

*Tomasz Schabek\**, *Lucas Ayres Barreira de Campos Barros\*\**

## THE MARKET, MACROECONOMIC, AND BEHAVIOURAL FACTORS IN EMERGING MARKETS: THE CASE OF POLAND

---

The study tests a broad set of market, macroeconomic, and behavioural factors in the Polish stock market using local and US data. In time series regressions, employing general-to-specific modelling and principal component analysis, the authors found that both local and foreign aggregate indicators significantly predict the behaviour of a broad portfolio of Polish stocks. However, no common factor is able to explain the cross-section of expected returns in Poland. Only firm-specific characteristics, in particular market/book value and momentum, show significance in the cross-sectional analysis. The results are consistent with recent methodological critiques, suggesting that most candidate factors fail to explain the cross-section of expected returns when more stringent inference procedures are adopted.

**Keywords:** market factors, behavioural factors, macroeconomic factors, Polish stock market, cross-section of expected returns.

**JEL Classification:** G12, G15

**DOI:** 10.15611/aoe.2021.1.06

### 1. INTRODUCTION

From the 1960s onwards, many models have attempted to explain stock market returns. In the pioneering Capital Asset Pricing Model (CAPM), only one (market) factor was supposed to explain the cross-section of expected returns. However, the unconvincing results from empirical tests of the CAPM soon prompted researchers to search for other explanatory variables. Some focused on macroeconomic factors in the context of the arbitrage pricing theory (APT). Others looked into assorted market variables, either individual or common to all firms, cf. Fama and French (1993) (FF). Expanding the FF model, Carhart (1997) added a proxy for momentum, and Pastor and Stambaugh (2003) proposed a liquidity factor. All these models may be classified as describing the behaviour of rational agents and thus fit into the neoclassical finance paradigm.

---

\* Faculty of Economics and Sociology, University of Lodz, Poland.

\*\* School of Economics, Business and Accounting, University of Sao Paulo, Brazil.

An alternative approach investigates the role of irrational investor sentiment in shaping stock market returns. It borrows from modern developments in psychology and related behavioural disciplines in trying to overcome the difficulty of rational-agent models to explain away a growing number of so-called anomalies in stock markets, including recurring bubbles and financial crises. Some of this research is summarized in Baker and Wurgler (2006, 2007).

The research goal of this paper was to discover the relation shaping the rates of return of stocks listed in the biggest emerging market in Central and Eastern Europe, the Polish one. Differently from other studies with similar goals, the authors empirically investigated the cross-section of expected returns using the rates of return of individual stocks and including a broad set of potentially relevant variables of all three types (behavioural, market and macroeconomic). Including a set of behavioural factors and introducing variables from the US as the biggest capital market, allows our research to contribute to the current literature. Most studies focus on one or two types of variables, e.g. market and behavioural, such as in Baker and Wurgler (2006), Verma and Soydemir (2006), or market and macroeconomic such as in Kryzanowski and Zhang (1992), Chordia and Shivakumar (2002), Cooper et al. (2004), Patra and Poshakwale (2006), Leledakis et al. (2003), Narayan et al. (2014). In addition, most studies examine only developed markets (Chan et al., 1998; Kumar and Lee, 2006).

There are few papers that holistically examine at least two types of explanatory variables in emerging markets. Verma and Soydemir (2006) estimate vector autoregression (VAR) models and report that US sentiment indicators influence emerging stock markets, controlling for selected macroeconomic and market variables. In contrast to Verma and Soydemir (2006) however, this study did not focus only on behavioural factors (sentiment) and included a much larger set of variables that potentially influence stock returns. Moreover, the authors used firm-level data rather than market indices. To summarize this contribution to the existing literature: (i) the authors use a broader set of variables that potentially explain the cross-section of expected stock returns, including market, macroeconomic and behavioural factors; (ii) unlike most previous studies, all the analyses were run using rates of returns of individual stocks instead of portfolios, as suggested by Ang et al. (2017), employing adjustments for multiple testing, as suggested by Harvey et al. (2016); and (iv) examined the largest emerging stock market in Central and Eastern Europe and investigated how it is simultaneously influenced both by local and US-based indicators.

Market factors relate to market-wide or firm-specific indicators that might influence stock returns, such as the price to earnings ratio (P/E), capitalization,

market returns, liquidity, and momentum. Harvey et al. (2016) categorized market-wide risk factors such as the market return as common factors, whereas firm-specific variables such as firm size are categorized as individual factors. Together with macroeconomic variables, they comprise what are called fundamental factors because they can be associated with firm fundamentals, i.e. its future cash flows or discount rates, in a rational-agent framework. These variables were gathered from the extant literature, e.g. Chen (1983), Chen et al. (1986), Cutler et al. (1989), Fama and MacBeth (1973), Fama (1990), Balduzzi et al. (2001), Flannery and Protopapadakis (2002), Pastor and Stambaugh (2003), Boyd et al. (2005), Acharya and Pedersen (2005), Chan and Faff (2005), Shanken and Weinstein (2006), Avramov and Chordia (2006), Fama and French (1993, 1996, 2012), Naes et al. (2011), Çakmaklı and van Dijk (2016).

Behavioural factors, on the other hand, relate to the mood, sentiment, fears or desires of investors, i.e. they are based on human psychology (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2004; Lawrence et al., 2007; Qian, 2009). While this literature is growing fast, it remains less developed than its neoclassical counterpart. Importantly, behavioural research in emerging markets is still scarce and mostly focused on Asian cases (Chih-Lun and Yeong-Jia, 2008; Meng-Fen et al., 2011; Richards, 2005; Su, 2011). However, it can be argued that the limits to arbitrage that justify the relevance of non-standard explanatory variables should be particularly acute in emerging stock markets, which tend to be smaller, less liquid, and less institutionally developed (Ansotegui et al., 2013; Galdi and Lopes, 2013; Szyszka, 2013; Zaremba 2016).

The study employed the Fama and MacBeth (1973) procedure to estimate a set of cross-sectional regressions based on a baseline empirical model using data on all regularly traded Polish stocks included in the WIG Index, plus aggregate indicators from both the US and Polish markets. From many possible multiple-factors models (e.g. Skočir and Lončarski, 2018) the authors decided to apply the three most commonly used. Three of the alternative specifications in this study are analogous to the well-known Fama-French 3-factor, the Carhart 4-factor, and the Pastor-Stambaugh 5-factor models. In addition, the authors estimated models including as explanatory variables, the sensitivities of the individual stock returns to macroeconomic and aggregate behavioural variables. These sensitivities are estimated in time-series regressions run separately for each of the sample stocks. However, in order to avoid redundancy and excessive collinearity, the authors only included in the individual time-series regressions the variables that significantly predicted the returns of an equally weighted portfolio comprising our 334 sample stocks. In addition, based on the extant literature, a principal component analysis was

applied to construct aggregate measures of investor sentiment from individual sentiment/behavioural indicators.

