately chosen to enable a comparative assessment of the CAPM model's performance under normal versus crisis conditions. Post-2021 data were excluded because they primarily reflect the recovery phase and policy normalization, rather than the acute impact of the pandemic itself.

Moreover, ending the dataset in late 2021 helps preserve statistical integrity and avoids excessive heterogeneity. The post-pandemic market dynamics—shaped by central bank interventions, liquidity expansions, and regulatory shifts—introduce structural changes that diverge from the foundational assumptions of the CAPM framework. To isolate the direct effects of the COVID-19 shock, the study confines its scope to the period ending in 2021.

Future research may extend the analysis to include post-2022 data in order to examine the long-term implications of the recovery phase on asset pricing models. However, the current study's objective is to evaluate the immediate and direct impact of the pandemic on market behavior, making the selected time frame both methodologically justified and aligned with the research question.

Collection of the Data

S&P 500 index was considered as a proxy for market portfolio, but it is surely not a true market portfolio, as including of every single security is practically impossible. Sample data used in the study consists of only 29 companies in Dow Jones Industrial Index observed over a 60-month period. Even though the efforts to avoid survivorship bias by using companies from various industries and market sizes, there may be some errors to be arised. Prices were collected for first trading day of each month. One of stock prices DOW was removed in the calculations since it was started by 2019. All stock prices and index prices have been collected from Eikon as adjusted closing prices for time interval started from 1.12.2016 to 1.12.2021. 61 stock prices have retrieved for 29 stocks and SP 500 index. The Capital Asset Pricing Model considered the expected return on individual securities by using the S&P 500 index as a market proxy.

Return index has been calculated and proposed instead of a traditional price index. Dividends and splits are ignored when calculating returns as the close prices have already been adjusted for them. The return index was calculated by using the following formula:

$$r_{i,t} = ln(\frac{price_{i,t}}{price_{i,t-1}}) \quad \textbf{(2)}$$

By this method, returns of those stock for each month get more normally distrubuted. 2 year benchmark has also been collected monthly for T-bond rates of the United States to test the CAPM model coefficients. Those benchmark rates have also collected from Eikon. For 60 month period, Apple has the highest average return with 2,99 % where S&P 500 index average return was 1,2 %. Microsoft, Salesforce and Nike stocks followed Apple stock with returns 2,86 %, 2,17 % and 2,17 % average respectively. Chevron, 3M, IBM and Wallgreens stocks have negative average return for the observed 60 months period.

Findings

After calculating average monthly returns by using the data located in Table 1., "first pass regression" and "second pass regression" studies have been executed in order to test the consistency of the CAPM model on the collected data.

Table 1. *Average Monthly Returns for Stocks and S&P 500 Index*

Index and Stocks	*Average Monthly Return*	*Index and Stocks*	*Average Monthly Return*
Apple Inc	2,99%	Procter & Gamble Co	0,97%
Microsoft Corp	2,86%	Goldman Sachs Group Inc	0,85%
Salesforce Inc	2,17%	Intel Corp	0,61%
Nike Inc	1,99%	Walt Disney Co	0,60%
Home Depot Inc	1,88%	Johnson & Johnson	0,58%
United Health Group Inc	1,69%	Amgen Inc	0,57%
Visa Inc	1,54%	Coca-Cola Co	0,44%
American Express Co	1,21%	Merck & Co Inc	0,42%
McDonald's Corp	1,21%	Travelers Companies Inc	0,39%
S&P 500 Index	*1,20%*	Boeing Co	0,35%
Caterpillar Inc	1,15%	Verizon Communications Inc	0,00%
Walmart Inc	1,10%	Chevron Corp	-0,02%
JPMorgan Chase & Co	1,10%	3M Co	-0,02%
Cisco Systems Inc	1,04%	International Business Machines Corp	-0,44%
Honeywell International Inc	1,01%	Walgreens Boots Alliance Inc	-1,09%

This table presents the average monthly returns of the 29 constituent stocks of the Dow Jones Industrial Average, alongside the S&P 500 index, over a 60-month period. It serves as a descriptive summary of return performance across firms and highlights the disparities in average returns, offering a basis for further risk-return analysis in the CAPM framework.

