Essays on Stop-loss Rules

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Abstract

Stop-loss rules are trading rules that involve selling a security when its price drops by a certain amount and buying the security back when its price rises above a pre-specified level. They are popularly used by practitioners. These rules are designed to protect gained profits as their sale trigger the price to be adjusted higher as prices increase. This thesis contributes to the literature on stop-loss rules in financial markets.

The first essay investigates the time-series and cross-sectional determinants of stop-loss rules for risk reduction in the U.S. stock market. It finds that, even though stop-loss rules have poorer mean returns to a mean-variance optimal benchmark, they are effective at stopping losses. These rules reduce overall and downside risk, especially during declining market states. The transaction costs analysis shows that the significant effectiveness of risk reduction holds for these rules with larger stop-loss thresholds.

Essay two examines the performance of stop-loss rules from the perspective of international equity market allocation. International diversification provides potential for larger returns but often induces higher risks. Thus, it is a natural setting to consider stop-loss rules from a global point-of-view. This essay finds that stop-loss rules are an important factor of international equity allocation in a parametric portfolio policy setting. These rules generate portfolios with larger mean and risk-adjusted returns. This result is economically stronger in declining markets. The outperformance is robust once the transaction costs are accounted for.

Essay three shows that stop-loss rules enhance the returns to stocks with lottery features. Individual investors have a strong preference for lottery stocks that typically have irregular enormous gains and frequent small losses. Stop-loss rules are useful at reducing losses and protecting gains from large price rises. This essay highlights that the sell signals of popular technical rules and time-series momentum rules are consistent with stop-loss rules, thereby effectively increasing the risk-adjusted returns of lottery stocks. These rules would have helped

investors avoid instances of major historical drawdowns and are particularly beneficial in recessionary markets. Some rules are robust to the inclusion of transaction costs.

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Chapter One

Overview

This chapter provides an overview of this thesis. Section 1.1 is the general introduction for studying stop-loss rules. Section 1.2 deals with the literature that relates to the stop-loss rules. Sections 1.3 – 1.5 discuss the main findings and the contribution of each essay in the thesis. Section 1.6 reviews the research outputs from the thesis. Section 1.6 concludes the chapter by mapping an outline for the rest of the thesis.

1.1 Introduction

Stop-loss rules are very prevalent in financial markets (e.g., Han, Zhou, and Zhu, 2016). A stop-loss rule involves selling a security when its price decreases to a pre-determined threshold and buying the security back once its price has risen to a pre-specified level in order to continue the trend of the rule. These rules help to protect investors from a larger price decline and limit their loss so as to maximise their average return.

Stop-loss rules are broadly used by practitioners. Using Google to search “stop loss”, returns around eight million results that discuss or mention such rules to mitigate losses. Toit (2015) suggests that stop-loss rules are efficient for investors. Capital.com News (2018) notes the stop-loss rules are designed to prevent losses. They propose ideas to correctly conduct stop-loss rules by using different settings of trigger points. These articles indicate the popularity of stop-loss rules among practitioners. However, these rules have been rarely studied in academia and there are mixed results regarding their effectiveness in prior studies. For instance, Kaminski and Lo (2014) reveal that stop-loss strategies add value under certain market conditions, such as momentum and regime-switching models. However, Lei and Li (2009) show that stop-loss rules neither increase nor reduce the losses for investors relative to a buy-and-hold strategy.

This thesis consists of three essays that contribute to the literature of stop-loss rules. Essay one is a pioneering study that highlights the difference between the trailing stop-loss rules and traditional stop-loss rules, which are either price based or time based. As a result, trailing stop-loss rules used in this thesis because trailing rules are more dynamic and broadly used in financial markets. This essay investigates the effectiveness of stop-loss rules in reducing risks when applied to common stocks in the U.S. market. Moreover, international diversification, which induces higher country-specific risks across different markets, is increasingly important for both institutional and retail investors. Essay two considers the performance of stop-loss rules from the perspective of international equity market allocation. This consideration sheds light for fund managers that are interested in techniques to mitigate risk in respective international portfolios. Essay three considers the effectiveness of stop-loss rules in the context of lottery stocks, which have irregular dramatic gains and frequent small losses. This area is attractive to individual investors, who typically have the preference for stocks with such lottery features.

The remainder of this chapter is organised as follows. Sections 1.2, 1.3, 1.4, and 1.5 provide a review of the relevant literature and the overview of each of the three essays. Section 1.6 presents the research output from this thesis. The remainder of the thesis is presented in Section 1.7.

1.2 Literature review

The section presents a review of the relevant literature across different fields in modern finance that relate to stop-loss rules. It covers the extensive literature on efficient market hypothesis, behavioural finance, quantitative trading strategies, and stop-loss rules.

The efficient market hypothesis, which evolves from random walk theory, is one of the most important concepts in modern finance. It suggests that publicly available information is fully reflected in current market prices. No investor is able to obtain abnormal returns in a market under this hypothesis. Behavioural finance argues that irrational investors' trading behaviour causes the price to deviate from the fundamentals, and that this deviation can be explained through psychological concepts. Behavioural finance challenges, but also supplants, the efficient markets hypothesis. Research extends the ideas from behavioural finance to investigate the profitability of quantitative trading rules that generally refer to two aspects, which are trend following rules and contrarian rules. Lastly, the section considers the extensive literature that discusses stop-loss rules, which are the focus of this thesis. Stop-loss rules are popular in financial markets but also show mixed results based on the existing studies.

1.3 Essay one

Stop-loss rules are widely used in financial markets but prior research shows that their effectiveness is mixed. For example, Wilcox and Crittenden (2009) show that stop-loss rules generate outperformance when applied to the S&P 500 index. While Lo and Remorov (2017) find that stop-loss strategies only add value in certain circumstances, with no substantial reduction in risk. Given the mixed results in extant studies, essay one reviews the literature and argues that stop-loss rules are either traditional or trailing stop rules. The latter rules are more dynamic and more popular with practitioners. This essay investigates the performance of trailing stop-loss rules, which have thresholds varying from 1% to 20%, compared to a mean-variance benchmark for U.S. stocks over the 1926 - 2016 period.

This essay finds that, even though stop-loss portfolios exhibit lower overall risk than their respective benchmarks, these rules induce lower returns and Sharpe ratios than their benchmark. This essay focuses on downside risk that the stop-loss rules are beneficial for. It finds that stop-loss portfolios have significantly lower downside risk relative to their benchmark. These rules are more effective at reducing downside risk over time, and especially during declining markets. Stop-loss rules perform better in reducing downside risk on stocks that are more volatile, more liquid, and have a lower book-to-market ratio.

This essay contributes to several strands of the literature. First, it reconciles the stop-loss literature that has positive results with those reveal negative results regarding the effectiveness of these rules. This essay indicates that stop-loss rules do add value by reducing overall risk and downside risk while investing U.S. common stocks. Second, it contributes to the literature that highlights the importance of the returns movement in addition to the average return. Prior studies consider that the price path of a popular momentum strategy may induce periods with large drawdowns, even though these strategies have positive total returns (e.g., Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). This essay shows that stop-loss rules can mitigate downside risk and prevent the periods of large declines.

1.4 Essay two

The second essay of this thesis investigates the effectiveness of stop-loss rules in the context of international equity allocation. Global asset allocation involves various country-specific risks, such as political risk in emerging markets (e.g., Erb, Harvey, and Viskanta, 1996; Diamonte, Liew, and Stevens, 1996). International equity flows have increased a lot in recent years (e.g., Portes and Rey, 2005). Given the increasing popularity in diversifying internationally, stop-loss rules may play an important role at reducing risk when allocating assets across different markets. Therefore, essay two proposes that stop-loss rules may improve risk-adjusted returns by cutting exposure to the markets with potential return declines due to the negative news.

This essay compares and contrasts the performance between a stop-loss portfolio with various stop thresholds and a naïve equal-weighted portfolio across 82 international equity markets over the 1973 - 2018 period. It finds the stop-loss rules add value to international equity allocation as a result of estimating the parametric portfolio policy model of Brandt, Santa-Clara, and Valkanov (2009). This essay reveals that stop-loss portfolios with thresholds from 1% to 4% have significantly larger returns than the equal-weight portfolio but their standard deviations are not statistically different from each other. Each stop-loss portfolio with thresholds less than 5% provides a higher Sharpe ratio as well as a higher certainty equivalent return than the equal-weight portfolio.

This essay indicates that the risk-adjusted returns or alphas of all stop-loss portfolios are significantly positive when controlling the Fama-French five risk factors and the momentum factor. Further, the performance between up and down markets is not statistically different. All the results are stronger for the rules with tight thresholds. Transaction costs are an important consideration in asset allocation research. This essay shows the break-even transaction costs of each stop-loss portfolio vary between four and eight basis points, which indicate that the outperformance of most stop-loss rules may cover the trading costs of six basis points, as calculated by following the method of Chung and Zhang (2014).

This essay adds to literature that considers stop-loss rules. It also contributes to papers that focus on international equity market allocation. The asset allocation decision process is an important determinant of investment outcome success (e.g., Brinson, Hood, and Beebower, 1986). Cross-border asset allocations are increasingly important over the past decades. Financial markets across the world have become increasingly open to foreign investors who have more opportunities to diversify the risk of their investments and obtain potential gains across various markets (e.g., Harvey and Zhou, 1993; Karolyi and Stulz, 2003; Chan, Covrig, and Ng, 2005). The stop-loss rules are an important determinant of international equity market allocation.

This essay contributes to the literature that highlights the importance of career risk for fund managers. Fund managers allocate a large amount of capital on behalf of individual and institutional investors, which directly affects the career of the managers. Ellul, Pagano, and Scognamiglio (2018) suggest that top managers in a hedge fund are likely to be demoted and incur high compensation losses if their funds are liquidated after two years of underperformance. The strategies that can successfully exclude underperforming assets are thus vital for fund managers. This essay indicates that stop-loss rules may help fund managers to enhance risk-adjusted performance when diversifying internationally.

1.5 Essay three

Lottery stocks, which represent a sizable proportion of common stocks, are particularly prevalent among individual investors (e.g., Kumar, 2009; Meng and Pantzalis, 2018). These stocks have a small probability to generate large gains, but also have a high probability to induce frequent losses. Stop-loss rules, which may exit positions before large losses, are a natural setting to be considered in the context of lottery stocks. The third essay of the thesis investigates whether stop-loss rules improve the returns to investment in lottery stocks.

The previous two essays reveal the popularity of stop-loss rules among investors, and how their effectiveness is stronger when applied to stocks with larger volatility. Lottery stocks form a natural setting to apply stop-loss rules. Moreover, this essay shows the similarity of sell signals between stop-loss rules and several popular trading strategies, such as moving average, trading range break, and time-series momentum rules. This essay, thus, includes these rules as "stop rules" in the analysis.

This essay finds that all stop rules add value when applied to lottery stocks, and that the results are stronger during a declining market. Harvey, Hoyle, Rattary, Sargaison, Taylor, and Van Hemert (2019) reveal that investors are increasingly careful about the impact of large drawdowns. This essay finds that stop rules are effective at adding value during periods of stock market drawdown, such as the market crash of 1987. Several of these rules also add value after the inclusion of transaction costs.

This essay adds to literature on stop-loss rules that is consistent with the previous two essays. Moreover, it contributes to the literature relating to technical trading rules and time-series momentum rules by examining their effectiveness in regards to sell signals. Prior studies show that these rules are profitable for practitioners (e.g., Schwager, 1993), but have also been shown to be impacted by data snooping bias (e.g., Sullivan, Timmerman, and White, 1999). Time-series momentum is shown to be an effective quantitative market timing technique (e.g., Moskowitz, Ooi, and Pedersen, 2012; Georgopoulou and Wang, 2017). This essay shows that technical trading rules and time-series momentum rules give similar sell signals to stop-loss. These rules can also prevent losses when investing lottery stocks.

Furthermore, this essay contributes to the literature on individual investors and lottery stocks. Individual investors tend to have behavioural bias, as noted in the extant research. They tend to trade too frequently, which causes losses (e.g., Barber and Odean, 2000; Barber, Lee, Liu, and Odean, 2009). They are not typically well diversified (e.g., Kelly, 1995; Polkovnichenko, 2005; Goetzmann and Kumar, 2008). As well, they have preference for stocks with lottery features (e.g., Bali, Cakici, and Whitelaw, 2011; Eraker and Ready, 2015; Hung and Yang, 2018). This essay documents that retail investors may benefit from stop rules given their preference in lottery stocks.

1.6 Research outputs from the thesis

Essay One:

This essay was published in the following journal:

- Dai, B., Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2020). Risk reduction using trailing stop-loss rules. *International Review of Finance.* https://doi.org/10.1111/irfi.12328

This essay was presented at the following conferences:

- New Zealand Finance Colloquium in Lincoln (2019).

- Australasian Finance and Banking Conference in Sydney (2019).
- New Zealand Finance Meeting in Auckland (2019).

Essay Two:

This essay has been accepted for publication in the following journal:

- Dai, B., Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2021). Do stop-loss rules add value in international equity market allocation?. *Applied Economics* - Forthcoming.

This essay was presented at the following conference:

- New Zealand Finance Colloquium in Auckland (2020).

1.7 Structure of the thesis

The rest of this thesis is organised as follows. Chapter Two reviews the literature on market efficiency, technical analysis, and stop-loss rules. In Chapter Three the first essay investigates the effectiveness of stop-loss rules in reducing risks in U.S. stock markets. In Chapter Four, the second essay, presents the effectiveness of stop-loss rules from the perspective of international equity allocation. Chapter Five contains essay three, which focuses on stop-loss rules when applied to stocks with lottery features. Chapter Six contains conclusions that summarise the findings and implications of each essay.

Chapter Two

Literature Review

The previous chapter provides an overview of the thesis. The stop-loss literature builds on studies in a number of areas, such as efficient market hypothesis, behavioural finance, and technical trading strategies. The first two concepts are important in modern finance. The work on technical trading strategies are an extension of the two concepts.

This chapter reviews the existing research that includes four sections. Section 2.1 provides an overview of the literature review. Section 2.2 discusses the efficient market hypothesis, which investors cannot obtain abnormal returns under this hypothesis. Section 2.3 surveys the literature in the area of behavioural finance that challenges the efficient market hypothesis and attributes the abnormal return to psychological factors. Section 2.4 investigates the profitability of trading strategies that is in conflict with efficient market hypothesis. Section 2.5 describes the literature that relates to stop-loss rules, which is the focus of the thesis. Section 2.6 concludes this chapter.

2.1 Introduction

This section provides a review of the relevant research on stop-loss rules in financial markets across different fields. The literature review has four main sub-sections. Firstly, it documents the efficient market hypothesis as one of the most important concepts in modern finance. Subsequently, it discusses the studies that are relevant to behavioural finance, which captures theories from psychology to explain the trading behaviours and price deviation. The finance literature in this area is considered as challenging but also regarded as supplanting the efficient markets hypothesis. Moreover, it covers the literature that documents the profitability of quantitative trading rules. This section documents two kinds of trading rules, which are trend following rules and contrarian rules. Lastly, it discusses the extensive literature in which the stop-loss rules are investigated. The stop-loss rules are the focus of this thesis. The relevant literature will be discussed in separate sub-sections in detail.

2.2 Efficient market hypothesis

The efficient market hypothesis is broadly acknowledged in academia over the past decades. It suggests that market prices should correctly and fully reflect all available information. Investors cannot obtain abnormal returns in a market based on the available information. Therefore, the stock price movements should present the characteristics of a random walk under this hypothesis. The new information and prices are uncorrelated to, and independent from, those from the past (Malkiel, 2003).

Samuelson (1965) provides the foundation of formal efficient market hypothesis that evolves from the random walk theory, which is statistically evident from papers such as Kendall (1953), Osborne (1959), and Osborne (1962). Further, Roberts (1967) and Fama (1970) develop a more comprehensive view of the efficient market hypothesis by proposing three levels, which are weak, semi-strong, and strong form, to indicate the degree of market efficiency. The "weak form efficient market" should reflect all information based on the past price. The "semi-strong form efficient market" should reflect all publicly available information. The "strong form efficient market" should reflect all information.

Some studies present viewpoints against the efficient market hypothesis. The perfectly efficient market reduces the private incentives for gathering information as it fails to generate abnormal returns (Grossman, 1976; Grossman and Stiglitz, 1980). Therefore, the market would be eliminated due to meaningless trading behaviours under this price system. Ball (1978) shows significant excess returns after a public earnings announcement across firms. Beja and Goldman (1980) introduce a disequilibrium model to show that taxes and trading costs can reduce the market efficiency. According to the context that the price deviates from the efficient market levels, Jensen (1978, p. 96) notes that the best way to explain the efficient market hypothesis is: "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t".

Further, the efficient market hypothesis is challenged in that the market is inefficient over long-term horizons due to the observed abnormal returns. Black (1986) notes that noise traders can cause prices to deviate from the fundamentals. De Bondt and Thaler (1985) show an overreaction of stock prices and criticise the efficient market hypothesis. There are even more studies that explore a variety of strategies to generate outperformance and, thus, dispute the market efficiency. The trading rules literature is discussed in section 2.4. Researchers' responses are presented through papers that challenge the efficient market hypothesis and attribute the abnormal returns to anomalies. Fama and French (1992) document that three factors, which are excess return on market, firm size, and book-to-market values, explain the unexplained anomalies, so as to support the efficient market hypothesis. Fama (1998) suggests the change of the return measurement will eliminate the anomalies. The underreaction has the same chance to occur with overreaction in the market. Therefore, the continuation of pre-event anomalies has the same possibility of occurring with the post-event reversal.

However, Loughran and Ritter (2000) disagree with the alternative returns measurement in Fama (1998) because the abnormal returns are predictable when using different methodologies. The multi-factor models cannot examine the market efficiency well because these models are only designed to test if certain returns patterns are different from their previous patterns. Barberis and Thaler (2002) use psychological methods to explain the anomalies and support the efficient market hypothesis.

A series of papers have documented the determinants that affect market efficiency. Chordia, Roll, and Subrahmanyam (2008) investigate the return predictability of order flows, which is an inverse indicator of market efficiency, and find the market efficiency is increased from 1993 to 2002. Further, Chordia, Roll, and Subrahmanyam (2011) find that the decreased intraday volatility and increased institutional trading activity enhance the market efficiency. Consistently, Manahov, Hudson, and Gebka (2014) indicate that the high frequency trading can improve price discovery, which enhances market efficiency. The insider traders result in imbalanced orders in the market and facilitate price discover (Aktas, De Bodt, and Van Oppens, 2008). Therefore, institutional traders, high frequency traders, and insider traders have a positive impact through increasing market efficiency.

Cross-listing is also relevant to market efficiency. Visaltanachoti and Yang (2010) find that foreign stocks take more time to achieve market efficiency than U.S. stocks listed in the NYSE due to the impact of information asymmetry. The market efficiency is also different, changing across different markets. Griffin, Kelly, and Nardari (2010) suggest that some trading rules have similar returns across developed and emerging markets, which run counter to the popular opinion that emerging markets have less efficiency than the developed markets. Fama and French (2017) observe that the five-factor model explains differently the anomalies from the viewpoint of international settings. The results for limitation of market efficiency measures are thus mixed in international markets.

The empirical studies regarding corporate governance also support the efficient market hypothesis. Basse, Klein, and Vigne (2021) report that the stable dividend policy can improve the efficient market hypothesis. There is numerous literature that test the validity of the efficient market in regards to cryptocurrencies. For instance, Bariviera (2017) observes that Bitcoin returns are shown as increasingly efficient since 2014. However, Hu, Valera, and Oxley (2019) notice that there is no empirical support for the efficient market by investigating 31 top market cap cryptocurrencies.

There are few existing studies that add profitability and investment factors to the Fama and French three-factor model (e.g., Fama and French, 2015; Hou, Xue, and Zhang, 2015; Fama and French, 2017). More recently, Hou, Xue, and Zhang (2020) suggest that the markets are increasingly efficient over time.

2.3 Behavioural finance

Psychology researchers link their works to finance and develop the field of behavioural finance. They capture ideas from psychology to explain trading behaviour and price movements in financial markets. Behavioural finance is widely considered as challenging, and even supplanting, the efficient markets theory.

The current evidence regarding psychological bias is still mixed. Psychological bias can be traced from the definition of heuristics (Hirshleifer, 2001). Tversky and Kahneman (1974) document people have three heuristics characteristics when making judgements: representativeness, availability biases, and anchoring. Fischhoff, Slovic, and Lichtenstein

(1977) prove that people are often overconfident, referring to an important belief regarding investors in financial markets. Similarly, the beliefs of optimism and wishful thinking result in similar biases to overconfidence. Conservatism, which is opposite to overconfidence, is another belief of people, and leads them to under-estimate probabilities. In addition, beliefs of people are not changed easily. Lord, Ross, and Lepper (1979) note that a person's belief is preserved for a very long once an opinion is formed.

Barberis and Thaler (2002) summarise a series of behavioural biases that are related to the preferences of investors in financial markets, based on findings in psychology. There are seven types of beliefs, namely overconfidence, optimism and wishful thinking, representativeness, conservatism, belief perseverance, anchoring, and availability biases.

De Bondt and Thaler (1985), whose paper is a milestone of behavioural finance, show that investors overreact to stock prices. They define the "losers" and "winners" portfolios based on the past market-adjusted returns and find the losers earn positive abnormal returns, whereas winners earn negative abnormal returns in the subsequent period of deciding "losers" and "winners". The overreaction also exists in the field of IPOs. Ritter (1991) finds the IPOs' long-run underperformance is negatively related to their initial returns. This may be due to the overreaction of the public to the recent performance of IPOs. On the other hand, the opposing contrarian strategy, which is due to the overreaction of investors, indicates that the underreaction of investors is found to be useful in exploiting abnormal returns. Jegadeesh and Titman (1993) propose the momentum strategy of buying "winners" and shorting "losers" to obtain abnormal returns, thus challenging the market efficiency hypothesis.

Further, Barberis, Shleifer, and Vishny (1998) propose two models to document the anomalies caused by overreaction and underreaction, based on the psychological evidence. They use two models to explain the reversed returns and trending returns, respectively. The decision of holding any one of the models depends on the investor's sentiment. Consistently, Daniel, Hirshleifer, and Subrahmanyam (1997) note the patterns of stocks' returns that may be due to overreaction and underreaction are according to the investors' overconfidence and biased self-attribution. They document that investors react differently to private signals and public information. Investors tend to overreact to their private information, but underreact to public information.

Moreover, behavioural finance studies indicate that the limits to arbitrage exist in financial markets. The efficient market hypothesis notes that it is impossible to earn abnormal returns and the actual price equals the fundamental value, which involves the present value of future cash flows that reflect all publicly available information. Friedman (1953) documents that the irrational traders cause mispricing that prevents trading from rational traders. The presence of irrational traders often results in the price deviating from its fundamental value. However, behavioural finance researchers argue that arbitrage can be costly and risky, which makes correcting mispricing unattractive. Barberis and Thaler (2002) note that there are three types of risks and costs that drive the limit to arbitrage. Firstly, fundamental risk is a key determinant, which occurs when arbitraging during periods with increasingly systematic risk that results in a further decline. Second, noise traders have an impact on arbitrageurs' behaviour. De Long, Shleifer, Summers, and Waldmann (1990) document that noise traders refer to the risk that the mispricing is increasingly severe in the short-term, so as to cause the losses for arbitrageurs. Thirdly, the implementation costs are one of risks, referring to transaction costs that make exploiting mispricing less attractive. Moreover, Abreu and Brunnermeier (2002) propose a synchronisation risk, which is caused through an arbitrageur being uncertain about the exact moment when their peers will exploit an opportunity. Therefore, the arbitrageurs should be careful when correcting mispricing through having a full understanding of the systematic risks.