Unlike most previous studies, these inferences were based not only on conventional (unadjusted) single-test  $t$ -statistics or  $p$ -values but also on  $t$ -statistics adjusted to accommodate multiple hypothesis testing. It was found that all but two explanatory variables failed to significantly explain the cross-section of expected returns in Poland. Specifically, none of the estimates related to macroeconomic and market sentiment factors were statistically significant at the conventional levels in the multivariate regressions. Similarly, market betas, either based on the WIG or the S&P500 market indices, did not significantly contribute to explain the cross-section of expected returns. The estimated coefficient for the price-to-book ratio is significant at the 5% level and the estimated coefficient for momentum is significant at the 10% level. These results are consistent with previous findings, suggesting that stocks with higher positive momentum and lower market/book value command higher expected returns. In line with Harvey et al. (2016) and Harvey and Liu (2018), this analysis suggests that methodological choices may critically influence conclusions when testing potential determinants of the cross-section of the expected returns. In particular, when more stringent inference procedures based on multivariate analyses are adopted, many seemingly relevant factors may turn out to be unimportant.

The remainder of the paper is organized as follows: Section 2 describes the data, variables and the methodological strategies, Section 3 presents and discusses the main results, and Section 4 concludes.

## 2. DATA, VARIABLES, AND METHOD

The authors attempted to use as many explanatory variables as possible, based on the list of common and individual factors that were found to explain the cross-section of expected returns in the extant literature (for an updated and comprehensive survey, see Harvey et al., 2016), the main limitation being data availability in the Polish market. In fact, many factors cannot be computed at all or they can only be computed for a very limited subset of firms.

The study used the data from the US market to place this research in an international settings and to test whether variables from the biggest and most important capital market influence Polish stock market returns. The US was chosen because it is the most relevant capital market in the world, and the majority of the biggest investing funds are located in the US, while the share of investors from abroad is relatively high in the Polish stock market (from

25% to 60% in the analysed period). Taking into account the ease of international capital investment, the US market is considered to be potentially the most impactful not only for the Polish market, but in general for all other markets.

Most of the data were taken from Bloomberg, complemented by Thomson-Reuters and several public sources, spanning 123 months in the period from October 2002 to December 2012. The sample period covers approximately four economic cycles, based on the estimates by Wośko (2007), who analysed business cycles in Poland and concluded that the average stock market cycle lasts for approximately 31 months. The length of the cycle used in this research is also similar to that indicted by Uribe and Mosquera (2016). Additionally, the authors obtained similar data from February 2000 to September 2002, comprising 31 months, and used it to estimate the starting values of the sensitivities (beta parameters) described in equation (2) below, i.e. the 'pre-estimation period'. To increase data availability, the sample was restricted to the shares included in the regulated WIG Index in December 2012. In line with Dimson (1979), the study further eliminated eight firms that were thinly traded in the period, i.e. those for which breaks in trading longer than 15 market sessions represented more than 0.5% of the total trading days in the sample period.

The common and individual factors are divided into three categories:

- (1) macroeconomic (e.g. industrial production, factory orders, new home sales, consumer price index, trade balance, unemployment rate, personal spending, and the composite leading indicators provided by the OECD);
- (2) market (e.g. stock market indices: S&P500 and WIG, capitalization, price-to-book value, momentum, and liquidity);
- (3) behavioural (e.g. consumer confidence, business confidence, consumer optimism, and analyst optimism). A number of the common factors are US-based and were used to examine the extent to which US macroeconomic, market, and behavioural indicators explain the cross-section of the expected returns in Poland.

Most of the variables used in this research are published by external sources. They are either used directly or after appropriate transformations (e.g. computing growth rates to address unit root issues). In addition, two proxies were computed for analyst optimism. The first (OPT I), is the ratio of positive recommendations to total recommendations released by the brokerage firms for each stock in each month. The second (OPT II), is the average premium or discount in analyst recommendations in comparison to the market price of each stock in each month. All variables and their sources are described in Tables 1 and 2 below.

Table 1  
US-based variables

Type	Acronym	Description	Type of transformation	Source
Market	rSP500	S&P500 Index	Rate of growth	Bloomberg
	IP_CHNG	Industrial production, monthly rate of growth	–	Bloomberg
Macroeconomic	NAPMPMI	ISM manufacturing index	Rate of growth	Bloomberg
	TMNOCHNG	Factory orders – monthly percent change of the value of new orders	–	Bloomberg
	NFP_TCH	Nonfarm payroll employment change	–	Bloomberg
	USURTOT	Unemployment rate	1st difference	Bloomberg
	MWINCHNG	Wholesale inventories	–	Bloomberg
	IMP1CHNG	Import price index (MoM)	–	Bloomberg
	PPI_CHNG	Producer price index (MoM)	–	Bloomberg
	CPUPXCHG	Consumer price index excluding food and energy (MoM)	–	Bloomberg
	CPT1CHNG	Capacity utilization	–	Bloomberg
	NHSLTOT	New home sales	Rate of growth	Bloomberg
	PITLCHNG	Personal income	–	Bloomberg
	SAARDTOT	Domestic vehicle sales	Rate of growth	Bloomberg
	CICRTOT	Consumer credit	–	Bloomberg
	PXFECCHNG	Producer price index excluding food and energy (MoM)	–	Bloomberg
	USTBTOT	Trade balance	1st difference	Bloomberg
	CPURNSA	Consumer price index NSA	Rate of growth	Bloomberg
	NHSPSTOT	Housing starts	–	Bloomberg
	DGNOCHNG	Durable goods orders	–	Bloomberg
	PCE_CRCH	Personal spending	–	Bloomberg
	USMMMNCH	Change in manufacture. payrolls	1st difference	Bloomberg
CPI_CHNG	Consumer price index (MoM)	–	Bloomberg	
INVENTUS	Business inventories – change in the total value of goods held in inventory by manufacturers, wholesalers and retailers (in %)	–	Bloomberg	
CHPMINDX	Chicago purchasing managers index or Chicago business barometer – summary of business activity in the Chicago region	–	Bloomberg	

CLIUS	Composite leading indicators (OECD), components of the variable are time series which show leading relationship with the reference series (GDP) at turning points	Rate of growth	OECD
OUTFGAF	Philadelphia Fed business outlook survey diffusion index general conditions	–	Bloomberg
CONCCONF	Consumer confidence – The Conference Board Consumer Confidence Index®, shows business conditions based on undertaken surveys on approximately 3,000 households	Rate of growth	Bloomberg
CONSENT	University of Michigan confidence index	Rate of growth	Bloomberg
BCIUS	Business confidence index (BCI), leading indicator for US (calculated by OECD)	Rate of growth	OECD
ECON_SIT	Economic situation survey index, shows economic situation – trends in US	–	OECD
Cons_pr_inf	Consumer prices (inflation) survey – shows future (expected by consumers) price trends in US	–	OECD
PU	Policy uncertainty – index measuring US policy uncertainty (Baker, Bloom and Davis, 2015)	Rate of growth	www.PolicyUncertainty.com
SENTUS	First component of PCA based on US-based behavioural variables	–	Author's calculations

Note: all variables were subjected to the augmented Dickey-Fuller (ADF) unit root test. When necessary, the variable was transformed (differences, growth rates) to ensure stationarity.

Source: authors' own.

