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Weekend effect and financial characteristics: is there any relation in Latin America?

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Abstract

This study seeks to investigate the presence of the weekend effect in six Latin American markets (Argentina, Brazil, Chile, Colombia, Mexico and Peru) and to show the relationship between the weekend effect and investment portfolios sorted by four financial characteristics: stock market liquidity, current liquidity ratio, market capitalization (size) and price-to-book ratio. Using an extension of the French (1980) Model and a portfolio study we identify a significant weekend effect in all countries and found a negative relation between the weekend effect and four financial characteristics: the weekend effect is stronger in portfolios that contain stocks with low market liquidity, securities with low current liquidity ratios, small cap stocks (size) and stocks with low price-to-book ratios. As opposed to previous studies, we suggest that the weekend effect may be influenced by the investment of institutional investors in securitized loans issued by companies with value stocks and tight current liquidity ratios, and by the investment of individual investors in small-cap and illiquid stocks.
JEL Classification: G14, N26
Keywords: Market anomalies, weekend effect, Latin America

Efecto fin de semana y características financieras: ¿existe alguna relación en América Latina?

Resumen

Este estudio busca investigar la presencia del efecto del fin de semana en seis mercados latinoamericanos (Argentina, Brasil, Chile, Colombia, México y Perú) y mostrar la relación entre el efecto del fin de semana y los portafolios de inversión clasificados por cuatro características financieras: liquidez bursátil, ratio de liquidez corriente, capitalización de mercado (tamaño) y el ratio de precio a valor en libros. Usando una extensión del modelo French (1980) y un estudio de portafolios, identificamos un efecto fin de semana significativo en todos los países y encontramos una relación negativa entre el efecto fin de semana y cuatro características financieras: el efecto fin de semana es más fuerte en los portafolios que contienen acciones con baja liquidez bursátil, acciones con baja liquidez corriente, acciones de baja capitalización bursátil (tamaño) y acciones con bajos índices de precio a valor en libros. A diferencia de los estudios anteriores, sugerimos que el efecto del fin de semana puede verse influido por la inversión de los inversionistas institucionales en préstamos titulizados emitidos por compañías con acciones de valor y ratios de liquidez corriente ajustados, y por la inversión de inversionistas individuales en acciones de baja capitalización bursátil e ilíquidas.
Clasificación JEL: G14, N26
Palabras clave: Anomalías bursátiles, efecto fin de semana, América Latina

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1. Introduction

A market anomaly is defined as "any event or time-span that can be used to produce abnormal returns in the financial markets" (Naik, 2014). In particular, we can differentiate between seasonal or calendar anomalies, such as the weekend effect and the January effect and anomalies related to the stock's mispricing related to financial characteristics, such as the size effect and price-to-book effect.

The weekend effect is a seasonal anomaly characterized by higher returns on Fridays while they are significantly lower returns on Mondays. However, it can be thought as a seasonal anomaly that has a significant and systematic different return in one or more days of the week with respect to the other days. Fields (1931) was the pioneer studying the weekend effect in the US market and, through the analysis of the Dow-Jones Index's returns, he obtained results that were in contrast with the market efficiency's hypothesis. In fact, Monday's returns were, on average, significantly lower than the other days of the week.

Several years later, Cross (1973) and French (1980) incorporate new findings and methodologies that make the identification of the phenomenon easier. Specifically, Cross (1973) proved that the Mondays' distribution differs widely than the Fridays' one. Meanwhile, French (1980) used a multiple linear regression with dummy variables that gather the returns from Tuesday to Friday, while the Monday's behavior was estimated by a constant. Since then, this methodology has been used and adapted by many other studies.

In recent years many studies have identified the weekend effect in different markets rather than the stock market. Floros and Salvador (2014) found seasonal patterns in major stock index future markets from Greece, the US and UK. However, the seasonal pattern in the futures market depends on the periods of low (positive weekend effect) or high volatility (negative weekend effect) due to the basis risk.

Mamede and Fernandes (2017) identified a lower return on Mondays rather than the other days of the week associated to daily returns of 2162 Brazilian Hedge Funds that did not have redemption restrictions while Dao, McGroarty and Urquhart (2016) were able to show a weekend overreaction in spot FX rates of 7 major rates and 9 emerging currency pairs with reversals in multiple horizons during the week after large weekend gaps. The weekend affect was also found in the cryptocurrency market. Caporale and Plastun (2018) studied several cryptocurrencies and found the day-of-the week effect was present only in the Bitcoin market because returns on Mondays are usually higher than the other days of week, but this effect is more random rather than persistent.

Hence, there is an ongoing debate on whether the weekend effect is a wandering effect that moves between a random walk and a certain day of the week or whether it really disappears in the long-run. Doyle and Huirong (2019) studied several major developed market indexes and found a wandering weekend effect whose pattern is unknown and therefore investors cannot profit from it. However, Olson, Mossman and Chou (2015) contain that the weekend effect has disappeared in the long-run.

Traditional explanations for the weekend effect has been refuted over several decades of research: Fridays closing and Monday reopening of short positions and short-sellling (Chen and Singal, 2003), measurement error and specialists related explanations (Keim and Stambaugh, 1984), non-synchronous trading as an explanation (Abraham and Ikenberry, 1994), among others. Cheong (2016) provides a good review of previous attempts to explain the weekend effect.

Recently, several new potential explanations have been put forward by some authors. Caporale and Zakirova (2017) studied the presence of the weekend effect in the Russian stock market found that once transactions costs (proxied by the Bid-Ask spread) are removed from total returns, calendar anomalies (including the weekend effect) disappear. This prompts towards the magnitude of transaction costs and the trading volume.

Richards and Willows (2019) investigated the trading behavior of 7200 UK investors and found that they prefer to selling their losses on Mondays. According to them, mornings and Mondays induce a bad mood compared with other days of the week, so investors may integrate the selling of losses with Monday mornings to create congruence between their emotions and their behavior. In the authors' words: "Monday mornings cannot get any worse, so why not sell that loss?". Nevertheless, are individual investors driving the Monday effect? It seems yes.

Dubois and Louvet (1996) evaluated the weekend effect in nine industrialized countries. They observed that Mondays' returns were, on average, lower and even negative compared to the other days; moreover, results show that the effect was bigger for US and UK. According to the authors, one possible explanation is that institutional investors are not participating in the market on Mondays, leaving only the individual ones to exercise a pressure over sales.

