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Essays on American Depositary Receipts: New Fears, Investor Attention and Financial Bubbles

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ESSAYS ON AMERICAN DEPOSITARY RECEIPTS: NEW FEARS, INVESTOR ATTENTION AND FINANCIAL BUBBLES

A Dissertation

by

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ABSTRACT

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This dissertation consists of four chapters, focusing on American Depositary Receipts (ADRs) and how they are affected by new measures of investor sentiment, new proxies of investor attention, and financial bubble detection. ADRs are negotiable certificates of ownership in foreign companies that are traded in the U.S. financial markets.

In Chapter I, I make a brief introduction of ADRs. The types of programs there are, the market capitalization and volume in general and to some specific countries.

In Chapter II, I show that negative investor sentiment measures, derived from internet aggregate search indices, have a contemporaneous negative effect on ADR stock indices and a second-day reversal behavior. To build the sentiment measure, I apply a similar methodology developed in recent literature to construct the Financial and Economic Attitudes Revealed by Search (FEARS) index. Moreover, evidence shows that this effect is greater for Latin American ADR indices at the aggregate level and on a country-specific level than for other regions. After matching the sample during times of turmoil, the results are consistent with the literature that employs this sentiment proxy with U.S. stock indices.

In Chapter III, I examine the effect of country-specific investor attention on ADR mispricing. Investor attention is measured by the amount of traffic a country profile receives on Wikipedia. A 2-Stage Least Squares (2SLS) model is employed to mitigate the potential endogeneity. Evidence shows that higher levels of investor attention have a negative impact on ADRs mispricing.

In Chapter IV, I utilize the Generalized Supremum Augmented Dickey-Fuller test methodology to identify and time-stamp the beginning and the end of financial bubbles in ADR stock indices. Evidence shows that there are multiple bubble episodes in the general ADR index, which correspond to bubble episodes in the S&P 500 during the preceding months of the 2008-2009 financial crisis. Moreover, I also identify several bubble periods on Latin American, European, and Asian ADR indices.

DEDICATION

To God, for giving me all that I am, all that I have, and for giving me the strength to push through the hardest times. To my loving wife, Andrea, who has filled my days with love and hope, and inspired me to become a better man every day. To my daughters, Emma and Cecilia, the light of my eyes and my best motivation. To my beloved parents, Milagro and Argenis, who always encouraged me to reach far and showed me the meaning of kindness and humility. To my parents-in-law, Eugenio and Cecilia, for embracing me like a son, and for your unconditional support throughout all these years. To my siblings, Jose and Juliana, and to the rest of my family for always being there for me.

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CHAPTER I

INTRODUCTION

1.1. American Depositary Receipts

The American Depositary Receipts (ADRs) are negotiable instruments that represent a portion of ownership in a foreign company. They are denominated in U.S. dollars and all the aspects surrounding the transaction take place in the U.S. financial markets. Many of them are listed in one of the major American stock exchanges such as the New York Stock Exchange (NYSE) or the NASDAQ. However, the great majority are traded over-the-counter (OTC).

The ADRs were introduced in the American capital markets back in 1927 when a U.S. bank offered shares from a popular U.K. department store to its customers. Ever since there has been thousands of firms who have decided to “cross-list” their shares with different purposes in mind, but mainly with the goal of gaining access to capitals from U.S. investors and increase international notoriety.

One ADR may be equivalent to one underlying share, but it is also common the case where one ADR is equivalent to a number of shares or a fraction of a share. For example, for a given company, one (1) ADR may be equivalent to ten (10) shares of their underlying stock, while for another company, one (1) underlying stock may be equivalent to ten (10) ADR shares. The purpose is to strategically price ADRs according to the average prices of similar stocks traded in the U.S. markets.

ADRs are considered by many investors as a great vehicle to internationally diversify risk from their portfolios. These instruments allow them to access shares from companies -in first instance- operating in foreign markets and affected by a different set of economic fundamentals, without the inconvenience of locating and hiring brokers in those countries and completing non-frictionless international transactions. However, most ADRs, as most U.S. shares, are not restricted to American investors, which means that international investors can also purchase these stocks.

For companies, establishing an ADR program, represents not only an opportunity to access a whole new market of capital funds, but to gain brand exposure and international recognition, especially among U.S. investors and consumers. As surveyed by Karolyi (2006), just by cross-listing, a firm can experience a positive impact on share prices, change the market risk exposures and liquidity. Moreover, it plays a strategic role for those companies willing to establish a toehold in the world's biggest economy, which in turn, opens the door to a vast list of growth opportunities.

1.1.1 ADRs Formation and Sponsorship

Overall, the process of creating these instruments starts when a foreign entity, firm or investor, approach to the depositary bank to consign their share of ownership in the foreign company. The shares are kept by the bank itself or in a custodian institution in the foreign country. After this first step, the bank then proceeds to issue the depositary receipts in the U.S. to the consigner, who is now able to trade these instruments in the U.S. stock market or OTC.

When the foreign company itself deposits its own shares to a depositary bank, the ADR program is a “Sponsored” ADR program[1]. These agreements usually determine activities related to the ADR maintenance, such as recordkeeping, shareholder communications, dividend payments and other services. When there is no cooperation agreement with the foreign company directly, but through a broker or dealer trying to establish a gateway to the U.S. financial markets, then the program is “Unsponsored”.

1.1.2 Types of ADRs

Since the characteristics, expectations and level of involvement of cross listed companies differ in terms of objectives and interests. Investors have classified ADRs into 4 major categories: Level I, Level II, Level III, and Special Regulation Programs. Each one has its own characteristics:

Level I: This is the entry level of cross-listing programs, which allows for trading presence alone through the over-the-counter (OTC) market. Capital raising events are not allowed, and the reporting requirements are scarce. It is the only type of facility that may be unsponsored. The SEC only requires them to file Form F-6. Information about these companies might be found on the issuer’s website, however accounting standards and languages used in the reports might differ from U.S. standards.

Level II: This level allows for trading the security on a major U.S. market, such as the New York Stock Exchange or NASDAQ, however it may not be used to issue additional stock. Along with the Form F-6, the non-U.S. company is required to register and file annual reports on Form 20-F with the SEC.

[1] This information was collected from the Securities and Exchange Commission website. For more information about the ADR program visit https://www.sec.gov/investor/alerts/adr-bulletin.pdf

Level III: this is the highest level of the ADR programs, and it is similar to the Level II with the only exception that it may be used to raise capital for the foreign issuer. It is required that the company files a registration statement on Form F-1, Form F-3, or Form F-4 along with the annual reports on Form 20-F.

Special Regulation Programs: there also exist a couple more programs that are restricted to only certain types of investors. The 144A DR program which was approved in 1990 by the SEC and is used by large U.S. institutional investors to make large private placements on foreign equity. This program does not allow shares to be traded on any of the major stock exchanges. Also, there is the Regulation S program which offers the possibility to expand into markets outside the U.S., these shares cannot be held by any U.S. person as determined by the SEC Regulation S, therefore are issued and registered to non-U.S. residents.

1.2. Relevance of the ADRs

The ADRs have become increasingly important, and their role in the U.S. financial markets have grown over the years as shown in Figure 1.1. According to Citibank ADR's website[2], the market capitalization of all ADRs reached its peak during 2011, with a total market value of $3,319 billion. However, in the following years there is a sharp decline, possibly affected by the European Credit Crisis, the slower growth of China, and the Brazilian economic crisis from 2014. In the recent years, there has been a period of recovery, and at the end of 2015, the total ADR market capitalization stands at $2,799 billion.

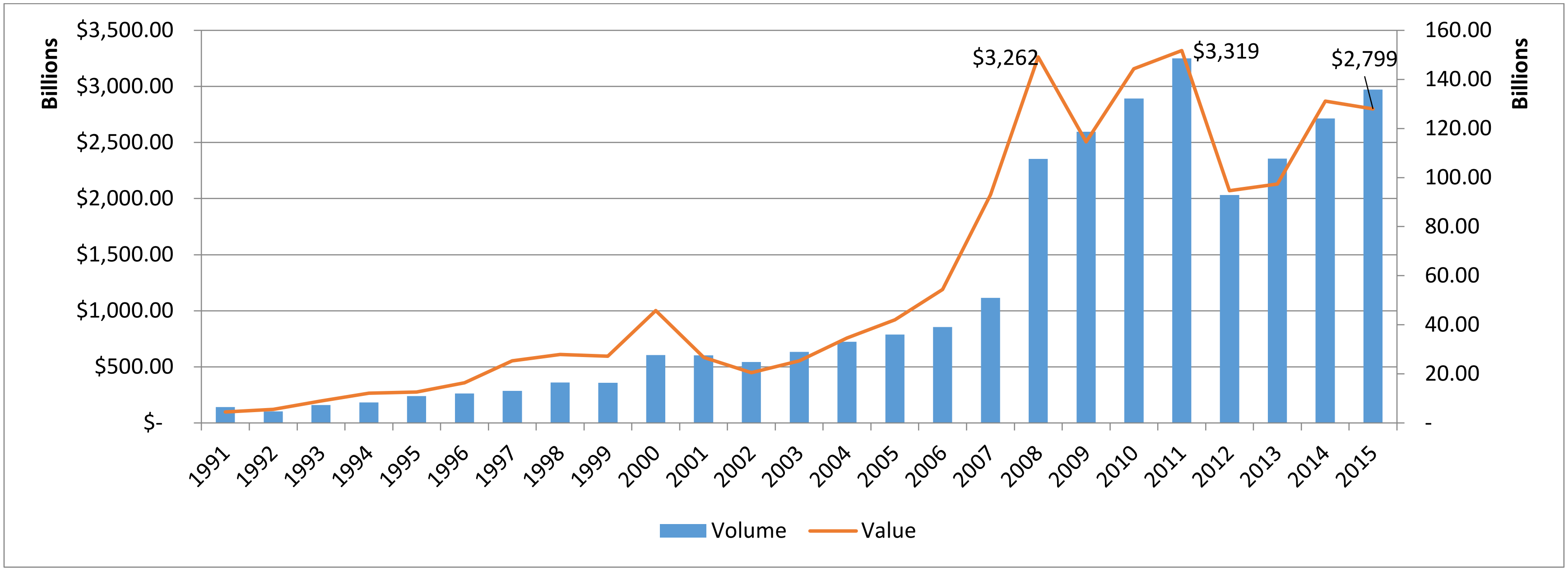
In Figure 1.2, I compare the U.S. market capitalization of all domestic listed companies (provided by the World Bank) against the market capitalization of ADRs. In 2008, the year of the

[2] https://www.citiadr.idmanagedsolutions.com/www/drfront_page.idms

financial crisis, the market value of cross-listed shares peaked its maximum value (22%) relative to the total U.S. market capitalization. By the end of 2015, after years of domestic markets recovery and international markets decline, ADRs represented only a 10% of the total U.S. stock market capitalization. Figure 1.3 shows the Bank of New York Mellon ADR index series and the S&P 500 index monthly observations in levels from January 1997 to December 2016. I observe that both series move together in general. However, after September 2005 the ADR index outperforms the S&P 500 substantially, even shortly after the financial crisis of 2008. After 2012, the ADR index fails to keep up with the growth of the S&P 500 and even experiences a decline from 2014 to 2016.

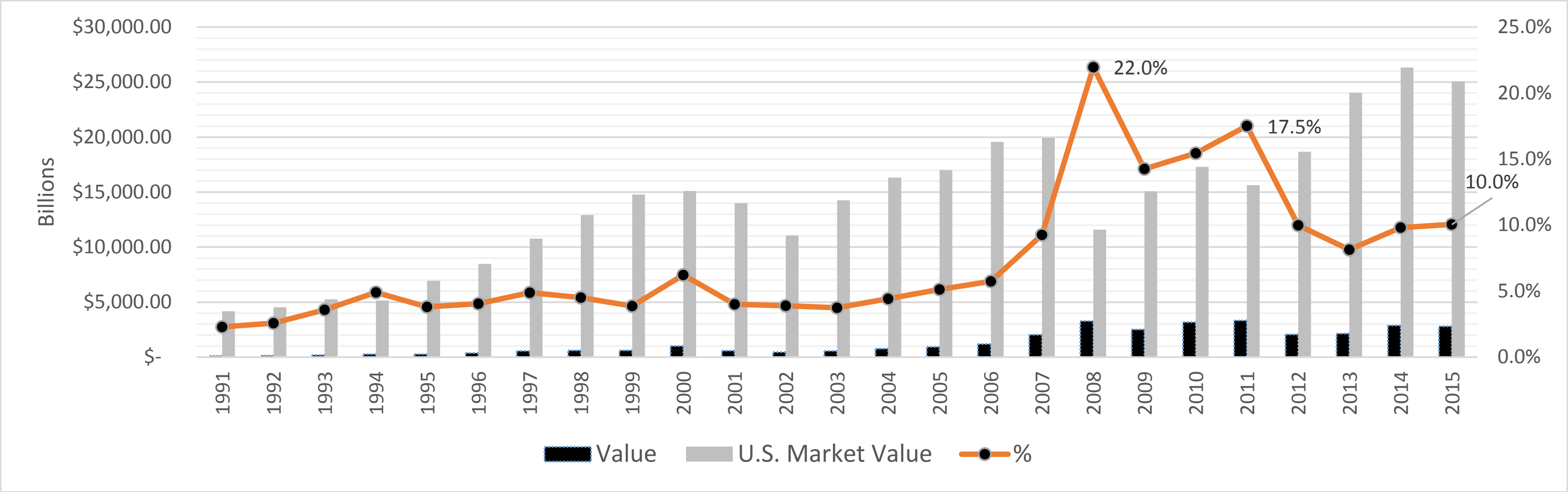
In Table 1.1, I present a list of the 20 countries with the highest volume and market capitalization as of 2015. China is the country with the highest market capitalization with $1,016 billion, followed by the United Kingdom with $501 billion; Brazil comes third with $289 billion. Interestingly, the country with the highest volume turnover is Brazil with 42,784 billion shares traded, followed by China with 25,040 billion and the United Kingdom with 12,855 billion. Among the major depositary banks for ADRs in the U.S., I find the Bank of New York, Citibank, JP Morgan and Deutsche Bank.

Figure 1.1: Volume and value of the ADR market over time



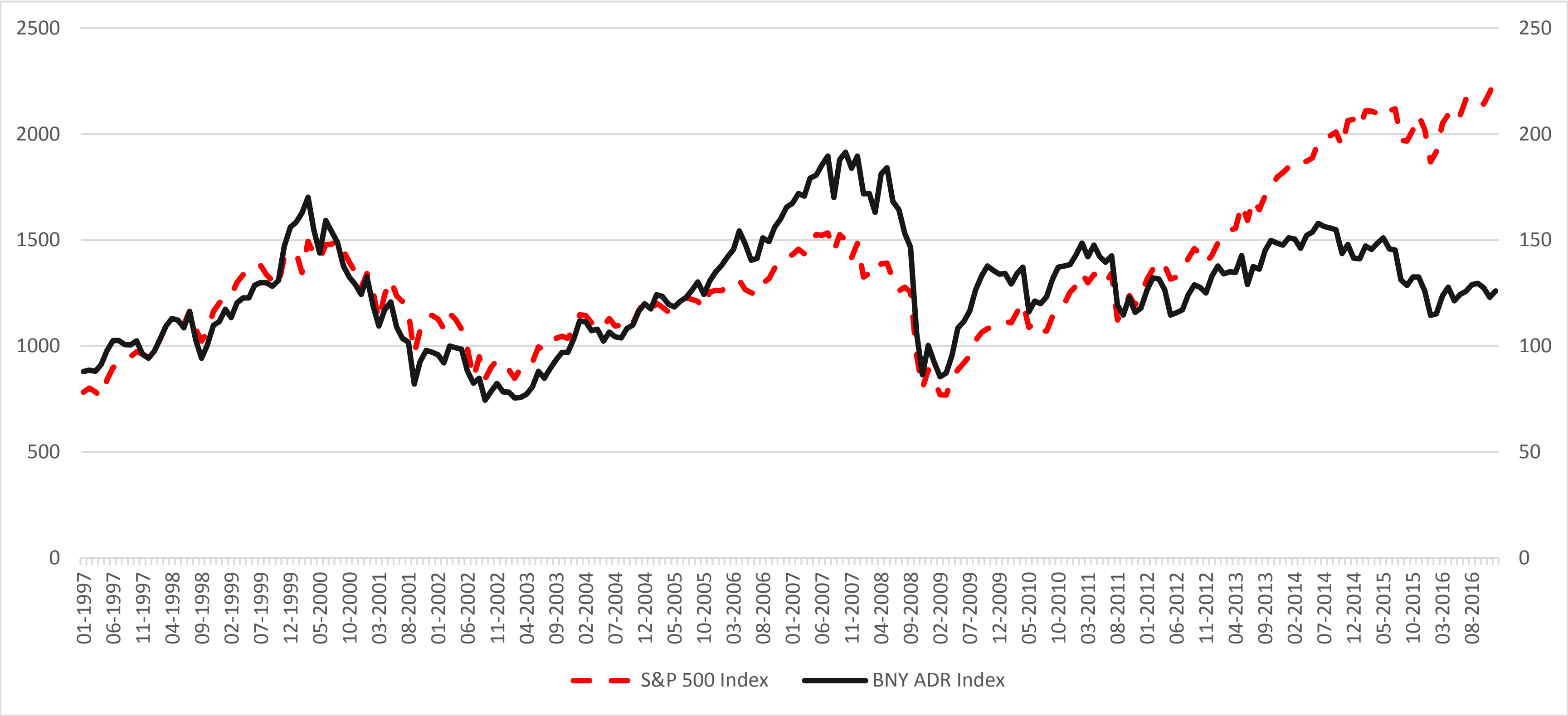
Note: This figure shows the volume in number ADR shares traded, and value of the ADR market as a whole from the years 1991 to 2015 (Value is expressed in billions of U.S. dollars on the left scale and represented with a line. While volume of traded ADRs is expressed in billions on the right side scale and is represented with a bar). Source: https://www.citiadr.idmanagedsolutions.com/www/drfront_page.idms

Figure 1.2: Market capitalization of the ADR market relative to the U.S. total market capitalization over time



Note: This figure shows the market capitalization of ADR shares traded and the market capitalization of the U.S. domestic firms listed in the American stock markets from years 1991 to 2015. (Values are expressed in billions of U.S. dollars on the left scale and represented with a line). The percentage is the total ADR market capitalization for a given year divided by the sum of the ADR market capitalization and the market capitalization of the U.S. domestic firms. Sources: https://www.citiadr.idmanagedsolutions.com/www/drfront_page.idms and World Bank Database.

Figure 1. 3 Bank of New York Mellon (BNY) ADR Index and S&P 500 Index over time



Note: This figure shows the monthly observations for the Bank of New York Mellon (BNY) ADR Index and the S&P 500 Index from January 1997 to December 2016. S&P 500 reference values on the left axis and the BNY ADR index reference values on the right axis. Source: Datastream.

Table 1.1: Volume and Value of ADR per country at the end of 2015

	Country	Volume of shares traded	Country	Market Capitalization in Millions
1	Brazil	42,784,850,995	China	$ 1,016,399.87
2	China	25,040,815,291	UK	$ 501,783.27
3	UK	12,855,944,729	Brazil	$ 289,217.12
4	Mexico	5,638,096,281	Switzerland	$ 102,144.68
5	Taiwan	5,288,674,056	Taiwan	$ 86,818.02
6	Greece	4,195,501,940	Israel	$ 86,023.26
7	Finland	4,046,869,818	Mexico	$ 82,850.96
8	India	3,992,850,837	India	$ 78,308.87
9	South Africa	3,561,864,188	France	$ 71,812.77
10	Japan	3,169,974,521	Japan	$ 62,876.17
11	Spain	3,133,826,332	Belgium	$ 51,145.91
12	Switzerland	2,489,972,109	Germany	$ 42,730.30
13	Australia	2,322,636,014	Australia	$ 39,161.64
14	France	2,284,674,973	Finland	$ 29,848.31
15	Russia	1,948,828,311	Spain	$ 29,272.53
16	Israel	1,799,020,708	S. Africa	$ 22,528.97
17	Hong Kong	1,182,606,951	Hong Kong	$ 22,356.98
18	Sweden	1,109,626,538	Denmark	$ 21,748.56
19	Germany	1,062,191,626	Argentina	$ 17,357.35
20	Netherlands	1,000,183,349	Luxembourg	$ 16,544.86

Note: This table shows the volume and market capitalization of ADRs per country of origin at the end of the year 2015. Market capitalization values are expressed in millions of U.S. dollars. Source: https://www.citiadr.idmanagedsolutions.com/www/drfront_page.idms

CHAPTER II

NEW FEARS IN THE ADR MARKETS

2.1. Introduction

There has been a long debate in the literature discussing the role of investor sentiment in the financial markets. Keynes (1936) coined the term “animal spirits” to describe the enthusiasm from investors, who often make asset prices move away from their fundamentals. However, evidence provided by De Long et al. (1990), Baker and Wurgler (2006), and Barberis et al. (1998), have shifted the debate to not whether investors sentiment impact financial markets but to which proxy of investor sentiment should be used, as stated by Baker and Wurgler (2007).

