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Research article

An augmented capital asset pricing model using new macroeconomic determinants

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ABSTRACT

Using the interview results of 26 experienced scholars, managers, and professional stock traders in conjunction with findings of recent studies in economics, we proposed an augmented asset pricing model using the macroeconomic determinants representing the macroeconomic state variables to explain the nexus between these risks and the U.S. stock returns. This non-traded factor model (MAPM) is inspired by and based on the macroeconomic theory and models and consists of the market return, U.S. prime rate, U.S. government long-term bond rate, and exchange rate of USD/EUR as in Eq. (1). Using the Bayesian approach (via two Bayes and t.Bayes estimators) and monthly returns of the S&P 500 stocks from 2007- 2019, our results showed the MAPM consistently yielded a statistically significant greater forecasting, explanatory power, and model adequacy compared to the most used capital asset pricing model (CAPM) in practice. Interestingly, our study found and confirmed (t-statistic > 3) that the last two macroeconomic determinants have a statistically significant positive effect on the stock returns, which also supports the MAPM. These findings suggest the MAPM is a more efficient and advantageous model compared to the CAPM. So, practitioners would be better off employing the MAPM over CAPM in practice and research.

1. Introduction

The simplest and most common benchmark asset pricing model in both practice and research is single-period and one-factor capital asset pricing model (CAPM, Sharpe, 1964) as shown in a report of survey results by a professional organization (The Association for Financial Professionals, 2013), a report by a leading financial services company (The Credit Suisse, 2013), and recent studies (Barillas and Shanken, 2018; Barillas et al., 2019; Chib et al., 2020). However, the CAPM possesses limitations in both research and practices (Barillas and Shanken, 2018; Gungor and Luger, 2019; Lee, 2019; Zhang, 2017, 2019). Therefore, researchers have augmented or propose alternatives to the CAPM. Jensen (1967) is the very first study that modified the CAPM. That study proposed a two-coefficient model by adding an intercept coefficient alpha (α) to the original CAPM to represent the stock's expected excess return when the market risk premium is zero (α equals zero in an efficient market). Recent studies confirmed the alpha existed for the real stocks (Barillas and Shanken, 2017; Fama and French, 1996b, 2015; 2018; Hou et al., 2015, 2020b; Hou et al., 2019, 2020a; Pham and Phuoc, 2020; Phuoc, 2018; Zhang, 2017). However, that study does not explore and capture other risks such as the firm's financial ratios and investment, stock momentum, and macroeconomic risks.

Other researchers headed in different directions. They attempted to verify that the relationship between the real stock returns and the firm's financial traits existed. Some very well-known and influential studies in this direction (Banz, 1981; Basu, 1983; Bhandari, 1988; Fama and French, 1992, 1993; 1995; Rosenberg et al., 1985) showed that, besides the market risk (beta), the stock returns also depended on the firm's market equity, leverage, book-to-market equity, earnings-to-price, and size. Using these findings, Fama and French (1992, 1993, 1995, 1996a) proposed the three-factor asset pricing model (FF3) consisting of the market and two traded factors: the SMB (size) and HML (value). Also, Fama & French (1992, 1993, 1995, 1996a) showed that the FF3 yielded greater beta and standard deviation compared to the original CAPM. Hence, the authors claimed that the FF3 could explain more of the relationship between the market and stock returns than the CAPM. After the FF3 was published, other studies (Aharoni et al., 2013; Fama and French, 2006, 2008; Novy-Marx, 2013; Titman et al., 2004) showed that

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the stock returns also depended on the firm's profitability and investment. Using this new finding, Fama and French (2015, 2016, Fama et al., 2017) augmented the FF3 with two more factors: the RMW (profitability) and CMA (investment). This model considers the five-factor asset pricing model (FF5). Fama and French (2015, 2016, Fama et al., 2017) also demonstrated that the FF5, in general, performed better than the FF3 in explaining the stock returns since the FF5's GRS statistic (Gibbons et al., 1989) is less than the FF3's. Additionally, Fama & French (2015) also pointed out that the HML factor was redundant in this model. Once again, Fama and French (2018) augmented the FF5 with one more factor, the UMD (momentum) using the findings of momentum factor-affected stock returns in the literature (Asness and Frazzini, 2013; Asness et al., 2013; Barroso and Santa-Clara, 2015; Carhart, 1997; Jegadeesh and Titman, 1993; Moskowitz et al., 2012; Stambaugh and Yuan, 2017). This new model considers the six-factor asset pricing model (FF6). Also, Fama and French (2018) showed that the FF6 yielded a smaller GRS statistic or higher max squared Sharpe ratio (Barillas and Shanken, 2017) compared to the FF5. So, the authors claimed that FF6 performed better than the FF5 in explaining the stock returns.

Overall, the FF3, FF5, and FF6 are more flexible than the CAPM, but they have big drawbacks for individual investors to apply in practice since these models are more complex due to the facts that they are traded factor models; the data are not always available, especially for the monthly or daily data. Also, the shortcomings of CAPM's assumptions are seen in the FF3, FF5, and FF6 models. In addition, Fama and French (1996a) claimed and showed that the FF3 yielded greater beta and standard deviation, hence, more explanation of the relationship between stock returns and beta, compared to the CAPM. However, the greater beta standard deviation means the longer beta confidence interval, which leads to the inefficient beta estimation, the main contribution of the CAPM. Besides, other studies showed that the FF3 fails to account for a wide array of asset pricing anomalies (Boons, 2016; Jegadeesh and Titman, 1993; Loughran and Ritter, 1995). Importantly, even Fama and French (2004) admitted and other studies (Berk, 1995; Ferson et al., 1999; Kim et al., 2011; Kothari et al., 1995; Lo and MacKinlay, 1990; MacKinlay, 1995; Wang and Wu, 2011) also pointed out that the traded factors, SMB, HML, and others employed in the FF3 (in FF5 and FF6 as well) do not have a solid background but brute-force ideas. So, these FF3, FF5, and FF6 are just ad-hoc models (Hou et al., 2019). Also, the FF5 is not driven by the valuation theory as claimed (Hou et al., 2019). Also, the HML (value), RMW (profitability), and CMA (investment) factors were shown to be non-significant in explaining the stock returns (Fama and French, 2015; Hou et al., 2015, 2020a,b; Kim et al., 2011; Kothari et al., 1995; Kubota and Takehara, 2017).