Many existing studies indicate that a lot of factors result in the deviation of price to fundamental value even though the efficient market hypothesis holds under certain situations. However, a range of studies highlight that arbitrage can still be risky and costly. Therefore, the mispricing should persist for a long time. Given these issues in behavioural finance, researchers investigate a series of trading rules to exploit abnormal returns. They are discussed in the next sub-section.

2.4 Quantitative trading strategies

2.4.1 Technical analysis

Technical analysis uses past information in an effort to predict future prices in order to generate abnormal returns (Zhu and Zhou, 2009). Existing studies have investigated a series of trading rules, which have been proven to be useful in generating outperformance. The existence of profitable technical analysis is definitely in opposition to the market efficiency hypothesis. The profitability of trading rules is used as a measurement of market efficiency.

Brock, Lakonishok, and LeBaron (1992) is one of the pioneering studies to examine the profitability of trading rules in order to test market efficiency. They examine stocks in the DJIA index and study three technical rules, which are the variable-length moving average (VMA), fixed-length moving average (FMA), and trading range break-out (TRB) rules. These trading rules are intrinsically a kind of trend following strategy. The VMA rules are used to generate buy (sell) signals when the short-term moving average is greater (less) than the long-term moving average by a pre-specified threshold. The FMA rules are consistent but only utilise the returns in the 10 days following the triggered day. TRB rules suggest the buy (sell) signal when the price reaches the recent maximum (minimum) price. These technical rules have strong predictability power in DJIA from 1897 to 1986. Further, Bessembinder and Chan (1998) improve Brock, Lakonishok, and LeBaron (1992) by adding estimated dividends, a lag of trading day, and transaction costs. They find the excess returns still exist but are just eliminated if the trading costs are taken into account.

Technical analysis has been investigated across different financial markets. It is widely used in currency markets. Neely and Weller (2003) test two models, which are genetic programmes and an optimised linear forecasting, in foreign exchange markets to find the unprofitability of these rules. In addition, there are few studies that focus on technical analysis in international markets. Griffin, Kelly, and Nardari (2010) study the predictability of a series of trading rules, including short-term reversal, post-earnings drift, and momentum strategies in 56 developed and emerging markets. They find some of these rules generate similar returns across the two types of markets. Furthermore, the predictability of technical analysis is investigated in bond markets. Goh, Jiang, Tu, and Zhou (2013) examine the moving averages and on-balance volume rules, which use the stock market volume as a proxy, and find significant forecasting power of these rules in both in-sample and out-sample testing for short-term and long-term government bonds.

The profitability of popular trading rules is also documented in the intraday data frequency. Marshall, Cahan, and Cahan (2008) use bootstrapping methods to study five intraday trading rule families, which are filter rules, moving average rules, support and resistance rules, channel breakouts, and on-balance volume rules, in the U.S. equity market. They find none of the five rules are profitable once the data snooping bias is considered during the sample period.

More recently, Han, Yang, and Zhou (2013) study the moving average timing rule and sort the portfolios into deciles by volatility, then cross-sectionally investigate the profitability of this rule. They find moving average timing portfolios outperform buy-and-hold portfolios.

Han, Zhou, and Zhu (2016b) also investigate a trend factor that exploits the information in moving average prices to form forecasted returns. This trend factor can even generate better performance than short-term and long-term reversals, and momentum factors.

2.4.2 Cross-sectional momentum

According to the behavioural issues mentioned in section 2.3, researchers find the use of underreaction behavioural issues can generate outperformance. Jegadeesh and Titman (1993) propose momentum strategies to obtain abnormal returns, which is attributed to the underreaction of investors in the stock market. They suggest that buying past winners' stocks and selling past losers' stocks in the previous period will generate positive abnormal returns in the subsequent period. However, the positive abnormal returns will disappear in the long-term. Moreover, Chordia and Shivakumar (2002) find the momentum payoff is positive during expansions and negative during recessions. The momentum strategies are studied in international markets. Chan, Hameed, and Tong (2000) examine the profitability of momentum strategies across 23 countries taking currency into account in order to differentiate the impact of currency movements. They find that most of the momentum profits are from stock markets and only a little is from currency markets.

On the other hand, existing papers point out some shortcomings of momentum strategies. Lesmond, Schill, and Zhou (2004) find that the outperformance generated by momentum can be diminished by high trading costs. Moreover, momentum strategy can have extreme negative returns, such as in 1932 and 2009 (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). The potential crash has important negative effects for fund managers, which emphasise the career risks and drawdown risks. It is thus necessary to control the downside performance in extreme years. Barroso and Santa-Clara (2015) scale a momentum portfolio by its volatility in the previous six months to manage the crash risk. Highly volatile stocks will not be considered under this method. Daniel and Moskowitz (2016) dynamically allocate the weights of a momentum portfolio as per its forecasted return and variance. This method can double the alpha, as well as the Sharpe ratio, for traditional momentum strategies.

2.4.3 Time-series momentum

Moskowitz, Ooi, and Pedersen (2012) argue that the traditional momentum literature focuses on cross-sectional aspects, as investors form portfolios upon the relative performance of securities. Unlike the traditional momentum strategies, they propose a time-series momentum, which emphasises the comparison in the performance of a stock's own past returns. They document time-series momentum in a series of futures and forwards contracts, such as equity indexes, currencies, and commodities. The 12-month excess returns of each instrument have a positive association with its future returns.

Goyal and Jegadeesh (2017) investigate the differences in performances between cross-sectional strategies and time-series strategies for individual stocks. They note the outperformance of a time-series momentum strategy is attributed to the positive net long investment in risky assets. The outperformance disappears when adjusting the net long investment for time-series momentum strategies. Moreover, Kim, Tse, and Wald (2016) suggest the positive abnormal returns of a time-series momentum strategy are attributable to scaling the portfolio by volatility. An asset with lower volatility will have higher weight in the time-series momentum portfolio. The comparison between the time-series momentum strategy and other trading rules is investigated. Marshall, Nguyen, and Visaltanachoti (2017) compare the time-series momentum strategy and the moving average rules. The returns of the two rules are highly correlated. The moving average rules can produce a signal earlier than a time-series momentum strategy under most instances.

2.4.4 Contrarian strategy

The overreaction hypothesis of investors also guides researchers to propose contrarian strategies and investigate the abnormal returns. It uses ideas that are opposite to the trend following strategies. De Bondt and Thaler (1985) find that the past losers' portfolios can outperform the past winners' portfolios by even 24.6% over three years after the portfolio formation. Lehmann (1990) uses weekly intervals to test the short-term returns reversal and finds it yields significantly positive profits after considering the trading costs and plausible bid-ask spreads. Moreover, Lakonishok, Shleifer, and Vishny (1994) find the investors over-estimate the growth of stocks with good past performance. The value stocks, which actually perform badly and are underpriced in the past, will perform well in the future. Fama and French (1993) document the three factors model to explain the unexplained anomalies in the traditional CAPM model. This model provides a way to select value stocks. Fama and French (1992) suggest that the outperformance is attributed to the higher risk of value stocks. Also, stocks with smaller market capitalisations tend to perform better than stocks with bigger market capitalisations. However, Lakonishok, Shleifer, and Vishny (1994) argue that the abnormal returns persist simply because a lot of investors do not know the value strategies.

Conrad, Gultekin, and Kaul (1997) point out that the profits of short-term contrarian strategies can be eliminated if taking bid-ask bounce into account. However, De Groot, Huij, and Zhou (2012) indicate that the diminished abnormal returns of short-term reversal strategies due to high trading costs can be recovered if excluding the small cap stocks and reducing turnover.

2.5 Stop-loss rules

Stop-loss rules are popular in financial markets. These rules refer to selling a security when its price decreases below a pre-specified threshold and buying the security back when its price increases above a certain level. Houthakker (1961) is a pioneering study that uses stop-loss sell orders and finds patterns.

Further, researchers note that there are two types of stop-loss rules - traditional and trailing stop-loss. The former rules are either price-based or time-based. Price based rules involve selling when its price falls by a certain percentage below the purchase price, regardless of the price movements since the purchase. Time-based rules involve selling if the price moves a certain percentage below the entry price within a specified time interval. The latter rules are dynamic by adjusting the sell trigger price upwards if the price moves higher. A position is then closed if the price subsequently declines by a given percentage below the new high price. The trailing stop-loss rules are, therefore, designed to protect profits. These features indicate that trailing stop-loss rules are more realistic for practitioners.

Trailing stop-loss rules are more popular than traditional stop-loss rules in the industry. Wilcox and Crittenden (2009) show that trailing stop-loss rules can earn an abnormal return when trading on the S&P 500 index. Clarke and Clarke (2011), Magliolo (2013), and Toit (2015) suggest that trailing stop-loss rules generate better performance than traditional stop-loss rules because the trailing rules better protect the gained profits. Several academic papers discuss theoretical aspects of trailing stop-loss rules. Glynn and Iglehart (1995) apply discrete-time random walk and continuous-time Brownian motion models with a positive drift to address the question of optimising the distance from the current price to the stop price. Abramov, Khan, and Khan (2008) provide models for characteristics of trailing stop rules, such as the average duration and duration variation of open positions. Fu and Zhang (2012) suggest trailing stop-loss rules are unlikely to perform well for stocks that have return paths consistent with Geometric Brownian motion.

Using a broader view across various stop-loss rules, Lei and Li (2009) study ordinary common stocks on the New York Stock Exchange and the American Stock Exchange from 1970 to 2005 and find that both types of stop-loss rules do not increase the buy-and-hold returns, but do reduce the standard deviation. Kaminski and Lo (2014) find that the stopping premium, which is the expected return difference between a given portfolio and the portfolio with stop-loss rules, is negative under random walk hypothesis and mean-reversion strategies, but positive under momentum and regime-switching models. Han, Zhou, and Zhu (2016) show that the stop-loss rules decrease the downside exposure of a momentum strategy in the U.S. market. Further, Lo and Remorov (2017) suggest that the time-based traditional stop-loss rules with smaller pre-specified thresholds will have poorer performance than a buy-and-hold strategy under a mean-variance framework due to the higher trading costs if applying the smaller pre-specified threshold to the rules. The multiple stock returns that have high serial correlations can produce a better performance in a buy-and-hold strategy with stop-loss rules than in a simple buy-and-hold strategy. Moreover, stop-loss rules can decrease the realised loss, as well as reduce disposition effects (Fischbacher, Hoffmann, and Schudy, 2017). Overall, most of the existing studies simultaneously find stop-loss rules do not increase the returns, but do reduce the risk of stocks.

According to the literature, we see that the stop-loss rules can even be overlaid onto an existing trading strategy. Some studies investigate stop-loss rules upon an existing trading rule. For example, Lei and Li (2009) and Lo and Remorov (2017) apply stop-loss rules to a simple buy-and-hold strategy. They are also applied to cross-sectional momentum strategies in Han, Zhou, and Zhu (2016). As a consequence, the stop-loss rules can be used as an overlaid trading rule to supplement the other trading rules.

2.6 Conclusions

This section reviews the literature that is relevant to stop-loss rules, which is the focus of this thesis. Prior studies indicate that the market is efficient if no investor can earn abnormal returns. However, some research shows that the prices can still deviate from fundamental value in financial markets. Behavioural finance researchers suggest such deviations are attributed to the psychological bias of investors. More recently, numerous studies against the efficient market hypothesis have examined the findings of various profitable trading strategies. However, there is literature that argues that the anomalies can be explained by some factors.

In general, there are still many studies that show the profitability of trading rules once the transaction costs are accounted for. Thus, successful trading rules should be vital for fund managers to close the positions of underperformed holdings. For individual investors, the trading rules are useful to overcome their psychological bias, so as to enhance the performance of their holdings.

Chapter Three

Essay One

The previous chapter documents the extant literature that motivates the research of stop-loss rules. These rules are of interest to academic researchers and market participants.

This chapter presents the essay one which investigates the performance of stop-loss rules at mitigating risks with a focus of U.S. market. An introduction of the chapter that includes its main contributions to the literature is presented in Section 3.1. Section 3.2 describes the data and the descriptions of the rules. Section 3.3 shows the empirical results and Section 3.4 concludes this chapter. The appendix to this chapter and the respective reference list are provided at the end of the thesis.

Risk Reduction Using Trailing Stop-Loss Rules

Abstract

We consider the effectiveness of trailing stop-loss rules which, unlike traditional stop-loss rules, involve the sale trigger price being moved higher to protect profits as prices rise. Our results indicate that while these rules have inferior mean returns to a mean-variance optimal benchmark, they are effective at stopping losses. The trailing stop-loss strategy reduces total risk and lessens downside risk, especially during declining market states. Transaction costs reduce the benefits of tighter stop-loss rules, but the rules with larger stop-loss thresholds remain useful after accounting for transaction costs.

JEL Classification Codes: G11, G12

Keywords: Trailing Stop-Loss Rule, Risk Reduction, Trading Strategy

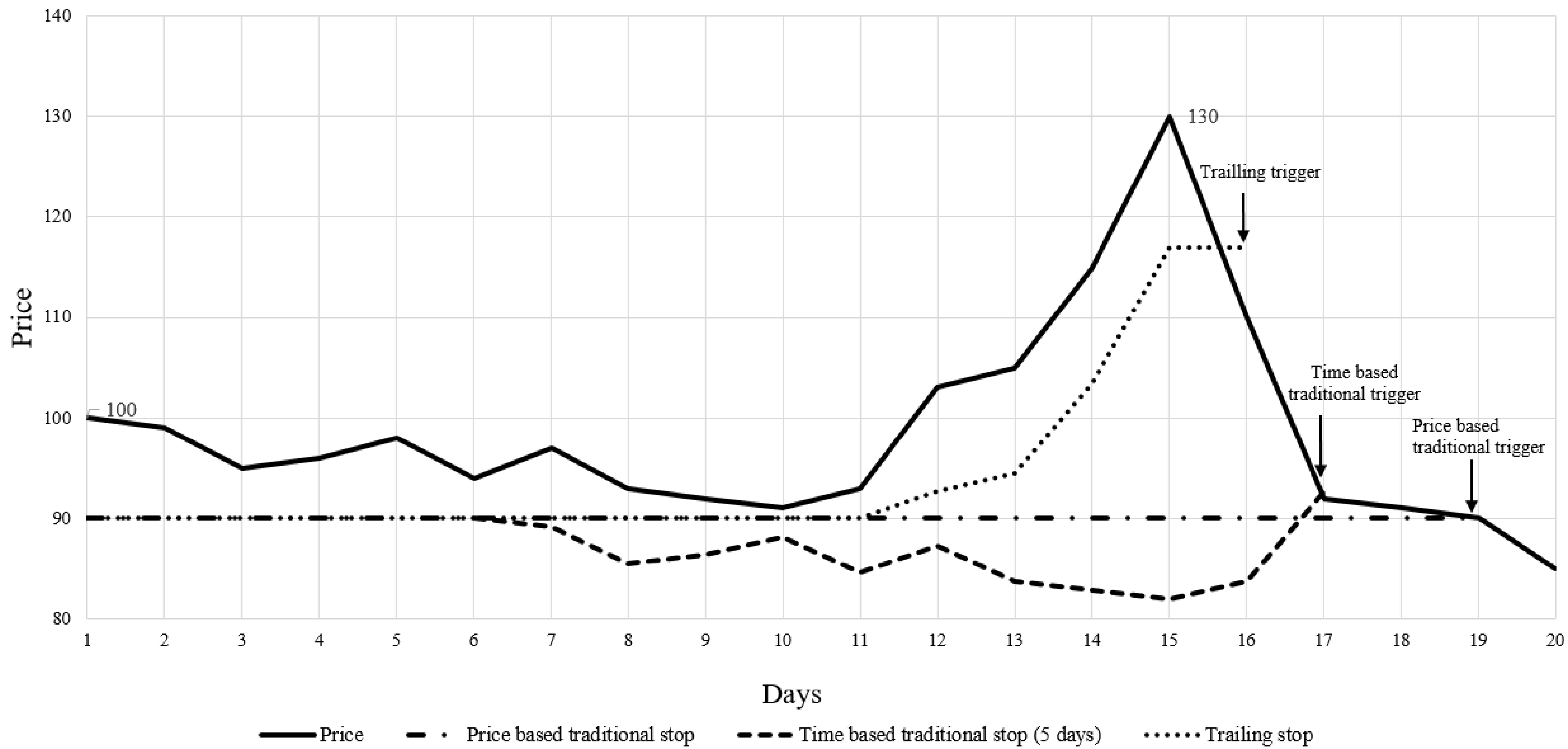
3.1 Introduction

Stop-loss rules are widely used in financial markets (e.g., Han, Zhou, and Zhu, 2016). The rules involve selling a security when its price drops below a pre-determined threshold and buying the security back when its price rises above a pre-specified level. However, research into their effectiveness show mixed results. For instance, Lo and Remorov (2017) find that stop-loss strategies only add value in certain circumstances, and that risk reduction is often not substantial.

There are two types of stop-loss rules - traditional and trailing stop-loss. Traditional stop-loss rules are either price-based or time-based. Price based traditional rules involve selling when the price falls a certain percentage below the purchase price, irrespective of the price path since the purchase price, while time-based rules involve selling if the price moves a certain percentage below the entry price within a specified time interval. In contrast, trailing stop-loss rules are more dynamic in that the sell trigger price is adjusted upwards if the price moves higher following a purchase. A position is then closed if the price subsequently declines a given percentage below the new high price. The trailing stop-loss rules are therefore designed to protect profits.[1] The purpose of this paper is to determine the extent to which trailing stop-loss (hereafter TSL) rules can protect against losses.

[1] Figure 3.1 plots the different sell trigger points of different stop-loss rules.

Figure 3.1: Stop price movements (10% threshold)



This figure shows the different stop prices of each stop-loss rules. The price is set to $100 at the beginning. The stop price of trailing stop-loss rules is increased only if the price increases. The price-based traditional stop-loss rules have a constant stop price over time. The time-based traditional stop-loss rules have the stop price based on the price at the beginning of the previous five days.

TSL rules are more popular than traditional stop-loss rules in the industry. Loton (2009) notes that a trailing stop-loss sell order is often used by trend-following investors to avoid the reversal of an upward trend. Wilcox and Crittenden (2009) show that trailing stop-loss rules work as an exit method and can earn an abnormal return in trading the S&P 500 index. Clarke and Clarke (2011), Magliolo (2013), and Toit (2015) suggest that trailing stop-loss rules outperform traditional stop-loss rules because trailing stops better protect the gained profits due to the stop price moving up as the price increases. Several academic papers discuss theoretical aspects of stop-loss rules. Glynn and Iglehart (1995) use discrete-time random walk and continuous-time Brownian motion models with a positive drift to document characteristics of trades using the trailing stop strategy and address the question of optimizing the distance from the current price to the stop. Abramov, Khan, and Khan (2008) provide models for characteristics of trailing stop strategies such as the average duration and duration variation of open positions. Fu and Zhang (2012) suggest trailing stop-loss rules are unlikely to perform well for stocks that have return paths consistent with Geometric Brownian motion.

One of the factors behind the popularity of trailing stop loss rules may be the investors' focus on percentage price declines from high points. Many commentators refer to a "correction" as having occurred when the price declines 10% from its recent high.[2] While traditional stop-loss rules are not referenced against recent high prices and declines from these levels, trailing stop loss rules are. The TSL rules are, therefore, consistent with the media attention around percentage price declines from recent high prices. The tight trailing stop-loss rules with a stop-loss threshold less than 10% is thus a mechanism that can be used to avoid corrections.

We investigate the performance of TSL rules compared to a benchmark for U.S. stocks over the 1926-2016 period. As the TSL strategy invests in the risk-free after the stop-loss level

[2] For instance, Sheetz (2018) notes, "The Nasdaq Composite Index on Thursday became the first major U.S. stock market benchmark to dip into a correction, dragged down by losses across all the major technology-related companies. A correction on Wall Street is defined as down more than 10 percent from its high."

is triggered, the appropriate benchmark should be the weighted average return from both risky assets and the risk-free asset. Therefore we compute the weight by maximizing the utility value of a mean-variance optimal investor. We form value-weight and equal-weight portfolios across TSL rules and their respective benchmarks. We consider several TSL thresholds, which vary from 1% to 20%. Our findings show that while TSL portfolios exhibit lower total risk than their benchmarks, the TSL strategy experiences lower returns. The TSL Sharpe ratios are also lower than their benchmark. However, measures of downside risk highlight the benefits of TSL rules. The Value-at-Risk and Expected Shortfall of the TSL portfolios show significantly lower downside risk relative to their benchmark. Further analyses show that TSL rules have become more effective at reducing downside risk through time, add more value to control downside risk in declining markets, and perform better regarding downside risk reduction on stocks that are more volatile, more liquid, and with a lower book-to-market ratio.

We consider the impact of realistic transaction costs on the performance of the TSL rule in terms of Sharpe ratio and downside risk. We find the TSL rule with a 20% threshold has the highest Sharpe ratio after adjusting for realistic transaction costs. Before taking into account the transaction cost, the TSL rules with the smallest thresholds, such as 5% or 10%, can achieve the lowest downside risk. However, after considering the transaction cost, we find a significantly higher downside risk among TSL portfolios with tight thresholds. Three factors drive such results. First, there is higher portfolio turnover among the TSL rules with tight thresholds. Second, the transaction cost is generally higher during the market declines which coincide with the period that the TSL rules trade. Third, in an extreme event such as the market crash, the transaction cost will also jump substantially, which increases the magnitude of downside risk after transaction cost. Nevertheless, the TSL rules with high thresholds (from 10% to 20%) still have significantly lower downside risk after transaction cost compared to their benchmarks. This is because the TSL strategies with large thresholds do not incur a much higher portfolio turnover, so their downside risks do not change significantly.

We contribute to several strands of the literature. First, we reconcile the stop-loss literature, which has reported mixed results regarding their effectiveness. Kaminski and Lo (2014) suggest that time-based traditional stop-loss rules underperform under random walk and mean-reversion markets but outperform under momentum and regime-switching models. Lo and Remerov (2017) consider various aspects of the downside risks of time-based traditional stop-loss rules. They find no evidence of consistent performance but document a positive relation between the extent of return serial correlation and the performance of these rules. However, Fischbacher, Hoffmann, and Schudy (2017) find that price based traditional stop-loss rules can reduce the impact of the disposition effect and decrease the realized losses. Several papers examine various aspects of TSL rules. Using traditional risk metrics, Lei and Li (2009) find that TSL rules neither increase nor reduce the losses experienced by investors relative to a buy and hold strategy. Clare, Seaton, Smith, and Thomas (2013) show that TSL rules do not add value to trend-following rules. However, Snorrason and Yusupov (2009) find that TSL rules outperform a buy-and-hold strategy in Sweden markets.

