Popularity versus Profitability: Evidence from Bollinger Bands

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Abstract

Many so-called return predictability anomalies disappear over time. One theoretical explanation is that investors arbitrage profits away through their trading. But investors have used technical analysis strategies for ages, so this argument may not necessarily hold for seemingly profitable trading technical analysis strategies. To verify whether such an argument has merit, we investigate what would happen if a completely new technical trading rule appeared that investors had never used before but which became more popular over time. Bollinger Bands, introduced in 1983, provide a natural experiment. Before their introduction, trading on Bollinger Bands would have been an extremely profitable trading strategy in international stock markets. However, ever since their introduction, their predictive power seems to have gradually decreased and has largely disappeared since the influential publication on Bollinger Bands in 2001. Moreover, their predictability disappeared in the US market first, where Bollinger Bands originated, and then in other international markets.

Keywords: Bollinger Bands, Technical Analysis, Return Predictability, Publication Impact.

JEL Classifications: G10, G12, G14

1. Introduction

Despite the ongoing debate in the academic literature on its profitability, technical analysis remains popularly used by practitioners. Among numerous technical indicators, techniques involving Bollinger Bands are some of the most widely used. In 1983, just over 30 years ago, John Bollinger introduced Bollinger Bands on the Financial News Network (which eventually became CNBC), where he was chief market analyst.¹ Ever since, Bollinger Bands gradually gained popularity among investors. In 2001, Bollinger published his influential work on this indicator, Bollinger on Bollinger Bands. In four years' time, the English version of the book witnessed seven editions.² As of this writing (2014), his book has been translated into 11 languages.³ Recent survey results suggest Bollinger Bands have become a technical analyst favorite. Abbey and Doukas (2012) find that, over the period 2004–2009, Bollinger Bands were the most favored technical indicator based on a sample of 428 individual currency traders dominating several popular technical indicators, including the relative strength index, moving average convergence divergence, and moving average crossovers. Ciana (2011) documents Bollinger Bands as the third most popular technical indicator worldwide among users of the Bloomberg Professional service from 2005 to 2010.⁴ Bollinger Bands were trademarked by Bollinger in 2011. Nowadays almost all major financial websites and analytical software providers, such as Yahoo and Bloomberg, incorporate Bollinger Bands. The growing attention to Bollinger Bands becomes apparent when we plot the annual number of news articles on Bollinger Bands published in the United States from the Factiva database.⁵ The first news article appears in 1993 and the number of articles rises steadily until 2001, when it reaches 77. It then jumps in 2002 to 157 news articles by year's end, more than double the 77 articles of the preceding year. This seems to be a good indication of the impact of the 2001 Bollinger on Bollinger Bands publication. Attention on Bollinger Bands continues to grow and the annual number of articles exceeded a thousand at its peak in 2011.

[Please insert Figure 1 here]

Did the increasing popularity affect the potential profits of Bollinger Bands-based trading strategies? This question is particularly interesting if we consider the long-debated "self-destructive" nature of many famous return predictability anomalies that have disappeared over time. By the self-destructiveness, researchers argue that the profitability of an efficient trading strategy can be fully eliminated by its own popularity among investors, because investors compete with each other to arbitrage away all trading opportunities. For example, by using the updated US stock market data that starts earliest in 1831 and ends in 2001, Schwert (2003) demonstrates that a variety of previously

¹ See <u>http://www.prweb.com/releases/2008/04/prweb814374.htm</u> and <u>http://www.bollingerbands.com/services/bb/rules.php</u>.

 ² See <u>https://st0.forex-mmcis.com/en_US/books/Other_Books/John_Bollinger_-_Bollinger_on_Bollinger_Band.pdf</u>.
³ The 11 languages include Chinese (simplified and traditional), French, German, Italian, Japanese, Korean,

Lithuanian, Russian, Turkish, and Spanish (<u>http://en.wikipedia.org/wiki/John Bollinger</u>).

⁴ The first and the second most popular indicators are the relative strength index and moving average convergence divergence, respectively.

⁵ Many previous studies use media coverage to measure investor attention (e.g., Barber & Odean, 2008; Fang & Peress, 2009). Due to data availability, we could only measure investor attention to Bollinger Bands in the United States. We exclude all discontinued sources from the data.

documented anomalies, including the size effect, the value effect, the weekend effect, and the dividend yield effect, seem to lose their predictive power after the papers that made them famous were published. In addition, the author finds that the small-firm turn-of-year effect and the predictive ability of variables such as dividend yield and inflation are much weaker. Schwert notes that the anomalies documented that have disappeared are likely to be those were implemented by practitioners into trading strategies, while the less-implemented anomalies became weaker but continued to exist. Similarly, McLean and Pontiff (2014) find that profitable trading studies from academic studies seem to disappear out of sample. Of course, evidence to support this argument is never conclusive, since correlation does not imply causation and some anomalies continue to exist even after they have been reported.⁶ Still it is the best indication we may be able to obtain from the data. However, if trading profits reported in academic studies can be traded away, we expect that, given the dramatically increased attention and popularity of Bollinger Bands, their profitability should have disappeared almost instantaneously

While examination of the profitability of a favorite technical indicator of practitioners is interesting in itself, the study of Bollinger Bands also provides an ideal opportunity to verify whether and how the popularity of trading strategies affects their profitability. Bollinger Bands, in this respect, seem an interesting natural experiment for the following reasons. First, unlike other popular technical analysis strategies, the trading strategy was not known before 1983. Second, the strategy is easy to implement. Like many technical indicators, Bollinger Bands use only information derived from historical prices to predict future returns. This means investors have easy access to the data. In addition, the strategy itself is relatively easy to implement, since it does not involve sophisticated financial modeling or parameter estimation. Third, based on newspaper articles and other key data, we have a reasonable indication of the increasing popularity over time and large enough data samples to measure profits over time. Lastly, the gradual development of Bollinger Bands in international markets may be of extra interest. Bollinger Bands originated in the US market and *Bollinger on Bollinger Bands* was published first in the United States. So if investors' usage has an impact on the strategy's profitability, we should expect the impact to show up in the United States first and then gradually affect other countries.

Our main result is that our evidence is consistent with the often heard hypothesis that potentially profitable trading strategies indeed quickly self-destruct with increasing popularity. To illustrate the main results of our paper, it may be good to compare the profitability of a Bollinger Band-based trading strategy on the Standard & Poor's (S&P) 500 with the popularity of Bollinger Bands from 1993 to 2013 (where we proxy popularity by the number of news articles in the Factiva database on Bollinger Bands, reported in Figure 1). We plot the results in Figure 2. The black solid line plots the annual returns of the strategy and the black dotted line plots the linear trend of the annual returns. Intriguingly, the returns are mostly negative during this period and such losses even have worsened over time. At the same time,

⁶ A number of studies document that the so-called Halloween/Sell in May effect persists out of sample (for instance, Andrade, Chhaochharia, & Fuerst, 2012; Grimbacher, Swinkels, & van Vliet, 2010; Jacobsen & Visaltanachoti, 2009; Zhang and Jacobsen, 2014). Moreover, as Bouman and Jacobsen (2002) document in their original study, the Sell in May effect was a well known market wisdom before the start of their sample, but the effect persisted in their sample.

Bollinger Bands have received growing attention from investors (as shown in Figure 1). Figure 3 shows annual returns before 1993. Bollinger Bands-based trading strategies seem to have worked well before the mid-1980s and the returns are generally positive for nearly 60 years; however, the returns are mostly negative afterward. The trend line indicates apparent downward profitability in this longer sample. Interestingly, the trend line intersects with the *x*-axis around the mid-1980s (i.e., Profit = 0) and this generally coincides with when Bollinger Bands were first introduced. This illustrates the main point of our paper.

[Please insert Figures 2&3 here]

More formally, we carry out statistical tests to examine profitability on an international sample. We include 14 major international stock markets: Australia, France, Germany, Hong Kong, Italy, Japan, Korea, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States, with both the Dow Jones Industrial Average (DJIA) and the S&P 500 for the latter. For each market, we use the longest sample available that starts between 1885 (DJIA) and 1971 (Madrid SE General Index) and all samples end in 2014. In addition to the full sample, we use three sub-samples that match the key dates of Bollinger Bands' development—before 1983, from 1983 to 2001, and since 2002—to allow a comparison on the profitability over time. Our results generally match with the preliminary check above. In the full sample, Bollinger Bands show strong predictive ability in all 14 markets. Buy (sell) signals produce significantly positive (negative) returns that are higher (lower) than the market returns in 14 (12) markets, respectively. Moreover, the average spread between returns conditional on buy and sell signals are statistically positive in all 14 markets. The average spread across 14 markets, 0.294%, is about 10 times higher than the corresponding average market return of 0.026%. We find even stronger profitability in using Bollinger Bands in the first sub-sample before 1983. While Bollinger Bands show strong profitability in all 14 markets as well, the average daily spread between buy and sell signals over 14 markets increases to 0.454%, compared to the average market return of 0.021% in this period. However, in the next sub-sample, from 1983 to 2001, Bollinger Bands' profitability decreases and even disappears in a number of markets. Buy (sell) signals generate higher (lower) returns than the market in 10 (eight) markets only and the average spread between conditional buy and sell returns is significantly positive in 11 markets. Note that Bollinger Bands lose their profitability in two US markets, where they originate, immediately in the period during which they are introduced. Lastly, since 2002, their profitability shrinks further to nearly none. Only in two markets, Italy and New Zealand, do Bollinger Bands still show possible predictive ability, although further evidence shows that such predictability is also largely weakened compared with before. More intriguingly, Bollinger Bands even generate significantly lower returns than the market in the S&P 500 market. The results from this sub-sample also confirm the importance of Bolllinger's influential publication, as studied by previous studies. In most international markets, the forecastability of Bollinger Bands disappeared after the 2001 publication.

Further investigation shows that in seven markets, returns of a Bollinger Bands-based strategy are significantly lower during 1983-2001 than those before 1983, with an average decline of -56% across all markets. And in all 14 markets except only Italy, returns are significantly lower after 2002, the average decline is -156%. More importantly, the declines after 2002 in all 14 markets are significantly lower than those during 1983-2001 suggesting an impact of the key publication. If we plot the annual returns, they

immediately changed from positive to negative in the US market in 1983; soon after in the Japanese market, around 1990; then in a number of European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets.

We conduct several additional robustness checks and find the conclusion holds. First, we use a different version of Bollinger Bands, "Squeeze," which Bollinger emphasizes as the best application of Bollinger Bands but that has not yet received any academic attention (Bollinger, 2001, p. 63). Second, to closely monitor profitability over time, we check the average returns per signal by using rolling window regressions and we also track the annual returns of Bollinger Bands-based trading strategies. Third, we take transaction costs into account and measure the economic significance of our findings by calculating both Jensen's α and Sharpe ratios. In addition, while the default version of Bollinger Bands aims to capture relatively medium-term trends, we alter the parameter settings as suggested in *Bollinger on Bollinger Bands* to measure the short- and long-term profitability. We also use GARCH(1,1) or robust regression models to estimate parameters instead of ordinary least squares (OLS) to account for possible heteroskedasticity or outlier problems. Our results remain similar.

Our results indicate that trading on Bollinger Bands may no longer be profitable (which may also explain why academic studies to date, discussed in detail in Section 3, have produced mixed results⁷). However, we feel the more general conclusion may be of greater interest, since our results suggest that no matter how profitable a trading result has been in the past, future performance may be strongly affected by how well known and popular the trading strategy becomes. In that sense, we feel our results have much wider implications. While it is often assumed that trading will make the profits of anomalies disappear, few studies to date have tried to see whether this actually happens and under what conditions. Our results warn about how investor trading can fully destroy such profitabile trading strategies may change the underlying return-generating process itself. Last but not least, although we cannot fully eliminate the possibility of data snooping, we take several measures to best avoid such a risk. We discuss this issue in more detail in the next section.

2. Anomalies and Data Snooping

Our analysis suggests that a historical profitable trading strategy can use its usefulness over time and this phenomenon may relate closely to the strategy's usage. Such a finding is in line with a strand of literature that suggests that many so-called return predictability anomalies disappear over time. For example, by using different methodologies, Mehdian and Perry (2002) and Gu (2003) reach the same conclusion, that the January effect has disappeared from US stock market indices since 1988. The former uses a sample from 1964 to 1998 and later a sample from 1957 to 2000. In addition, based on up-to-

⁷ Studies on Bollinger Bands include those of Leung and Chong (2003), Balsara, Chen, and Zheng (2007, 2009), Lento, Gradojevic, and Wright (2007), Lento (2009), Mühlhofer (2009), Butler and Kazakov (2010), Lento and Gradojevic (2011), and Abbey and Doukas (2012).

date US stock market data, Schwert (2003) comprehensively studies the persistence of a variety of anomalies on samples that start at the earliest in 1831 and end in 2001. The author finds that the size effect, the value effect, the weekend effect and the dividend yield effect seem to lose their predictive power after the papers that made them famous were published. In addition, Schwert finds that the small-firm turn-of-year effect and the predictive ability of variables such as dividend yield or inflation are much weaker. In another comprehensive study, Marguering, Nisser, and Valla (2006) use a sample from 1960 to 2003 to examine the persistence of several well-known stock market calendar anomalies on US stock market indices before and after their publication. The authors provide strong evidence that the weekend effect, the holiday effect, the time-of-the-month effect and the January effect disappeared after these anomalies were published. The turn-of-the-month effect still seems present and the smallfirm effect has recently resurrected. The anomalies have disappeared not only in the US market, but also in many international stock markets. In the UK stock market, Dimson and Marsh (1999) study the smallfirm effect and conclude that the size effect not only disappeared but even reversed since its publication during their sample from 1955 to 1998. Zhang and Jacobsen (2013) use over 300 years of monthly UK stock market data to examine the persistence of monthly seasonals and conclude that monthly seasonals are largely sample specific. Fountas and Segredakis (2002) conclude that the January effect has largely disappeared for 18 emerging markets from 1987 to 1995. Using a longer sample over more countries, Darrat, Li, Liu, and Su (2011) also suggest that the January effect persists in only three of the 34 international stock markets they examine from 1988 to 2010.⁸

Researchers point to the importance of data-snooping bias in explaining the disappeared anomalies. After taking into account possible data-snooping bias by using a bootstrap methodology, Sullivan, Timmermann, and White (2001) find that a number of anomalies no longer hold out of sample on 100 years of US stock market data from 1897 to 1996, including day of the week effects, week of the month effects, month of the year effects, turn of the month effects, turn of the year effects and holiday effects. Other studies reconsider the profitability of historically useful trading strategies by using fresh samples, suggested by Lakonishok and Smidt (1990) as the best remedy to safeguard against data snooping. For example, Fang, Jacobsen, and Qin (2013) find that classic technical indicators such as moving averages and trading range breakouts lose their predictive ability out of sample in the US market, not just in a

⁸ While studies such as those of Sullivan, Timmermann, and White (2001), Schwert (2003), Marquering, Nisser, and Valla (2006), and Zhang and Jacobsen (2013) provide in-depth overviews of the evidence of various return predictability anomalies, we only briefly describe the anomalies here. The January effect was first noticed by Rozeff and Kinney (1976) on the New York Stock Exchange from 1904 to 1974. It refers to the phenomenon of statistically significant differences in mean returns among months due primarily to large January returns. Lakonishok and Smidt (1988) document persistently anomalous returns around the turn of the week, the turn of the month, and the turn of the year and around holidays on the DJIA from 1896 to 1986. The size effect refers to small-capitalization firms earning higher average returns than those predicted by the capital asset pricing model, or CAPM (Banz 1981; Reinganum 1983). Keim (1983) and Reinganum (1983) show that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks in January. This anomaly became known as the small-firm turn of the year effect. The weekend effect was first documented by French (1980), who documents that the average return to the S&P composite portfolio is reliably negative over weekends in the period 1953–1977. Basu (1977, 1983) notes that firms with high earnings-to-price ratios earn positive abnormal returns relative to the CAPM, which is referred to as the value effect.

later period, from 1987 to 2012, but also in an earlier period, from 1885 to 1896. This indicates that the in-sample results are likely to be sample specific.

While data snooping remains a possible explanation for the disappeared anomalies, a competing explanation is investor overuse, which eliminates all trading opportunities of a true anomaly. This explanation is worth noting, especially if we consider anomalies that persist after accounting for data snooping. For example, Sullivan Timmermann, and White (1999) utilize a bootstrap methodology to validate the predictive ability of technical indicators, including moving averages and trading range breakouts, found by Brock, Lakonishok, and LeBaron (1992) on the DJIA from 1897 to 1986. While the authors find the positive in-sample results are robust to data-snooping bias, they fail to confirm the positive results out of sample on a 10-year fresh sample from 1987 to 1996. They suggest that one reason could be the markets having become more efficient, which eliminates such arbitrage opportunities. McLean and Pontiff (2014) study the out-of-sample predictability of 95 published characteristics that show to predict cross-sectional stock returns, and they find statistical biases seem to reduce the predictability by 25%, while investors' learning reduces the predictability by 31% after accounting for statistical biases.