Barillas and Shanken (2018) tried to examine the FF5 and q-factor model (Hou et al., 2015). Using the Bayesian approach and Sharpe ratio, their study confirmed the six-factor model (BS) using the market, investment, return-on-equity (profitability), size, value, and momentum. Hence, this BS includes both traded and non-traded factors. This BS also showed that the size and momentum factors were not redundant factors as FF5 and q-factor models claimed, respectively. Roy and Shijin (2018) tried to extend the FF5 with the human capital component based on the findings of other studies (Belo et al., 2014; Belo et al., 2017; Kim et al., 2011; Kuehn et al., 2017; Roy and Shijin, 2017). Again, the models proposed by Barillas and Shanken (2018) and Roy and Shijin (2018) are more flexible compare to the CAPM, FF3, and FF5. However, they have similar weaknesses as the FF3, FF5, and FF6.

Due to the criticism of FF3 and other existing asset pricing models in the literature, Kim et al. (2011) proposed a revised version of both FF3 and Jagannathan and Wang (1996)' models. Their study argued that the future labor income growth, a macroeconomic state variable, captures the nature of economic risks that the size and value factors in the FF3 hope to depict. Also, the authors argued that future labor income growth was a better factor than the current income growth (see Jagannathan and Wang, 1996) to represent the return on human capital. Hence, their model consists of market, consumption growth, and future labor income growth. The authors showed that this three-factor model outperformed both the FF3 and CAPM in terms of explanatory power. Another study, using the q-theory of investment, Hou et al. (2015) argued for an empirical four-factor q-model (q^4 model) including the market, ME (size), 1/A (investment), and return-on-equity (profitability) factors. The authors showed that the q-factor model largely summarizes the cross-section of average stock returns. Also, in many cases, the q-factor model outperformed the FF3 and Carhart (1997) 4-factor model in capturing the significant anomalies. Similarly, Hou et al. (2019) revised the q^4 by adding one more factor, the expected investment growth. Their new model, the q^5 (Hou et al., 2020a,b), yielded strong explanatory power in the cross-section and outperformed the q^4, FF5, FF6, and the Barillas and Shanken (2018)' six-factor model in terms of maximum Sharpe ratio.

One of the three parameters of the CAPM is the market risk premium, but the market is not clearly stated. In reality, there are many different markets and these markets have different performances, especially the markets locate in different countries. To make matters worse, many firms – especially multinational firms – are affected by the exchange rate risks. Hence, some studies (Adler and Dumas, 1983; Agmon, 1972; Grauer et al., 1976; Lessard, 1974, 1976; Solnik, 1974a, 1974b) proposed and worked on the international asset pricing model (IAPM) by adding factors to the CAPM related to the exchange rate risks, such as the exchange rate risk premium. Generally, in the real world, IAPM is more flexible compare to the CAPM. Therefore, it is a good theoretical model in asset pricing – but not easily applied in practice by individual investors. Importantly, this model often yielded poor results in empirical research as shown in some studies (Solnik, 1977; Wallingford and Bicksler, 1974).

Other studies attempted to examine the relationship between the stock returns and the macroeconomic state variables. Those studies (Bower et al., 1984; Goldenberg and Robin, 1991; Roll and Ross, 1983, 1984; Ross, 1976) developed and worked on the arbitrage pricing theory (APT), a flexible but complex model, consisting of multiple macro-economic risks such as the inflation rate, exchange rate, GNP growth rate, etc. Those studies showed that the APT outperformed the CAPM in terms of explanatory power. However, there is not a consensus among the researchers and individual investors of how many and what risks should be in the model (Dhrymes et al., 1984). Other studies (Latham, 1989; Shanken, 1982) showed that the APT does not imply an exact linear risk-return relation and is very hard to test empirically. Finally, Latham (1989) showed that the APT is not consistent with either the single-period model or the multiperiod model.

Our study differs from other studies and contributes to the literature as follows. Firstly, we employed the qualitative research techniques using interviews (Krueger et al., 2001; Opdenakker, 2006) of, totally, 26 experts of three different groups to explore possible economic determinants affecting stock returns. The reason we interviewed three groups is that we wanted to avoid bias in the results. Also, the number of experts that employed in our qualitative study is consistent with Fang et al. (2019) – six experts of two different groups, Kumar et al. (2017) – 15 experts of only one group, Raj and Sah (2019) – 10 experts of two different groups, and Wu et al. (2019) – 17 experts of two different groups. In fact, we interviewed 16 scholars with a minimum of seven years of teaching and research in the fields of economics and finance, 5 industry managers with a minimum of 5 years in seniority position, and 5 professional stock traders. Based on the results of our interviews, the findings of recent studies in the fields of economics and finance (Ang and Bekaert, 2007; Barinov et al., 2018; Bernanke and Gertler, 1999; Boons, 2016; Campbell and Yogo, 2006; Dai and Zhou, 2020; Dai and Zhu, 2020; Goyal and Welch, 2008; Gungor and Luger, 2019; Kroencke, 2017; Lee, 2019), and the availability of the related data, our study proposed adding three macroeconomic determinants/risks (the U.S. prime rate, the U.S. government long-term bond rate, and the exchange rate of USD/EUR) to the original CAPM to explain the nexus between the risks and the U.S. stock returns. These macroeconomic determinants are proxies for the macroeconomic state variables. The number of macroeconomics determinants (three) matched with other studies suggested (Bower et al., 1984; Goldenberg and Robin, 1991; Roll and Ross, 1983). This augmented CAPM (hereinafter, the MAPM), a non-traded factor model as in Eq. (1) includes the excess market return of the original CAPM and the U.S. prime rate, the U.S. government long-term bond rate, and the exchange rate of USD/EUR. Importantly, this MAPM is inspired by and based on the macroeconomic theory and models, a requirement for an asset pricing model as suggested by other studies (Hou et al., 2020a,b; Fama and French, 2018). Then, we employed the quantitative research method using the Bayesian approach to confirm our proposed model, the MAPM. Also, only the S&P 500 stocks, the largest U.S stocks, were purposefully employed in this study to examine the performance of both the MAPM and CAPM and the three proposed macroeconomic determinants. The reason is to minimize the faulty anomalies claim with microcap stocks that discovered in a recent study (Hou et al., 2020a,b).