Table 2  
Poland-based variables

Type	Acronym	Description	Type of transformation	Source
Market	rWIG	WIG Index, broadest Polish stock index	Rate of return	Bloomberg
	CAP	Capitalization – total current market value of the firm's outstanding shares	Logarithm	Bloomberg
	PBV	Price of share divided by book value per share	Logarithm	Bloomberg
	MOM	Momentum – cumulative value of one monetary unit compounded by the firm's rates of return from previous 9 months	Logarithm	Author's calculations
Macroeconomic	LIQ	Liquidity – as in Amihud (2002), see equation (3)	Logarithm	Author's calculations
	EQPORTF	Equally weighted portfolio of all sample firms	Rate of growth	Author's calculations
	Export	Export	1st difference of rate of growth	NBP – National Bank of Poland
	Import	Import	Rate of growth	NBP – National Bank of Poland
	Infl	Consumer Price Index	–	NBP – National Bank of Poland
	M3	M3 money supply	Rate of growth	NBP – National Bank of Poland
	M1	M1 money supply	Rate of growth	NBP – National Bank of Poland
	PMIPL	Purchasing manager index, index of economic activity in the manufacturing sector calculated by Markit Economics	Rate of growth	Bankier.pl
	Industry	Industrial production	Rate of growth	GUS – Polish Central Statistical Office
	Sales	Total retail trade (volume)	Rate of growth	OECD
	Unemp	Unemployment rate	1st difference	OECD
	Reserv	Total official reserves of central bank	Rate of growth	NBP
	CLIPL	Composite leading indicators – components of the variable are time series which shows leading relationship with the reference series (GDP) at turning points	–	OECD



WKG	Economic climate index – this index includes changes in the economic situation in Poland in the previous 12 months and anticipation of changes in the economic situation in Poland for the subsequent 12 months, based on surveys by Ipsos	Rate of growth	Ipsos-Demoskop		
WOK	Consumer optimism index – based on surveys by Ipsos, it is calculated from responses to 11 questions related to various economic variables (e.g., inflation, GDP, savings)	Rate of growth	Ipsos-Demoskop		
BCIPL	Business confidence indicator (BCI) for Poland	Rate of growth	OECD		
Pengab	Pengab index describes the status of the banking sector	Rate of growth	Bankier.pl		
OPT I	Analysts optimism indicator – share of positive recommendations in total recommendations released	–	Author's calculations		
OPT II	Analysts optimism indicator – average premium or discount in analyst recommendations in comparison to the share's market price	–	Author's calculations		
k2	Business climate index – based on surveys of 5000 manufacturing firms, presents general climate in the industry. Questions in surveys relate to current and expected economic situation. Rest of the business indexes described below represents economic situation in particular sectors of the economy.	Rate of growth	GUS – Polish Central Statistical Office		
k3	Business climate index published by local statistical office (GUS) for revenues in industry sector.	Rate of growth	GUS – Polish Central Statistical Office		
k5	Business climate index related to employment in industry.	Rate of growth	GUS – Polish Central Statistical Office		
k6	Business climate index describing general conditions in construction sector.	Rate of growth	GUS – Polish Central Statistical Office		
k7	Business climate index – related to revenues in construction sector.	Rate of growth	GUS – Polish Central Statistical Office		
k8	Business climate index – related to employment in construction sector.	Rate of growth	GUS – Polish Central Statistical Office		
SENT_PL	First component of PCA based on all Poland-based behavioural variables	–	Author's calculations		

Note: all variables were subjected to the augmented Dickey-Fuller (ADF) unit root test. When necessary, the variable was transformed (differences, growth rates) to ensure stationarity.

Source: authors' own.

Equation (1) below shows the main empirical model estimated using the classical Fama and MacBeth (1973) procedure. The Fama-MacBeth method has been widely used in the literature because it addresses the concern that the idiosyncratic errors might be highly correlated in each period because of economy-wide shocks that affect firms, which could make conventionally computed standard errors highly misleading. The first step in the Fama-MacBeth procedure is to estimate a set of cross-sectional regressions, in this case, 123 regressions using monthly data for 334 shares. This procedure results in 123 sets of estimated coefficients. Subsequently, the authors used these time series to compute averages, standard deviations, and  $t$ -statistics, to test the statistical significance of each coefficient.

$$r_t^i = \gamma_0 + \gamma_1 \beta_{mkt,t-1}^i + \gamma_2 CAP_{t-1}^i + \gamma_3 PBV_{t-1}^i + \gamma_4 MOM_{t-1}^i + \dots + \gamma_5 LIQ_{t-1}^i + \sum_{j=1}^k \delta_j \beta_{macro,j,t-1}^i + \sum_{j=1}^h \theta_j \beta_{sent,j,t-1}^i + \varepsilon_t^i, \quad (1)$$

where  $r_t^i$  is the rate of return of stock  $i$  in month  $t$ , with  $i=1,\dots,334$ , and  $t=1,\dots,123$ ;  $\beta_{mkt,t-1}^i$  is the sensitivity of the (expected) return of the  $i$ -th stock to changes in the return of either the WIG ( $\beta_{WIG,t-1}^i$ ) or the S&P500 ( $\beta_{SP500,t-1}^i$ ) market index, measured in month  $t-1$ ;  $CAP_{t-1}^i$ ,  $PBV_{t-1}^i$ ,  $MOM_{t-1}^i$ ,  $LIQ$  represent capitalization, the price-to-book ratio, momentum and liquidity measures;  $\beta_{macro,j,t-1}^i$  is the sensitivity of the expected return of the  $i$ -th stock to changes in the  $j$ -th macroeconomic variable, with  $j=1,\dots,k$ ;  $\beta_{sent,t-1}^i$  is the sensitivity of the expected return of the  $i$ -th stock to changes in the  $j$ -th behavioural (i.e. market sentiment) variable, with  $j=1,\dots,h$ ; and  $\varepsilon_t^i$  is the idiosyncratic error term.

Equation (1) may be estimated using the full set of explanatory variables or different subsets of variables, so that it can be made to resemble, e.g. the 3-factor Fama-French model, the 4-factor Carhart model, or the 5-factor Pastor-Stambaugh model. However the authors noted that the classical Fama-French approach uses portfolios of stocks as the base assets, whereas this study used only individual stocks. Although it has been argued that using portfolios allows more precise estimates of factor loadings, this approach has been criticized by, among others, Shanken (1992), Kim (1995), and Berk (2000). In particular, Ang et al. (2017) showed that using portfolios as the base assets actually leads to larger standard errors and less precise estimates of risk premiums. Additionally, previous research shows that the results of asset pricing tests can be dramatically influenced by the particular way of grouping stocks into portfolios. Therefore, besides enhancing precision, using individual stocks has a lower potential to introduce biases into the empirical analysis.

Some of the explanatory variables in equation (1) must be estimated using time-series regressions, as described in equation (2) below. Specifically, for each stock  $i$  the authors estimated a set of 123 rolling window ordinary least squares time-series regressions, with a window length equal to 31 months (roughly the average size of one business cycle in Poland), where the dependent variable is the rate of return of the stock and the explanatory variables are a set of market, macroeconomic, and behavioural (common) factors. Then, the authors collected the estimated betas (sensitivities) and used them as explanatory variables in equation (1).

$$r_t^i = \alpha^i + \beta_{WIG}^i r_t^{WIG} + \beta_{SP500}^i r_t^{SP500} + \dots + \sum_{j=1}^k \beta_{macro,j}^i F_{j,t}^{macro} + \sum_{j=1}^h \beta_{sent,j}^i F_{j,t}^{sent} + u_t^i \quad (2)$$

The first 31-month window was from February 2000 to September 2002, the second from March 2000 to October 2002, and so on. Using this algorithm, the study separately estimated equation (2) for each of the 123 rolling 31-month windows and each of the 334 stocks, where  $r_t^i$  is the rate of return of stock  $i$  in month  $t$ ;  $r_t^{WIG}$  is the rate of return of the WIG market index;  $r_t^{SP500}$  is the rate of return of the S&P500 market index;  $F_{j,t}^{macro}$  is the  $j$ -th macroeconomic variable, with  $j=1, \dots, k$ ;  $F_{j,t}^{sent}$  is the  $j$ -th behavioural variable, with  $j=1, \dots, h$ ; and  $u_t^i$  is the idiosyncratic error term. Thus, 123 estimates were produced for each (beta) parameter in equation (2) for each firm (the total number of estimates for each coefficient is therefore  $334 \times 123 = 41,082$ ).