Draper and Paudyal (2002) study the returns of 452 London Stock Exchange's securities. Results indicate that the trade volume and the order size diminish on Mondays. To explain this, they include variables such as the trade activity, the news, the dividend payment date and the accounting period, among others. However, regardless of all the controls, Mondays maintain a different behavior compared to the rest of the week. Hence, perhaps institutional investors are also refraining from trading.

Ülkü and Rogers (2018) studied the behavior of individual and institutional investors in three emerging markets (Korea, Taiwan and Thailand) and found that individual investors do not contribute to the Monday effect, but institutional investors' trading activity. Institutional investors contribute in two ways: 1) their net trading becomes more negative on Mondays, and 2) they refrain from trading, in particular from buying, on Mondays, which induces a Monday effect when they are in a sustained trend of buying. The latter mechanism is a new partial explanation of the Monday effect.

What type of stocks are the ones that most likely cause the Monday effect? Birru (2018) studied the effect of the speculative strategy of purchasing (long) stocks minus selling (short) stocks only on Mondays and Fridays in the three main US indexes: NYSE, AMEX and NASDAQ between 1963 and 2013. He invested and disinvested in the stocks in the first decile against stocks of the tenth decile of the distribution with respect to 19 variables associated with anomalies in previous studies such as idiosyncratic volatility, size, illiquidity, ROA, and so on.

Every anomaly has two legs: speculative and no-speculative. The speculative leg is related to stocks that are mispriced and are more difficult to arbitrage, while the non-speculative leg is related to well-known stocks that act like a bond-type security. For example, let's take the anomaly related to "size", it is known since Banz (1981) that stocks from small companies provide higher returns rather than stocks from larger companies because they are more risky.

Hence, the speculative part of the strategy would be to purchase (long) small cap stocks and the non-speculative leg of the strategy would be to sell (short) large cap stocks. The speculative leg of the strategy will depend upon the anomaly.

Birru (2018) found for three different time frames that the speculative leg of the strategy was the responsible of the higher returns on Fridays and lower returns on Mondays and that this result is robust against macroeconomic new announcements, firms' specific news and other factors. He also found that the weekend effect is not driven by the behavior of institutional investors because they have a preference for large and liquid stocks (non-speculative leg of the strategy), while individual investors have a preference for small and non-liquid stocks that can outperform the market (speculative leg of the strategy).

What remains clear from the previous review is that the weekend effect has appeared in other developed and emerging markets different from the stock market; that the effect remains stronger in different developed and emerging stock markets, that the weekend

effect is not due to the active trading of institutional investors and that the possible causes of the weekend effect are related to firm's characteristic (anomalies).

Why study the Latin American markets? Because they represent an attractive investment opportunity for individual investors from all around the world, especially due to their low return correlation with developed markets in the absence of financial turbulence. For some years they have had impressive growth and returns, for instance the MSCI Brazil and MSCI Peru rose by 61 % and 52 % respectively in 2016 (Borzykowski, 2017). Furthermore, there are three important facts: the local issuance of securitization in the market has steadily increase through the years (Scatigna and Tovar, 2007), institutional investors are investing more in securitized assets or in general in marketplace lending instruments (Johnson, 2018), and firms in Latin America rely more on short-term debt rather than long-term debt because it is cheaper (Valcacer et al. 2017).

Securitization transforms illiquid and risky assets into more liquid and less risky ones and has several advantages: investments in securitized assets are less sensitive to volatile periods, it has low correlation with fixed-income investments, and it leads to a broader diversification of the investment portfolio because you can invest in real-state assets, public projects, and more (Goodson, 2018).

The most important players in the Latin American stock exchanges are Pension Funds because they move more than 70 % of the daily market capitalization in the region. They are restricted in their investment by the investment grade and liquidity of the securities, so they should invest in securities classified BBB or more and they must be liquid. Hence, financial analysts will select securities from big companies rather than from small ones and that will have greater liquidity rather than less. However, they also can invest in collateralized debt issued by companies whose stocks fall short in the rating classification.

The higher level of leverage eventually will pass through the company's stock return and we should observe more institutional investments in companies with low price-to-book ratios because they are more indebted. Besides, the fact that Latin American companies are relying more on short-term debt rather than long-term one means that institutional investors end up investing in long-term debt of companies with tight or low current liquidity ratios too

The number of individual investors that invest through brokerage companies in Latin American markets has increased steadily through the years, in Brazil there more than one million of individual investors and in Peru more than half a million (El Economista, 2019). Hence, if the hypothesis of Ülkü and Rogers (2018) is right and institutional investors refrain themselves from purchasing on Mondays, then due to the behavioral hypothesis (i.e. investors start with a low mood on Mondays and end up with a high mood on Fridays) we should observe individual investors investing more in small-cap and illiquid stocks reinforcing the weekend effect.

Given the above we aim to identify the presence of the weekend effect in the Latin American region and to show that its intensity is higher in portfolios with small stocks, lower market liquidity, lower short-term financial performance (lower current liquidity ratio) and greater financial distress (lower price-to-book ratio).

The contribution of this paper to the literature is to show that investments according to specific financial characteristics are influencing the weekend effect in Latin America, in particular that the weekend effect might be influenced by the investment of institutional investors in collateralized loans issued by companies with value stocks and tight current liquidity ratios, and by the investment of individual investors in small-cap and illiquid stocks, a sign of the presence of the behavioral hypothesis in the region. Additional to the role of individual investors explained by Birru (2018), we propose that not only individual, but also institutional investors have a role in the reinforcement of the weekend effect in Latin America.

In the next section we conduct a brief literature review focused in the particular

behavior of the weekend effect in emerging markets with a Latin American focus. In the third section we explain our methodology, and in the fourth and fifth sections we present and discuss our results. In the last section we conclude.

2. Literature review

The weekend effect has also been detected in several studies related to emerging markets. For instance, In Asia, Aggarwal and Rivoli (1989) studied the weekend effect in Hong Kong, Singapore, Malaysia and Philippines stock exchanges and found the presence that Tuesday's prices reflected Mondays' New York events (Aggarwal Rivoli, 1989).

Nageswari et. al. (2011) analyzed the SP CNX 500 Index's returns from India from April 2002 until March 2010. This Index includes 50 stocks from 22 sectors and their conclusion was that returns were higher on Fridays and lower on Mondays (Nageswari, Selvam, Gayathri, 2011).

