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ISM and Stock Market Returns

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Abstract:

We want to study if the Purchasing Managers Index (PMI), the main indicator within the Institute For Supply Management Manufacturing Report On Business predicts future excess stock market returns. Hence, we intend to test if the leading macroeconomic indicator, the PMI, at time (t) predicts excess stock market returns at time (t+1). The time lag (t+1) is considered short-term, one to three months. To test for predictability, we will use ordinary least squares (OLS) regression models, both univariate, bivariate and pooling return predictive models. Statistical evidence such as correlation, statistical significance and economic magnitude of the coefficients, will influence whether we will be able to conclude for predictability.

Chapter 1: Introduction and Motivation

The question to be studied:

Does the monthly Purchasing Management Index (PMI), conducted by The Institute For Supply Management, predict future excess stock market returns?

Motivation:

The Institute For Supply Management Manufacturing Report on Business, henceforth ISM, is considered by many economists to be the most reliable near-term barometer of the US economy since it is indicative of the direction of the manufacturing sector as well as the overall economy. According to Joseph E. Stiglitz, former chairman of President Clinton's Council of Economic Advisors, the ISM has one of the shortest reporting lags of any macroeconomic time series and gives an important early outlook of the economy. Michael J. Boskin, Ph.D., professor of economics, Hoover Institute senior fellow at Stanford University; and former chairman of President Bush's Council of Economic Advisors, said "The ISM Manufacturing Report On Business is extremely useful. The PMI, the surveys composite index, gives the earliest indication each month of the health of the manufacturing sector. It is an essential component for assessing the state of the economy." ("ISM - ISM Report On Business® - The Institute for Supply Management™ Manufacturing and Non-Manufacturing Report on Business®," n.d.). Additionally, as Koenig (2002) points out, there are two main advantages of the ISM. First, its timeliness. The ISM is consistently released at 10. a.m. on the first business day each month, based on the previous month's questionnaires.

Secondly, due to the ISM's nature as survey responses, the monthly data is typically subject to only small revisions at most (Lahiri, Monokroussos, 2013). Based on the facts above, our motivation behind the study is to reveal whether an economic indicator with these types of characteristics also can be used to predict future excess stock market returns.

Our contribution:

Our findings add to the literature on stock market return predictability. However, according to Jones and Tuzel (2012), the vast majority of research conducted on stock market return predictability, such as Campbell and Shiller (1988) or Keim and Stambaugh (1986), have focused almost exclusively on price-based predictors. For instance, variables such as dividend yield or the term spread are constructed entirely or in part from security prices. Such endogenous variables tend to have high quarterly and yearly autocorrelation coefficients, which raises the possibility that any evidence favouring return predictability is in fact due to severe statistical biases, as outlined by Stambaugh (1999). On the other hand, the PMI is constructed based on survey responses from purchasing and supply executives across the U.S and does not rely on any price data. Moreover, we want to specifically focus on short term return predictability at the one to three-month time horizon. In addition, we want to test whether the potential predictive effect of the PMI on future excess stock market returns is subsumed by a set of well-known macroeconomic indicators from the literature. These control variables are: dividend yield, stock variance, term spread, default yield spread, inflation, and detrended Treasury bill rates (Li, Wang, Yu, 2017).

Addressing the issue:

We are going to make an empirical study where we obtain and analyse macroeconomic data in order to examine the relationship between the PMI and its predictive power on future excess stock market returns. We will obtain the data from Bloomberg and Amit Goyal's website. Then, we will build univariate, bivariate and pooling return predictive regression models, in order to test and examine various relationships between the PMI and future excess stock market returns. Statistical evidence such as correlation, statistical significance and economic magnitude of the coefficients, will influence whether we will be able to conclude for predictability.

Summary of the results:

This paper documents that the PMI on a standalone basis is an economically significant negative predictor of future excess stock market returns over a one to three-month time horizon. In the early subsample the results from the univariate regressions are more powerful than those seen in the full sample, as the PMI coefficient is statistically significant at the 5% level across all horizons. However, in the late subsample as well as with the non-overlapping sample, we fail to find evidence for a statistically significant relationship between the PMI and future excess stock market returns.

Organization of the thesis:

The paper proceeds as follows: In Chapter 2 we review relevant literature and state the relevance and motivation behind our research question. In Chapter 3 we present the methodology to be used when conducting our research, and in Chapter 4 we describe the data sources and variable construction. In Chapter 5 our main results are discussed and presented. Lastly, Chapter 6 concludes.

Chapter 2: Literature Review

Relevant articles:

A study conducted by Li, Wang, Yu (2017) highlights the relationship between aggregate expected investment growth (AEIG) and future excess stock market returns. Li, Wang, Yu (2017) propose a bottom-up measure of aggregate investment plans, referred to as the aggregate expected investment growth (AEIG), by aggregating the firm-level expected investment growth (EIG). The researchers conducted several empirical studies and ran both univariate, bivariate and pooling return predictive regressions where the researchers controlled for other popular macroeconomic return predictors such as the Treasury bill rate, dividend yield and the term spread. In their paper, the researchers document that AEIG is a strong negative predictor of future excess stock market returns. An increase in AEIG is associated with a declining stock market, with an adjusted in-sample R^2 of 18.5% at the one-year horizon. The return predictive power is not subsumed by other macroeconomic variables that are well-known for predicting stock market returns (Li, Wang, Yu, 2017).

Similar to our intended research the main predictive variable of Li, Wang, Yu (2017) is a leading macroeconomic indicator based on future expectations, which is used to predict future excess stock market returns. Furthermore, Li, Wang, Yu (2017) use many of the same macroeconomic control variables known from the literature, as we intend to use.