Data on several indicators of investor sentiment were collected, eight for the US market and twelve for the Polish market (US and Polish indicators differ because of differences in data availability), including proxies for analyst optimism and several indices related to consumer confidence and business confidence. These indicators, described in Tables 1 and 2, are similar to the ones used in previous research (e.g. Fisher and Statman, 2003; Qiu and Welch, 2006; Lemmon and Portniaguina, 2006; Ferrer et al., 2016). Since they are all proxies for the same concept, the authors followed related research (e.g. Brown and Cliff, 2004; Baker and Wurgler, 2006, 2007) and applied principal component analysis (PCA) in order to construct an aggregate measure of investor sentiment from the individual sentiment/behavioural variables. Therefore, it was possible to include in equation (2) both the individual indicators and the first component of PCA, which aggregates all behavioural variables. These variables were used

in separate specifications to avoid collinearity in the general-to-specific modelling (GETS) approach mentioned below.

However, before estimating equation (2) for each month and sample firm, the authors took a step back and applied a selection algorithm in order to choose the indicators that are actually relevant in explaining rates of return in the Polish market. The goal was to avoid redundancy and excessive collinearity among the variables included in equation (2), given the data collected on 24 US and 11 Polish macroeconomic variables. Thus, adding the rate of return on the market portfolio (US and Polish) and the set of behavioural and macroeconomic indicators, one obtains 59 candidate explanatory variables, many of which are surely redundant. In implementing the selection algorithm, the study used the general-to-specific modelling (GETS) approach, described in Hendry and Krolzig (2005). This selection method starts with the estimation of the general unrestricted model (GUM) including all explanatory variables. Then, statistically irrelevant variables are removed sequentially until a more parsimonious specification is reached, without losing much explanatory power. This procedure (which is usually automated within statistical packages) has been used primarily in empirical macroeconomic modelling but also in finance (e.g. Gnimmassoun, 2015; Hassan and Al Refai, 2012; Nell and Thirlwall, 2018).

The GUM specification is similar to equation (2), the main difference being that the dependent variable is the monthly rate of return of an equally weighted portfolio including the 334 sample stocks. In addition, instead of using rolling windows a single time-series encompassing the entire sample period was used. The set of explanatory variables include all the indicators mentioned above, except the return of the WIG index, which highly correlates with the dependent variable.

After the application of the selection algorithm one obtains a well-behaved and parsimonious model containing five variables that contribute substantively to explain the variation of the equally weighted portfolio returns. These results are shown in Table 3 below.

Interestingly, three of the selected explanatory variables refer to the US market: the return of the S&P500 index; the growth rate of the value of goods held in inventory by manufacturers, wholesalers, and retailers in the US; and the first component of the PCA including the eight US investor sentiment proxies. Therefore, both market, macroeconomic and behavioural US-based factors appear to play important roles in explaining the aggregate Polish stock market. The remaining selected explanatory variables are Polish macroeconomic indicators.

Table 3

Time-series regression results, after applying the GETS selection algorithm. The dependent variable is the monthly rate of return of an equally weighted portfolio including all sample stocks

Explanatory variables	Estimates
<i>Intercept</i>	-1.9485*** (-5.544)
<i>SP500</i>	0.7518*** (7.181)
<i>INVENTUS</i>	-0.0314*** (-3.263)
<i>PMIPL</i>	0.5049*** (3.116)
<i>CLIPL</i>	0.0197*** (5.589)
<i>SENTUS</i>	0.0120** (2.496)
Observations	154
R-squared	0.54067
R-squared (adjusted)	0.52516

Note: final specification after applying the general-to-specific modelling (GETS) selection algorithm described in Hendry and Krolzig (2005). Diagnostics include normality, autocorrelation, and heteroscedasticity tests. The dependent variable is the monthly rate of return of an equally weighted portfolio including the 334 sample stocks. The initial set of explanatory variables included 58 indicators – we exclude the return of the WIG index because it is highly correlated with the dependent variable. *SP500* is the rate of return of the S&P500 Index; *INVENTUS* (business inventories) is the change in the total value of goods held in inventory by manufacturers, wholesalers, and retailers in the US (rate of growth); *PMIPL* (purchasing manager index) is the index of economic activity in the Polish manufacturing sector computed by Markit Economics (rate of growth); *CLIPL* (composite leading indicators) – components of this variable are time series which show leading relationship with the Polish GDP series at turning points, computed by OECD; *SENTUS* is the first component of the PCA based on US-based behavioural variables. The table shows OLS coefficient estimates – *t*-statistics are shown in parentheses. \*\* and \*\*\* indicate statistical significance at the 5% and 1% levels, respectively.

Source: authors calculations in PcGets.

These selected variables, plus the return of the WIG market index, are subsequently included in equation (2), which is estimated separately for each stock using 123 31-month rolling windows. The estimated coefficients (betas or sensitivities) were then used as explanatory variables in equation (1). In addition, the authors included in the baseline model represented by equation

(1) the firm-level measures of capitalization, price-to-book ratio, momentum, and liquidity. As described in Table 2, the Amihud (2002) measure of liquidity was used, given by

$$LIQ_t^i \equiv \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{|R_{t,d}^i|}{MV_{t,d}^i}, \quad (3)$$

where  $R_{t,d}^i$  is the  $i$ -th stock rate of return in day  $d$  and month  $t$ ;  $MV_{t,d}^i$  is the trading volume of the  $i$ -th stock in monetary value in day  $d$  and month  $t$ ; and  $Days_t^i$  is the number of days with quotations for stock  $i$  in month  $t$ .

The main inferences are based on the estimation of equation (1) including either all the explanatory variables or subsets of the explanatory variables. Initially, following almost all of the extant related literature, the study used unadjusted individual  $t$ -statistics (or their corresponding  $p$ -values) to test the hypotheses about the significance of each factor, whilst being aware of the critique of the empirical asset pricing literature offered by Harvey et al. (2016). The authors showed that it may be unwarranted to rely on conventional (i.e. unadjusted) single-test individual  $t$ -statistics to establish significance of factors because it fails to account for the fact that a multiplicity of candidate factors are being tested by one or more researchers using roughly the same cross-section of stock returns. For example, Harvey et al. (2016) documented that 316 different (although in many cases highly correlated) factors were tested using US data from 1967 to 2012. The problem with ignoring the multiple testing framework is that the overall type I error rate (i.e. the probability of finding a factor to be significant when it is not, a false discovery) may be much higher than the desired (conventional) significance level (typically 5% or 10%). Therefore, in order to keep the (family-wise) type I error rate equal to the chosen significance level, an adjustment for multiple testing should be made.