Secondly, we found only one asset-pricing model study (Roy and Shijin, 2018) in the literature employing the frequentist approach and both parametric and non-parametric estimators. In contrast, our study employed the Bayesian approach via both parametric and non-parametric Bayes estimators to obtain consistency in the results of the model comparisons.

Thirdly, the recent influential studies in the literature employed either r-squared or adjusted r-squared to measure the model of fit in the model comparisons (Barillas and Shanken, 2017, 2018; Fama and French, 2016, 2018; Hou et al., 2015, 2019; 2020a,b; Zhang, 2017) even though the r-squared or adjusted r-squared would easily increase just by adding more independent factors in the model. This means the r-squared and adjusted r-squared alone may not be sufficient to measure the model fit. Hence, our study employed both adjusted r-squared (Bayesian r-square or R2B) and posterior mean deviance (D_bar), a component of deviance information criterion (DIC), to measure the model fit/adequacy to obtain consistency in the results of our model comparisons.

Fourthly, it is worth noting that the recent influential studies (Fama and French, 2016, 2018; Hou et al., 2019, 2020a,b; Zhang, 2017) did not employ the model error in their model comparisons. Hence, our study employed both the mean square error (MSE) and model variance (Sigma2) to measure the forecasting power and efficiency of the model and their confidence intervals in our model comparisons.

Finally, unlike the recent asset-pricing model studies (Barillas and Shanken, 2017, 2018; Fama and French, 2015, 2016, 2018; Hou et al., 2019, 2020a,b), we employed both the confidence interval approach instead of p-value and test hurdle of the absolute t-statistic of both 2.78 and 3.0 in our asset pricing model comparisons (Dyckman, 2016; Dyckman and Zeff, 2019; Halsey, 2019; Harvey et al., 2015; Hou et al., 2020a, b; Lewellen et al., 2010; Wasserstein and Lazar, 2016).

Using the S&P 500 stocks from 2007- 2019, the empirical results showed the MAPM consistently yielded a statistically significant lesser model error and greater model fit/adequacy compared to the CAPM. In other words, in asset pricing work, the MAPM yielded greater forecasting, explanatory power, and model adequacy compared to the CAPM. Our empirical results also found and confirmed (t-statistic > 3) that the last two macroeconomic determinants, the U.S. government long-term bond rate, and the exchange rate of USD/EUR), have a statistically significant positive effect on the stock returns. These findings suggest the MAPM is a more efficient and advantageous asset pricing model compared to the CAPM. So, our findings may help both the policy-makers and investors to draft their decisions in monetary policy and investment, respectively.

The remainder of this paper is organized as follows. Section 2 describes the MAPM. Section 3 is the Data and Methodologies. In this section, we provide the details of the data. We also present and reason for the Bayesian approach and both parametric and non-parametric Bayes estimators used in this study. Then, we set up the benchmarks and rationalize both the proposed benchmarks and confidence interval approach in the model comparisons between the CAPM and MAPM. Finally, we present the results and interpretations in section 4. Conclusions are also provided in section 5. The References are at the end.

2. The MAPM

The MAPM utilized the simplicity, availability, and ease of accessed data and the flexibility of the CAPM, APT, and IAPM. This model also indirectly incorporated the stock related characteristics of the FF5, q^4, q^5, and Roy and Shijin (2018)' models. Finally, Jensen's alpha also added to the MAPM. Therefore, the MAPM showed the relationship between the excess return on the stock i, $i = 1, 2, 3, \ldots, N$ at the time t, $t = 1, 2, \ldots, n$ and the market, prime rate, government long-term bond risk premiums, and exchange rate as follows:

$$R_{it} - RF_t = \alpha_i + \beta_i(RM_t - RF_t) + \gamma_i(US_t - RF_t) + k_i(LTB_t - RF_t) + \lambda_i EX_t + \varepsilon_{it} \quad (1)$$

where,

- R_{it}: the return on the stock i at the time t,
- RM_t: the return of the market portfolio at the time t,
- RF_t: the risk-free rate at the time t,
- α_i: Jensen's alpha coefficient (alpha) of the stock i,
- β_i: the stock i's sensitivity to the market portfolio (beta),
- γ_i: the interest risk coefficient (gamma) that the stock i is bearing,
- US_t: the U.S. prime rate at the time t,
- k_i: the government long-term bond yield rate risk coefficient (kappa) that the stock i is bearing,
- LTB_t: the government long-term bond rate at the time t,
- λ_i: the exchange rate risk coefficient (lambda) that the stock i is bearing,
- EX_t: the exchange rate of USD/EUR at the time t,
- ε_{it}: the random error term that has mean zero and variance σ^2 (Sigma2).

To evaluate the MAPM, we examined and compared its performance against the most used asset pricing model in practice, the CAPM, using both parametric and non-parametric Bayes estimators for consistency in the results and both advanced and common statistical measures (as described in Methodologies). We also examined how the U.S prime rate, the U.S. government long-term bond rate, and the exchange rate of USD/EUR affected the stock returns.