Another relevant research paper is “Investment Plans and Stock Returns” by Lamont (2000). Lamont (2000) investigates the hypothesis that when the discount rate falls, investments should rise. Thus, with time-varying discount rates and instantly changing investments, investments should positively covary with current stock returns and negatively covary with future stock returns. However, Lamont (2000) finds that post-war annual aggregate U.S. data on stock returns and non-residential investment growth contradict these implications. According to Lamont (2000), investment plans explain more than three-quarters of the variation in real annual aggregate investment growth. Furthermore, investment plans have substantial forecasting power for excess stock returns.

Similar to Li, Wang, Yu (2017), Lamont’s (2000) main predictive variable, investment plans, is a leading macroeconomic indicator which the researcher uses to predict future excess stock market returns. The investment plans data are from a survey of capital expenditure plans conducted by the U.S. Commerce Department, which was sent out on a quarterly basis to corporate and noncorporate firms. Comparable to the ISM, Lamont’s main predictive variable does not rely on security prices, and the survey respondent’s answers are based on their own future expectations.

Appropriateness of our chosen methodology and data:

The methodology used in both articles is relevant for our research since a set of predictive variables are used to predict future excess stock market returns. The researchers have conducted their studies with various forms of OLS regression models, both univariate, bivariate and pooling return predictive regression models. Also, they perform several robustness checks on their main results, by controlling their main predictive variable for various control variables and by performing subsample analyses. Since the motivation behind our research thesis is to analyze the predictability the PMI has on future excess U.S stock market returns, we will rely on a similar type of methodology.

With regards to the data, The U.S Commerce department discontinued the investment plans survey in 1993 (Lamont, 2000), which makes it problematic to use the survey today as a variable to predict future excess stock market returns. Furthermore, the AEIG variable, used by Li, Wang, Yu (2017) must be estimated in several steps, which may seem like a complicated and tedious process. However, the benefit of our research data is that it is publicly available and does not require to be estimated. In addition, the ISM is a monthly survey which makes it available at a higher frequency, than for instance the quarterly investment plans survey used by Lamont (2000).

Chapter 3: Methodology

As mentioned in Chapter 2, our research methodology is based on regression analysis, primarily aimed at describing and evaluating the relationship between a given dependent variable and one or more independent variables. OLS is the most common method used to fit a line to the data (Brooks, 2014). Our dependent variable is the value-weighted excess returns on the S&P 500 Composite Index, and our main independent variable is the PMI, the composite index within the ISM. In addition, we intend to control the PMI for dividend yield, the term spread, stock variance, default yield spread, inflation and Treasury bill rates.

We intend to run several types of predictive regressions with the PMI, both univariate, bivariate and pooling predictive regression models. In the univariate case the dependent variable, denoted by Y_t, depends only on one predictive variable, denoted by X_{1t-1}. The relationship between the dependent and predictive variable can be expressed the following way:

$$Y_t = \beta_1 + \beta_2 X_{1t-1} + u_t$$

The subscript t (=1, 2, 3, …) denotes time, β_1 is a constant and u_t is the residual term that captures all outside random influences on Y_t which cannot be modeled (Brooks, 2014).

When adding predictors, we can build bivariate and pooling predictive regression models, by generalizing the simple model to one with k-1 regressors:

$Y_t = \beta_1 + \beta_2 X_{2t-1} + \beta_3 X_{3t-1} + \ldots + \beta_k X_{kt-1} + u_t$, $t = 1,\ldots,T$

Each coefficient is now known as a partial regression coefficient, interpreted as representing the partial effect of the given predictive variable on the dependent variable, after holding constant, or eliminating the effect of all other predictive variables (Brooks, 2014).

We intend to interpret the economic magnitude of the PMI coefficient, its statistical significance based on Newey and West (1987) heteroscedastic and autocorrelation consistent t-statistics, as well as the in-sample adjusted R^2.

Chapter 4: Data

To obtain information needed to conduct our research we have used data from several sources. Return data for the S&P 500 Index and the risk-free rate come from the Center for Research in Security Prices (CRSP) database. The PMI data is collected from Bloomberg, and our macroeconomic control variables are from Amit Goyal's website. Our full sample is based on the monthly ISM survey from February 1948 to December 2017.

The ISM is a monthly survey based on data compiled from more than 400 purchasing and supply executives across 20 manufacturing industries in the US. Survey responses reflect the change in the current month compared to the previous month for 10 indicators: New Orders, Backlog of Orders, New Export Orders, Imports, Production, Supplier Deliveries, Inventories, Customers' Inventories, Employment and Prices ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.).

Diffusion indexes are then created based on the responses to these survey questions. For instance, for production, the possible responses to the question ''What is the trend for production?'' are positive, neutral or negative (compared to the preceding month). The resulting diffusion index is created by adding the percentage of positive responses to half the percentage of neutral responses. This number varies between 0 and 100 and represents the percentage of companies that increased their production during the month. Basically, a level above 50 indicates that more executives are reporting increases for that variable than are reporting decreases (Lahiri, Monokroussos, 2013).

Our main predictive variable, the PMI, is the equally weighted composite index of the five diffusion indexes within the ISM: New Orders, Production, Employment, Supplier Deliveries and Inventories. The composite index ranges from 0 to 100, with 50 being the critical level which signals if the manufacturing sector is in expansion or contraction (Lahiri, Monokroussos, 2013). The survey is consistently released at 10. a.m. on the first business day each month, based on the previous month's questionnaires ("ISM-ISM Report – December 2017 Manufacturing ISM® Report On Business®," n.d.).