However, correctly implementing one of the available multiple testing adjustments is not straightforward because it depends on several assumptions, including the number of factors being tested, the degree of dependence of the tests, the comparability of the testing methods, and the comparability of the datasets used. Harvey et al. (2016) computed a few suggested thresholds for  $t$ -statistics that are applicable only to US-based empirical studies but it remains unclear which precise threshold is more appropriate. In any case, the main point of Harvey et al. (2016) is that more stringent significance thresholds should be adopted when multiple hypotheses are being tested simultaneously using the same cross-sectional data and comparable methods.

To address this issue, two adjustment procedures were employed, aiming to ensure that the family-wise type I error rate does not exceed the chosen significance level  $\alpha$  (i.e. to ensure that the probability of at least one false discovery in the multiple testing setting is no greater than  $\alpha$ ). First, Bonferroni's adjustment was used, which is the most conservative and well-known procedure. Next, the more sophisticated Holm's adjustment was implemented, which is uniformly more powerful than Bonferroni's adjustment, i.e. it is more likely to reject a null hypothesis that should be rejected (Harvey et al., 2016).

### 3. RESULTS

Tables 4 and 5 show the results of the estimation, using the Fama and MacBeth (1973) procedure, of several alternative specifications based on equation (1). Table 4 presents the estimates of specifications that are analogous to the classical Fama-French 3-factor model, the Carhart 4-factor model, and the Pastor-Stambaugh 5-factor model. In all cases, the market betas (i.e. the sensitivity of the expected return of the stock to changes in the return of the market index, either the WIG or the S&P500) of Polish firms do not significantly predict their monthly rates of return. Therefore, in this sample period, higher market betas are not significantly associated with higher expected returns in Poland. The coefficient estimates for the measure of firm capitalization are negative and significant at the conventional levels in all specifications, implying that larger firms command lower expected returns. The estimated coefficients for the price-to-book ratio are negative, suggesting that firms with higher market/book value have lower expected returns, on average. However, these estimates are significant at the conventional levels in some but not all specifications. The estimated coefficients for the proxy for momentum are positive and significant at the conventional levels in all specifications, suggesting that firms experiencing high positive momentum tend to have higher returns. These results are broadly consistent with related research undertaken in developed (e.g. Benz, 1981; Jegadeesh and Titman, 1993; Fama, 1981; Fama and French, 1993, 2012; Acharya and Pedersen, 2005) and emerging markets (e.g. Borys and Zemcik, 2011; Borys, 2001; Yoshinaga and Castro, 2012; De Silva, 2005; Bundoo, 2008). Finally, the estimated coefficients for the proxy for stock liquidity are close to zero and not significant at the conventional levels, suggesting that stock liquidity is not relevant to explain the cross-section of expected returns in Poland.

Table 4

Estimates based on model (1) using specifications analogous to classical models describing the cross-section of expected returns

Model / Explanatory variables		<i>Intercept</i>	$\beta_{WIG}$	$\beta_{SP500}$	<i>CAP</i>	<i>PBV</i>	<i>MOM</i>	<i>LIQ</i>
Analogous to the Fama French 3-factor model	(i)	0.0516** (4.29)	-0.0005 (-0.16)		-0.0050** (-3.77)	-0.00288 (-1.04)		
	(ii)	0.0483** (4.05)		0.00281 (1.25)	-0.0049** (-3.71)	-0.00287 (-1.06)		
Analogous to the Carhart 4-factor model	(iii)	0.0474** (4.06)	-0.0018 (-0.65)		-0.005** (-3.79)	-0.005** (-2.41)	0.0226** (3.27)	
	(iv)	0.0445** (3.84)		0.0014 (0.69)	-0.005** (-3.74)	-0.005** (-2.36)	0.0229** (3.35)	
Analogous to the Pastor-Stambaugh 5-factor model	(v)	0.0599** (4.24)	-0.0011 (-0.38)		-0.004** (-2.26)	-0.005** (-2.28)	0.0229** (3.37)	0.0011 (0.98)
	(vi)	0.0587** (3.99)		0.0017 (0.84)	-0.004** (-2.22)	-0.005** (-2.22)	0.0234** (3.44)	0.0012 (1.07)

Note: the dependent variable is the individual stocks' monthly rate of return;  $\beta_{WIG}$  and  $\beta_{SP500}$  represent the sensitivity of the individual stock's expected rate of return to changes in the WIG index and in the S&P500 index, respectively; *CAP* represents the firm's market capitalization; *PBV* – the firm's price-to-book ratio; *MOM* – the stock's momentum; and *LIQ* – the stock's liquidity measure, as in Amihud (2002). Following Fama and MacBeth (1973), we compute each coefficient estimate as a mean from the set of OLS cross-sectional regression estimates, one for each of the 123 sample months; *t*-statistics, shown in parentheses, are given by  $\frac{m}{s(m)/\sqrt{n}}$  where *m* is the mean and *s*(*m*) is the standard deviation of the *n* cross-sectional coefficient estimates (*n* = 123). \* and \*\* indicate statistical significance at the 10% and 5% levels, respectively, using single-test critical values (i.e. unadjusted for multiple testing).

Source: authors calculations in EViews.

Table 5 presents the estimates for specifications that also include as explanatory variables either a subset or the complete set of macroeconomic and behavioural sensitivities (betas) estimated in equation (2) after the application of the GETS selection algorithm. The results show that the coefficient estimates for all these sensitivities are, in the majority of specifications, close to zero and not significant at the conventional levels, suggesting that macroeconomic and behavioural factors are not relevant explanatory factors for cross-sectional expected returns in the Polish market. On the other hand, the inferences discussed above regarding the market-wide and firm-specific variables are similar. In particular, when estimating the regression containing the complete set of explanatory variables the authors found non-significant coefficient estimates for the market beta and for the



Table 5. Estimates based on model (1) using specifications analogous to classical models describing the cross-section of expected returns

Model / Explanatory Variables	<i>Intercept</i>	$\beta_{WIG}$	<i>CAP</i>	<i>PBV</i>	<i>MOM</i>	<i>LIQ</i>	$\beta_{INVENTUS}$	$\beta_{PMIPL}$	$\beta_{CLIPL}$	$\beta_{SENTUS}$
1) Models including capitalization, P/BV, macroeconomic and behavioural variables	(i)	0.0498** (4.23)	-0.0047** (-3.62)	-0.0037 (-1.34)			-0.0152 (-0.71)			
	(ii)	0.0519** (4.28)	0.0007 (0.21)	-0.0051** (-3.74)	-0.0038 (-1.35)			-0.0006 (-0.36)		
	(iii)	0.0486** (4.05)	-0.0016 (-0.50)	-0.0044** (-3.38)	-0.0033 (-1.21)				0.1527** (2.30)	
	(iv)	0.0517** (4.29)	0.0009 (0.25)	-0.0052** (-3.86)	-0.0033 (-1.16)					-0.0124 (-0.20)
2) Models including capitalization, momentum, macroeconomic and behavioural variables	(v)	0.0478** (4.13)	-0.0000 (-0.29)	-0.0056** (-4.17)		0.0161** (2.22)	-0.0102 (-0.54)			
	(vi)	0.0514** (4.43)	0.0000 (0.01)	-0.0062** (-4.58)		0.0169** (2.32)		-0.0019 (-1.19)		
	(vii)	0.0481** (4.14)	-0.0015 (-0.53)	-0.0056** (-4.13)		0.0177** (2.32)		0.0839 (1.42)		
	(viii)	0.0510** (4.38)	-0.0002 (-0.08)	-0.0062** (-4.48)		0.0178** (2.53)				-0.0142 (-0.24)
3) Models including capitalization, liquidity, macroeconomic and behavioural variables	(ix)	0.0646** (4.37)	0.0016 (0.50)	-0.0048** (-2.69)		0.0010 (0.87)	0.0107 (0.58)			
	(x)	0.0667** (4.65)	0.0020 (0.59)	-0.0053** (-2.92)		0.0009 (0.80)		-0.0013 (-0.92)		
	(xi)	0.0633** (4.42)	0.0007 (0.20)	-0.0046** (-2.58)		0.0009 (0.84)		0.0765 (1.42)		
4) Full specification	(xii)	0.0660** (4.51)	0.0020 (0.60)	-0.0054** (-2.98)		0.0008 (0.75)				-0.0054 (-0.09)
	(xiii)	0.0607** (4.08)	0.0016 (0.53)	-0.0041** (-2.31)		0.0224** (2.72)	-0.0131 (-0.38)	-0.0028 (-1.40)	-0.0174 (-0.14)	0.0065 (0.10)