Therefore, whether an anomaly persists or not can relate closely to its popularity among investors. Put differently, how fast investors learn about the strategies, whether investors use trading strategies based on the anomaly, and how many investors use the strategies matter. However that may not be the full story as some anomalies seem to persist. For example, a number of studies confirm the out of sample persistence of the Halloween indicator since it was first documented by Bouman and Jacobsen (2002) out of sample (for instance, Andrade, Chhaochharia, & Fuerst, 2012; Grimbacher, Swinkels, & van Vliet, 2010; Jacobsen and Visaltanachoti, 2009; Zhang and Jacobsen, 2014). The persistence may be because investors do not trade on these anomalies; alternatively, an anomaly may become a self-fulfilling prophecy (as opposed to a self-defeating prophecy), which is not likely to last long, or there may be institutional or psychological barriers in place that make the anomalies persist. For example, as Bouman and Jacobsen (2002) suggest, if the Halloween effect is caused by investors taking vacations during the summer, it may persist if that behavior does not change.

Previous studies document additional results that support the argument. Peyer and Vermaelen (2009) suggest the buyback anomaly persists in the US market in a fresh sample from 1991 to 2001 and suggest open market repurchases are a response to market overreactions to bad news. Since a repurchase is a unique event in the life of a company, individual shareholders cannot learn from their mistakes. Moreover, tender offers are too infrequent an event to attract professional arbitrageurs, which may well explain the persistence of this anomaly. As another example, Lev and Nissim (2004) show that the accrual anomaly persists in US stock returns from 1965 to 2002 and they suggest the main reason might be because firms with extreme accruals have characteristics that are unattractive to most institutional investors. Individual investors are unable to profit from trading on accruals information due to the high transaction and information costs associated with implementing a consistently profitable accruals strategy. In an international context, Pincus, Rajgopal, and Venkatachalam (2007) re-examine the accrual anomaly in 20 countries from 1994 to 2002 and find it persists in Canada, Australia, the United

Kingdom, and the United States. They also conclude that the anomaly is more likely to occur in countries with a common law tradition, that allow the extensive use of accrual accounting, or with a lower concentration of share ownership and these factors reveal earnings management and barriers to arbitrage. Baker, Bradley, and Wurgler (2010) show that the low volatility anomaly has even strengthened in the US market over the 41 years between 1968 and 2008 and this is due to investors' preference for risk and the typical institutional investor's mandate to maximize the ratio of excess returns and tracking error relative to a fixed benchmark without resorting to leverage. In addition, such activity discourages arbitrage activity in high-alpha, low-beta stocks and low-alpha, high-beta stocks.⁹

In our case of Bollinger Bands, although we cannot fully eliminate the possibility that the gradually decreasing profitability of Bollinger Bands is simply a result of data snooping, previous studies show that data-driven results are likely to change immediately out of sample (e.g., Fang, Jacobsen, & Qin 2013), instead of our finding of gradual elimination. Moreover, our results are best safeguarded against data snooping throughout several measures. First, we use the longest sample available for each country. Second, the Bollinger Bands themselves are less examined in the literature compared to classical technical indicators, such as moving averages and trading range breakouts; we also use the original default settings of the Bollinger Bands instead of searching for other trading strategies to fit the sample. Third, our sample is international and we include all countries for which we are able to obtain at least 10 years of daily data for each sub-sample.

3. Bollinger Bands

We discuss parameter settings and existing evidence of Bollinger Bands in more detail in this section. Bollinger Bands generally include three parameters, with the following default settings (Bollinger, 2001, p. 23):

- A middle band = 20-day moving averages of the underlying prices,
- An upper band = middle band + 2*standard deviations of the underlying prices, and
- A lower band = middle band 2*standard deviations of the underlying prices.

We write Bollinger Bands with the default settings as (20,2), where the first and the second numbers represent the number of days used to form the middle band and the number of standard deviations used to form the upper and lower bands, respectively. Bollinger (2001, p. 53) suggests that a window of

⁹ Bouman and Jacobsen (2002) document that returns from November to April are significantly higher than returns from May to October in 19 stock markets from 1970 to 1998. This is referred to as the Halloween effect or the sell in May effect. Ikenberry, Lakonishok, and Vermaelen (1995) investigate the stock price performance of firms that announced an open market share repurchase between 1980 and 1990 and they find average abnormal buy-and-hold returns of 12.1% over the four years following the announcement. This is referred to as the buyback anomaly. Sloan (1996) pioneered the documentation of the accruals anomaly. The author finds a negative association between accounting accruals (the non-cash component of earnings) and subsequent stock returns in a sample of US stocks from 1962 to 1991. Finally, the low volatility anomaly refers to high-volatility and high-beta stocks substantially underperforming low-volatility and low-beta stocks in US markets, as first noticed by Black (1972), Black, Jensen, and Scholes (1972), and Haugen and Heins (1975).

20 days capture reasonable intermediate-term price fluctuations and, in statistical terms, the ± 2 standard deviations should contain about 95% of the price variations. This means that the price falling outside the bands signals a potential market change. The basic application of Bollinger Bands, namely, the volatility breakout method, generates a buy (sell) signal when the underlying price closes outside the upper (lower) band: "Perhaps the most elegant direct application of Bollinger Bands is a volatility-breakout system" (Bollinger, 2001, p. 127).

Other than the breakout method, Bollinger (2001, p. 119) specifically recommends another method of using Bollinger Bands: the Squeeze: "The Squeeze ... is without doubt the most popular Bollinger Bands topic." This version of Bollinger Bands introduces another parameter, called the BandWidth (Bollinger, 2001, p. 63):

BandWidth = (Upper BB – Lower BB)/Middle BB

BandWidth shows how wide the Bollinger Bands are by depicting volatility as a function of its average. The intuition is that when the volatility falls to historical lows, the market is likely to experience a major change. The standard version of the Squeeze will generate a buy (sell) signal under two conditions: (1) The price breaks the upper (lower) band and (2) BandWidth drops to its six-month minimum. So, in fact, using BandWidth filters the signals of the volatility breakout method. In addition, Bollinger (2001, p. 24) also recommends several alternative parameter settings, such as (10, 1.9) and (50, 2.1), to capture relatively short- and long-term price variations.

We use an example from *Bollinger on Bollinger Bands* to illustrate. The black bar charts in the upper panel of the graph in Figure 4 plot the underlying stock prices and the gray lines plot the upper, middle, and lower Bollinger Bands of the prices. The lower panel of the graph plots the associated BandWidth readings. By using the volatility breakout method, trading signals will be generated at points A through D on the graph. Meanwhile, the Squeeze method only generates a signal at point B, when BandWidth reaches its six-month minimum (as highlighted in the circle in Figure 4).

[Please insert Figure 4 here]

Current academic evidence on Bollinger Bands is generally mixed. We provide a brief review here on current empirical evidence. Several papers document evidence on aggregate stock markets. Balsara, Chen, and Zheng (2009) find that using Bollinger Bands underperforms the market between 1990 and 2007 for three major US stock market indices (the DJIA, the NASDAQ, and the S&P 500), although significant positive returns are observed for a contrarian version of Bollinger Bands. Butler and Kazakov (2010), in contrast, claim positive results when using Bollinger Bands on the DJIA from 1990 to 2009. Instead of using the default parameter settings, the authors use a computer algorithm to optimize the parameters of Bollinger Bands. Leung and Chong (2003) find that the use of Bollinger Bands outperforms the use of moving average envelopes in the G7 and the four Asian Tiger countries from the period 1985 to 2000. The only authors who examine the profitability of Bollinger Bands on individual stocks, Balsara, Chen, and Zheng (2007) observe significant positive returns on buy trades generated by a contrarian version of Bollinger Bands from 1990 to 2005 in the Chinese stock market.

The use of Bollinger Bands is also examined in other financial markets. Lento, Gradojevic, and Wright (2007) and Lento and Gradojevic (2011) study the profitability of Bollinger Bands in several US and Canadian aggregate stock markets, as well as forex markets, for the period 1995 to 2004. They conclude that Bollinger Bands do not beat the market anywhere, although profitability may improve when for a contrarian version of Bollinger Bands or a combined signal approach with other technical indicators such as trading range breakouts, moving averages, or filter rules. Lento (2009) extends tests on Bollinger Bands to several Asian-Pacific stock and forex markets in various sample periods ranging from 1987 to 2005, including the countries Australia, India, Indonesia, Korea, Japan, Hong Kong, Singapore, and Taiwan. The author finds that the contrarian version of Bollinger Bands can generate profit in these countries. Additionally, in the forex market, Abbey and Doukas (2012) test the profitability of Bollinger Bands in individual currency trading and find that technical currency traders who use the Bollinger Bands underperform relative to their peers who do not use it. Lastly, in the real estate market, Mühlhofer (2009) applies Bollinger Bands on the US National Property Index from 1978 to 2010 and documents results that support their predictability.

4. Data and Methodology

Our study includes 14 major stock market indices from 13 countries: Australia, France, Germany, Hong Kong, Italy, Japan, Korea, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States. A number of seminal works find that technical trading strategies generate superior returns on the DJIA (e.g., Alexander 1961; Brock, Lakonishok, & LeBaron 1992) and that the S&P 500 proxies for the overall US stock market performance. Therefore we study both the DJIA and the S&P 500 for the United States. Our sample includes all countries that have daily stock market data available before 1973, allowing for at least 10 years for the first sub-sample. For each market we use the longest available daily data from the Global Financial Data¹⁰ database. The DJIA has the longest sample, starting in 1885, with Spain having the shortest sample, starting in 1971. All of our samples end in March 2014. This provides us sample periods ranging from 44 years to 130 years for the different markets. We study the predictive ability of Bollinger Bands for the full sample and three sub-samples: before 1983, from 1983 to 2001, and after 2002. We best avoid data-snooping bias in our results by using the longest samples and as many markets as we can. We follow the methodology of Brock, Lakonishok, and LeBaron (1992) and specifically test the following two null hypotheses:

H1: $R_{buy} - R_{sell} = 0$.

H2: R_{buy/sell} = R_m.

We run the following OLS regression for each country to test the null hypothesis H1 that the average returns conditional on Bollinger Bands buy and sell signals are equal. If the Bollinger Bands do not produce useful trading signals, the buy and sell signals should not generate statistically different returns. Therefore, β should not be statistically different from zero in the following regression:

¹⁰ See <u>www.globalfinancialdata.com</u>.

$$R_t = \alpha + \beta D_{t-1} + \varepsilon_t$$

where

- R_t represents the daily log-returns of a market index,
- D_{t-1} is a dummy variable that equals one (zero) when a buy (sell) signal is generated, and
- ε_t represents the residual term.

We further study the buy and sell signals separately by H2. We use *t*-tests to determine whether the average buy/sell returns are significantly different from the same period market returns. If Bollinger Bands produce useful trading signals, the conditional buy (sell) returns should be higher (lower) than the market returns. We use White standard errors to correct for the potential heteroskedasticity problem and a conservative 10% significance level.

5. Main Results

5.1 H1

We report our main results from using the Bollinger Bands default settings (20, 2) in Table 1. The first three columns report the market index and the sample period used for each country. We then report our results for the full sample and the three sub-sample periods. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, we report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively.

[Please Insert Table 1 here]

In the full sample, the breakout method generates a significantly positive R_{buy} - R_{sell} in all 14 stock markets and these returns are all significantly higher than the average market returns. The average return of the breakout method is 0.294% across the 14 countries, compared to the same period average market return of 0.026%. The results from the first sub-sample before 1983 indicate the even stronger predictive power of Bollinger Bands. Again, in all 14 markets, R_{buy} - R_{sell} is significantly positive, indicating that Bollinger Bands generate useful buy and sell signals. The average R_{buy} - R_{sell} across the 14 markets (0.454%) is higher than the average market return (0.021%); it is also higher than the full-sample average R_{buy} - R_{sell} (0.294%), indicating stronger predictive power in the first sub-sample than in the full sample.

Bollinger Bands seem to initially show strong predictive power, but the power starts decreasing after 1983. From 1983 to 2001, investors start hearing about Bollinger Bands and begin putting them into practice, although the seminal book *Bollinger on Bollinger Bands* was not yet published. While remaining profitable in most markets (11 out of 14), Bollinger Bands no longer produced significant positive R_{buy}-R_{sell} in Japan or the United States. It is worth noting that Bollinger Bands' profitability disappears instantly in the two major US stock markets (the S&P 500 and the DJIA) since 1983, when Bollinger

Bands were first introduced. Moreover, the predictive power of Bollinger Bands drops more dramatically after 2001, with its increasing fame from *Bollinger on Bollinger Bands*. R_{buy} - R_{sell} is only significantly positive in Italy and New Zealand but not the other 12 markets. Moreover, R_{buy} - R_{sell} is even significantly negative in the French stock market and in the S&P 500 market. During the last sub-sample period, the average R_{buy} - R_{sell} drops dramatically to 0.002%, compared to 0.454% before the introduction of Bollinger Bands in 1983 and 0.296% before the publication of *Bollinger on Bollinger Bands*.

The gradually decreasing predictive power is consistent with the use of the Squeeze method. The Squeeze method generates significant positive returns in nine markets in both the full sample and the first sub-sample before 1983, the number of markets reducing to seven after 1983 and falling to only one after 2001. Nevertheless, it may be interesting to note that the Squeeze method does not seem to beat the volatility breakout method in terms of the number of international markets in which it shows predictive ability, although it is stated to be "the best method" by Bollinger (2001, p. 119).

5.2 H2

More explicitly, the buy or sell signals may possibly still work well separately, on their own. We then test H2 and present the results for the breakout method and Squeeze method in Tables 2 and 3, respectively. The two tables have the same layouts. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference.

[Please Insert Table 2&3 here]

Table 2 shows that, generally, the Bollinger Band breakout method generates more buy signals than sell signals, which is consistent with the overall uptrend of the stock markets. Moreover, the buy (sell) signals produce significant positive (negative) returns that are significantly higher (lower) than the market returns in 12 markets in the full sample and in the first sub-sample. This result indicates that using buy signals or sell signals alone generates superior returns before 1983. However, since 1983, using buy signals or sell signals only seems to show decreased profitability. During 1983 to 2001, the buy signals generate higher returns than the markets in only 10 markets and the sell signals generate lower returns than the markets. Like the results of testing H1, since 2002, both buy and sell signals generate useful signals only in Italy and New Zealand markets and the sell signals alone even generate significantly higher returns than the market in the S&P 500.

The results for the Squeeze method in Table 3 are similar. Note that the Squeeze method produces much fewer signals then the breakout method due to the precondition set by BandWidth. To illustrate, the breakout method produces 3579 buy signals and 2985 sell signals on the DJIA across the full sample

from 1885 to 2014, which results in an annual average of 51.69 signals. In contrast, the Squeeze method produces only 99 buy signals and 81 sell signals during the same period, that is, 1.42 signals per year. Due to this limited number of trading signals, even during periods when Bollinger Bands have predictive power, the breakout method performs better than the Squeeze method, although the Squeeze method is stated as the best approach in *Bollinger on Bollinger Bands*.

Therefore, our evidence from buy or sell signals alone is consistent with those from H1. Bollinger Bands indeed generate useful signals before 1983, but not afterward. Performance worsens over time. Bollinger Bands first lose their predictive ability in the United States, immediately after 1983, and then in other countries. Bollinger Bands generally show very limited predictive power since 2002.

5.3 Rolling Window Regressions

To check the stability of our results and to more closely monitor what happens to predictability over time, we conduct rolling window regressions for the above OLS estimation of H1 for the Bollinger Band breakout method.¹¹ The rolling samples are 10 years long and roll ahead one month each time. We perform the task for each of our sample markets and plot the results in Figure 5.

[Please Insert Figure 5 here]

The solid black lines plot the average $R_{buy} - R_{sell}$ over time, and the black dotted lines plots the 90% confidence bounds. The plots uncover a clearly decreasing profitability in most of the sample markets, including the Australian, German, French, Hong Kong, New Zealand, Singapore, Swiss, UK, and US stock markets. Note that, in Table 1, although the Bollinger Bands still generate positive returns in New Zealand since 2002, profitability also shows a significant downward trend. In countries such as Germany, Hong Kong, Japan, Korea, and Switzerland, the problem of widening confidence bounds—especially in the later stage of the sample periods—can also lead to unstable indications over time. Nevertheless, Italy seems to be the exception for which Bollinger Bands provide useful indications throughout.