Our macro control variables are dividend yield, the term spread, stock variance, default yield spread, inflation and Treasury bill rates. Stock Variance (SVAR) is computed as the sum of squared daily returns on the S&P 500 Index. Dividend yield (DP) is the difference between log of dividends and log of lagged index values, where dividends are twelve-month moving sums of dividends paid on the S&P 500 index. Treasury bill rates (TBL) are the detrended 3-month yields on US Treasury bills using the Hodrick-Prescott filter. The term spread (TMS) is the difference between the yield on long-term U.S government bonds (10-year yield) and the 3-month Treasury bill rate. The default yield spread (DFY) is the difference between BAA- and AAA- rated U.S corporate bond yields. Inflation (INFL) is the Consumer Price Index (All urban consumers) from the Bureau of Labour Statistics (Welch, Goyal, 2007).

Table 1: Summary statistics

Panel A of this table reports the mean, standard deviation (Std), 1st order autocorrelation (AC(1)), skewness (Skew), and kurtosis (Kurt) of the monthly S&P 500 return sample and our monthly return predictive variables. These variables include log of the Purchasing Management Index (PMI), a dummy variable taking the value 1 if the PMI is ≥ 50 and 0 if the PMI is < 50 (PMI DV), dividend yield (DP), term spread (TMS) defined as the difference between the yield on long term US government bonds (10-year yield) and the 3-month Treasury bill rate, stock variance (SVAR) defined as the sum of squared daily returns on the S&P 500 Index, default yield spread (DFY) defined as the difference between BAA- and AAA-rated US corporate bond yields, inflation (INFL) from the monthly consumer price index for all urban consumers, and detrended 3-month yields on U.S Treasury bills (TBL) using the Hodrick-Prescott filter. The means and standard deviations of TMS, SVAR, INFL and TBL are multiplied by 100. Panel B reports the pairwise correlation coefficients of these variables. The sample is monthly from February 1948 to December 2017.

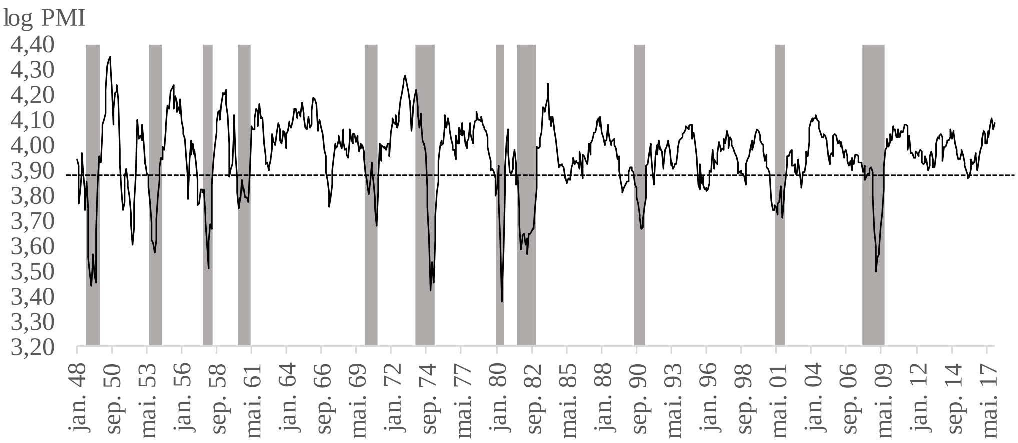
Panel A: Summary statistics									
Vars.	S&P 500	PMI	PMI DV	DP	TMS	SVAR	DFY	INFL	TBL
Mean	0,56	3,96	0,70	-3,49	1,69	0,19	0,95	0,28	0,00
Std	4,15	0,15	0,46	0,44	1,37	0,40	0,43	0,38	0,81
AC(1)	0,05	0,94	0,78	0,99	0,96	0,48	0,97	0,50	0,89
Skew	-0,67	-0,87	-0,89	-0,16	-0,09	11,20	1,88	0,06	0,16
Kurt	2,42	1,48	-1,22	-0,62	-0,02	164,84	4,96	2,48	4,45
Panel B: Correlation matrix									
Vars.	S&P 500	PMI	PMI DV	DP	TMS	SVAR	DFY	INFL	TBL
S&P 500	1,00								
PMI	-0,06	1,00							
PMI DV	0,00	0,77	1,00						
DP	0,08	-0,17	-0,20	1,00					
TMS	0,06	0,00	0,09	-0,26	1,00				
SVAR	-0,11	-0,16	-0,12	-0,11	0,14	1,00			
DFY	0,01	-0,44	-0,29	0,12	0,27	0,32	1,00		
INFL	-0,07	0,07	0,00	0,18	-0,22	-0,13	0,09	1,00	
TBL	-0,14	0,04	-0,02	-0,01	-0,58	-0,05	-0,16	0,19	1,00

The log of the PMI has a standard deviation of 0.15 and the 1st order autocorrelation coefficient is 0,94. As for the third and fourth order moments of the PMI distribution, we observe a negative skewness (-0,87) with a kurtosis of (1,48).

Panel B of Table 1 reports the correlation matrix of the predictive variables. The macroeconomic return predictor that has the most negative correlation with the PMI is the default yield spread, with a correlation coefficient of -0,44. Intuitively a high PMI indicates a strong performing economy and thus investors demand a lower premium for investing in riskier corporate bonds. Furthermore, we observe a negative correlation of -0,17 and -0,18 between the PMI and DP and SVAR respectively. A high PMI could be indicative of an elevated stock market level and thus periods with a low DP ratio. Higher stock variance could be associated with higher uncertainty about the performance of the economy and thus a lower PMI.