3. Data and Methodologies

3.1. Data

Only the S&P 500 stocks, the largest U.S stocks, were purposefully selected due to their efficiency to examine the performance of both the MAPM and CAPM and how the three macroeconomic determinants affect the stock returns. Besides, we wanted to avoid bias in the data due to the most recent financial crisis that had a strong negative effect on both the macroeconomics and stock market, especially the financial stocks as shown in two studies (Bullard et al., 2009; Smaga, 2014). So, the medium-horizon monthly returns of the 450 S&P 500 stocks and three macroeconomic determinants from 2007- 2019 were collected from the Federal Reserve Economic Data (FRED). The risk-free rate was the three-month U.S. Treasury secondary market rate. The S&P 500 index considered the market because it is widely considered the best gauge of large-cap U.S. stocks.

3.2. Methodologies

3.2.1. The approach and estimators

Our study employed a Gibbs sampler, a Markov chain Monte Carlo (MCMC), on the real data and the Bayesian approach (via two Bayes estimators and weakly informative normal priors) as in our previous study (Pham and Phuoc, 2020; Phuoc and Pham, 2020).

3.2.2. Benchmarks

We evaluated and compared the performance of the MAPM against the CAPM using the following benchmarks: i) the model error (MSE and Sigma2) since these statistics showed the model forecasting power and precision, respectively. The model with a lower MSE and Sigma2 would be a preferred model in practice. ii) The second benchmark was the model fit/adequacy (R2B and posterior mean deviance (D_bar)) since they provided information about the explanatory power of the model and model adequacy. The model with a greater R2B and/or lower D_bar would be a preferred model (Pham and Phuoc, 2020; Phuoc and Pham, 2020; Spiegelhalter et al., 2002, 2014; Van der Linde, 2005).

In model comparisons, we employed the mean and 95% confidence interval of the mean difference of benchmarks as suggested and employed by other studies (Dyckman, 2016; Dyckman and Zeff, 2019; Halsey, 2019; Lewellen et al., 2010; Pham and Phuoc, 2020; Phuoc and Pham, 2020).

3.2.3. The effect of the U.S. prime rate, the government long-term bond rate, and the exchange rate of USD/EUR on the S&P 500 stock returns

Furthermore, we evaluated the MAPM by looking at how the U.S prime rate, the U.S. government long-term bond rate, and the exchange rate of USD/EUR affected the stock returns. If these three factors were found significantly affecting the stock returns, then it would provide more evidence supporting the MAPM over CAPM – since the main contribution of the CAPM is that the stock returns depend only on market risk. Again, we used the mean, 95% confidence interval of the mean, and test hurdle of the absolute *t*-statistic of both 2.78 and 3 to exam these macroeconomic determinants as suggested by Harvey et al. (2015) and Hou et al. (2020a,b).

4. Results and discussion

We assumed that the original CAPM holds for a stock if the beta is not zero. So, we eliminated the stocks if their betas were zero from our analyses. Panel (a) of Figure 1 showed that the CAPM using the Bayes estimator yielded the 95% confidence interval of the beta of seven stocks including zero. Similarly, Panel (b) of Figure 1 showed that CAPM using the t.Bayes estimator yielded the 95% confidence interval of the beta of three stocks including zero (two of those three stocks were the same stocks as in the case of CAPM using the Bayes estimator). These findings mean that the CAPM might not hold for eight stocks (seven and one stocks from Panel (a) and (b), respectively). Therefore, we decided to eliminate these 8 stocks (442 stocks remained) in our next analyses. The finding that the CAPM might not hold for only 8 stocks (1.7% of big U.S stocks) shows the support for use of the CAPM in both practice and research. This is consistent with other studies (The Association for Financial Professionals, 2013; Barillas and Shanken, 2018; Barillas et al., 2019; Chib et al., 2020; Da et al., 2012; Fama and French, 1996b).

In contrast with the CAPM, we assumed that the MAPM does not hold for a stock if all coefficients beta, gamma, kappa, and lambda from Eq. (1) were all zero. The MAPM using the Bayes estimator yielded the 95% confidence interval (not shown here) of the beta, gamma, kappa, and lambda of six stocks including zero (those six stocks were the same stocks as in the case of the CAPM using Bayes estimator). However, the MAPM using the t.Bayes estimator yielded the 95% confidence interval (not shown here) of the beta, gamma, kappa, and lambda of only one stock including zero (this stock is one of the six stocks in the case of MAPM using the Bayes estimator). These findings mean that the MAPM might not hold for only six stocks (1.3% of big U.S. stocks). Therefore, we could claim that in asset pricing work, the MAPM worked with more U.S stocks compared to the CAPM.

4.1. The model errors

4.1.1. The MSE

Panels (a) and (b) of Figure 2 showed that the differences between two MSE's of the CAPM and MAPM were distributed on both sides of zero. However, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of MSE using the Bayes estimator of 0.749 and (0.018, 1.480), respectively. Similarly, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of MSE using the t.Bayes estimator of 0.161 and (-0.088, 0.411), respectively. These findings mean that in asset pricing work, the CAPM yields a statistically significant greater MSE (greater model error or lesser forecasting power) compare to the MAPM.

4.1.2. The Sigma2

Panels (a) and (b) of Figure 3 showed that the differences between the two Sigma2s of the CAPM and MAPM were positive for the majority of stocks, especially in the case of the t.Bayes estimator. Importantly, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of Sigma2 using the Bayes estimator of 0.747 and (0.02, 1.48), respectively. Also, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of Sigma2 using the t.Bayes estimator of 0.257 and (0.102, 0.411), respectively. Again, these findings mean that for an asset pricing work, the CAPM yields a statistically significant greater Sigma2 (lesser model precision and efficiency) compare to the MAPM.