For each stock the first pass regression calculated as follow,

$$r_{i,t} = \alpha_i + \beta_i r_{SP,t} \tag{3}$$

by using the regression module on excel the results have been produced for each stock and S&P 500 index. Also calculated the coefficeints, α, β and R^2 by using of the slope, intercept and Rsq functions to test and assure the consistency with the results where all found same and accurate.

According to first pass regression results based on formula (3), Boeing has the highest beta with 1,9477 as Goldman Sachs Group and American Express follows with 1,4621, 1,3639 respectively in 60 monts periodin spite of being the most aggressive stocks according to beta.

Value, average returns of Boeing is 0,35 very low respective to other stocks return. This can be explained by covid-19 pandemic since effect worstly airline stock in that period.

Table 2. *First Pass Regression's Results*

Index and Stocks	*Average Monthly Return*	*Beta*	*Alpha*	*Index and Stocks*	*Average Monthly Return*	*Beta*	*Alpha*
Boeing Co	0,35%	1,9477	-0,0199	Caterpillar Inc	1,15%	0,8753	0,0009
Goldman Sachs Group Inc	0,85%	1,4621	-0,0091	Microsoft Corp	2,86%	0,8685	0,0182
American Express Co	1,21%	1,3639	-0,0043	UnitedHealth Group Inc	1,69%	0,8589	0,0066
Apple Inc	2,99%	1,2663	0,0147	3M Co	-0,02%	0,8512	-0,0104
Chevron Corp	-0,02%	1,2655	-0,0154	Cisco Systems Inc	1,04%	0,8168	0,0006
Salesforce Inc	2,17%	1,2263	0,0069	Coca-Cola Co	0,44%	0,7510	-0,0046
JPMorgan Chase & Co	1,10%	1,2096	-0,0036	Johnson & Johnson	0,58%	0,6830	-0,0024
Honeywell International Inc	1,01%	1,0385	-0,0024	McDonald's Corp	1,21%	0,6761	-0,0046
Home Depot Inc	1,88%	1,0290	0,0064	Intel Corp	0,61%	0,6119	-0,0013
International Business Machines Corp	-0,44%	1,0156	-0,0167	Walgreens Boots Alliance Inc	-1,09%	0,6051	-0,0182
Walt Disney Co	0,60%	1,0143	-0,0062	Merck & Co Inc	0,42%	0,5287	-0,0022
S&P 500 Index	**1,20%**	**1,0000**	**0,0000**	Amgen Inc	0,57%	0,5283	-0,0006
Visa Inc	1,54%	0,9901	0,0035	Walmart Inc	1,10%	0,4796	0,0053
Travelers Companies Inc	0,39%	0,8863	-0,0068	Verizon Communications Inc	0,00%	0,3602	-0,0044
Nike Inc	1,99%	0,8818	0,0092	Procter & Gamble Co	0,97%	0,3548	0,0054

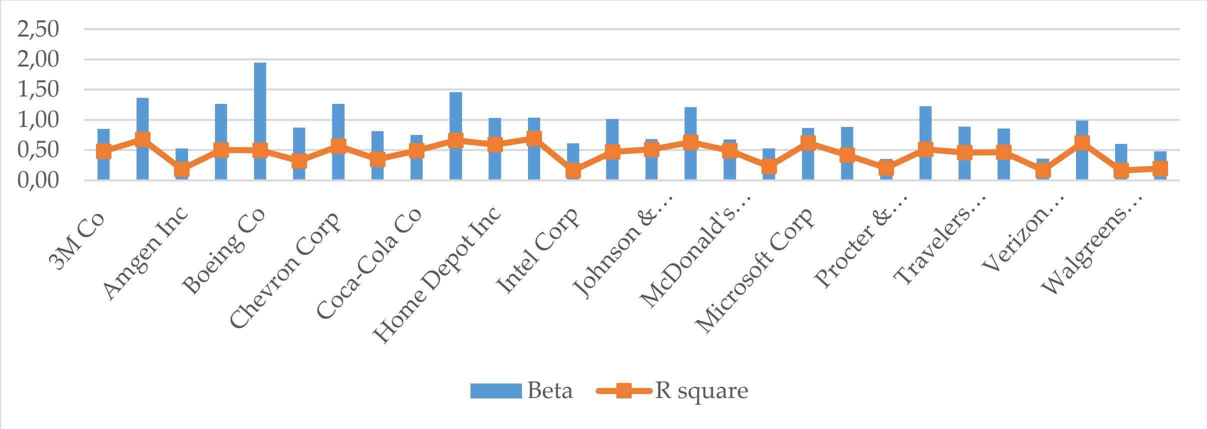
According to first pass regression results, all of the stocks have significant betas at 95% confidence interval. have beta are significant. But only 3 stocks alpha is statistically significant. This table displays the outcomes of the first-pass regression, where individual stock returns were regressed against market returns (S&P 500 index) to estimate their beta and alpha coefficients. These values are critical for measuring systematic risk and evaluating the stock's relative sensitivity to market movements.