Ariss et. al. (2011) studied the weekend effect in the Gulf Council Countries (GCC): Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates. Similar to other international markets, calendar anomalies prevailed in GCC stock markets. They conclude that this result may be the result of a low trading volume of trading and liquidity, and perhaps the presence of few sophisticated individual investors that exploit completely intra-week arbitrage opportunities. However, this arbitrage opportunity is mainly restricted to GCC nationals only because there are still some resilient regulatory restrictions on stock ownership by non-GCC investors in those markets.

Tilică and Oprea (2014) studied the day-of-the week effect in the Romanian Stock Market and they found that returns on Fridays were higher than in other days of the week, so they called it "Friday effect". They suggested that it may be due volatility seasonality.

In an attempt to make a broader study about the weekend effect in emerging markets, Seif et.al. (2017) studied this anomaly around the world in what the Financial Times Stock Exchange Group (FTSE) called "advanced-emerging stock markets". This group included Brazil, Czech Republic, Hungary, Malaysia, Mexico, Poland, South Africa, Taiwan and Turkey. They found that Fridays' returns were significantly higher than other days of the week. Although they were unable to provide an explanation to this anomaly, they showed that this effect was not due to non-synchronous trading neither due to volatility seasonality.

In Latin America, Espinosa (2007) analyzed the presence of the weekend effect in Chile by applying the French model to the daily closing prices of the IPSA stock index. He found support for the day-of-the week effect because there is an expected negative return on Mondays (Espinosa, 2007). The author explained that this may arise because Chilean firms disclose bad events to the market on Mondays, which can contribute to the low mood of investors those days.

In Colombia, Rivera (2009) applied a time-series model to identify the presence of the weekend effect in the IBB index of the Bogota Stock Exchange, in the IBOMED Index of the Medellin Stock Exchange and in the IGBC Index of Colombia Stock Exchange between the years 1992-2006. The author found out that Tuesdays are the days with the lowest returns and the higher volatility, but he didn't provide a possible explanation for it (Rivera, 2009).

Kristjanpoller (2010) examines the markets of Argentina, Brazil, Colombia, Chile, Mexico, and Peru, using their market indexes and applying French's model. He finds evidence of the weekend effect in a time-span that goes from 1993 to 2007. Specifically he founds that returns on Mondays are the lowest ones and returns on Fridays the highest ones and concluded that a possible explanation of this may lie in the domain of behavioral finance. (Kristjanpoller, 2010). Later on, Kristjanpoller (2012) performed a more complete analysis including different non-linear models to test for the weekend effect and found consistent support for negative returns on Mondays and positive returns on Fridays in

the same previous six Latin American markets. He also found that returns on Mondays are the ones with the highest volatility and returns on Fridays are the ones with the lowest volatility.

Using stochastic dominance Kritsjanpoller and Muñoz (2012) found also support for the weekend effect in Latin American Markets. Furthermore, Rojas and Kristjanpoller (2014) also obtained support for the weekend effect in Latin America even when they adjust the statistical test from committing a Type I error (i.e. to reject wrongly the null hypothesis of not having significant returns) using the so-called Bonferroni correction.

For the Brazilian market, Santana and Manzoli (2014) identified the weekend effect using the BOVESPA Index, specifically, they found negative returns in Mondays that were accentuated in high volatility as with the sub-prime crisis.

Rojas and Kristjanpoller (2015) found a strong weekend effect related to the trading volume in six Latin American markets (Argentina, Brazil, Colombia, Chile, Mexico, and Peru) because trading volume decreases on Mondays and Fridays and reaches its peak on Wednesdays. Furthermore, it seems that returns cause the trading volume and not the other way around.

Arbelaez and Rosso (2016) studied seasonal anomalies in the four Latin American countries that belong to the so called "Pacific Alliance" (Colombia, Chile, Mexico and Peru). They also conduct the Bonferroni correction and found support for the weekend effect in Colombia, Chile and Peru. Although, they listed the traditional series of possible explanations, they did not propose any explanation for the effect.

Winkelried and Iberico (2018) offered further support to the weekend effect in Latin American markets, through an extreme bounds analysis, they proved the existence of a significantly negative Monday effect, which is in most of the cases offset by a significantly positive Friday effect.

According to the previous review, we conclude that the vast majority of the studies in emerging markets support the presence of the weekend effect, and that most of them do not provide a plausible explanation of the effect besides the behavioral hypothesis, the trading of individual expert traders, the trading volume and episodes of high volatility. In this research we build investment portfolios according to selected financial characteristics, so we are able to offer an alternative explanation of the weekend effect for Latin American markets where not only individual, but also institutional investors do play a role.

3. Methodology

We use Morgan Stanley Capital International (MSCI) daily value-weighted indexes in US dollars for six Latin American countries (Argentina, Brazil, Colombia, Chile, Mexico and Peru) to test for the presence of the weekend effect. Besides, we use investment portfolios elaborated according to financial ratios in US dollars and in the same countries to show that the weekend effect is stronger in portfolios with low current liquidity ratios, low price-to-book ratios, small market capitalization and low market liquidity.

We test two hypotheses: 1) there is a weekend effect in Latin America and 2) the weekend effect is stronger in investment portfolios with low current liquidity ratios, low price-to-book ratios, small market capitalization and low market liquidity. Both hypotheses are interrelated, but the second goes deeper than the first because it identifies the investment criteria that leads to a stronger weekend effect.

As we already explain, individual investors and institutional investors do have a role in the emergence of the weekend effect in Latin America. Individual investors behave like the behavioral hypothesis (i.e. individual investors have low mood on Mondays and high mood on Fridays), so when they have a high mood (i.e. Fridays) they invest in speculative investments related to small-cap stocks and/or stocks with low market liquidity and when they have a low mood (i.e. Mondays) they sell their losses.

Institutional investors behave more like to what we call "the marketplace for loans"

hypothesis because they end up investing in collateralized debt issued by small-cap companies with low market liquidity too, buy eventually the higher indebtedness of these companies will decrease their current ratios and their price-to-book ratios due to the higher financial risk. Furthermore, if institutional investors have an investment mandate to purchase structured instruments and they refrain from trading on Mondays, there will be lower returns on Mondays and higher returns on Fridays. In other words, individual and institutional investors will make speculative investments so the weekend effect will be stronger in Latin American markets and there is no reason to believe that it will disappear.