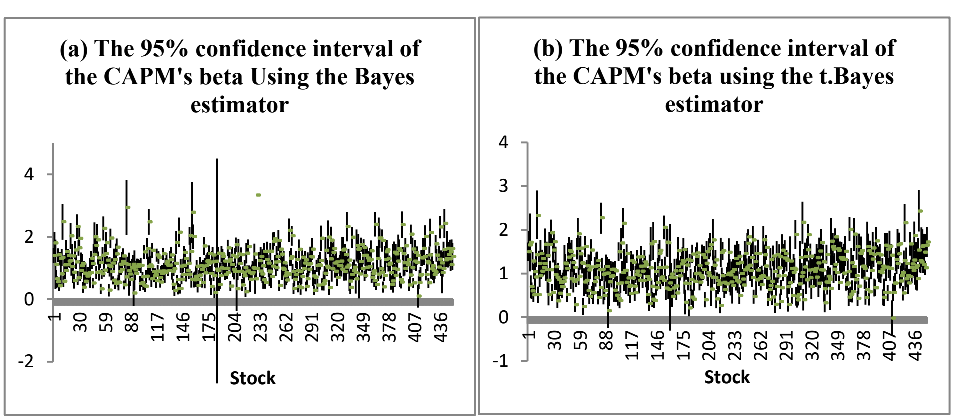

Figure 1. The 95% confidence intervals of the CAPM's beta. Notes: This figure reported the 95% confidence intervals of beta using the CAPM and Bayes, (Panel (a)) and t.Bayes (Panel (b)) estimators of 450 S&P 500 stocks. Panel (a) also showed seven stocks (91, 185, 207, 230, 231, 296, and 411) with zeroed betas. Panel (b) also showed three stocks (91, 161, and 411) with zeroed betas.

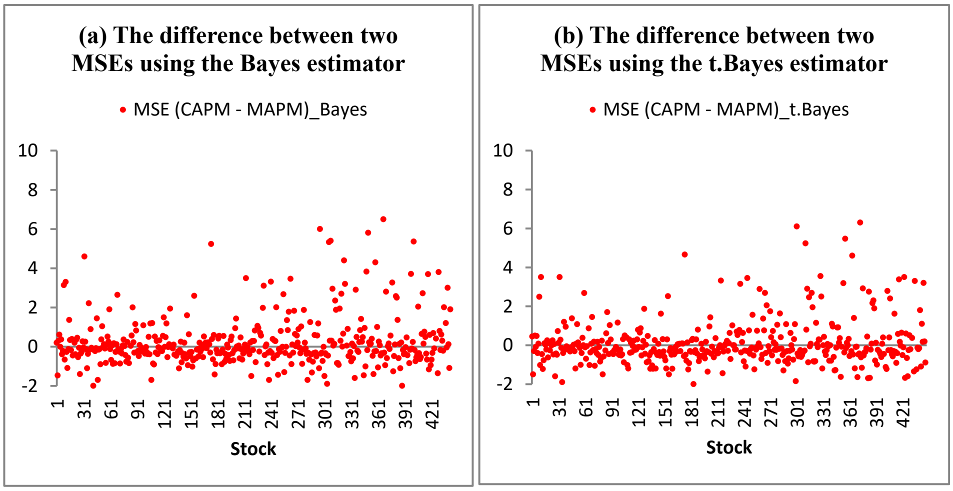

Figure 2. The differences between CAPM and MAPM in terms of MSE. Notes: This figure reported the differences between CAPM and MAPM in terms of MSE using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 442 S&P 500 stocks. For each stock, we calculated the MSE from both CAPM and MAPM using Bayes estimators. Then, we took the difference between these two MSEs. We also calculated the sample mean of all these differences of MSEs (mean difference). We repeated the same process for CAPM and MAPM using t.Bayes estimator. Besides, Panels (a) and (b) showed the means difference of these MSEs of 0.749 and 0.161, respectively.

Table 1. The differences between CAPM and MAPM.

Evaluation Criterion		Estimator Used	Mean from CAPM	Mean from MAPM	The Difference Between the CAPM and MAPM	
					Mean Difference	95% Confidence Interval of Mean Difference
Model error	MSE	Bayes	133.83	133.08	0.749	(0.018, 1.480)
		t.Bayes	139.47	139.31	0.161	(-0.088, 0.411)
	Sigma2	Bayes	135.75	135.01	0.747	(0.02, 1.48)
		t.Bayes	26.72	26.47	0.257	(0.102, 0.411)
Model fit/adequacy	R2B	Bayes	0.30	0.30	-0.002	(-0.003, -0.001)
		t.Bayes	0.65	0.66	-0.0032	(-0.0042, -0.0022)
	D_bar	Bayes	955.58	955.17	0.411	(0.129, 0.694)
		t.Bayes	939.16	938.34	0.827	(0.527, 1.127)

Note: This table reported the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of model error (MSE and Sigma2) and model fit/adequacy (R2B and D_bar) using both Bayes and t.Bayes estimators of the S&P 500 stocks.