Furthermore, when does predictability start turning downward? Before 1983, Bollinger Bands provided reasonably stable predictability in all 14 countries. Given that our sample of the DJIA starts earliest (in 1885), with the exception of a short period during the 1930s, Bollinger Bands consistently deliver positive returns for nearly 100 years until 1983. After the Bollinger Bands go public in 1983, however, their predictability on the DJIA drops significantly and it starts dropping on the S&P 500 after the late 1980s. After this, we gradually start to observe downward predictability in Australia, Germany, France, Hong Kong, Spain, and the United Kingdom. In contrast, predictability in Italy, Korea, Japan, New Zealand, Singapore, and Switzerland remains relatively stable until 2001. Since 2002, however, the predictability of Bollinger Bands' has decreased in nearly all markets. Moreover, during this period, Bollinger Bands' returns have changed from positive to negative, first around 1997 for the S&P 500 and the Japanese stock market and then gradually for the stock markets of Australia, Germany, France, Hong

¹¹ Due to the limited number of trading signals, we do not present the results for the Squeeze method.

Kong, Switzerland, Spain, and the United Kingdom through March 2014. The decreasing predictability through time closely matches the rising publicity of the Bollinger Bands.

5.4 Economic Significance

Previous evidence suggests that the predictability of some technical indicators can disappear after accounting for transaction costs (e.g., Bessembinder & Chan 1995; Bajgrowicz & Scaillet 2012). In addition, does the changing risk affect our results? To account for these issues, we evaluate the economic significance of our results by including 1% in transaction costs when switching between riskfree assets¹² and the market. We therefore go long on Bollinger Bands' buy signals and short on their sell signals and we invest in risk-free assets when there is no signal. As examined in the introduction, we first extend our analysis on the gross annual returns of the above strategy to all our sample countries. We plot the results in Figure 6. The graphs show significantly decreasing returns over time in nearly all markets, with Italy being the only exception. Indeed, the strategy generated superior annual returns as high as 90.01% in the Singapore market in 1987; examples of significant returns also include 64.29% in the Korean market in 1962 and around 50% in the Italian market in 1981, in New Zealand market in 1987, in the Spanish market in 1986, and in the UK market in 1975. In all markets, the strategy generally delivered positive returns before 1983 but, even then, the returns largely turned negative after 2001 in all markets: immediately in the US market in 1983; soon after in the Japanese market, around 1990; then in a number of European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets.

[Please Insert Figure 6 here]

We then take into account transaction costs and risk and Table 4 reports our results. For each market, we first report the Sharpe ratios of the buy-and-hold strategy and of the standard Bollinger Band (20, 2) strategy. Then we report the t-statistics testing the null hypothesis that the two Sharpe ratios (in parentheses) equal the Sharpe ratios of the Bollinger Bands.¹³ In addition we calculate Jensen's α for the Bollinger Band strategy, with the t-statistics in parentheses testing their difference from zero.¹⁴ Panels A and B report our results for the breakout method and the Squeeze method, respectively.

¹² We use the following risk-free rates for our analysis; three-month Treasury bill rates for Australia, France, Germany, Italy, Japan, New Zealand, Singapore, Spain, Switzerland, the United Kingdom, and the United States. In some countries, when the three-month Treasury bill rates are not available, we use the following; Hong Kong's three-month interbank rates, Japan's seven-year government bond yield, Korea's 12-month Treasury bill rates, Korea's three-year government bond yield, New Zealand's six-month Treasury bill rates, Singapore's three-month interbank rates, the Bank of Spain's discount rate, Switzerland's three-month deposit rates, and the US central bank discount rate. We obtain all risk-free rates from the Global Financial Data database.

¹³ The significance test on the Sharpe ratios is performed according to the methodology proposed by Lo (2002) and de Roon, Eiling, Gerard, and Hillion (2012).

¹⁴ We run the following regression to calculate Jensen's alpha: $r_{BB} - r_f = \alpha + \beta (r_m - r_f) + \varepsilon_t$, where r_{BB} represents the returns from using Bollinger Bands, r_f represents the risk-free rates, and r_m represents the market returns.

[Please Insert Table 4 here]

Our results remain similar, considering their economic significance. For the breakout method, in the full sample, the Bollinger Bands generate significantly higher Sharpe ratios than in five markets. Before 1983, Bollinger Bands generated higher Sharpe Ratios in 10 markets; from 1983 to 2001, the number of markets drops to two, and in the last sub-sample, from 2002 on, only in one market (Italy) do Bollinger Bands still beat the market. The results from Jensen's α criteria are similar: Bollinger Bands produce significant positive α values in seven countries in the full sample. The number of markets (11) is highest in the sub-sample before 1983; then it reduces to seven after 1983 and further drops to one (Italy) after 2002. Our results do not seem to change after accounting for risk and transaction costs, with Bollinger Band predictability gradually ceasing to exist with increasing public attention. Intriguingly, however, the Squeeze method seems to lose most of its predictability after accounting for risk and transaction costs, largely due to the limited signals it generates, which results in investing in risk-free assets most of the time.

6. Decline in Profitability

Our sub-sample analysis above indicates apparent declines in Bollinger bands' profitability over time with their increasing popularity. In this section, we apply more formal statistical tests to directly compare the profitability across different sub-samples. Such tests tell us the sizes of declines and their statistical significance. We follow the methodology used by McLean and Pontiff (2014) and run the following regression to test the profitability of the same Bollinger Bands-based strategy above:

$$R_{BB} = \alpha + \beta_s D_s + \beta_p D_p + \varepsilon_t \tag{2}$$

where

- R_{BB} represents the daily returns of the Bollinger Bands–based trading strategy,
- D_s is a dummy variable that equals one (zero) when the trading day is within the period 1983 2001, and
- D_P is a dummy variable that equals one (zero) when the trading day is within the period 2002 2014, and
- ε_t represents the residual term.

Bollinger Bands show strong profitability before 1983, we then refer to this period as the in-sample period, and we refer the periods 1983-2001 and 2002-2014 as the post-sample (but before publication) and post-publication periods to match the key dates of Bollinger Bands, denoted by D_s and D_p respectively. Therefore, if the introduction in 1983 and the publication in 2001 reduce the profitability, β_s and β_p should be significantly negative and their magnitudes capture the sizes of the declines. Moreover, we use *f*-test to test the difference between D_s and D_p . This further sheds lights on two issues. First, our analysis above show that the profitability decreases during 1983-2001 but disappears in most countries since 2002, therefore we expect the 2001 publication has a greater impact than the 1983

introduction, that is, D_p should be statistically smaller than D_s . Second, as discussed in Section 2, if the out-of-sample decline in profitability is due to statistical biases but not the popularity of a trading strategy, we expect D_s and D_p to be statistically equal.

We present our results in Table 5. We first report our sample countries, and then the coefficient estimates with corresponding t-stats for D_s and D_p respectively in the next four columns. In column 5, we report our f-test results testing the null hypothesis $D_s = D_{p.}$ Next, we report the average daily returns of the Bollinger Bands-based trading strategy R_{BB} , followed by the percentage post-sample and post-publication declines in profitability calculated from D_s/R_{BB} and D_p/R_{BB} respectively. Lastly, we report the differences between the post-sample and post-publication declines.

[Please Insert Table 5 here]

The results add further strength to our previous findings. In seven markets, D_s are statistically negative, indicating the significant drops in profitability since the 1983 introduction. The average decline is -56% across all markets and the Japanese market experiences the greatest decline of -138%. Next, D_p are significantly negative in all 14 markets expect only Italy, indicating the impact of the 2001 publication. And the declines from this period are all significantly greater than those from the 1983 introduction, even for Italy – this means that even while the strategy still shows some profitability in Italy (as shown in Table 1), its profitability is decreasing too. The average post-publication decline reaches -156% and the greatest decline of -238% happens in the French market. The average difference in declines from the two periods of -100% highlights the impact the publication may have- although the profitability drops since the introduction of the strategy, the publication seems to plays an important role that may have lead investors to fully arbitrage any trading opportunity away. We also pool results from all countries together and run the same regression as above. The results are similar, even with different estimation methods of standard errors including country fixed-effects, country clustering and standard OLS. These results are available upon request.

7. Robustness Checks

7.1 Alternative Parameter Settings (10, 1.9) and (50, 2.1)

Bollinger (2001, p. 24) suggests that the default version of Bollinger Bands (20, 2) aims to capture intermediate-term trends, while the alternative versions (10, 1.9) and (50, 2.1) work better for relatively short- and long-terms, respectively. That is, we use 10-day (50-day) moving averages of closing prices as the middle band and the upper and lower bands are 1.9 (2.1) standard deviations from the middle band for short-term (long-term) investing. The shorter (longer) underlying period of the middle band, with tighter (wider) BandWidth, captures smaller (greater) price fluctuations. We test the predictability of these two versions of Bollinger Bands, for both the breakout and Squeeze methods. We present our results for Bollinger Bands (10, 1.9) in Tables 5 and 6, and those for Bollinger Bands (50, 2.1) in Tables 7 and 8.

[Please Insert Table 6 to Table 9 here]

The tables have same layouts as in Tables 2 and 3 and the results remain more or less the same. As expected, the short-term version (10, 1.9) produces more trading signals than the default version (20, 2), while the long-term version (50, 2.1) produces many fewer trading signals. For example, for the breakout method, the default version (20, 2) generates 51.69 signals annually, on average, the short-term version (10, 1.9) generates 64.65 signals per year, and the long-term version generates 39.20 signals per year on the full sample of the DJIA. Using the breakout method, both the alternative versions of Bollinger Bands generate (marginally) significant positive R_{buy} - R_{sell} before 1983 in all 14 markets. Then, from 1983 to 2001, R_{buy} - R_{sell} becomes insignificant in three markets for the short-term version (10, 1.9) and in seven markets for the long-term version (50, 2.1). Last, R_{buy} - R_{sell} becomes insignificant in 12 and 13 markets for the short- and long-term Bollinger Band versions, respectively, after 2002. The decreasing predictability also holds if we use the buy or sell signals alone. While the problem of the limited number of trading signals may mask the trend to some degree, especially for the long-term version (50, 2.1), we generally observe a similar decreasing trend when using the Squeeze method.

7.2 Alternative BandWidth Settings

For the Squeeze method, we set the precondition on BandWidth to a six-month minimum by default, which may be too strict. We then repeat our analysis using three alternative BandWidth settings. The first alternative BandWidth setting triggers a trading signal when BandWidth reaches its six-month low, instead of a six-month minimum, where BandWidth is defined as a six-month low when it falls in the bottom 10% of its distribution. The second and third alternative settings set the BandWidth to three-month and 12-month minima to capture relatively short- and long-term low values of BandWidth. We present our results in Table 9.

[Please Insert Table 10 here]

Table 9 has the same layout as Table 1. Generally, our results remain similar: The Squeeze method shows decreasing predictability across time in its alternative versions, although the trend is weaker when BandWidth is defined as its 12-month minimum. In this case, more price fluctuations are smoothed out, which leads to an even lower number of trading signals than for the default version, which can mask the underlying trend.

7.3 Other Robustness Checks

Alternatively, we use the GARCH(1, 1) model to further check our results for potential heteroskedasticity problems, as well as the robust regression for possible outliers, and we again find similar results. Our results are also robust to the 2008 global financial crisis if we exclude sample periods since 2008. We present these robustness check results in Tables 10 to 12, respectively. Our results also remain the same if we consider economic significance without transaction costs, if we consider a 10-day holding period after a trading signal is generated, or if we use the Wald test instead of the t-test. Also, we construct a

time variable that equals 1/100 in the first trading day and increases by 1/100 in each consecutive day in our sample, and we regress the time variable against returns of the Bollinger Bands-based strategy for each country, the estimates are all significantly negative confirming the significant downward profitability over time. To save space, these results are available upon request.

[Please Insert Table 11, 12&13 here]

8. Conclusion

Bollinger Bands have received growing attention since the introduction in 1983 in the United States and, in particular, since publication of the book *Bollinger on Bollinger Bands* in 2001. Associated with this growing popularity, we discover the gradual downward profitability of using Bollinger Bands in international stock markets. Using Bollinger Bands indeed generates superior returns before 1983, whereas the returns turn negative in the United States immediately after 1983 and in the Japanese market around 1990; then in European stock markets, including the UK, Swiss, French, and German stock markets; and, lastly, in Asian-Pacific stock markets, including the Australian, Korean, and Hong Kong markets. Since 2002, Bollinger Bands have largely lost their predictive ability in major stock markets. Our results indicate the impact of investor overuse on the profitability of a useful trading strategy and warn of the danger of investing in many so-called return predictability anomalies.

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Table 1: International Results on Bollinger Bands (20, 2)

This table reports the international results on the predictability of Bollinger bands (20, 2). The first three columns report the market index and the sample period used for each country. We then report our results for the full sample and the three sub-sample periods. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, we report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. We use a 10% significance level and White standard error corrected t-statistics.

				Full Sample			Before 1983			1983-2001			Since 2002	
Country	Index	Period	R _m (*10 ⁻³)	R _{buy} -R _{sell} (*10 ⁻³)	t-stats	R _m (*10 ⁻³)	R _{buy} -R _{sell} (*10	⁻³) t-stats	R _m (*10 ⁻³)	R _{buy} -R _{sell} (*10) ⁻³) t-stats	R _m (*10 ⁻³)	R _{buy} -R _{sell} (*10	⁻³) t-stats
				Panel A: Breako	ut Metho	od (20,2)								
Australia	ASX All-Ordinaries	Jan 1958 - Mar 2014	0.26	3.48	7.36	0.21	5.04	9.95	0.40	3.25	3.03	0.15	0.03	0.02
France	CAC All-Tradable Index	Sep 1968 - Mar 2014	0.27	1.90	3.22	0.11	4.11	5.67	0.53	2.39	2.54	0.04	-2.46	-1.65
Germany	CDAX Composite Index	Jan 1970 - Mar 2014	0.18	2.74	5.08	0.00	4.25	9.16	0.34	3.43	3.91	0.12	-0.50	-0.34
Hong Kong	Hang Seng Composite Index	Nov 1969 - Mar 2014	0.45	4.33	3.65	0.50	8.17	3.69	0.57	4.18	2.04	0.21	-0.07	-0.04
Italy	Banca Commerciale Italiana Index	Dec 1956 - Mar 2014	0.19	3.96	7.14	0.12	3.70	4.51	0.45	4.19	4.17	-0.07	3.86	3.53
Japan	Nikkei 225 Stock Average	May 1949 - Mar 2014	0.25	1.57	2.97	0.39	2.50	4.05	0.06	-0.31	-0.30	0.10	1.55	0.95
Korea	Korea SE Stock Price Index	Jan 1962 - Mar 2014	0.44	2.65	3.05	0.62	3.41	2.24	0.31	2.02	1.78	0.34	1.40	0.92
New Zealand	New Zealand SE All-Share Capital Index	Jan 1970 - Mar 2014	0.20	3.91	8.03	0.18	4.65	9.75	0.26	4.72	4.74	0.12	1.77	2.30
Singapore	Singapore FTSE Straits-Times Index	Jul 1965 - Mar 2014	0.33	5.79	8.08	0.53	7.03	7.94	0.22	7.19	5.09	0.21	0.92	0.77
Spain	Madrid SE General Index	Aug 1971 - Mar 2014	0.26	4.30	6.48	-0.26	8.25	9.96	0.63	4.78	4.64	0.07	-0.23	-0.16
Switzerland	Switzerland Price Index	Jan 1969 - Mar 2014	0.19	2.01	3.71	-0.02	3.60	5.17	0.40	2.04	2.12	0.10	-0.49	-0.41
UK	FTSE All-Share Index	Dec 1968 - Mar 2014	0.27	2.19	3.75	0.24	5.31	4.81	0.39	2.09	2.63	0.11	-1.66	-1.34
US	S&P 500 Composite Price Index	Jan 1928 - Mar 2014	0.20	1.14	2.54	0.14	1.95	3.74	0.44	0.46	0.40	0.16	-2.28	-1.69
US	Dow Jones Industrials Average	Jan 1885 - Mar 2014	0.18	1.22	3.78	0.13	1.57	4.56	0.47	0.99	0.76	0.16	-1.57	-1.34
Average			0.26	2.94		0.21	4.5	4	0.39	2.9	96	0.13	0.0	2
				<u>Panel B: Squeez</u>	e Metho	<u>d (20,2)</u>						-		
Australia	ASX All-Ordinaries	Jan 1958 - Mar 2014	0.26	3.08	2.32	0.21	4.95	2.57	0.40	3.02	1.07	0.15	-0.16	-0.06
France	CAC All-Tradable Index	Sep 1968 - Mar 2014	0.27	0.65	0.25	0.11	2.90	0.84	0.53	0.06	0.01	0.04	-1.58	-0.33
Germany	CDAX Composite Index	Jan 1970 - Mar 2014	0.18	4.58	1.79	0.00	4.32	2.43	0.34	13.01	3.00	0.12	-3.88	-0.89
Hong Kong	Hang Seng Composite Index	Nov 1969 - Mar 2014	0.45	1.87	0.42	0.50	12.71	1.71	0.57	-6.17	-1.09	0.21	-6.31	-0.89
Italy	Banca Commerciale Italiana Index	Dec 1956 - Mar 2014	0.19	6.55	3.36	0.12	6.10	2.37	0.45	7.45	2.29	-0.07	4.98	1.01
Japan	Nikkei 225 Stock Average	May 1949 - Mar 2014	0.25	4.96	2.55	0.39	6.75	2.95	0.06	-6.02	-1.40	0.10	11.48	3.32
Korea	Korea SE Stock Price Index	Jan 1962 - Mar 2014	0.44	13.52	1.13	0.62	14.41	0.70	0.31	16.56	2.49	0.34	-0.08	-0.02
New Zealand	New Zealand SE All-Share Capital Index	Jan 1970 - Mar 2014	0.20	3.33	1.41	0.18	5.31	1.55	0.26	5.17	1.04	0.12	-8.10	-9.14
Singapore	Singapore FTSE Straits-Times Index	Jul 1965 - Mar 2014	0.33	5.44	2.39	0.53	1.47	0.48	0.22	9.80	2.40	0.21	3.21	0.89
Spain	Madrid SE General Index	Aug 1971 - Mar 2014	0.26	6.92	2.90	-0.26	7.75	2.57	0.63	9.84	2.51	0.07	-0.72	-0.17
Switzerland	Switzerland Price Index	Jan 1969 - Mar 2014	0.19	3.71	1.92	-0.02	5.86	4.03	0.40	8.39	3.74	0.10	-2.39	-0.63
UK	FTSE All-Share Index	Dec 1968 - Mar 2014	0.27	4.08	2.22	0.24	3.90	0.87	0.39	5.84	2.07	0.11	1.40	0.63
US	S&P 500 Composite Price Index	Jan 1928 - Mar 2014	0.20	1.91	1.43	0.14	3.50	2.21	0.44	-0.35	-0.20	0.16	-2.47	-0.57
US	Dow Jones Industrials Average	Jan 1885 - Mar 2014	0.18	2.94	2.68	0.13	4.54	3.45	0.47	-1.17	-0.50	0.16	-5.61	-4.25
Average			0.26	4.54		0.21	6.0	3	0.39	4.6	57	0.13	-0.7	3