American Depositary Receipts are negotiable certificates that represent a piece of ownership in a foreign company. These instruments were created to facilitate the trade of non-U.S. companies’ stocks in the U.S. capital markets. Previous studies propose that U.S. investors obtain diversification benefits by including ADRs in their portfolios, as suggested by Jiang (1998) and Alaganar and Bhar (2001).

In this study, I target the effect of a novel U.S. based investor sentiment called FEARS (Financial and Economic Attitudes Revealed by Search) recently developed by Da et al. (2015) on American Depositary Receipts (ADRs) returns. I am particularly interested in studying ADRs because they represent securities listed in two markets: their home country and the U.S. For each market, the asset is subject to the same set of fundamentals and similar idiosyncratic risk, but different macroeconomic conditions, risk premiums and investor’s sentiment as escribed by Suh

(2003) and Grossmann et al. (2007). Therefore, evaluating the effect of this negative investor sentiment proxy on ADR index returns allows determination of the short-term spillover effect on cross-listed securities. This effect is easier to measure on ADRs than on the underlying security due to non-synchronous trading in the case of European and Asian ADRs. Also, even though the ADR general index returns correlate highly with U.S. market returns[3], this correlation is not perfect, and this constitutes another reason to study this asset class separately. Moreover, when I evaluate regional and country-specific index returns[4] and U.S. market returns, the correlation coefficients are smaller.

I contribute to the literature by examining the relationship between U.S. investor's sentiment and cross-listed securities returns in a high-frequency manner. Similar to U.S. stock returns, the results show there exists a negative contemporaneous relationship between this negative investor sentiment and the ADR aggregate market returns, followed by a positive next day reversal. I test a set of 30 country-specific ADR indices returns, as well as equally and value-weighted ADR portfolio returns. The results are also consistent in all the cases, except for a few countries in which the evidence is not statically significant.

Traditionally, investor sentiment proxies used in previous research belong to either the "bottoms up" approach introduced by Baker and Wurgler (2006) or the survey-based approach originally used by Brown and Cliff (2004). The former is built upon macroeconomic anomalies such as the closed-end fund discount, stock exchange share turnover, first-day returns on IPOs,

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[3] The correlation coefficients between the general ADR index and the U.S. market returns, proxied by the S&P 500, is .91.

[4] The correlation coefficient between U.S. market returns, proxied by the S&P 500, and regional ADR indices such as Latin American, Europe, and Asia, are .80, .90, and .87 respectively. This correlation is even lower for countries like Brazil (.75), China (.76), Japan (.75) and Russia (.66).

the equity share in new issues, and the dividend premium. The latter uses survey-based instruments to capture the optimism (pessimism) from investors in weekly and monthly intervals.

Google Trends provides information for Search Volume Indices (SVI). These indices rank the relative search index popularity for each keyword used in their search engines in a scale from 0 to 100. Using SVIs to form an investors sentiment index, Da et al. (2015) showed that negative investor sentiment contemporaneously affects the S&P 500 returns in the same trading day, followed by a positive reversal adjustment in the following days. This index is constructed by aggregating economically negative search queries of U.S. internet users for terms such as "Inflation," "Crisis" and "Unemployment." The use of SVI follows a multidisciplinary trend in research that seeks to use aggregate internet search queries as a reflection of the public's interests and concerns.

In this chapter, I follow their approach and generate an index of aggregate negative SVI for a list of 30 search terms previously identified as negatively correlated with the market[5]. My high-frequency sentiment index spans from January 1st, 2004 to December 31st, 2016, a period with both economic turmoil and subsequent economic growth. I then observe the effects of that negative sentiment on a set of ADR indices to assess its effect on the aggregate market of cross-listed securities.

There are two key benefits of using the SVI method to build this sentiment measure. First, I can test the hypotheses using daily data. This would not be possible to achieve using survey data (only available on a weekly or a monthly basis). Second, it also allows me to measure the contemporaneous effects (and short-term reversal) of changes in the U.S.

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[5] Da et al. (2015) identify these search terms as having the highest negative correlation with stock market returns from July 2004 to December 2011. Even though my findings are consistent with theirs, there is a possibility that the list of search terms could have changed by including the additional periods covered in this study.

household’s opinions, measured by their internet search patterns and not only institutional investors or individual investors sentiment. Moreover, this method reduces sampling biases such as the observed in survey-based studies as explained by Singer (2002) or to an indirect proxy of sentiment derived from market anomalies such as the “bottoms up” approach present in Baker and Wurgler (2006), criticized by Qiu and Welch (2004).

According to the World Bank, the percentage of internet users in the U.S. population during the year 2016 was 76.16%. This statistic represents a solid reason to consider this sentiment index as an accurate representation of the U.S. population’s concerns and interests. In Figure 2.1 I show the SVI on google trends for the word “crisis” from January 2004 until December 2016.

The remainder of the chapter is organized as follows. Section 2.2 discusses the previous literature. Section 2.3 explains the data and methodology, including a detailed description of the construction of this index and its differences with the original FEARS proposed by Da et al. (2015). Section 2.4 presents the empirical results. Section 2.5 performs robustness tests, including the use of the original FEARS index. Section 2.6 concludes.

2.2. Literature Review

The use of SVI data, in general, is becoming a significant source of information considering its uses in finance empirical studies. For example, using Google Trends, Vozlyublennaia (2014) found that a shock to returns causes a long-term change in investors’ attention. Using stock tickers, Da et al. (2011) found a positive relationship between increases in the SVI’s and an increase in the stock prices and a subsequent price reversal within a year. Also, Irresberger et al. (2015) were able to explain bank stock underperformance with the SVI for terms like “bank run” and “financial crisis.”

Similar to the SVI method, other studies have focused on using different internet sources of information to show the effects of investor sentiment on stock markets, i.e. Siganos et al. (2014) used Facebook's Gross National Happiness Index to show how a positive return on Mondays followed increases in the overall good mood from Sundays. Also, Zhang et al. (2016) used a twitter sentiment proxy to explain stock performances in 11 international stock markets.

According to some authors, cross-listed securities have become a portfolio diversification tool which provides a significant improvement of the risk-return trade-off as reported by Jiang (1998). These findings are consistent with the ones presented by Ely and Salehizadeh (2001), who found that American Depositary Receipts have created a level of cointegration with ordinary shares that long-term investors utilize them as a substitute for ordinary foreign stocks. However, when studying the fundamentals from both markets, the U.S. and the home country, they found both markets to be important sources of information, consequently relevant to the asset pricing process. Similarly, Peterburgsky and Yang (2013) found that investing in the underlying shares is more useful for diversification purposes than ADRs when the U.S. stock market returns are low and when the U.S. economy is underperforming. Moreover, Gagnon and Karolyi (2010a) showed that even though the cross-listing of companies has slowed during the past few years, the globalization effect has been growing, suggesting that ADRs can still be considered an international market cointegration factor.

Most of the ADR related research that involves investor sentiment has focused on explaining deviations from the price parity condition between the ADR and the underlying security. Such deviations are commonly known as ADR mispricing (Suh 2003, Grossman et al. 2007, Beckmann et al. 2015). In a similar line of literature, Hwang (2011) used country-specific popularity among the U.S. population to explain the mispricing behind Country Closed-End

Funds (CCEF's) and ADRs, showing that stocks from more (less) popular countries are likely to exhibit a premium (discount) in their cross-listed securities. However, to this date, no other study has observed the contemporaneous effect of high-frequency investor sentiment on ADRs returns using a sentiment proxy such as the one employed in this study.

2.3. Data and Methodology

In this section, I discuss the data sources and methodology and provide details on the construction of the sentiment measure.

2.1.1 The SVI Sentiment Index

The main idea of this segment is to describe the building of the SVI sentiment index. Instead of using text analytics literature to identify the words with economic meanings (see Tetlock 2007; Tetlock et al. 2008). I start by collecting daily search volume indices for a set of 30 search terms, previously identified in Da et al. (2015), that report the largest negative correlation with the market[6]. In Table 2.1, I list the search terms used to construct the index.

Using Google Trends (www.google.com/trends), I download the daily search volume index for each search term from January 1, 2004 to December 31, 2016. Each index ranges between 0 and 100, depending on the number of searches for the specific word or term in a specific time. Therefore, during times pessimism about the future performance of stock markets, the aggregate search for these negative economic search terms increases. In Figure 2.1 I observe a spike in the search term "Crisis" reach a 100 during 2008, the year when the financial crisis reached its peak of public attention. However, given that our period of analysis also includes

[6] These are the top 30 search terms with the highest negative correlation with the S&P 500 from January 1, 2004 to December 31, 2011.

times of relative economic growth, I encounter some search terms to have values of "0" for an important number of periods (i.e., Google Trends does not report observations for the term "Car Donate" in the first quarter of 2010).

Google Trends allows me to filter the results by their geographic location of the query. Since our main interest is the U.S. household search historical information, I restrict the results to show only those from U.S. internet users. After compiling the observations for each search term, I proceed to calculate the daily change in search term j as:

$$\Delta SVI_{j,t} = \ln\left(SVI_{j,t}\right) - \ln\left(SVI_{j,t-1}\right)$$

As shown in Figure 2.2, the SVI changes for each search term present several issues that have to be addressed before continuing. The first is seasonality; it is easily observable how the index depicts a cyclical pattern towards the end of the week where users reduce their searching habits and internet usage overall. To address this issue, I regress each SVI change in a set of day-of-the-week and monthly dummies and keep the residuals. Secondly, I winsorize the data at the 5% level (2.5% on each tail) to reduce the effect of extreme values in the data, and finally to make each series comparable (the standard deviation for the term "Unemployment" is 3 times greater than for the term "Crisis") and address potential heteroscedasticity problems, I adjust each series by their standard deviation. With our list of deseasonalized, winsorized and standardized changes in 30 search terms that I proceed to calculate the average to obtain our index:

$$NewFEARS_t = \frac{1}{30} \times \sum_{j=1}^{30} \Delta SVI_{jt}$$

2.1.2 Additional Data

I collect daily data from different sources to proceed with our study, I download the Bank of New York Mellon ADR index[7], regional ADR indices for Asia, Europe, and Latin America, and country-specific ADR indices for Australia, Belgium, Brazil, Chile, China, Colombia, Denmark, France, Finland, Germany, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, Norway, Peru, Philippines, Russia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, and United Kingdom along with their respective exchange rate from Datastream. The Trade Weighted U.S. Dollar Index: Broad [DTWEXB], is retrieved from FRED, Federal Reserve Bank of St. Louis[8]. I also obtain ADR returns by constructing equally weighted portfolios and value-weighted portfolios using all available ADRs from CRSP from July 2004 to December 2015.

One benefit of using returns of ADR indices instead of individual stock returns is to prevent illiquid securities from driving the results of our research as explained by Hwang (2011) who finds that securities from more popular countries exhibit a higher turnover. Furthermore, the Bank of New York Mellon ADR indices are used as a benchmark for several Exchanged Traded Funds (ETFs)[9]. Moreover, Kabir et al. (2011) found there exists a substitutability effect of investing in ADRs and their respective country indices.

I retrieve the Chicago Board Options Exchange (CBOE) daily market volatility index (VIX)[10] directly from their website, which measures the implied volatility of options trading in

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[7] This index contains almost every American Depositary Receipt available in the market.
[8] This data is available for download through https://fred.stlouisfed.org/series/DTWEXB
[9] More information about ETF's using BNY Mellon ADR indices as benchmarks can be found at https://www.adrbnymellon.com/assets/resources/etf_factsheet-jan_2017.pdf
[10] This data is available for download at http://www.cboe.com/micro/vix/historical.aspx

the S&P 500 stock index, also commonly known as "investor fear index"[11]. This measure is widely used in the literature including Baker and Wurgler (2007) as a proxy for investor sentiment. To include a high-frequency measure for macroeconomic activity, I collect the Aruoba-Diebold-Scotti (ADS)[12] index from the Federal Reserve Bank of Philadelphia. This is a seasonally adjusted index that encompasses a series of economic indicators such as weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. The average value of the ADS is zero, for example during the 2007-2008 crisis, the index dropped to its maximum negative value of -4.0, while a value of positive 1.0 was achieved in early 2010. Including this variable in the model, will account for essential macroeconomics conditions that affect financial markets.

To measure the economic policy uncertainty (EPU) I obtain an index developed by Baker, Bloom and Davis (2015)[13]. This index has three components; the first quantifies newspaper coverage of policy-related economic uncertainty. The second reflects the number of federal tax code provisions set to expire in future years, and the third component uses disagreement among economic forecasters as a proxy for uncertainty. The reason for its inclusion is to control for all the negative sentiment that policymakers and financial analysts could induce into the markets with their announcements in the news, ultimately, affecting the mainstream public opinion that feeds a climate of uncertainty.

Lastly, I download the original daily FEARS index used in Da et al (2015) from Professor Joseph Engelberg's website and is available from July 1, 2004, to December 30, 2011.

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[11] I test for the stationarity condition of the VIX series in levels using the Augmented Dickey-Fuller test. The null hypothesis of the presence of a unit root is rejected with a t-statistic of -5.978.
[12] This data is available for download at https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index
[13] This data is available for download at http://www.policyuncertainty.com/us_daily.html

The construction of their index differs slightly from the one I estimate in this study, in the sense that they identify the 30 search terms with the highest t-statistic values during 6-month periods by using expanding rolling regressions from a larger list of 118 search terms. However, in their study, they only report the 30 search terms with the highest t-statistic values over their entire sample period. I use these 30 search terms to construct my sentiment measure. The yearly correlation coefficient between the New FEARS and the FEARS from Da et al. (2015) is presented in Figure 2.3, for all time is 0.4309. Initially, I interpret this rather small coefficient as a limitation in my study in favor of the dynamic nature of the original FEARS on selecting the top 30 search terms every interval of time. However, the results I present in this study provide similar results regardless the sentiment I use. Also, the fact that the correlation coefficients increase closer and during the financial crisis suggest that both sentiment indices are relevant and more comparable during times of financial turmoil.

2.4. Results

2.1.3 FEARS and ADR Returns

To estimate the marginal effect of the New FEARS index on ADR returns, I employ the following regression model:

$$return_{i,t+k} = \beta_0 + \beta_1 NewFEARS_t + \sum_m \gamma_m Control_{i,t}^m + u_{i,t}$$

where $return_{i,t+k}$ is the index i's return on day $t + k$. To evaluate the two day cumulative returns then $return_{i,[t+1,t+2]}$ is defined. I include the contemporaneous $NewFEARS_t$, which is the variable of interest in this study. Consistent with previous studies (Da et al., 2015), I expect a negative sign in the β_1 coefficient for the same-day returns and a positive coefficient for the following days returns (k > 0 ; $k = 2$). Even though ADRs represent shares from companies originally listed abroad, this asset class is traded in the U.S. and therefore subject to swift changes in American investors' expectations. A vector of control variables $Control_{i,t}^{m}$ includes up to 5 lags of the index or portfolio returns, changes in the economic policy uncertainty (∆EPU), changes in the macroeconomic factors (∆ADS) and the daily values of the CBOE volatility measure (VIX). The last control variable I include is the changes in the exchange rate, which is commonly used in the ADR pricing literature to observe for fluctuations in the currency. I use the changes in the exchange rate for a basket of U.S. trade-weighted (∆ FX U.S. T-W) currencies when estimating the general ADR index returns. The country-specific exchange rate versus the U.S. dollar is only used when I estimate the regressions for country-specific ADR indices. Following Tetlock (2007) and Da et al (2015), I include 5 previous days lagged returns in the model. However, after testing for different specifications, I observe that results are consistent regardless of the number of lags included.

Table 2.2 displays the summary statistics for the main variables used in this study. The ADR index exhibit a slightly positive mean, which represents a small but overall positive return for the period of our study. On an annual basis, the average ADR index returns are 3.8% compared to 6.9% for the same period in the S&P 500[14], these are considerably lower returns when compared to the domestic global market returns. The mean for the New FEARS is 0 by construction as already described in the methodology section. Changes in ADS have an average close to 0 which suggests that over the time of our study the economic conditions have been both equally good and bad. Also, the U.S. trade-weighted currency exchange rate has an average

[14] I use 252 trading days as the average to calculate the annualized returns and U.S. dollar appreciation

change of 0.0033 which suggest a subtle appreciation of the U.S. dollar (0.84% on a yearly basis) compared to its trading partners during the timespan of this study.

Table 2.3 reports the baseline regressions using the general BNY ADR index returns as the dependent variable. The New FEARS coefficient is negative as expected and statistically significant to the 1% level. This means that when the aggregate index of negative search terms increases, the ADR stock prices decrease, causing a contemporaneous negative return. Even though coefficients are negative and significant, at first glance, the size is lower than the ones obtained by Da et al (2015). However, in the robustness section I match the sample of their study and the results are more similar. In model 1, a one standard deviation increase in the new FEARS index (0.390602) represents a 13 basis points decrease in the ADR returns. Different from Da et al. (2015), I do not observe any significant reversal effect on the next day (*t+1*) returns (column 2), the second day after (*t+2*) (column 3), nor the cumulative of both (column 4). In models 5, 6 and 7 I estimate the model with subtle changes. I include the changes in the trade-weighted U.S. dollar conversion rate to control for changes in the U.S. dollar appreciation, remove the lagged returns and changes in EPU and ADS. As expected, the coefficient for the New FEARS remains negative and statistically significant in all estimated models. Also, not surprisingly, the coefficient for the changes in the U.S. currency against a basket of trade-weighted currencies is negative and significant, which means that when the dollar appreciates respect to other currencies, the ADR returns decline. The inclusion of the exchange rate increases explanatory power of the model from 3.5% to 16.2%.

Next, I construct an equally-weighted and a value-weighted portfolio with all ADRs available from CRSP and calculate the returns for the period between July 1, 2004, and March 31, 2015. I use the same regression model (1) and report the results in Table 2.4. The results are consistent with the previously obtained in Table 2.3 for both portfolios. The New FEARS index coefficient is both negative and statistically significant at the 1% level for all contemporaneous (*t*) returns (columns 1, 5, 6, and 10). Moreover, I observe the reversal effect on next-day (*t*+1) returns, the coefficients are (columns 2 and 7) positive and significant at the 10% level. This means that increases in New FEARS have a negative same-day effect but quickly reverse by almost half the next trading day. An interesting finding is that the New FEARS coefficients are almost twice the size found in the BNY ADR returns index. A unit increase in the standard deviation of the New FEARS sentiment represents a drop of almost 26 basis points for the equally-weighted portfolio returns and 23 basis points in the returns respectively for the value-weighted.

2.1.4 FEARS and ADR Regional and Country Indices Returns

This section presents the results for the effect of the New FEARS index on ADR indices returns composed by regional and country-specific cross-listed securities. Table 2.5 shows the negative effect of the New FEARS Index on contemporary returns for Asia, Europe, and Latin America. Interestingly, the coefficients for Latin American ADR returns is almost twice the observed for the Asian and European indices, which implies that Latin American ADRs have a higher level of susceptibility to waves of negative U.S. investor’s sentiment.

Furthermore, in Table 2.6, I estimate the main model on the returns of ADR indices by country and observe that the New FEARS index negatively affects the contemporaneous returns for all countries except Denmark, Finland, India, Indonesia, Peru, Philippine, and Turkey. Also, the statistical significance varies depending on the country, but overall the coefficients are similar.