Table 3. *Significance of Alphas and Betas*

Index and Stocks	*Beta*	*Significance of Beta at 5%*	*Alpha*	*Significance of Alpha at 5% confidence interval*	*Index and Stocks*	*Beta*	*Significance of Beta at 5% confidence interval*	*Alpha*	*Significance of Alpha at 5% confidence interval*
Boeing Co	1,9477	Significant	-0,0199	Insignificant	Caterpillar Inc	0,8753	Significant	0,0009	Insignificant
Goldman Sachs Group Inc	1,4621	Significant	-0,0091	Insignificant	Microsoft Corp	0,8685	Significant	0,0182	Significant
American Express Co	1,3639	Significant	-0,0043	Insignificant	UnitedHealth Group Inc	0,8589	Significant	0,0066	Insignificant
Apple Inc	1,2663	Significant	0,0147	Insignificant	3M Co	0,8512	Significant	-0,0104	Insignificant
Chevron Corp	1,2655	Significant	-0,0154	Significant	Cisco Systems Inc	0,8168	Significant	0,0006	Insignificant
Salesforce Inc	1,2263	Significant	0,0069	Insignificant	Coca-Cola Co	0,7510	Significant	-0,0046	Insignificant
JPMorgan Chase & Co	1,2096	Significant	-0,0036	Insignificant	Johnson & Johnson	0,6830	Significant	-0,0024	Insignificant
Honeywell International Inc	1,0385	Significant	-0,0024	Insignificant	McDonald's Corp	0,6761	Significant	-0,0046	Insignificant
Home Depot Inc	1,0290	Significant	0,0064	Insignificant	Intel Corp	0,6119	Significant	-0,0013	Insignificant
International Business Machines Corp	1,0156	Significant	-0,0167	Significant	Walgreens Boots Alliance Inc	0,6051	Significant	-0,0182	Insignificant
Walt Disney Co	1,0143	Significant	-0,0062	Insignificant	Merck & Co Inc	0,5287	Significant	-0,0022	Insignificant
S&P 500 Index	**1,0000**		**0,0000**		Amgen Inc	0,5283	Significant	-0,0006	Insignificant
Visa Inc	0,9901	Significant	0,0035	Insignificant	Walmart Inc	0,4796	Significant	0,0053	Insignificant
Travelers Companies Inc	0,8863	Significant	-0,0068	Insignificant	Verizon Communications Inc	0,3602	Significant	-0,0044	Insignificant
Nike Inc	0,8818	Significant	0,0092	Insignificant	Procter & Gamble Co	0,3548	Significant	0,0054	Insignificant

Table 3 shows the statistical significance of the beta and alpha coefficients obtained from the first-pass regression. Betas were tested at a 95% confidence level to assess their explanatory power regarding market-related risk, while alphas were evaluated for any consistent excess returns independent of market performance.

Graph 1. *Beta and R-Squared for Each Stock as Regressed on S&P 500*



By using of first-pass regreesion results on average the S&P 500 describes about 43 % of the variation of 29 stocks, with an average beta of 0,91. If the stocks with R^2 smaller than 0,3 excluded, the S&P 500 describes almost 51% of the variation in stocks return with an average beta 1,04.