This table reports the international results on Bollinger bands (20, 2) breakout method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³	³) t-stats	N(sell) F	R _{sell} (*10 ⁻³) t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
	-			Full Samp	le (20,2)			-	
Australia	0.26	1610	1.98	7.30	1168	-1.50	-6.44	3.48	7.36
France	0.27	1191	1.30	2.96	900	-0.60	-2.18	1.90	3.22
Germany	0.18	1211	1.37	3.70	920	-1.37	-4.26	2.74	5.08
Hong Kong	0.45	1301	2.75	4.22	812	-1.57	-2.97	4.33	3.65
Italy	0.19	1541	3.14	8.86	1259	-0.82	-2.78	3.96	7.14
Japan	0.25	1844	1.65	4.89	1362	0.08	-0.51	1.57	2.97
Korea	0.44	1633	3.32	5.60	1142	0.67	0.38	2.65	3.05
New Zealand	0.20	1307	2.45	9.26	903	-1.46	-5.77	3.91	8.03
Singapore	0.33	1457	3.15	8.16	1025	-2.64	-7.32	5.79	8.08
Spain Sucitor and	0.26	1066	2.49	5.66	875	-1.81	-4.80	4.30	6.48
Switzerland UK	0.19	1116	1.09	2.96	937	-0.92	-3.33	2.01 2.19	3.71
	0.27	1154	1.05	2.35	951	-1.15	-3.92	-	3.75
S&P 500	0.20	2203 3579	0.78 0.99	2.24 4.35	1804 2985	-0.36 -0.23	-2.00 -2.04	1.14	2.54 3.78
DJIA	0.18	3579		4.35 Before 198		-0.25	-2.04	1.22	5.76
Australia	0.21	756	2.72	8.67	566	-2.32	-7.64	5.04	9.95
France	0.21	365	2.07	3.80	330	-2.04	-4.00	4.11	5.67
Germany	0.00	347	2.07	6.38	322	-2.19	-6.57	4.25	9.16
Hong Kong	0.50	444	4.08	3.26	247	-4.10	-3.20	8.17	3.69
Italy	0.12	698	3.33	6.56	580	-0.37	-0.93	3.70	4.51
Japan	0.39	1066	2.18	5.97	726	-0.32	-2.02	2.50	4.05
Korea	0.62	779	4.55	4.27	420	1.15	0.43	3.41	2.24
New Zealand	0.18	381	2.61	7.90	297	-2.04	-6.44	4.65	9.75
Singapore	0.53	673	4.12	8.41	351	-2.91	-6.00	7.03	7.94
Spain	-0.26	241	3.90	7.25	249	-4.35	-7.20	8.25	9.96
Switzerland	-0.02	327	1.67	3.67	337	-1.93	-4.20	3.60	5.17
UK	0.24	350	2.39	3.31	333	-2.93	-4.76	5.31	4.81
S&P 500	0.14	1463	1.07	2.93	1257	-0.88	-2.99	1.95	3.74
DJIA	0.13	2770	1.22	5.21	2450	-0.35	-2.21	1.57	4.56
			<u>1</u>	.983 - 200)1 (20, 2)			_	
Australia	0.40	546	2.01	3.61	374	-1.24	-3.11	3.25	3.03
France	0.53	574	1.96	2.99	329	-0.43	-1.57	2.39	2.54
Germany	0.34	590	1.76	3.21	354	-1.67	-3.60	3.43	3.91
Hong Kong	0.57	575	2.61	2.50	327	-1.57	-2.02	4.18	2.04
Italy	0.45	548	3.70	5.56	395	-0.49	-1.39	4.19	4.17
Japan	0.06	489	0.86	1.28	395	1.17	1.61	-0.31	-0.30
Korea	0.31	580	2.94	3.77	501	0.92	0.82	2.02	1.78
New Zealand	0.26	560	3.36	6.61	376	-1.36	-2.89	4.72	4.74
Singapore	0.22	478	3.33	4.41	425	-3.86	-5.48	7.19	5.09
Spain	0.63	565	2.81	4.13	352	-1.97	-3.98	4.78	4.64
Switzerland	0.40	553	1.44	2.42	337	-0.60	-1.84	2.04	2.12
	0.39	532	0.95	1.38	363	-1.14	-3.15	2.09	2.63
S&P 500	0.44	491 528	0.65	0.42 0.02	304 288	0.19	-0.41	0.46	0.40
DJIA	0.47	320	0.48	Since 200.	a (aa a)	-0.51	-1.52	0.99	0.76
Australia	0.15	308	0.14	-0.02	228	0.11	-0.06	0.03	0.02
France	0.04	252	-1.31	-1.45	241	1.14	1.17	-2.46	-1.65
Germany	0.12	274	-0.36	-0.51	244	0.14	0.03	-0.50	-0.34
Hong Kong	0.21	282	0.97	0.80	238	1.04	0.81	-0.07	-0.04
Italy	-0.07	295	1.65	2.39	284	-2.21	-2.92	3.86	3.53
Japan	0.10	289	1.07	1.01	241	-0.48	-0.55	1.55	0.95
Korea	0.34	274	0.61	0.29	221	-0.79	-1.08	1.40	0.92
New Zealand		366	0.90	2.11	230	-0.88	-2.18	1.77	2.30
Singapore	0.21	306	0.73	0.75	249	-0.19	-0.51	0.92	0.77
Spain	0.07	260	0.47	0.41	274	0.69	0.67	-0.23	-0.16
Switzerland	0.10	236	-0.52	-0.78	263	-0.03	-0.18	-0.49	-0.41
UK	0.11	272	-0.50	-0.80	255	1.16	1.33	-1.66	-1.34
S&P 500	0.16	249	-0.64	-0.93	243	1.64	1.71	-2.28	-1.69
DJIA	0.16	281	-0.28	-0.58	247	1.29	1.42	-1.57	-1.34

This table reports the international results on Bollinger bands (20, 2) Squeeze method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³) t-stats	N(sell) R	R _{sell} (*10 ⁻³) t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
	_		H	ull Samp	le (20,2)				
Australia	0.26	33	2.16	1.21	24	-0.92	-0.65	3.08	2.32
France	0.27	27	1.83	0.71	17	1.18	0.33	0.65	0.25
Germany	0.18	36	0.51	0.19	19	-4.07	-1.74	4.58	1.79
Hong Kong	0.45	28	5.37	1.39	18	3.50	0.69	1.87	0.42
Italy	0.19	39	4.59	2.21	26	-1.96	-0.89	6.55	3.36
Japan	0.25	38	1.69	0.76	31	-3.27	-1.67	4.96	2.55
Korea	0.44	37	12.23	3.64	34	-1.29	-0.51	13.52	1.13
New Zealand	0.20	23	1.82	0.94	24	-1.51	-1.00	3.33	1.41
Singapore	0.33	29	4.43	1.76	32	-1.01	-0.61	5.44	2.39
Spain	0.26	22	5.74	2.10	20	-1.18	-0.53	6.92	2.90
Switzerland	0.19	19	3.59	1.52	27	-0.11	-0.16	3.71	1.92
UK	0.27	34	1.78	0.83	26	-2.30	-1.22	4.08	2.22
S&P 500	0.20	62 99	1.66 2.64	0.99 2.29	49 81	-0.25	-0.28 -0.41	1.91 2.94	1.43 2.68
DJIA	0.18	99		2.29 efore 198	81 3 (20, 2)	-0.30	-0.41	2.94	2.00
Australia	0.21	16	4.18	2.11	7	-0.76	-0.34	4.95	2.57
France	0.11	7	0.70	0.17	6	-2.20	-0.60	2.90	0.84
Germany	0.00	9	-1.52	-0.80	5	-5.84	-2.28	4.32	2.43
Hong Kong	0.50	10	5.72	0.76	7	-6.99	-0.91	12.71	1.71
Italy	0.12	20	5.07	1.80	11	-1.03	-0.31	6.10	2.37
Japan	0.39	27	2.40	1.13	20	-4.35	-2.29	6.75	2.95
Korea	0.62	21	18.47	3.37	16	4.06	0.57	14.41	0.70
New Zealand	0.18	5	-0.23	-0.16	7	-5.54	-2.66	5.31	1.55
Singapore	0.53	11	3.01	0.79	10	1.53	0.31	1.47	0.48
Spain	-0.26	6	3.53	1.10	7	-4.22	-1.23	7.75	2.57
Switzerland	-0.02	4	4.73	1.19	14	-1.14	-0.52	5.86	4.03
UK	0.24	7	0.98	0.17	6	-2.93	-0.67	3.90	0.87
S&P 500	0.14	37	2.65	1.32	37	-0.85	-0.52	3.50	2.21
DJIA	0.13	68	3.43	2.60	67	-1.11	-0.97	4.54	3.45
				983 - 200					
Australia	0.40	8	2.22	0.52	11	-0.80	-0.41	3.02	1.07
France	0.53	9	2.99	0.68	7	2.93	0.59	0.06	0.01
Germany	0.34	11	5.32	1.62	8	-7.69	-2.23	13.01	3.00
Hong Kong	0.57	12	7.15	1.23	5	13.32	1.54	-6.17	-1.09
Italy	0.45	13	5.85	1.50	10	-1.60	-0.50	7.45	2.29
Japan	0.06	7	-2.85	-0.58	6	3.18	0.58	-6.02	-1.40
Korea	0.31	7 5	7.70	1.22	13	-8.86	-2.07	16.56	2.49
New Zealand	0.26		4.03	0.80	15	-1.14	-0.52	5.17	1.04
Singapore	0.22	13	6.33 9.20	1.50 2.28	12 9	-3.46	-0.87	9.80	2.40
Spain Switzerland	0.63 0.40	10 6	9.20 6.00	2.20 1.43	6	-0.64 -2.38	-0.32 -0.71	9.84 8.39	2.51 3.74
UK	0.40	15	1.57	0.51	12	-2.56 -4.27	-0.71 -1.81	5.84	2.07
S&P 500	0.39	13	0.47	0.01	6	0.83	0.09	-0.35	-0.20
DJIA	0.44	15	0.47	0.01	9	1.73	0.35	-1.17	-0.20
Alfa	0.47	15		Since 200.	- (1.75	0.55	1.17	0.50
Australia	0.15	9	-1.50	-0.49	6	-1.34	-0.36	-0.16	-0.06
France	0.04	11	1.60	0.36	4	3.18	0.44	-1.58	-0.33
Germany	0.12	16	-1.64	-0.48	6	2.23	0.35	-3.88	-0.89
, Hong Kong	0.21	6	1.24	0.17	6	7.55	1.18	-6.31	-0.89
Italy	-0.07	6	0.24	0.06	5	-4.74	-0.88	4.98	1.01
Japan	0.10	4	4.82	0.60	5	-6.67	-0.97	11.48	3.32
Korea	0.34	9	1.19	0.17	5	1.27	0.14	-0.08	-0.02
New Zealand	0.12	13	1.77	0.89	2	9.86	2.07	-8.10	-9.14
Singapore	0.21	5	2.60	0.46	10	-0.61	-0.22	3.21	0.89
Spain	0.07	6	2.18	0.35	4	2.91	0.38	-0.72	-0.17
Switzerland	0.10	9	1.48	0.35	7	3.87	0.85	-2.39	-0.63
UK	0.11	12	2.52	0.69	8	1.12	0.24	1.40	0.63
S&P 500	0.16	12	-0.13	-0.08	6	2.35	0.41	-2.47	-0.57
DJIA	0.16	16	1.22	0.35	5	6.83	1.24	-5.61	-4.25

Table 4: Economic Significance Tests of Bollinger Bands (20, 2)

This table reports results on the economic significance tests of Bollinger bands (20, 2) for the full and the three subsamples. For each market, we first report the Sharpe ratios of the buy-and-hold strategy and of the standard Bollinger Band (20, 2) strategy. Then we report the t-statistics testing the null hypothesis that the two Sharpe ratios (in parentheses) equal the Sharpe ratios of the Bollinger Bands. In addition we calculate Jensen's α for the Bollinger Band strategy, with the t-statistics in parentheses testing their difference from zero. Panels A and B report our results for the breakout method and the Squeeze method, respectively. We use a 10% significance level and White standard error corrected t-statistics.