Figure 1: PMI and NBER recessions

This figure plots the time series of log PMI from February 1948 to December 2017 along with The National Bureau Of Economic Research (NBER) recessions indicated by the shaded regions. The PMI is the equally weighted composite index of the five diffusion indexes within the ISM: New Orders, Production, Employment, Supplier Deliveries and Inventories. The composite index ranges from 0 to 100, with 50 being the critical level (indicated by the horizontal line), signaling if the manufacturing sector is in expansion or contraction.



Visual inspection suggests that the PMI tends to rise gradually during expansionary periods and remain above the 50 level, indicated by the horizontal line. Historically the PMI has fallen sharply below the 50 level during NBER recessions. It also seems that fluctuations in the PMI have become less severe over time.

Chapter 5: Results and Analysis

In this section, we analyze the relationship between the PMI and future excess stock market returns. Since the PMI is a diffusion index, which ranges between 0 and 100, we intend to analyze its predictability based on its level and with regards to its 50 level, which signals growth (≥ 50) or contraction (< 50) in the manufacturing sector for a given month. Hence, we use a dummy variable (PMI DV) which takes the value 1 if the PMI is ≥ 50 and 0 if the PMI is < 50.

5.1 Main results:

Sections 5.1.2 to 5.1.4 report the results from return predictive regressions with a monthly overlapping return sample. Our predicted variable is the log of the cumulative monthly excess return on the value-weighted S&P 500 Index. To calculate the excess return we have used the difference between the log of value-weighted S&P 500 returns and the log of the risk-free rate. This is repeated for one month, two months and three months, respectively. For each specification of the predictive regressions, we report the beta coefficient, the Newey and West (1987) heteroscedastic and autocorrelation consistent t-statistic and the in-sample adjusted R^2.

5.1.2 Univariate return predictive regressions:

Table 2: Univariate return predictive regressions

Table 2 reports the coefficients from univariate return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI, the PMI dummy variable (PMI DV) which takes the value 1 if the PMI is ≥ 50 and 0 if the PMI is < 50, dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL) and the detrended 3-month Treasury bill rate (TBL) using the Hodrick-Prescott filter. The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from February 1948 to December 2017.

Vars.	PMI	PMI DV	DP	TMS	SVAR	DFY	INFL	TBL
1M	-1,73	-0,04	0,73	0,19	-1,14	0,09	-0,74	-0,70
t_{NW}	(-1,41)	(-0,10)	(-2,18)	(-1,64)	(-2,91)	(0,17)	(-1,65)	(-4,29)
R^2_{Adj}	0,26	-0,12	0,47	0,29	1,07	-0,11	0,34	1,73
2M	-3,36	0,04	1,45	0,36	-0,86	0,16	-0,94	-1,12
t_{NW}	(-1,47)	(0,05)	(2,25)	(1,58)	(-0,96)	(0,16)	(-1,03)	(-3,66)
R^2_{Adj}	0,56	-0,12	0,99	0,54	0,20	-0,11	0,24	2,16
3M	-5,52	-0,21	2,19	0,54	-1,00	0,39	-1,78	-1,51
t_{NW}	(-1,75)	(-0,22)	(2,33)	(1,62)	(-0,70)	(0,29)	(-1,37)	(-3,22)
R^2_{Adj}	1,10	-0,10	1,55	0,90	0,17	-0,07	0,72	2,64

The first column in Table 2 shows that at all horizons the coefficient on the PMI is negative, which indicates that there is a negative relationship between the PMI and future excess stock market returns. At the one-month horizon the coefficient of the PMI is -1,73, but the Newey-West t-statistic of -1.41 fails to reject the null hypothesis of the coefficient being statistically different from zero at the 10% level. The predictive power of the PMI at the one-month horizon, indicated by an adjusted R^2 of 0,26% is exceeded by all other macro return predictors, except for DFY, which has an adjusted R^2 of -0,11%. The magnitude of the PMI coefficient and the associated adjusted R^2 from the predictive regression increases with the horizon. At the two-month horizon the PMI coefficient becomes -3,36 with a Newey-West t-statistic of -1.47. The adjusted R^2 of 0.56% at the two-month horizon indicates that the PMI can explain 0.56% of the variation in the excess return the following two months. This predictability is only exceeded by DP and TBL with reported adjusted R^2 of 0,99% and 2,16%, respectively at the two-month horizon. At the three-month horizon the PMI coefficient becomes -5,52, with a Newey-West t-statistic of -1,75 indicating statistical significance at the 10% level. The adjusted R^2 increases from 0.56% to 1.1%. Although the predictability of the PMI is only statistically significant at the three-month horizon, the PMI appears to have economic significance at all horizons. For example, at the one-month horizon a one standard deviation increase in log PMI of 0,15 is associated with a -0,26% decrease in monthly excess returns. This increases to -0,83% at the three-month horizon.

Table 2 also reports the return predictability of other macroeconomic variables as well as the PMI dummy variable. From column two we see that PMI DV by itself has neither economic nor any statistically significant return predictability across all horizons. These findings may indicate that the 50 level in isolation is insufficient to be used for predicting future returns. However, in line with previous literature regarding the return predictability of business cycle indicators, our results show that DP and TMS are positively related to future stock market returns. On the other hand, INFL and TBL are negatively related to future stock market returns (Yu, Li, Wang, 2017).

5.1.3 Bivariate return predictive regressions:

Table 3: Bivariate return predictive regressions

Column one in Table 3 reports the results for the PMI from the univariate return predictive regressions presented in Table 2. The remaining columns report the coefficients from bivariate return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI and each of the macro control variables one at a time: dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from February 1948 to December 2017.