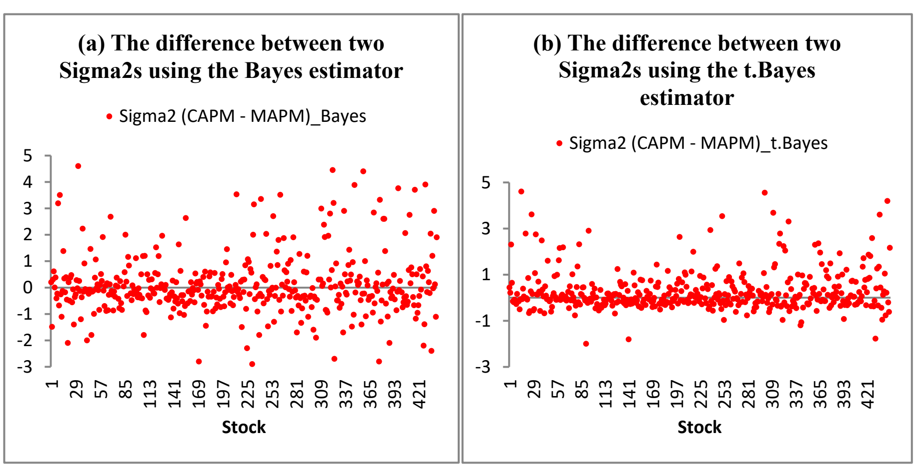

Figure 3. The differences between CAPM and MAPM in terms of Sigma2. Notes: This figure reported the differences between CAPM and MAPM in terms of Sigma2 using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 442 S&P 500 stocks. For each stock, we calculated the Sigma2 from both CAPM and MAPM using Bayes estimators. Then, we took the difference between these two Sigma2s. We also calculated the sample mean of all these differences of Sigma2s (mean difference). We repeated the same process for CAPM and MAPM using t.Bayes estimator. Besides, Panels (a) and (b) showed the means difference of these two Sigma2s of 0.747 and 0.257, respectively.

4.2. The model fit/adequacy

4.2.1. The R2B

Panels (a) and (b) of Figure 4 showed that the differences between the two R2Bs of the CAPM and MAPM were distributed on both sides of zero. However, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of R2B using the Bayes estimator of -0.002 and (-0.003, -0.001), respectively. Also, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of R2B using the t.Bayes estimator of -0.0032 and (-0.0042, -0.0022), respectively. These findings mean that in asset pricing work, the CAPM yields a statistically significant lower R2B (lesser model fit and explanatory power) compare to the MAPM.

4.2.2. The D_bar

Panels (a) and (b) of Figure 5 showed that the differences between the two D_bars of the CAPM and MAPM were distributed on both sides of

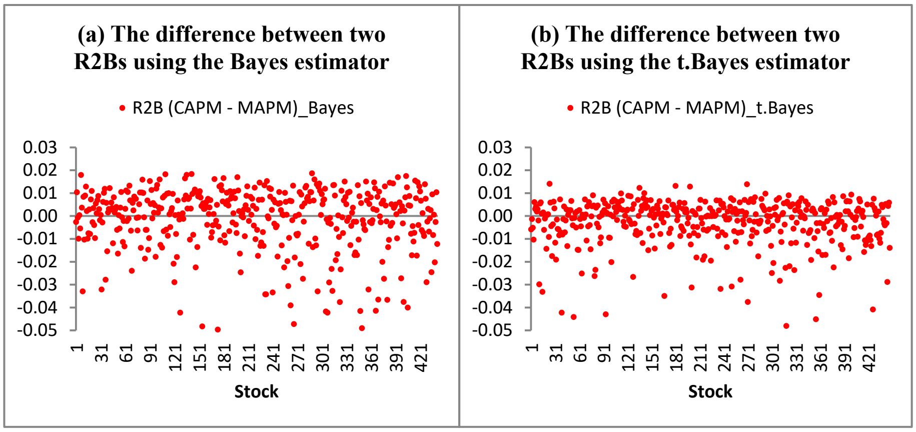

Figure 4. The differences between CAPM and MAPM in terms of R2B. Notes: This figure reported the differences between CAPM and MAPM in terms of R2B using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 442 S&P 500 stocks. For each stock, we calculated the R2B from both CAPM and MAPM using Bayes estimators. Then, we took the difference between these two R2Bs. We also calculated the sample mean of all these differences of R2Bs (mean difference). We repeated the same process for CAPM and MAPM using t.Bayes estimator. Besides, Panels (a) and (b) showed the means difference of these R2Bs of -0.002 and -0.0032, respectively.

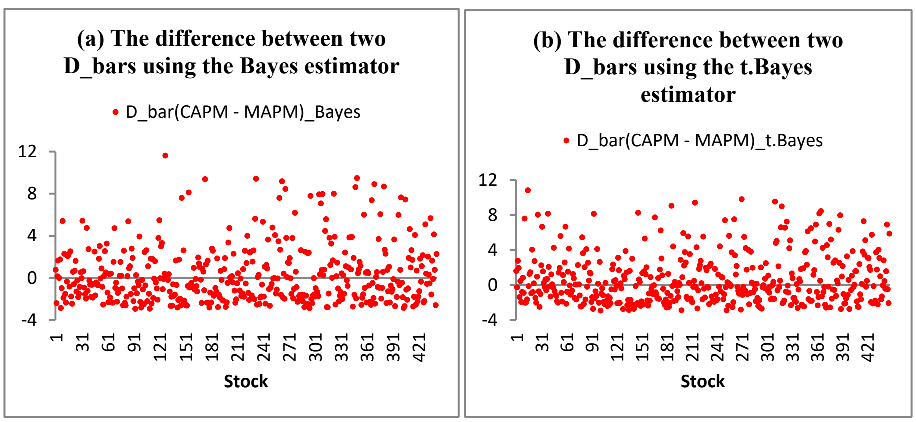

Figure 5. The differences between CAPM and MAPM in terms of D_bar. Notes: This figure reported the differences between CAPM and MAPM in terms of D_bar using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 442 S&P 500 stocks. For each stock, we calculated the D_bar from both CAPM and MAPM using Bayes estimators. Then, we took the difference between these two D_bars. We also calculated the sample mean of all these differences of D_bars (mean difference). We repeated the same process for CAPM and MAPM using t.Bayes estimator. Besides, Panels (a) and (b) showed the means difference of these D_bars of 0.411 and 0.827, respectively.