Table 4. *R^2 for Each Stocks After First Pass Regression*

Index and Stocks	*Beta*	*Alpha*	*R square*	*Index and Stocks*	*Beta*	*Alpha*	*R square*
Honeywell International Inc	1,0385	-0,0024	0,691043925	3M Co	0,8512	-0,0104	0,483105929
American Express Co	1,3639	-0,0043	0,676963628	International Business Machines Corp	1,0156	-0,0167	0,46865555
Goldman Sachs Group Inc	1,4621	-0,0091	0,660496959	UnitedHealth Group Inc	0,8589	0,0066	0,466319109
JPMorgan Chase & Co	1,2096	-0,0036	0,628693254	Travelers Companies Inc	0,8863	-0,0068	0,461113376
Visa Inc	0,9901	0,0035	0,61750954	Nike Inc	0,8818	0,0092	0,42042085
Microsoft Corp	0,8685	0,0182	0,617381551	Walt Disney Co	1,0143	-0,0062	0,410979862
Home Depot Inc	1,0290	0,0064	0,59184252	Cisco Systems Inc	0,8168	0,0006	0,351814523
Chevron Corp	1,2655	-0,0154	0,565081916	Caterpillar Inc	0,8753	0,0009	0,325163483
Salesforce Inc	1,2263	0,0069	0,511877448	Merck & Co Inc	0,5287	-0,0022	0,234413345
Johnson & Johnson	0,6830	-0,0024	0,510648821	Procter & Gamble Co	0,3548	0,0054	0,204841463
Apple Inc	1,2663	0,0147	0,500634733	Walmart Inc	0,4796	0,0053	0,198387306
Boeing Co	1,9477	-0,0199	0,49788092	Amgen Inc	0,5283	-0,0006	0,182636868
Coca-Cola Co	0,7510	-0,0046	0,489917555	Verizon Communications Inc	0,3602	-0,0044	0,167254091
McDonald's Corp	0,6761	-0,0046	0,489917555	Walgreens Boots Alliance Inc	0,6051	-0,0182	0,16433376
				Intel Corp	0,6119	-0,0013	0,162364737

This table presents the R-squared values from the first-pass regression results. It indicates the proportion of variance in individual stock returns that is explained by market returns, highlighting the strength of the linear relationship implied by the CAPM model.

Next, the second pass regression executed by the excel function using the following equation

$$E(r_i) = \gamma_0 + \gamma_1\beta_i + \varepsilon \quad \textbf{(4)}$$

by using of the result for β_i and $E(r_i)$ values calculated in the first pass regression.

Based on the theory of CAPM, under equilibrium conditions of CAPM, γ_0 should be equal to risk free rate in the market and γ_1 should be equal to $E(R_m) - r_f$

Table 5. *Second Pass Regression's Results*

Summary Output

Regression Statistics	
Multiple R	0,1967033
R Square	0,0386921
Adjusted R Sqare	0,0030885
Standard Error	0,0090543
Observations	29

ANOVA	*Df*	*SS*	*MS*	*F*	*Significane F*
Regression	1	8,90969E-05	8,90969E5	1,0867358	0,30644058
Residual	27	0,00221368	8,19858E5		
Total	28	0,00230274			

	Coefficiens	*Standard Error*	*t Stat*	*P-value*	*Lower %95*	*Upper %95*	*Lower 95,0%*	*Upper 95,0%*
Kesişim	0,0047645	0,00471781	1,0098338	0,3215399	-0,00491595	0,0144446	-0,0049155	0,0144446
Beta	0,0050381	0,00483364	1,0424655	0,3064408	-0,00487896	0,0149563	-0,0048786	0,0149563

The results in Table 5 summarize the second-pass regression, which investigates the linear relationship between expected returns and estimated betas across stocks. The regression line represents the empirical Security Market Line (SML), and the analysis evaluates how well CAPM explains the cross-sectional variation in returns.