2.5. Robustness Tests

To construct the New FEARS index I follow the steps of Da et al. (2015) with some key modifications. I only incorporate the top 30 negative search terms reported in their paper with the highest negative correlation, while in their paper, they used an expanding rolling regression on 118 (unreported) search terms to identify which 30 are the most significant in 6-month time windows. Also, they evaluate a shorter time period than my study (2004-2011). Although the methodology is similar, I suspect that the statistical power of the original index could be superior, since it refreshes its constituents to the most negative SVI's every six-month interval. Nevertheless, in Table 2.7 I estimate the effect of the original FEARS to the BNY ADR indices returns and I observe that the effect is consistent with our previous findings with the only difference that a standard deviation change in the FEARS (0.3548) accounts for approximately 21 basis points in the ADR index contemporaneous returns. Also, I observe a positive and statistically significant next day reversal on the returns on $t+1$, and the cumulative of $t+1$ and $t+2$, meaning that an increase in a negative sentiment today negatively affects the ADR returns the same day but positively affects the returns the following day. I also model our New FEARS for the same time period as the original FEARS, the coefficient increases from the one observed on Table 2.3, this result suggests that this sentiment has a greater impact during times of turmoil.

I then proceed to test the effect of both the FEARS and the New FEARS on the value-weighted ADR portfolio returns for the same period. In the results reported in Table 2.8, the coefficients for the FEARS and the New FEARS at time *t* are very similar (-0.769***) and (-0.726***) respectively. However, the reversal effect of the sentiment on the next-day returns is only statistically significant at the 10% level for the New FEARS. These results suggest that both the FEARS and the New FEARS are indeed similar in spite of the differences in the methodology for their calculation. Meaning that the simple form of FEARS or New FEARS can also be used for further studies. Also, these results show that the effectiveness of using the original FEARS or New FEARS does not lie much on the way it is calculated, but on the financial climate during the time span included in the empirical sample.

In table 2.9, I address concerns related to the potential serial autocorrelation in the error terms of the main regression model used to estimate the coefficients. It may be plausible that previous returns or omitted variables affect the same day returns and the New FEARS alike (i.e., previous days returns). To alleviate such concerns, I estimate the main regression model using the Newey-West (1994) automatic lag selection in covariance matrix estimator. This nonparametric method automatically selects the number of autocovariances to use in computing a heteroskedasticity and autocorrelation consistent covariance matrix. This procedure is asymptotically equivalent to one that is optimal under a mean squared error loss function. The results show that regardless of the model utilized, the New FEARS has a negative impact on the BNY ADR Index returns, with statistically significant negative coefficients. In Model 1, a standard deviation increase in the New FEARS is associated with 12.6 basis points decrease in the ADR Index returns. In column 5, I include the trade-weighted changes in the exchange rate, the New FEARS coefficient is less prominent but still affects daily returns by 11.1 basis points in response to a one standard deviation increase of the New FEARS.

2.6. Conclusions

Using a daily index composed by historical internet search queries for a set of negative economic search terms, I show that increases in the volume of searches like "recession" and "crisis" have a negative effect on the returns of aggregate indices of cross-listed firms. The results show the negative effect of this novel measure of sentiment on contemporaneous ADR indices returns and a subsequent next day reversal just as reported on the S&P 500 by Da et al

(2015). These effects are consistent when I evaluate ADR equally-weighted and value-weighted portfolios, regional ADR indices for Asia, Europe and Latin America and most country-specific indices as well. When comparing the coefficients, I realize that Latin American ADRs are generally more affected by changes in the New FEARS relative to European and Asian countries. Even though ADRs can be considered a long-term diversification tool for many investors, these securities are susceptible to contemporaneous increases in U.S. investor's uncertainty and pessimism. These findings are of particular relevance for day-traders and the general investors overall. Also, it is worth to mention that policymakers could incorporate ADRs in the list of securities that are susceptible to swift changes in the investor sentiment indices, more specifically those that function at a high-frequency manner.

This study expands the literature that utilizes high-frequency investor's sentiment measures derived from internet usage data, as they begin to emerge as useful sources of information for understanding the effects of human behavior in financial markets. I also help expand the literature on the effects of U.S. investor's sentiment on American Depositary Receipts. I find that even though ADRs represent a piece of ownership in an underlying asset originally traded in another country, their indices returns are affected just like any other domestic stock market index like the S&P 500.

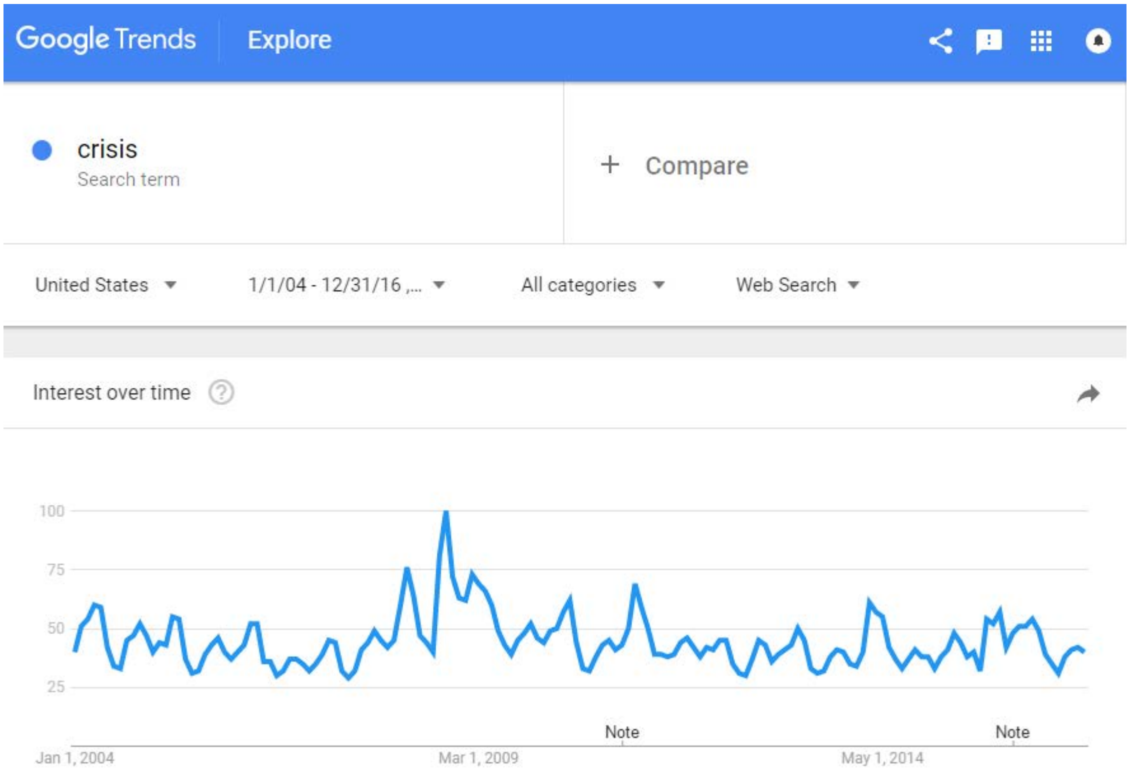
There are several ways to expand this study, considering that internet usage data has only been available for a few years, yet it offers an outstanding opportunity and challenge for scholars and academicians to continue to explore. More concrete ideas on how to expand can be directed at looking at spillover effects of the FEARS into other countries' financial markets and building similar investor sentiment measures for other countries. Another way to expand the literature could be developed by searching terms specifically relevant for ADRs from each country (e.g., "price of oil" for oil-producing countries, "steel import tariffs" for iron ore exporting countries, etc). Also, further studies could evaluate the role of the FEARS on ADR mispricing.

Table 2.1: List of negative search terms

	Search Term
1	Gold Prices
2	Recession
3	Gold Price
4	Depression
5	Great Depression
6	Gold
7	Economy
8	Price Of Gold
9	The Depression
10	Crisis
11	Frugal
12	GDP
13	Charity
14	Bankruptcy
15	Unemployment
16	Inflation Rate
17	Bankrupt
18	The Great Depression
19	Car Donate
20	Capitalization
21	Expense
22	Donation
23	Savings
24	Social Security Card
25	The Crisis
26	Default
27	Benefits
28	Unemployed
29	Poverty
30	Social Security Office

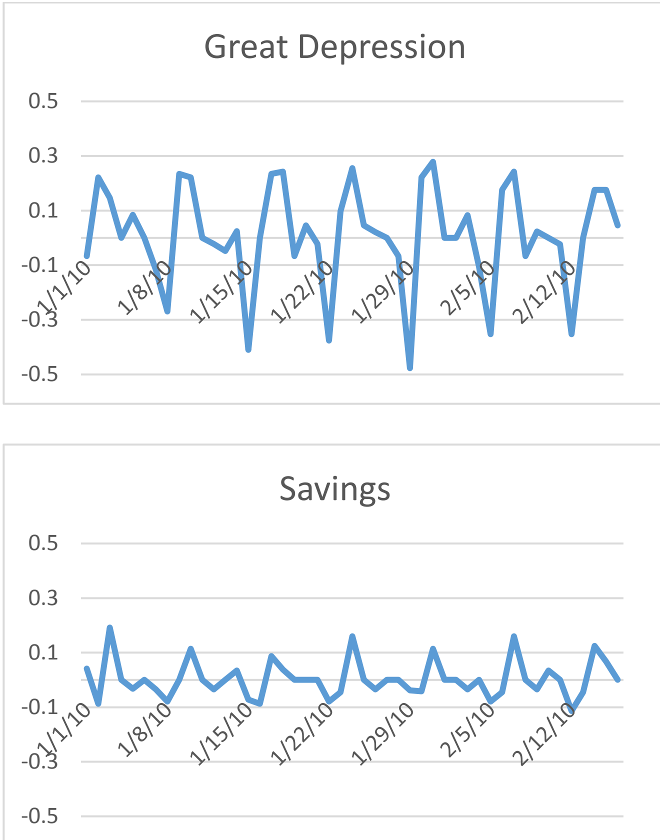
Note: This table shows the 30 search terms reported by Da et al (2015) to have the highest negative correlation with the market. The terms are organized from most negative to least negative according to Da et al. (2015).

Figure 2.1: Sample of SVI on google for the word "crisis"



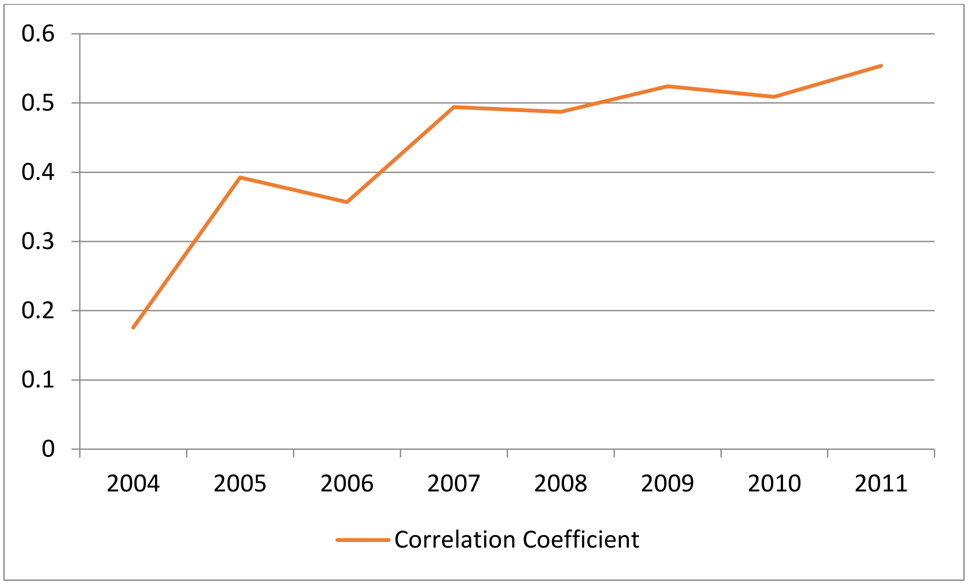
Source: Google Trends (www.google.com/trends). SVI for the word "Crisis" from January 2004 until December 2016

Figure 2.2: SVI change for the terms "Great Depression" and "Savings"



Note: This figure shows the ΔSVI for the search terms "Great Depression" and "Savings" from 1/1/2010 to 2/17/2010.

Figure 2.3: Correlation Coefficient between New FEARS and FEARS from 2004–2011



Note: This figure reports the correlation coefficient between the original FEARS and the New FEARS constructed in this study for the years 2004-2011.

Table 2.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
BNY ADR Index Returns	3,273	0.01516	1.441065	-11.2691	15.3246
New FEARS	3,273	0	0.390602	-2.15085	2.032069
FEARS	1,891	0	.3548865	-254975	3.186447
VIX	3,273	19.1041	9.085081	9.89	80.86
ΔEPU	3,273	-4.90975	54.4314	-303.55	393.67
ΔADS	3,273	0.00006	0.014291	-0.07089	0.084694
Δ FX U.S. T-W	3,246	0.0033327	0.392902	-3.3854	2.3692
EW ADR Returns	2,707	0.585929	1.41851	-9.30381	14.49933
VW ADR Returns	2,707	0.41679	1.449276	-10.90896	15.02934

Note: This table reports summary statistics on the main variables used in this chapter. ADR Index returns are the single day returns from the BNY Mellon ADR Index. New FEARS is the sentiment measure of interest. FEARS is the original index used by Da et al. (2015) collected from Dr. Engelberg website. The VIX is the implied volatility of the S&P 500 index calculated by the Chicago Board of Exchange. ΔEPU is the change in the Economic Policy Uncertainty index, ΔADS represents the changes in the Arouba-Diebold-Scotti business conditions index, the Δ FX U.S. T-W denotes the changes in exchange rate fluctuations between the U.S. dollar and a basket of trade-weighted currencies, EW ADR Returns represent the returns of an equally-weighted portfolio of ADRs, and VW ADR Returns represent the returns of a value-weighted portfolio of ADRs. Most daily data was collected from January 1st 2004 through December 31st 2016, except for the EW and VW ADR returns which is only available from July 1st 2004 to December 31st 2015.

Table 2.3: New FEARS and ADR index returns

Independent variables	Dependent variable: BNY ADR index returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)	Ret (*t*)	Ret (*t*)
New FEARS	-0.323***	-0.0110	0.0231	0.0120	-0.316***	-0.259***	-0.286***
	(0.0879)	(0.0631)	(0.0724)	(0.0843)	(0.0829)	(0.0768)	(0.0668)
VIX	-0.0216***	0.00406	0.00271	0.00678	-0.0217**	-0.0180**	0.0215***
	(0.00708)	(0.00516)	(0.00650)	(0.00910)	(0.00848)	(0.00733)	(0.00620)
ΔEPU	2.92e-05	-0.00114*	0.00125*	0.000106		0.000366	0.000166
	(0.000833)	(0.000643)	(0.000688)	(0.000890)		(0.000699)	(0.000609)
ΔADS	-3.566	-2.864	-2.828	-5.691		-3.313	-3.685
	(2.567)	(3.126)	(2.671)	(4.740)		(2.889)	(2.453)
Ret(*t*)		-0.0703**	-0.0477	-0.118**			
		(0.0322)	(0.0451)	(0.0570)			
Ret(*t-1*)	-0.0922***	-0.0539*	0.000713	-0.0532	-0.0913***		-0.143***
	(0.0314)	(0.0299)	(0.0325)	(0.0475)	(0.0325)		(0.0284)
Ret(*t-2*)	-0.0691	-0.0118	-0.00352	-0.0153	-0.0684*		-0.0496
	(0.0448)	(0.0370)	(0.0367)	(0.0463)	(0.0366)		(0.0350)
Ret(*t-3*)	-0.0250	-0.0115	-0.0374	-0.0489	-0.0244		-0.0171
	(0.0356)	(0.0345)	(0.0445)	(0.0437)	(0.0354)		(0.0302)
Ret(*t-4*)	-0.0228	-0.0543	0.00505	-0.0492	-0.0224		-0.0223
	(0.0361)	(0.0433)	(0.0404)	(0.0456)	(0.0335)		(0.0331)
Ret(*t-5*)	-0.0595	-0.0155	-0.0232	-0.0386	-0.0588		-0.0391
	(0.0439)	(0.0396)	(0.0436)	(0.0582)	(0.0457)		(0.0396)
ΔFX U.S. T-W						-1.258***	-1.336***
						(0.0957)	(0.0923)
Constant	0.441***	-0.0652	-0.0265	-0.0918	0.442***	0.368***	0.439***
	(0.121)	(0.0937)	(0.108)	(0.160)	(0.143)	(0.131)	(0.102)
Observations	3,268	3,267	3,266	3,266	3,268	3,246	3,241
R-squared	0.035	0.014	0.007	0.015	0.033	0.140	0.162

Note: This table relates the BNY ADR Index daily returns to the New FEARS. The dependent variable is the contemporaneous returns for the BNY Mellon ADR Index. The independent variable is the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS), lagged returns up to 5 lags and the changes in exchange rate fluctuations between the U.S. dollar and a basket of trade-weighted currencies (Δ FX U.S. T-W). The standard errors are bootstrapped and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4: New FEARS and equally-weighted and value-weighted ADR portfolio returns

	Dependent variable: ADR Equally-Weighted portfolio returns					Dependent variable: ADR Value-Weighted portfolio returns				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Independent variables	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)
New FEARS	-0.661***	0.289*	-0.0637	0.281	-0.652***	-0.596***	0.260*	-0.102	0.186	-0.588***
	(0.179)	(0.157)	(0.136)	(0.209)	(0.137)	(0.162)	(0.143)	(0.126)	(0.174)	(0.126)
VIX	-0.0163**	0.00488	0.00165	0.00670	-0.0159***	-0.0182**	0.00369	-9.20e-05	0.00421	-0.0182***
	(0.00809)	(0.00691)	(0.00808)	(0.0120)	(0.00616)	(0.00769)	(0.00958)	(0.00788)	(0.0111)	(0.00601)
ΔEPU	0.000385	-0.000667	0.00215***	0.00214*	6.35e-05	0.000484	-0.000932	0.00201**	0.00169*	0.000178
	(0.000886)	(0.000892)	(0.000811)	(0.00110)	(0.000795)	(0.000967)	(0.000823)	(0.000940)	(0.000907)	(0.000796)
ΔADS	-4.018	-4.192	-4.893	-8.968	-3.864	-5.011*	-5.243	-4.877	-10.43**	-4.802**
	(3.529)	(3.796)	(3.575)	(5.737)	(2.999)	(3.039)	(3.903)	(3.174)	(5.148)	(2.338)
Ret(*t*)		0.0278	-0.00264	0.0230			-0.0492	-0.0596	-0.110*	
		(0.0382)	(0.0434)	(0.0658)			(0.0397)	(0.0497)	(0.0623)	
Ret(*t-1*)	-0.00160	-0.000594	0.00225	-0.00981	-0.0680**	-0.0782**	-0.0584	-0.0100	-0.0777	-0.154***
	(0.0425)	(0.0516)	(0.0393)	(0.0702)	(0.0312)	(0.0365)	(0.0496)	(0.0414)	(0.0745)	(0.0264)
Ret(*t-2*)	-0.0152	0.00511	0.0170	0.0105	0.00940	-0.0723	-0.00701	-0.0126	-0.0277	-0.0536
	(0.0462)	(0.0429)	(0.0415)	(0.0527)	(0.0439)	(0.0544)	(0.0391)	(0.0438)	(0.0549)	(0.0466)
Ret(*t-3*)	-0.00655	0.00860	-0.0268	-0.0197	0.00523	-0.0221	-0.0189	-0.0225	-0.0419	-0.0108
	(0.0367)	(0.0453)	(0.0423)	(0.0748)	(0.0416)	(0.0364)	(0.0501)	(0.0489)	(0.0800)	(0.0366)
Ret(*t-4*)	-0.00551	-0.0335	0.00570	-0.0238	-0.0145	-0.0347	-0.0288	-0.00638	-0.0323	-0.0433
	(0.0394)	(0.0519)	(0.0488)	(0.0643)	(0.0334)	(0.0453)	(0.0536)	(0.0463)	(0.0570)	(0.0393)
Ret(*t-5*)	-0.0456	0.00246	-0.00634	0.00366	-0.0171	-0.0391	-0.0143	-0.00990	-0.0201	-0.0215
	(0.0526)	(0.0407)	(0.0416)	(0.0728)	(0.0416)	(0.0631)	(0.0417)	(0.0485)	(0.0745)	(0.0428)
ΔFX U.S. T-W					-1.432***					-1.494***
					(0.113)					(0.129)
Constant	0.363***	-0.0447	0.0230	-0.0309	0.354***	0.401***	-0.0220	0.0512	0.0144	0.402***
	(0.140)	(0.122)	(0.134)	(0.212)	(0.108)	(0.131)	(0.159)	(0.134)	(0.197)	(0.102)

Observations	2,233	2,146	2,144	2,059	2,211	2,233	2,146	2,144	2,059	2,211
R-squared	0.031	0.007	0.010	0.010	0.173	0.037	0.014	0.011	0.019	0.181