Note: the dependent variable is the individual stocks' monthly rate of return;  $\beta_{WIG}$  represents the sensitivity of the individual stock's expected rate of return to changes in the WIG index; *CAP* – the firm's market capitalization; *PBV* – the firm's price-to-book ratio; *MOM* – the stock's momentum; *LIQ* – the stock's liquidity measure, as in Amihud (2002);  $\beta_{INVENTUS}$ ,  $\beta_{PMIPL}$ ,  $\beta_{CLIPL}$  and  $\beta_{SENTUS}$  – the sensitivity of the individual stock's expected rate of return to changes in the variables *INVENTUS*, *PMIPL*, *CLIPL*, and *SENTUS*, respectively (see descriptions in Table 3). Following Fama and MacBeth (1973), we compute each coefficient estimate as the mean from a set of OLS cross-sectional regression estimates, one for each of the 123 sample months; *t*-statistics, shown in parentheses, are given by  $\frac{m}{s(m)/\sqrt{n}}$  where *m* is the mean and *s*(*m*) is the standard deviation of the *n* cross-sectional coefficient estimates (*n* = 123). \* and \*\* indicate statistical significance at the 10% and 5% levels, respectively, using single-test critical values (i.e. unadjusted for multiple testing).

Source: authors calculations in EViews.

liquidity proxy, negative and significant coefficient estimates for capitalization and the price-to-book ratio, and a positive and significant coefficient estimate for the momentum proxy. A battery of diagnostic tests was run to make sure that the inferences are not adversely affected by typical regression complications, such as excessive collinearity among the explanatory variables; e.g. our variance inflation factor statistics are in all cases comfortably below the threshold for excessive collinearity suggested by Kutner et al. (2004).

Next, Bonferroni's adjustment was used to compute a  $t$ -statistic threshold that accounts for the fact of testing multiple candidate factors using the same cross-section of expected returns. Specifically, following the GETS selection algorithm, ten candidate factors were obtained, i.e. testing ten different hypotheses in the cross-sectional regressions. In this setting, Bonferroni's adjustment consists of computing threshold  $p$ -values that are equal to the significance level  $\alpha$  divided by the number of null hypotheses, yielding 0.5% when  $\alpha=5\%$  and 1% when  $\alpha=10\%$ . Using these  $p$ -value thresholds, it was also possible to compute adjusted  $t$ -statistic thresholds (i.e. critical values) for a two-sided test based on the standard normal distribution. These  $t$ -statistic thresholds are approximately 2.81 ( $\alpha=5\%$ ) and 2.58 ( $\alpha=10\%$ ). Using these critical values and comparing with the reported  $t$ -statistics in Tables 4 and 5, one notes that the estimated coefficients for capitalization, price-to-book value and momentum are the only ones that are significant at the 5% or the 10% level in one or more specifications. However, it seems more appropriate that the inferences were based on the multivariate models including all explanatory variables simultaneously (actually reporting regressions containing up to 9 explanatory variables to avoid including the returns of the WIG and of the S&P500 market indices simultaneously in order to avoid excessive collinearity. This choice does not affect the multiple testing setting, however). In this case, only the estimated coefficients for price-to-book value and momentum remain significant at the 10% level, whereas only the estimated coefficient for price-to-book value is significant at the 5% level. This inference is unchanged when employing the sequential  $p$ -value analysis as suggested by Holm's adjustment procedure, described in detail in Harvey et al. (2016). Therefore, applying a more stringent multiple testing framework using multiple regressions results in the non-significance of all but two (at most) candidate factors. Specifically, higher expected returns are significantly associated with higher positive momentum and lower price-to-book ratios in the Polish stock market. The significant value of intercepts indicates that there is an additional, not explained premium for risk of stocks. The results shows that this premium is positive, and indicates that there exist other factors not included in this model. Fama and MacBeth (1973) in their original study also reported positive and

significant values. One of the significant differences between Fama and MacBeth's US market sample and the sample used in this study is that the Polish stock market (measured as an equally weighted portfolio of all stocks) increased its value by almost 19% per year in the analysed period, meanwhile growth in the US was much smaller (ca. 7%). This underlines some of the challenges in the analysis of emerging markets.

## CONCLUSION

To the best of the authors knowledge, this is one of the first attempts to shed light on the determinants of the cross-section of expected returns in emerging markets using a broad set of candidate factors, encompassing common and individual market indicators, macroeconomic variables and proxies for market sentiment. In addition, the study explored the role played by the US-based market index, macroeconomic variables and behavioural variables.

The data collected on Polish stocks included in the WIG Index, spanned 123 months, plus a 31-month 'pre-estimation' period. Following previous behavioural research, the first step in this analysis was to construct aggregate measures of investor sentiment based on both the Polish and US markets using principal component analysis (PCA). Then, the authors applied a structured general-to-specific algorithm to select, among 59 Polish and US-based indicators that are common to all firms (market, macroeconomic and behavioural), the ones that are most relevant to explain the returns of an equally weighted portfolio comprising the 334 sample stocks. Three US-based indicators among the variables were found that are significant explanatory factors for the returns of the aggregate Polish stock market: the return of the S&P500 index, a macroeconomic indicator, and the first component of the PCA of proxies for investor sentiment.

The selected indicators, both local and US-based, were subsequently used in a set of time-series regressions, from which the study estimated the sensitivity of the expected returns of each stock to variations of each indicator (i.e. estimating a time-series of betas for each indicator). Finally, ten explanatory variables were used, including estimated sensitivities and individual firm-level characteristics, in the cross-sectional regressions. The Fama and MacBeth (1973) procedure was employed to estimate several alternative specifications based on the baseline model, including specifications analogous to the well-known Fama-French 3-factor, Carhart 4-factor, and the Pastor-Stambaugh 5-factor models.

Based on conventional single-test  $t$ -statistics or  $p$ -values, it was found that firms with higher market capitalization and higher price-to-book ratio command lower expected returns, on average, whereas firms experiencing high positive momentum are expected to have higher returns. These results are broadly consistent with previous evidence from both developed and emerging markets. However, when the adjusted inferences were taken into consideration, the multiple testing setting using either Bonferroni's or Holm's adjustment procedures, only the estimated coefficient for price-to-book value was significant at the 5% level, whereas the estimate for momentum was significant at the 10% level. On the other hand, regardless of the use of adjusted or unadjusted testing procedures, the study found that higher market betas, either based on the WIG or the S&P500 market indices, were not significantly associated with higher expected returns in Poland. Analogously, the cross-section of expected returns seems to be unrelated to stock liquidity and to the set of macroeconomic and behavioural factors.