Second, we contribute to a broader strand of the literature that highlights the importance and implications of the path of returns in addition to the average return. Shleifer and Vishny (1997) point out that asset managers who manage capital on behalf of outside investors often avoid volatile arbitrage opportunities due to the risk that their investors will request the return of their capital during periods of drawdown. Moreover, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) consider the price path of a popular momentum strategy and highlight that while the overall average return is positive, there can be periods where large losses are incurred. TSLs are specifically designed to limit downside risk and prevent periods of large losses.

The rest of this paper proceeds as follows: Section 2 contains a description of the data and trading rules. The results are presented and discussed in Section 3. Section 4 concludes the paper.

3.2 Data and trading rules

3.2.1 Data

We examine the performance of the TSL rule using all common stocks from the CRSP database. Our sample includes 25,997 common stocks with share codes of 10, 11, and 12 in the U.S. markets from 1 July 1926 to 30 December 2016.[3] Bessembinder (2018) highlights the importance of considering delisting returns, so we follow his approach and compound the two returns if both the regular return in the last trading day and the delisting return are available.[4] We ignore the impact of delisting returns for stocks that have missing delisting returns from the CRSP database.[5]

3.2.2 Description of the rules

Our TSL approach involves selling the stock when it declines X% from its high price and buying it back when it increases X% above its low price. The initial trailing stop loss trigger

[3] All missing returns are deleted.
[4] Some stocks have missing returns, which are deleted, in the last trading day. We compound the delisting return to the last existing return for these stocks.
[5] The definitions of missing delisting codes are divided into four types. -55: "CRSP has no sources to establish a value after delisting or is unable to assign a value to one or more known distributions after delisting." -66: "more than ten trading periods between a security's last price and its first available price on a new exchange." -88: "the stock is still active." -99: "security trades on a new exchange after delisting, but CRSP currently has no sources to gather price information."

price (STP) is set at X% below the price the stock is purchased at. If the stock price does not increase, the STP remains at this initial level. However, if the stock price increases beyond the initial purchase price, the STP is increased so that it is X% below each new high price. When the price falls below the STP, a sell signal is generated.

Lo and Remorov (2017) note that traditional stop-loss rules with one day delay in the transaction can increase the performance as it captures some reversed returns in the day after the trigger. This is a more practical way for investors to close a position on the day following the trigger. Therefore, we exit a position on the day following the STP being hit regardless of the price movement on that day. We enter a position in T-bills at the end of the day the stock is sold.

We maintain the T-bills position until the stock price rises above the buy trigger price (BTP), which is initially set at X% above the closing price on the day the previous long position was exited. As with the STP, the BTP decreases each day if the price falls below the price the long price was exited. Equation (3.1) shows the position of TSL approach mathematically:

$$S_t = \begin{cases} 0, if \ \frac{P_t}{STP} - 1 \leq -X\% \ and \ S_{t-1} = 1 \\ 1, if \ \frac{P_t}{BTP} - 1 \geq X\% \ and \ S_{t-1} = 0 \end{cases} \tag{3.1}$$

where S_t is the position in a stock if it equals to 1 and in T-bills if it equals to 0. X% is the stop-loss threshold we use from 1% to 20%. P_t is the closing stock price on day t. Our focus on trailing stop-loss rules differs from that of Lo and Remerov (2017) who make their trading decisions on time-based traditional stop-loss rules. However, we compare the current price with the historical highest price since the day we enter a position in the stock no matter how long it is taken.

The return is named TSL return in the TSL approach. The TSL return equals to either stock return or T-bills rate depending on the long position in either the stock or T-bills on the trading day. Equation (3.2) indicates the TSL return mathematically:

$$R_{t,TSL} = \begin{cases} R_{t,STOCK}, if\ S_t = 1 \\ R_{t,RF}, if\ S_t = 0 \end{cases} \tag{3.2}$$

We construct both value-weight or equal-weight portfolio returns for each of the TSL thresholds and compare their performances with those of benchmark portfolios. A benchmark portfolio involves simple value-weight and equal-weight portfolios that incorporate with risk-free assets by assuming an investor with a mean-variance utility function as shown in equations (3.3a) and (3.3b) below:

$$Max_w\ U = \mu_m - \frac{1}{2} * \sigma_m^2 \tag{3.3a}$$

$$w^* = \frac{\mu_m}{\sigma_m^2} \tag{3.3b}$$

where μ_m and σ_m^2 are mean and variance of excess stock portfolio returns estimated from the 10-year rolling window, respectively. w^* is the optimal weighted allocated to the stock portfolio, and 1-w^* is allocated to the risk-free asset. We restrict the value of w^* between 0 and 1.

3.3 Results

3.3.1 Summary statistics

Table 3.1 contains monthly returns, standard deviations, and Sharpe ratios for the benchmark and TSL portfolios with the four thresholds of 1%, 5%, 10%, and 20%. The results for value-weight portfolios in Panel A are consistent with those for equal-weight portfolios in Panel B. In general, the results indicate that mean returns are lower for most of the TSL strategies than the benchmark. For example, Panel A shows that the value-weight benchmark portfolio's monthly return of 0.76% is statistically larger than that of value-weight TSL portfolios with 1%, 5%, and 10% thresholds. Only the 20% TSL portfolio has a higher monthly return than the benchmark; however, this outperformance is not statistically significant. Similarly, the results based on equal-weight returns in Panel B show that TSL rules do not add value with all TSL portfolio returns being approximately half of the return on the benchmark portfolio.

While TSL rules do not seem useful in improving return performance, they are effective at reducing portfolio risk. The total risk, as measured by the standard deviation of returns, is significantly lower for each of the TSL rules than its corresponding benchmark. In Panel A, the return standard deviation ranges between 2.84% for the 1% TSL portfolio and 3.91% for the 20% TSL portfolio, and they are all significantly lower than the 4.48% standard deviation of the benchmark. The results in Panel B exhibit a similar pattern. However, the better performance in risk reduction for TSL portfolios is insufficient to offset their worse performance in return, which results in relatively low Sharpe ratios for these TSL portfolios compared to the benchmark. Out of the eight comparisons between a TSL portfolio and its corresponding benchmark, four exhibits significantly lower Sharpe ratios. Only the 20% TSL portfolio yields a Sharpe ratio of 0.13 larger than the 0.11 Sharpe ratio for the value-weight benchmark; however, the higher risk-adjusted excess return is not statistically significant.

Table 3.1: Summary statistics

Variable	*RF*	*Benchmark*	TSL *1%*	TSL *5%*	TSL *10%*	TSL *20%*
Panel A: Value-weight						
Return (%)	0.28	0.76	0.43	0.45	0.63	0.79
			<.0001	<.0001	0.04	0.65
Std Dev (%)	0.25	4.48	2.84	3.10	3.43	3.91
			0.00	0.00	0.00	0.00
Sharpe Ratio		0.11	0.05	0.06	0.10	0.13
PSR			-1.77	-1.76	-0.19	0.77
Panel B: Equal-weight						
Return (%)	0.28	2.04	1.02	0.96	1.04	1.21
			<.0001	<.0001	<.0001	<.0001
Std Dev (%)	0.25	7.68	3.68	3.82	4.22	4.88
			0.00	0.00	0.00	0.00
Sharpe Ratio		0.23	0.20	0.18	0.18	0.19
PSR			-1.01	-1.99	-2.00	-1.55

This table presents the TSL and benchmark results for all common stocks with share codes of 10, 11, and 12 from CRSP. The sample period is from July 1926 to December 2016. We conduct a TSL approach with thresholds of 1%, 5%, 10%, and 20%. In Panel A, we display the return, standard deviation, and Sharpe ratio for value-weight portfolios. The PSR (Probabilistic Sharpe ratio) is a Z-score that shows the confidence level that the Sharpe ratio of a TSL portfolio is greater than that of the benchmark. The return and standard deviation are reported in percent. We display the *p*-value that tests the difference between a TSL portfolio and its benchmark under each return and standard deviation. Panel B shows the results of the same measurements for equal-weight portfolios.

3.3.2 Downside risk

In this section, we focus on downside risk and examine if TSL rules help reduce this risk. We employ Value-at-Risk (VaR) and Expected Shortfall (ES) analyses at 1% and 5% levels. The VaR indicates a potential loss level of the TSL or benchmark portfolios under a certain confidence level. The ES is the average loss beyond the VaR under the confidence level.

Table 3.2 shows the VaR and ES results, which indicate that the downside risk is generally lower for value-weight portfolios in Panel A than for equal-weight portfolios in Panel

B. Additionally, each of the TSL portfolios has higher VaR and ES than the benchmark. For example, in Panel A, the 1% VaR and 1% ES of value-weight benchmark portfolios are -11.41% and -16.78% respectively while these two measures are increased to -7.40% and -9.13% for the TSL portfolio with a 5% stop loss threshold. Panel B results show that the equal-weight benchmark portfolio has the 1% VaR and 1% ES of -17.34% and -21.07%, respectively, which are statistically lower than the corresponding VaR and ES of -7.84% and -9.56% for the TSL portfolio with a 5% threshold. Therefore, the results in Table 3.2 suggest that TSL rules significantly add value by reducing downside risk. The results hold across both confidence levels of 1% and 5%.[6]

Table 3.2: Downside risk

Variable	*Benchmark*	TSL *1%*	TSL *5%*	TSL *10%*	TSL *20%*
Panel A: Value-weight					
VaR (1%)	-11.41%	-8.67%	-7.40%	-7.27%	-9.08%
		0.00	0.00	0.00	0.01
Expected shortfall (1%)	-16.78%	-10.45%	-9.13%	-9.42%	-11.94%
		0.00	0.00	0.00	0.00
VaR (5%)	-6.48%	-3.96%	-4.00%	-4.49%	-5.33%
		0.00	0.00	0.00	0.00
Expected shortfall (5%)	-10.03%	-6.39%	-6.11%	-6.20%	-7.62%
		0.00	0.00	0.00	0.00
Panel B: Equal-weight					
VaR (1%)	-17.34%	-8.15%	-7.84%	-7.83%	-9.38%
		0.00	0.00	0.00	0.00
Expected shortfall (1%)	-21.07%	-10.88%	-9.56%	-9.28%	-11.24%
		0.00	0.00	0.00	0.00
VaR (5%)	-8.30%	-4.25%	-4.28%	-4.36%	-5.17%
		0.00	0.00	0.00	0.00
Expected shortfall (5%)	-12.94%	-6.48%	-6.18%	-6.14%	-7.59%
		0.00	0.00	0.00	0.00

This table displays the Value-at-Risk (VaR) and Expected Shortfall (ES), which are two measures of downside risks, for TSL and respective benchmark portfolios. Panel A shows the results of value-weight

[6] Appendix 1 shows the downside risk for delisted stocks only. The outperformance of TSL rules regarding the reduction in downside risk is still significant when constructing equal-weight portfolios that consist of delisted stocks. Appendix 2 shows additional results for downside risk if we apply TSL rules on a monthly frequency; that is, we sell (buy) a stock at the end of the following month if its price hits the TSLTP (BTP) at the end of the current month. The TSL rules still generate significantly less downside risk than the benchmark in most cases.

portfolios and Panel B reports the results of equal-weight portfolios. We display *p*-value under each result. *P*-values are estimated by 1,000 bootstrapped samples.

3.3.3 Time-series determinants of downside risk

In this section, we consider the performance of TSL rules though time. We focus on downside risk as it is reasonable to assume that stop-loss rules were developed to "stop losses" rather than minimize risk measures such as volatility. We select both VaR and ES are at the 1% level as downside exposures. For a given TSL rule or the benchmark, we accordingly compute their monthly return for individual stocks and then estimate the 1% VaR and ES values across all stocks in a month. We compare TSL rules' downside risk values with those computed from the benchmark returns in the same month. This process yields two time-series of monthly differences in VaR and ES between TSL rules and the benchmark. We use these time-series differences in VaR and ES to examine if the performance of TSL rules relative to the benchmark is dependent on periods, business cycles, or market states concerning downside risk reduction. This method studies the downside risk from the view of individual stocks rather than the portfolio view in the previous section. All coefficients in this section are displayed in percent with their associated *p*-values placed directly underneath in italics.

3.3.3.1 Sub-period analysis

We investigate the effectiveness of TSL rules at reducing downside risk over time by four sub-periods, as shown in the equations below.

$$VaR(TSL)_t - VaR(BM)_t = \alpha + \beta_1 Subperiod_{1949-1971} + \beta_2 Subperiod_{1972-1995} + \beta_3 Subperiod_{1996-2016} + \varepsilon_t \quad (3.4a)$$

$$ES(TSL)_t - ES(BM)_t = \alpha + \beta_1 Subperiod_{1949-1971} + \beta_2 Subperiod_{1972-1995} + \beta_3 Subperiod_{1996-2016} + \varepsilon_t \quad (3.4b)$$

where *VaR(TSL)* and *VaR(BM)* are the VaR values at a specific level for a TSL rule and the benchmark in a month, similarly, *ES(TSL)* and *ES(BM)* are the ES values at a specific level for a TSL rule and the benchmark in a month. We divide our sample period to four sub-periods with the first sub-period of 1926–1948 is used as the reference period. Three respective dummy variables capture the other three sub-periods. For example, $Subperiod_{1949-1971}$ is equal to 1 for the months within the 1949–1971 period and zero otherwise.

The regression results reported in Table 3.3 show that the difference in downside risk between TSL rules and the benchmark is increasing over time. This evidence is consistently robust for both downside risk measures. Besides, although the most recent sub-period of 1996–2016 indicates the highest downside risk difference between TSL rules and the benchmark across the eight regression specifications, the 1972–1995 sub-period exhibits the largest periodic change in the outperformance of TSL rules over the benchmark.

Table 3.3: Sub-periods analysis

Dep. Var	*Constant*	*1949-1971*	*1972-1995*	*1996-2016*	*R-square*
		Panel A: VaR (1%)			
1% TSL - BM	-0.82	2.43	8.27	9.51	0.4475
	0.00	*<.0001*	*<.0001*	*<.0001*	
5% TSL - BM	-0.43	2.56	8.07	9.92	0.4265
	0.13	*<.0001*	*<.0001*	*<.0001*	
10% TSL - BM	0.20	1.98	7.45	9.76	0.4226
	0.47	*<.0001*	*<.0001*	*<.0001*	
20% TSL - BM	0.62	0.77	6.09	8.70	0.4017
	0.02	*0.04*	*<.0001*	*<.0001*	
		Panel B: Expected shortfalls (1%)			
1% TSL - BM	-0.75	2.77	9.46	11.37	0.4811
	0.01	*<.0001*	*<.0001*	*<.0001*	
5% TSL - BM	-0.49	2.98	9.35	12.02	0.4728
	0.11	*<.0001*	*<.0001*	*<.0001*	
10% TSL - BM	0.25	2.60	8.75	11.71	0.4521
	0.43	*<.0001*	*<.0001*	*<.0001*	
20% TSL - BM	0.98	1.18	7.37	10.56	0.4279
	0.00	*0.01*	*<.0001*	*<.0001*	

This table shows regression results for the difference between the TSL approach and the benchmark regarding two downside risk measurements, Value-at-Risk (VaR) and Expected shortfall (ES), over four sub-periods. The period from 1926 to 1948 is set as the constant. The other three sub-periods are captured by dummy variables. For instance, $Subperiod_{1949–1971}$ is equal to 1 for the months within the 1949–1971 period and zero otherwise. The 1%, 5%, 10%, and 20% thresholds are applied to the TSL approach. The coefficients are in percent. We display *p*-value under each coefficient in the table.

3.3.3.2 Business cycles analysis

We study the difference in downside risk reduction between TSL approaches and the benchmark during expansions and recessions determined by the National Bureau of Economic Research (NBER)[7]. The equations are estimated as below:

$$VaR(TSL)_t - VaR(BM)_t = \alpha + \beta_1 Recession_t + \varepsilon_t \tag{3.5a}$$

$$ES(TSL)_t - ES(BM)_t = \alpha + \beta_1 Recession_t + \varepsilon_t \tag{3.5b}$$

[7] https://www.nber.org/

where the dependent variables are defined as in equations (3.4a) and (3.4b) above. *Recession* is a binary indicator that is equal to 1 for a month in a recession period as classified by NBER, and zero otherwise.

The results are displayed in Table 3.4, which indicates that there is no evidence showing the outperformance of TSL rules in downside risk reduction is different between expansions and recessions. Specifically, the constant, representing the effect of expansions, is significantly positive while the *Recession* coefficient is small and statistically insignificant suggesting that TSL rules are generally effective but not higher during recessions than during expansions. This finding is seen for both VaR and ES regressions with different TSL thresholds.

Table 3.4: Business cycles analysis

Dep. Var	*Constant*	*Recession*	*R-Square*
	Panel A: VaR (1%)		
1% TSL - BM	4.23	-0.18	0.00
	<.0001	*0.70*	
5% TSL - BM	4.69	-0.12	0.00
	<.0001	*0.80*	
10% TSL - BM	4.93	0.09	0.00
	<.0001	*0.86*	
20% TSL - BM	4.45	-0.02	0.00
	<.0001	*0.97*	
	Panel B: Expected shortfalls (1%)		
1% TSL - BM	5.12	-0.10	0.00
	<.0001	*0.85*	
5% TSL - BM	5.56	-0.11	0.00
	<.0001	*0.84*	
10% TSL - BM	5.95	-0.03	0.00
	<.0001	*0.96*	
20% TSL - BM	5.70	-0.12	0.00
	<.0001	*0.82*	

This table shows regression results of the difference between the TSL approach and the benchmark regarding two downside risk measurements, Value-at-Risk (VaR) and Expected shortfall (ES), in changing business cycles. The period of business cycles is from NBER. *Recession* is a binary variable equal to 1 for a month in a recession period as classified by NBER, and zero otherwise. The 1%, 5%, 10%, and 20% thresholds are applied to the TSL approach. The coefficients are in percent. We display *p*-value under each coefficient in the table.

3.3.3.3 Market states analysis

In this section, we study the difference of downside measures between TSL rules and the benchmark during different market states. Following Cooper, Gutierrez Jr, and Hameed (2004), we classify our sample period into the UP market and DOWN market states based on the CRSP value-weighted index. The market is UP if the CRSP market return is non-negative in a calendar month; otherwise, we deem the market as DOWN in that calendar month.

We use the following two equations to examine if DOWN and UP market states exhibit a difference in the downside risk reduction performance of TSL rules against the benchmark:

$$VaR(TSL)_t - VaR(BM)_t = \alpha + \beta_1 DOWN_t + \varepsilon_t \qquad (3.6a)$$

$$ES(TSL)_t - ES(BM)_t = \alpha + \beta_1 DOWN_t + \varepsilon_t \qquad (3.6b)$$

where the dependent variables are defined as in equations (3.4a) and (3.4b) above. *DOWN* is a binary variable that is equal to 1 if the CRSP value-weight index return is negative in a month, and zero otherwise.

The results are shown in Table 3.5. Both VaR results in Panel A and ES results in Panel B suggest the TSL approaches have substantially lower downside exposures than the benchmark during DOWN markets. The constant and the coefficient of the DOWN markets are positive and highly significant for all four stop-loss thresholds. Besides, the magnitude of the *DOWN* coefficient relative to the constant suggests that not only the TSL approach reduces more downside risk over the benchmark during UP markets, but this outperformance of the TSL rules increases to approximately double during DOWN markets. This finding supports the Lo and Remorov (2017) that the time-based traditional stop-loss rules have better performance than the buy-and-hold strategy when returns have the characteristics of relatively higher autocorrelation, i.e., during DOWN markets. Overall, our results show that the TSL approach helps investors to reduce the downside exposure, especially during DOWN markets.

Table 3.5: Market states analysis

Dep. Var	*Constant*	*Down*	*R-square*
Panel A: VaR (1%)			
1% TSL - BM	2.65	4.11	0.1150
	<.0001	*<.0001*	
5% TSL - BM	2.98	4.49	0.1277
	<.0001	*<.0001*	
10% TSL - BM	3.33	4.31	0.1203
	<.0001	*<.0001*	
20% TSL - BM	3.09	3.59	0.0944
	<.0001	*<.0001*	
Panel B: Expected shortfalls (1%)			
1% TSL - BM	3.68	3.76	0.0744
	<.0001	*<.0001*	
5% TSL - BM	4.01	4.05	0.0805
	<.0001	*<.0001*	
10% TSL - BM	4.42	4.04	0.0812
	<.0001	*<.0001*	
20% TSL - BM	4.37	3.47	0.0656
	<.0001	*<.0001*	

This table shows regression results of the difference between the TSL approach and the benchmark regarding two downside risk measurements, Value-at-Risk (VaR) and Expected shortfall (ES), in changing market states. We follow Cooper, Gutierrez Jr, and Hameed (2004) to determine the UP and DOWN markets, based on monthly CRSP value-weighted index returns. The 1%, 5%, 10%, and 20% thresholds are applied to the TSL approach. The coefficients are in percent. We display *p*-value under each coefficient in the table.

3.3.4 Cross-sectional determinants

In this section, we compare and contrast a series of cross-sectional factors that may impact the effectiveness of TSL rules above the benchmark at reducing downside risk. We investigate six cross-sectional factors: size, B/M ratio, liquidity, volume, price, and volatility. Size is the monthly average market value of each stock. They are displayed in units of 1 million.

We use the annual common equity, which is obtained from COMPUSTAT, in the previous year divided by the market value in the current month as the monthly B/M ratio. The B/M ratio regression is restricted between 1980 and 2016 as the common equity ratio is only available during that time. For the liquidity, we follow Karolyi, Lee, and Van Dijk (2012) to take the inverse of the natural log of Amihud ratio plus a constant as indicated in the equation below:

$$Liq_{i,t} \equiv -\log\left(1 + \frac{|R_{i,t}|}{P_{i,t}VOL_{i,t}}\right) \tag{3.7}$$

where $R_{i,t}$, $P_{i,t}$, and $VOL_{i,t}$ are the return, price, and trading volume of stock i on day t. We calculate the average of daily liquidity ratios in each month as the monthly liquidity measure. For volume and price, we calculate the average daily volume and prices each month, respectively. The volume is reported in units of 1000. The volatility is measured by taking the standard deviation of daily returns in each month. All independent variables are displayed in their natural logarithm.

We investigate the impact of cross-sectional characteristics on the downside performance between each TSL rule and the benchmark by employing Fama-Macbeth regressions. We focus on the 1% VaR and ES that are computed cross-sectionally. i.e., we assign the constant 1% VaR and ES for a certain stock over time. This process is reasonable as each stock has a certain downside risk when looking backward, and its cross-sectional characteristics have a stable magnitude relative to other stocks within each specific period. We compare the downside risk measurements with those computed from the benchmark returns for the same stock. This generates two cross-sectional differences in VaR and ES between each TSL rule and the benchmark. We investigate whether the downside risk reduction of TSL rules relative to the benchmark is dependent on six factors, as mentioned above. We display the regression results for VaR in Table 3.6 and ES in Table 3.7. All coefficients are reported in percent.