Note: This table reports the equally-weighted (EW) and value-weighted (VW) ADR portfolio daily returns to the New FEARS. The dependent variables in columns 1 and 2 are contemporaneous returns. The independent variable is the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS), lagged returns up to 5 lags and the changes in exchange rate fluctuations between the U.S. dollar and a basket of trade-weighted currencies (Δ FX U.S. T-W). The standard errors are bootstrapped and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5: New FEARS and ADR regional indices returns

	Dependent variable: Regional ADR Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables	Asia	Europe	Latin America	Asia	Europe	Latin America
New FEARS	-0.306***	-0.288***	-0.571***	-0.264***	-0.241***	-0.509***
	(0.0835)	(0.0958)	(0.110)	(0.0877)	(0.0633)	(0.120)
ΔFX U.S. T-W				-0.943***	-1.364***	-1.450***
				(0.0887)	(0.0967)	(0.136)
VIX	-0.0173**	-0.0185***	-0.0193*	-0.0176***	-0.0182***	-0.0203**
	(0.00767)	(0.00702)	(0.0116)	(0.00678)	(0.00640)	(0.00963)
ΔEPU	0.000230	0.000154	0.000753	0.000420	0.000286	0.00100
	(0.000860)	(0.000872)	(0.00105)	(0.000638)	(0.000688)	(0.000863)
ΔADS	-3.321	-2.765	-5.664	-3.879	-2.800	-6.177
	(2.670)	(2.497)	(3.602)	(2.926)	(2.371)	(3.843)
Constant	0.361***	0.376***	0.433**	0.367***	0.369***	0.449***
	(0.134)	(0.117)	(0.199)	(0.119)	(0.109)	(0.165)
Observations	3,273	3,273	3,273	3,246	3,246	3,246
R-squared	0.017	0.019	0.018	0.081	0.159	0.097

Note: This table reports the regression results for the Regional ADR indices daily returns to the New FEARS. The dependent variable in column 1and 4 is the Asia ADR index daily returns, in column 2 and 5 the Europe ADR index daily returns and in column 3 and 6 the Latin America ADR index daily returns. The independent variable is the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS), and the changes in exchange rate fluctuations between the U.S. dollar and a basket of trade-weighted currencies (Δ FX U.S. T-W). The standard errors are bootstrapped and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6: New FEARS and ADR country-specific indices returns

(1) Country-specific ADR Index Returns	(2) New FEARS	(3) Std.Errors	(4) Controls	(5) R^2
Australia	-0.262***	(0.0878)	Yes	0.252
Belgium	-0.155*	(0.0903)	Yes	0.057
Brazil	-0.437***	(0.116)	Yes	0.222
Chile	-0.333***	(0.0656)	Yes	0.230
China	-0.333***	(0.109)	Yes	0.016
Colombia	-0.328***	(0.0851)	Yes	0.134
Denmark	-0.103	(0.0865)	Yes	0.054
France	-0.331***	(0.0862)	Yes	0.139
Finland	-0.0854	(0.160)	Yes	0.042
Germany	-0.282***	(0.0972)	Yes	0.135
India	-0.129	(0.108)	Yes	0.107
Indonesia	-0.00385	(0.107)	Yes	0.070
Ireland	-0.193**	(0.0861)	Yes	0.079
Israel	-0.170**	(0.0661)	Yes	0.018
Italy	-0.400***	(0.0867)	Yes	0.159
Japan	-0.210***	(0.0808)	Yes	0.036
Korea	-0.377***	(0.105)	Yes	0.162
Mexico	-0.238**	(0.0932)	Yes	0.222
Netherlands	-0.236**	(0.102)	Yes	0.123
Norway	-0.405***	(0.114)	Yes	0.203
Peru	-0.203	(0.148)	Yes	0.021
Philippines	-0.190	(0.119)	Yes	0.057
Russia	-0.327*	(0.169)	Yes	0.096
South Africa	-0.283**	(0.135)	Yes	0.147
Spain	-0.408***	(0.121)	Yes	0.135
Sweden	-0.200*	(0.111)	Yes	0.114
Switzerland	-0.200**	(0.0814)	Yes	0.059
Taiwan	-0.191*	(0.105)	Yes	0.054
Turkey	-0.176	(0.142)	Yes	0.213
United Kingdom	-0.217***	(0.0665)	Yes	0.186
Observations	3273			

Note: This table reports the regression results for the Country-specific ADR indices daily returns to the New FEARS. The dependent variable in each row is the contemporaneous returns for Australia, Belgium, Brazil, Chile, China, Colombia, Denmark, France, Finland, Germany, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, Norway, Peru, Philippine, Russia, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, and United Kingdom. The independent variable is the New FEARS index and its coefficient is reported in column 2. The independent variable reported in column 2 is the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS), and the changes in the exchange rate of the U.S. dollar to the currency of each country are included but not reported. The standard errors are bootstrapped and displayed in column 3 and R-squared in column 5. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7: FEARS and the BNY ADR Index

	Dependent variable: BNY ADR index returns									
	Original FEARS					New FEARS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Independent variables	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)
FEARS	-0.583***	0.250*	0.170	0.420**	-0.478***					
	(0.164)	(0.132)	(0.117)	(0.166)	(0.167)					
New FEARS						-0.463***	0.0927	0.00825	0.101	-0.469***
						(0.138)	(0.109)	(0.109)	(0.155)	(0.140)
VIX	-0.0215***	0.00264	0.00147	0.00411	-0.0198***	-0.0207**	0.00248	0.00147	0.00395	-0.0190***
	(0.00792)	(0.00897)	(0.00754)	(0.0116)	(0.00611)	(0.00841)	(0.00773)	(0.00800)	(0.00968)	(0.00600)
ΔEPU	2.88e-05	-0.00179*	0.00176**	-3.24e-05	-0.000149	9.17e-05	-0.00183*	0.00173*	-9.15e-05	-9.64e-05
	(0.00100)	(0.000953)	(0.000796)	(0.00116)	(0.000893)	(0.000997)	(0.00102)	(0.00105)	(0.00128)	(0.000883)
ΔADS	-3.674	-3.026	-3.093	-6.119	-3.589	-3.858	-3.061	-3.170	-6.231	-3.840
	(4.804)	(4.164)	(3.757)	(4.917)	(2.870)	(3.485)	(3.736)	(3.194)	(5.500)	(3.519)
ΔFX U.S. T-W					-1.737***					-1.751***
					(0.111)					(0.116)
Ret(*t*)		-0.0891**	-0.0523	-0.141**			-0.0938**	-0.0565	-0.150**	
		(0.0372)	(0.0466)	(0.0661)			(0.0441)	(0.0500)	(0.0657)	
Ret(*t-1*)	-0.119***	-0.0656	0.0101	-0.0555	-0.200***	-0.119***	-0.0675	0.00811	-0.0594	-0.201***
	(0.0351)	(0.0570)	(0.0321)	(0.0613)	(0.0290)	(0.0417)	(0.0565)	(0.0326)	(0.0505)	(0.0305)
Ret(*t-2*)	-0.0790	-0.0162	0.0142	-0.00196	-0.0545	-0.0794	-0.0155	0.0150	-0.000479	-0.0537
	(0.0590)	(0.0449)	(0.0461)	(0.0537)	(0.0476)	(0.0503)	(0.0463)	(0.0438)	(0.0568)	(0.0453)
Ret(*t-3*)	-0.0204	0.000790	-0.0376	-0.0368	-0.00516	-0.0255	0.00339	-0.0356	-0.0322	-0.00856
	(0.0397)	(0.0450)	(0.0541)	(0.0595)	(0.0420)	(0.0397)	(0.0474)	(0.0555)	(0.0605)	(0.0324)
Ret(*t-4*)	-0.00676	-0.0601	-0.00372	-0.0638	-0.0105	-0.00467	-0.0599	-0.00309	-0.0630	-0.00799
	(0.0448)	(0.0595)	(0.0536)	(0.0638)	(0.0377)	(0.0409)	(0.0521)	(0.0496)	(0.0557)	(0.0397)
Ret(*t-5*)	-0.0549	-0.0317	-0.0264	-0.0580	-0.0317	-0.0562	-0.0309	-0.0257	-0.0567	-0.0318

	(0.0481)	(0.0443)	(0.0512)	(0.0697)	(0.0407)	(0.0527)	(0.0448)	(0.0545)	(0.0680)	(0.0483)
Constant	0.490***	-0.0339	0.00285	-0.0311	0.433***	0.472***	-0.0298	0.00306	-0.0267	0.413***
	(0.144)	(0.169)	(0.141)	(0.216)	(0.116)	(0.154)	(0.145)	(0.149)	(0.175)	(0.105)
Observations	1,891	1,891	1,891	1,891	1,874	1,891	1,891	1,891	1,891	1,874
R-squared	0.049	0.025	0.011	0.025	0.213	0.042	0.022	0.010	0.021	0.211

Note: This table reports the regression results for the BNY ADR Index daily returns to the FEARS and the New FEARS for the same time period from July 1st 2004 to December 30th 2011. The dependent variables are contemporaneous returns (column 1 and 5) and future returns (columns 2, 3, 6, and 7). The cumulative returns for the first 2 days (column 4 and 8). The independent variable is the FEARS index and the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS) and lagged returns up to 5 lags. The standard errors are bootstrapped and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.8: FEARS and the value-weighted ADR portfolio

	Original FEARS					New FEARS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ind. variables	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)	Ret (*t*)	Ret (*t*+1)	Ret (*t*+2)	Ret [*t*+1, *t*+2]	Ret (*t*)
FEARS	-0.769***	0.212	0.0632	0.271	-0.558***					
	(0.203)	(0.155)	(0.151)	(0.233)	(0.152)					
New FEARS						-0.726***	0.336*	-0.0819	0.281	-0.731***
						(0.208)	(0.179)	(0.192)	(0.269)	(0.203)
VIX	-0.0188**	0.00379	-0.000330	0.00411	-0.0181**	-0.0174**	0.00311	-0.000196	0.00348	-0.0166**
	(0.00767)	(0.00835)	(0.00786)	(0.0126)	(0.00748)	(0.00700)	(0.00578)	(0.00810)	(0.0129)	(0.00788)
ΔEPU	0.000294	-0.00123	0.00208*	0.00164	-0.000176	0.000327	-0.00124	0.00208*	0.00164	-0.000150
	(0.00118)	(0.000987)	(0.00117)	(0.00133)	(0.000897)	(0.00106)	(0.00119)	(0.00111)	(0.00120)	(0.000802)
ΔADS	-6.105	-6.273	-6.102	-12.73*	-5.534	-6.016	-6.252	-6.129	-12.72**	-5.466
	(4.409)	(4.812)	(4.783)	(6.642)	(3.764)	(3.699)	(3.848)	(4.537)	(5.321)	(4.029)
ΔFX U.S. T-W					-1.579***					-1.611***
					(0.120)					(0.122)
Ret(*t*)		-0.0580	-0.0638	-0.124**			-0.0572	-0.0671	-0.125*	
		(0.0412)	(0.0571)	(0.0622)			(0.0365)	(0.0660)	(0.0756)	
Ret(*t-1*)	-0.0860***	-0.0699	-0.00400	-0.0829	-0.171***	-0.0878**	-0.0679	-0.00594	-0.0820	-0.177***
	(0.0333)	(0.0565)	(0.0424)	(0.0673)	(0.0358)	(0.0401)	(0.0563)	(0.0454)	(0.0717)	(0.0423)
Ret(*t-2*)	-0.0792	-0.00427	-0.00642	-0.0192	-0.0591	-0.0804	-0.00445	-0.00585	-0.0189	-0.0590
	(0.0483)	(0.0487)	(0.0435)	(0.0504)	(0.0553)	(0.0548)	(0.0372)	(0.0498)	(0.0770)	(0.0615)
Ret(*t-3*)	-0.0108	-0.0147	-0.0248	-0.0408	0.00373	-0.0176	-0.0126	-0.0247	-0.0381	-0.00118
	(0.0395)	(0.0471)	(0.0581)	(0.0899)	(0.0409)	(0.0487)	(0.0500)	(0.0597)	(0.0938)	(0.0382)
Ret(*t-4*)	-0.0285	-0.0310	-0.0140	-0.0425	-0.0405	-0.0272	-0.0317	-0.0136	-0.0430	-0.0395
	(0.0469)	(0.0564)	(0.0548)	(0.0754)	(0.0497)	(0.0468)	(0.0544)	(0.0604)	(0.0669)	(0.0423)
Ret(*t-5*)	-0.0383	-0.0262	-0.0148	-0.0352	-0.0157	-0.0408	-0.0257	-0.0141	-0.0348	-0.0163
	(0.0605)	(0.0509)	(0.0646)	(0.0735)	(0.0579)	(0.0638)	(0.0408)	(0.0579)	(0.0795)	(0.0410)
Constant	0.439***	-0.0277	0.0594	0.0158	0.419***	0.398***	-0.00600	0.0513	0.0341	0.371**
	(0.150)	(0.162)	(0.155)	(0.251)	(0.139)	(0.132)	(0.109)	(0.152)	(0.251)	(0.150)
Observations	1,570	1,511	1,511	1,452	1,554	1,570	1,511	1,511	1,452	1,554
R-squared	0.047	0.017	0.013	0.024	0.195	0.042	0.018	0.013	0.024	0.198

Note: This table reports the regression results for an ADR value-weighted portfolio daily returns, built with all ADRs available on CRSP to the FEARS and the New FEARS for the same time period from July 1st 2004 to December 30th 2011. The dependent variables are contemporaneous returns (column 1 and 5) and future returns (columns 2, 3, 6, and 7). The cumulative returns for the first 2 days (column 4 and 8). The independent variable is the FEARS index and the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS) and lagged returns up to 5 lags. The standard errors are bootstrapped and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.9: New FEARS and the BNY ADR Index, Estimated with Newey-West (1994)

Independent Variables	(1) Ret (*t*)	(2) Ret (*t*)	(3) Ret (*t*)	(4) Ret (*t*)	(5) Ret (*t*)	(6) Ret (*t*)	(7) Ret (*t*)	(8) Ret (*t*)
New FEARS	-0.323**	-0.306**	-0.328**	-0.325**	-0.286***	-0.259***	-0.290***	-0.289***
	(0.133)	(0.132)	(0.138)	(0.134)	(0.104)	(0.0977)	(0.106)	(0.104)
VIX	-0.0216***	-0.0180***	-0.0193***	-0.0203***	-0.0215***	-0.0180***	-0.0199***	-0.0206***
	(0.00640)	(0.00504)	(0.00547)	(0.00600)	(0.00587)	(0.00504)	(0.00548)	(0.00583)
ΔEPU	2.92e-05	0.000211	0.000175	4.08e-05	0.000166	0.000366	0.000287	0.000188
	(0.000648)	(0.000578)	(0.000584)	(0.000612)	(0.000485)	(0.000462)	(0.000453)	(0.000467)
ΔADS	-3.566	-3.113	-3.297	-3.399	-3.685	-3.313	-3.551	-3.593
	(3.446)	(2.805)	(3.016)	(3.246)	(3.347)	(2.829)	(3.116)	(3.240)
Ret(*t-1*)	-0.0922***		-0.0844***	-0.0897***	-0.143***		-0.138***	-0.141***
	(0.0219)		(0.0200)	(0.0221)	(0.0274)		(0.0262)	(0.0281)
Ret(*t-2*)	-0.0691			-0.0658	-0.0496			-0.0463
	(0.0583)			(0.0595)	(0.0420)			(0.0429)
Ret(*t-3*)	-0.0250				-0.0171			
	(0.0274)				(0.0307)			
Ret(*t-4*)	-0.0228				-0.0223			
	(0.0208)				(0.0218)			
Ret(*t-5*)	-0.0595*				-0.0391			
	(0.0357)				(0.0371)			
ΔFX U.S. T-W					-1.336***	-1.258***	-1.339***	-1.337***
					(0.162)	(0.136)	(0.162)	(0.160)
Constant	0.441***	0.371***	0.395***	0.414***	0.439***	0.368***	0.406***	0.420***
	(0.105)	(0.0816)	(0.0892)	(0.0994)	(0.0947)	(0.0819)	(0.0891)	(0.0957)
Observations	3,268	3,273	3,272	3,271	3,241	3,246	3,245	3,244
R-squared	0.035	0.019	0.026	0.030	0.162	0.140	0.159	0.160

Note: This table reports the Newey-West (1994) regression results for the BNY ADR Index daily returns to the New FEARS. The dependent variable is the contemporaneous returns for the BNY Mellon ADR Index. The independent variable is the New FEARS index and a set of control variables including the implied volatility of the S&P 500 (VIX) index, the changes in the Economic Public Uncertainty (ΔEPU) index, the changes in the Arouba-Diebold-Scotti business conditions index (ΔADS), lagged returns up to 5 lags and the changes in exchange rate fluctuations between the U.S. dollar and a basket of trade-weighted currencies (Δ FX U.S. T-W). The standard errors are robust and displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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CHAPTER III

INVESTOR ATTENTION AND COUNTRY-SPECIFIC ADR MISPRICING

3.1. Introduction

There is a growing body of literature that shows the effects of investors' attention on securities and financial markets. In the past few years, individual investors have had so many different investments options available that grabbing their attention has become increasingly important (Barber and Odean, 2007).

American Depositary Receipts (ADRs) are instruments traded in the U.S. that represent a portion of ownership in public firms listed in another country's stock exchange. These certificates are generally issued by U.S. banks, and many of them are publicly traded in American stock markets such as the New York Stock Exchange or the NASDAQ. They're often seen as a convenient vehicle for U.S. investors who seek to diversify their portfolios, removing major inconveniences such as directly buying the underlying shares from their original stock markets. According to the "law of one price," ADRs and their underlying stocks converge to one price once adjusted for the exchange rate (Kato et al. 1990), considering that both are expected to generate the same stream of cash flows and pose the same level of risk.

Even though ADRs epitomize their underlying securities price behavior, it is not uncommon to see deviations from the price parity condition. These deviations can have a positive or negative value for which they are commonly known as premiums or discounts, but the phenomena as a whole are known as ADR mispricing. The study of mispricing is particularly relevant for traders who can benefit from these price deviations as shown by Suarez (2005).

This chapter examines the impact of country-specific investor attention on ADR mispricing. I show that increases in the level of public interest in a particular country, expressed by the number of views to Wikipedia's country profile website, reduce the level of mispricing for a list of 1,840 companies from 20 different matched countries. Similar to Eichler (2012), I implement a 2SLS model to address the potential endogeneity, using the number of United Nations World Heritage sites and the FIFA World Cup ranking score as instruments. I also control for firm-specific characteristics including liquidity, firm size, ADR program level, and financial crisis. Finally, I show that this effect is consistent across multiple industries.

Investor's attention may be an important factor conducing ADR mispricing. According to Van Nieuwerburgh and Veldkamp (2010), U.S. investors benefit the most from acquiring more information, investing, and holding on stocks from companies they already know much about. As a consequence, lower level of investors' attention towards foreign stocks traduces itself into greater equity home bias. Mondria et al. (2010) showed that when the U.S. investors home bias is lower, the more attention they pay to a country's stock. Moreover, the more information investors possess, the more efficient the ADR market becomes and the less room for deviations from the price parity condition exist as shown by Eichler (2012). Lastly, Tang and Zhu (2017) find that increases in searches for ADRs tickers on popular internet search engines is related to contemporaneous abnormal returns.

The use of household internet usage data has become increasingly important for several disciplines of scholarly research in the past years. The growth and relevance of the internet in our day-to-day activities represent a unique opportunity to observe trends and discover the dynamics of investors' attention like never before. Thanks to initiatives such as Google Trends and Wikipedia Trends, it is now possible to collect data from aggregate users search history and discover its informational content on financial assets and markets. More specifically, I argue that Wikipedia country profile visit history constitutes a better measure of investor attention compared to the ones used in previous studies. While I employ a direct measure of country-specific attention, past literature either uses a search volume index (SVI) as in Mao and Wei (2013) or the number of clicks on search engine results from websites hosted in a particular country as in Eichler (2012). The main problem with the former is that observations are scaled in proportion to a specific country and time span which does not allow for an unbiased cross-country study. The limitation of the latter is that there are several websites hosted in foreign servers and also the well-known practice of geographically tailored websites, which ultimately may lead to misrepresentative results. I obtain the number of times that internet users open a country's profile page on Wikipedia and use it as a proxy for investor attention to a country's ADRs. The choice of this proxy is based on Wikipedia's unquestionable position as the most popular encyclopedia freely available on the internet. In any case, the reliability of Wikipedia as a source of information is not relevant for the purpose of this study, but its popularity among users[15].