	Fu	ull Sample		Be	fore 1983		19	83 - 2001		Si	ince 2002	
	Sharpe _{B&F}	H Sharpe _{BE}		Sharpe _{B&H}	Sharpe _{BB}		Sharpe _{B&H}	Sharpe _{BB}		Sharpe _{B&H}	Sharpe _{BB}	α
Country	(*10 ⁻²)	(*10 ⁻²)	(*10 ⁻⁴)	(*10 ⁻²)	(*10 ⁻²)	(*10 ⁻⁴)	(*10 ⁻²)	(*10 ⁻²)	(*10 ⁻⁴)	(*10 ⁻²)	(*10 ⁻²)	(*10 ⁻⁴)
	T				A: Breako		od (20,2)			T		
Australia	0.85	3.51	1.90	0.54	9.33	3.85	1.63	2.38	1.89	0.27	-3.74	-1.64
_		(1.97)	(4.37)	4.50	(4.63)	(7.30)		(0.30)	(1.89)		(1.42)	(-2.06)
France	0.80	0.00	0.06	-1.53	5.12	2.19	3.93	1.55	0.95	-0.63	-4.94	-3.48
C	0.55	(0.55)	(0.12)	2.00	(2.78)	(2.94)	2.75	(1.08)	(1.22)	0.07	(1.52)	(-3.20)
Germany	0.55	1.82	1.00	-2.86	9.48	2.65	2.75	3.04	1.67	-0.07	-2.32	-1.58
Hong Kong	1.64	(0.86) 2.54	(2.18) 2.89	1.34	(4.85) 5.67	(5.51) 6.55	2.65	(0.13) 2.54	(2.37) 3.72	0.46	(0.80) -2.15	(-1.43) -1.49
Hong Kong	1.04	(0.61)	(2.87)	1.54	(1.72)	(3.07)	2.05	(0.05)	(2.14)	0.40	(0.92)	(-1.22)
Italy	-0.06	3.67	2.43	-0.77	3.26	2.30	2.03	3.55	2.36	-1.73	4.69	2.39
,		(2.94)	(4.52)		(2.16)	(2.73)		(0.71)	(2.45)		(2.24)	(2.54)
Japan	1.18	0.03	0.03	2.48	1.95	1.17	0.22	-1.99	-1.33	0.03	-1.43	-1.07
		(0.95)	(0.07)		(0.32)	(2.01)		(0.94)	(-1.50)		(0.53)	(-0.83)
Korea	0.31	1.02	0.97	0.08	2.06	2.90	-0.51	0.30	0.31	1.92	-0.92	-0.27
		(0.65)	(1.09)		(1.32)	(1.65)		(0.39)	(0.27)		(1.02)	(-0.21)
New Zealand	-0.21	4.94	2.34	-0.44	11.63	3.49	-0.27	5.18	3.18	0.10	0.37	0.11
		(3.55)	(5.19)		(4.84)	(6.53)		(2.39)	(3.51)		(0.10)	(0.17)
Singapore	1.89	6.45	4.19	3.22	14.21	7.33	1.23	5.74	5.60	0.93	-0.17	0.04
		(2.94)	(5.70)		(4.07)	(6.00)		(1.83)	(4.28)		(0.40)	(0.04)
Spain	0.59	4.03	2.63	-6.22	16.13	7.68	3.76	5.37	3.51	-0.05	-2.37	-1.63
		(2.20)	(4.29)		(7.65)	(7.38)		(0.72)	(3.67)		(0.81)	(-1.41)
Switzerland	1.11	0.52	0.45	-1.49	4.67	1.86	4.00	0.61	0.70	-0.06	-2.42	-1.50
	0.00	(0.39)	(0.99)	0.10	(2.33)	(2.77)	2.50	(1.46)	(0.92)	0.25	(0.81)	(-1.53)
UK	0.68	0.29 (0.27)	0.24 (0.46)	-0.19	5.02 (2.23)	3.34 (3.03)	2.56	0.30	0.32 (0.45)	-0.25	-5.10 (1.70)	-3.14 (-3.21)
S&P 500	0.97	-1.06	-0.44	0.49	0.30	0.24	3.26	(1.00) -2.08	-0.50	0.46	-5.41	-3.22
3&F 300	0.57	(1.91)	(-1.21)	0.49	(0.15)	(0.54)	5.20	(2.19)	(-0.53)		(2.05)	(-3.24)
DJIA	0.80	-0.98	-0.51	0.41	-0.28	-0.19	3.36	-1.98	-0.46	0.66	-4.52	-2.42
2011	0.00	(1.95)	(-1.67)	0.1.1	(0.66)	(-0.55)	5.50	(2.19)	(-0.43)		(1.82)	(-2.64)
		<u> </u>	1 - 1	Pane	I B: Squeez		od (20,2)	1 -1	1 1			<u> </u>
Australia	0.85	-0.39	-0.02	0.54	1.52	0.04	1.63	-0.85	-0.03	0.27	-2.67	-0.11
		(1.05)	(-0.58)		(0.55)	(1.13)		(1.19)	(-0.62)		(1.20)	(-1.53)
France	0.80	-1.03	-0.05	-1.53	-0.60	-0.03	3.93	-1.05	-0.05	-0.63	-1.32	-0.07
		(1.37)	(-1.12)		(0.39)	(-0.43)		(2.32)	(-0.66)		(0.28)	(-0.77)
Germany	0.55	-0.14	-0.01	-2.86	-0.94	-0.03	2.75	2.52	0.17	-0.07	-2.61	-0.23
		(0.52)	(-0.15)		(0.79)	(-0.57)		(0.11)	(1.74)		(1.06)	(-1.52)
Hong Kong	1.64	-0.02	0.00	1.34	1.90	0.22	2.65	-0.36	-0.03	0.46	-2.23	-0.19
		(1.23)	(-0.05)		(0.23)	(1.02)		(1.42)	(-0.25)		(1.07)	(-1.28)
Italy	-0.06	1.14	0.07	-0.77	1.24	0.08	2.03	1.72	0.10	-1.73	-0.01	0.00
Japan	1.18	(1.01) 0.33	(1.43) 0.00	2.48	(1.13) 1.20	(1.07) 0.05	0.22	(0.15)	(1.17) -0.13	0.03	(0.70) 2.29	(-0.03) 0.09
заран	1.10	(0.77)	(0.10)	2.40	(0.82)	(0.69)	0.22	-2.63 (1.36)	(-1.78)		(0.90)	(1.31)
Korea	0.31	0.65	0.34	0.08	0.77	0.77	-0.51	2.61	0.24	1.92	-1.03	-0.07
Koreu	0.51	(0.30)	(1.03)	0.00	(0.39)	(0.84)	0.51	(1.55)	(1.86)	1.52	(1.21)	(-0.62)
New Zealand	-0.21	-0.33	-0.02	-0.44	1.07	0.04	-0.27	-0.21	-0.02	0.10	-2.50	-0.09
	-	(0.09)	(-0.41)		(0.58)	(0.53)	-	(0.03)	(-0.15)		(1.04)	(-1.45)
Singapore	1.89	0.61	0.05	3.22	-1.49	-0.06	1.23	1.66	0.12	0.93	0.47	0.03
		(0.91)	(0.75)		(1.60)	(-0.49)		(0.21)	(1.12)		(0.18)	(0.30)
Spain	0.59	1.11	0.06	-6.22	2.60	0.11	3.76	2.79	0.17	-0.05	-2.49	-0.12
		(0.37)	(1.12)		(2.95)	(1.20)		(0.46)	(1.88)		(1.00)	(-1.44)
Switzerland	1.11	-0.31	-0.01	-1.49	0.25	0.01	4.00	2.36	0.06	-0.06	-2.12	-0.13
		(1.07)	(-0.33)		(0.71)	(0.14)		(0.78)	(1.63)		(0.85)	(-1.22)
UK	0.68	0.08	0.00	-0.19	0.04	0.00	2.56	0.78	0.05	-0.25	-0.96	-0.04
		(0.45)	(0.09)		(0.10)	(-0.02)		(0.84)	(0.58)		(0.29)	(-0.55)
S&P 500	0.97	-0.96	-0.04	0.49	-0.18	-0.01	3.26	-2.66	-0.09	0.46	-2.82	-0.15
DUA	0.00	(2.04)	(-1.44)		(0.57)	(-0.21)	2.25	(2.85)	(-1.85)		(1.32)	(-1.63)
DJIA	0.80	-0.40	-0.02	0.41	0.32	0.03	3.36	-2.36	-0.11	0.66	-4.28	-0.18
		(1.44)	(-0.51)		(0.10)	(0.76)		(2.74)	(-1.63)		(1.99)	(-2.49)

Table 5: Decline of Profitability

This table reports results on the declines in profitability of the Bollinger Bands-based trading strategy. We first report our sample countries, and then the coefficient estimates with corresponding t-stats for D_s and D_p respectively in the next four columns. In column 5, we report our f-test results testing the null hypothesis $D_s = D_p$. Next, we report the average daily returns of the Bollinger Bands-based trading strategy R_{BB} , followed by the percentage post-sample and post-publication declines in profitability calculated from D_s/R_{BB} and D_p/R_{BB} respectively. Lastly, we report the differences between the post-sample and post-publication declines. We use a 10% significance level and White standard error corrected t-statistics.

Country	Ds	t-stats	Dp	t-stats	ChiSq	R _{BB}	Post-sample	Post-publication	Difference
	(*10 ⁻³)		(*10 ⁻³)			(*10 ⁻³)	Decline	Decline	
Australia	-0.16	-1.53	-0.56	-5.65	11.11	0.50	-31%	-112%	-81%
France	-0.19	-1.84	-0.77	-5.65	17.55	0.32	-60%	-238%	-178%
Germany	-0.11	-1.34	-0.56	-4.45	10.72	0.35	-32%	-158%	-126%
Hong Kong	-0.48	-1.83	-1.01	-4.01	6.83	0.56	-87%	-182%	-95%
Italy	0.10	0.77	-0.18	-1.39	4.07	0.58	17%	-32%	-48%
Japan	-0.37	-3.48	-0.28	-1.92	0.29	0.27	-138%	-106%	32%
Korea	-0.54	-2.39	-0.84	-3.70	3.38	0.65	-84%	-130%	-46%
New Zealand	0.06	0.61	-0.39	-4.60	16.65	0.58	11%	-66%	-77%
Singapore	-0.71	-3.73	-1.35	-7.85	15.04	0.75	-95%	-179%	-85%
Spain	-0.44	-3.31	-1.11	-6.90	18.24	0.58	-77%	-193%	-116%
Switzerland	-0.13	-1.29	-0.45	-3.69	6.48	0.25	-53%	-181%	-129%
UK	-0.35	-2.75	-0.80	-5.31	13.35	0.36	-97%	-223%	-125%
S&P 500	-0.06	-0.70	-0.39	-3.39	6.28	0.18	-35%	-218%	-184%
DJIA	-0.04	-0.47	-0.35	-3.40	5.88	0.21	-20%	-164%	-144%
Average							-56%	-156%	-100%

This table reports the international results on Bollinger bands (10, 1.9) breakout method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³	t-stats	N(sell) F	R _{sell} (*10 ⁻³) t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
			<u>Fu</u>	II Sample	e (10,1.9)			-	
Australia	0.26	2022	2.21	9.12	1557	-1.62	-7.84	3.82	10.41
France	0.27	1479	1.66	4.39	1235	-0.71	-2.84	2.37	5.04
Germany	0.18	1524	1.27	3.76	1229	-1.48	-5.21	2.75	6.35
Hong Kong	0.45	1564	3.17	5.40	1100	-0.49	-1.59	3.67	3.93
Italy	0.19	1822	2.99	9.07	1624	-1.48	-5.16	4.47	9.59
Japan	0.25	2336	1.75	5.81	1827	-0.11	-1.24	1.86	4.32
Korea	0.44	1941	3.42	6.25	1572	-0.43	-1.67	3.85	5.84
New Zealand	0.20	1536	2.82	11.57	1231	-1.34	-6.16	4.16	11.01
Singapore	0.33	1796	3.24	9.24	1393	-2.71	-8.62	5.95	10.49
Spain	0.26	1327	2.90	7.40	1119	-1.72	-5.13	4.62	8.81
Switzerland	0.19	1471	1.17	3.65	1231	-1.31	-5.12	2.49	5.83
UK	0.27	1474	1.27	3.40	1216	-1.16	-4.43	2.44	5.15
S&P 500	0.20	2859	0.91	3.09	2342	0.02	-0.73	0.89	2.48
DJIA	0.18	4455	1.05	5.13	3755	0.02	-0.86	1.02	3.91
					3 (10,1.9)				
Australia	0.21	959	3.07	10.98	775	-2.64	-9.94	5.72	14.14
France	0.11	445	3.16	6.48	426	-2.19	-4.80	5.36	8.69
Germany	0.00	450	2.01	6.98	418	-2.34	-7.89	4.35	11.38
Hong Kong	0.50	516	4.36	3.75	339	-1.79	-1.84	6.14	3.36
Italy	0.12	792	2.99	6.22	740	-0.90	-2.15	3.89	5.51
Japan	0.39	1411	2.25	7.03	998	-0.33	-2.37	2.58	5.30
Korea	0.62	902	4.47	4.46	607	-0.49	-1.07	4.96	4.22
New Zealand	0.18	457	2.83	9.34	410	-2.66	-9.50	5.49	13.44
Singapore	0.53	787	4.01	8.71	535	-3.60	-8.74	7.60	10.68
Spain	-0.26	296	4.73	9.53	317	-4.19	-7.71	8.92	12.88
Switzerland	-0.02	445	1.73	4.35	435	-2.03	-4.95	3.76	6.71
UK	0.24	440	2.45	3.77	421	-2.94	-5.31	5.39	6.07
S&P 500	0.14	1913	1.36	4.34	1610	-0.49	-2.06	1.85	4.43
DJIA	0.13	3501	1.30	6.24	3024	-0.26	-1.98	1.57	5.61
Australia	0.40	667	2.08	<u>83 - 200.</u> 4.11	<u>1 (10,1.9)</u> 478	-1.21	-3.41	3.28	3.91
France	0.40	675	2.08	3.77	478	-0.66	-2.29	2.86	3.91
Germany	0.33	707	1.64	3.18	478 504	-0.00	-2.29	3.18	3.95 4.70
Hong Kong	0.54	679	3.62	4.03	451	-0.65	- 3.90 -1.34	4.27	2.79
Italy	0.37	622	3.99	6.42	431 514	-1.69	-3.56	5.68	6.64
Japan	0.43	583	1.01	1.64	520	0.71	-3.30 1.07	0.30	0.33
Korea	0.00	685	3.47	4.88	662	-0.45	-1.16	3.92	0.55 4.42
New Zealand	0.26	676	3.98	8.63	516	-0.79	-2.16	4.77	6.32
Singapore	0.20	609	3.75	5.58	541	-3.18	-5.08	6.93	5.99
Spain	0.63	678	3.51	5.91	472	-1.66	-4.01	5.18	6.61
Switzerland	0.40	681	1.54	2.92	467	-1.41	-3.90	2.95	4.06
UK	0.39	689	1.45	2.90	474	-1.08	-3.42	2.52	3.97
S&P 500	0.44	606	0.52	0.19	434	0.06	-0.71	0.46	0.53
DJIA	0.47	628	0.32	-0.18	429	0.25	-0.41	0.14	0.15
	0.17	020		nce 2002		0.20	0111	0121	0.10
Australia	0.15	396	0.32	0.32	304	0.35	0.32	-0.02	-0.03
France	0.04	359	-1.24	-1.61	331	1.11	1.31	-2.36	-2.06
Germany	0.12	367	-0.36	-0.59	307	-0.22	-0.38	-0.14	-0.11
Hong Kong	0.21	369	0.69	0.58	310	1.15	1.04	-0.46	-0.34
Italy	-0.07	408	1.46	2.45	370	-2.37	-3.53	3.83	4.35
Japan	0.10	342	0.95	0.96	309	-0.75	-0.91	1.71	1.28
Korea	0.34	354	0.62	0.33	303	-0.28	-0.68	0.90	0.73
New Zealand		403	0.85	2.07	305	-0.51	-1.58	1.36	2.35
Singapore	0.21	400	0.96	1.22	317	-0.43	-0.93	1.39	1.40
Spain	0.07	353	0.19	0.15	330	0.57	0.59	-0.38	-0.32
Switzerland	0.10	345	-0.27	-0.56	329	-0.23	-0.48	-0.04	-0.04
UK	0.11	345	-0.57	-0.99	321	1.05	1.32	-1.61	-1.57
S&P 500	0.16	340	-0.92	-1.45	298	2.71	3.25	-3.63	-3.24
DJIA	0.16	326	-0.44	-0.85	302	2.59	3.35	-3.03	-3.00