According to second pass regression results SML line is $E(r_i) = 0{,}00476 + 0{,}00503\beta_i$. *As we mentioned above r_f should be equal to 0,00477.* Average yearly risk free rate has been calculated by relative of 2 year benchmark treasury bond rate given between the periods as 1,32 %. Monthly average risk free rate calculated as 0,11 %. On th other hand, according to

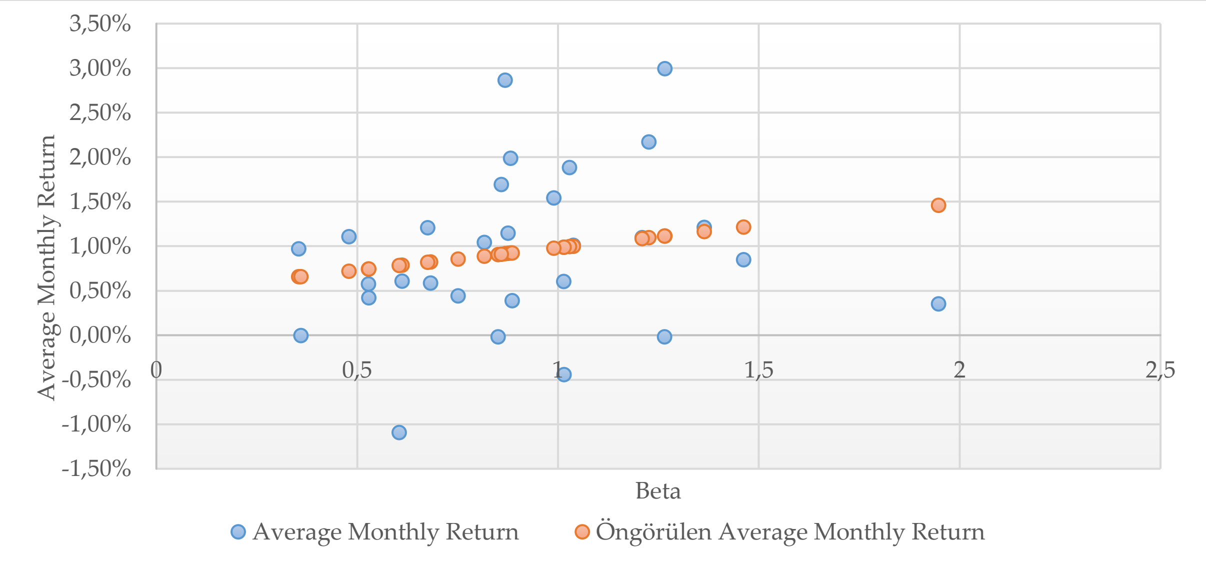
SML line equation, r_f should be equal to 0,476% which is almost 4 times bigger than the actual calculated risk free rate.

$E(R_m) - r_f$ is calculated by use of $E(R_m)$ = 14,45 % and risk free rate r_f = 1,32 % and found as 13,14% yearly. Since we regress monthly return we calculate $E(R_m) - r_f$ = 0,010946 monthly. The estimation made for γ_1 *calculated as 0,00503 which as mentioned, should be equal to* $E(R_m) - r_f$. But regression result is almost half of the actual excess return.

Second pass regression result line as shown in the figure below, is being typically linear and having upward sloping, where the CAPM model's functional form is supported. However, the R^2 value 0,038 is not well-fitting, for the outlier appears in the linear regression. In other words, the goodness of fit does not strongly support the security market line's trend. As a result, it appears that beta is not the only factor priced by the market. Furthermore, the estimated beta coefficient has a little impact on the expected return, and the security market line is rather 'flat.'

Based on those results the empirical tests of CAPM seems as failed and explanatory parameters adjustments may be needed to get more accurate results.