We anticipate that the search for information related to a particular country can be caused by either positive or negative news. For example, the views of Brazil's page spiked during the recent 2014 Soccer World Cup, which can be considered a positive event overall but the same peaks of interest spark when negative events happen. Therefore, in this study I do not seek to

[15] According to Alexa.com and Similarweb.com, two popular internet traffic measuring companies, Wikipedia stands as the 5th and 12th website with most daily visits on the internet, respectively. More information can be found on https://www.similarweb.com/website/wikipedia.org and https://www.alexa.com/siteinfo/wikipedia.org

clarify whether interest in a given country corresponds to a premium (discount), but to assess the high (low) level of mispricing generated by investors' country-specific attention as a mechanism to obtain and reduce information asymmetry. In that sense, an investor seeking for more information about a particular country on the internet will be prone to learn more about the country's ADRs, the natural consequence of doing so, is that by learning more about a country he reduces the information asymmetry, therefore adjusting the price to its pair value and reduce the mispricing. It is also worth mentioning, that Wikipedia country profiles display a section with condensed economic information such as overall economic policy, GDP, unemployment, main industries, significant mergers, etc. Information that could be used by investors as a *prima facie* step into finding securities from that country or, in this case, ADRs.

The remainder of the chapter is organized as follows. Section 2 presents the relevant literature, Section 3 discusses the data and methodology used in this study. Section 4 presents the estimation results and empirical findings and Section 5 concludes.

3.2. Literature Review

3.2.1 ADR Mispricing

There has been a debate in the literature on whether ADR mispricing exist or not. Early findings suggest there exist no mispricing on cross-listed securities, therefore it is not possible for arbitrageurs to benefit. In this line, Rosenthal (1983) examined the weak form efficiency of American Depository Receipts traded in the U.S. He showed the weak form efficiency is supported by the serial correlation and run tests for a sample of NASDAQ listed ADRs, his study spans from the years 1974–1978. Later, Kato et al. (1990) also found evidence for the law of one price in their study of foreign stocks from Australia, England, and Japan. They observed no significant difference between both the ADR and the underlying stock's prices and attribute the small differences in the return correlation to differences in markets timing. Similarly, Park and Tavakkol (1994), found evidence of no mispricing using a sample of Japanese stocks. However, more recent studies found that such mispricing exist and it is possible for investors to benefit from arbitrage opportunities (Wahab et al., 1993; Suarez, 2005; Alsayed and McGroarty, 2012; Ansotegui et al., 2013; and Ghadhab and Hellara, 2015). The factors influencing the mispricing (and the limits to arbitrage) are still open for the literature to address. Foerster and Karolyi (2000) showed that investment barriers, account for the long-run difference in the performance of cross-listed firms. Maldonado and Saunders (1983) argued that such barriers represent an arbitrage opportunity to unrestricted investors, while Kadiyala and Subrahmanyam (2004) determined that ADRs from countries with foreign ownership restrictions are sold at a premium of around 11.33% respect of their counterparts. Similarly, Arquette et al. (2008), found that expected currency appreciation in the Chinese cross-listed stocks, have a negative effect on the discounts for a sample of both the ADRs listed on the NYSE and the H-Shares listed on the Hong Kong market. According to Hsu and Wang (2008), trading volume and macro events generate heterogeneous expectations between two markets and explains the variation in price spreads. Chan et al. (2008) showed that higher levels of liquidity in the ADR, respect to their underlying share, leads to higher premiums (mispricing).

Another stream of the mispricing literature attribute these deviations to investor's sentiment as one of the causes. Grossmann et al. (2007) looked at a sample of ADRs from nine countries and determine that transaction costs, lower dividend payments, and differences in the consumer sentiment from the U.S. and the home country have an effect on the mispricing. Hwang (2011) studied the effect of country-specific sentiment and found that country popularity among U.S. investors is also responsible for premiums and discounts in the price parity condition for ADR and country closed-end funds. Lately, Beckmann et al. (2015) attributed the mispricing to information asymmetry with the underlying stock, along with freedom scores from the home country, listing level and idiosyncratic risk. Finally, Wu et al. (2017) examined the effect of local and global investor sentiment on the mispricing, also finding a strong role of idiosyncratic risk as a major cause.

3.2.2 Investor Attention

The role of investor attention on stock markets has been increasingly studied from different perspectives. Barber and Odean (2007) showed that individual investors are startled by the amount of investment options, therefore they make their investment decisions based on information provided by the news, stocks with greater volume, single day abnormal returns, etc. They only make investment choices based on preference after their limited attention has put together their choice set.

Van Nieuwerburgh and Veldkamp (2010), started their discussion from the point that U.S. investors can benefit from diversifying their portfolios by including foreign stocks and that information asymmetry was no longer a major problem in today's world to justify the home bias. However, they observed that U.S. investors benefit the most from expanding the information on stock they already know much about, leading to an increase in the home bias and paying lower attention to stock from any other country.

One of the first studies to use Wikipedia historic page view information was, Moat et al. (2013), and with this information they showed early signs of stock market moves during the last financial crisis. Da et al. (2011) used the Search Volume Indices (SVI) from google to show that increases in the searches for companies is related to a subsequent stock price increase within the following two weeks. Eichler (2012) related investor attention to ADR mispricing using the number of times internet users visit websites domiciled in a particular country as a proxy for investor attention. His study uses a sample of 537 ADRs for a period of 3 months. Tang and Zhu (2017) studied how increases in the search volume indices (SVI) is related to contemporary abnormal returns for a set of ADRs, implying that higher levels of attention are associated to greater returns.

3.3. Data and Methodology

This study employs two-stage least squares (2SLS) regressions using monthly data from January 2008 to December 2014. The data on ADRs is extracted from Datastream and the country-specific attention measure, Wikipedia views, is obtained from Wikipediatrends.com website. The sample consists of 1,840 ADRs from 31 countries for a total number of 130,788 firm-monthly observations. The date interval selection is based on data availability for the Wikipedia views measure.

We compute ADR mispricing based on Eichler (2012), who adopts an absolute mispricing measure that is calculated as the percentage deviation of the ADR price from the price implied by the home-country underlying stock:

$$ADR\ mispricing_{it} = \left|\frac{ADR\ price_{it} - Underlying\ stock\ price_{it}}{Underlying\ stock\ price_{it}}\right|, \qquad (1)$$

where the ADR price of firm *i* on month *t* in U.S. dollars is adjusted by the ADR ratio (number of foreign shares represented by one ADR) and the underlying stock price of firm *i* on month *t* is converted from its local currency to U.S. dollars.

This study is situated in the intersection of the work from Hwang (2011), who shows that country-specific popularity is relevant for ADR mispricing and the work of Eichler (2012), who finds that investor attention is also a determinant of mispricing. Therefore, our main hypothesis is that more investor attention leads to less mispricing of the ADR relative to the price of the underlying share. Therefore, I expect our model to find a negative association between investor attention and mispricing, which is consistent with less arbitrage opportunities when investors pay more attention to a security from a more popular country, and vice-versa.

The investor attention measure, Wikipedia views, is the number of times that internet users open a country's profile page on Wikipedia, the most important free online encyclopedia. I adopt this measure as a proxy for investor attention to a country's ADRs. I consider this to be a better proxy than the ones from previous literature because it is not subject to scaling biases (e.g., proxies using search volume indices) or foreign-host website bias (e.g., proxies that ignore that a country's webpage may be hosted by foreign countries servers). Moreover, our study spans for seven years of monthly observations and includes 1,840 ADRs, including level I ADRs, which are known to exhibit greater information asymmetry and therefore present higher mispricing.

We show graphical evidence of a negative relationship between ADR mispricing and country-specific investor attention. Figure 3.1 display some of the countries with the highest and lowest levels of ADR mispricing expressed in percentages. I find that that the highest levels of ADR mispricing correspond to the countries with the smallest numbers of Wikipedia views such as Greece (above 55% mispricing in 2012 with only 56.4 million Wikipedia views), Russia (above 35% mispricing in 2009 against 100.5 million views), Argentina (above 32% mispricing in 2013 vs. 52.7 million views). At the same time, I observe that the lowest levels of ADR mispricing are from countries that have the largest numbers of Wikipedia views such as the United Kingdom (less than 8% mispricing in 2010 against 3.6 billion Wikipedia views) and Japan (6% mispricing in 2010 vs. 3.0 billion views) as shown in Figure 3.2.[16]

[16] Figures 3.1 and 3.2 report, respectively, the ADR mispricing levels and Wikipedia views of selected countries which have much greater or much lower levels than average.

Aware of the potential endogeneity problem that could arise from the ADR mispricing affecting the number of visits to the Wikipedia profile pages. I employ a two-stage least squares (2SLS) regression model that corresponds to the following equations:

$$ADR\ mispricing_i = \alpha + \beta_1 \ln(Wikipedia\ views)_i + \beta_2' X + u, \qquad (2)$$

$$\ln(\text{Wikipedia views})_i = \pi 0 + \pi_1' \text{Z} + \pi_2' \text{X} + \text{v}_i, \qquad (3)$$

where the dependent variable in the second-stage regression is ADR mispricing, Wikipedia views is the explanatory variable of interest, α is the constant, u is the residual and X is a vector of the following control variables. 1/P is the inverse price of the underlying stock which is often used in the ADR literature as a proxy for transaction costs. Dividend yield is the dividend as a percentage of the underlying stock price. Volume is the log of the ADR trading volume. Following Mollick and Assefa (2013), I include a crisis dummy variable that assumes the value of 1 between January 2008 and June 2009, following the NBER's Business Cycle Expansions and Contractions[17]; otherwise zero. Market value is the log of the product of the number of outstanding shares times the current price of the underlying stock. Amihud is an "illiquidity" measure that is calculated by dividing the absolute value of an ADR return by its respective trading value: the higher value the lower liquidity, it is retrieved from Amihud (2002). Level I dummy is a binary variable that is equal to 1 for the ADRs of level I; otherwise zero.

The dependent variable in the first-stage regression is Wikipedia views, π_0 is a constant, v_i is the residual and Z is a vector of instrumental variables (IVs). The instruments are drawn from Eichler (2012), who uses the FIFA World Cup ranking score of a country's national soccer

[17] The National Bureau of Economic Research (NBER) U.S. Business Cycle Expansions and Contractions is defined from December 2007 and June 2009. Since the data for this study begins on January 2008, we use that as the starting point for the dummy. More information can be found at http://www.nber.org/cycles.html

team and the number of United Nations World Heritage sites as instrumental variables for investor attention. I assume these instruments to be exogenous since I cannot imagine reverse causation from ADR mispricing to the performance of a national soccer team or the number of heritage sites declared by the United Nations located in a country and I do not expect to have omitted variables related to both ADR mispricing and those investor attention measures.

Table 3.1 shows the descriptive statistics. Panel A reports the number of observations, mean, median and standard deviation of ADR mispricing and Wikipedia views for each year in the sample, from 2008 to 2014. Panel B shows the summary statistics of the entire sample for the measures in this study. The mean and median values of ADR mispricing are 10.80% and 1.91%, respectively. The values of mispricing are higher in the years 2008 and 2009, consistent with the 2008-2009 financial crisis. The mean and median values of Wikipedia views are 585,921 and 534,750, respectively. The number of views grows from 2008 to 2010 and then the trend reverts until the last year in the sample. The absolute value of returns, a measure used to construct the Amihud's illiquidity measure (Amihud $= \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|\text{ADR returns}|_{i,d}}{\text{ADR trading value}_{i,d}}$), has a mean of 0.08 and a median of 0.04. The inverse price (1/P) of the underlying stock, a proxy for transaction costs has a mean of 0.31/$ and median of 0.07/$. The mean and median values of the ADR trading volumes are 10,683 and 187, respectively. Market value has a mean of $12,883 and a median of $4,656. The dividend yield averages 3.01% with a median of 2.03%.

Table 3.2 reports the correlation matrix. ADR mispricing and has a negative relationship with Wikipedia views, volume and market value, and is positively associated with absolute returns, inverse price, dividend yield and the crisis dummy, in line with previous literature. Most of the correlation among the regressors are mild, except for the medium correlation between volume and market value (0.53), which indicates that more valuable firms have higher trading volumes, and the medium-high negative link between volume and the Level I dummy (-0.62), showing that Level I ADRs' trading volume is smaller than the ones from ADRS of other levels (II and III).

3.4. Results

Tables 3.3-3.5 reports 2SLS estimation results for 1,840 ADRs from 31 countries. The dependent variable is ADR mispricing and Wikipedia views is the proxy for country-specific investor attention. FIFA World Cup ranking score and UN World Heritage sites are adopted as instrumental variables to control for the potential endogeneity bias, especially from a possible reverse causation from mispricing to investor attention: higher arbitrage opportunities that may potentially grab financial market's interest in ADRs of a specific country. The instrument specification tests reject both null hypotheses of weak instrument relevance and overidentification biases for all regressions in Tables 3.3-3.5[18].

Table 3.3 shows 2SLS regression results for the entire sample, with the total number of observations varying between 51,943 and 52,589. Wikipedia views displays a negative coefficient that ranges from -3.3 to -2.8. To interpret this level-log regression coefficient, *ceteris paribus*, if investor attention increases by 1 percent, I expect ADR mispricing to decrease by around 3 percent. The coefficients in all six specifications are economically and statistically significant at the 1% level. The control variables display the expected signs: inverse price (1/P), dividend yield, crisis dummy, Amihud and Level I dummy are positive and highly significant; volume and market value are negative and highly significant.

[18] The first-stage results table for estimations presented in Table 3.3 are available on Table 3.6. This table also display the Wu Hausman endogeneity tests statistics, Sanderson-Windmeijer (SW) first-stage chi-squared test of underidentification statistics and F-statistics tests of weak identification of individual endogenous regressors.

Table 3.4 exhibits 2SLS regressions by ADR level. The first three columns correspond to a subsample of Level I ADRs with a number of observations ranging from 38,838 to 47,841. The last three columns are regressions with a subsample of Levels II and III ADRs totaling around 13,200 observations. Evidence shows that investor attention, proxied by Wikipedia views, has a stronger negative impact on ADR mispricing for Level I ADRs: the coefficients range from -4.246 to -3.406 versus the smaller coefficients for the Levels II and III ADR subsample which vary from -1.786 to -1.525. From the control variables, the inverse price (1/P) has a stronger positive effect on mispricing for Levels II and III than for Level I ADRs; the coefficient for dividend yield is larger for the Level I ADRs; crisis is associated with higher mispricing for the Level I ADRs than for the Levels II and III ADRs subgroup; market value has a stronger negative effect on mispricing of the Level I ADRs; and the Amihud's illiquidity coefficient suggests a higher sensitivity to changes in the degree of liquidity for Levels II and III ADRs (305.9) than the ones in Level I (10.29).

Table 3.5 displays 2SLS regressions by sector. I find that investor attention has a negative and highly significant (to the 1% level) impact on ADR mispricing for most sectors. Telecommunications (-11.50), followed by technology (-9.98), industrials (-6.54), consumer services (-4.56), basic materials (-3.235), oil and gas (-2.54) and health care (-2.38) are the sectors where higher investor attention has a negative impact on mispricing. Statistical insignificance of Wikipedia views coefficients in three sectors (consumer goods, financials, and utilities) may indicate that these sectors are less sensitive to the marginal impact of investor attention. In fact, the lack of significance for utilities and financials are in line with corporate finance literature which often exclude those sectors due to the former's regulated nature and the latter's spotty historic coverage of firms (e.g., Fama and French 2001). Among the control variables, overall results are in line with our previous findings.

Table 3.6 shows the first stage regression results. Wikipedia profile views is the dependent variable. Coefficients for the number of United Nations World Heritage sites is positive and significant, meaning that more number of these sites have a positive impact on investor attention. Inversely, the FIFA World Cup ranking score has a negative and statistically significant coefficient, meaning that those countries with higher numbers in the list of standings are less popular in the eyes of the Wikipedia users. More importantly, the Wu-Hausman test statistic for all models is significant (e.g., 129.12*** for specification 1). This means that the variables being tested must be treated as endogenous, which confirms the selection of the 2SLS estimator as the right choice. Also, the Sanderson-Windmeijer Underidentification and the Sanderson-Windmeijer Weak identification tests are both positive and statistically significant. These tests operate under the null that a particular endogenous regressor in question is unidentified or weakly identified.

The numbers in parentheses are White heteroscedasticity-consistent standard errors. The scripts ***, ** and * denote significance at the 1%, 5% and 10% levels. The Wu Hausman F-test report the test statistics, the H0 is that regressor is exogenous. The Sanderson-Windmeijer are first-stage chi-squared and F statistics tests of underidentification and weak identification of individual endogenous regressors.

3.5. Conclusions

In this chapter, I show how country specific investor attention has a negative effect on ADR mispricing. High Wikipedia country profile views are related to lower ADR mispricing for a sample of 1,840 cross-listed securities from 31 different countries. I employ a 2SLS model using the FIFA World Cup ranking score of a country's national soccer team and the number of United Nations World Heritage as instruments to control for endogeneity. This is the first study to use Wikipedia views as proxy for investor's attention and its effects on mispriced securities.

These results confirm the previous findings from Eichler (2012). Also, consistent with previous literature (Beckmann et al. 2015), the program level is relevant to determine the mispricing. Level I ADRs exhibit a larger mispricing than level II and level III ADRs, this effect is even greater during the crisis period. Results are also consistent when estimated by industry for most industries except for consumer goods, financials, and utilities. Lastly, all the tests for appropriateness, overestimation, underidentification and weak underidentification provide robustness to the empirical results.

However, this study is not without its limitations. First, I retrieve the monthly country profile views from Wikipedia in English. Even though it is reasonable to think most non-English speaking countries would use their native language to access Wikipedia information, these English written pages are available for all users on the internet to access[19]. Although, according to a website ranking site (alexa.com), 22.8% of the total Wikipedia traffic comes from U.S. users, while Japan (6.6%) and China (5.9%) come second and third, respectively. Second, I could also argue that profile views would only be relevant if the country is known to have a culture and the resources for investing. In which case, controlling for the level of education and gross domestic product could also be relevant. Lastly, a country with more population would probably have more Wikipedia users looking for information, in which case controlling for population could also make sense. However, in this last case, I can see that a country such as Japan, which

[19] Except for China, where the Chinese version of Wikipedia faces a government ban. For that reason, Chinese users have to turn to Wikipedia in other languages.

holds the second place in the number of Wikipedia users per month, is not the most populated country from the list in this study.

Future research can address some limitations from the present study. First, country population, gross domestic product (GDP), and educational level could be used as control variables for country popularity proxied by the Wikipedia profile views. A country's population could also drive the number of visits a given profile receives on a periodical basis. Also, for similar reasons, a more educated country could also draw more attention and its nationals would perhaps be more actively looking to invest. Second, if and when data is available, the country popularity measure could be retrieved in other languages to contrast the results from the English country profiles. Since ADRs are not restricted to U.S. investors only, perhaps the attention from foreign investors who regularly trade in the U.S. could also affect ADR prices.