This table reports the international results on Bollinger bands (10, 1.9) Squeeze method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³)	t-stats	N(sell)	R _{sell} (*10 ⁻³)	t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
			<u>Fu</u>	ll Sample	e (10,1.	<u>9)</u>			
Australia	0.26	40	4.39	2.91	37	-3.02	-2.22	7.41	5.19
France	0.27	30	2.91	1.26	35	-2.66	-1.51	5.57	2.94
Germany	0.18	36	3.05	1.62	36	-1.84	-1.14	4.89	2.62
Hong Kong	0.45	30	5.17	1.39	34	-3.75	-1.31	8.92	3.38
Italy	0.19	46	4.92	2.58	24	-1.49	-0.66	6.41	2.53
Japan	0.25	51	2.72	1.50	42	-0.53	-0.43	3.25	1.74
Korea	0.44	39	0.61	0.05	37	-1.86	-0.71	2.47	0.73
New Zealand	0.20	37	1.68	1.08	33	-2.24	-1.68	3.92	2.50
Singapore	0.33	31	3.28	1.31	46	-1.33	-0.90	4.61	2.40
Spain Switzerland	0.26	25 28	2.52	0.92	23	-1.17	-0.56	3.69	1.32
Switzerland UK	0.19 0.27	28 39	1.24 1.04	0.57 0.45	45 30	-1.36 -1.93	-1.06 -1.13	2.60 2.97	1.58 1.68
S&P 500	0.27	59 79	4.34	0.45 3.18	50 61	-1.93	-1.15	5.76	3.81
DJIA	0.20	114	4.34 2.47	2.30	73	-1.42 -1.61	-1.10	4.08	3.78
AIG	0.18	114		fore 198.			-1.45	4.00	3.78
Australia	0.21	19	3.77	2.06	16	-4.04	-2.25	7.81	4.76
France	0.11	5	7.87	1.85	14	-2.38	-1.00	10.26	2.00
Germany	0.00	8	3.01	1.49	9	-2.40	-1.26	5.41	1.31
, Hong Kong	0.50	7	9.78	1.13	6	-3.26	-0.42	13.04	2.08
Italy	0.12	18	4.44	1.49	8	1.51	0.32	2.93	0.70
Japan	0.39	34	4.09	2.32	23	0.44	0.03	3.64	2.04
Korea	0.62	18	-2.98	-0.63	17	-1.38	-0.34	-1.60	-0.34
New Zealand	0.18	8	2.62	1.22	13	-1.80	-1.25	4.43	2.27
Singapore	0.53	11	1.02	0.16	16	-2.74	-1.26	3.76	1.90
Spain	-0.26	7	4.33	1.43	2	-7.72	-1.24	12.04	4.60
Switzerland	-0.02	7	-0.23	-0.07	18	-2.27	-1.19	2.04	0.95
UK	0.24	10	1.34	0.30	7	-0.37	-0.14	1.71	0.49
S&P 500	0.14	49	4.47	2.61	43	-0.94	-0.61	5.41	3.08
DJIA	0.13	89	3.07	2.64	62	-1.43	-1.18	4.50	3.72
Australia	0.40	10	<u>19</u> 6.57	<u>83 - 200.</u> 1.98	1 (10,1.) 12	<u>9)</u> -3.22	-1.27	9.79	3.24
		10	0.97	0.14	12	-3.22 -2.30	-1.27	3.27	5.24 0.98
France Germany	0.53 0.34	12	3.19	0.14 1.15	12	-2.30 -4.49	-0.91 -2.02	7.68	0.98 3.53
Hong Kong	0.54	13	5.73	1.15	18	-4.49	-1.02	9.85	2.61
Italy	0.37	15	7.33	2.05	9	-5.12	-1.29	12.45	2.88
Japan	0.45	11	0.45	0.10	6	-1.78	-0.34	2.23	0.48
Korea	0.31	11	8.31	1.66	13	-2.95	-0.74	11.26	1.70
New Zealand	0.26	16	1.26	0.38	12	-2.83	-1.02	4.08	1.19
Singapore	0.22	14	7.64	1.88	20	-0.29	-0.15	7.93	2.35
Spain	0.63	11	3.55	0.81	13	-0.83	-0.44	4.37	1.12
Switzerland	0.40	11	3.17	0.96	17	-0.55	-0.41	3.72	1.51
UK	0.39	17	3.18	1.29	16	-2.91	-1.48	6.09	2.82
S&P 500	0.44	13	3.07	0.91	12	-3.08	-1.17	6.15	1.64
DJIA	0.47	11	-1.73	-0.68	9	-2.00	-0.69	0.27	0.10
			<u>Si</u>	nce 2002	2 (10,1.9	<u>9)</u>			
Australia	0.15	11	3.48	1.08	9	-0.96	-0.33	4.44	1.40
France	0.04	13	2.80	0.70	9	-3.58	-0.76	6.37	2.30
Germany	0.12	11	2.86	0.62	9	4.02	0.80	-1.15	-0.28
Hong Kong	0.21	10	1.22	0.21	10	-3.37	-0.74	4.59	1.00
Italy	-0.07	13	2.82	0.88	7	-0.25	-0.04	3.07	0.75
Japan	0.10	6	-0.85	-0.15	13	-1.69	-0.41	0.84	0.19
Korea	0.34	10	-1.41	-0.37	7	-1.02	-0.24	-0.39	-0.07
New Zealand	0.12	13	1.62	0.81	8	-2.07	-0.93	3.70	1.89
Singapore	0.21	6	-2.76	-0.62	10	-1.17	-0.37	-1.59	-0.55
Spain	0.07	7	-0.92	-0.18	8	-0.10	-0.03	-0.82	-0.15
Switzerland	0.10	10	0.16	0.02	10	-1.11	-0.33	1.26	0.35
UK	0.11	12	-2.25	-0.68	7	-1.28	-0.30	-0.97	-0.25
S&P 500	0.16	17	4.93	1.51	6	-1.55	-0.32	6.47	1.23
DJIA	0.16	14	2.00	0.57	2	-5.14	-0.62	7.14	3.01

This table reports the international results on Bollinger bands (50, 2.1) breakout method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³)	t-stats	N(sell) _F	R _{sell} (*10 ⁻³) t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
			<u>Fu</u>	ll Sample	e (50,2.1)			•	
Australia	0.26	1288	1.49	4.71	820	-1.05	-4.07	2.54	4.44
France	0.27	951	1.48	3.13	733	-1.05	-3.00	2.52	3.42
Germany	0.18	875	0.74	1.51	683	-0.62	-1.91	1.36	1.81
Hong Kong	0.45	1136	2.63	3.75	577	0.00	-0.56	2.63	1.70
Italy	0.19	1186	2.51	6.18	907	-0.68	-2.04	3.18	4.54
Japan	0.25	1535	1.01	2.44	1003	0.46	0.56	0.55	0.79
Korea	0.44	1368	3.16	4.88	763	1.88	1.96	1.28	1.24
New Zealand	0.20	1067	2.03	6.88	706	-1.63	-5.66	3.66	6.18
Singapore	0.33	1256	2.73	6.48	758	-2.07	-5.13	4.79	5.13
Spain	0.26	850	2.63	5.43	658	-0.53	-1.60	3.16	3.65
Switzerland	0.19	996	1.17	3.03	725	-0.50	-1.84	1.67	2.35
UK	0.27	936	1.32	2.89	682	-1.00	-3.00	2.32	2.96
S&P 500	0.20	1795	0.91	2.49	1331	-0.39	-1.83	1.30	2.07
DJIA	0.18	2802	0.87	3.31	2176	-0.34	-2.20	1.21	2.72
Australia	0.21	609			3 (50, 2.1,		F 73	4 29	6.40
Australia	0.21	608 219	2.29	6.52 2 71	408	-2.00	-5.72	4.28	6.49 E 0E
France	0.11	318	2.15	3.71	237	-2.56	-4.25	4.71	5.05
Germany Hong Kong	0.00 0.50	243 365	1.13 4.38	2.97 3.24	224 175	-1.67 -0.50	-4.24 -0.59	2.80 4.88	4.08 1.65
Italy	0.12	554 900	2.64 1.46	4.64 3.31	378	0.44 -0.34	0.48 -1.76	2.21 1.80	2.06 2.37
Japan Korea	0.39 0.62	637	1.40 4.40	3.75	515 303	-0.34 1.10	0.34	3.30	2.57
New Zealand	0.02	297	4.40 2.31	6.19	268	-2.17	- 6.49	4.48	7.48
Singapore	0.18	582	3.60	6.74	208	-2.17	-3.51	5.54	5.29
Spain	-0.26	168	3.13	5.00	149	-3.16	-4.03	6.29	5.62
Switzerland	-0.20	252	1.25	2.43	304	-1.11	-2.29	2.36	2.96
UK	0.02	322	2.81	3.82	239	-2.82	-3.95	5.64	4.21
S&P 500	0.14	1188	1.14	2.86	938	-0.90	-2.66	2.03	2.78
DJIA	0.14	2198	0.99	3.70	1778	-0.48	-2.41	1.47	3.18
2001	0.10	2250		83 - 2001				2117	0.20
Australia	0.40	469	1.21	1.69	240	0.16	-0.37	1.04	0.91
France	0.53	502	1.77	2.44	292	-1.48	-3.09	3.25	2.89
Germany	0.34	477	1.04	1.43	262	-1.14	-2.31	2.18	1.85
Hong Kong	0.57	494	2.62	2.34	247	-0.99	-1.30	3.61	1.49
Italy	0.45	471	3.18	4.37	298	-1.56	-2.60	4.74	4.15
Japan	0.06	403	0.69	0.93	303	2.35	2.94	-1.66	-1.20
Korea	0.31	506	2.79	3.34	308	2.58	2.43	0.21	0.15
New Zealand	0.26	464	2.68	4.75	288	-1.10	-2.14	3.78	3.14
Singapore	0.22	453	2.67	3.39	313	-3.21	-4.00	5.88	3.15
Spain	0.63	461	3.14	4.32	289	-0.60	-1.72	3.74	3.00
Switzerland	0.40	537	1.40	2.30	217	-0.18	-0.87	1.58	1.06
UK	0.39	442	0.99	1.35	254	-1.73	-3.69	2.72	2.44
S&P 500	0.44	469	0.63	0.39	180	-0.37	-1.01	1.00	0.51
DJIA	0.47	441	0.66	0.36	201	-0.84	-1.71	1.51	0.79
					(50, 2.1)				
Australia	0.15	211	-0.18	-0.45	172	-0.51	-0.83	0.33	0.22
France	0.04	131	-1.27	-1.03	204	1.34	1.26	-2.61	-1.42
Germany	0.12	155	-0.77	-0.74	197	1.27	1.07	-2.04	-1.06
Hong Kong	0.21	277	0.34	0.14	155	2.16	1.56	-1.82	-0.71
Italy	-0.07	161	0.07	0.15	231	-1.36	-1.59	1.43	1.02
Japan	0.10	232	-0.17	-0.26	185	-0.40	-0.42	0.23	0.10
Korea	0.34	225	0.50	0.16	152	2.02	1.35	-1.51	-0.67
New Zealand		306	0.78	1.65	150	-1.69	-3.24	2.46	2.19
Singapore	0.21	221	0.55	0.42	219	-0.56	-0.95	1.11	0.75
Spain Switzerland	0.07	221	1.19	1.09	220	1.34	1.23	-0.14	-0.08
Switzerland	0.10	207	0.46	0.43	204	0.07	-0.03	0.39	0.24
UK	0.11	172	-0.63	-0.78	189	2.29	2.41	-2.92	-1.74
S&P 500	0.16	138	-0.10	-0.23	213	1.81	1.80	-1.91	-1.20
DJIA	0.16	163	-0.17	-0.34	197	1.52	1.54	-1.70	-1.02

This table reports the international results on Bollinger bands (50, 2.1) Squeeze method. We consequently report the results for the full sample and the three sub-samples in four different panels. For each sample period, we first report our sample markets and the average market returns as benchmarks in the first and second columns, respectively. In the next three columns, we report the number of buy signals generated and the average buy returns with the t-statistics from testing H2. We perform the same test for the sell signals and report our results. In the last two columns, we repeat our results from Table 1 for R_{buy} - R_{sell} and the t-statistics testing H1 for easy reference. We use a 10% significance level and White standard error corrected t-statistics.

Country	R _m (*10 ⁻³)	N(buy)	R _{buy} (*10 ⁻³)	t-stats	N(sell)	R _{sell} (*10 ⁻³)	t-stats	R _{buy} -R _{sell} (*10 ⁻³)	t-stats
		r		II Sample					
Australia	0.26	29	3.45	1.91	13	-2.49	-1.10	5.94	1.84
France	0.27	19	4.06	1.44	12	0.29	0.01	3.77	1.12
Germany	0.18	24	1.16	0.45	16	0.57	0.15	0.59	0.22
Hong Kong	0.45	22	10.15	2.44	10	-16.58	-2.88	26.73	3.18
Italy	0.19	21	5.58	1.99	28	-0.41	-0.26	5.99	2.06
Japan	0.25	28	1.40	0.52	23	-2.65	-1.19	4.05	1.23
Korea	0.44	37	3.39	0.91	17	6.23	1.21	-2.84	-0.62
New Zealand	0.20	32	1.25	0.72	8	-5.06	-1.79	6.31	2.04
Singapore	0.33	31	2.78	1.09	20	-0.34	-0.24	3.11	1.63
Spain	0.26	16	3.81	1.16	15	-4.54	-1.52	8.35	3.39
Switzerland	0.19	17	-0.60	-0.33	15	5.11	1.95	-5.72	-1.51
UK	0.27	25	1.34	0.50	18	-0.97	-0.49	2.31	0.70
S&P 500	0.20	37	0.95	0.39	36	4.04	1.99	-3.09	-1.77
DJIA	0.18	76	1.47	1.06	40	-0.97	-0.68	2.44	1.54
A	0.24	47		fore 1983			4.00	0.02	
Australia	0.21	17	3.70	1.91	9	-4.32	- 1.80	8.03	2.24
France	0.11	3	1.91	0.33	3	5.05	0.91	-3.14	-1.09
Germany	0.00	6	3.45	1.48	5	-2.48	-0.97	5.93	1.67
Hong Kong	0.50	5	41.46	4.21	5	-20.47	-2.16	61.93	3.09
Italy	0.12	11	4.06	1.07	9	1.80	0.41	2.27	0.59
Japan	0.39	13	2.08	0.66	17	0.43	0.02	1.65	0.52
Korea	0.62	14	5.05	0.69	7	11.26	1.16	-6.21	-0.77
New Zealand	0.18	12	0.89	0.44	3	-7.74	-2.41	8.63	1.48
Singapore	0.53	17	4.87	1.73	7	-1.95	-0.64	6.82	3.07
Spain	-0.26	4	-1.80	-0.36	7	-6.74	-2.02	4.94	1.15
Switzerland	-0.02	7	-2.11	-0.69	2	-3.93	-0.69	1.82	0.32
UK	0.24	11	2.99	0.79	5	-2.15	-0.46	5.14	0.71
S&P 500	0.14	19	0.68	0.20	25	2.85	1.17	-2.17	-0.99
DJIA	0.13	60	0.83	0.51	32	-1.19	-0.72	2.02	1.11
Australia	0.40	5	9.73	<u>83 - 2001</u> 2.12	0	<u>1)</u>			
France	0.53	11	3.64	0.95	7	-1.48	-0.49	5.12	1.37
Germany	0.34	8	-1.14	-0.41	4	-2.84	-0.63	1.70	0.44
Hong Kong	0.57	11	2.00	0.26	4	-11.13	-1.27	13.13	1.29
Italy	0.45	7	9.43	1.83	12	-0.84	-0.35	10.28	1.88
Japan	0.45	6	0.64	0.11	2	-11.93	-1.28	12.57	0.80
Korea	0.31	15	3.72	0.83	7	0.22	-0.01	3.50	0.57
New Zealand	0.26	15	2.73	0.91	2	-0.48	-0.10	3.20	0.61
Singapore	0.20	8	1.75	0.29	5	1.84	0.25	-0.09	-0.02
Spain	0.63	5	7.07	1.21	4	-4.19	-0.81	11.26	2.43
Switzerland	0.00	8	0.06	-0.10	8	3.53	0.92	-3.47	-0.59
UK	0.39	8	2.18	0.57	9	-4.17	-1.53	6.36	1.42
S&P 500	0.44	14	0.54	0.04	6	7.83	1.73	-7.29	-1.98
DJIA	0.47	14	4.26	1.32	5	1.89	0.30	2.37	1.02
2001	0.1.7			nce 2002			0.50	2107	1.01
Australia	0.15	7	-1.64	-0.46	4	1.63	0.29	-3.27	-0.50
France	0.04	5	6.27	0.98	2	-0.64	-0.07	6.91	0.73
Germany	0.12	10	1.62	0.32	7	4.69	0.82	-3.08	-0.69
, Hong Kong	0.21	6	-1.00	-0.19	1	-18.92	-1.26	17.92	19.92
Italy	-0.07	3	2.17	0.33	7	-2.50	-0.54	4.67	1.17
Japan	0.10	9	0.91	0.16	4	-11.12	-1.43	12.03	1.44
Korea	0.34	8	-0.14	-0.09	3	8.53	0.95	-8.67	-0.93
New Zealand		5	-2.31	-0.81	3	-5.43	-1.44	3.12	0.75
Singapore	0.21	6	-1.80	-0.42	8	-0.29	-0.12	-1.51	-0.56
Spain	0.07	7	4.69	0.83	4	-1.03	-0.15	5.72	1.37
Switzerland	0.10	2	2.00	0.23	5	11.27	2.14	-9.26	-2.33
UK	0.11	6	-2.82	-0.59	4	7.71	1.26	-10.53	-6.51
S&P 500	0.16	4	3.66	0.54	5	5.47	0.92	-1.81	-0.44
DJIA	0.16	2	1.22	0.13	3	-3.30	-0.50	4.52	0.79
				-				-	-

Table 10: International Results on Bollinger Bands Squeeze Method with Alternative BandWidth Settings

This table reports the international results on Bollinger bands (20, 2) Squeeze method with Alternative BandWidth settings. We consequently report the results for the full sample and the three sub-samples in. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. We use a 10% significance level and White standard error corrected t-statistics.