	Control.	PMI	DP	TMS	SVAR	DFY	INFL	TBL
1M	PMI	-1,73	-1,40	-1,73	-2,28	-2,01	-1,61	-1,58
	t_{NW}	(-1,41)	(-1,13)	(-1,40)	(-2,03)	(-1,75)	(-1,28)	(-1,34)
	Control	-	0,65	0,19	-1,27	-0,21	-0,70	-0,69
	t_{NW}	-	(1,79)	(1,64)	(-3,30)	(-0,41)	(-1,54)	(-4,20)
	R^2_{Adj}	0,26	0,59	0,54	1,58	0,18	0,55	1,92
2M	PMI	-3,36	-2,71	-3,35	-3,82	-3,92	-3,21	-3,13
	t_{NW}	(-1,47)	(-1,19)	(-1,47)	(-1,79)	(-1,80)	(-1,40)	(-1,43)
	Control	-	1,30	0,35	-1,08	-0,43	-0,86	-1,10
	t_{NW}	-	(1,87)	(1,59)	(-1,16)	(-0,44)	(-0,93)	(-3,60)
	R^2_{Adj}	0,56	1,30	1,09	0,93	0,51	0,73	2,62
3M	PMI	-5,52	-4,56	-5,51	-6,10	-6,23	-5,24	-5,21
	t_{NW}	(-1,75)	(-1,44)	(-1,75)	(-2,02)	(-2,03)	(-1,64)	(-1,72)
	Control	-	1,93	0,54	-1,36	-0,54	-1,64	-1,47
	t_{NW}	-	(1,90)	(1,64)	(-0,90)	(-0,39)	(-1,24)	(-3,14)
	R^2_{Adj}	1,10	2,24	1,99	1,50	1,06	1,69	3,60

Column four and five show that controlling the PMI for SVAR and DFY increases both the economic and statistical significance of the PMI coefficient across all horizons, compared to the univariate case in column one. At the one-month horizon the PMI coefficient becomes -2,28 (SVAR) and -2,01 (DFY), with Newey-West t-statistics of -2,03 (SVAR) and -1,75 (DFY) indicating statistical significance at the 5% and 10% level respectively. At the two-month horizon, the PMI coefficient becomes -3,82 (SVAR) and -3,92 (DFY) and the coefficients are statistically significant at the 10% level. At the three-month horizon, the magnitude of the PMI further increases to -6,10 (SVAR) and -6,23 (DFY), and the results are significant at the 5% level for both coefficients. We also note that the PMI coefficient remains statistically significant at the 10% level when controlling for TBL and TMS at the three-month horizon.

On the other hand, column two and six show that controlling PMI for DP and INFL reduces the economic and statistical significance of the PMI coefficient across all horizons. For instance, at the three-month horizon the PMI coefficient ranges from -4,56 to -5,24 (t-statistic ranging from -1,44 to -1,64), when controlling for DP and INFL respectively. However, the results are no longer statistically significant at the 10% level.

Lastly, Table 3 shows that the predictive power of the PMI, regarding the adjusted R^2, increases for all specifications except when controlling the PMI for DFY. For instance, with TBL at the three-month horizon the adjusted R^2 becomes 3,6% compared to 1,1% in the univariate case.

5.1.4 Pooling return predictive regressions:

Table 4: Pooling return predictive regressions

Table 4 reports the results from pooling return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log of PMI, log of dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from February 1948 to December 2017. Each column reports the beta coefficient and t-statistic for each macro variable within the pooling predictive regression for the specified time horizon. Each regression's adjusted R-squares is reported in the final column.

	PMI	DP	TMS	SVAR	DFY	INFL	TBL
1M	-1,76	0,65	0,05	-1,33	-0,03	-0,72	-0,61
t_{NW}	(-1,61)	(1,92)	(0,43)	(-3,11)	(-0,08)	(-2,10)	(-3,43)
R^2_{Adj}							3,65
2M	-3,61	1,53	0,23	-0,93	-0,70	-0,68	-0,88
t_{NW}	(-1,77)	(2,36)	(0,99)	(-1,03)	(-0,86)	(-0,87)	(-2,70)
R^2_{Adj}							3,85
3M	-5,60	2,43	0,44	-1,20	-0,95	-1,43	-1,01
t_{NW}	(-1,93)	(2,55)	(1,34)	(-0,77)	(-0,83)	(-1,34)	(-2,18)
R^2_{Adj}							5,87

Table 4 shows that the return predictive power of the PMI is not subsumed in the pooling predictive regressions when controlling for all macro variables. Column one shows that the PMI coefficient remains a negative predictor of future excess stock returns across all horizons, when controlling for all macro variables simultaneously. Its magnitude increases from -1.76 at the one-month horizon to -5.60 at the three-month horizon and the results are statistically significant at the 10% level at the two- and three-month horizon.

5.1.5 Sub-conclusion for main results:

To summarize the findings on the PMI from Section 5.1.2 to 5.1.4 we find that the PMI on a standalone basis is an economically significant negative predictor of future excess stock market returns at the one to three-month time horizon. For instance, at the three-month horizon a one standard deviation increase in log PMI of 0,15 is associated with a -0,83% decrease in monthly excess returns. Furthermore, the results are statistically significant at the 10% level at the three-month horizon. On the other hand, the 50 level in isolation (PMI DV) is insufficient to be used for predicting future excess stock market returns.

When controlling the PMI for SVAR and DFY the PMI becomes a statistically significant negative predictor of future excess returns across all horizons. At the one-month horizon the results are statistically significant at the 5% level and 10% level when controlling for SVAR and DFY respectively. A further improvement of these results are seen at the three-month horizon, where the PMI coefficient becomes statistically significant at the 5% level in both cases. We also observe that the PMI coefficient remains statistically significant at the 10% level at the three-month horizon when controlling for TMS and TBL. However, these results no longer hold when controlling for DP or INFL.