Figure 3.1: Mispricing in selected countries, expressed in percentages

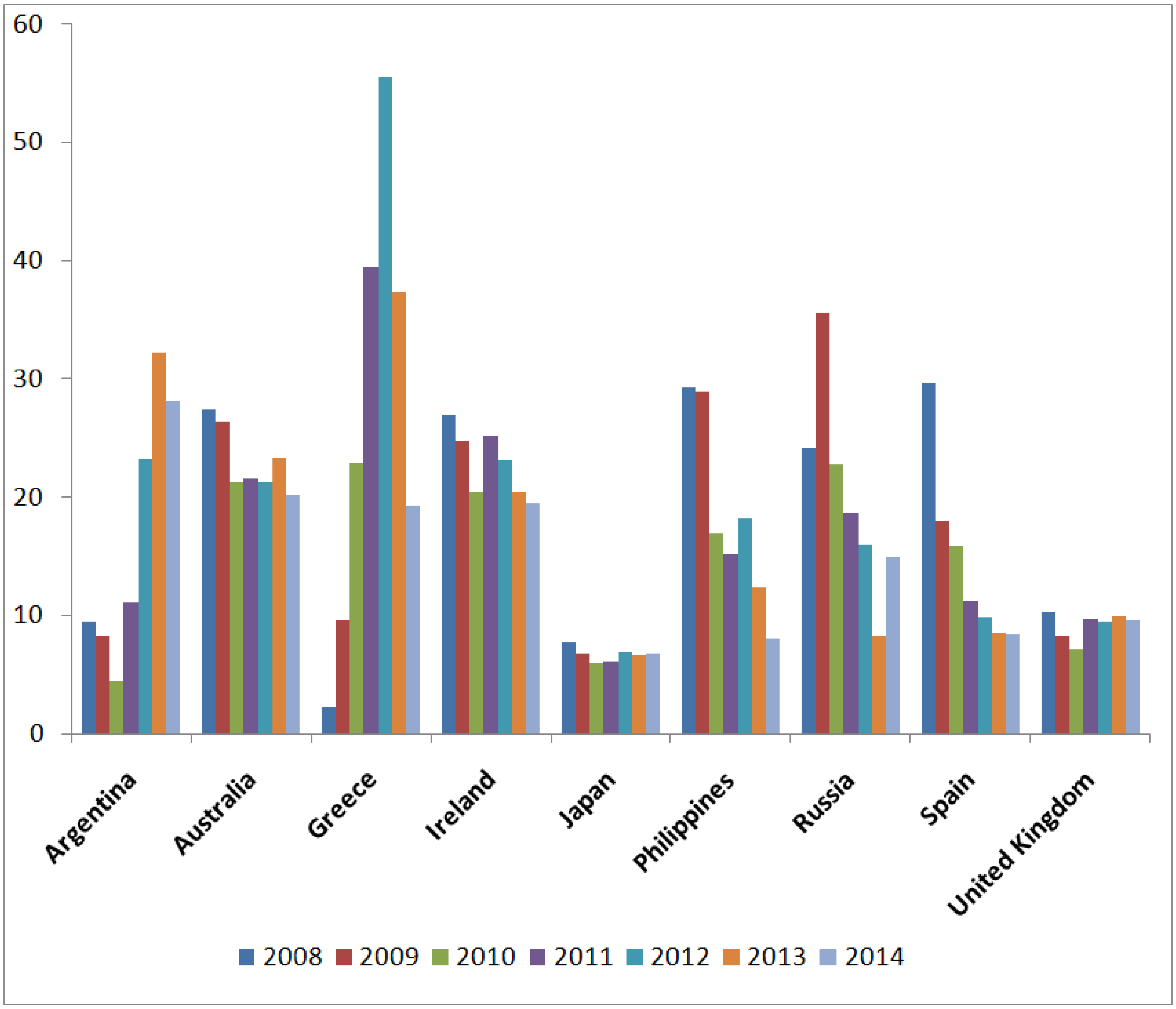


Figure 3.2: Wikipedia country profile views for selected countries, in billions

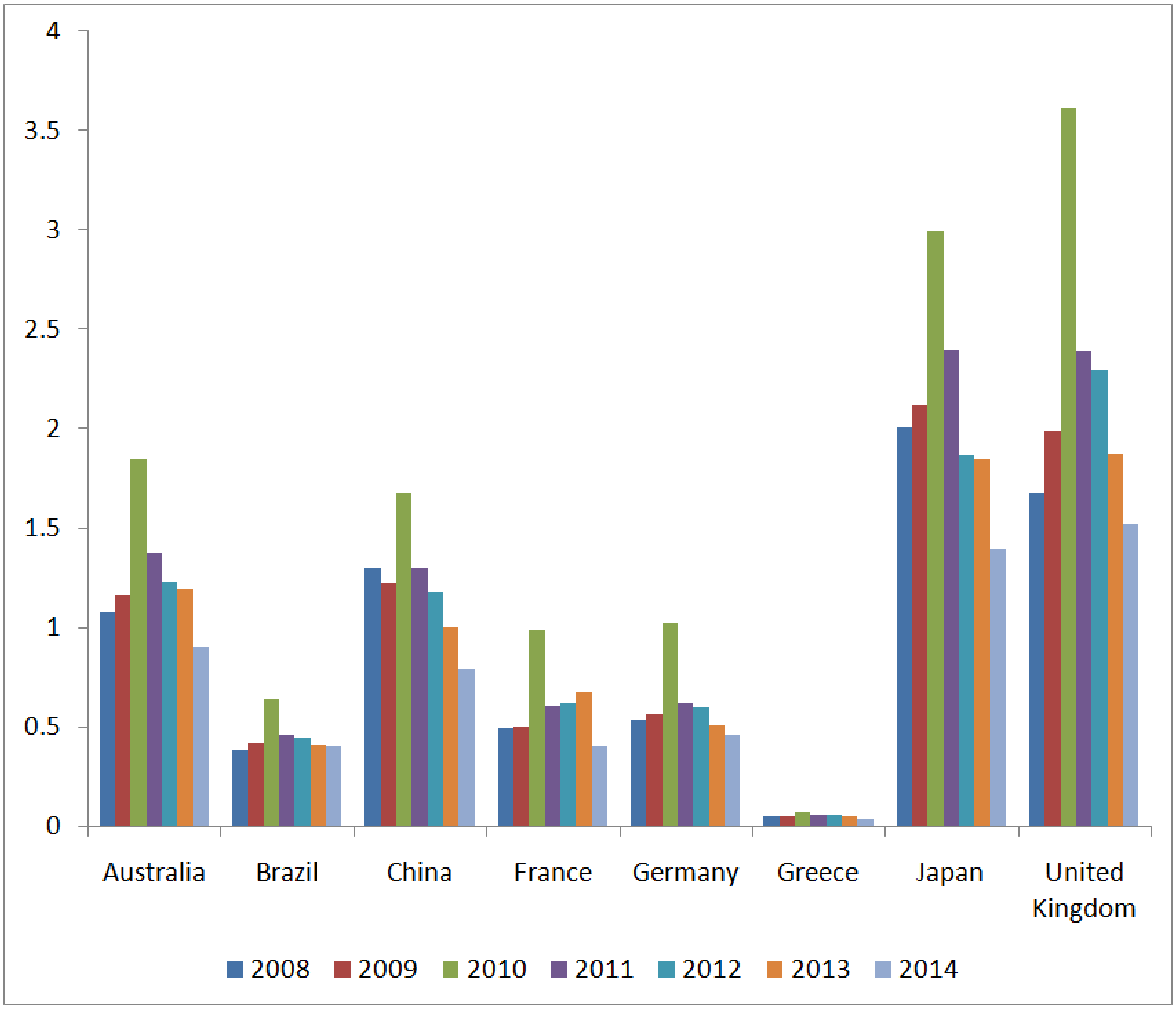


Table 3.1: Descriptive statistics

Panel A: ADR mispricing and Wikipedia views, by year.

Year	ADR mispricing (%)				Wikipedia views			
	N	Mean	Median	Stdev	N	Mean	Median	Stdev
2008	7,045	13.37	2.45	23.66	18,684	513,558	518,252	205,266
2009	8,997	12.01	2.23	22.04	18,684	551,424	538,390	211,600
2010	10,634	10.27	1.75	20.05	18,684	880,516	877,292	404,554
2011	12,287	10.97	2.06	20.81	18,684	624,778	539,379	347,113
2012	13,705	11.04	2.03	20.73	18,684	577,293	569,911	222,872
2013	15,038	10.42	1.80	20.25	18,684	531,014	522,260	199,788
2014	16,387	9.40	1.48	19.10	18,684	422,864	417,640	168,333

Panel B: American Depositary Receipts, from 2008 to 2014.

Variable	N	Mean	Median	Stdev
Mispricing (%)	84,093	10.80	1.91	20.70
Wikipedia views	130,788	585,921	534,750	296,012
|Returns|	83,798	0.08	0.04	0.50
1/P	84,673	0.31	0.07	3.07
Volume	68,753	10,683	187	50,245
Market Value	85,564	12,883	4,656	27,079
Dividend Yield (%)	85,642	3.01	2.03	5.41
Crisis	130,788	0.21	0.00	0.41

Note: This table reports the summary statistics for the variables used in this study. The time span is from January 2008 through December 2014.

Table 3.2: Correlation coefficients

	Mispricing (%)	Wikipedia views	|Returns|	1/P	Volume	Market Value	Dividend Yield (%)	Crisis	Level I dummy
Mispricing	1								
Wikipedia views	-0.023	1							
|Returns|	0.0307	-0.002	1						
1/P	0.0926	0.006	0.018	1					
Volume	-0.0907	-0.0354	-0.0231	-0.0221	1				
Market Value	-0.1218	0.0539	-0.046	-0.0997	0.5298	1			
Dividend Yield	0.1075	-0.0611	0.026	0.0938	0.0339	-0.0802	1		
Crisis	0.0696	-0.0444	0.0261	-0.0014	0.1521	-0.0121	0.0396	1	
Level I dummy	0.0351	0.1227	0.0077	0.0191	-0.6226	-0.1709	-0.0325	-0.1106	1

Note: This table reports the correlation coefficients for the variables used in this study. The time span is from January 2008 through December 2014.

Table 3.3: 2SLS estimation results

Independent variables	Dependent variable: ADR mispricing					
	(1)	(2)	(3)	(4)	(5)	(6)
Wikipedia views	-3.295***	-3.231***	-2.892***	-2.815***	-3.270***	-2.989***
	(0.242)	(0.242)	(0.242)	(0.234)	(0.250)	(0.247)
1/P	1.078***	1.079***		3.107***		2.973***
	(0.141)	(0.140)		(0.366)		(0.351)
Dividend Yield	1.579***	1.547***	1.646***	1.306***	1.488***	1.318***
	(0.0681)	(0.0677)	(0.0786)	(0.0645)	(0.0661)	(0.0643)
Volume	-0.387***	-0.425***	-0.247***			
	(0.0162)	(0.0164)	(0.0188)			
Crisis		2.508***				2.112***
		(0.177)				(0.177)
Market Value			-0.668***	-0.740***		-0.669***
			(0.0546)	(0.0443)		(0.0445)
Amihud				11.32***	15.29***	11.17***
				(3.754)	(4.077)	(3.682)
Level I dummy					1.625***	1.347***
					(0.117)	(0.118)
Constant	48.46***	47.49***	48.43***	46.65***	44.88***	47.00***
	(3.227)	(3.219)	(3.230)	(3.150)	(3.264)	(3.259)
Observations	52,589	52,589	52,582	51,943	51,953	51,943
Number of ADRs	1,840	1,840	1,840	1,840	1,840	1,840
F-statistic of 2SLS regression	288.88***	261.42***	253.45***	192.93***	186.7***	163.7***
P-value of instrument relevance	0.00	0.00	0.00	0.00	0.00	0.00
Hansen overidentification statistic	141.819***	157.596***	131.539***	59.328***	78.002***	99.205***
R^2	2.2%	2.8%	2.4%	2.1%	1.0%	2.5%

Note: This table reports estimation results of 2SLS instrumental variable regressions. I assume Wikipedia view as the endogenous variable, while the number of United Nations World Heritage sites and the FIFA World Cup ranking score are used as instruments. The numbers in parentheses are White heteroscedasticity-consistent standard errors. The scripts ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 3.4: 2SLS regressions by ADR level

Independent variables	Dependent variable: ADR mispricing					
	Level I			Levels II and III		
	(1)	(2)	(3)	(4)	(5)	(6)
Wikipedia views	-4.246***	-4.066***	-3.406***	-1.786***	-1.525***	-1.540***
	(0.426)	(0.418)	(0.366)	(0.250)	(0.237)	(0.234)
1/P	2.178***		2.559***	3.572***		3.142***
	(0.344)		(0.480)	(0.564)		(0.511)
Dividend Yield	3.062***	2.410***	1.368***	1.069***	1.062***	1.067***
	(0.140)	(0.124)	(0.0905)	(0.0758)	(0.0760)	(0.0753)
Crisis	3.496***		2.717***	1.012***		1.040***
	(0.299)		(0.246)	(0.207)		(0.208)
Market Value		-3.743***	-1.002***		-0.368***	-0.280***
		(0.0739)	(0.0655)		(0.0445)	(0.0450)
Amihud			10.29***			305.9*
			(3.536)			(178.6)
Constant	60.52***	91.55***	56.72***	25.60***	26.09***	24.95***
	(5.650)	(5.687)	(4.986)	(3.268)	(3.239)	(3.239)
Observations	47,841	47,742	38,828	13,228	13,228	13,115
Number of ADRs	1,322	1,322	1,322	235	235	235
F-statistic of 2SLS regression	252.88***	1052.3***	139.34***	73.51***	86.44***	56.17***
P-value of instrument relevance	0.00	0.00	0.00	0.00	0.00	0.00
Hansen validity test statistic	4.939**	124.495***	53.863***	394.323***	443.09***	400.478***
R^2	5.6%	11.9%	2.3%	3.2%	2.8%	3.6%

Note: This table reports estimation results of 2SLS instrumental variable regressions by ADR level. The first three columns display results for Level I, while the last three columns show results for Levels II and III together. I assume Wikipedia view as the endogenous variable, while the number of United Nations World Heritage sites and the FIFA World Cup ranking score are used as instruments. The numbers in parentheses are White heteroscedasticity-consistent standard errors. The scripts ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 3.5: 2SLS regressions by sector

Independent variables	Dependent variable: ADR mispricing									
	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
Wikipedia views	-3.235***	0.0171	-4.560***	0.412	-1.970***	-6.537***	-2.544***	-9.977***	-11.50***	1.019
	(0.452)	(0.518)	(0.542)	(0.656)	(0.276)	(0.910)	(0.787)	(1.423)	(1.089)	(1.055)
1/P	1.901***	4.129***	15.90***	-2.530***	14.66***	-0.551	9.990***	5.300***	-7.688	7.164***
	(0.425)	(0.703)	(2.914)	(0.958)	(1.600)	(3.590)	(1.911)	(0.966)	(6.765)	(2.704)
Dividend Yield	-0.0800	2.958***	0.455***	1.978***	0.799***	0.685***	0.242	-1.742***	0.993***	-0.620***
	(0.193)	(0.225)	(0.152)	(0.184)	(0.0943)	(0.214)	(0.249)	(0.223)	(0.239)	(0.141)
Volume	-0.803***	-0.373***	-0.928***	-0.478***	-0.429***	-0.114*	-0.0481	-0.621***	0.354***	0.167***
	(0.0654)	(0.0385)	(0.0881)	(0.0563)	(0.0349)	(0.0596)	(0.0845)	(0.0552)	(0.119)	(0.0637)
Crisis	3.664***	3.152***	1.094***	4.552***	0.529***	1.770***	-0.273	0.888***	1.292*	1.423**
	(0.516)	(0.408)	(0.392)	(0.540)	(0.172)	(0.490)	(0.467)	(0.272)	(0.716)	(0.557)
Amihud	6.575	12.96	35.47***	11.73	19.41*	16.25**	-2.930	31.92*	263.4**	58.70***
	(7.128)	(7.900)	(13.00)	(8.319)	(10.14)	(6.697)	(2.182)	(18.95)	(114.7)	(15.44)
Level I dummy	-1.343***	0.995***	-2.007***	-3.480***	-1.950***	-0.247	3.468***	0.662**	1.379*	2.627***
	(0.361)	(0.231)	(0.293)	(0.411)	(0.195)	(0.675)	(0.552)	(0.327)	(0.726)	(0.548)
Constant	51.32***	1.265	68.51***	2.559	29.74***	91.07***	36.24***	137.6***	150.4***	-11.02
	(6.384)	(6.722)	(7.577)	(8.345)	(3.688)	(11.82)	(10.90)	(18.90)	(14.01)	(13.63)
Observations	5,766	8,279	5,019	8,168	2,579	9,313	2,804	2,597	2,704	3,251
Number of ADRs	173	211	161	225	119	303	89	80	51	77
F-statistic of regression	50.44***	64.11***	28.57***	46.78***	44.14***	18.66***	43.35***	38.88***	19.49***	12.40***
IV relevance (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen overid. statistic	7.629***	80.375***	15.235***	18.648***	0.859	97.527***	67.308***	0.876	99.569***	0.508
R^2	3.20%	10.80%	8.60%	4.80%	15.80%	2.50%	9.00%	5.40%	9.70%	0.031

Note: This table reports estimation results of 2SLS instrumental variable regressions by industry. I assume Wikipedia view as the endogenous variable, while the number of United Nations World Heritage sites and the FIFA World Cup ranking score are used as instruments. The numbers in parentheses are White heteroscedasticity-consistent standard errors. The scripts ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table 3.6: First stage estimation results

Independent variables	Dependent variable: Wikipedia Views					
	(1)	(2)	(3)	(4)	(5)	(6)
UN World Heritage Sites	0.017***	0.017***	0.016***	0.016***	0.016***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FIFA Ranking	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1/P	0.003	0.003		0.045***		0.361***
	(0.002)	(0.002)		(0.011)		(0.011)
Dividend Yield	-0.020***	-0.020***	-0.017***	-0.020***	-0.018***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Volume	-0.002***	-0.001**	-0.006***			
	(0.001)	(0.001)	(0.001)			
Crisis		-0.039***				-0.028***
		(0.005)				(0.005)
Market Value			0.020***	0.012***		0.018***
			(0.002)	(0.001)		(0.001)
Amihud				-0.055	-0.103***	-0.073**
				(0.036)	(0.035)	(0.036)
Level I dummy					-0.104***	0.110***
					(0.004)	(0.004)
Constant	12.83***	12.83***	12.67***	12.70***	12.74***	12.58***
	(0.005)	(0.005)	(0.013)	(0.013)	(0.005)	(0.140)
Observations	52,589	52,589	52,582	51,943	51,953	51,943
Wu-Hausman F-test	129.117***	130.28***	104.20***	108.84***	118.35***	110.31***
Sanderson-Windmeijer Underidentification Chi-sq	13,062***	13,043***	12,721***	12,991***	12,453***	12,234***
Sanderson-Windmeijer Weak identification F-test	6,530.63***	6,521.10***	6,360.13***	6,495.07***	6,225.91***	6,115.96***
Number of ADRs	1,840	1,840	1,840	1,840	1,840	1,840
R^2	20.2%	20.3%	20.5%	20.4%	21.2%	21.5%

Note: This table reports estimation results of the first-stage regressions of the instruments on the variable of interest. I assume Wikipedia view as the endogenous variable, while the number of United Nations World Heritage sites and the FIFA World Cup ranking score are used as instruments. The numbers in parentheses are White heteroscedasticity-consistent standard errors. The scripts ***, ** and * denote significance at the 1%, 5% and 10% levels. The Wu Hausman F-test report the test statistics, the H0 is that regressor is exogenous. The Sanderson-Windmeijer are first-stage chi-squared and F statistics tests of underidentification and weak identification of individual endogenous regressors.

CHAPTER IV

BUBBLES IN THE ADR MARKETS: BOOM AND BUST

4.1. Introduction

Capturing rational and irrational deviations from asset prices has become increasingly important for both practitioners and academicians. Speculative bubbles and episodes of price exuberance are among the most studied exceptions to efficient markets. Detecting and date stamping episodes of price exuberance can be a key to policymakers and finance professionals to determine the presence of a financial bubble.

In this chapter, I implement a newly available technique to detect and date stamp the beginning and the end of speculative bubbles in American Depositary Receipts indices. The purpose of this chapter is to determine the presence of multiple bubbles, for which I employ the recently available Supremum Augmented Dickey-Fuller (SADF) and Generalized Supremum Augmented Dickey-Fuller (GSADF) procedures, introduced by Phillips, Wu and Yu (2011) PWY hereafter, and Philips, Shi and Yu (2015) PSY hereafter, to determine the periods of price exuberance in a set of indices composed by ADRs. Moreover, I look into regional ADR indices from Asia, Europe, and Latin America and country-specific indices.

American Depositary Receipt (ADR) constitute an important setting to measure and evaluate bubble episodes. I am particularly interested in finding the start and the end dates of these bubble for general, regional, and country-specific ADR indices. In figure 1.3, I show that the general ADR index outperforms the growth of the S&P 500 for the years 2006 through 2008, and shortly in the midst of the financial crisis. In light of these evidence, this study helps to understand if those episodes where actually financial bubbles, especially for Latin American countries such as Brazil and Mexico which experienced a major economic growth. Moreover, after the financial crisis that shocked the U.S. financial markets in 2008-2009, I find this study to be of particular relevance to answer several questions. For example, do ADR indices exhibit periods of price exuberance? Are these episodes as frequent in some regions (countries) as they are in others?

And how long do these bubbles last? These findings are also relevant to understand the dynamics of the start and the end of the bubbles when they exist, as this could help identify and generate awareness across investors about a tendency of bubble formation in cross-listed securities depending on the country or regional index.