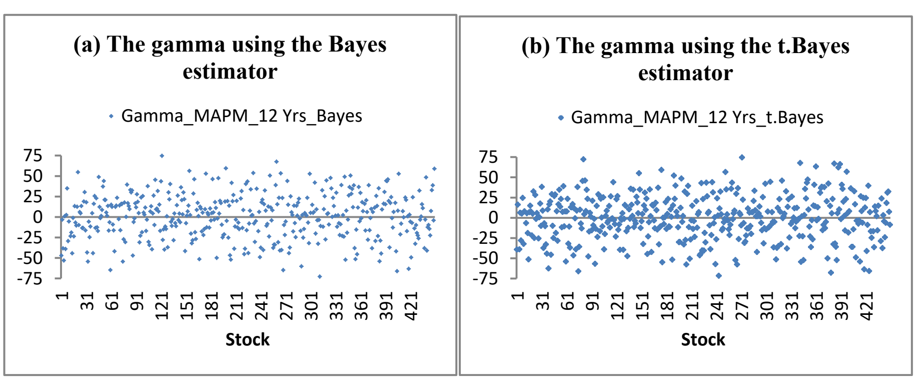

Figure 6. The gamma and distribution. Notes: This figure reported the gamma and distribution using both Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 450 S&P 500 stocks. For each stock, we derived the gamma. Then, we calculated the sample mean, confidence interval, and *t*-statistic.

Table 2. The mean and 95% confidence interval of the MAPM's coefficients.

Coefficient	Estimator Used	Mean	95% Confidence Interval	*t*-statistic
Gamma	Bayes	-1.17	(-4.18, 1.84)	-0.76
	t.Bayes	-2.78	(-5.75, 0.19)	-1.84
Kappa	Bayes	2.36	(1.38, 3.33)	4.76
	t.Bayes	1.61	(0.79, 2.42)	3.86
Lambda	Bayes	2.01	(1.41, 2.62)	6.52
	t.Bayes	1.27	(0.71, 1.83)	4.44

Note: This table reported the mean and 95% confidence interval of the gamma, kappa, and lambda using both Bayes and t.Bayes estimators of 450 S&P 500 stocks.

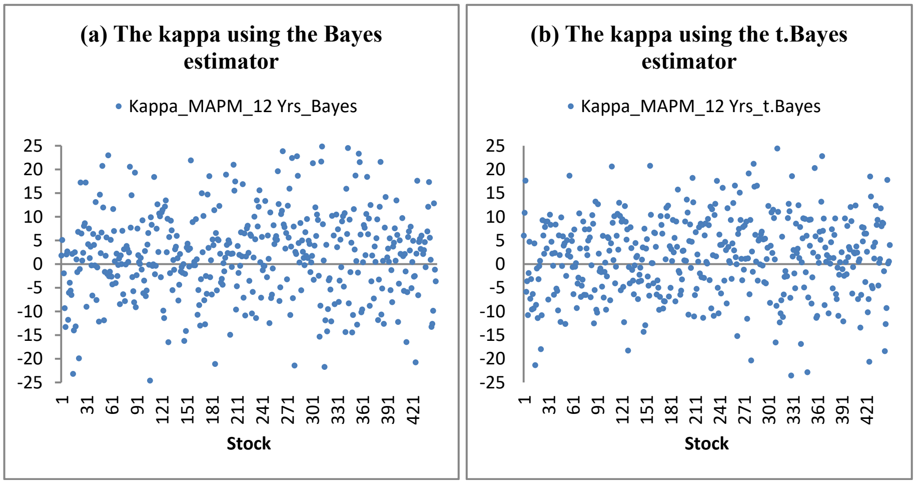

Figure 7. The kappa and distribution. Notes: This figure reported the kappa and distribution using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 450 S&P 500 stocks. For each stock, we derived the kappa. Then, we calculated the sample mean, confidence interval, and *t*-statistic.

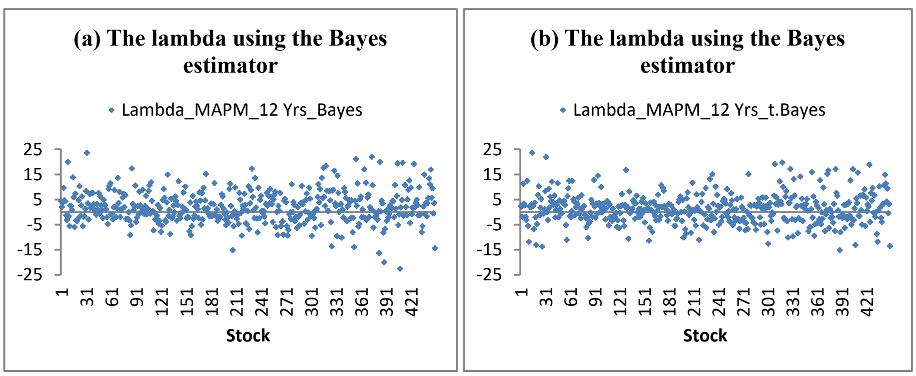

Figure 8. The lambda and distribution. Notes: This figure reported the lambda and distribution using Bayes (Panel (a)) and t.Bayes (Panel (b)) estimators of 450 S&P 500 stocks. For each stock, we derived the lambda. Then, we calculated the sample mean, confidence interval, and *t*-statistic.

zero. However, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of D_bar using the Bayes estimators of 0.411 and (0.129, 0.694), respectively. Similarly, Table 1 illustrates the mean difference and 95% confidence interval of the mean difference between CAPM and MAPM in terms of D_bar using the t.Bayes estimator of 0.827 and (0.527, 1.127), respectively. Once more, these findings mean that the CAPM yields a statistically significant higher D_bar (lesser model adequacy) compare to the MAPM.

To summarize, this study shows that the MAPM yields greater precision, forecasting, and explanatory power than the CAPM in asset pricing via the S&P 500 stocks. However, Table 1 does not show how the three macroeconomic determinants affecting the S&P 500 stock returns. So, we would examine this issue in the next section.