Lastly, the return predictive power of the PMI does not vanish in the pooling predictive regressions when controlling for all macro variables simultaneously. The results are statistically significant at the 10% level at the two- and three-month horizon.

5.2 Robustness checks:

To further analyze the return predictability of the PMI we conduct two robustness checks. First, we divide the PMI time series into two subsamples and repeat our main analysis with one early and one late subsample. Secondly, to minimize the effect of autocorrelation of errors on the statistical inferences, due to overlapping returns, we repeat the main predictive regressions using a non-overlapping sample (Yu, Li, Wang, 2017).

5.2.1 Subsample analysis:

For our subsample analysis we divide the full sample time series of the PMI into two subsamples and repeat the monthly overlapping regressions within each subsample. The early subsample ranges from February 1948 to December 1982 and the late subsample ranges from January 1983 to December 2017. For each specification of the return predictive regressions, we report the beta coefficient, the Newey-West t-statistic, and the in-sample adjusted R^2.

5.2.1.1 Early subsample return predictive regressions:

Table 5: Univariate and bivariate return predictive regressions

Table 5 reports the results from the early subsample ranging from February 1948 to December 1982. The first column reports the coefficients from univariate return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI. All other columns report the results from bivariate return predictive regressions using the PMI and each of the macro control variables one at a time: dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages.

	Control.	N/A	DP	TMS	SVAR	DFY	INFL	TBL
1M	PMI	-2,44	-1,29	-2,12	-2,48	-2,60	-2,36	-2,23
	t_{NW}	(-1,96)	(-0,97)	(-1,80)	(-1,93)	(-2,07)	(-1,81)	(-1,96)
	Control	-	1,77	0,60	-0,35	-0,13	-1,04	-0,91
	t_{NW}	-	(2,49)	(3,57)	(-0,22)	(-0,24)	(-2,17)	(-4,88)
	R^2_{Adj}	0,97	1,97	3,32	0,74	0,75	1,93	5,21
2M	PMI	-4,62	-2,29	-4,09	-4,42	-5,08	-4,51	-4,36
	t_{NW}	(-1,97)	(-0,91)	(-1,81)	(-1,81)	(-2,12)	(-1,82)	(-1,99)
	Control	-	3,61	1,10	1,88	-0,39	-1,69	-1,50
	t_{NW}	-	(2,76)	(3,37)	(0,71)	(-0,34)	(-1,99)	(-4,34)
	R^2_{Adj}	1,83	4,08	5,73	1,77	1,66	3,11	7,41
3M	PMI	-6,87	-3,39	-6,18	-6,43	-7,68	-6,68	-6,63
	t_{NW}	(-2,02)	(-0,97)	(-1,91)	(-1,88)	(-2,26)	(-1,89)	(-2,09)
	Control	-	5,42	1,60	4,30	-0,72	-2,81	-2,11
	t_{NW}	-	(2,96)	(3,20)	(1,38)	(-0,44)	(-2,32)	(-3,78)
	R^2_{Adj}	2,76	6,22	8,24	3,11	2,68	5,33	9,93

From Table 5 we see that the results from the univariate and bivariate return predictive regressions in the early subsample are more powerful than those seen in the full sample. Results from the univariate regressions in column one show that the PMI negatively predicts future stock returns, and the results are statistically significant at the 5% level across all horizons. Furthermore, the economic magnitude of the PMI coefficient increases compared to the full sample results. For instance, at the three-month horizon the magnitude of the PMI coefficient is -6,87 compared to -5,52 in Table 2. The predictive power measured by the adjusted R^2 also improves across all horizons, as the PMI explains 2,76% of the variation in future excess returns over three-month compared to 1,10% in the full sample.

Additionally, column two to seven show that the PMI coefficient remains statistically significant across all horizons when controlling for all macro variables, except DP. The results are statistically significant at the 5% level when controlling for TBL and DFY, and at the 10% level when controlling for TMS, SVAR and INFL.

Table 6: Pooling return predictive regressions

Table 6 reports the coefficients from pooling return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log of PMI, dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The early subsample is monthly from February 1948 to December 1982. Each column reports the beta coefficient and t-statistic for each macro variable within the pooling predictive regression for the specified time horizon. Each regression's adjusted R-squares is reported in the final column.

	PMI	DP	TMS	SVAR	DFY	INFL	TBL
1M	-0,59	2,19	-0,25	0,77	0,12	-0,93	-1,09
t_{NW}	(-0,45)	(3,17)	(-1,07)	(0,44)	(0,25)	(-2,12)	(-4,04)
R^2_{Adj}							6,45
2M	-1,35	4,06	-0,17	4,15	-0,11	-1,54	-1,69
t_{NW}	(-0,57)	(3,31)	(-0,38)	(1,91)	(-0,11)	(-1,92)	(-3,59)
R^2_{Adj}							11,02
3M	-1,72	6,07	-0,21	8,39	0,02	-2,83	-2,41
t_{NW}	(-0,55)	(3,58)	(-0,34)	(3,05)	(0,01)	(-2,47)	(-3,25)
R^2_{Adj}							17,32

Table 6 shows that the main results are not maintained in the pooling return predictive regressions with the early subsample. Column one shows that across all horizons we fail to capture a statistically significant relationship between the PMI and future excess stock market returns when controlling for all macro return predictors simultaneously. Furthermore, the magnitude of the PMI coefficient has been severely reduced across all horizons compared to the full sample results presented in Table 4. For instance, at the three-month horizon the PMI coefficient becomes -1,72 (t-statistic = -0,55) compared to -5,60 (t-statistic = -1,93) with the full sample. Although the adjusted R^2 increases materially, reaching 17,32% at the three-month horizon, it must be seen in relation with the strong statistical significance of DP, SVAR, INFL and TBL.