Our results show the TSL approach is more effective at reducing downside risk for stocks with higher liquidity, volume, volatility, and the lower B/M ratio. We estimate Fama-Macbeth regressions as the equations below:

$$VaR(TSL)_{i,t} - VaR(BM)_{i,t} = \alpha_{i,t} + \beta_1 Size + \beta_2 BM + \beta_3 Liquidity + \beta_4 Volume + \beta_5 Price + \beta_6 Volatility + \varepsilon_{i,t} \tag{3.8a}$$

$$ES(TSL)_{i,t} - ES(BM)_{i,t} = \alpha_{i,t} + \beta_1 Size + \beta_2 BM + \beta_3 Liquidity + \beta_4 Volume + \beta_5 Price + \beta_6 Volatility + \varepsilon_{i,t} \tag{3.8b}$$

Table 3.6: Cross-sectional analysis based on 1% VaR

Dep. Var	*Constant*	*Size*	*B/M ratio*	*Liquidity*	*Volume*	*Price*	*Volatility*
1% TSL - BM	7.47	-0.01					
	<.0001	*0.8120*					
	8.38		-0.39				
	<.0001		*<.0001*				
	7.24			20.89			
	<.0001			*<.0001*			
	6.66				0.34		
	<.0001				*<.0001*		
	7.18					-0.06	
	<.0001					*0.2401*	
	9.01						0.95
	<.0001						*<.0001*
	10.69	-0.82	-0.27	24.47	0.82	-0.03	0.73
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.6060*	*0.0002*
5% TSL - BM	8.25	-0.03					
	<.0001	*<.0001*					
	8.91		-0.29				
	<.0001		*<.0001*				
	7.86			21.43			
	<.0001			*<.0001*			

	7.41				0.35		
	<.0001				*<.0001*		
	7.88					-0.11	
	<.0001					*0.0544*	
	10.07						1.20
	<.0001						*<.0001*
	12.00	-0.90	-0.21	27.06	0.80	-0.06	0.89
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.4486*	*<.0001*
10% TSL - BM	8.75	-0.14					
	<.0001	*<.0001*					
	8.91		-0.25				
	<.0001		*<.0001*				
	7.97			14.99			
	<.0001			*<.0001*			
	7.58				0.37		
	<.0001				*<.0001*		
	8.61					-0.35	
	<.0001					*<.0001*	
	12.13						2.23
	<.0001						*<.0001*
	13.22	-0.89	-0.25	24.26	0.76	-0.20	1.30
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.0043*	*<.0001*
20% TSL - BM	8.31	-0.45					
	<.0001	*<.0001*					
	7.43		-0.27				
	<.0001		*<.0001*				
	6.35			-5.46			
	<.0001			*0.0045*			
	6.10				0.29		
	<.0001				*<.0001*		
	8.73					-0.96	
	<.0001					*<.0001*	
	13.82						3.96
	<.0001						*<.0001*
	13.76	-0.96	-0.41	21.09	0.79	-0.57	1.84
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*

This table indicates how cross-sectional factors affect stop-loss rules' effectiveness in reducing downside risks regarding 1% Value-at-Risk (VaR) by Fama-Macbeth regression. Six cross-sectional determinants, which are size, B/M ratio, liquidity ratio, volume, price, and volatility, are studied as independent variables in their natural logarithm. Each variable is on a monthly basis. The coefficients are displayed in percent. We display P-value under each coefficient in the table.

Table 3.7: Cross-sectional analysis based on 1% expected shortfall

Dep. Var	*Constant*	*Size*	*B/M ratio*	*Liquidity*	*Volume*	*Price*	*Volatility*
	7.38	0.19					
	<.0001	*<.0001*					
	9.03		-0.35				
	<.0001		*<.0001*				
	7.87			24.68			
	<.0001			*<.0001*			
1% TSL - BM	7.19				0.43		
	<.0001				*<.0001*		
	7.15					0.16	
	<.0001					*0.0079*	
	8.20						0.20
	<.0001						*0.2720*
	10.49	-0.72	-0.16	25.65	0.81	0.01	0.55
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.8934*	*0.0010*
	8.09	0.20					
	<.0001	*<.0001*					
	9.61		-0.25				
	<.0001		*<.0001*				
	8.55			27.39			
	<.0001			*<.0001*			
5% TSL - BM	7.98				0.44		
	<.0001				*<.0001*		
	7.68					0.19	
	<.0001					*0.0060*	
	8.98						0.29
	<.0001						*0.1677*
	11.67	-0.85	-0.10	26.07	0.84	0.06	0.65
	<.0001	*<.0001*	*0.0062*	*<.0001*	*<.0001*	*0.3882*	*0.0002*
	8.59	0.12					
	<.0001	*0.0027*					
	9.61		-0.19				
	<.0001		*0.0012*				
	8.75			23.25			
	<.0001			*<.0001*			
10% TSL - BM	8.26				0.48		
	<.0001				*<.0001*		
	8.43					-0.03	
	<.0001					*0.6714*	
	10.90						1.19
	<.0001						*<.0001*
	12.77	-0.77	-0.10	23.68	0.77	-0.12	1.08
	<.0001	*<.0001*	*0.0118*	*<.0001*	*<.0001*	*0.0890*	*<.0001*

	8.39	-0.25					
	<.0001	*<.0001*					
	8.21		-0.21				
	<.0001		*0.0007*				
	7.16			1.67			
	<.0001			*0.5169*			
20% TSL - BM	6.81				0.41		
	<.0001				*<.0001*		
	8.92					-0.75	
	<.0001					*<.0001*	
	13.29						3.28
	<.0001						*<.0001*
	13.69	-0.91	-0.26	23.33	0.84	-0.48	1.66
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*

This table shows how cross-sectional factors affect the effectiveness of TSL rules in cutting downside risks regarding 1% Expected Shortfall (ES) by Fama-Macbeth regressions. Six cross-sectional determinants, which are size, B/M ratio, liquidity ratio, volume, price, and volatility, are studied as independent variables in their natural logarithm. Each variable is on a monthly basis. The coefficients are displayed in percent. We display P-value under each coefficient in the table.

Tables 3.6 and 3.7 show a positive relationship between downside risk and liquidity, volatility, and volume. The coefficients of the liquidity measure are generally larger when applying a tight threshold, such as 5%. The TSL approach is more effective in reducing downside risk over the benchmark for more liquid stocks. The positive coefficients of volume and volatility imply the TSL approach helps to reduce downside risks for stocks with larger trading volume and volatility. The TSL rule with a 10% threshold reduces the most downside risk for stocks with more trading volume, while the TSL rule with a 20% threshold reduces the most downside risk for more volatile stocks. Furthermore, our results indicate a negative association between the B/M ratio and downside measures in both Table 3.6 and Table 3.7. This suggests the TSL approach performs well at reducing downside risks for growth stocks, especially when applying the 10% threshold.

On the other hand, the relationship between some cross-sectional determinants and the reduction in the downside risk of the TSL approach is inconsistent across Tables 3.6 and 3.7. For example, the price has a negative relationship with the outperformance of the TSL approach above the benchmark in controlling downside risk regarding most thresholds in Table 3.6. However, the association is changed to positive when applying 1% or 5% thresholds in Table 3.7. Moreover, our results in Table 3.6 report that size negatively affects the effectiveness of the TSL approach at reducing downside risk. Nevertheless, the results in Table 3.7 show a positive relationship between size and the downside performance except when applying the 20% threshold. Overall, our results clearly show that the TSL approach is effective at decreasing downside risks over the benchmark for stocks with characteristics of higher liquidity, volume, volatility, and the lower B/M ratio.

3.3.5 Transaction costs

In this section, we investigate the impact of transaction costs on the downside risk performance of TSL rules compared to the benchmark. We deduct transaction costs from our portfolio returns before examining the downside performance of TSL rules. We use the estimated transaction costs following Abdi and Ranaldo (2017), which provide the estimated spreads for U.S. common stocks. We follow Stoll (2000) to estimate the spreads of stocks that do not have the estimated spread information from Abdi and Ranaldo (2017) by running a pooled regression of the stocks' spreads that are available in the database on their monthly volume, return variance, market value, and price level. The equation is estimated below:

$$s = \alpha_0 + \alpha_1 logVOL + \alpha_2\sigma^2 + \alpha_3 logMV + \alpha_4 logP + \varepsilon \tag{3.9}$$

where *s* is transaction costs we need to estimate, *VOL* is monthly dollar volume, σ^2 is the return variance within each month, *MV* is the stock's monthly market value, *P* is the stock's average closing price within each month, and ε is the error term.

Panels A and B of Table 3.8 contain the downside risk results net of transaction costs. In general, transaction costs significantly worsen the downside risk for both TSL portfolios and their benchmarks. However, the transaction cost effect is larger for TSL portfolios due to their more frequent rebalancing. Despite this adverse effect of transaction costs, TSL portfolios still outperform the benchmarks in reducing downside risk when larger stop-loss rules are applied. For example, a value-weight portfolio with a 20% TSL threshold has an ES of -13.91%, which is lower than the value-weight benchmark portfolio’s ES of -17.13% once the realistic transaction costs are accounted for.

In addition to analyzing the realistic transaction costs adjusted downside risk, we estimate breakeven transaction costs focusing on downside returns. The realistic transaction costs cover the whole period while breakeven transaction costs solely focus on the crisis period. Specifically, for a TSL portfolio and its corresponding benchmark, we calculate the average number of trades generated in months where the return is lower than their 1% VaR values, respectively. We then estimate the breakeven transaction cost by dividing the 1% VaR difference between this TSL portfolio and its benchmark by the difference between their average number of trades. We repeat this process for each pair of TSL and benchmark and different VaR and ES thresholds.

We report the results in Panel C for value-weight portfolios and in Panel D for equal-weight portfolios. The results indicate that the TSL rules have positive breakeven transaction costs across all thresholds. The breakeven transaction costs have a range between 43 and 1909 basis points across value-weight and equal-weight portfolios. These numbers are smaller when applying tighter TSL thresholds. Goyenko, Holden, and Trzcinka (2009) note the mean of monthly effective spreads for U.S. stocks is 290 basis points, which is lower than the breakeven transaction costs for TSL rules with a threshold larger than 10%. This is consistent with results in Panel A and B that suggest the TSL rules with the larger thresholds can cover the transaction costs and achieve a significantly less downside risk than the benchmark.

Overall, our results show the optimal TSL rule that reduces the most downside risk is when applying a 20% threshold. The optimal TSL threshold should be decided on the performance, downside risk, and the transaction cost. The results of performance in Table 3.1 show the 20% value-weight TSL rule has a larger return and Sharpe ratio than the corresponding benchmark. The results of downside risk in Table 3.2 report that TSL rules with 5% or 10% thresholds reduce the most downside risk, but they generally incur more frequent rebalancing and more trading costs. The transaction does reduce the performance and increase the portfolio downside risk. Our TSL rule with a 20 % threshold yields the lower downside risk than the benchmark consistently across value-weight and equal-weight portfolios after accounting for its transaction costs. Taking all three factors into account, the optimal threshold is the TSL rule with a 20% threshold, given its higher Sharpe ratio and lowest downside risk after transaction cost.

Table 3.8: Transaction costs

Variable	*Benchmark*	TSL *1%*	TSL *5%*	TSL *10%*	TSL *20%*
Panel A: Transaction costs adjusted downside risk of value-weight portfolios					
VaR (1%)	-11.49%	-18.90%	-12.81%	-10.46%	-10.45%
Expected shortfall (1%)	-17.13%	-20.62%	-15.33%*	-13.20%***	-13.91%**
VaR (5%)	-6.54%	-10.24%	-6.75%	-5.74%**	-5.97%**
Expected shortfall (5%)	-10.32%	-14.81%	-10.35%	-8.42%***	-8.62%***
Panel B: Transaction costs adjusted downside risk of equal-weight portfolios					
VaR (1%)	-19.34%	-28.68%	-22.16%	-19.37%	-15.13%***
Expected shortfall (1%)	-24.56%	-31.57%	-26.40%	-21.74%*	-18.65%***
VaR (5%)	-10.07%	-20.82%	-15.19%	-11.07%	-8.71%***
Expected shortfall (5%)	-15.82%	-25.36%	-19.74%	-15.59%	-12.69%***
Panel C: Break-even transaction costs of value-weight portfolios					
VaR 1% (bp)		43.41	140.30	238.94	356.99
ES 1% (bp)		100.61	267.50	425.61	742.55
VaR 5% (bp)		43.50	105.49	184.28	282.00
ES 5% (bp)		62.73	166.30	353.53	591.13
Panel D: Break-even transaction costs of equal-weight portfolios					
VaR 1% (bp)		165.04	340.94	646.20	1547.01
ES 1% (bp)		182.84	413.21	800.99	1909.39
VaR 5% (bp)		77.22	165.68	365.19	964.82
ES 5% (bp)		123.25	278.73	630.59	1648.82

This table displays the transaction costs related results for both value-weight and equal-weight portfolios formed by TSL rules and the respective benchmarks. Panel A and B show the downside risk that incorporates realistic transaction costs. All the results are reported on a monthly basis. *, **, and *** indicate the statistical significance of *p*-values based on robust standard errors at 10%, 5%, and 1% levels, respectively. The *p*-values are estimated from 1,000 bootstrapped samples. Panel C and D show the breakeven transaction costs regarding downside risk. These numbers are in basis point.

3.4 Conclusions

Stop-loss rules are popular among participants in financial markets. Traditional stop-loss rules include price-based rules (where security is sold when the price drops a fixed percentage below the purchase price) and time-based rules (where security is only sold if the pre-specified price decline occurs within a given time interval). Trailing stops, in contrast, are more flexible as the stop price is adjusted upwards if the price moves higher following the purchase. Security is then sold when the price declines by a pre-specified percentage below the new high price.

We consider the performance of trailing stop-loss (TSL) rules for U.S. stocks and compare that to a benchmark that incorporates a mean-variance objective function for the 1926 – 2016 period. Our results indicate that TSL rules have lower returns than the respective benchmark. However, they do a good job of stopping losses. They perform particularly well at reducing downside risk, as measured by VaR and Expected Shortfall. We find the optimal TSL rule that reduces the most downside risk is when applying a 20% threshold. Moreover, we find the risk reduction of TSL rules has become more effective over time, performs better when the overall market is declining, and adds more value to stocks with more volatility, higher liquidity and lower book-to-market ratios. Further, we account for realistic stock spreads before the downside risk is computed and estimate breakeven transaction costs for the downside risk. Our results indicate that transaction costs reduce the effectiveness of stopping losses when applying tighter thresholds. However, TSL rules can still significantly reduce downside risk when applying larger thresholds.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Bochuan Dai
Name/title of Primary Supervisor:	Professor Ben Marshall

In which chapter is the manuscript /published work: Chapter 3

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Dai, B., Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2020). Risk reduction using trailing stop-loss rules. International Review of Finance. https://doi.org/10.1111/irfi.12328

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Bochuan is the main author of this paper and while his supervisors have made substantial contributions - which is reflected by co-authorship - the papers are essentially the work Bochuan. He obtained the data, generated the results, and wrote the paper. The supervisors provided detailed advice and answers to Bochuan's questions about as he completed the paper.

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Chapter Four

Essay Two

International equity flows increased substantially in recent years (e.g., Portes and Rey, 2005). It is thus interesting to examine whether stop-loss rules enhance the performance when diversifying internationally.

This chapter presents the second essay which investigates the performance of stop-loss rules from a perspective of international equity market allocation that covers a sample of 82 indices. An introduction of the chapter that includes its main contributions to the literature is presented in Section 4.1. Section 4.2 describes the data and the descriptions to form the portfolio. Section 4.3 shows the empirical results and Section 4.4 concludes this chapter. The appendix to this chapter and the respective reference list are provided at the end of the thesis.

Do Stop-loss Rules Add Value in International Equity Market Allocation?

Abstract

We consider the performance of stop-loss rules in international equity market allocation. Diversifying internationally gives the potential of larger risk-adjusted returns, but often involved higher risks so it is a natural setting to consider these rules. Our results indicate that stop-loss rules, which involve closing positions that decline by a pre-specified percentage, are important determinant of asset allocation in a parametric portfolio policy setting. They generate portfolios that have superior mean and risk-adjusted returns for investors. This result holds in general but is economically stronger in declining markets. The outperformance is robust to the inclusion of transaction costs.

JEL Classification Codes: G11, G12
Keywords: Asset Allocation, Stop-Loss Rule

4.1 Introduction

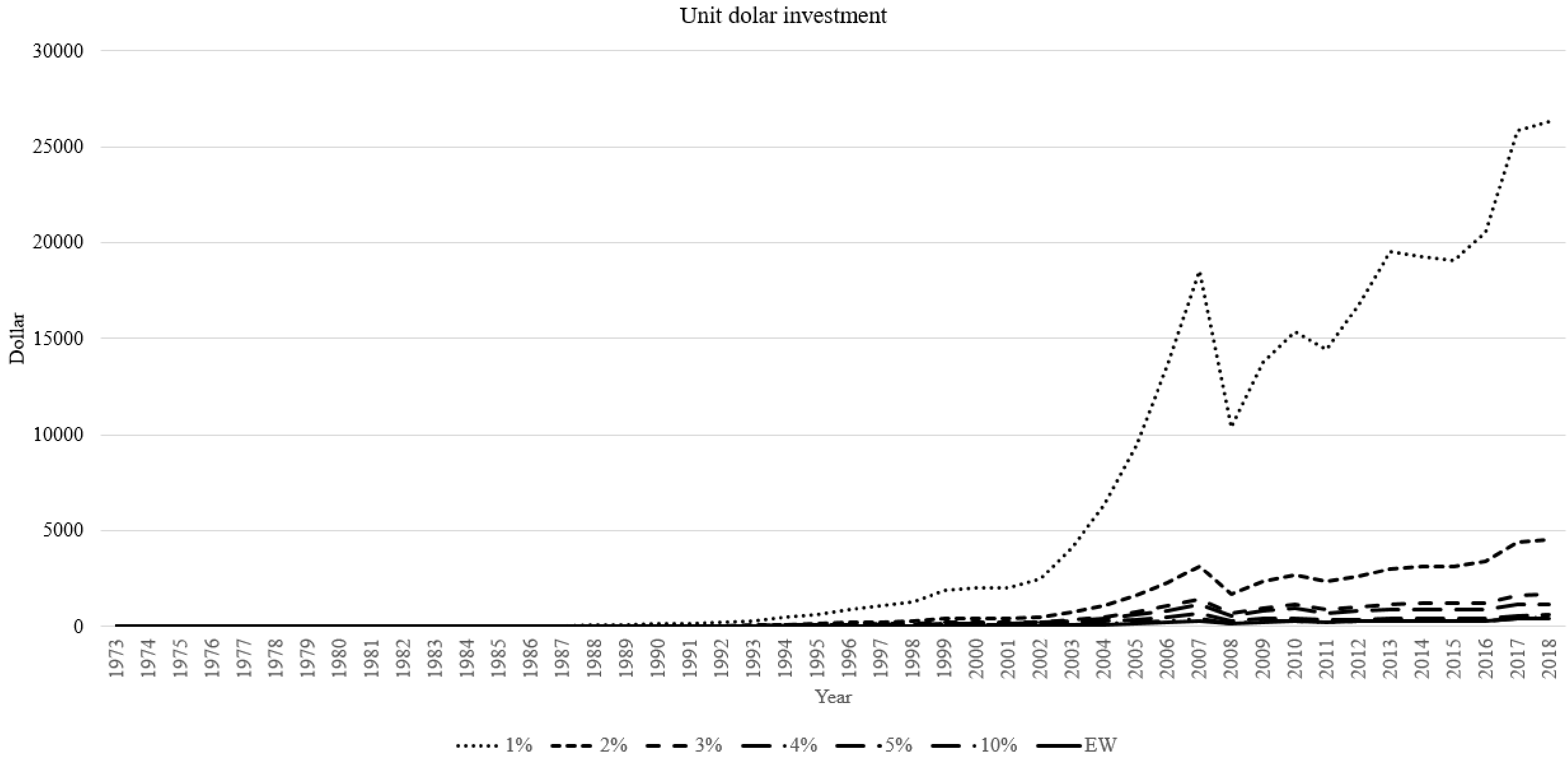
Stop-loss rules involve selling an asset when its price drops by a pre-determined threshold and buying the asset back when its price rises by a pre-specified amount. These rules are a popular risk mitigation technique with practitioners (Han, Zhou, and Zhu, 2016a), but there is relatively little academic research in this area. We consider the stop-loss rule in the context of international asset allocation. Baltzer, Stolper, and Walter (2013) note that international portfolio diversification helps investors obtain a larger risk-adjusted return, compared with investing in a single market. However, as Erb, Harvey, and Viskanta (1996) indicate, global asset allocation does involve various country-specific risks. For instance, political risk is an important return determinant, particularly in emerging markets (e.g., Diamonte, Liew, and Stevens, 1996). Butler and Joaquin (2002) point out that in bear market periods international stock market correlations are higher than normal and the expected gains to international diversification do not occur. Moreover, Han, Zhou, and Zhu (2016b) note that mechanical or technical trading rules can be particularly useful in settings when there are differences in the timing of receiving information or differences in the response to information by heterogeneous investors. This characterizes many international equity markets. We, therefore, propose, that international asset allocation is a natural setting in which to consider whether stop-loss rules add value through reducing risk.

We investigate whether stop-loss (SL hereafter) rules add value to international equity allocation as follows: We start with an equally weighted portfolio of N international equity indices and hold this portfolio until one of the equity indices falls by a pre-specified amount and hits a stop-loss. The position is then closed and the capital is reallocated across the remaining holdings. The exited market is then re-entered following an increase of a pre-specified percentage with a 1/N weight that comes from a proportional reduction of the allocation in the other N-1 holdings.

We compare and contrast the performance between the SL portfolio with various stop thresholds and a naïve equal-weighted (EW) portfolio across 82 international equity markets over the 1973 – 2018 period. We investigate the performance of SL rules in several ways. First, we examine whether the stop-loss rules are determinants of international asset allocation under the parametric portfolio policy model of Brandt, Santa-Clara, and Valkanov (2009). The results show the SL signal indicator is positive and statistically significant, which suggests that SL rules add value to international equity allocation. Second, we investigate the in-sample performance of SL rules from a view of traditional metrics. We find that SL portfolios with thresholds from 1% to 4% have significantly larger returns than the EW portfolio.[8] There is no statistically significant difference in standard deviations of the SL and EW portfolios. Moreover, the Sharpe ratio of each of the SL portfolios with thresholds less than 5% is larger than that of the EW portfolio. We also follow Rapach, Ringgenberg, and Zhou (2016) and construct the certainty equivalent return to examine the utility for investors with different risk aversion levels. Our results suggest that each SL portfolio with thresholds less than 5% provides a higher certainty equivalent return than the EW portfolio for investors with risk-aversion coefficients of one, three, or five.

[8] Figure 4.1 shows the changing value of an investment that begins with one dollar for the EW portfolio and SL portfolios with thresholds from 1% to 5% and 10%, respectively.

Figure 2.1 Unit dollar investment



Note: This figure shows the change in an investment that starts with a unit dollar for the EW portfolio as well as the SL portfolios with thresholds from 1% to 5% and 10%. The compounding is based on the annual return of the respective portfolio. The data is from 1973 to 2018.