The sample includes daily closing prices and dollar value observations adjusted by distributed dividends from January, 3rd 2005 to December 31st 2014. In order to avoid as much as possible missing values we require a presence ratio (market liquidity) equal or higher than 75 % for each year during the period 2005-2014. The presence ratio is calculated as the number of quoting days per year divided by the total number of trading days within a year (see Table 1). We choose this sample period because it is the period of a steadily increase of institutional investors' investments in local collateralized debt issues in the six Latin American markets (Cheikhrouhou et.al, 2007).

Table 1. Total number of liquid stocks per country per year

Year	Argentina	Brazil	Chile	Colombia	Mexico	Peru
2005	54	200	74	20	68	25
2006	58	208	82	25	76	35
2007	66	296	90	22	81	46
2008	66	325	74	26	77	40
2009	60	314	76	27	84	38
2010	66	324	91	33	82	40
2011	64	321	87	33	82	34
2012	56	306	88	32	81	168
2013	68	305	83	32	93	217
2014	66	307	84	28	98	264

Source: Own elaboration.

Table 1 shows the number of stocks with a presence ratio (market liquidity) equal or higher than 75 % for each of the years 2005-2014. The presence ratio is calculated as the number of quoting days per year divided by the total number of trading days within a year. Source: Economatica and Bloomberg.

In Table 2 we show that, by applying the previous filters, we end up having a total sample of 1578 companies during the period of 2005-2014. Note that the number of companies in Table 2 is higher than in Table 1 because it is not the same company the one that is included in the portfolio analysis because we rebalance the portfolio every year. As we can see, the highest number of listed companies comes from Brazil (43 %), followed by Peruvian companies (23 %), Chilean (12 %) companies and the Mexican ones (12 %). Concerning the industry, Table 3 shows that the finance and insurance sector is the prevalent one (19 %) together with electric power sector (10 %).

Table 2. Total number of different liquid stocks per country (2005-2014)

Country	Number of companies	Percentage of the total
Argentina	113	7 %
Brazil	671	43 %
Chile	197	12 %
Colombia	59	4 %
Mexico	182	12 %
Peru	356	23 %

Source: Own elaboration.

Table 2 shows the total number of stocks with a presence ratio (market liquidity) equal or higher than 75 % during the years 2005-2014 (consolidated results). The presence ratio is calculated as the number of quoting days per year divided by the total number of trading days within a year. Source: Economatica and Bloomberg.

Table 3. Total number of liquid stocks per sector

Sector	Number of companies	Percentage of the total
Agriculture & Fisheries	45	3 %
Metallurgy	74	5 %
Chemical	49	3 %
Construction	65	4 %
Electronics	18	1 %
Electric Power	165	10 %
Finance and Insurance	292	19 %
Food & Beverage	104	7 %
Funds	34	2 %
Industrial Machinery	13	1 %
Mining	56	4 %
Nonmetallic Mining	39	2 %
Oil & Gas	52	3 %
Other	211	13 %
Pulp & Paper	26	2 %
Software & Data	8	1 %
Telecommunication	107	7 %
Textile	49	3 %
Trade	83	5 %
Transportation Serv.	50	3 %
Vehicle & Parts	38	2 %

Source: Own elaboration.

Table 3 shows the total number of stocks per sector with a presence ratio (market liquidity) equal or higher than 75 % during the years 2005-2014 (consolidated results). The presence ratio is calculated as the number of quoting days per year divided by the total number of trading days within a year. Source: Economatica and Bloomberg.

We will use the following expression to calculate the companies' continuously compounded returns:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-x}}\right)^{1/x} \tag{1}$$

Where: $R_{i,t}$ is the return of the firm i in the period t; $P_{i,t}$ the price of stock i in period t; $P_{i,t-x}$ the stock price i in period $t-x$; and, finally, x the number of days between the value of period t and $t-x$.

In order to identify the weekend effect we will use an extension of the French Model (1980):

$$R_{i,t} = \sum_{i=1}^{5} \beta_i * \gamma_i + \ \varepsilon_t \tag{2}$$

Where: $R_{i,t}$ is the average return of the stock MSCI index or of the investment portfolio in period t; β_i the average return of day i; γ_i is the dummy variable for day i (Monday, Tuesday,..., Friday) and ε_t is the error term. We expand the model by including total risk and momentum variables, obtaining the following version:

$$R_{i,t} = \sum_{i=1}^{5} \beta_i * \gamma_i + \ \vartheta_t + \lambda + \ \varepsilon_t \tag{3}$$

Where: ϑ_t is the MSCI index or the portfolio's return total risk in the period t, calculated for the last 7 days; λ is the momentum, which refers to the overreaction that some stocks have during the last week due to the release of new information; and ε_t is the error term. Due to the fact that there is a correlation between daily returns and because they suffered from a significant downside risk in emerging markets, we model the errors under an E-GARCH (p,q) specification.

We, therefore, follow the equation:

$$y_t = \varepsilon_t \sqrt{h_t} \tag{4}$$

Where: $logh_t = \alpha_o + \beta_1 log(h_{t-1}) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$

Therefore, the E-GARCH model incorporate a dynamic structure in the heteroscedastic volatility equation represented by the expression $\beta_1 log\,(h_{t-1})$ with autoregressive components of the disturbance and asymmetric effect, represented by the expressions $\alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| and \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ respectively.

We estimate equations (2) and (3) with the daily returns of the value-weighted MSCI index that corresponds to each Latin American market. Then, we estimate only equation (3) for investment portfolios constructed on the basis of each one of the four firms' financial characteristics: market capitalization (Size), market liquidity (Bid-Ask Spread), current liquidity ratio (current assets/current liabilities), and price-to-book ratio.

For each financial characteristic we create two equally-weighted portfolios for every country (Argentina, Brazil, Chile, Colombia, Peru and Mexico). Then we set the percentile 50 of every distribution as our threshold and build two investment portfolios per characteristic. Every year we rebalance the portfolio with the classification of the previous year and we continue doing so from 2005 until 2014.

4. Results

Table 4 show the descriptive statistics of stock returns and the financial characteristics and Table 5 shows the Unit Root Tests of variables in equation (3). In general we have enough variability to form two different portfolios per financial characteristic and we have stationary series to run equation (3).