The remainder of this chapter is organized as follows. Section 2 describes the relevant literature related to this topic. Section 3 discusses the methodology and empirical strategy. Section 4 describes the data used for the empirical examination. Section 5 presents the results and discussion and Section 6 concludes.

4.2. Literature Review

4.2.1. Financial Bubbles

The literature about speculative bubbles is extensive and varied. Different authors have implemented diverse techniques to capture and expose periods of price exuberance. Integration and Cointegration tests Diba and Grossmann (1988a and 1988b), variance bound tests (Leroy and Porter, 1981; Shiller ,1981) , specification tests (West, 1987), Chow and CUSUM-type tests (Homm and Breitung, 2012), and SADF and GSADF Supremum Augmented Dickey-Fuller (SADF) and Generalized Supremum Augmented Dickey-Fuller (GSADF) procedures, introduced by Phillips, Wu and Yu (2011) PWY hereafter, and Philips, Shi and Yu (2015). The last two are implemented in this paper to test for speculative bubbles in the ADRs markets.

There is a growing body of literature utilizing the SADF and GSADF methodology to identify bubbles in different asset prices such as: food commodity markets (Etienne et al., 2014), housing markets (Pavlidis et al., 2013), Real Estate Investement Trusts (Escobari and Jafarinejad, 2016), and Latin American financial markets (Escobari et al. 2017).

4.2.2. American Depositary Receipts

With very few exceptions (single-listed depositary receipts), ADRs are cross-listed securities, which means they actively trade in more than one stock market at a time. In equilibrium, the price parity condition for both securities should hold once adjusted for the exchange rate, given that both assets represent the same stream of cash flows and expectations about these are homogeneous for both investors home and abroad. Also, in the presence of differences between the home and abroad price, profit-maximizing investors should take advantage through arbitrage. However, a long list of literature shows this price parity condition does not always meet due to limits to arbitrage (Gagnon and Karolyi, 2010b, Beckmann et al., 2015), transaction costs (Grossmann et al., 2007), investor sentiment (Suh, 2003, Grossmann et al., 2007, Hwang 2011), and limited investor attention (Eichler, 2012) among others.

According to Suh (2003) ADR price movements are influenced by U.S. market sentiment because they are traded in the U.S. Aquino and Poshakwale (2006) also confirm that innovations in the U.S. stock market have a greater effect than the ones from the home country. Therefore I assume that the U.S. market has a greater influence on ADR price movements than the ones from their home countries.

4.3. Methodology

4.3.1. Links between Bubbles and Explosive Behavior

I use the recently developed Supremum Augmented Dickey-Fuller (SADF) and General Supremum Augmented Dickey-Fuller (GSADF) test statistics proposed in PWY and PSY, to detect the beginning and the end of periods where explosive behavior is exhibited. One of the greatest benefits of using these estimation methods is that I do not need to consider fundamentals as part of the study. However, the empirical evidence showing a period of price exuberance can mistakenly be confused with that of a bubble if the market fundamentals grow unexpectedly faster than previously. Earlier literature (Escobari et al. 2017, and Harvey et al., 2016) defined B_t as a bubble, where B_t is the difference between the after-dividend price P_t of an asset and the market fundamental P_t^f i.e., $B_t = P_t - P_t^f$.

Furthermore, define R_f as the risk-free interest rate, D_t as the dividend received or payoff from the asset, and let U_t denote the unobserved market fundamentals. Then, I can write the following asset pricing equation for the market fundamentals:

$$P_t^f = \sum_{i=0}^{\infty} \left(\frac{1}{1+R_f}\right)^i E_t(D_{t+i} + U_{t+i}) \tag{1}$$

In the absence of bubbles, the degree of stationarity of P_t^f will determine the degree of stationarity of P_t. Meaning it would entirely depend on the values for D_t and U_t. For example, if the dividend series (payoffs) is integrated of order one, and the fundamentals are either stationary or integrated of order one, then the asset price is at most integrated of order one. If the bubble series satisfies the submartingale property $E_t(B_{t+1}) = (1 + R_f)B_t$, asset prices P_t will be explosive in the presence of bubbles. Hence, if D_t is stationary after differencing and U_t is at most integrated of order one, then empirical evidence of explosive behavior as captured by the SADF and GSADF procedure, can be used to determine the presence of bubbles.

The most important feature of the GSADF relies on its ability to identify explosive behaviors in a random walk series, and to determine the beginning and the end of those explosive episodes. Also, different from the SADF, the GSADF is able to determine multiple episodes of price exuberance within the same series. Furthermore, it can even detect bubbles that are occurring in real time, which constitutes a major tool for finance professional and researchers alike.

4.3.2. Date Stamping Explosive Behavior

To assess for explosive behavior and identify the start and the end of the bubble periods, I start with the following Augmented Dickey–Fuller (ADF) regression equation:

$$\Delta P_t = a_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} y^{i}_{r_1,r_2} \Delta P_{t-i} + \varepsilon_t \tag{2}$$

where, P_t is the corresponding ADR or market index, ΔP_t denotes first differences, the error term is assumed to follow a normal distribution, i.e., $\varepsilon \sim iid\ N\left(0, \sigma^2_{r_1,r_2}\right)$, and r_1 and r_2 denote fractions of the total sample size that specify the starting and ending points of each subsample period. The k lagged difference terms are included to control for autocorrelation, with k being determined by the Akaike information criterion. My interest relies on the following test statistic:

$$\mathrm{ADF}^{r_2}_{r_1} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})}. \tag{3}$$

To detect episodes of explosive behavior, PWY propose a recursive procedure on the estimation of $\mathrm{ADF}^{r_2}_{r_1}$ using different subsamples of data. The test statistic is defined as the supremum value of the $\mathrm{ADF}^{r_2}_{0}$ as defined by

$$\mathrm{SADF}(r_0) = \sup_{r_2 \in [r_0,1]} \mathrm{ADF}^{r_2}_{0} \tag{4}$$

According to PWY, when the SADF statistic exceeds the right tail critical values from its limit distribution[20], there is a bubble. They explain this as a two-step process, first determining the presence of price exuberance using the ADF statistic, and then proceeding to determine which windows have the presence of such behavior.

Homm and Breitung (2012) find that the SADF has greater power than the methods in Bhargava (1986) and the modified Busetti and Taylor (2004). Moreover, PSY introduce the GSADF which is a double recursive procedure to complement the forward recursive nature of the SADF statistic. This method allows detection of multiple episodes of explosive behavior and to determine the start and the end of such periods. It uses a rolling estimation windows by allowing r_1 and r_2 to change across a greater number of subsamples where r_0 is the minimum window size. PSY takes the SADF from each shift in end-period, as in PWY, but then constructs a series of statistics by changing the beginning point of each period and running the first loop each time. From this series of SADF statistics, PSY takes the greatest value and assigns that as the GSADF statistic. Explosive behavior is then identified when the GSADF test statistic is greater than its right tail critical values.

The GSADF then takes the following form:

$$\mathrm{GSADF}(r_0) = \sup_{r_1 \in [0, r_2 - r_0], r_2 \in [r_0, 1]} \mathrm{ADF}_{r_1}^{r_2} \tag{5}$$

[20] The limit distribution of the SADF statistic is given by

$$\sup_{r_2 \in [r_0, 1]} \frac{\int_0^1 W dW}{\int_0^1 W^2}$$

where r_1 and r_2 are the beginning and ending points of each sample in the recursive estimation[21]. The null hypothesis is that there exist no explosive periods within the sample, therefore, the rejection of the null implies that at least one episode of price exuberance was present in the series.

Once the explosive behavior is detected, I use a backward SADF (BSADF) series to thoroughly identify the windows in which I find price exuberance. The BSADF process is constructed by moving the initial observation window r_1 backward instead of r_2 forward and provides consistent estimates of the origination and termination points of each bubble (Phillips et al., 2015). The BSADF statistic is defined as:

$$\mathrm{BSADF}_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \mathrm{SADF}_{r_1}^{r_2} \tag{4}$$

The dates of the beginning and closing periods of price exuberance are identified as the first and last dates within each window where the *BSADF* statistic is greater than the right tail critical values of its own distribution. Furthermore, note the actual limit distributions of each test, because they are not standard, must be calculated via Monte Carlo simulations (see, e.g., Pavlidis et al., 2017).

4.4. Data

To study and date-stamp the bubble periods in the aggregate ADR market, I collect several indices, all issued and maintained by the Bank of New York Mellon (BNY). The BNY

[21] The limit distribution of the GSADF statistic is given by

$$\sup_{r_1 \in [0, r_2 - r_0], r_2 \in [r_0, 1]} \left\{ \frac{\frac{1}{2} r_w [W(r_2)^2 - W(r_1)^2 - r_w] - \int_0^1 W(r) dr [W(r_2) - W(r_1)]}{r_w^{\frac{1}{2}} \left[r_w \int_{r_w}^{r2} W(r)^2 dr - \left[\int_{r_w}^{r2} W(r)^2 dr \right]^2 \right]^2} \right\}$$

ADR main index tracks all Depositary Receipts traded on the NYSE, NYSE MKT and NASDAQ. To study regional episodes I include regional ADR sub-indices containing only ADRs from Asia, Europe and Latin America. To further expand this study, I include the 5 country-specific indices for Brazil, China, Japan, Mexico, and United Kingdom. All indices and sub-indices are obtained from Datastream International. These indices are market capitalization weighted and span from February 1998 through August 2017, yielding 235 monthly observations. Since all ADR indices use prices expressed in U.S. Dollars, I adjust the ADR indices using the U.S. Consumer Price Index (CPI) obtained from the Organisation for Economic Co-operation and Development (OECD) online database.

Table 4.1 reports the descriptive statistics for the indices used in this study. Panel A reports each index in nominal values while Panel B reports the inflation adjusted indices. I observe the standard deviation for emerging markets like Brazil, China and Mexico to be 4 or 5 times the one reported for developed markets such as Japan or United Kingdom.

4.5. Results

I follow PSY and PWY strategy to identify the SADF and GSADF statistics and to determine the beginning and the end of the multiple bubble episodes for each one of the inflation adjusted indices. Panel A from Table 4.2 reports the test statistics for the SADF and the GSADF tests. Table 4.2 Panel B reports the respective critical values obtained through Monte Carlo simulations with 2,000 replications. The smallest window of observations (r_0) is determined following PSY's recommended minimum window size rule ($r_0 = 0.01 + 1.8/\sqrt{T}$) where T is the number of observations (T=235); therefore for this sample size $r_0 = 0.1274$, which corresponds to a smallest window of 30 observations.

All ADR Indices show statistically significant GSADF test statistics, which means that the null hypothesis of no bubbles is rejected for all the ADR indices. However, the SADF test statistics reports statistically significant bubble periods only for the regional BNY Latin America ADR, Brazil ADR, China ADR, and Mexico ADR. The superiority of the GSADF in terms of samples and subsamples evaluated was already discussed by PSY and two other empirical studies (Escobari et al., 2017, and Chang et al., 2016). They all conclude that the main limitation of the SADF test is that the initial observation for every window in the recursive estimation is set to be $r_{1\ =0}$, which is overcome by the GSADF allowing the initial window to start at 0 but move throughout the sample $r_1 \in\ [0,\ r_2 - r_0]$.

The main drawback of these estimations is that the test statistics only constitute evidence in favor of financial bubbles as suggested by Etienne et al. (2015). To graphically observe the periods of price exuberance I report the details of this analysis in Figure 4.1 for the BNY ADR Index of all ADRs. Figure 4.2 reports the regional sub-indices for Asia, Europe and Latin America. Lastly, Figure 4.3 depicts the bubble episodes present at country-specific ADR indices for Argentina, Brazil, China, Japan, Mexico, and the United Kingdom. All the ADR indices studied exhibit bubble episodes during several months of 2007, which is commonly known as the buildup period of the financial crisis that shock the markets during 2008.

The general ADR index display two major bubble periods, one throughout 2007 which corresponds to the preceding months of the financial crisis of 2008 – 2009, and another right in the middle of the crisis from November 2008 to March 2009. Coinciding with the periods of rapid increase observed in Figure 3.1. This slightly mild recovery period might have been motivated due to the approval and implementation of the Troubled Asset Relief Program (TARP) which was signed into law during the previous month of October 2008. Although, ADRs were not part of this program, it is clear that its consequences improved the conditions of financial markets in general.

In the case of the regional indices, Asia exhibits several short-lived bubbles during 2006 and 2007. Similarly, Europe index shows a pattern similar to the general ADR index, the first episode from January 2007 through February 2007, May 2007 through August 2007, and October 2007 through December 2007. Latin America is the regional index with longer bubble periods, the first starts from December 2004 through March 2005, the second from July 2005 through July 2006, and the last from September 2006 through August 2008. Different from the other regions, Latin American ADRs do not exhibit a bubble during late 2008.

Overall, Latin American countries (Brazil and Mexico) display more and longer explosive periods in contrast to other countries in this study. The test detects two major episodes in Brazil (July 2005 – July 2006, and December 2006 – August 2008), while for Mexico there is a long-lasting financial bubble episode from August 2005 through April 2008.

The index for China shows two main bubbles. The first from November 2006 to February 2007 and from April 2007 to January 2008. For Japan, there is only one bubble episode from April 2006 to May 2006. The test also identifies a bubble during the bounce back period after crisis. Lastly, the UK ADR index shows some short episodes between 2001 and 2002, and more importantly a bubble from June 2007 through November 2007. The bounce back from the financial crisis from November 2008 through April 2009 also appears in this series.

4.6. Conclusions

In this chapter, I use a novel methodology to detect and time stamp financial bubbles in a series of American Depositary Receipt indices, from general to regional and country-specific indices. I show that those episodes overlap specially during the period that antecede the 2008-

2009 financial crisis. However, Latin America (both countries and regional indices) exhibit larger and longer bubble episodes than other countries and regions in this study. Developed countries such as United Kingdom and Japan also present multiple bubble episodes but are rather short lived compared to the ones from emerging countries like China, Brazil and Mexico.

These findings are supportive of the results obtained in Chapter III, where higher levels of attention are dedicated to countries like Japan and the UK, and less so for countries like China and Brazil (see Figure 3.2). It is possible to think that countries under more scrutiny and analyst attention are subject to less price speculation. While for developing countries with soaring economies it is understandable for these substantial price deviations and explosive behavior to occur. There are implications for practitioners and policymakers alike. Understanding the regions' propensity to form substantial deviations from fundamentals would help improve the forecasts and pricing of such securities. Policymakers could also incorporate more information about the behavior of these securities, because even though ADRs represent foreign stocks they are traded in the U.S. and therefore form part of American financial markets.

Future studies could address the discovery of linkages between ADR indices bubbles and American based market indices such as the S&P 500 or the Russell 2000 to observe the spillover effect of the U.S. markets onto ADR indices. Also, the contagion effect between different country-specific and region-specific indices could be examined to understand the dynamics between bubble formations. To study the contagion effects, future research could use methodologies such as the developed in Greenaway-McGrevy and Phillips (2016). Furthermore, the creation of matching portfolios of ADRs and their respective underlying securities would also help identify when and where those bubble episodes start at the firm-specific level.

Table 4.1: Descriptive statistics

Panel A - Nominal indices	Mean	Median	Maximum	Minimum	Std. Dev.
Classic ADR	129.02	128.78	196.90	72.76	25.66
Asia ADR	124.62	127.08	180.44	68.09	26.57
Europe ADR	128.38	125.99	194.98	73.47	24.86
Latin America ADR	216.12	209.66	496.95	52.17	118.61
Brazil ADR	232.84	209.99	619.09	39.98	147.90
China ADR	299.71	339.76	661.24	78.851	140.22
Japan ADR	90.75	87.07	168.81	52.27	20.83
Mexico ADR	241.69	270.51	450.33	64.00	109.39
United Kingdom ADR	117.07	116.41	170.16	64.12	20.10

Panel B - Inflation Adjusted indices					
Real ADR index	63.05	0.612	98.76	36.49	12.65
Real Asia ADR index	60.60	0.588	103.98	35.26	11.90
Real Europe ADR index	63.06	0.598	102.25	34.57	13.82
Real Latin America ADR index	50.42	0.909	228.52	28.79	50.42
Real Brazil ADR	108.77	92.39	284.69	22.06	64.35
Real China ADR	140.20	156.59	313.63	48.23	55.31
Real Japan ADR	45.19	41.04	99.71	24.60	14.08
Real Mexico ADR	113.35	118.65	217.31	39.14	43.95
Real United Kingdom ADR	57.51	54.88	84.88	30.17	11.37

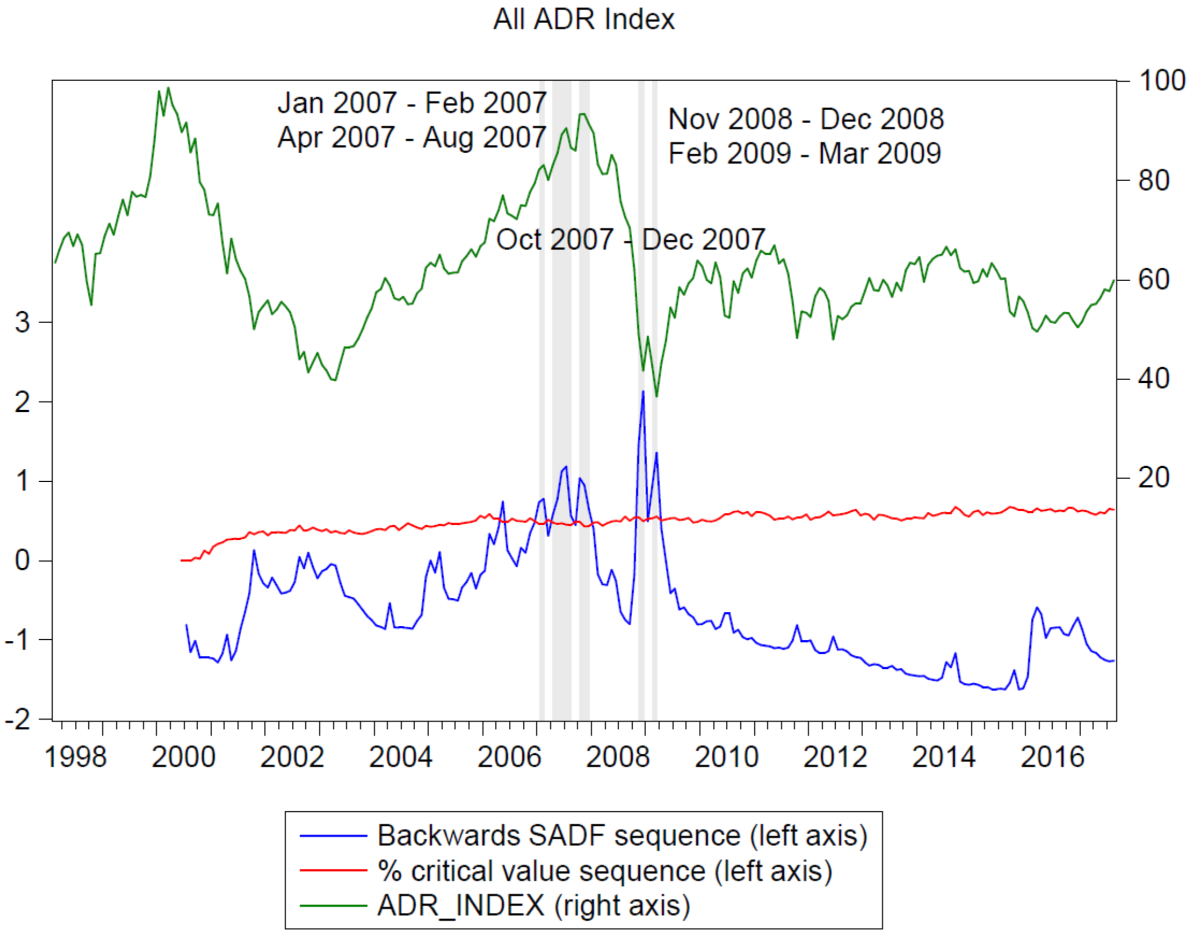
Notes: This table reports the descriptive statistics. The monthly ADR market capitalization weighted and free-float adjusted indices are collected from Datastream International and is provided by the Bank of New York Mellon ADR Division. As of July 2017, the index is comprised of 323 U.S. exchange-listed traded American Depositary Receipts representing non-U.S. securities. The regional indices are selected firms from each region, the Asian ADR index includes 138 firms, the Europe Index 92 firms, and the Latin America 73 firms. The Consumer Price Index (CPI) is obtained from the Organisation for Economic Co-operation and Development (OECD) database. The monthly inflation adjusted ADR indices are calculated by dividing the monthly ADR indices by the CPI to adjust for inflation over the time frame of this study. The sample spans from February 1998 to August 2017 which yields a total of 235 monthly observations.