		Full Sample			Before 1983			1983-2001			Since 2002	
Country	R _m (*10 ⁻	³) R _{buy} -R _{sell} (*10 ⁻³)) t-stats	R _m (*10 ⁻³) R_{buy} - R_{sell} (*10 ⁻³)	t-stats	R _m (*10 ⁻³) R _{buy} -R _{sell} (*10 ⁻³) t-stats	R _m (*10 ⁻³	³) R _{buy} -R _{sell} (*10 ⁻³)	t-stats
				<u>Squee</u> .	ze Method (20,2):	Bandwi	dth=6-mc	onth low				
Australia	0.26	3.77	5.88	0.21	5.54	6.65	0.40	3.81	3.12	0.15	-0.76	-0.57
France	0.27	1.16	1.05	0.11	5.28	3.29	0.53	0.82	0.42	0.04	-2.79	-1.32
Germany	0.18	3.93	3.97	0.00	5.20	4.92	0.34	6.18	4.00	0.12	-2.11	-0.74
Hong Kong	0.45	5.99	3.34	0.50	11.70	2.87	0.57	3.79	1.52	0.21	2.37	0.80
Italy	0.19	4.70	4.91	0.12	4.69	3.20	0.45	4.38	2.77	-0.07	5.03	2.61
Japan	0.25	4.23	5.33	0.39	4.98	5.38	0.06	1.62	1.02	0.10	6.11	2.36
Korea	0.44	6.05	2.40	0.62	8.03	1.58	0.31	7.45	2.98	0.34	0.53	0.26
New Zealand	0.20	5.26	6.57	0.18	5.19	4.59	0.26	5.88	3.95	0.12	4.34	2.39
Singapore	0.33	5.50	5.75	0.53	6.06	5.02	0.22	7.24	3.91	0.21	2.34	1.30
Spain Switzerland	0.26	4.43	4.02	-0.26	5.45	3.55	0.63	5.12	3.29	0.07	1.59	0.61
Switzerland	0.19	3.36	3.48	-0.02	4.67	2.89	0.40	5.03	3.11	0.10	-0.26	-0.15
	0.27	2.17	1.78	0.24	3.09	1.79	0.39	3.43	1.55	0.11	-1.29	-0.80
S&P 500	0.20	2.70	4.09 5.71	0.14	4.01	4.86 6.32	0.44 0.47	0.89	0.55	0.16	-1.30	-0.94
DJIA	0.18	3.13		0.13 Saueeze l	3.81 Method (20,2): Bar			1.19 n minimum	0.56	0.16	0.21	0.13
Australia	0.26	3.87	2.97	0.21	6.14	2.52	0.40	3.26	1.81	0.15	1.98	0.97
France	0.27	3.37	1.65	0.11	8.29	3.20	0.53	0.86	0.22	0.04	0.49	0.15
Germany	0.18	4.72	2.50	0.00	5.70	3.64	0.34	8.81	2.80	0.12	-3.92	-0.97
Hong Kong	0.45	4.51	1.14	0.50	7.58	1.14	0.57	-0.90	-0.16	0.21	4.59	0.53
Italy	0.19	6.27	3.42	0.12	7.32	2.80	0.45	5.79	1.71	-0.07	5.41	1.33
Japan	0.25	4.75	3.27	0.39	7.51	4.25	0.06	-3.89	-1.42	0.10	5.74	1.54
Korea	0.44	7.76	1.26	0.62	7.15	0.63	0.31	12.67	3.84	0.34	-2.47	-0.78
New Zealand	0.20	4.79	2.78	0.18	5.16	2.27	0.26	9.51	2.46	0.12	-5.57	-2.96
Singapore	0.33	4.59	2.44	0.53	3.49	1.38	0.22	6.80	1.88	0.21	0.76	0.27
Spain	0.26	6.72	3.18	-0.26	11.14	3.45	0.63	6.09	2.04	0.07	1.35	0.30
Switzerland	0.19	4.05	2.30	-0.02	3.88	1.71	0.40	7.51	2.28	0.10	-1.18	-0.34
UK	0.27	4.63	2.70	0.24	9.14	1.52	0.39	4.89	2.16	0.11	0.93	0.46
S&P 500	0.20	3.02	2.83	0.14	4.78	3.60	0.44	-0.41	-0.24	0.16	-0.72	-0.27
DJIA	0.18	3.09	3.36	0.13	4.48	4.13	0.47	0.02	0.01	0.16	-3.11	-1.21
		1.00	-		<u>Aethod (20,2): Ban</u>				0.50	0.45	1.00	
Australia	0.26	1.08	0.84	0.21	3.10	2.88	0.40	1.26	0.59	0.15	-1.26	-0.44
France	0.27	-2.94	-1.04	0.11	-1.85	-0.74	0.53	-0.22	-0.05	0.04	-10.38	-2.62
Germany	0.18	2.40	0.64	0.00	3.31	1.19	0.34	10.40	1.43	0.12	-4.37	-0.76
Hong Kong	0.45	-3.02	-0.67	0.50	-0.30	-0.08	0.57	-4.40	-1.39	0.21	-13.32	-1.43
Italy	0.19	5.06	1.94	0.12	-1.02	-0.30	0.45	8.40	2.95	-0.07	9.02	1.21
Japan	0.25	4.55	1.63	0.39	8.26	2.37	0.06	-8.72	-1.35		7.46	3.49
Korea	0.44	4.94	0.90	0.62	-0.58	-0.07	0.31	19.80	2.16	0.34	0.33	0.07
New Zealand	0.20	4.61	1.54	0.18	-1.21	-0.43	0.26	3.42	0.73	0.12		•
Singapore	0.33	5.47	1.57	0.53	-4.40	-0.84	0.22	17.00	2.77	0.21	-1.45	-0.36
Spain Switzerland	0.26	3.29	1.48	-0.26	3.56	1.51	0.63	3.44	1.11	0.07	2.18	0.32
Switzerland	0.19	0.96	0.36	-0.02	5.90	2.74	0.40	3.05	2.87	0.10	-3.00	-0.67
UK S&D EOO	0.27	2.10	1.23	0.24	0.16	0.04	0.39	3.60	1.48	0.11	0.30	0.14
S&P 500	0.20	-0.30	-0.17	0.14	0.79	0.38	0.44	-1.26	-0.54	0.16	-1.13	-0.22
DJIA	0.18	2.65	1.67	0.13	3.73	2.05	0.47	-1.10	-0.23	0.16	-3.80	-2.22

Table 11: International Results on Bollinger Bands (20, 2) – GARCH (1, 1)

This table reports the international results on Bollinger bands (20, 2) using GARCH (1, 1) estimates. We consequently report the results for the full sample and the three sub-samples in. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, we report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. We use a 10% significance level and White standard error corrected t-statistics.

		Full Sample			Before 1983			1983-2001			Since 2002	
Country	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats
					Panel A: Brea							
Australia	0.26	2.53	12.11	0.21	3.92	13.68	0.40	0.91	1.76	0.15	0.19	0.39
France	0.27	1.61	4.36	0.11	3.86	5.86	0.53	1.72	2.85	0.04	-3.33	-4.09
Germany	0.18	2.82	9.54	0.00	3.54	9.16	0.34	2.95	5.75	0.12	-1.86	-2.52
Hong Kong	0.45	2.45	3.43	0.50	5.05	4.04	0.57	2.22	1.99	0.21	-0.40	-0.56
Italy	0.19	2.64	7.35	0.12	2.39	4.37	0.45	3.52	4.44	-0.07	1.87	3.55
Japan	0.25	0.52	1.76	0.39	0.52	1.43	0.06	-0.34	-0.52	0.10	1.51	1.33
Korea	0.44	1.53	5.57	0.62	1.84	4.80	0.31	0.97	1.40	0.34	1.42	1.24
New Zealand	0.20	3.63	9.63	0.18	4.20	9.14	0.26	4.87	7.00	0.12	1.55	3.12
Singapore	0.33	4.30	12.08	0.53	5.78	11.39	0.22	3.78	3.60	0.21	1.60	1.90
Spain	0.26	4.13	11.75	-0.26	5.93	10.75	0.63	4.76	7.38	0.07	-2.36	-3.28
Switzerland	0.19	2.17	6.56	-0.02	3.83	5.65	0.40	2.20	5.39	0.10	-0.70	-0.81
UK	0.27	1.75	4.41	0.24	3.79	4.52	0.39	1.99	3.45	0.11	-1.87	-2.91
S&P 500	0.20	1.07	4.70	0.14	1.72	6.21	0.44	-0.16	-0.27	0.16	-1.97	-2.76
DJIA	0.18	1.09	6.07	0.13	1.41	6.72	0.47	0.45	0.82	0.16	-0.56	-0.95
					<u>Panel B: Sque</u>	eeze Meth	od (20,2 <u>)</u>					
Australia	0.26	3.01	1.59	0.21	4.55	1.64	0.40	2.27	0.56	0.15	-0.15	-0.03
France	0.27	0.65	0.26	0.11	2.90	0.62	0.53	0.79	0.12	0.04	-2.95	-0.75
Germany	0.18	5.53	1.75	0.00	4.32	1.83	0.34	13.00	2.10	0.12	-3.84	-0.55
Hong Kong	0.45	2.50	0.49	0.50	0.50	0.10	0.57	-6.17	-0.84	0.21	-5.67	-0.68
Italy	0.19	6.55	2.58	0.12	6.10	1.45	0.45	6.62	1.19	-0.07	4.98	0.75
Japan	0.25	4.91	2.46	0.39	6.68	2.59	0.06	-6.03	-0.99	0.10	11.50	1.50
Korea	0.44	13.70	0.40	0.62	14.70	0.21	0.31	16.60	1.45	0.34	-0.08	-0.01
New Zealand	0.20	3.56	1.73	0.18	6.56	1.41	0.26	0.16	0.04	0.12	-8.10	-0.96
Singapore	0.33	5.44	2.06	0.53	1.48	0.41	0.22	9.42	1.67	0.21	3.21	0.42
Spain	0.26	6.92	2.20	-0.26	7.20	1.90	0.63	9.85	1.58	0.07	-0.72	-0.11
Switzerland	0.19	4.12	2.14	-0.02	5.86	1.07	0.40	8.39	2.59	0.10	-2.40	-0.38
UK	0.27	4.09	2.10	0.24	-0.89	-0.12	0.39	6.50	1.72	0.11	1.40	0.47
S&P 500	0.20	1.43	1.26	0.14	2.55	1.41	0.44	-0.26	-0.07	0.16	-5.84	-3.90
DJIA	0.18	2.60	2.15	0.13	4.55	3.17	0.47	-1.17	-0.39	0.16	-5.59	-3.67

Table 12: International Results on Bollinger Bands (20, 2) – Robust Regression

This table reports the international results on Bollinger bands (20, 2) using robust regression estimates. We consequently report the results for the full sample and the three sub-samples in. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, we report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. We use a 10% significance level and White standard error corrected t-statistics.

		Full Sample			Before 1983			1983-2001			Since 2002	
Country	R _m (*10 ⁻³) R	_{buy} -R _{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	chi-stats	R _m (*10 ⁻³) R _b	_{uy} -R _{sell} (*10 ⁻³)	chi-stats
					Panel A: Brea					•		
Australia	0.26	2.82	103.86	0.21	4.56	163.85	0.40	1.71	10.46	0.15	-0.30	0.21
France	0.27	1.35	11.32	0.11	3.58	30.02	0.53	0.93	2.28	0.04	-2.81	10.33
Germany	0.18	2.58	61.27	0.00	3.91	84.75	0.34	2.03	14.00	0.12	-0.16	0.03
Hong Kong	0.45	1.63	6.77	0.50	6.58	16.94	0.57	1.20	1.67	0.21	-0.41	0.27
Italy	0.19	3.61	79.82	0.12	3.58	31.52	0.45	3.58	24.90	-0.07	3.62	27.91
Japan	0.25	0.80	6.06	0.39	2.21	31.98	0.06	-1.19	3.29	0.10	-1.10	1.09
Korea	0.44	2.45	33.89	0.62	3.05	27.97	0.31	3.34	17.89	0.34	-1.34	2.33
New Zealand	0.20	3.02	89.03	0.18	4.32	125.69	0.26	3.15	22.39	0.12	1.49	7.37
Singapore	0.33	3.39	76.40	0.53	4.66	89.31	0.22	3.83	23.46	0.21	0.31	0.14
Spain	0.26	4.36	94.33	-0.26	7.50	109.61	0.63	3.95	32.44	0.07	0.18	0.04
Switzerland	0.19	1.10	9.93	-0.02	2.60	19.51	0.40	0.35	0.49	0.10	-0.64	0.60
UK	0.27	1.65	16.58	0.24	4.67	27.72	0.39	1.05	3.79	0.11	-0.69	0.93
S&P 500	0.20	0.57	5.47	0.14	1.38	20.94	0.44	-1.34	6.32	0.16	-1.28	3.57
DJIA	0.18	0.72	12.14	0.13	1.21	25.94	0.47	-1.48	7.37	0.16	-0.99	2.79
					<u>Panel B: Sque</u>	eeze Meth	od (20,2)					
Australia	0.26	3.10	5.74	0.21	4.93	4.01	0.40	1.56	0.45	0.15	1.34	0.30
France	0.27	0.81	0.09	0.11	-1.81	0.65	0.53	-3.88	0.59	0.04	-1.15	0.05
Germany	0.18	5.57	8.83	0.00	4.70	3.76	0.34	9.88	6.64	0.12	-0.60	0.03
Hong Kong	0.45	0.72	0.04	0.50	3.93	0.74	0.57	-4.73	0.66	0.21	-4.89	0.39
Italy	0.19	5.30	11.78	0.12	6.61	9.47	0.45	5.06	3.87	-0.07	3.85	0.50
Japan	0.25	4.61	5.94	0.39	5.81	6.31	0.06	-5.23	1.10	0.10	10.55	6.63
Korea	0.44	4.43	4.01	0.62	3.47	2.17	0.31	9.48	3.14	0.34	-0.47	0.01
New Zealand	0.20	1.02	0.27	0.18	4.45	1.25	0.26	0.80	0.02	0.12	-8.34	14.04
Singapore	0.33	4.41	4.54	0.53	1.63	0.67	0.22	8.04	3.79	0.21	3.81	0.55
Spain	0.26	5.18	5.33	-0.26	5.58	3.85	0.63	7.57	3.48	0.07	-1.34	0.06
Switzerland	0.19	3.38	2.86	-0.02	6.24	8.04	0.40	8.20	9.54	0.10	-4.63	1.10
UK	0.27	3.27	3.27	0.24	2.14	0.21	0.39	6.07	4.24	0.11	0.55	0.06
S&P 500	0.20	1.03	0.93	0.14	2.50	3.95	0.44	-0.77	0.09	0.16	-5.82	4.11
DJIA	0.18	1.43	1.99	0.13	3.50	7.31	0.47	-2.11	0.70	0.16	-5.84	18.61

Table 13: International Results on Bollinger Bands (20, 2) Adjusted for the 2008 Crisis

This table reports the international results on Bollinger bands (20, 2) excluding the 2008 crisis period. We consequently report the results for the full sample and the three sub-samples in. For each sample period, we report the market returns R_m , the average spread between conditional buy and sell returns R_{buy} - R_{sell} , and the t-statistics testing H1, that R_{buy} - R_{sell} is not different from zero. Moreover, we report the results for both the volatility breakout method and the Squeeze method in Panels A and B, respectively. We use a 10% significance level and White standard error corrected t-statistics.

	Full Sample			Before 1983			1983-2001			Since 2002		
Country	R _m (*10 ⁻³)	R _{buy} -R _{sell} (*10 ⁻³	t-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	t-stats	R _m (*10 ⁻³)	R_{buy} - R_{sell} (*10 ⁻³)	t-stats	R _m (*10 ⁻³)	$R_{buy}-R_{sell}(*10^{-3})$	t-stats
	-				Panel A: Break		hod (20,2)					
Australia	0.26	3.77	7.74	0.21	5.04	9.95	0.40	3.25	3.03	0.15	-0.84	-0.78
France	0.27	2.68	4.77	0.11	4.11	5.67	0.53	2.39	2.54	0.04	-1.01	-0.58
Germany	0.18	3.06	5.95	0.00	4.25	9.16	0.34	3.43	3.91	0.12	-1.59	-0.84
Hong Kong	0.45	5.05	3.81	0.50	8.17	3.69	0.57	4.18	2.04	0.21	-0.58	-0.38
Italy	0.19	3.77	6.50	0.12	3.70	4.51	0.45	4.19	4.17	-0.07	2.81	2.32
Japan	0.25	1.60	3.09	0.39	2.50	4.05	0.06	-0.31	-0.30	0.10	2.05	1.11
Korea	0.44	2.56	2.77	0.62	3.41	2.24	0.31	2.02	1.78	0.34	0.28	0.11
New Zealand	0.20	4.13	7.88	0.18	4.65	9.75	0.26	4.72	4.74	0.12	1.12	1.42
Singapore	0.33	6.21	7.91	0.53	7.03	7.94	0.22	7.19	5.09	0.21	-1.12	-0.73
Spain	0.26	5.17	8.20	-0.26	8.25	9.96	0.63	4.78	4.64	0.07	0.15	0.10
Switzerland	0.19	2.30	4.15	-0.02	3.60	5.17	0.40	2.04	2.12	0.10	-0.85	-0.56
UK	0.27	2.77	4.63	0.24	5.31	4.81	0.39	2.09	2.63	0.11	-1.73	-1.10
S&P 500	0.20	1.34	2.97	0.14	1.95	3.74	0.44	0.46	0.40	0.16	-2.82	-2.08
DJIA	0.18	1.32	4.04	0.13	1.57	4.56	0.47	0.99	0.76	0.16	-2.02	-1.53
					<u>Panel B: Squee</u>	ze Metl	nod (20,2)					
Australia	0.26	3.38	2.52	0.21	4.95	2.57	0.40	3.02	1.07	0.15	-2.57	-1.61
France	0.27	1.82	0.61	0.11	2.90	0.84	0.53	0.06	0.01	0.04	8.38	2.58
Germany	0.18	8.76	3.91	0.00	4.32	2.43	0.34	13.01	3.00	0.12	5.12	2.11
Hong Kong	0.45	4.24	0.90	0.50	12.71	1.71	0.57	-6.17	-1.09	0.21	-5.43	-0.75
Italy	0.19	6.34	3.42	0.12	6.10	2.37	0.45	7.45	2.29	-0.07	4.06	1.77
Japan	0.25	4.74	2.39	0.39	6.75	2.95	0.06	-6.02	-1.40	0.10	10.76	2.98
Korea	0.44	16.18	1.18	0.62	14.41	0.70	0.31	16.56	2.49	0.34	4.62	0.73
New Zealand	0.20	3.91	1.43	0.18	5.31	1.55	0.26	5.17	1.04	0.12	-8.48	-8.28
Singapore	0.33	5.34	2.11	0.53	1.47	0.48	0.22	9.80	2.40	0.21	0.97	0.13
Spain	0.26	7.17	2.81	-0.26	7.75	2.57	0.63	9.84	2.51	0.07	-3.19	-0.51
Switzerland	0.19	5.18	2.90	-0.02	5.86	4.03	0.40	8.39	3.74	0.10	-0.15	-0.04
UK	0.27	4.37	2.12	0.24	3.90	0.87	0.39	5.84	2.07	0.11	0.60	0.21
S&P 500	0.20	2.14	1.52	0.14	3.50	2.21	0.44	-0.35	-0.20	0.16	-5.40	-0.81
DJIA	0.18	3.30	2.91	0.13	4.54	3.45	0.47	-1.17	-0.50	0.16	-7.09	-9.48