Table 4. Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Max**	**Min**	**Mean**	**Median**	**St. Dev.**	**Kurtosis**	**Skewness**	**N**
MSCI returns	0.167	-0.187	0.0032	0.000351	0.0175	13.77	-0.631	215,504
Size (MM)	143	0	5	4.54	11.9	42.64	5.673	191,590
Price-to-Book Ratio	142.2	0.0663	2.139	2.139	1.957	826.9	14.08	165,255
Market Liquidity	15.49	0.01	1.047	1.047	1.645	15.08	3.03	178,003
Current Liquidity Ratio	34.7	0	1.652	1.652	2.097	140.7	10.04	67,187

Source: Own elaboration.

Table 4 shows the descriptive statistics for the full sample during the years 2005-2014 for companies with a presence ratio equal or higher than 75 %. The variables are MSCI daily continuously compounded returns in US dollars; the company's size in millions of dollars; the price-to-book ratio; the market liquidity approximated by the Bid-Ask Spread; and the current liquidity ratio. N is the total number of observations

Table 5. Results of the unit roots tests

Variable	**ADF**		**Philips-Perron**	
	With intercept	**With intercept and trend**	**With intercept**	**With intercept and trend**
MSCI	-18.3016	-5.0668	-47.0015	-67.6537
Portfolio stock returns	-64.25	-57.7566	-80.4422	-80.4422
Total risk	-12.0609	-4.9962	-34.892	-41.0779
Momentum	-16.8511	-5.7109	-23.9578	-26.4048

Source: Own elaboration.

Table 5 presents the calculated t-statistics for both the Augmented Dickey Fuller and the Philips Perron unit root tests for the dependent and the additional independent variables in equation (3). In

general, the absolute value of calculated t-statistics are greater than the absolute value of the MacKinnon's critical values, so we reject the null hypothesis and the series are stationary. Critical values of MacKinnon -4.01 (1 %), -3.43(5 %) and -3.14(10 %)

To detect the presence of the weekend effect, we analyze the effect based on the indexes for each country of our sample. Table 6 details the results of the model without control variables (equation 2). As we can see the signs of the coefficients for Mondays and Fridays are correct, but they are only significant for Colombia and Chile and in the case of Chile the highest returns are on Thursdays and not on Fridays.

Table 6. Identification of the weekend effect with value-weighted MSCI Indexes (Model without control variables)

		Mon β1	**Tue β2**	**Wed β3**	**Thur β4**	**Frid β5**
PERU	*coefficient*	-0,00066	0,00055	0,00114	0,00003	0,00152
	t-statistic	-0,70830	0,59102	125,378	0,02952	1,62642*
ARGENTINA	*coefficient*	-0,00103	0,00091	0,00044	-0,00025	0,00143
	t-statistic	-0,95795	0,85700	0,41402	-0,23164	131,530
BRAZIL	*coefficient*	-0,00036	-0,00019	0,00034	0,00033	0,00096
	t-statistic	-136,072	-118,538	133,985	132,724	0,95818
COLOMBIA	*coefficient*	-0,00139	-0,00054	0,00140	0,00077	0,00207
	t-statistic	-1,85093**	-0,721955	1,86728**	102,936	2,76368***
CHILE	*coefficient*	-0,00132	-0,000423	0,00035	0,00137	0,00091
	t-statistic	-2,10495**	-0,672775	0,55644	2,17365***	144,848
MEXICO	*coefficient*	-0,00051	0,0000409	0,00025	0,0004	0,00040
	t-statistic	-0,68082	0,054312	0,33690	0,52981	0,52392

Source: Own elaboration.

Table 6 shows the coefficient and t-statistic (t) of estimating with E-GARCH (1,1) the time series model without control variables (equation 2). Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

Table 7 shows the results of estimating equation (3) with the E-GARCH (1,1) model with control variables. We also conduct the same regressions using GARCH (1,1) but the results were not better (not reported). The control variables are total risk (calculated as the standard deviation of the stock return within the last seven trading days) and momentum (calculated as the difference between the contemporaneous stock return and the stock return lagged seven trading days).

Table 7. Identification of the weekend effect with value-weighted MSCI Indexes (Model with control variables)

		Mon β1	**Tue β2**	**Wed β3**	**Thur β4**	**Frid β5**	**Risk α**	**Mom λ**
PERU	*coefficient*	-0,00034	0,00092	0,00147	0,00036	0,00187	0,01773	-0,0001
	t-statistic	-1,79991**	1,80909**	130,728	2,31968***	1,66260*	1,88111**	0,50220
ARGENTINA	*coefficient*	0,00177	0,00363	0,00324	0,00256	0,00426	0,03880	-0,00003
	t-statistic	132,267	2,71571***	2,44906***	1,92778**	3,16503***	1,91203**	-3,48968***
BRAZIL	*coefficient*	-0,00019	0,00037	0,00090	0,00088	0,00151	0,00001	0,00375
	t-statistic	-1,75668*	1,69817*	1,72721*	1,71670*	1,62725*	1,76878**	0,19024
COLOMBIA	*Coefficient*	-0,00101	-0,00002	0,00188	0,00125	0,00245	0,03234	-0,00002
	t-statistic	-1,66144*	-0,023663	1,97376**	13,059	2,56690**	1,66606*	-0,74204
CHILE	*coefficient*	-0,00194	-0,001052	-0,00033	0,00071	0,00027	0,00001	-0,02436
	t-statistic	-2,51768***	-1,661716*	-0,43251	1,91363**	0,34408	1,65880*	-124,016
MEXICO	*coefficient*	-0,00064	0,000168	0,00038	0,00052	0,00054	0,000000	-0,00755
	t-statistic	-1,65081*	1,705091*	138,751	1,73072*	1,82682**	0,19386	-0,38151

Source: Own elaboration.

Table 7 shows the coefficient and t-statistics (t) of estimating with E-GARCH (1,1) the time series model with control variables (equation 3). Here the control variables are total risk (calculated as the standard deviation of the stock return within the last seven trading days) and momentum (calculated as the difference between the contemporaneous stock return and the stock return lagged seven trading days). Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

In Table 7 the signs are correct and statistically significant for Peru, Colombia, Brazil, Chile and Mexico, but not for Argentina. Note that Fridays are positive and statistically

significant for Argentina, but Mondays are not. Furthermore, total risk is significant in all countries with the exception of Mexico and there are reversals only in the case of Argentina.

Overall, according to our results, the weekend effect is present in Peru, Colombia, Brazil, Chile and Mexico and it is characterized by lower returns on Mondays and higher returns on Fridays (Peru, Colombia and Mexico) or on Thursdays (Chile). Argentina shows highest returns on Fridays too, but its returns on Mondays are positive albeit are the lowest of the week.