4.3. The effect of the macroeconomic determinants on the S&P 500 stock returns

The S&P 500 stocks are the large U.S stocks and known to be efficient. The main contribution of the CAPM is that the returns on stocks depend only on the market. However, the empirical results in the previous section showed that the MAPM consistently yielded a statistically significant greater precision, forecasting, and explanatory power in asset pricing compared to the CAPM. So, it is well worth it to examine and confirm the effect of the U.S. prime rate (gamma), U.S. government long-term bond risk premiums (kappa), and the exchange rate of USD/EUR (lambda) on the S&P 500 stock returns via the MAPM using the mean, confidence interval, and test hurdle of absolute *t*-statistic of both 2.78 and 3 that suggested by two recent influential studies (Harvey et al., 2015; Hou et al., 2020a,b). Panels (a) and (b) of Figure 6 showed that the gamma using the Bayes and t.Bayes estimator, respectively, of almost all of the stocks, were not zero; were distributed on both sides of zero. Importantly, Table 2 illustrates the mean, 95% confidence interval, and *t*-statistic of the gamma using the MAPM and Bayes estimator of -1.17, (-4.18, 1.84), and -0.76, respectively. Similarly, Table 2 illustrates the mean, 95% confidence interval *t*-statistic of the gamma using the MAPM and t.Bayes estimator of -2.78, (-5.75, 0.19), and -1.84, respectively. These findings mean that the U.S. prime rate has a negative effect, on average, on the stock returns. However, it does not clear the test hurdle of the absolute *t*-statistics of either 2.78 or 3. This finding contradicts some previous studies (Dai and Zhou, 2020; Dai and Zhu, 2020; Wong et al., 2005) but is consistent with others (Bernanke and Gertler, 1999; Kim, 2003).

Next, we examined the kappa. Panels (a) and (b) of Figure 7 showed that kappa using the Bayes and t.Bayes estimators, respectively, of almost all of the stocks, were not zero; were distributed on both negative and positive sides. Importantly, Table 2 illustrates the mean, 95% confidence interval, and *t*-statistic of the kappa using the MAPM and Bayes estimator of 2.36, (1.38, 3.33), and 4.76, respectively. Similarly, Table 2 illustrates the mean, 95% confidence interval, and *t*-statistic of the kappa using the MAPM and t.Bayes estimator of 1.61, (0.79, 2.42), and 3.86, respectively. These findings mean that the U.S. government long-term bond rate has a statistically significant positive effect on the stock returns and clears the test hurdle of the absolute *t*-statistic of both 2.78 and 3. This finding is consistent with some studies (Dai and Zhou, 2020; Dai and Zhu, 2020) but contradicts others (Anderson et al., 2008; Campbell et al., 2019; Jareño and Negrut, 2016; Wong et al., 2005).

Finally, we examined the lambda. Panel (a) and (b) of Figure 8 showed that lambda using the Bayes and t.Bayes estimators, respectively, of almost all of the stocks, were not zero; were distributed on both positive and negative sides. Importantly, Table 2 illustrates the mean, 95% confidence interval, and *t*-statistic of the lambda using the MAPM and Bayes estimator of 2.01, (1.41, 2.62), and 6.52, respectively. Similarly, Table 2 illustrates the mean, 95% confidence interval, and *t*-statistic of the lambda using the MAPM and t.Bayes estimator of 1.27, (0.71, 1.83), and 4.44, respectively. These findings mean that the exchange rate of USD/EUR has a statistically significant positive effect on the stock returns and clears the test hurdle of the absolute *t*-statistic of both 2.78 and 3. This finding is consistent with some studies (Ajayi and Mougoué, 1996; Ajayi et al., 1998) but contradicts others (Kim, 2003; Nieh and Lee, 2001).

5. Conclusions

The CAPM is the most commonly used asset pricing model in practice, even with its deficiencies. Using both the qualitative and quantitative research methods, our research proposed adding three macroeconomic determinants/risks (the U.S. prime rate, the U.S. government long-term bond rate, and the exchange rate of USD/EUR) to the original CAPM to explain the nexus between the risks and the U.S. stock returns. The MAPM, a non-traded factor model, is more flexible than the CAPM and very easy to apply since the data are always available. Unlike the other traded factor models, this MAPM is inspired by and based on the macroeconomic theory and models. Using a Gibbs sampler, the Bayesian approach (via both parametric and non-parametric Bayes estimators), confidence interval approach, model error (MSE and Sigma2), and model fit/adequacy (R2B and D_bar), we examined and compared the performance of both CAPM and MAPM on the S&P 500 stocks from 2007-2019. This study found: 1) the MAPM worked with more U.S stocks than the CAPM. 2) the MAPM consistently yielded a statistically significant greater forecasting, explanatory power, and model adequacy compared to the CAPM. 3) Both the U.S. government long-term bond rate and exchange rate of USD/EUR had a statistically significant positive effect on the S&P 500 stock returns and cleared the test hurdle of absolute *t*-statistic of both 2.78 and 3. These findings question the main contribution of the CAPM of that the stock returns depend only on the market; therefore, this is another piece of evidence supporting the MAPM over the CAPM in asset pricing. These conclusions suggest that the MAPM is a more efficient and advantageous asset pricing model compared to the CAPM. Since the MAPM's data is always available, the investors and firm managers would be better off employing the MAPM over the CAPM to predict the stock returns and a firm's cost of equity in practice. Also, these findings may help both the policy-makers and investors to draft their decisions in monetary policy and investment, respectively.

For the smaller U.S. stocks and less efficient markets, we expect that the MAPM will yield even better performance compared to the CAPM. Practitioners such as the investors and a firm's managers are advised to consider the MAPM over CAPM in their asset pricing work and cost of equity estimation.

Declarations

Author contribution statement

L.T. Phuoc and C.D. Pham: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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