Further, we account for the Fama-French five risk factors and the momentum factor as another way of determining whether the performance of SL portfolios can be attributed to risk-taking. Our results indicate that the risk-adjusted returns or alphas of all SL portfolios are significantly positive. Cooper, Gutierrez, and Hameed (2004) and Orlov (2016) demonstrate that momentum and carry trade respectively perform differently in different market states. We, therefore, test whether SL portfolios perform better in one state and find the difference in performance between up and down markets, is not statistically significant. All of our results are stronger when applying tight thresholds to each equity index. For example, the largest risk-adjusted return appears when applying the 1% threshold while it is smallest when the 10% threshold is applied. Transaction costs are an important consideration in asset allocation research. For instance, Lesmond, Schill, and Zhou (2004) find that transaction costs likely subsume the returns to the momentum trading strategy. We find the break-even transaction costs of each SL portfolio are positive and vary between four and eight basis points.

Our paper contributes to the literature in several ways. First, we add to papers that consider various aspects of stop-loss rules. The theoretical model of Kaminski and Lo (2014) suggests that these rules underperform under random walk and mean-reversion market characteristics but outperform under momentum and regime-switching models. Further, Lo and Remorov (2017) study the performance of SL rules when applying to individual U.S. stocks. They show that return serial correlation has a positive impact on the performance of SL rules. Lei and Li (2009) apply SL rules to individual common stocks and find that SL rules neither increase nor reduce the losses for investors based on samples include past and simulated returns. SL rules can also be added to a popular trading rule to avoid the shortcoming of the existing trading rule. Han, Zhou, and Zhu (2016a) show that SL rules reduce the downside risk and double the Sharpe ratio of momentum strategies in the U.S. equity market. Fischbacher, Hoffmann, and Schudy (2017) indicate that SL rules can reduce the impact of the disposition effect.

Second, we contribute to papers that focus on international equity market allocation. Brinson, Hood, and Beebower (1986) indicate that the asset allocation decision process is an important determinant of investment outcome success. Portes and Rey (2005) note that portfolio flows, especially international equity flows, have increased substantially in recent years. Financial markets across the world have become increasingly open to foreign investors (e.g., Harvey and Zhou, 1993; Karolyi and Stulz, 2003). Investors have more opportunities to diversify the risk of their investments and obtain potential gains across various markets (Chan, Covrig, and Ng, 2005). Consequently, investors can take advantage of allocating their investments across international portfolios. However, Amadi and Bergin (2006) note the turnover rate is higher for assets invested in foreign markets than domestic markets. Thus, the transaction costs are important in affecting the capital flows across countries. Thapa and Poshakwale (2010) show the markets with lower transaction costs attract more foreign investments.

Third, we contribute to a wider strand of literature that highlights the importance of career risk for fund managers. Chevalier and Ellison (1997) suggest that mutual fund managers have a strong consideration of their career while making risky decisions. Further, the historical performance of a fund has a significant effect on its managers. Chevalier and Ellison (1999) note that the performance and actions of fund managers are directly related to the prospects of their future careers. Brown, Goetzmann, and Park (2001) find the chance of being re-employed as a manager is rare if a fund manager is disengaged. Ellul, Pagano, and Scognamiglio (2018) suggest that top managers in a hedge fund are likely to be demoted and incur high compensation losses if their funds are liquidated after two-years of underperformance. As a consequence, fund managers take an interest in various methods that can successfully exclude underperforming assets in their managed funds.

The rest of this paper proceeds as follows. Section 2 contains a description of the data, the portfolio formation using stop-loss rules. The results are presented and discussed in Section 3, while Section 4 concludes the paper.

4.2 Data and methodology

4.2.1 Data

Following the dataset in Pukthuanthong and Roll (2015), we source global equity indices data from Thomson Reuters Datastream, covering a daily index for up to 82 countries from January 1973 to June 2018.

Datastream provides two types of country indexes: the return index, and the price index. We follow Pukthuanthong and Roll (2015) and use the return index that includes the reinvested dividend in the first instance. However, we use the price index if it spans a longer period than the return index.[9] All indices are based on USD. Thus, this study provides an insight from the perspective of US investors. The global risk-free data for 25 developed countries are drawn from the Kenneth French data library.

[9] See Appendix one for the data overview and Appendix two for the summary statistics across indices.

4.2.2 Stop-loss rules and portfolio formation

We form an internationally diversified portfolio by allocating capital equally to each international index at the start of our sample period. A stop-loss trigger price (SLTP) is set at a pre-specified threshold below the price of each index at the beginning of its data series. If the price of the index does not increase, the SLTP remains at this level. However, if the price of the index increases beyond the purchase price the SLTP is increased so that it is a certain threshold below each new high price. Then, when the index falls below the SLTP, a sell signal is generated. The position in this index is closed the next day regardless of the price movement on that day, and the capital that was previously in this index is reallocated to the remaining open positions in proportion to their current value on the same day. Later, if the exited index increases in value by a pre-specified threshold, a position size of 1/N is established, where N is the total number of international indices. The funds for this re-establishment are from other held indices by rebalancing proportionally to their current value.

Our benchmark is an equal-weighted (EW) portfolio that allocates capital equal to the index in each market at the start of our data series. It requires daily rebalancing to ensure the capital is evenly invested across all holding indices.

4.3 Results

4.3.1 Parametric portfolio policy

We examine whether the stop-loss rules are relevant characteristics determining the optimal asset allocation following Brandt, Santa-Clara, and Valkanov (2009). Equation (4.1) shows the objective function which is the maximized utility function:

$$\underset{\theta}{Max}\ \frac{1}{T}\sum_{t=0}^{T-1} u\left(\sum_{i=1}^{N_t}\left(\overline{w}_{i,t}+\frac{1}{N_t}\theta^{\intercal}\hat{x}_{i,t}\right)R_{i,t+1}\right) \quad (4.1)$$

where $\overline{w}_{i,t}$ is the weight of index i on day t for the benchmark portfolio, which is the EW portfolio in this study. N_t is the number of indices on day t. $R_{i,t+1}$ is the return for each index i on day $t+1$. $\hat{x}_{i,t}$ is the signal from the stop-loss rule, which is a dummy variable that equals to 1 when SL rules suggest the open position for an index on day t; otherwise, it equals to 0 during the periods that SL rules advise the closed position. θ is the parameter of the SL signal indicator. If the signal $\hat{x}_{i,t}$ is a meaningful signal, the estimated coefficient θ will be significantly different from zero. We take the difference between each stop-loss dummy and their mean on day t to ensure they have zero mean.

Table 4.1 contains the estimated coefficient (θ) of the stop-loss rule indicator under the parametric portfolio policy. We conduct stop-loss rules with thresholds from 1% to 5% and 10%. The *t*-statistics are estimated from 1,000 bootstrapped samples. Our results in Panel A show that the coefficient of the SL indicator is positive and significantly different from zero across all SL portfolios and larger when tight stop-loss thresholds are applied. This means the historical data suggest that it is optimal to increase (decrease) the allocated weight relative to the benchmark when the SL rules advise the open (close) position. The coefficients θ are the highest (lowest) at 6.55 (1.76) with a 1% (10%) trailing stop loss threshold and monotonically declines with an increase in the threshold. These coefficients mean a buy signal suggested by the 1% (10%) stop-loss rule indicates that the increase in weight is 4.08% (1.06%) relative to the EW portfolio.[10] These positive coefficients suggest that the SL rules add significant value to the international equity market allocation and perform better particularly for actively managed portfolios that have smaller SL thresholds. Moreover, the average absolute weight is larger for the SL portfolios with the tighter thresholds. These SL portfolios also have more extreme positions. For instance, the average maximum weight allocated to each index on a day can be as high as 0.47 and the average minimum weight can be as low as -0.34.

Glen and Jorion (1993) note that short sales are prohibited in some foreign markets. Panel B indicates that SL rules still add value to the international stock market allocation when short sales are not allowed in the market. The results for the SL portfolios under a short-selling restriction are consistent with Panel A. The coefficient of SL rules, θ, is smaller than in the unrestricted case and it is stronger under the tighter SL thresholds. Hence, SL rules do add value to international equity market allocation once the short-selling is constrained. Compared with the unconstraint model, the absolute weight drops to around 0.03 for each SL portfolio. In Panel A, the unconstraint case allocates more extreme weights for the tightly stopping portfolios. However, the extreme weights in Panel B are reduced, with the largest maximum weight dropping to 0.36 when applying a 1% threshold.

[10] The average number of countries (N) is 53 in our sample. The average of stop-loss dummy (X) is 0.68.

Table 4.1: Parametric portfolio policy results

Variable	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
			Panel A: Unrestricted holdings			
λ	6.55	6.50	5.09	4.24	3.14	1.76
$t(\lambda)$	10.94	13.78	9.81	8.13	6.06	4.25
$\overline{\lvert w_{\iota,t}\rvert}$	0.08	0.08	0.06	0.05	0.04	0.03
$\overline{Max(w_{\iota,t})}$	0.47	0.47	0.38	0.33	0.26	0.18
$\overline{M\iota n(w_{\iota,t})}$	-0.34	-0.34	-0.25	-0.20	-0.13	-0.04
			Panel B: Short-sale restricted holdings			
λ	4.68	3.75	3.15	2.98	2.32	1.76
$t(\lambda)$	12.65	15.49	22.02	17.11	16.24	6.02
$\overline{\lvert w_{\iota,t}\rvert}$	0.03	0.03	0.03	0.03	0.03	0.03
$\overline{Max(w_{\iota,t})}$	0.36	0.30	0.26	0.25	0.21	0.18
$\overline{M\iota n(w_{\iota,t})}$	0.00	0.00	0.00	0.00	0.00	0.00

Note: This table reports the estimate of the portfolio policy that has a stop-loss variable as a characteristic. Following Brandt, Santa-Clara, and Valkanov (2009), we use the equation below to construct the optimized utility function. Our benchmark portfolio is the equal-weighted portfolio.

$$\underset{\theta}{Max}\ \frac{1}{T}\sum_{t=0}^{T-1} u\,(\sum_{i=1}^{N_t}\left(\overline{w}_{i,t}+\frac{1}{N_t}\theta^{\intercal}\hat{x}_{i,t}\right)R_{i,t+1})$$

We source country-level equity index data from Datastream between January 1973 and June 2018. The equal-weighted portfolio allocates weights evenly across all equities over time. The stop-loss portfolios applying a variety of stop-loss thresholds to each holding equity from the beginning of each country's index. We conduct stop-loss rules with thresholds from 1% to 5% and 10%. We present the theta and respective *t*-stat for each stop-loss threshold. *T*-stat is calculated by 1,000 bootstrapping standard errors for each stop-loss threshold. Panel A shows the estimated theta and significance of the portfolio policy. Panel B displays estimated theta and its significance of the portfolio policy with the short-sale restriction. Some important weights are reported in both panels. The $\overline{\lvert w_{\iota,t}\rvert}$ is to calculate the cross-sectional average weights on each day, and then take the time-series average. $\overline{Max(w_{\iota,t})}$ and $\overline{M\iota n(w_{\iota,t})}$ weights are the time-series average of the daily maximum and minimum weights.

4.3.2 Returns and Sharpe ratios

While the parametric portfolio policy results indicate the importance of SL rules in adding value to international equity market allocation, they should be considered as an in-sample test and do not quantify the raw or risk-adjusted returns that an investor applying this approach would receive. We focus on this out-of-sample performance aspect in this section.

In Table 4.2, we report the core results for both the EW portfolio and the six SL portfolios. The table contains the monthly returns, Sharpe ratios, and utility analysis for the EW portfolio and the SL portfolios with six thresholds from 1% to 10%. Our results indicate that the SL rules significantly help to improve the performance of internationally diversified portfolios.

Table 4.2: Core results

Variable	EW	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
Panel A: Summary statistics							
Return	0.012	0.020	0.017	0.015	0.014	0.013	0.013
		<.0001	<.0001	0.001	0.008	0.252	0.458
Median return	0.013	0.024	0.020	0.018	0.015	0.015	0.015
		<.0001	<.0001	<.0001	<.0001	0.000	0.006
STD	0.043	0.043	0.044	0.045	0.045	0.047	0.047
		0.423	0.520	0.775	0.776	0.960	0.981
SR	0.19	0.37	0.29	0.24	0.23	0.19	0.18
Panel B: Utility Analysis							
CER 1	0.011	0.019	0.016	0.014	0.013	0.012	0.011
CER 3	0.009	0.017	0.014	0.012	0.011	0.010	0.009
CER 5	0.007	0.015	0.012	0.010	0.009	0.007	0.007

Note: This table compares and contrasts core results for both equal-weighted and stop-loss portfolios. The equal-weighted portfolio allocates weights evenly across all equities. The stop-loss portfolios apply various stop-loss thresholds from the beginning of each country's index. We conduct stop-loss rules with thresholds from 1% to 5% and 10%. Panel A reports average monthly returns (Return), median monthly returns (Median return), standard deviation (STD), and Sharpe ratio (SR). Their *p*-value is shown below each of them. Panel B shows the utility for investors with risk aversion levels of 1, 3, and 5. The sample period is from January 1973 to June 2018.

The results in panel A indicate that the monthly return of the EW portfolio is 0.012, whereas the returns vary from 0.013 to 0.020 for the SL portfolios. The returns are stronger when smaller SL thresholds, such as 1%, are applied, which is consistent with Table 4.1 results. The *p*-value shows that the larger return of each SL portfolio over the EW portfolio is statistically significant except when a 5% or 10% threshold is applied. The risk, for which we use the return standard deviation as a proxy, is 0.043 for the EW portfolio. Each SL portfolio has a risk of around 0.045, which is up to 0.4% larger than for the EW portfolio. However, the higher risk of SL portfolios is not statistically significantly different from that of the EW portfolio. Further, the larger risk of SL portfolios is offset by the larger return. Hence, the Sharpe ratio of the EW portfolio is 0.19, whereas it can be up to 0.37 for the 1% SL portfolios.

In Panel B, we report the Certainty Equivalent Return (CER) for investors with three risk aversion levels following Rapach, Ringgenberg, and Zhou (2016), using the equation:

$$CER = R - 0.5\gamma\sigma^2 \tag{4.2}$$

where γ is the risk aversion level. R and σ are the mean and standard deviation of monthly returns, respectively. The *CER* of the EW portfolio has a range between 0.007 and 0.011. Our results show that each tight SL portfolio with a threshold between 1% and 5% generates a larger *CER* than the EW portfolio for investors who have normal risk aversion levels. The *CER* is especially better when smaller thresholds are applied.

4.3.3 Success rate

For a better understanding of the ability of SL rules to time the market, we investigate the success rate for EW and a series of SL portfolios. The success rate is a ratio that shows the number of days in which the return of an SL portfolio is larger than that of the EW portfolio within a certain period since a sell signal is generated.

We report the results for six SL portfolios in Table 4.3. We compare the return of each SL portfolio with the EW portfolio within comparison windows of 5 days, 10 days, and 30 days. Each comparison window starts from the day that the SL rules close the position for any of the equity indices in the portfolio. We calculate the ratio that the number of days in which the returns of the SL portfolio are larger than that of the EW portfolio in each comparison window. Our results indicate that the SL rules can generate significantly larger returns than the EW portfolio since these rules generate a sell signal each time. The success rate for each SL portfolio with thresholds between 1% and 5% is around 56%, which is significantly larger than the 50% based on the binomial test.[11] There is also a tendency for the success rate to be larger for portfolios that apply the lower SL thresholds. The SL portfolio with a 10% threshold has the lowest success rate of 51% in the 5-day comparison window.

Table 4.3: Success rate

Comparison window	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
5 days	0.57	0.57	0.55	0.54	0.54	0.51
	<.0001	<.0001	<.0001	<.0001	<.0001	0.139
10 days	0.57	0.57	0.55	0.54	0.54	0.52
	<.0001	<.0001	<.0001	<.0001	<.0001	0.094
30 days	0.57	0.57	0.56	0.55	0.54	0.53
	<.0001	<.0001	<.0001	<.0001	<.0001	0.011

Note: This table reports the success rate for stop-loss portfolios. The stop-loss portfolios are applied by various stop-loss thresholds from the beginning of each country's index. We conduct stop-loss rules with thresholds from 1% to 5% and 10%. We compare the daily return of stop-loss portfolios above the equal-weighted portfolio within periods of 5, 10, and 30 days, respectively, since the day that stop-loss rules trigger a sale of any asset in a portfolio. We then calculate the ratio that the stop-loss portfolios have a larger return than the equal-weighted portfolio within each comparison window as the success rate. We display the *p*-value underneath each success rate. The null hypothesis is that the success rate equals to 50%. The sample period is from January 1973 to June 2018.

4.3.4 Factor models

In Sections 4.3.2 we show that the SL portfolios perform better than the EW portfolio from the perspectives of return and Sharpe ratio. In this section, we investigate the performance of SL portfolios with thresholds between 1% and 10% against models based on the Fama and

[11] We create a random active portfolio and find that it has a success rate of 50.7%. The SL portfolios still have a significantly higher success rate than the random strategy.

French factors. We obtain the global Fama-French 5 factors that cover 25 developed markets from the French Kenneth database. The sample period is from November 1990 to June 2018.

Following Fama and French (1993) and Fama and French (2015), we compare and contrast the risk-adjusted returns or alphas among the SL portfolios with six thresholds by taking into consideration several combinations of Fama-French factors as in the equations:

$$R_{t,SL} - R_{t,RF} = \alpha + \beta_{mkt} Mkt - RF_t + \beta_{smb} SMB_t + \beta_{hml} HML_t + \varepsilon_t \quad (4.3)$$

$$R_{t,SL} - R_{t,RF} = \alpha + \beta_{mkt} Mkt - RF_t + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{mom} MOM_t + \varepsilon_t \quad (4.4)$$

$$R_{t,SL} - R_{t,RF} = \alpha + \beta_{mkt} Mkt - RF_t + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{rmw} RMW_t + \beta_{cma} CMA_t + \varepsilon_t \quad (4.5)$$

where $R_{t,SL}$ and $R_{t,RF}$ are the monthly returns of the SL portfolio and the global monthly risk-free rates, respectively. *Mkt-RF*, *SMB*, *HML*, *MOM*, *RMW*, and *CMA* are the global monthly market excess return, the monthly return of global SMB (Small Minus Big), HML (High Minus Low), MOM (Momentum), RMW (Robust Minus Weak), and CMA (Conservative Minus Aggressive) factors, respectively. Therefore, these alphas take the impact of market, size, value, profitability, investment, and momentum out of our models. Our results in Table 4.4 show that all SL portfolios have significantly positive alphas after a series of Fama-French factors are controlled. These alphas indicate a similar trend to SL portfolios' return and Sharpe ratio, in that the tight SL rules generate better results.

Table 4.4: Factor models

Variable	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
Panel A: Three factors						
Alpha	0.009	0.008	0.006	0.005	0.004	0.004
	<.0001	<.0001	<.0001	0.000	0.003	0.009
Mkt_RF	0.827	0.832	0.857	0.850	0.895	0.938
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
SMB	0.382	0.353	0.383	0.403	0.429	0.492
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
HML	0.216	0.205	0.200	0.197	0.197	0.184
	0.000	0.000	0.000	0.000	0.001	0.003
Adj R-squared	0.665	0.695	0.695	0.701	0.685	0.703
Panel B: Three factors plus momentum						
Alpha	0.009	0.008	0.006	0.005	0.004	0.003
	<.0001	<.0001	<.0001	0.000	0.005	0.019
Mkt_RF	0.838	0.833	0.858	0.856	0.901	0.946
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
SMB	0.371	0.352	0.382	0.398	0.422	0.485
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
HML	0.238	0.207	0.201	0.208	0.210	0.199
	0.000	0.000	0.001	0.000	0.001	0.002
MOM	0.045	0.003	0.004	0.024	0.027	0.031
	0.230	0.930	0.921	0.503	0.482	0.427
Adj R-squared	0.666	0.694	0.694	0.700	0.684	0.702
Panel C: Five factors						
Alpha	0.009	0.007	0.006	0.005	0.004	0.003
	<.0001	<.0001	<.0001	0.001	0.011	0.037
Mkt_RF	0.831	0.848	0.855	0.837	0.881	0.928
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
SMB	0.414	0.395	0.409	0.415	0.453	0.520
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
HML	0.337	0.295	0.331	0.337	0.401	0.376
	0.000	0.000	<.0001	<.0001	<.0001	<.0001
RMW	0.220	0.247	0.193	0.130	0.225	0.234
	0.043	0.015	0.065	0.205	0.043	0.037
CMA	-0.249	-0.197	-0.265	-0.273	-0.400	-0.379
	0.028	0.064	0.016	0.012	0.001	0.001
Adj R-squared	0.674	0.703	0.703	0.707	0.700	0.716

Note: This table reports the abnormal return, alpha, of stop-loss portfolios above the global risk-free rate, with a consideration of various global Fama-French risk factors and a momentum factor. The stop-loss portfolios are applied by several stop-loss thresholds from the beginning of each country's index. The thresholds of stop-loss rules are set from 1% to 5% and 10%. The sample period is from November 1990 to June 2018.

We control three Fama-French factors, which are *Mkt-RF*, *SMB,* and *HML*, and display the results in Panel A. Our results show that the alphas have a range from 0.004 to 0.009 per month and all of them are significantly positive across the SL portfolios with six thresholds. The size of the alpha is larger when applying smaller SL thresholds. The beta of the three factors is positive, indicating a significantly positive relationship between these Fama- French factors and the return of the SL portfolios.

Moreover, we account for three Fama-French factors as well as the momentum factor and report their results in Panel B. The significantly positive alphas vary between 0.003 and 0.009 per month across the SL portfolios with six thresholds. The betas are significant across three Fama-French factors, whereas the beta of the momentum factor is insignificant, showing that the positive returns of the SL portfolio are not attributed to the momentum factor.

We consider the five Fama-French factors and report their results in Panel C, which show that the alphas drop slightly, to the range between 0.003 and 0.009. The alpha is significantly positive for each SL portfolio. Four of the five Fama-French factors show a significant impact on the performance of the SL portfolios, except the RMW factor, which is insignificant when applying thresholds of 3% and 4%. The only Fama-French factor that has a significantly negative beta is CMA. The betas are positive for all other factors. All these factors' signs are consistent with the factor returns in Fama and French (2017), except the CMA.

4.3.5 Market conditions

In this section, we investigate the risk-adjusted performance of the SL portfolios under different market conditions (different market states) and report the results in Table 4.5. Momentum strategies can have varying performance under different market states (e.g., Cooper, Gutierrez, and Hameed, 2004). Besides, Orlov (2016) shows the carry trade strategies also perform differently under changing market states. We study the difference of returns between the SL portfolios and the risk-free rate once the Fama-French factors are accounted for during different market states. Following Hameed, Kang, and Viswanathan (2010), we construct two indicators: a *UP* market and a *DOWN* market. We use the MSCI world index to determine whether the markets are *UP* or *DOWN*. The market is *UP* if the mean return is non-negative in a calendar month. Otherwise, we deem the market as *DOWN* in that calendar month.