In order to assess the relationship between the weekend effect and each financial characteristic we define an intensity ratio of the weekend effect. The intensity ratio is calculated as the number of times in which the daily Friday's returns exceeds the Monday's ones divided by the number of times the daily Friday's returns were below the Monday's ones. Hence, if there is no weekend effect the intensity ratio will be less or equal to 1 otherwise there will be a weekend effect.

In Table 8 we can see that the weekend effect is not only stronger in the portfolios that contain small cap stocks, but also the weekend effect is significant in portfolios with large cap stocks in all countries with the exception of Argentina. It is also interesting that the difference of intensity between both portfolios is small with the exception of Brazil and this probably because individual investors know that is a good idea to have investments in small cap stocks because they could provide higher positive returns than large cap stocks (speculative investments). It seems like in Brazil the battle lies in selecting properly the more interesting small cap companies.

Table 9 shows the weekend effect related to the stock market liquidity, we use the measurement called Bid-Ask Spread as a proxy to form the two investment portfolios per country. As we can see, in all countries the intensity ratio is higher than 1 and it is more intense in portfolio 2 (that contains the less liquid stocks) than in portfolio 1 (that contains the more liquid stocks). Hence, the weekend effect is stronger in less liquid stocks probably due to the speculative investments of individual investors.

It is interesting to note that for portfolio 1 the intensity ratio tends to be lower, with the exception of Brazil, so for liquid stocks there is no much effect related to market liquidity and differences may be due to portfolio rebalancing conducted by institutional investors.

Furthermore, the weekend effect is significant in all countries with the exception of Argentina and Brazil were Monday's returns are the lowest but not significant.

Table 10 shows that in general investing in companies with low current liquidity ratio is associated with a higher intensity ratio, so the weekend effect is stronger rather than investing in portfolios with high current liquidity ratios. In this case, companies with a tight short-term liquidity are preferred by individual investors because they represent speculative investments. Although the weekend effect is not significant in all countries it is present in all countries with the proper sign or with the lowest return on Mondays and the higher return on Fridays with the exception of Chile that higher returns are on Thursdays. Another explanation is that institutional investors are also investing in these firms in virtue of the "marketplace for loans" hypothesis.

The most interesting result for Argentina is being given in Table 11. There we see that the weekend effect is present in all countries, but significant in Argentina, Peru, Colombia and Chile. We find again traces of the "marketplace for loans" hypothesis and the behavioral hypothesis because the weekend effect is stronger in portfolios with low price-to-book ratios or portfolios that are built using value stocks instead of growth stocks. The difference in the intensity ratios between portfolios is not really big in Colombia and Chile, but is it huge in Brazil.

Table 8. The weekend effect and market capitalization (size)

		Mon β1	Tue β2	Wed β3	Thur β4	Frid β5	Risk α	Mom λ	Intensity
		PERU							
Portfolio 1	*coefficient*	-0.00083	-0.00136	0.0009	0.00016	0.00029	0.08777	-0.06197	
	t-statistic	-1.74275*	-1.5885	1.37364	0.06704	1.822235***	2.54223***	-1.913**	0.65
Portfolio 2	*coefficient*	-0.00268	0.00058	0.00058	-0.00267	-0.00044	0.16708	0.01314	0.84
	t-statistic	-1.99656**	2.22473***	1.215	-1.01694	-2.1619***	1.2803	2.18475***	
		ARGENTINA							
Portfolio 1	*coefficient*	-0.00136	0.000148	0.001481	0.000133	0.001525	0.025922	0.004149	
	t-statistic	1.320772	0.144673	1.791169*	0.134116	1.665773*	2.164872	0.107315	2.12
Portfolio 2	*coefficient*	-0.00119	-0.00022	0.001241	0.000626	0.002662	0.050776	-0.01047	3.25
	t-statistic	-1.35685	-0.25255	0.695461	0.74558	3.051854***	2.321972***	-0.2283	
		BRAZIL							
Portfolio 1	*coefficient*	-0.00008	0.001117	0.00095	0.000971	0.003525	-0.055705	0.008579	
	t-statistic	-1.795806*	0.898412	0.7548967	0.774641	2.790256***	-1.310783	0.400517	11.64
Portfolio 2	*coefficient*	-0.00046	0.000901	0.001287	0.001808	0.004851	0.120878	0.034982	41.94
	t-statistic	-1.683255*	0.760664	1.082439	1.525523	4.042136***	2.730291***	1.65558*	
		COLOMBIA							
Portfolio 1	*coefficient*	-0.00383	-0.00117	-0.000085	-0.0003	0.001078	0.129562	0.014678	1.28
	t-statistic	-4.0781***	-1.25857	-0.096833	-0.003988	1.741576*	3.316516***	0.702394	
Portfolio 2	*coefficient*	-0.00425	-0.00145	0.000771	0.000032	0.001785	0.125313	0.009382	
	t-statistic	3.961351***	-1.36143	0.773408	0.03198	1.665139*	3.126906***	0.42876	1.42
		CHILE							
Portfolio 1	*coefficient*	-0.00082	0.000995	0.000888	0.002099	0.000326	0.000326	-0.03936	1.40
	t-statistic	-1.640348*	1.684637*	1.674971*	1.726667*	0.418829	0.418829	-1.6843*	
Portfolio 2	*coefficient*	-0.00212	-0.00045	-0.000454	0.00194	0.000913	0.000913	-0.037	1.43
	t-statistic	-2.8227***	-0.61637	-0.616367	1.834556*	1.2227	1.2227	0.67103	
		MEXICO							
Portfolio 1	*coefficient*	-0.00106	0.001575	0.000719	0.000512	0.001333	-0.041121	0.032121	0.25
	t-statistic	-2.2096***	1.804863**	0.825512	0.591157	1.725787*	-1.130024	1.729848*	
Portfolio 2	*coefficient*	-0.00061	0.000448	-0.000267	0.000271	0.000554	-0.012432	0.022052	1.90
	t-statistic	-1.665277*	0.490253	-0.29458	0.3004	1.623161*	-0.302169	1.039427	

Source: Own elaboration.