5.2.1.2 Late subsample return predictive regressions:

Table 7: Univariate and bivariate return predictive regressions

The first column in Table 7 reports the coefficients from univariate return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M), and 3-months (3M) onto log PMI. All other columns report the results from bivariate return predictive regressions using the PMI and each of the macro control variables one at a time: dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The late subsample is monthly from January 1983 to December 2017.

	Control.	N/A	DP	TMS	SVAR	DFY	INFL	TBL
1M	PMI	0,59	0,78	0,72	-1,28	0,12	0,67	0,63
	t_{NW}	(0,19)	(0,25)	(0,23)	(-0,55)	(0,04)	(0,22)	(0,21)
	Control	-	1,08	-0,07	-1,34	-0,28	-0,18	-0,22
	t_{NW}	-	(1,97)	(-0,34)	(-3,83)	(-0,33)	(-0,24)	(-0,67)
	R^2_{Adj}	-0,02	0,37	-0,43	2,21	-0,40	-0,44	-0,34
2M	PMI	0,71	1,16	0,91	-0,95	0,00	0,47	0,80
	t_{NW}	(0,13)	(0,21)	(0,16)	(-0,21)	(0,00)	(0,09)	(0,15)
	Control	-	2,08	-0,11	-1,19	-0,40	0,51	-0,30
	t_{NW}	-	(2,03)	(-0,30)	(-1,45)	(-0,26)	(0,31)	(-0,50)
	R^2_{Adj}	-0,23	1,01	-0,42	0,53	-0,41	-0,40	-0,36
3M	PMI	-1,22	-0,39	-1,13	-3,52	-1,79	-1,39	-1,07
	t_{NW}	(-0,17)	(-0,56)	(-0,15)	(-0,59)	(-0,26)	(-0,21)	(-0,15)
	Control	-	3,10	-0,05	-1,66	-0,31	0,36	-0,31
	t_{NW}	-	(2,11)	(-0,10)	(-1,15)	(-0,15)	(0,15)	(-0,36)
	R^2_{Adj}	-0,21	1,79	-0,45	0,85	-0,43	-0,43	-0,37

In our late subsample, we observe weaker results with regards to the predictive power of the PMI. Column one in Table 7 shows that across all horizons we fail to find statistically significant results for the PMI coefficient. Likewise, the economic magnitude of the PMI coefficient has been severely reduced, compared to the full sample results. Furthermore, the PMI seems to fit the late subsample poorly as the adjusted R^2 is negative at all horizons. For instance, at the one-month horizon the PMI coefficient is 0,59 (t-statistic = 0,19) with an adjusted R^2 of -0,02%. Lastly, results from column two to seven show that controlling the PMI for other macro variables does not seem to improve the weak results from the univariate case in column one. Across all horizons, we fail to find a statistically significant relationship between the PMI and future excess stock market returns.

Table 8: Pooling return predictive regressions

Table 8 reports the coefficients from pooling return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI, dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The late subsample is monthly from January 1982 to December 2017. Each column reports the beta coefficient and t-statistic for each macro variable within the pooling predictive regression for the specified time horizon. Each regression's adjusted R-squares is reported in the final column.

	PMI	DP	TMS	SVAR	DFY	INFL	TBL
1M	-0,77	1,33	-0,25	-1,34	-0,37	-0,74	-0,61
t_{NW}	(-0,31)	(2,10)	(-1,24)	(-3,97)	(-0,47)	(-1,34)	(-1,83)
R^2_{Adj}							2,66
2M	-1,14	2,83	-0,42	-0,85	-1,39	-0,11	-0,93
t_{NW}	(-0,24)	(2,28)	(-1,08)	(-1,38)	(-0,90)	(-0,08)	(-1,55)
R^2_{Adj}							1,75
3M	-3,71	4,03	-0,38	-1,26	-1,79	-0,61	-0,88
t_{NW}	(-0,58)	(2,13)	(-0,71)	(-0,99)	(-0,77)	(-0,32)	(-1,05)
R^2_{Adj}							2,65

Results from Table 8 confirm the weak results observed for the PMI in the late subsample. Column one shows that across all horizons we fail to find statistically significant results for the PMI coefficient when controlling for all macro variables simultaneously.

5.2.1.3 Sub-conclusion for subsample analysis:

Results from the univariate regressions with the early subsample are more powerful than those seen with the full sample, as the PMI coefficient is statistically significant at the 5% level across all horizons. Furthermore, results from the bivariate regressions show that the PMI coefficient remains statistically significant across all horizons when controlling for all macro variables except DP. The results are statistically significant at the 5% level when controlling for TBL and DFY, and at the 10% level when controlling for TMS, SVAR and INFL. Nevertheless, the main results are not maintained in the pooling return predictive regressions for the early subsample. When controlling the PMI for all macro control variables simultaneously, we fail to find statistically significant results across all horizons.

In the late subsample both univariate, bivariate, as well as pooling return predictive regression models fail to find a statistically significant relationship between the PMI and future excess stock market returns. As such, the late subsample does not provide any evidence for the predicting ability of the PMI, in contrast to the findings in the early and full sample.

5.2.2 Non-overlapping return sample:

Table 9: Univariate and bivariate return predictive regressions

Table 9 reports the results from non-overlapping return predictive regressions. The first column reports the coefficients from univariate return predictive regressions of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI. All other columns report the results from bivariate return predictive regressions using the PMI and each of the macro control variables one at a time: dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. The sample is monthly from February 1948 to December 2017.