Our model controls the global Fama-French five factors, which are obtained from the French Kenneth data library, as proxies of risks. The regression without the intercept is:

$$R_{t,SL} - R_{t,RF} = \beta_{up}UP_t + \beta_{down}DOWN_t + \beta_{mkt}(Mkt - RF_t) + \beta_{smb}SMB_t + \beta_{hml}HML_t + \beta_{rmw}RMW_t + \beta_{cma}CMA_t + \varepsilon_t \tag{4.6}$$

Our results show that both betas of *UP* and *DOWN* markets are significantly positive. This shows that the SL portfolios have positive risk-adjusted performance during both market states. Further, the beta of the *DOWN* market is larger than the beta of the *UP* market. The SL rules can, thus, generate better performance during the *DOWN* market when compared with the *UP* market. However, the larger risk-adjusted return of the *DOWN* market above that of the *UP* market is not statistically significant. The SL portfolios have better performance when tight thresholds are applied. For example, the beta is 0.008 during the *UP* market and 0.01 during the *DOWN* market when applying a 1% threshold. However, the betas are smaller when a 10% threshold is applied. In that case, the beta of the *UP* market drops to 0.003 and the beta of the *DOWN* market is 0.004.

Moreover, the betas of the five risk factors are consistent with their respective betas in Panel C of Table 4.4. The performance of the SL portfolios is positively related to four of the five risk factors except for the *RMW* factor when the threshold% is applied. The *CMA* factor has a significantly negative impact on the performance of the SL portfolios.

Table 4.5: Performance under different market states

Variable	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
UP	0.008	0.006	0.005	0.006	0.003	0.003
	0.001	0.004	0.041	0.011	0.227	0.295
DOWN	0.010	0.007	0.007	0.004	0.005	0.004
	0.000	0.006	0.012	0.153	0.085	0.176
Mkt_RF	0.853	0.854	0.873	0.821	0.898	0.940
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
SMB	0.407	0.393	0.402	0.420	0.447	0.516
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
HML	0.333	0.294	0.328	0.340	0.398	0.374
	0.000	0.000	0.000	<.0001	<.0001	<.0001
RMW	0.212	0.245	0.187	0.136	0.220	0.230
	0.052	0.017	0.076	0.191	0.050	0.042
CMA	-0.244	-0.195	-0.260	-0.277	-0.396	-0.376
	0.033	0.068	0.018	0.011	0.001	0.002
Adj R-squared	0.709	0.729	0.723	0.724	0.713	0.727

Note: This table indicates the abnormal return, alpha, of stop-loss portfolios above risk-free rate during different market conditions. A variety of Fama-French risk factors are taken into account. We follow Hameed, Kang, and Viswanathan (2010) to construct two binary indicators: an *UP* market and a *DOWN* market, which are based on the MSCI world index. The market is *UP* if the mean return is non-negative in a calendar month. Otherwise, we deem the market as *DOWN* in that calendar month. The stop-loss portfolios are applied by stop-loss thresholds from the beginning of each country's index. The thresholds of stop-loss rules are set from 1% to 5% and 10%. The sample period is from November 1990 to June 2018.

4.3.6 Transaction costs

The previous sections show that each SL portfolio performs better than the EW portfolio. We take the transaction costs into account to examine whether the outperformance still exists when the SL portfolios are actively trading among international equity indices. Thapa and Poshakwale (2010) indicate the importance of transaction costs in international asset allocation. Moreover, Lesmond, Schill, and Zhou (2004) show that transaction costs have a certain impact on the returns to the momentum trading rule.

The break-even costs are calculated by the difference between the return of the EW portfolio and an SL portfolio, divided by the difference between their turnover ratios. These results indicate the maximum allowance of transaction costs for each trading.

Table 4.6 reports the turnover ratio as well as the break-even transaction costs of the full sample and a subsample of the *UP* and *DOWN* market. Our results show that break-even transaction costs are positive and that they are mostly larger when applying tight thresholds and during *DOWN* markets, compared with the full sample.

Table 4.6: Turnovers and break-even transaction costs

Variable	EW	SL (1%)	SL (2%)	SL (3%)	SL (4%)	SL (5%)	SL (10%)
Panel A: Monthly turnover ratio							
All	0.20	9.58	6.04	4.24	3.14	2.46	1.00
UP	0.20	8.56	5.17	3.50	2.53	1.98	0.82
DOWN	0.21	10.99	7.25	5.27	3.98	3.13	1.26
Panel B: Break-even transaction cost (BP)							
All		8.27	7.72	6.83	7.05	4.14	7.04
UP		6.28	5.72	3.68	6.33	3.53	16.82
DOWN		10.42	9.69	9.69	7.66	4.66	-1.03

Note: This table demonstrates turnover ratios and transaction costs for the equal-weighted portfolio and stop-loss portfolios. We follow Hameed, Kang, and Viswanathan (2010) to construct two binary indicators: an *UP* market and a *DOWN* market, which are based on the MSCI world index. The market is *UP* if the mean return is non-negative in a calendar month. Otherwise, we deem the market as *DOWN* in that calendar month. Panel A shows a monthly turnover ratio across time as well as during *DOWN* markets. Panel B displays break-even transaction costs over time as well as during *DOWN* markets. The numbers are displayed in basis points in Panel B. The equal-weighted portfolio allocates weights evenly across all assets. The stop-loss portfolios use different stop-loss thresholds from the beginning of each country's index. The thresholds of stop-loss rules are set from 1% to 5% and 10%. The sample period is from January 1973 to June 2018.

Not surprisingly, the results in Panel A show that the monthly turnover ratio of each of the SL portfolios is larger than that of the EW portfolio. The monthly turnover ratio of the EW portfolio is 0.2. The turnover ratio of the SL portfolios is at least 1.00 when applying 10%

thresholds. The highest turnover ratio of the SL portfolio is 9.58 when applying a 1% threshold. Moreover, the turnover ratio is larger for each SL portfolio during the *DOWN* market. These portfolios have a range of turnover ratios between 0.82 and 8.56 under the *UP* market and between 1.26 and 10.99 under the *DOWN* market. This suggests that the SL rules incur more active trading during the *DOWN* market.

The results of the break-even transaction cost analysis in Panel B are displayed in basis points. They show that the SL portfolios have larger break-even transaction costs when applying either the larger or smaller SL thresholds. The break-even transaction costs under a *DOWN* market are larger than for the full sample except for the 10% SL portfolio. For instance, the full sample has the highest break-even transaction costs, of 8.27 bp, when a 1% threshold is applied. However, the SL portfolio has the highest break-even transaction costs of 10.42 bp, under the *DOWN* market when the 1% threshold is applied. We follow Chung and Zhang (2014) to calculate the actual spreads for 17 foreign countries ETFs that traded in the U.S. market as per Levy and Lieberman (2013). For the U.S. ETF, we adopt a SPY that tracks the S&P 500 index. We find the actual spreads can be less than 6 bp in the recent five years. It suggests that the outperformance of SL portfolios can cover the trading costs with an exemption of applying the 5% threshold.

4.4 Conclusions

Stop-loss rules are popular in financial markets. These rules involve selling a security when its price drops below a pre-determined level and buying the security back when its price rises above a pre-specified level. Investors often use these rules to protect gained profits and avoid equity corrections because the pre-determined price is increased with increases in the security's price. Commonly, international diversification helps investors to earn a larger risk-adjusted performance than investing in a single market.

We examine whether stop-loss rules add value to international equity allocation. We start with an equal-weighted portfolio that includes various international equity indices and applies stop-loss rules to each index at the beginning of our data series. This portfolio is kept until one of the equity indices falls by a pre-specified amount, which then triggers the stop-loss rule. We subsequently close the position of this index and reallocate its capital across the remaining holding indices. The closed index is re-entered following a rise with a pre-specified percentage.

We compare and contrast the performance between the stop-loss portfolio with various stop thresholds and an equal-weighted buy-and-hold portfolio across 82 international equity markets from 1973 to 2018. We use an optimized utility function that considers stop-loss rules as a characteristic, to show that stop-loss rules significantly add value to international equity markets allocation. Our results provide evidence that stop-loss thresholds of 1-5% and 10% each result in portfolio returns that are statistically significantly larger than that of the equal-weighted portfolio. However, the risk of the SL portfolio is not significantly different from that of the EW portfolio. Additionally, the outperformed return of the stop-loss portfolio can offset its high risk, thus, generating a larger Sharpe ratio than the equal-weighted portfolio. For example, the Sharpe ratio of equal-weighted portfolios is 0.19, while it can be as high as 0.37 for a stop-loss portfolio that has a 1% threshold.

The utility to investors of most stop-loss portfolios is larger than that of an equal-weighted portfolio when investors have various risk aversion levels of one, three, or five. We compare the return between each stop-loss portfolio and the equal-weighted portfolio within multiple periods of 5, 10, and 30 days since each time at which the stop-loss rules signal to exclude an index from the portfolio. Our results show that the stop-loss portfolios, on average, have a 56% success rate, which gives a significantly better return than the equal-weighted portfolio within each comparison window. The alphas or risk-adjusted returns still exist after accounting for some prevalent Fama-French factors, such as the Fama-French five factors and the momentum factor. We find that the risk-adjusted return of stop-loss portfolios is better during the declining market, compared with the expanding market. However, the alphas are not significantly different between the two market states.

Our results indicate that the stop-loss portfolios perform better when applying smaller thresholds to each equity index. We find that the break-even transaction costs can be up to 8.27 bp when a 10% threshold is applied. Hence, the outperformance of each stop-loss portfolio above the equal-weighted portfolio can offset transaction costs, and the results are especially better during the declining market for stop-loss portfolios that have a range of thresholds from 1% to 5%.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Bochuan Dai
Name/title of Primary Supervisor:	
In which chapter is the manuscript /published work:	Chapter 4

Please select one of the following three options:

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Bochuan Dai collected, collated and cleaned the datasets before completing all the empirical analysis. Bochuan Dai then wrote the draft working paper and submit to Applied Economics. The supervisors provided detailed advice and answers to Bochuan's questions as he completed the paper. Bochuan is the main author of this paper and while his supervisors have made substantial contributions, which is reflected by co-authorship. The papers are essentially the work from Bochuan.

( ) It is intended that the manuscript will be published, but it has not yet been submitted to a journal

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Chapter Five

Essay Three

Chapter three and four indicate that stop-loss rules add value when investing U.S. stocks and in international asset allocation. This chapter contains essay three which examines the performance of a series of stop rules when applied to lottery stocks. An introduction of the chapter that includes its main contributions to the literature is presented in Section 5.1. Section 5.2 describes the data and the descriptions of the selected stop rules. Section 3.3 shows the empirical results and Section 3.4 concludes this chapter. The appendix to this chapter and the respective reference list are provided at the end of the thesis.

Lottery Stocks and Stop-loss Rules

Abstract

We show that stop-loss rules increase the returns to investment in stocks with lottery features. These stocks, which are popular with individual investors, typically have sporadic big gains and frequent small losses. However, stop-loss rules can reduce losses and allow investors to receive the gains from large price increases. We also highlight the sell signals of popular technical rules are like stop-loss rules and are effective at increasing lottery stock risk-adjusted returns. These rules could help investors avoid instances of major historical drawdowns, are particularly beneficial in declining markets, and are robust to the inclusion of transaction costs.

JEL Classification Codes: G11, G12
Keywords: Lottery Stocks, Stop-loss Rules, Trading Strategies, Individual Investors

5.1 Introduction

We investigate whether stop-loss rules improve the returns to investment in lottery stocks. These stocks, which have a high probability of losses and a small probability of large gains, represent a sizable proportion of all individual stocks (e.g., Meng and Pantzalis, 2018)[12]. Lottery stocks are particularly popular with individual investors (e.g., Kumar, 2009), with the frantic activity in GameStop in early 2021 being a recent example. This share price increased over 1,700 percent in two months and then declined 84% in four days. (e.g., Phillips and Lorenzz, 2021).

Stop-loss rules, which are mechanical trading rules that indicate a stock should be sold when its price declines by a certain amount, are also popular with investors (e.g., Han, Zhou, and Zhu, 2016). While still in its infancy, research shows that many stop-loss strategies underperform a buy and hold approach. Still, outperformance is possible when there is a high serial correlation in returns (e.g., Lo and Remorov, 2017).

We show that stop-loss rules are similar to the rules used to generate sell signals in several popular technical trading strategies and time-series momentum. We, therefore, include these rules in our analysis. Our stop rules consist of four "families." First, Trailing Stop-Loss (SL) rules involving selling when a price moves a certain percentage below its recent high price (e.g., Dai, Marshall, Nguyen, Visaltanachoti, 2020). Second, Moving Average (MA) rules indicate a sell signal when the price closes below the average of historical prices (e.g., Brock, Lakonishok, and LeBaron, 1992). Third, Trading Range Break (TRB) rules generate a sell signal when a price moves below the lowest price over a specific historical period (e.g., Brock, Lakonishok, and LeBaron, 1992). Fourth, Time Series Momentum (TSMOM) rules generate a

[12] Meng and Pantzalis (2018) suggest that more than 20% of all publicly listed stocks can be categorized with lottery features.

sell signal when the price falls below the price a specified number of periods ago (e.g., Moskowitz, Ooi, and Pedersen, 2012). We apply the Kumar (2009) definition of lottery stocks based on stock price, idiosyncratic skewness, and idiosyncratic volatility and combine lottery stocks into an index.

Our empirical analysis spans the 1926 – 2019 period. We apply the stop rules to the CRSP market index and the lottery stock index. We also apply stop rules to the small stock index that shares many of the features of lottery stocks and are more readily identifiable, so we are interested in establishing the effectiveness of stop rules on these as well.

The results indicate that stop rules add value to investors in lottery stocks. Seventeen of the 19 stop rules generate return gains in lottery stocks, and none of them add value when applied to the market index. Moreover, given the stop rules signal exiting an equity investment and moving to a T-bill investment, the stop strategy's risk is lower. The raw return improvements, therefore, also represent increases in risk-adjusted returns. The results are stronger in recessions but also hold in expansions. The stop rules effectively add value during periods of stock market decline, such as the stock market crash of 1987. These rules also add value inclusive of transaction costs. We also show that stop rules are more effective on small stocks than on other stocks.

Our paper contributes to several strands of the literature. First, we add to work on stop-loss rules. Early theoretical work uses different simulated return processes to address the puzzle of optimizing the stop point relative to the current price (e.g., Glynn and Iglehart, 1995). Empirical work includes Lei and Li (2009), who find stop-loss rules do not add value, and Kaminski and Lo (2014) suggest that stop-loss rules underperform under random walk and mean-reversion processes but outperform under momentum and regime-switching models. Consistently, Lo and Remerov (2017) show that stop-loss rules can add value when there is a serial correlation in returns. Han, Zhou, and Zhu (2016) also find stop-loss rules reduce the downside risk and improve momentum strategies' Sharpe ratio. Finally, Fischbacher, Hoffmann, and Schudy (2017) suggest that stop-loss rules can reduce the disposition effect's impact.

Second, showing that the sell signals of popular technical trading strategies and time-series momentum strategies are effective stop-loss rules, we add to this literature. These rules are profitable with practitioners (e.g., Schwager, 1993) but have also been shown to be impacted by data snooping bias (e.g., Sullivan, Timmerman, and White, 1999). However, Zhu and Zhou (2009) show, using a theoretical model, that technical analysis can add value in uncertain environments, and Han, Yang, and Zhou (2013) show technical analysis is a valuable tool in cross-sectional asset allocation. Time-series momentum is an effective quantitative market timing technique by various authors, including Moskowitz, Ooi, and Pedersen (2012) and Georgopoulou and Wang (2017). More recently, Ebert and Hilpert (2019) suggest that investor preference for positive skewness is related to technical analysis's popularity.

Third, we contribute to the lottery stock literature. There is extensive evidence that individual investors are attracted to stocks with lottery features (e.g., Bali, Cakici, and Whitelaw, 2011; Eraker and Ready, 2015; Hung and Yang, 2018). Similarly, Barberis and Huang (2008) suggest investor preference for stocks with positive skewness and their inclination to overweight low probability events, consistent with Kahneman and Tversky's prospect theory (1979).

Fourth, we add to the literature on individual investors. A preference for stocks with lottery features is one characteristic of these investors, but there are also others. They tend to trade too much, which results in losses (e.g., Barber and Odean, 2000; Barber, Lee, Liu, and Odean, 2009). They are not typically well-diversified (e.g., Kelly, 1995; and Polkovnichenko, 2005; Goetzmann and Kumar, 2008). Individual investors also have a strong local bias (e.g., Seasholes and Zhu, 2010). However, there is evidence individual investors can outperform the market (e.g., Coval, Hirshleifer, and Shumway, 2005).

This paper shows that stop rules add value in the context of lottery stocks, which are popular among individual investors. The findings help these investors prevent losses that are frequently incurred when investing lottery stocks.

The rest of the paper is organized as follows: Section 2 contains a description of the data and the stop rules. The results are displayed and discussed in Section 3. Section 4 concludes the paper.

5.2 Data and stop rules

5.2.1 Data

We identify lottery stocks using the approach of Kumar (2009). We include common stocks with share codes of 10 and 11 and examine the price at the end of month t-1, idiosyncratic skewness, and idiosyncratic volatility across daily returns between month t-6 and t-1.[13] We select stocks in the lowest 50th price percentile, highest 50th idiosyncratic volatility percentile, and highest 50th idiosyncratic skewness percentile.[14] Last, we form a value-weighted lottery stock index on a daily rebalance basis by using market capitalization on the previous trading day. Our sample period covers from 1926 to 2018, and the CRSP market index is the entire market's proxy. The small stock index is the smallest decile of stock returns from Ken French's data library. The daily risk-free rate is also from Ken French's data library.

[13] The idiosyncratic skewness is calculated using the previous six months daily residuals obtained from the four-factor model. We calculate the idiosyncratic volatility as the standard deviation of residuals from a four-factor model within the previous six months.

[14] We have also tried percentiles of 10^{th} or 25^{th} and the results are robust.

Table 5.1: Data summary

	(1)	(2)	(3)	(1) – (2)	(1) – (3)
Variable	Lottery index	Market index	Small index		
Mean	0.0001	0.0004	0.0005	-0.0003***	-0.0004***
				0.00	0.00
Median	0.0006	0.0007	0.0010	-0.0001**	-0.0004***
				0.02	0.00
Std Dev	0.018	0.011	0.013	0.008***	0.005***
				0.00	0.00
Sharpe ratio	0.001	0.027	0.030	-0.025***	-0.029***
				0.00	0.00
Max	0.530	0.157	0.344	0.373***	0.186
				0.00	0.24
Min	-0.192	-0.171	-0.168	-0.020	-0.024**
				0.96	0.03
Skewness	1.489	-0.129	1.056	1.618***	0.433
				0.01	0.39
Kurtosis	49.299	16.780	45.096	32.519**	4.203
				0.05	0.48
VaR (1%)	-0.052	-0.030	-0.038	-0.021***	-0.014***
				0.00	0.00
VaR (5%)	-0.026	-0.015	-0.018	-0.011***	-0.008***
				0.00	0.00
ES (1%)	-0.075	-0.044	-0.055	-0.031***	-0.020***
				0.00	0.00
ES (5%)	-0.043	-0.025	-0.031	-0.017***	-0.012***
				0.00	0.00

This table shows the summary statistics for the time series of lottery stock, CRSP market, and small stock indices sourced from Ken French's data library. We follow Kumar (2009) to identify lottery stocks. We include common stocks with share codes of 10 and 11 and examine their price, idiosyncratic skewness, and volatility. The Value-at-Risk (VaR) and Expected Shortfall (ES) are two measures of downside risks. The sample is from 1926 to 2018. We display the *p*-value that is estimated by 1,000 bootstrapped samples under each difference variable. Statistically significant values at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively.

Table 5.1 contains summary statistics for the time series of lottery stock, market, and small stock index returns. These indicate that lottery stocks have lower mean and median returns, a higher standard deviation of returns, and a lower Sharpe ratio than both the market and small stock indices. However, the maximum return is over three times as high as the maximum market return.[15] This confirms the lottery aspect of these stocks. There is also more

[15] The lottery index maximum gain was on 4 August 1932. For the market and small stock indices, the maximum gains were on 15 March 1933 and 5 September 1939.

skewness and kurtosis in the lottery stock index returns. The measures of downside risk indicate the larger downside in lottery stocks. Both the VaR and expected shortfall results are also more negative. This evidence of a more significant downside in lottery stocks indicates that stop rules which effectively limit the downside have more potential to add value to these stocks.

5.2.2 Stop rules

We use four families of stop rules. First is the trailing stop loss rules (SL). Second is the sell signals of moving average technical trading rules (MA). The third is the sell signals of the trading range break technical trading rules (TRB). Fourth is the sell signals of time-series momentum rules (TSMOM). Our SL rules involve the stop-loss thresholds of 1%, 3%, 5%, 10%, and 20%. The technical rules have different look-back periods of 50, 100, 150, and 200 days.

The SL rules involve selling when the price drops by a certain amount from its high price and only repurchasing it when it increases by a pre-specified level above its low price. They are expressed as the equations below:

$$SL\_SELL_{t,X\%}: P_t - HIGH \cdot (1 - X\%) < 0 \tag{5.1a}$$

$$SL\_BUY_{t,X\%}: P_t - LOW \cdot (1 + X\%) > 0 \tag{5.1b}$$

where X% represents a threshold of either 1%, 3%, 5%, 10%, or 20%. LOW refers to the lowest price since the last buying while $HIGH$ is the highest price since the last selling.

MA rules maintain a position in the market until the prices fall below the moving average. They generate the buy signals when the prices rise above the moving average, as shown below:

$$MA\_SELL_{t,n}: P_t - MA_{t-n} < 0 \tag{5.2a}$$

$$MA\_BUY_{t,n}: P_t - MA_{t-n} > 0 \tag{5.2b}$$

where the n is a look-back period, which can be 50, 100, 150, or 200 days. A sell signal is generated on day t when the current price drops below the moving average since day $t - n$. These rules create a buy signal when the current price increases above the moving average since day $t - n$.[16]

TRB rules generate a sell signal when its price drops below the local minimum price over a certain look-back period. A buy occurs when the price increases above the local maximum, as shown in the equations below:

$$TRB\_SELL_{t,n}: P_t - LOW_{t-n} < 0 \tag{5.3a}$$

$$TRB\_BUY_{t,n}: P_t - HIGH_{t-n} > 0 \tag{5.3b}$$

where the n is a look-back period that can be 50, 100, 150, or 200 days. A sell signal is generated on day t when the current price drops below the local minimum since day $t - n$. These rules create a buy signal when its current price increases above the local maximum since day $t - n$.

Timeseries momentum rules involve selling when the price falls below a historical price

[16] Brock, Lakonishok, and LeBaron (1992) also conduct fixed-length MA rules that record the performance for ten days after the signal day. In this study, we focus on the variable MA rules that trading continuously to ensure a fair comparison with other stop rules.

and buying when it rises above a historical price, as shown below.[17]:

$$TSMOM\_SELL_{t,n}: P_t - P_{t-n} < 0 \tag{5.4a}$$

$$TSMOM\_BUY_{t,n}: P_t - P_{t-n} > 0 \tag{5.4b}$$

where the n is a look-back period that can be 50, 100, 150, or 200 days. A sell signal is generated on day t when the current price falls below the price on day $t - n$. These rules create a buy signal when the current price increases above the price on day $t - n$.