Table 8 shows the coefficients and t-statistics (t) of estimating with E-GARCH (1,1) the time series model with control variables (equation 3) within portfolios. We group stocks in two portfolios depending on their market capitalization (size) and we use the percentile 50 as our threshold to build the two portfolios. Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

Table 9. The weekend effect and market liquidity (Bid-Ask Spread)

		Mon β1	Tue β2	Wed β3	Thur β4	Frid β5	Risk α	Mom λ	Intensity
	PERU								
Portfolio 1	*coefficient*	-0.000501	0.000794	0.000565	0.000959	0.001819	-0.022367	-0.010304	2.4
	t-statistic	1.773278*	0.760047	1.663536*	1.915516**	1.728554**	-0.595485	-0.488752	
Portfolio 2	*coefficient*	-0.001217	-0.000421	0.000305	0.000766	0.0017	0.044614	0.002732	4.63
	t-statistic	-1.83023**	-0.429855	0.309058	0.785319	1.731277*	1.699319*	0.12994	
	ARGENTINA								
Portfolio 1	*coefficient*	-0.00164	-0.0000368	0.001538	0.00043	0.002002	-0.01894	0.035265	2.22
	t-statistic	-1.428149	-0.324084	1.68021*	0.388083	1.73613*	-0.412199	1.662145*	
Portfolio 2	*coefficient*	-0.00064	0.000238	0.000238	0.000314	0.002269	0.042847	0.021065	4.55
	t-statistic	-0.844894	0.315263	1.548802	0.43183	2.99135***	1.951425***	0.47654	
	BRAZIL								
Portfolio 1	*coefficient*	0.000295	0.000827	0.001274	0.001782	0.004435	0.10463	0.022988	14.03
	t-statistic	0.250526	0.706702	1.079109	1.613165	3.724116***	2.467329***	1.06673	
Portfolio 2	*coefficient*	0.000176	0.002377	0.001723	0.001763	0.005212	0.102159	0.021716	28.61
	t-statistic	0.150761	2.042253***	1.673264*	1.51008	4.418132***	2.397203***	1.01244	
	COLOMBIA								
Portfolio 1	*coefficient*	-0.004212	-0.001592	0.000159	-0.00045	0.000981	0.142224	0.015299	1.23
	t-statistic	-4.099221***	-0.656235	0.165119	-0.469145	3.941514***	3.465405***	0.695521	
Portfolio 2	*coefficient*	-0.000176	-0.002377	0.001723	0.001763	0.005212	0.102159	0.021716	28.61
	t-statistic	-2.15076***	-1.042253	1.51008	1.51008	4.418132***	2.397203***	1.01244	
	CHILE								
Portfolio 1	*coefficient*	-0.001807	0.000642	0.000261	0.002037	0.000223	-0.03194	-0.02049	2.12
	t-statistic	-2.160697***	0.776877	0.319208	2.477663***	0.268035	-0.956022	-0.76426***	
Portfolio 2	*coefficient*	-0.00754	0.000609	0.000523	0.002539	0.001407	-0.99582	0.001328	2.87
	t-statistic	-2.173271***	0.966017	0.99471	4.025934***	0.20876	-0.06204	-2.23808***	
	MEXICO								
Portfolio 1	*coefficient*	-0.000424	0.001591	0.000791	0.000746	0.00158	-0.05979	0.016208	2.73
	t-statistic	-2.426288***	0.680181	0.802835	0.761251	1.689848*	-1.481233	1.771001	
Portfolio 2	*coefficient*	-0.0006	0.00117	0.00019	0.00085	0.00147	-0.02726	0.00576	21.86
	t-statistic	-2.08575***	0.665362	0.2544	1.15454	1.970155**	-0.66766	0.2734	

Source: Own elaboration.

Table 9 shows the coefficients and t-statistics (t) of estimating with E-GARCH (1,1) the time series model with control variables (equation 3) within portfolios. We group stocks in two portfolios depending on their stock market liquidity (Bid-Ask spread). We use the percentile 50 as our threshold to build the two portfolios. Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

Table 10. The weekend effect and current liquidity ratio

		Mon β1	Tue β2	Wed β3	Thur β4	Frid β5	Risk α	Mom λ	Intensity
	PERU								
Portfolio 1	*coefficient*	-0.00011	0.00182	0.00127	0.00143	0.00267	0.05595	-0.02813	1.92
	t-statistic	-2.1007***	1.70875*	1.18417	1.33641	2.48773***	1.185642**	-1.72901*	
Portfolio 2	*coefficient*	-0.00144	-0.00106	-0.00014	0.00062	0.00133	0.05122	0.01772	25.68
	t-statistic	-1.82991**	-1.97006**	0.13691	0.6205	1.82676**	1.96748**	1.84254**	
	ARGENTINA								
Portfolio 1	*coefficient*	-0.00105	0.000876	0.001103	0.000175	0.001769	0.086354	0.036792	2.68
	t-statistic	-1.22131	0.0101232	1.320923	0.209735	2.042469***	0.797221	1.678819*	
Portfolio 2	*coefficient*	-0.00091	0.000141	0.000893	0.000601	0.00207	-0.01503	0.035045	3.28
	t-statistic	-0.92653	0.145246	0.937161	0.319256	2.10293***	-0.0332	1.59833	
	BRAZIL								
Portfolio 1	*coefficient*	0.000562	0.001186	0.001385	0.003094	0.004888	0.113522	0.03327	7.7
	t-statistic	1.669131*	0.996201	1.150712	1.745075**	4.0333801***	2.706674***	1.676757*	
Portfolio 2	*coefficient*	0.00015	0.000938	0.00109	0.001617	0.004436	0.093512	0.001032	28.57
	t-statistic	1.726698*	1.796638***	0.918154	1.664655*	3.697525***	2.15168***	0.480426	
	COLOMBIA								
Portfolio 1	*coefficient*	-0.00403	-0.00263	-0.00085	-0.00084	-0.00033	0.174637	0.028942	0.92
	t-statistic	-1.69546*	-2.40230***	-0.827876	-0.82429	-0.29349	4.204607***	1.310261	
Portfolio 2	*coefficient*	-0.00434	-0.001193	0.0000431	-0.00052	0.001603	0.16975	-0.00933	1.37
	t-statistic	-1.73247*	-1.197916	0.046233	-0.55451	1.679622*	4.660274***	-0.44889	
	CHILE								
Portfolio 1	*coefficient*	-0.00122	0.000791	0.000697	0.001992	0.00084	-0.05941	-0.02444	1.69
	t-statistic	-1.66524*	1.065442	1.944855**	1.95674*	1.121437	-1.44343	-1.14185	
Portfolio 2	*coefficient*	-0.00063	0.000903	0.000595	0.002626	0.001293	-0.11641	-0.00305	3.05
	t-statistic	-1.91238*	1.72489*	0.880653	1.87563	1.88237***	-2.63102	-0.14198	
	MEXICO								
Portfolio 1	*coefficient*	-0.00054	0.001554	0.000786	0.000779	0.001884	-0.06706	0.008265	2.49
	t-statistic	0.601152	1.743681*	0.888265	0.885287	2.101929***	-1.772	0.393764	
Portfolio 2	*coefficient*	-0.00009	0.00143	0.000542	0.000921	0.001093	-0.04514	-0.01246	13.14
	t-statistic	-0.09576	1.534327	0.583804	0.99452	1.664344*	-1.11249	-0.58981	

Source: Own elaboration.