Table 4.2: The SADF test and the GSADF test statistics

Panel A. Test Statistics	ADR Indices	
	(1)	(2)
Indices	SADF	GSADF
BNY ADR Index	-0.306	2.138**
BNY Asia ADR	-0.425	2.207**
BNY Europe ADR	-0.238	2.268**
BNY Latin America ADR	2.849***	2.942***
Brazil	3.201***	3.373***
China	2.386***	5.444***
Japan	-0.494	2.506**
Mexico	2.502***	2.879***
United Kingdom	0.116	2.826**
Panel B. Finite sample critical values		
90%	1.098	1.879
95%	1.376	2.108
99%	1.889	2.830

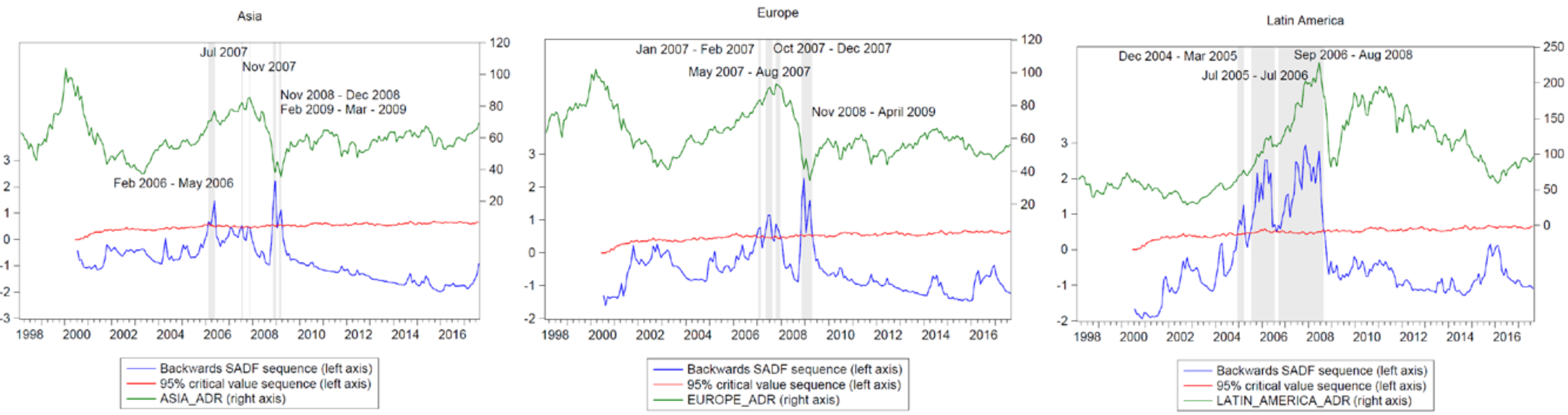
Notes: This table reports the SADF and GASDF statistics for the inflation adjusted price indices following PWY and PSY. The 95% critical values are obtained through Monte Carlo simulations with 2000 replications (sample size 235). The sample spans from February 1998 to August 2017 which yields a total of 235 monthly observations.***, **, and * denote statistical significance at the 1%, 5%, and 10% respectively.

Figure 4.1: GSADF results for general ADR Index



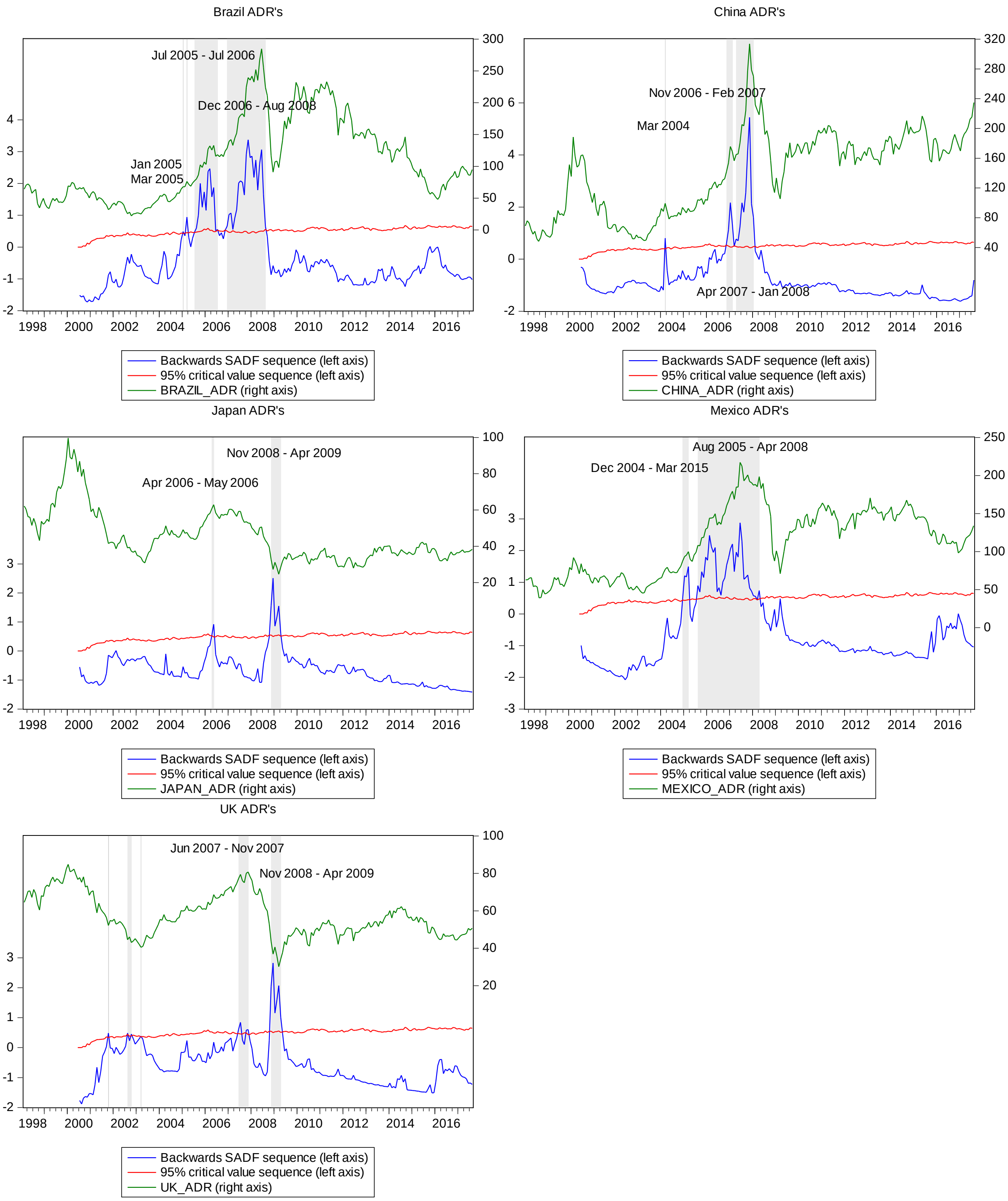
Notes: The inflation-adjusted stock indices are obtained from Datastream International (right axis). The sample spans from February 2008 to August 2017 with the total number of monthly observations being 235. The Backward Supremum Augmented Dickey-Fuller (BSADF, left axis) follows Phillips et al. (2015). The shaded areas are the bubble periods identified by the BSADF. The 95% critical value sequence (left axis) based on Monte Carlo simulations with 2000 replications (the sample size is 235 and the smallest window has 30 observations).

Figure 4.2: GSADF results for regional ADR indices



Notes: The inflation-adjusted stock indices are obtained from Datastream International (right axis). The sample spans from February 1998 to August 2017 with the total number of monthly observations being 235. The Backward Supremum Augmented Dickey-Fuller (BSADF, left axis) follows Phillips et al. (2015). The shaded areas are the bubble periods identified by the BSADF. The 95% critical value sequence (left axis) based on Monte Carlo simulations with 2000 replications (the sample size is 235 and the smallest window has 30 observations).

Figure 4.3: GSADF results for country-specific ADR indices



Notes: The inflation-adjusted stock indices are obtained from Datastream International (right axis). The sample spans from February 1998 to August 2017 with the total number of monthly observations being 235. The Backward Supremum Augmented Dickey-Fuller (BSADF, left axis) follows Phillips et al. (2015). The shaded areas are the bubble periods identified by the BSADF. The 95% critical value sequence (left axis) based on Monte Carlo simulations with 2000 replications (the sample size is 235 and the smallest window has 30 observations).

REFERENCES

Alaganar, V. T., & Bhar, R. (2001). Diversification gains from American depositary receipts and foreign equities: evidence from Australian stocks. *Journal of International Financial Markets, Institutions & Money*, 11(1), 97-113.

Alsayed, H., & McGroarty, F. (2012). Arbitrage and the Law of One Price in the market for American depository receipts. *Journal of International Financial Markets, Institutions & Money*, *22*(5), 1258-1276.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.

Ansotegui, C., Bassiouny, A., & Tooma, E. (2013). The proof is in the pudding: Arbitrage is possible in limited emerging markets. *Journal of International Financial Markets, Institutions & Money*, 23, 342-357.

Arquette, G. C., Brown, W. O., & Burdekin, R. C. (2008). U.S. ADR and Hong Kong H-share discounts of Shanghai-listed firms. *Journal of Banking & Finance*, 32(9), 1916-1927.

Aquino, K. P., & Poshakwale, S. (2006). Price determinants of American Depositary Receipts (ADR): a cross-sectional analysis of panel data. *Applied Financial Economics*, 16(16), 1225-1237.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives*, 21(2), 129.

Baker, S. R., Bloom, N., & Davis, S. J. (2015). Measuring economic policy uncertainty (No. w21633). National Bureau of Economic Research.

Barber, Brad M., and Terrance Odean. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies* 21.2 (2007): 785-818.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307-343.

Beckmann, K. S., Ngo, T., & Wang, D. (2015). The informational content of ADR mispricing. *Journal of Multinational Financial Management*, 32, 1-14.

Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market Integration and Contagion. *Journal of Business*, 78(1).

Bhargava, A. (1986). On the theory of testing for unit roots in observed time series. *The Review of Economic Studies*, 53(3), 369-384.

Board of Governors of the Federal Reserve System (U.S.), Trade Weighted U.S. Dollar Index: Broad [DTWEXB], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DTWEXB, October 10, 2017.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11(1), 1-27.

Busetti, F., & Taylor, A. R. (2004). Tests of stationarity against a change in persistence. *Journal of Econometrics*, 123(1), 33-66.

Chan, J. S., Hong, D., & Subrahmanyam, M. G. (2008). A tale of two prices: Liquidity and asset prices in multiple markets. *Journal of Banking & Finance*, 32(6), 947-960.

Chang, T., Gil-Alana, L., Aye, G. C., & Ranjbar, O. (2016). Testing for bubbles in the BRICS stock markets. *Journal of Economic Studies*, 43(4), 646-660.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24(8), 1177-1199.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461-1499.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all fears investor sentiment and asset prices. *Review of Financial Studies*, 28(1), 1-32.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4), 703-738.

Diba, B. T., & Grossman, H. I. (1988a). Explosive rational bubbles in stock prices?. *The American Economic Review*, 78(3), 520-530.

Diba, B. T., & Grossman, H. I. (1988b). The theory of rational bubbles in stock prices. *The Economic Journal*, 98(392), 746-754.

Durbin, J. (1970). Testing for serial correlation in least-squares regressions when some of the regressors are lagged dependent variables. *Econometrica* 38: 410–421.

Eichler, S. (2012). Limited investor attention and the mispricing of American Depositary Receipts. *Economics Letters*, 115(3), 490-492.

Ely, D., & Salehizadeh, M. (2001). American depositary receipts: an analysis of international stock price movements. *International Review of Financial Analysis*, 10(4), 343-363.

Engelbert, Joseph website. FEARS index. Last accessed 12/10/2016 http://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/research.htm

Escobari, D., & Jafarinejad, M. (2016). Date stamping bubbles in real estate investment trusts. *The Quarterly Review of Economics and Finance*, 60, 224-230.

Escobari, D., Garcia, S., & Mellado, C. (2017). Identifying bubbles in Latin American equity markets: Phillips-Perron-based tests and linkages. *Emerging Markets Review*, 33, 90-101.

Etienne, X. L., Irwin, S. H., & Garcia, P. (2014). Bubbles in food commodity markets: Four decades of evidence. *Journal of International Money and Finance*, 42, 129-155.

Fama, E. F., & French, K. R. (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay?. *Journal of Financial Economics*, 60(1), 3-43.

Foerster, S. R., & Karolyi, G. A. (2000). The long-run performance of global equity offerings. *Journal of Financial and Quantitative Analysis*, 35(4), 499-528.

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5), 2223-2261.

Gagnon, L., & Karolyi, G. A. (2010a). Do International Cross-Listings Still Matter? Evidence on Financial Globalization and Crises, Thorsten Beck, Sergio Schmukler, Stijn Claessens, eds., Elsevier North-Holland Publishers, 2010. Available at SSRN: https://ssrn.com/abstract=1638197

Gagnon, L., & Karolyi, G. A. (2010b). Multi-market trading and arbitrage. *Journal of Financial Economics*, 97(1), 53-80.

Ghadhab, I., & Hellara, S. (2015). The law of one price, arbitrage opportunities and price convergence: Evidence from cross-listed stocks. *Journal of Multinational Financial Management*, 31, 126-145.

Greenaway-McGrevy, R., & Phillips, P. C. (2016). Hot property in New Zealand: Empirical evidence of housing bubbles in the metropolitan centres. *New Zealand Economic Papers*, 50(1), 88-113.

Grossmann, A., Ozuna, T., & Simpson, M. W. (2007). ADR mispricing: Do costly arbitrage and consumer sentiment explain the price deviation?. *Journal of International Financial Markets, Institutions & Money*, 17(4), 361-371.

Harvey, D. I., Leybourne, S. J., Sollis, R., & Taylor, A. R. (2016). Tests for explosive financial bubbles in the presence of non-stationary volatility. *Journal of Empirical Finance*, 38, 548-574.

Homm, U., & Breitung, J. (2012). Testing for speculative bubbles in stock markets: a comparison of alternative methods. *Journal of Financial Econometrics*, 10(1), 198-231.

Hsu, J., & Wang, H. Y. (2008). Why do price spreads between domestic shares and their ADRs vary over time?. *Pacific Economic Review*, 13(4), 473-491.

Hwang, B. H. (2011). Country-specific sentiment and security prices. *Journal of Financial Economics*, 100(2), 382-401.

Irresberger, F., & Weiss, G. N. (2015). Depositor Sentiment. Working Paper.

Irresberger, F., Mühlnickel, J., & Weiß, G. N. (2015). Explaining bank stock performance with crisis sentiment. *Journal of Banking & Finance*, 59, 311-329.

Jiang, C. X. (1998). Diversification with American depository receipts: the dynamics and the pricing factors. *Journal of Business Finance & Accounting*, 25(5-6), 683-699.

LeRoy, S. F., & Porter, R. D. (1981). The present-value relation: Tests based on implied variance bounds. *Econometrica: Journal of the Econometric Society*, 555-574.

Kabir, M. H., Hassan, M. K., & Maroney, N. (2011). International diversification with American depository receipts (ADRs). *Pacific-Basin Finance Journal*, 19(1), 98-114.

Kadiyala, P., & Subrahmanyam, A. (2004). Divergence of U.S. and Local Returns in the After-market for Equity Issuing ADRs. *European Financial Management*, 10(3), 389-411.

Karolyi, G. A. (2006). The world of cross-listings and cross-listings of the world: Challenging conventional wisdom. *Review of Finance*, 10(1), 99-152.

Kato, K., Linn, S., & Schallheim, J. (1990). Are there arbitrage opportunities in the market for American depository receipts?. *Journal of International Financial Markets, Institutions & Money*, 1(1), 73-89.

Keynes, J. M. (1936). The general theory of interest, employment and money.

Maldonado, R., & Saunders, A. (1983). Foreign exchange restrictions and the law of one price. *Financial Management*, 19-23.

Mao, Q., & Wei, K. C. J. (2013). Country-specific attention and security returns. In the China International Conference in Finance, Shanghai.

Moat, H. S., Curme, C., Avakian, A., Kenett, D. Y., Stanley, H. E., & Preis, T. (2013). Quantifying Wikipedia usage patterns before stock market moves. *Scientific reports*, 3, 1801.

Mollick, A. V., & Assefa, T. A. (2013). US stock returns and oil prices: The tale from daily data and the 2008–2009 financial crisis. *Energy Economics*, *36*, 1-18.

Mondria, J., Wu, T., & Zhang, Y. (2010). The determinants of international investment and attention allocation: Using internet search query data. *Journal of International Economics*, 82(1), 85-95.

Newey, W.K. & K.D. West, 1994. Automatic Lag Selection in Covariance Matrix Estimation. *Review of Economic Studies*, Vol. 61, No. 4, pp. 631-653.

OECD (2017), Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 24 October 2017)

OECD (2017), Share prices (indicator). doi: 10.1787/6ad82f42-en (Accessed on 24 October 2017)

Park, J., & Tavakkol, A. (1994). Are ADRs a dollar translation of their underlying securities? The case of Japanese ADRs. *Journal of International Financial Markets, Institutions and Money*, *4*(1-2), 77-87.

Pavlidis, E. G., Paya, I., & Peel, D. A. (2017). Testing for speculative bubbles using spot and forward prices. *International Economic Review*, *58*(4), 1191-1226.

Pavlidis, E., Yusupova, A., Paya, I., Peel, D. A., Martínez-García, E., Mack, A., & Grossman, V. (2013). Monitoring housing markets for episodes of exuberance: an application of the Phillips et al.(2012, 2013) GSADF test on the Dallas Fed International House Price Database.

Peterburgsky, S., & Yang, Y. (2013). Diversification potential of ADRs, country funds and underlying stocks across economic conditions. *Applied Financial Economics*, 23(3), 199-219.

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56(4), 1043-1078.

Phillips, P. C., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values?. *International Economic Review*, 52(1), 201-226.

Qiu, L., & Welch, I. (2004). Investor sentiment measures (No. w10794). National Bureau of Economic Research.

Rosenthal, L. (1983). An empirical test of the efficiency of the ADR market. *Journal of Banking & Finance*, 7(1), 17-29.

Shiller, R. J. (1981). The use of volatility measures in assessing market efficiency. *The Journal of Finance*, 36(2), 291-304.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization*, 107, 730-743.

Singer, E. (2002). The use of incentives to reduce nonresponse in household surveys. *Survey nonresponse*, 51, 163-177.

Suarez, E. D. (2005). Arbitrage opportunities in the depositary receipts market: Myth or reality?. *Journal of International Financial Markets, Institutions & Money*, 15(5), 469-480.

Suh, J. (2003). ADRs and U.S. Market Sentiment. *The Journal of Investing*, 12(4), 87-95.

Tang, W., & Zhu, L. (2017). How security prices respond to a surge in investor attention: Evidence from Google Search of ADRs. *Global Finance Journal*, 33, 38-50.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139-1168.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, 63(3), 1437-1467.

U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, October 20, 2017.

Van Nieuwerburgh, S. & Veldkamp, L (2010). Information Acquisition and Under-Diversification, *The Review of Economic Studies*, Volume 77, Issue 2, 1 April 2010, Pages 779–805.

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, 41, 17-35.

Wahab, M., Lashgari, M., Cohn, R. J., & Cohn, R. (1993). Arbitrage opportunities in the American depository receipts market revisited. *Journal of International Financial Markets, Institutions & Money*, 2(3-4), 97-130.

West, K. D. (1987). A Specification Test for Speculative Bubbles. *The Quarterly Journal of Economics*, 102(3), 553-580.

World Bank. (2018). Market capitalization of listed domestic companies (current US$). Retrieved from https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=US. (Accessed on 24 May 2018)

Wu, Q., Hao, Y., & Lu, J. (2017). Investor sentiment, idiosyncratic risk, and mispricing of American Depository Receipt. *Journal of International Financial Markets, Institutions & Money*, 51, 1-14.

Zhang, W., Li, X., Shen, D., & Teglio, A. (2016). Daily happiness and stock returns: Some international evidence. *Physica A: Statistical Mechanics and its Applications*, 460, 201-209.

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