Taken together, the results suggest that most of the candidate factors available in the Polish stock market fail to consistently explain the cross-sectional variation of expected returns, and that the best candidates relate to firm-specific characteristics, in particular, market/book value and momentum. In addition, the analysis indicates that the results can be substantially affected by methodological choices such as: including multiple factors simultaneously in the empirical model; using individual stocks instead of portfolios as base assets; and adjusting inferences for multiple testing. One implication for related research is that some of the reported factor discoveries (i.e. factors that significantly explain the cross-section of expected returns) may be reversed if more reliable/stringent statistical procedures are adopted. A similar lesson seems to be conveyed by the recent US-based methodology-oriented studies by Harvey et al. (2016) and Harvey and Liu (2018). Interesting avenues that the authors have left for further research include the application of the bootstrap-based factor selection method advanced by Harvey and Liu (2018) and the extension of this analysis to a multi-country setting.

## REFERENCES

- Acharya, V. V., Pedersen, H. L., *Asset pricing with liquidity risk*, "Journal of Financial Economics", No. 77, pp. 375–410, 2005.
- Amihud, Y., *Illiquidity and stock returns: cross-section and time-series effects*, "Journal of Financial Markets", No. 5 (1), pp. 31–56, 2002.
- Ang, A., Liu, J., Schwarz, K., *Using individual stocks or portfolios in tests of factor models*, Working Paper, Available at SSRN: <https://ssrn.com/abstract=1106463>, 2017.

- Ansotegui, C., Bassiouny, A., Tooma, E., *The proof is in the pudding: Arbitrage is possible in limited emerging markets*, “Journal of International Financial Markets, Institutions & Money”, No. 23, pp. 342–357, 2013.
- Avramov, D., Chordia, T., *Asset pricing models and financial market anomalies*, “Review of Financial Studies”, No. 19 (3), pp. 1001-1040, 2006.
- Baker, M., Wurgler, J., *Investor sentiment and the cross-section*, “Journal of Finance”, No. 61 (4), pp. 1645–1680, 2006.
- Baker, M., Wurgler, J., *Investor sentiment in the stock market*, “Journal of Economic Perspectives”, No. 21(2), pp. 129–151, 2007.
- Baker, S. R., Bloom, N., Davis, S. J., *Measuring economic policy uncertainty*, National Bureau of Economic Research, Working Paper 21633, <http://www.nber.org/papers/w21633>, 2015.
- Balduzzi, P., Elton, J. E., Green, C. T., *Economic news and bond prices: evidence from the U.S. treasury market*, “Journal of Financial and Quantitative Analysis”, No. 36(4), pp. 523–543, 2001.
- Banz, R. W., *The relationship between return and market value of common stocks*, “Journal of Financial Economics”, No. 9 (1), pp. 3–18, 1981.
- Berk, J. B., *Sorting out sorts*, “The Journal of Finance”, No. 55(1), pp. 407–427, 2000.
- Borys, M. M., *Testing multi-factor asset pricing models in the Visegrad countries*, “Czech Journal of Economics and Finance”, No. 61(2), pp. 118–139, 2001.
- Borys, M. M., Zemcik, P., *Size and value effects in the Visegrad countries*, “Emerging Markets Finance & Trade”, No. 47 (3), pp. 50–68, 2011.
- Boyd, J. H., Hu, J., Jagannathan, R., *The stock market's reaction to unemployment news: why bad news is usually good for stocks*, “Journal of Finance”, No. 6(2), pp. 649–672, 2005.
- Brown, G. W., Cliff, T. M., *Investor sentiment and the near-term stock market*, “Journal of Empirical Finance”, No. 11, pp. 1–27, 2004.
- Bundoo, S. K., *An augmented Fama and French three-factor model: new evidence from an emerging stock market*, “Applied Economics Letters”, No. 15(15), pp. 1213–1218, 2008.
- Carhart, M. M., *On persistence in mutual fund performance*, “Journal of Finance”, No. 52(1), pp. 57–82, 1997.
- Çakmaklı, C., Van Dijk, D., *Getting the most out of macroeconomic information for predicting excess stock returns*, “International Journal of Forecasting”, No. 32(3), pp. 650-668, 2016.
- Chan, H. W., Faff, W. R., *Asset pricing and the illiquidity premium*, “Financial Review”, No. 40(4), pp. 429–458, 2005.
- Chan, L. K. C., Karceski, J., Lakonishok, J., *The risk and return from factors*, “Journal of Financial & Quantitative Analysis”, No. 33(2), pp. 159–188, 1998.
- Chen, N., *Some empirical tests of the theory of arbitrage pricing*, “Journal of Finance”, No. 38(5), pp. 1393–1414, 1983.
- Chen, N., Roll, R., Ross, S., *Economic forces and the stock market*, “Journal of Business”, No. 59(3), pp. 382–403, 1986.
- Chih-Lun, H., Yeong-Jia, G., *Are happy investors likely to be overconfident?*, “Emerging Markets Finance & Trade”, No. 44(4), pp. 33–39, 2008.
- Chordia, T., Shivakumar, L., *Momentum, business cycle, and time-varying expected returns*, “Journal of Finance”, No. 57(2), pp. 985–1019, 2002.

- Cooper, M., Gutierrez Jr, C. R., Hameed, A., *Market states and momentum*, "Journal of Finance", No. 59(3), pp. 1345–1365, 2004.
- Cutler, D. M., Poterba, M. J., Summers, H. L., *What moves stock prices?*, "Journal of Portfolio Management", No. 15(3), pp. 4–12, 1989.
- De Silva, A. C., *Modeling and estimating a higher systematic co-moment asset pricing model in the Brazilian stock market*, "Latin American Business Review", No. 6 (4), pp. 85–101, 2005.
- Dimson, E., *Risk measurement when shares are subject to infrequent trading*, "Journal of Financial Economics", No. 7 (2), pp. 197–226, 1979.
- Fama, E. F., *Stock returns, real activity, inflation, and money*, "American Economic Review", No. 71 (4), pp. 545–565, 1981.
- Fama, E. F., *Stock returns, expected returns, and real activity*, "Journal of Finance", No. 45 (4), pp. 1089–1108, 1990.
- Fama, E. F., French, R. K., *The cross-section of expected stock returns*, "The Journal of Finance", No. 47 (2), pp. 427–465, 1992.
- Fama, E. F., French, R. K., *Common risk factors in the returns on stocks and bonds*, "Journal of Financial Economics", No. 33, pp. 3–56, 1993.
- Fama, E. F., French, R. K., *Multifactor explanations of asset pricing anomalies*, "Journal of Finance", No. 51(1), pp. 55–84, 1996.
- Fama, E. F., French, R. K., *Size, value, and momentum in international stock returns*, "Journal of Financial Economics", No. 105, pp. 457–472, 2012.
- Fama, E. F., MacBeth, D. J., *Risk, return, and equilibrium: Empirical tests*, "Journal of Political Economy", No. 81 (3), pp. 607–636, 1973.
- Ferrer, E., Salaber, J., Zalewska, A., *Consumer confidence indices and stock markets' meltdowns*, "European Journal of Finance", No. 22 (3), pp. 195–220, 2016.
- Fisher, K. L., Statman, M., *Consumer confidence and stock returns*, "Journal of Portfolio Management", No. 30(1), pp. 115–128, 2003.
- Flannery, M. J., Protopapadakis, A. A., *Macroeconomic factors do influence aggregate stock returns*, "Review of Financial Studies", No. 15 (3), pp. 751–782, 2002.
- Galdi, F. C., Lopes, B. A., *Limits to arbitrage and value investing: Evidence from Brazil*, "Latin American Business Review", No. 14 (2), pp. 107–137, 2013.
- Gnimassoun, B., *The importance of the exchange rate regime in limiting current account imbalances in sub-Saharan African countries*, "Journal of International Money and Finance", No. 53, pp. 36–74, 2015.
- Harvey, C. R., Liu, Y., Zhu, H., *...and the cross-section of expected returns*, "The Review of Financial Studies", No. 29 (1), pp. 5–68, 2016.
- Harvey, C. R., Liu, Y., *Lucky factors*. Working Paper, Available at SSRN: <https://ssrn.com/abstract=2528780>, 2018.
- Hassan, G. M., Al Refai, M. H., *Can macroeconomic factors explain equity returns in the long run? The case of Jordan*, "Applied Financial Economics", No. 22 (13), pp. 1029–1041, 2012.
- Hendry, D. F., Krolzig, M. H., *The properties of automatic GETS modelling*, "The Economic Journal", No. 115(502), pp. 32–61, 2005.