Table 10 shows the coefficients and t-statistics (t) of estimating with E-GARCH (1,1) the time series model with control variables (equation 3) within portfolios. We group stocks in two portfolios depending on their current liquidity ratio (current assets divided by current liabilities). We use the percentile 50 as our threshold to build the two portfolios. Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

Table 11. The weekend effect and price-to-book ratio

		Mon β1	Tue β2	Wed β3	Thur β4	Frid β5	Risk α	Momen λ	Intensity
	PERU								
Portfolio 1	*coefficient*	-0.00191	-0.00016	0.00016	0.00119	0.00044	0.00095	0.04176	0.77
	t-statistic	1.75071*	-1.6680*	0.06241	0.48941	1.87830**	2.00644***	1.8021**	
Portfolio 2	*coefficient*	-0.0011	-0.00109	-0.00024	0.00075	0.00221	0.00186	0.00639	3.01
	t-statistic	-1.96868**	-1.970**	-0.21581	1.67325*	1.95840**	2.04912***	1.80202**	
	ARGENTINA								
Portfolio 1	*coefficient*	-0.00045	1.58E-03	0.00301	0.001436	0.002767	-0.03176	0.027181	1.57
	t-statistic	-1.691964*	1.756958*	3.388221	1.624937	3.01686***	-0.66932	1.247874	
Portfolio 2	*coefficient*	-0.002301*	-0.00154	-0.00154	-0.00054	0.001316	0.044846	0.04969	5.16
	t-statistic	-2.342022*	-1.57704	-1.57704	-0.57245	1.637304*	1.001175	2.264144***	
	BRAZIL								
Portfolio 1	*coefficient*	-0.00036	0.000115	0.00015	0.002031	0.0048	0.0855	0.006923	12.30
	t-statistic	0.316004	1.663447*	1.309194	1.773102**	4.151112***	2.056062***	0.322771	
Portfolio 2	*coefficient*	-2.3E-05	0.000629	0.001105	0.00149	0.004517	0.121879	0.02948	194.86
	t-statistic	-0.01912	0.519978	0.519978	1.227992	3.674106***	2.783743***	1.365932	
	COLOMBIA								
Portfolio 1	*coefficient*	-0.00284	-0.00067	-0.00067	-0.00049	0.00187	0.095423	0.012752	1.36
	t-statistic	-2.97069***	-0.69696	-0.9137	0.548099	1.928501**	2.351247***	0.610436	
Portfolio 2	*coefficient*	-0.00421	-0.00171	0.000355	-0.00089	0.001504	0.143573	0.023761	1.66
	t-statistic	3.686903***	-1.49376	0.333582	-0.83776	1.705158*	3.502616***	1.024415	
	CHILE								
Portfolio 1	*coefficient*	-0.00109	0.000383	0.000383	0.00227	0.000764	-0.04771	-0.02111	1.48
	t-statistic	-1.720408*	0.545623	0.545623	1.713334*	1.07229	-0.15571	-1.9823**	
Portfolio 2	*coefficient*	-0.00161	0.000352	0.000352	0.00312	0.000775	-0.03997	-0.00753	1.7
	t-statistic	-2.2926***	0.469644	0.465964	1.834657*	1.01931	-0.35568	-0.90459	
	MEXICO								
Portfolio 1	*coefficient*	-0.00054	0.001554	0.000786	0.000779	0.001884	-0.06706	0.008265	1.06
	t-statistic	0.601152	1.743681*	0.888265	0.885287	2.101929***	-0.772	0.393764	
Portfolio 2	*coefficient*	-9E-06	0.00143	0.000542	0.000921	0.001093	-0.04514	-0.01246	9.79
	t-statistic	-0.09576	1.534327	0.583804	0.99452	1.664344*	-1.11249	-0.58981	

Source: Own elaboration.

Table 11 shows the coefficients and t-statistics (t) of estimating with E-GARCH (1,1) the time series model with control variables (equation 3) within portfolios. We group stocks in two portfolios depending on their price-to-book ratio and we use the percentile 50 as our threshold to build the two portfolios. Source: Bloomberg. Own elaboration. ***statistically significant at 1 %; ** statistically significant at 5 %; *statistically significant at 10 %.

5. Conclusion

Overall our results support the hypothesis of the existence of weekend effect in the six Latin American emerging markets, but individual investors in each country seem to emphasize in the use of certain financial characteristics to select stocks for their portfolios and institutional investors are also influencing the effect through their investments in collateralized loans.

Individual and institutional investors will behave differently in different markets, so the weekend effect will have different intensities in different countries (Ritter and Chopra, 1989). In particular, Market capitalization (size) is important in all countries and especially in Brazil, price-to-book is important in all countries, but especially in Argentina. Stock market liquidity is important in all countries, but especially in Peru, Colombia, Chile and Mexico. Finally, current liquidity ratio is also important in all countries, but especially in Peru, Colombia and Chile.

Our results are consistent with the ones of Birru (2018) with respect to the individual investors' behavioral hypothesis, but different with respect to institutional investors. Institutional investors cannot only refrain themselves from purchasing on Mondays Ülkü and Rogers (2018), but they also increasingly invest in collateralized debt issued by small cap and illiquid companies, and these companies eventually will end up being more indebted with tight current liquidity ratios and low price-to-book ratios (i.e. marketplace for loans hypothesis).

We just made the first step towards explaining the weekend effect because many questions remain such as: is the weekend effect stronger in certain industries? Why? What is the frequency that institutional investors use to rebalance their investment portfolios? Why do they refrain from investing on Mondays? How the change in their investment mandates affect the weekend effect? Future research should be directed towards answering these and other related questions.

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