	Control.	N/A	DP	TMS	SVAR	DFY	INFL	TBL
1M	PMI	-1,73	-1,40	-1,73	-2,28	-2,01	-1,61	-1,58
	t_{NW}	(-1,41)	(-1,13)	(-1,40)	(-2,03)	(-1,75)	(-1,28)	(-1,34)
	Control	-	0,65	0,19	-1,27	-0,21	-0,70	-0,69
	t_{NW}	-	(1,79)	(1,64)	(-3,30)	(-0,41)	(-1,54)	(-4,20)
	R^2_{Adj}	0,26	0,59	0,54	1,58	0,18	0,55	1,92
2M	PMI	-3,46	-2,76	-3,43	-4,29	-3,81	-3,16	-3,18
	t_{NW}	(-1,49)	(-1,16)	(-1,47)	(-1,82)	(-1,66)	(-1,34)	(-1,43)
	Control	-	1,36	0,34	-1,81	-0,26	-1,43	-1,11
	t_{NW}	-	-1,73	(1,39)	(-0,98)	(-0,27)	(-1,64)	(-3,13)
	R^2_{Adj}	0,46	1,12	0,79	0,90	0,25	0,99	2,37
3M	PMI	-4,64	-3,65	-4,65	-5,06	-5,10	-4,24	-4,56
	t_{NW}	(-1,44)	(-1,09)	(-1,44)	(-1,61)	(-1,61)	(-1,31)	(-1,46)
	Control	-	1,90	0,40	-1,08	-0,36	-1,59	-1,22
	t_{NW}	-	(1,54)	(1,17)	(-1,06)	(-0,32)	(-1,30)	(-2,02)
	R^2_{Adj}	0,64	1,73	0,93	1,09	0,32	0,97	2,21

Column one shows that the results from the univariate regressions regarding the economic significance of the PMI coefficient are in line with the results from the overlapping sample. However, in the non-overlapping sample we fail to capture statistically significant results for the PMI coefficient across all time horizons. Furthermore, the results in the remaining columns are only statistically significant when controlling for SVAR and DFY at the one and two-month horizon.

Table 10: Pooling return predictive regressions

Table 10 reports the coefficients from pooling return predictive regressions with a non-overlapping sample of log of cumulative excess value-weighted returns on the S&P 500 Index over 1-month (1M), 2-month (2M) and 3-months (3M) onto log PMI, dividend yield (DP), term spread (TMS), stock variance (SVAR), default yield spread (DFY), inflation (INFL), and the detrended 3-month Treasury bill rate (TBL). The t-statistics based on Newey-West standard errors (t_{NW}) are in parentheses. Adjusted R-squares (R^2_{Adj}) are reported in percentages. Each column reports the beta coefficient and t-statistic for each macro variable within the pooling predictive regression for the specified time horizon. Each regression's adjusted R-squares is reported in the final column.

	PMI	DP	TMS	SVAR	DFY	INFL	TBL
1M	-1,76	0,65	0,05	-1,33	-0,03	-0,72	-0,61
t_{NW}	(-1,61)	(1,92)	(0,43)	(-3,11)	(-0,08)	(-2,10)	(-3,43)
R^2_{Adj}							3,65
2M	-3,15	1,48	0,14	-1,88	-0,11	-1,44	-0,87
t_{NW}	(-1,38)	(2,12)	(0,58)	(-0,82)	(-0,12)	(-2,20)	(-2,27)
R^2_{Adj}							3,49
3M	-3,89	2,47	0,31	-1,11	-0,46	-1,83	-0,83
t_{NW}	(-1,20)	(2,10)	(0,97)	(-0,97)	(-0,44)	(-1,59)	(-1,31)
R^2_{Adj}							4,02

Similar to the results from the subsample analysis, column one in Table 10 shows that controlling the PMI for all macro variables simultaneously fails to capture a statistically significant relationship between the PMI and future excess stock market returns, when using a non-overlapping sample.

Chapter 6: Conclusion

This paper documents that the PMI on a standalone basis is an economically significant negative predictor of future excess stock returns over a one to three-month time horizon. Its magnitude increases with the horizon, and the results become statistically significant at the 10 % level at the three-month horizon. In the early subsample the results from the univariate regressions are more powerful than those seen in the full sample, as the PMI coefficient is statistically significant at the 5% level across all horizons. However, in the late subsample as well as with the non-overlapping sample, we fail to find evidence for a statistically significant ability to predict future excess stock market returns with the PMI.

When controlling the PMI for stock variance (SVAR) and the default yield spread (DFY) the PMI becomes a statistically significant negative predictor of future excess returns across all horizons. At the one-month horizon, the results are statistically significant at the 5% level and 10% level when controlling for SVAR and DFY respectively. A further improvement of these results is seen at the three-month horizon, where the PMI coefficient becomes statistically significant at the 5% level in both cases. We also observe that the PMI coefficient remains statistically significant at the three-month horizon when controlling for the term spread (TMS) and the 3-month Treasury bill rate (TBL). However, these results do not hold when controlling for dividend yield (DP) or inflation (INFL). As in the univariate case, the results for the PMI coefficient are stronger in the early subsample and statistically insignificant in the late subsample.

In the full sample, the return predictive power of the PMI does not vanish in the pooling predictive regressions when controlling for all macro variables simultaneously. The results are statistically significant at the 10% level at the two- and three-month horizon. However, these results do not hold after performing robustness checks. With regards to the early and late subsample, the pooling predictive regressions do not provide any evidence for the predictive ability of the PMI. When controlling the PMI for all macro control variables simultaneously, the results are statistically insignificant across all horizons. The same results are evident with the non-overlapping sample.

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