5.3 Results

5.3.1 Core results

We identify that the sell signals generated by popular technical trading and time-series momentum rules appear to be like those from the stop-loss rules. We, therefore, include these as stop rules. However, we are not aware of any work that compares the sell signals generated by these rules to those from stop-loss rules, so we start with this analysis. In Appendix 1, we document the proportion of days that each stop rule signals a sell signal. The average ratio across all the stop rules is 0.47 on the lottery stock index and 0.29 on the market index. This indicates that the extra volatility and greater downside movements of the lottery stock index result in more sell signals. TRB rules signal the most sell signals with proportions of 0.502 or more, while SL rules have ratios ranging from 0.343 to 0.453. In Appendix 2, we document the relative number of times that MA, TRB, and TSMOM rules generate sell signals that

[17] Moskowitz, Ooi, and Pedersen (2012) develop timeseries momentum. They suggest scaling positions by volatility, but we following Marshall, Nguyen, and Visaltanachoti (2017) and use a more simplistic approach.

coincide with SL rules. The average proportion across the SL rules with the five thresholds is 0.67. The MA rules tend to be the most closely related, with ratios as high as 0.871. We conclude that the sell signals of MA, TRB, and TSMOM rules are indeed related to those from SL rules.

Table 5.2 contains the results for tests that compare the four families of stop rules' performance on three indices, the lottery stock index, a CRSP market index, and a small stock index. We include the small stock index for comparison purposes as many small stocks share some of the features of lottery stocks, and small stock index performance is more widely followed.[18] "Sell > 0" is the proportion of days following a stopping rule generating a sell signal, and the index has positive raw returns. Effective stop rules should have a ratio less than 0.5 as this indicates there are more days with negative than positive returns following a stopping rule sell signal.

The results indicate that 11 of the 17 stop rules have proportions less than 0.5 when applied to the lottery stock index. All MA stop rules have ratios less than 0.5, and four of the five SL rules do. None of the stop rules have a proportion less than 0.5 when applied to the market index, and just two of the 17 rules have ratios less than 0.5 when applied to the small stock index.

We assume that money is invested in T-bills following a stopping rule sell signal. We, therefore, define "Sell savings" as the T-bill return minus the return on the stock index in periods when a stopping rule has indicated a sell. A well-performed stop rule will have more significant sell savings as this shows the stock index has had more significant negative returns on average following the sell signal. We also investigate whether these returns are statistically significantly different from zero.

The stop rules perform very well on lottery stocks. Fifteen of the 17 stop rules generate

[18] We do not report small stock results in subsequent tables, but these are available on request.

positive sell savings, and each of these is statistically significant. The stop rule families that perform the best are the MA and SL families, with all of their rules producing positive savings. The magnitude of savings ranges from 3.88 to 11.23 basis points per day or above 0.8% to 2.2% per month. None of the stop rules add value to the market index. However, the SL rules do add value to the small stock index. Eleven of the 17 rules yield sell savings that are statistically different to zero. Once again, the MA and SL rules families perform the best with 100% and 80% of individual rules, respectively generating savings that are statistically different to zero.

Table 5.2: Standard test results

	Lottery stock index			Market index			Small stock index		
Rules	Sell > 0	Sell savings (bp)	t-stat	Sell > 0	Sell savings (bp)	t-stat	Sell > 0	Sell savings (bp)	t-stat
MA (50)	0.486	**10.31**	5.54	0.527	-0.63	-0.41	0.497	**8.31**	5.46
MA (100)	0.491	**8.61**	4.75	0.518	-0.07	-0.04	0.504	**6.42**	4.14
MA (150)	0.493	**6.55**	3.59	0.516	-0.07	-0.04	0.507	**3.97**	2.47
MA (200)	0.496	**5.42**	2.92	0.513	0.34	0.18	0.506	**2.83**	1.70
TRB (50)	0.492	**8.06**	4.53	0.529	-1.77	-1.16	0.512	**4.37**	2.91
TRB (100)	0.500	**4.34**	2.34	0.524	-1.57	-0.98	0.523	0.65	0.41
TRB (150)	0.506	1.30	0.70	0.515	-1.05	-0.61	0.520	-0.51	-0.31
TRB (200)	0.503	**3.88**	2.21	0.514	-0.91	-0.52	0.521	-0.41	-0.23
TSMOM (50)	0.490	**8.02**	4.39	0.527	-1.20	-0.77	0.512	**4.95**	3.28
TSMOM (100)	0.498	**5.20**	2.76	0.517	0.03	0.02	0.514	**3.13**	1.96
TSMOM (150)	0.502	**3.62**	1.94	0.512	-0.07	-0.04	0.509	2.14	1.29
TSMOM (200)	0.501	3.01	1.55	0.514	0.17	0.09	0.519	-0.46	-0.26
SL (1%)	0.502	**6.43**	3.33	0.546	-2.33	-1.79	0.507	**6.66**	4.54
SL (3%)	0.489	**11.23**	5.79	0.536	-2.15	-1.38	0.503	**8.21**	5.26
SL (5%)	0.492	**9.34**	4.60	0.532	-2.72	-1.55	0.499	**7.73**	4.76
SL (10%)	0.483	**9.24**	4.61	0.518	-2.22	-0.94	0.508	**4.61**	2.53
SL (20%)	0.495	**5.90**	2.56	0.515	-4.13	-1.38	0.512	2.15	0.84

This table displays the results that compare four stop rules families' performance on three indices, the lottery stock index, a CRSP market index, and a small stock index that is sourced from Ken French's data library. We follow Kumar (2009) to identify lottery stocks. We include common stocks with share codes of 10 and 11 and examine their price, idiosyncratic skewness, and volatility. The *Sell > 0* is the proportion of days following a stopping rule generating a sell signal with positive raw returns. The *Sell savings* are the T-bill return minus the stock index return in periods when a stopping rule generates sell signals. The sample period is from1926 to 2018. We display the *t*-ratios testing the difference of *Sell savings* from zero. The statistically significant *Sell savings* at the 10% level are in bold.

5.3.2 Business cycles

The sell signals of stop rules have more considerable sell savings than the market across all periods when applied to the lottery stocks. However, we now investigate whether there is much variation in their performance on lottery stocks over time. In this section, we consider whether stop rules result in sell savings differently across business cycles of expansions and recessions, as determined by the National Bureau of Economic Research (NBER)[19] . Henkel, Martin, and Nardari (2011) show that the return predictors perform differently across business cycles with the stronger predictability during contractions, so we feel that stop rules may be particularly effective in recessionary periods.

[19] https://www.nber.org/

Table 5.3: Business cycles

	Expansion			Recession		
Rules	Sell > 0	Sell savings (bp)	t-stat	Sell > 0	Sell savings (bp)	t-stat
MA (50)	0.495	**7.49**	4.25	0.455	**20.35**	3.57
MA (100)	0.499	**6.43**	3.75	0.468	**15.49**	2.96
MA (150)	0.502	**4.32**	2.48	0.469	**12.89**	2.59
MA (200)	0.505	**2.99**	1.68	0.472	**11.80**	2.44
TRB (50)	0.499	**5.89**	3.50	0.468	**15.23**	2.89
TRB (100)	0.509	**2.84**	1.71	0.475	8.38	1.62
TRB (150)	0.517	-1.20	-0.70	0.478	7.32	1.53
TRB (200)	0.512	**2.62**	1.66	0.480	7.09	1.49
TSMOM (50)	0.497	**6.10**	3.55	0.466	**14.61**	2.64
TSMOM (100)	0.506	**3.81**	2.23	0.476	**9.08**	1.71
TSMOM (150)	0.513	1.12	0.63	0.472	**9.92**	2.07
TSMOM (200)	0.511	0.83	0.45	0.476	**8.27**	1.68
SL (1%)	0.513	**4.30**	2.41	0.457	**15.19**	2.29
SL (3%)	0.500	**7.33**	4.03	0.444	**27.68**	4.21
SL (5%)	0.504	**6.10**	3.26	0.442	**22.74**	3.26
SL (10%)	0.492	**7.00**	3.79	0.447	**18.19**	2.68
SL (20%)	0.507	2.36	1.02	0.466	**14.88**	2.61

This table displays results across NBER business cycles when applying stop rules to the lottery stock index. *Sell > 0* is the proportion of days following a stopping rule generating a sell signal with positive raw returns. *Sell savings* is the T-bill return minus the return on the stock index in periods when a stopping rule generates sell signals. The sample period is from1926 to 2018. We display the t-ratios testing the difference of *Sell savings* from zero on the right, respectively. All statistically significant Sell savings at the 10% level are in bold.

The results indicate that the proportion of returns more significant than 0 following stop rule sell signals is only less than 0.5 for 4 out of 17 stop rules in expansions. However, in recessions, all rules have proportions less than 0.5. Stop rules are also reasonably consistent at producing sell savings across recessions and expansions, with 13 (14) of the 17 rules generating positive savings in expansions and recessions. However, the savings tend to be larger in recessions, from 0.83-7.49 basis points per day during expansion to 7.09-27.68 basis points per day in recession.

5.3.3 Drawdowns

The average returns earned by investors have always been a focus in the literature. However, researchers have begun documenting the implications of large drawdowns or crashes in returns in more recent times. For instance, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) document that the popular momentum strategy can suffer from crashes and significant drawdowns. Harvey, Hoyle, Rattary, Sargaison, Taylor, and Van Hemert (2019) state that investors are increasingly focused on mitigating the impact of large drawdowns.

Table 5.4 contains results comparing and contrasting the performance stop rules on lottery stocks across eight famous historical drawdown periods, as noted in Harvey, Hoyle, Rattary, Sargaison, Taylor, and Van Hemert (2019). Panel A documents the "sell rate", or the proportion days of stop rules that are not in the market during each drawdown. A successful stop rule should avoid as many trading days as possible within each drawdown. Panel B contains the terminal wealth results that assume an initial investment of $100 and gains from the T-bill return minus the return on the stock index on days following a sell signal of each stop rule. An effective stop rule should have a terminal wealth that is larger than $100.

Table 5.4: Drawdowns

Rules	Black Monday	Gulf War	Asian Crisis	Tech Burst	Financial Crisis	Euro crisis1	Euro crisis2	2018Q4	Mean
Peak day	25-Aug-87	16-Jul-90	17-Jul-98	1-Sep-00	9-Oct-07	23-Apr-10	29-Apr-11	20-Sep-18	
Trough day	19-Oct-87	11-Oct-90	31-Aug-98	9-Oct-02	9-Mar-09	2-Jul-10	3-Oct-11	24-Dec-18	
Panel A: Sell rate									
MA (50)	**1.00**	**1.00**	**1.00**	0.76	0.87	0.66	0.81	0.92	0.88
MA (100)	**1.00**	**1.00**	**1.00**	0.91	0.96	0.50	0.94	0.86	0.90
MA (150)	0.82	**1.00**	**1.00**	0.97	0.98	0.24	0.92	0.82	0.84
MA (200)	0.49	**1.00**	**1.00**	**1.00**	0.99	0.22	0.81	0.82	0.79
TRB (50)	**1.00**	**1.00**	**1.00**	0.84	0.93	0.58	**1.00**	0.82	0.90
TRB (100)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	0.00	0.87	0.77	0.83
TRB (150)	0.18	**1.00**	**1.00**	0.97	**1.00**	0.00	0.73	0.62	0.69
TRB (200)	**1.00**	**1.00**	**1.00**	0.97	**1.00**	0.00	**1.00**	0.62	0.82
TSMOM (50)	**1.00**	**1.00**	**1.00**	0.81	0.87	0.48	0.94	**1.00**	0.89
TSMOM (100)	**1.00**	**1.00**	**1.00**	0.91	0.99	0.08	0.91	0.79	0.83
TSMOM (150)	0.18	**1.00**	**1.00**	0.97	0.97	0.06	0.60	0.82	0.70
TSMOM (200)	0.00	**1.00**	**1.00**	0.97	0.99	0.06	0.43	0.76	0.65
SL (1%)	0.79	0.73	0.75	0.56	0.50	0.54	0.52	0.56	0.62
SL (3%)	**1.00**	0.81	0.69	0.59	0.56	0.62	0.52	0.67	0.68
SL (5%)	**1.00**	0.73	**1.00**	0.63	0.59	0.46	0.61	0.79	0.73
SL (10%)	0.33	**1.00**	**1.00**	0.60	0.44	0.66	0.76	0.79	0.70
SL (20%)	0.00	**1.00**	0.63	0.63	0.67	0.36	0.37	0.61	0.53
Panel B: Terminal wealth									
MA (50)	137.2	159.1	150.4	607.3	241.5	110.0	141.8	151.5	212.3
MA (100)	137.2	159.1	150.4	685.1	297.2	103.8	143.0	149.4	228.1
MA (150)	135.2	159.1	150.4	670.3	312.0	104.8	144.5	145.6	227.7
MA (200)	130.3	159.1	150.4	801.0	315.5	104.1	129.7	145.6	241.9
TRB (50)	137.2	159.1	150.4	651.3	286.6	114.2	157.7	145.6	225.3
Table 5.4 contd.									
TRB (100)	137.2	159.1	150.4	801.0	316.2	100.0	147.8	138.3	243.7

TRB (150)	126.4	159.1	150.4	687.5	316.2	100.0	144.0	127.3	226.4
TRB (200)	137.2	159.1	150.4	687.5	316.2	100.0	157.7	127.3	229.4
TSMOM (50)	137.2	159.1	150.4	463.7	276.9	104.3	156.9	153.0	200.2
TSMOM (100)	137.2	159.1	150.4	692.4	317.2	94.6	142.1	143.5	229.6
TSMOM (150)	126.4	159.1	150.4	725.1	303.5	100.1	142.4	145.6	231.6
TSMOM (200)	100.0	159.1	150.4	705.5	312.1	103.4	143.2	137.0	226.3
SL (1%)	130.6	150.8	139.1	537.5	299.5	124.5	144.9	127.9	206.9
SL (3%)	137.2	157.1	139.2	820.4	246.7	122.1	108.8	135.4	233.4
SL (5%)	137.2	144.4	150.4	827.4	135.7	104.5	137.0	134.9	221.4
SL (10%)	130.3	159.1	150.4	763.8	122.6	102.9	140.6	143.5	214.1
SL (20%)	100.0	159.1	135.3	630.0	186.0	108.2	125.2	130.5	196.8

This table displays results that compare and contrast the performance of stop rules across eight novel drawdowns noted in Harvey, Hoyle, Rattray, and Van Hemert (2019). Panel A contains the proportion that days of stop rules are not in the market during each drawdown. The stop rules that have a sell rate of 1 are in bold. Panel B displays the terminal wealth that assumes an initial wealth of $100 and gains from the T-bill return minus the stock index return on days following a sell signal of each stop rule. The sample period is from1926 to 2018.

The Panel A results indicate that the stop rules generate correct sell signals to avoid drawdowns, such as Black Monday, Gulf War, and Asian crisis. Fourteen of 17 stop rules suggest avoiding the entire Gulf war and Asian crisis periods. Nine of 17 stop rules successfully avoid the entire drawdown of Black Monday. The MA rule with the 100 look-back periods and the TRB rule with the 50 look-back periods have the largest average sell rate of 0.9 across eight drawdowns. The SL rules have lower sell rates than the other rules on average, but these rules are still effective at avoiding most of the drawdown days.

The Panel B results indicate that the stop rules, on average, add substantial value during the periods of large drawdowns. Many of the terminal wealth numbers are substantially large than the $100 nominal starting value. The largest increases in terminal wealth occur during the tech bubble bursting, which likely indicates the magnitude of the decline in lottery stocks during this period. We conclude that stop rules are particularly good at adding value during a significant decrease in the equity market.

5.3.4 Decomposing stop rule performance

The previous sections clearly show that the stop rules add value in stopping losses, especially during a declining market. Table 5.5 compares the sell savings of stop rules with those of a hypothetical perfect strategy, which can always correctly signal being out of the market on days that the market declines. We decompose the sell savings into "Missed", "Correct", and "Incorrect" sell. "Missed" refers to the excess return on days where the index declined, but a stopping rule does not create a sell signal. "Correct" is the excess return on days when a stopping rule signaled a sell and the index declined. "Incorrect" is the excess return on days when the stop rule generated a sell signal but the index increases. "Missed" and "Correct" sum to form "Perfect", while "Net Savings" refers to the difference between correct and incorrect sell savings.

Table 5.5: Daily sell savings (bp)

Rules	Perfect	Missed	Correct	Incorrect	Net savings
	56.51				
MA (50)		22.88	33.63	28.61	5.02
MA (100)		22.99	33.52	29.21	4.31
MA (150)		23.48	33.04	29.77	3.27
MA (200)		23.57	32.94	30.25	2.69
TRB (50)		23.36	33.16	29.11	4.05
TRB (100)		24.13	32.38	30.19	2.19
TRB (150)		24.56	31.95	31.29	0.66
TRB (200)		24.66	31.85	29.85	2.00
TSMOM (50)		23.76	32.76	28.82	3.94
TSMOM (100)		24.36	32.15	29.58	2.58
TSMOM (150)		25.46	31.05	29.31	1.75
TSMOM (200)		25.75	30.76	29.33	1.43
SL (1%)		27.01	29.50	26.58	2.92
SL (3%)		26.80	29.72	24.81	4.91
SL (5%)		28.23	28.28	24.41	3.88
SL (10%)		28.76	27.75	23.89	3.86
SL (20%)		32.91	23.61	21.58	2.03

This table results compare the sell savings of stop rules with those of a perfect strategy. *Perfect* refers to the saving or excess (T-bill return – stock index) return from a perfect strategy, which always correctly signals out of the stock market on days of market declines. *Missed* is the excess return missed by each stop rule due to it not signaling to be out of the market on days of index declines. *Correct* is the excess return on days that a stop rule signals to be out of the market and the index declines. *Incorrect* is the excess return on days a stopping rule signals to be out of the market and the index increases. *Net Savings* is the difference between correct and incorrect savings. The sample period is from 1926 to 2018. All results are in basis point.

The results indicate that 15 of the 17 SL rules have larger "Correct" than "Missed" daily averages, so the SL rules provide investors with more of the gains on offer from avoiding days of negative return than they miss out. The MA and TSMOM rules are the best performers based on this metric. SL rules have the lowest "Incorrect" returns, which suggests they are less likely, on average, to signal a time out of the market when it increases. All stop rules have positive net savings varying from an average of 0.66 basis points per day to 5.02 basis points per day, with MA and SL rules generating the most significant savings. The results in Appendix 3 indicate that all stop rules' net savings are over three times larger in recessions than expansions.

However, the pattern of MA and SL rules generating the largest net savings is still evident.

Table 5.6 contains the results for the decomposition of signals based on proportions. "Correct signals" is the proportion of total days that the stop rule signals to be out of the market when the index declines. "Perfect sells captured" is the proportion of days the index drops that the stop rule signals to be out of the market.

The results indicate that 12 of 17 stop rules generate correct signals more than 50% of the time. MA and SL rules again perform the best. However, none of the proportions are above 0.52. Taken together with the results in Table 5.5, this indicates stop rules are particularly effective at avoiding significant price declines. There are 48% or more days where stocks decline that the stop rules do not avoid, but they still generate meaningful savings. The "Perfect sells captured" present results from a different perspective but indicate a similar thing. Eleven of the 17 proportions are greater than 0.50, but none are above 0.54. The MA and TRB rules are the best performers based on this metric. The results in Appendix 4 continue the theme of stop rules adding much more value in recessions. The "Perfect sells captured" proportions are frequently above 0.60 and are as high as 0.848.

Table 5.6: Signals decompositions

Rules	Correct signals	Perfect sells captured
MA (50)	0.514	0.525
MA (100)	0.509	0.533
MA (150)	0.507	0.530
MA (200)	0.504	0.525
TRB (50)	0.508	0.535
TRB (100)	0.500	0.529
TRB (150)	0.494	0.527
TRB (200)	0.497	0.538
TSMOM (50)	0.510	0.526
TSMOM (100)	0.502	0.522
TSMOM (150)	0.498	0.504
TSMOM (200)	0.499	0.498
SL (1%)	0.498	0.474
SL (3%)	0.511	0.468
SL (5%)	0.508	0.442
SL (10%)	0.517	0.453
SL (20%)	0.505	0.363

This table decomposes the sell signals into two proportions. *Correct signals* are the proportion of total days when the stop rule signals to be out of the market that the index declines. *Perfect sells captured* the ratio of days the index falls that the stop rule signals to be out of the market. The sample period is from 1926 to 2018.

5.3.5 Transaction costs

We estimate the break-even transaction costs by comparing the returns across the stop rules to a buy-and-hold strategy. The results, which we present in Table 5.7, indicate that many stop rules appear to add value after considering transaction costs. There is considerable variation in the number of sell signals generated, ranging from 31 for the TRB (200) rule to 2,065 for the SL (1%) rule. Fewer sell signals contribute to more significant break-even transaction costs, and while they are positive across all stop rules, there is considerable variation in their magnitude. For instance, the TRB rule with a 200-day look-back period has the largest break-even transaction costs of 15%, while the SL rule with a threshold of 1% has the most negligible break-even transaction costs of 0.4%. As a proxy for trading lottery stocks' costs, we use the small stock transaction cost estimates from Frazzini, Israel, and Moskowitz

(2018). They document realized trading costs based on market impact and implantation shortfall for actual trades and estimate mean small-stock transaction costs to range from 19-20 basis points. Others such as Chung and Zhang (2014) report larger transaction cost estimates, but we conclude that stop rules add value after transaction costs are accounted for. In particular, the stop rules that signal fewer trades have particularly large breakeven transaction costs. The Appendix 5 results indicate that break-even transaction costs are even larger in recessions.

Table 5.7: Transaction costs

Rules	Sell trades	Break-even transaction cost (%)
MA (50)	594	2.1
MA (100)	394	2.6
MA (150)	290	2.7
MA (200)	280	2.3
TRB (50)	130	7.5
TRB (100)	71	7.4
TRB (150)	54	2.9
TRB (200)	31	15.1
TSMOM (50)	509	1.9
TSMOM (100)	331	1.9
TSMOM (150)	297	1.5
TSMOM (200)	261	1.4
SL (1%)	2065	0.4
SL (3%)	841	1.6
SL (5%)	492	2.3
SL (10%)	207	5.4
SL (20%)	84	8.5

This table displays the number of sell transactions as well as the break-even transaction cost across stop rules. Sell trades are the number of transactions that the stop rule suggests to be out of the market. The break-even transaction cost is the return reduction to those of the buy-and-hold strategy. The sample period is from 1926 to 2018.

5.4 Conclusions

This paper considers whether stop-loss rules add value to investors in lottery stocks. Stop-loss rules, which are mechanical rules which signal that a stock should be sold when it declines by a certain amount, are popular with investors. Still, the evidence in the academic literature regarding their effectiveness is mixed. There is reason to believe that these rules might benefit lottery stocks as these stocks have frequent losses and infrequent large gains. If stop rules can avoid the losses, we can improve the performance of lottery stock investment.

We show that the sell signals generated by popular technical trading and time-series momentum rules are similar to those generated by stop losses rules. These "stop rules" are very effective on lottery stocks. The results hold in general and are particularly evident during recessions and periods of market crises.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Bochuan Dai
Name/title of Primary Supervisor:	Professor Ben Marshall
In which chapter is the manuscript /published work:	Chapter 5

Please select one of the following three options:

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- Please provide the full reference of the Research Output:

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- The percentage of the manuscript/published work that was contributed by the candidate: 70.00

- Describe the contribution that the candidate has made to the manuscript/published work:
  Bochuan Dai collected, collated and cleaned the datasets before completing all the empirical analysis. Bochuan Dai then wrote the draft working paper and submit to Financial Analysts Journal. The supervisors provided detailed advice and answers to Bochuan's questions as he completed the paper. Bochuan is the main author of this paper and while his supervisors have made substantial contributions, which is reflected by co-authorship. The papers are essentially the work from Bochuan.