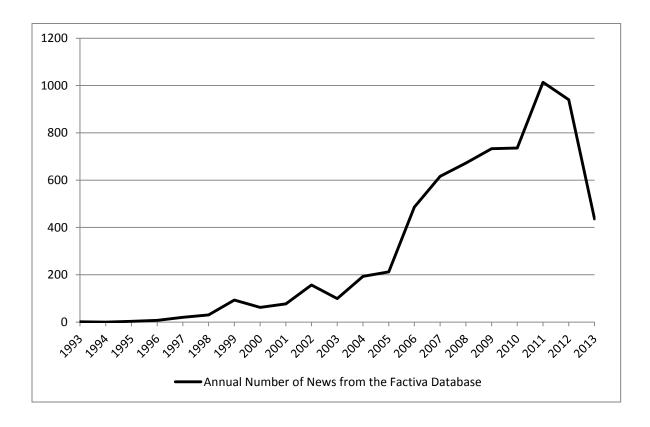
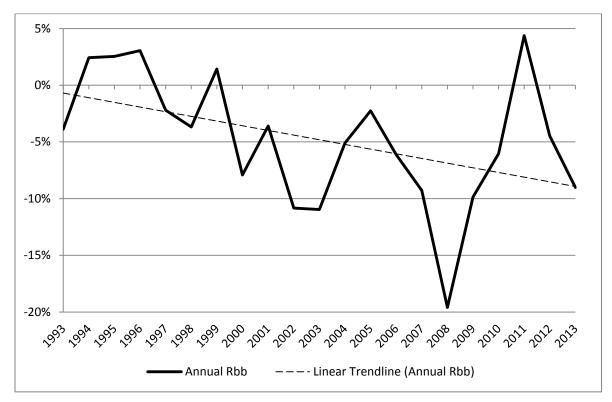
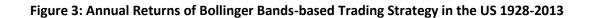
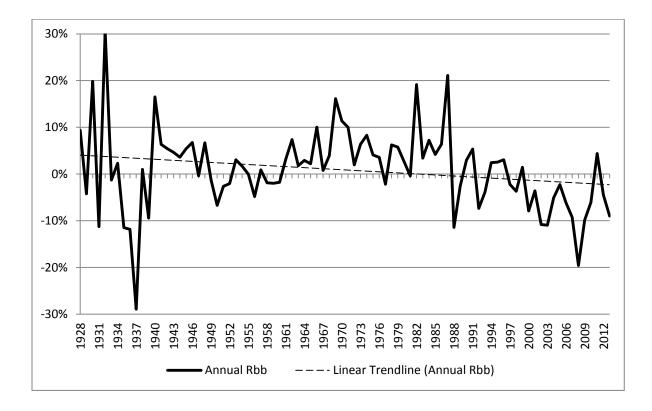


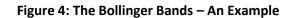
Figure 1: Popularity of Bollinger Bands in the US 1993-2013

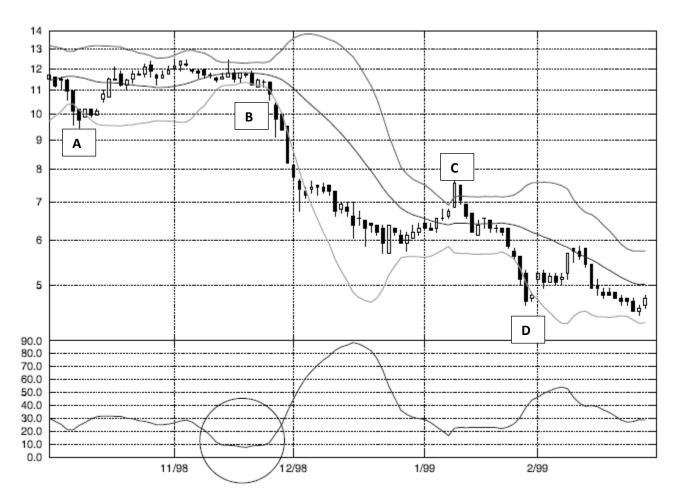
Figure 2: Annual Returns of Bollinger Bands-based Trading Strategy in the US 1993-2013



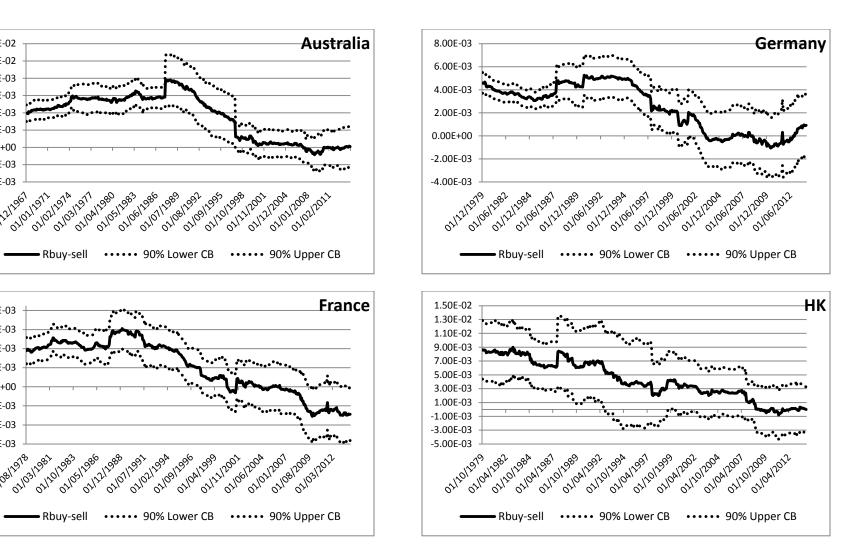








(Source: Bollinger, 2001, p. 130, Figure 16.3)



1.20E-02

1.00E-02

8.00E-03

6.00E-03 4.00E-03

2.00E-03

0.00E+00

-2.00E-03 -4.00E-03

8.00E-03

6.00E-03

4.00E-03

2.00E-03

0.00E+00

-2.00E-03

-4.00E-03

-6.00E-03

01/08/1978

01/12/1961

Figure 5 Continued

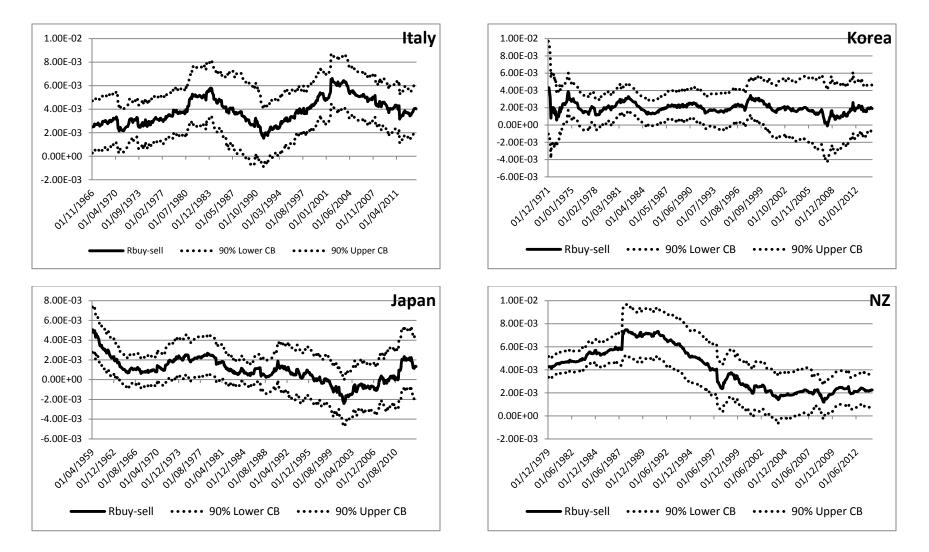
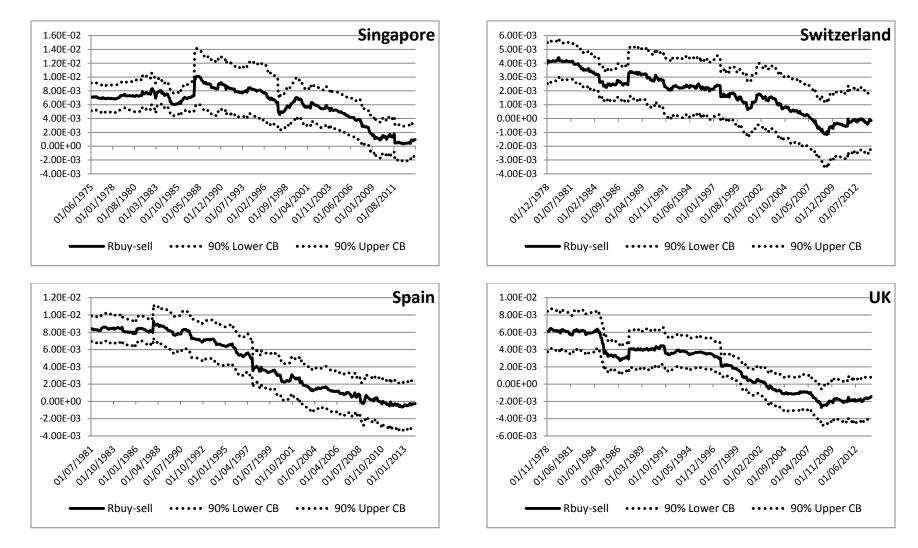
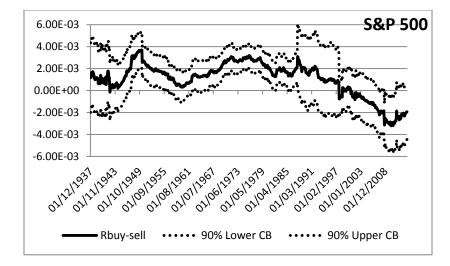
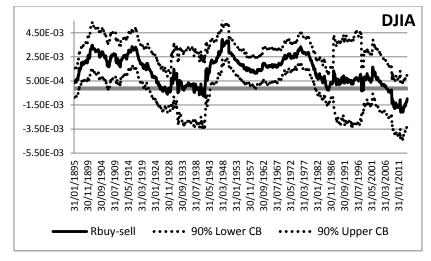
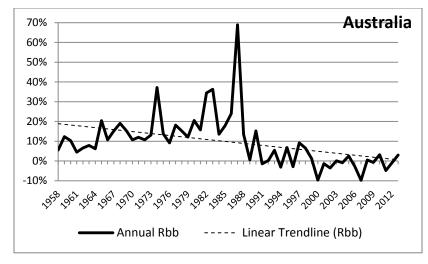


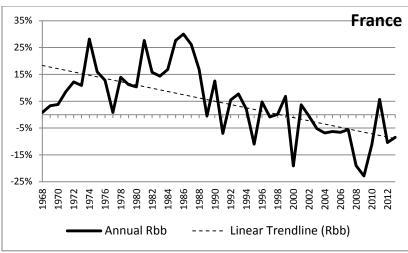
Figure 5 Continued

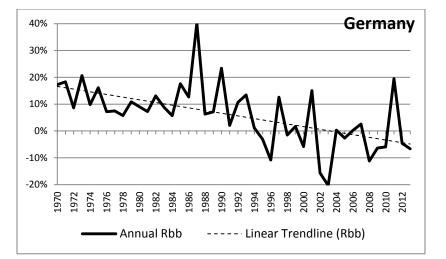












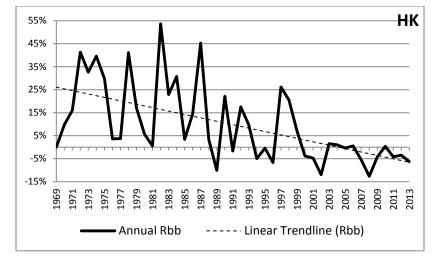


Figure 6: Annual Returns of Using Bollinger Bands (20, 2) in International Stock Markets

Figure 6 Continued

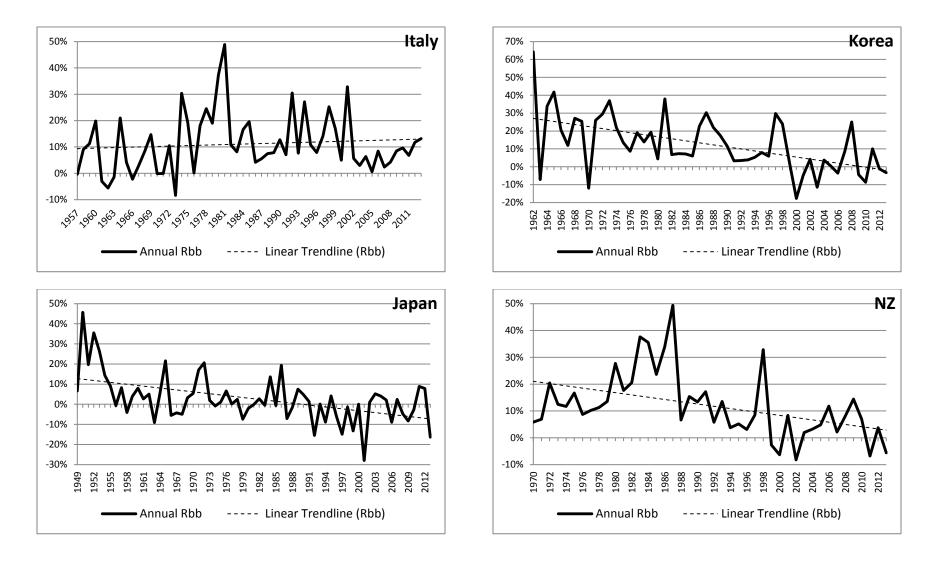


Figure 6 Continued

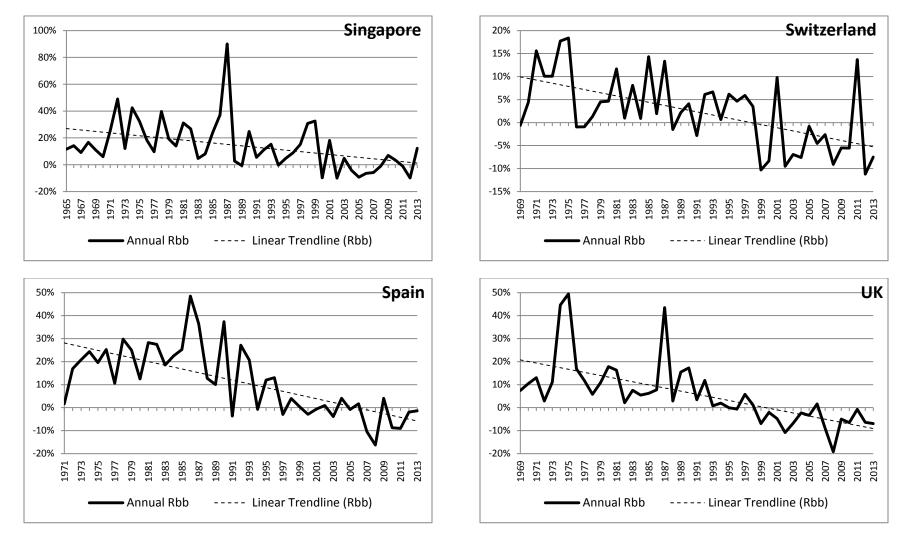


Figure 6 Continued