Graph 2. *SML Line*



According to First-Pass Regression Findings; Beta coefficients for all stocks were statistically significant at the 95% confidence level. High-beta stocks: Boeing (β = 1.95), Goldman Sachs (β= 1.46) Low-beta stocks: Procter & Gamble (β = 0.35), Verizon (β = 0.36) R^2 analysis: The S&P 500 index explained 43% of the variation in Dow 30 stocks, increasing to 51% after removing low R^2 stocks. On the other hand Second-Pass Regression Findings illustrates; Estimated Security Market Line (SML) is $E(ri) = 0.00476 + 0.00503\beta i$. The risk-free rate estimate from the regression (0.476%) was significantly higher than the actual market rate (0.11%). The market risk premium prediction was lower than expected, suggesting additional risk factors influence *stock* returns beyond beta. Our study has some interpretation & CAPM's limitations; Beta Alone is Not Sufficient: CAPM assumes that systematic risk is the only relevant risk, yet empirical evidence suggests that firm-specific factors and alternative risk factors (e.g., size, momentum) influence returns. Security Market Line Deviations: The empirical SML deviates significantly from theoretical predictions, indicating potential mispricing. COVID-19 Impact on Stocks: Stocks like Boeing showed extreme deviations due to sector-specific shocks, revealing CAPM's limitations in capturing external shocks.

Conclusion

Sharpe (1964) and Lintner (1965) stated that the exercised version of the CAPM has never achieved empirical success. Empirical work of the model significantly figures out that the relation between average return and market beta is smooth and almost vertical from the start, (the risk premium per unit of market beta is lower) rather than model's supposed to produce. This outcome is considered duly invalidation of the most implementations stated by the model. In primitive empirical works, the Black (1972) approach to the model, where accommodation produces a more vertical line on average return- beta tradeoff, produced more success. But, in the late 1970s, uncovering variables started to appear in the studies such as size, various price ratios, and momentum consolidated to the explanation of average returns derived from the market beta. These findings suffocate the CAPM's market portfolio prediction's efficiency, resulting in market betas suffice to explain expected returns. Concurrently the problems are to invalidate most implementations of the CAPM. Contemporary and future works may show that the CAPM's problems disappear as more accurate proxies or benchmarks for the market portfolio are considered. The CAPM is a theoretical model based on Markowitz Portfolio Selection Model. It is taught the CAPM, as an introduction to the fundamental concepts of portfolio theory and asset pricing, to promote and discussed more advanced models to be built on it, and with warnings that despite its logicality and simplicity, the CAPM's empirical shortcomings probably invalidate its use in implications. This study was undertaken to test whether the CAPM is useful and significantly relates to and explains the risk and return relationship between the market trend and stocks, considering the existence of a risk-free asset. However, other risk factors rather than the beta also have been effective for explaining share returns. Investors therefore should be cautious when executing the model to evaluate and assess their investment decisions and performances. The CAPM postulates that the only relevant risk for an asset is the market risk,

since firm-specific risk is eliminated in calculations while the particular asset is included in a well-diversified portfolio. Starting with the first regression execution, where significant results have been revealed on the returns of those stocks with the market return. Lack of significance discovered as of executing the second pass regression. The Security Market Line (SML) where the systematic or market risks at various levels, illustrates those various marketable securities, plotted against the expected return of the market at any given time, was unaligned with the market conditions.

Given the structural differences between developed and emerging markets, further studies should investigate how CAPM performs in economies characterized by liquidity constraints, limited market efficiency, and heightened volatility. A comparative analysis against alternative asset pricing models could provide deeper insights into their applicability in these financial environments.

In addition, future research should incorporate multi-factor approaches, including the Fama-French three-factor model and Arbitrage Pricing Theory (APT), to evaluate their relative explanatory power in capturing asset returns, particularly in emerging market settings where CAPM assumptions may not hold as strongly. Additionally, studies should explore CAPM's validity in emerging markets by accounting for market inefficiencies, liquidity constraints, and additional risk factors that influence asset pricing.

Moreover, the findings of this study highlight how the COVID-19 pandemic introduced asymmetric shocks that disproportionately impacted certain sectors, especially those sensitive to travel, energy, and supply chain disruptions. These distortions revealed clear limitations of the CAPM, particularly its inability to capture non-linear and time-varying risk factors during extreme conditions. As such, future empirical models would benefit from incorporating multi-dimensional risk structures. Well-established alternatives, such as the Fama-French multifactor models, the Carhart four-factor model, or even hybrid approaches integrating behavioral and macroeconomic variables, could yield better predictive power and robustness in volatile market environments. Therefore, the scope of asset pricing research must evolve in line with global uncertainty and structural market changes.

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