- Jegadeesh, N., Titman, S., *Returns to buying winners and selling losers: Implications for stock market efficiency*, "Journal of Finance", No. 48 (1), pp. 65–89, 1993.
- Kim, D., *The errors in the variables problem in the cross-section of expected stock returns*, "Journal of Finance", No. 50, pp. 1605–1634, 1995.
- Kryzanowski, L., Zhang, H., *Economic forces and seasonality in security returns*, "Review of Quantitative Finance & Accounting", No. 2 (3), pp. 227–244, 1992.
- Kumar, A., Lee, C. M. C., *Retail investor sentiment and return comovements*, "The Journal of Finance", No. 61 (5), pp. 2451–2486, 2006.
- Kutner, M. H., Nachtsheim, J. Ch., Neter, J., *Applied linear regression models*. McGraw-Hill Irwin, 2004.
- Lawrence, E. R., McCabe, G., Prakash, J. A., *Answering financial anomalies: Sentiment-based stock pricing*, "Journal of Behavioral Finance", No. 8 (3), pp. 161–171, 2007.
- Leledakis, G. N., Davidson, I., Karathanassis, G., *Cross-sectional estimation of stock returns in small markets: The case of the Athens Stock Exchange*, "Applied Financial Economics", No. 13 (6), pp. 413–426, 2003.
- Lemmon, M., Portniaguina, E., *Consumer confidence and asset prices: Some empirical evidence*, "Review of Financial Studies", No. 19 (4), pp. 1499–1529, 2006.
- Meng-Fen, H., Tzu-Yi, Y., Yu-Tai, Y., Jen-Sin, L., *Evidence of herding and positive feedback trading for mutual funds in emerging Asian countries*, "Quantitative Finance", No. 11 (3), pp. 423–435, 2011.
- Naes, R., Skjeltorp, A. J., Odegaard, A. B., *Stock market liquidity and the business cycle*, "Journal of Finance", No. 66 (1), pp. 139–176, 2011.
- Narayan, P. K., Narayan, S., Thuraisamy, S. K., *Can institutions and macroeconomic factors predict stock returns in emerging markets?*, "Emerging Markets Review", No. 19, pp. 77–95, 2014.
- Nell, K., Thirlwall, P. A., *Explaining differences in the productivity of investment across countries in the context of 'new growth theory'*, "International Review of Applied Economics", No. 32 (2), pp. 163–194, 2018.
- Patra T., Poshakwale, S., *Economic variables and stock market returns: evidence from the Athens stock exchange*, "Applied Financial Economics", No. 16(13), pp. 993–1005, 2006.
- Pastor, L., Stambaugh, F. R., *Liquidity risk and expected stock returns*, "Journal of Political Economy", No. 111(3):, pp. 642–685, 2003.
- Qian, H., *Time variation in analyst optimism: An investor sentiment explanation*, "Journal of Behavioral Finance", No. 10 (3), pp. 182–193, 2009.
- Qiu, L., Welch, I., 2006. *Investor sentiment measures*, Working Paper. Available at SSRN: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=589641](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=589641), 2006.
- Richards, A., *Big fish in small ponds: The trading behavior and price impact of foreign investors in Asian emerging equity markets*, "Journal of Financial & Quantitative Analysis", No. 40 (1), pp. 1–27, 2005.
- Shanken, J., *On the estimation of beta-pricing models*, "Review of Financial Studies", No. 5 (1), pp. 1–33, 1992.
- Shanken, J., Weinstein, I. M., *Economic forces and the stock market revisited*, "Journal of Empirical Finance", No. 13 (2), pp. 129–144, 2006.

- Skočir, M., Lončarski, I., *Multi-factor asset pricing models: Factor construction choices and the revisit of pricing factors*, “Journal of International Financial Markets, Institutions and Money”, No. 55, pp. 65–80. <https://doi.org/10.1016/j.intfin.2018.02.006>, 2018.
- Su, D., *An empirical analysis of industry momentum in Chinese stock markets*, “Emerging Markets Finance & Trade”, No. 47 (4), pp. 4–27, 2011.
- Szyska, A., *Behavioral finance and capital markets. How psychology influences investors and corporations*. Palgrave Macmillan, New York 2013.
- Uribe, J. M., Mosquera, S., *A comparative analysis of stock market cycles*, “Macroeconomics and Finance in Emerging Market Economies”, No. 9(3), pp. 241–261. <https://doi.org/10.1080/17520843.2015.1123744>, 2016.
- Verma, R., Soydemir, G., *The impact of U.S. individual and institutional investor sentiment on foreign stock markets*. Journal of Behavioral Finance, No. 7 (3), pp. 128–144, 2006.
- Wośko, Z., *Cyclical behaviour of the Polish stock market and the business cycle*. “Zeszyty Naukowe Uniwersytetu Szczecińskiego. Finanse, Rynki Finansowe, Ubezpieczenia”, No. 6 (2), pp. 559–570, 2007.
- Yoshinaga, C. E., Castro, F., *The relationship between market sentiment index and stock rates of return: A panel data analysis*, “Brazilian Administration Review”, No. 9 (2), pp. 189–210, 2012.
- Zaremba, A., *Investor sentiment, limits on arbitrage, and the performance of cross-country stock market anomalies*, “Journal of Behavioral and Experimental Finance”, No. 9, pp. 136–163, 2016.

*Received: October 2018, revised: July 2020*

**Acknowledgement:** *This work was supported by the National Science Centre (Poland) under grant number: DEC-2014/12/T/HS4/00168. We thank Jerzy Gajdka, Janusz Brzeszczyński, Waldemar Tarczyński, and Radosław Pastusiak for their helpful comments and suggestions. The doctoral thesis that laid the foundations for this work was awarded by the Committee of the IX edition of the President’s National Bank of Poland Contest for Best Doctoral Thesis 2016. Tomasz Schabek would like to thank the Committee for the award and support.*