○ It is intended that the manuscript will be published, but it has not yet been submitted to a journal

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Date:	3-Jun-2021

This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis.

Chapter Six

Conclusion

Stop-loss rules are popular in financial markets. The thesis investigates these rules in the context of U.S. common stocks, international equity market allocation, and lottery stocks. This chapter concludes the thesis by summarising the main findings across three essays in Section 6.1. Section 6.2 suggests the areas for future research in stop-loss rules.

6.1 Major findings and implications

6.1.1 Essay one

Stop-loss rules are prevalent among investors in financial markets. Essay one shows that the traditional stop-loss rules are either price-based whereby a security is sold when its price drops by a certain percentage below its purchase price, or time-based that sells a security when its price drops to the pre-specified price within a given period. However, Trailing Stops are more flexible as the stop price is adjusted upwards if the price moves higher following the purchase. A security is then sold when its price declines by a pre-specified percentage below the each new high price.

The first essay compares the performance of trailing stop-loss rules to a mean-variance benchmark for the 1926-2016 period in U.S. market. The results show the lower returns of trailing stop-loss rules compared to the respective benchmark. But these rules perform well for stopping losses. They do extremely well at mitigating downside risk, as measured by VaR and Expected Shortfall. Essay one finds the optimal trailing stop-loss rule with a threshold of 20% reduces the most downside risk. Moreover, the risk reduction of trailing stop-loss rules are more effective over time. They can be implemented better during a declining market, and add more value to stocks with more volatility, higher liquidity and lower book-to-market ratios. This essay takes realistic stock spreads into account before computing the downside risk in order to estimate breakeven transaction costs for the downside risk. The transaction costs do reduce the effectiveness of stopping losses for these rules with tighter thresholds. However, trailing stop-loss rules with larger thresholds still significantly reduce downside risk.

In summary, this essay shows the evidence that the trailing stop-loss rules significantly add value at reducing downside risks. These findings help investors to protect their gained profits, and provide implications for efficiently trading during the declining markets.

6.1.2 Essay two

The second essay examines whether stop-loss rules add value to international equity allocation. We construct an equal-weight portfolio (EW) that covers various international equity indices and apply stop-loss rules to each index at the beginning of respective data series. The position of an index is closed once its price falls by a certain amount. The capital is then reallocated across the remaining holding indices. The closed index should be re-entered when there is an increase with a certain percentage.

More specifically, essay two compares and contrasts the performance between the stop-loss portfolio with various thresholds and an equal-weight buy-and-hold portfolio across 82 international equity markets that cover between 1973 and 2018. An optimized utility function accounts for stop-loss rules as a characteristic which initially indicates the effectiveness of stop-loss rules in international equity markets allocation. The results show that stop-loss rules with thresholds of 1-5% and 10% each generates significantly larger portfolio returns than that of the EW. But there is no significant difference between the risk of the stop-loss portfolio and that of the EW. Moreover, the larger return of the stop-loss portfolio can offset its high risk and result in a larger Sharpe ratio than the EW.

The results indicate that most stop-loss portfolios can generate larger utility to investors than an EW when investors have risk aversion levels of one, three, or five. The results show that the stop-loss portfolios, on average, have a 56% success rate, which gives a significantly better return than the EW within each comparison window across 5, 10, and 30 days since each trigger day. The alphas or risk-adjusted returns still exist after accounting for some popular Fama-French factors, such as the Fama-French five factors and the momentum factor. The risk-adjusted return of stop-loss portfolios is better when the market is declining. However, the alphas are not significantly different across either recessionary or expansionary market states.

In general, the stop-loss portfolios with smaller thresholds have better performance when applied to each equity index. The break-even transaction costs can be up to 8.27 bp when applying a threshold of 10% threshold. Thus, the outperformance between each stop-loss portfolio in excess of the EW can offset transaction costs, and perform especially better during a declining market for stop-loss portfolios that have a range of thresholds from 1% to 5%.

Overall, essay two provides a comprehensive view of applying stop-loss rules to an international equity market setting, which is different from trading within a single market. The findings show that the stop-loss rules significantly add value when allocating capitals globally so as to show the usefulness for participants that are focused on investing across markets that have varying risks.

6.1.3 Essay three

Essay three considers whether stop-loss rules add value to investors in lottery stocks. Lottery stocks make up for a large proportion of common stocks and are very popular among individual investors (e.g., Kumar, 2009; Meng and Pantzalis, 2018). In general, these stocks have a small probability to generate large returns but a high probability to cause regular losses. Given the evidence in the academic literature that shows the mixed results regarding the effectiveness of stop-loss rules, it is reasonable to believe that the stop-loss rules should be useful in trading stocks with lottery features.

Essay three suggests that the stop-loss rules can generate similar sell signals with several popular trading rules, such as moving average, trading range break, and time-series momentum rules. As a consequence, this essay includes these rules as “stop rules” in the analysis. It is of interest to investigate whether stop rules can avoid the frequent losses of lottery stocks so as to improve their overall performance. The results reveal the "stop rules" are very effective when applied to lottery stocks. The results are particularly stronger during recessions and periods of market crises, such as Black Monday in 1987 and Gulf war in 1990.

To conclude, these findings provide strong evidence for individual investors who have a preference to invest in lottery stocks. It may be effective to help those investors to avoid historical drawdowns and generate even better performance during declining markets.

6.2 Future areas of research

The first essay considers the effectiveness of trailing stop-loss rules at reducing downside risks in the U.S. equity markets. It uses VaR and expected shortfalls as measures of downside risks. Future studies can try diverse downside risk measures to further examine whether the choice of these measures affect the effectiveness at mitigating downside risks. Moreover, this essay investigates fixed stop-loss thresholds between 1% and 20%. The future research may employ dynamic stop-loss thresholds that are determined by the market conditions under different periods. It will, thus, be beneficial to investors to obtain the optimal stop-loss performance.

The second essay investigates the stop-loss rules from a perspective of international equity allocation. This essay indicates that the stop-loss rules significantly add value in international asset allocation across 82 country indices. However, the government policy and market risk are different across countries. Future research may focus on few market with some special characteristics. Deeper investigation within each market is necessary when studying stop-loss rules in the international settings.

Essay three provides some evidence of stop-loss rules for enhancing performance of lottery stocks. The essay may help individual investors to reduce risks by using “stop rules”, given their preference for stocks with lottery features. It is of interest to examine the lottery stocks in the markets with different features. For instance, emerging markets are growing fast to make up for a larger part of the world economy. Future research can further examine whether the stop rules perform differently when applied to the lottery stocks in different emerging markets.

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Appendix A

For Essay One

Appendix A.1
Downside Risk for Delisted Stocks

Variable	Benchmark	TSL 1%	TSL 5%	TSL 10%	TSL 20%
Panel A: Value-weighted					
VaR (1%)	-11.61%	-12.66%	-11.80%	-11.44%	-12.26%
		0.30	0.38	0.41	0.29
Expected shortfall (1%)	-15.69%	-18.34%	-14.71%	-15.34%	-16.65%
		0.18	0.35	0.50	0.34
VaR (5%)	-5.80%	-5.93%	-5.83%	-6.30%	-7.38%
		0.46	0.43	0.21	0.02
Expected shortfall (5%)	-9.42%	-10.23%	-9.50%	-9.32%	-10.83%
		0.21	0.46	0.45	0.04
Panel B: Equal-weighted					
VaR (1%)	-18.85%	-11.02%	-9.98%	-9.50%	-10.63%
		0.00	0.00	0.00	0.00
Expected shortfall (1%)	-22.12%	-14.12%	-12.58%	-13.99%	-13.27%
		0.00	0.00	0.01	0.00
VaR (5%)	-9.38%	-5.95%	-5.48%	-5.56%	-6.44%
		0.00	0.00	0.00	0.00
Expected shortfall (5%)	-14.16%	-8.65%	-8.24%	-8.46%	-8.88%
		0.00	0.00	0.00	0.00

This table displays the Value-at-Risk (VaR) and Expected Shortfall (ES), which are two measures of downside risks, for TSL and respective benchmark portfolios for delisted stocks. Panel A shows the results of value-weight portfolios and Panel B reports the results of equal-weight portfolios. We display *p*-value under each result. The *p*-values are estimated from 1,000 bootstrapped samples.

Appendix A.2
Downside Risk (Monthly)

Variable	*Benchmark*	TSL *1%*	TSL *5%*	TSL *10%*	TSL *20%*
		Panel A: Value-weight			
VaR (1%)	-10.87%	-10.27%	-9.49%	-9.32%	-10.03%
		0.20	0.04	0.02	0.12
Expected shortfall (1%)	-16.37%	-15.77%	-13.82%	-13.08%	-13.46%
		0.33	0.05	0.01	0.06
VaR (5%)	-6.53%	-3.88%	-3.78%	-4.29%	-5.20%
		0.00	0.00	0.00	0.00
Expected shortfall (5%)	-9.93%	-7.38%	-7.21%	-7.18%	-7.95%
		0.00	0.00	0.00	0.00
		Panel B: Equal-weight			
VaR (1%)	-15.47%	-12.05%	-12.09%	-10.56%	-11.09%
		0.02	0.00	0.00	0.00
Expected shortfall (1%)	-19.30%	-16.23%	-15.83%	-14.45%	-14.18%
		0.06	0.01	0.00	0.00
VaR (5%)	-8.60%	-4.79%	-4.85%	-4.97%	-5.52%
		0.00	0.00	0.00	0.00
Expected shortfall (5%)	-12.56%	-8.36%	-8.02%	-8.05%	-8.59%
		0.00	0.00	0.00	0.00

This table displays the Value-at-Risk (VaR) and Expected Shortfall (ES), which are two measures of downside risks for TSL and respective benchmark portfolios. The TSL and benchmark portfolios are conducted on the monthly frequency. Panel A shows the results of value-weight portfolios, and Panel B reports the results of equal-weight portfolios. We display *p*-value under each result. The *p*-values are estimated from 1,000 bootstrapped samples.

Appendix B

For Essay Two

Appendix B.1: Data overview

Country	Start Date	PI/RI	Country	Start Date	PI/RI	Country	Start Date	PI/RI	Country	Start Date	PI/RI
ARGENTINA	19/10/1989	PI	FINLAND	2/01/1991	RI	LUXEMBURG	2/01/1992	RI	SLOVAKIA	14/09/1993	PI
AUSTRALIA	1/01/1973	RI	FRANCE	1/01/1973	RI	MALAYSIA	2/01/1980	PI	SLOVENIA	31/12/1993	PI
AUSTRIA	1/01/1973	RI	GERMANY	31/12/1964	RI	MALTA	27/12/1995	PI	SOUTH AFRICA	1/01/1973	RI
BAHRAIN	31/12/1999	PI	GHANA	29/12/1995	RI	MAURITIUS	29/12/1995	RI	SOUTH KOREA	31/12/1974	PI
BANGLADESH	1/01/1990	PI	GREECE	1/03/2001	RI	MEXICO	4/01/1988	PI	SPAIN	2/01/1974	PI
BELGIUM	1/01/1973	RI	HK	2/01/1990	RI	MOROCCO	31/12/1987	PI	SRI LANKA	2/01/1985	PI
BOTSWANA	29/12/1995	RI	HUNGARY	2/01/1991	PI	NAMIBIA	31/01/2000	RI	SWEDEN	28/12/1979	PI
BRAZIL	7/04/1983	RI	ICELAND	31/12/1992	PI	NETHERLAND	1/01/1973	RI	SWITZERLAND	1/01/1973	RI
BULGARIA	20/10/2000	PI	INDIA	2/01/1987	PI	NEW ZEALAND	4/01/1988	RI	TAIWAN	31/12/1984	PI
CANADA	30/12/1964	RI	INDONESIA	2/04/1990	RI	NIGERIA	30/06/1995	RI	THAILAND	2/01/1987	RI
CHILE	2/01/1987	PI	IRELAND	1/01/1973	RI	NORWAY	2/01/1980	RI	TRINIDAD	29/12/1995	RI
CHINA	3/04/1991	PI	ISRAEL	23/04/1987	PI	OMAN	22/10/1996	PI	TUNISIA	31/12/1997	PI
COLOMBIA	10/03/1992	RI	ITALY	1/01/1973	RI	PAKISTAN	30/12/1988	PI	TURKEY	4/01/1988	PI
COTE D'IVOIRE	29/12/1995	RI	JAMAICA	29/12/1995	RI	PERU	2/01/1991	PI	UKRAINE	30/01/1998	RI
CROATIA	2/01/1997	PI	JAPAN	4/01/1973	RI	PHILIPPINE	2/01/1986	PI	UAE	31/05/2005	PI
CYPRUS	3/09/2004	PI	JORDAN	21/11/1988	PI	POLAND	16/04/1991	RI	UK	1/01/1965	RI
CZECH	9/11/1993	RI	KENYA	11/01/1990	PI	PORTUGAL	5/01/1988	RI	US	4/01/1988	RI
DENMARK	31/12/1969	RI	KUWAIT	28/12/1994	PI	ROMANIA	19/09/1997	PI	VENEZUELA	3/01/1994	RI
ECUADOR	2/08/1993	PI	LATVIA	3/01/2000	RI	RUSSIA	1/09/1995	PI	ZIMBABWE	6/04/1988	PI
EGYPT	2/01/1995	PI	LEBANON	31/01/2000	RI	SAUDI ARABIA	31/12/1997	RI			
ESTONIA	3/06/1996	PI	LITHUANIA	31/12/1999	RI	SINGAPORE	1/01/1973	RI			

Note: This table shows the start date and index type for 82 countries or districts included in the study. The start date indicates the date that the country's data starts in the Datastream. PI/RI shows two types of indices which are price index or return index. We use the return index if both price and return indices are available for a country. We use the price index if it has a longer period than the return index. The sample period is from January 1973 to June 2018.

Appendix B.2: Summary statistics across indices

Country	N	Min	Max	Mean	Std	Country	N	Min	Max	Mean	Std
ARGENTINA	345	-0.414	1.193	0.011	0.133	ICELAND	307	-0.750	0.234	0.007	0.079
AUSTRALIA	546	-0.433	0.251	0.011	0.069	INDIA	378	-0.297	0.420	0.011	0.088
AUSTRIA	546	-0.342	0.373	0.010	0.065	INDONESIA	339	-0.500	1.000	0.015	0.177
BAHRAIN	223	-0.396	0.584	0.003	0.060	IRELAND	546	-0.251	0.431	0.011	0.069
BANGLADESH	280	-0.305	0.767	0.009	0.105	ISRAEL	375	-0.221	0.215	0.010	0.070
BELGIUM	546	-0.323	0.244	0.010	0.057	ITALY	546	-0.231	0.274	0.009	0.074
BOTSWANA	271	-0.166	0.459	0.014	0.058	JAMAICA	271	-0.211	0.453	0.014	0.079
BRAZIL	423	-0.674	1.092	0.024	0.185	JAPAN	546	-0.177	0.258	0.007	0.058
BULGARIA	213	-0.441	0.417	0.015	0.095	JORDAN	356	-0.191	0.236	0.005	0.050
CANADA	546	-0.271	0.208	0.008	0.055	KENYA	342	-0.252	0.530	0.002	0.077
CHILE	378	-0.253	0.197	0.011	0.065	KUWAIT	283	-0.201	0.162	0.006	0.046
CHINA	327	-0.440	0.881	0.015	0.125	LATVIA	222	-0.269	0.385	0.014	0.074
COLOMBIA	316	-0.280	0.200	0.010	0.079	LEBANON	222	-0.250	0.455	0.008	0.094
COTE D'IVOIRE	271	-0.199	0.333	0.016	0.067	LITHUANIA	223	-0.364	0.452	0.012	0.075
CROATIA	258	-0.412	0.444	0.007	0.088	LUXEMBURG	318	-0.272	0.184	0.009	0.056
CYPRUS	166	-0.433	0.537	-0.007	0.132	MALAYSIA	462	-0.340	0.489	0.006	0.081
CZECH	296	-0.260	0.675	0.012	0.086	MALTA	271	-0.185	0.244	0.006	0.053
DENMARK	546	-0.257	0.204	0.011	0.056	MAURITIUS	271	-0.271	0.233	0.010	0.056
ECUADOR	299	-0.225	0.548	0.001	0.064	MEXICO	366	-0.369	0.407	0.015	0.090
EGYPT	282	-0.318	0.326	0.008	0.086	MOROCCO	367	-0.148	0.228	0.009	0.048
ESTONIA	265	-0.378	0.409	0.014	0.094	NAMIBIA	222	-0.165	0.149	0.013	0.057
FINLAND	330	-0.277	0.296	0.012	0.079	NETHERLAND	546	-0.309	0.242	0.011	0.054
FRANCE	546	-0.227	0.282	0.011	0.065	NEW ZEALAND	366	-0.186	0.300	0.010	0.061
GERMANY	546	-0.248	0.241	0.009	0.063	NIGERIA	277	-0.377	0.492	0.012	0.088
GHANA	271	-0.178	0.274	0.002	0.067	NORWAY	462	-0.306	0.248	0.011	0.076
GREECE	208	-0.348	0.260	0.001	0.098	OMAN	261	-0.221	0.320	0.005	0.061
HK	342	-0.292	0.309	0.012	0.071	PAKISTAN	355	-0.364	0.341	0.011	0.088

Appendix B.2 contd.

Country	N	Min	Max	Mean	Std	Country	N	Min	Max	Mean	Std
HUNGARY	330	-0.390	0.565	0.011	0.096	PERU	330	-0.397	0.612	0.020	0.105
PHILIPPINE	390	-0.294	0.540	0.012	0.095	SWEDEN	463	-0.265	0.254	0.010	0.065
POLAND	327	-0.352	1.015	0.015	0.123	SWITZERLAND	546	-0.182	0.164	0.010	0.050
PORTUGAL	366	-0.286	0.233	0.005	0.063	TAIWAN	403	-0.383	0.545	0.012	0.104
ROMANIA	250	-0.375	0.333	0.008	0.108	THAILAND	378	-0.325	0.409	0.014	0.098
RUSSIA	274	-0.562	0.560	0.018	0.132	TRINIDAD	271	-0.185	0.165	0.010	0.040
SAUDI ARABIA	247	-0.249	0.208	0.011	0.071	TUNISIA	247	-0.166	0.168	0.006	0.042
SINGAPORE	546	-0.372	0.632	0.011	0.084	TURKEY	366	-0.423	0.717	0.014	0.155
SLOVAKIA	298	-0.305	1.155	0.008	0.104	UKRAINE	246	-0.413	0.787	0.008	0.123
SLOVENIA	203	-0.266	0.240	0.007	0.073	UAE	158	-0.334	0.363	0.001	0.098
SOUTH AFRICA	546	-0.353	0.198	0.012	0.080	UK	546	-0.212	0.549	0.010	0.062
SOUTH KOREA	523	-0.371	0.682	0.009	0.089	US	366	-0.168	0.114	0.009	0.040
SPAIN	534	-0.273	0.254	0.004	0.068	VENEZUELA	294	-0.955	1.726	0.041	0.239
SRI LANKA	402	-0.175	0.351	0.008	0.074	ZIMBABWE	223	-0.438	1.450	0.081	0.221

Note: This table indicates the summary statistics across 82 countries in our sample. *N* is the number of monthly returns for each index. *Min* and *Max* are the minimum and maximum monthly returns of each index over time, respectively. *Mean* is the average monthly return of each index. *Std* is the standard deviation of the monthly returns for each index over time.

Appendix C

For Essay Three

Appendix C.1: Sell proportions

	Lottery stock index	Market index
MA (50)	0.487	0.349
MA (100)	0.500	0.317
MA (150)	0.499	0.295
MA (200)	0.497	0.277
TRB (50)	0.502	0.345
TRB (100)	0.505	0.316
TRB (150)	0.509	0.283
TRB (200)	0.516	0.273
TSMOM (50)	0.491	0.336
TSMOM (100)	0.496	0.303
TSMOM (150)	0.483	0.281
TSMOM (200)	0.476	0.260
SL (1%)	0.453	0.383
SL (3%)	0.437	0.309
SL (5%)	0.415	0.267
SL (10%)	0.418	0.187
SL (20%)	0.343	0.138

This table shows the proportion of days that each stop rule suggests to be out of the market when applied to the lottery index and a CRSP market index. We follow Kumar (2009) to identify lottery stocks. We include common stocks with share codes of 10 and 11 and examine their price, idiosyncratic skewness, and volatility. The sample period is from1926 to 2018.

Appendix C.2: Sell signals comparison

Rules	SL (1%)	SL (3%)	SL (5%)	SL (10%)	SL (20%)
MA (50)	0.626	0.745	0.825	0.761	0.739
MA (100)	0.608	0.684	0.759	0.762	0.837
MA (150)	0.586	0.652	0.695	0.728	0.871
MA (200)	0.574	0.640	0.671	0.700	0.868
TRB (50)	0.570	0.643	0.736	0.770	0.808
TRB (100)	0.549	0.588	0.622	0.687	0.856
TRB (150)	0.536	0.559	0.574	0.606	0.821
TRB (200)	0.550	0.580	0.597	0.591	0.772
TSMOM (50)	0.586	0.665	0.741	0.756	0.793
TSMOM (100)	0.565	0.603	0.638	0.684	0.847
TSMOM (150)	0.538	0.586	0.598	0.608	0.808
TSMOM (200)	0.524	0.560	0.577	0.575	0.752

This table documents the proportion of days that technical and time-series momentum stop rules suggest to be out of the market consistent with those of stop-loss rules. The sample period is from 1926 to 2018.

Appendix C.3: Daily return savings across business cycles (bp)

Rules	Perfect	Missed	Correct	Incorrect	Net savings
Panel A: Expansion					
	50.18				
MA (50)		22.58	27.60	24.13	3.47
MA (100)		23.65	26.53	23.56	2.97
MA (150)		24.80	25.38	23.44	1.94
MA (200)		25.57	24.61	23.30	1.31
TRB (50)		23.58	26.60	23.84	2.76
TRB (100)		26.02	24.16	22.88	1.28
TRB (150)		27.34	22.84	23.36	-0.53
TRB (200)		26.82	23.36	22.17	1.19
TSMOM (50)		23.62	26.56	23.74	2.83
TSMOM (100)		25.86	24.32	22.63	1.69
TSMOM (150)		27.42	22.76	22.29	0.47
TSMOM (200)		27.89	22.29	21.95	0.34
SL (1%)		24.65	25.53	23.62	1.91
SL (3%)		24.88	25.30	22.14	3.16
SL (5%)		26.45	23.73	21.24	2.48
SL (10%)		26.95	23.23	20.38	2.85
SL (20%)		32.38	17.80	17.10	0.71
Panel B: Recession					
	85.49				
MA (50)		24.25	61.24	49.13	12.11
MA (100)		19.97	65.52	55.11	10.41
MA (150)		17.41	68.09	58.76	9.33
MA (200)		14.39	71.10	62.07	9.03
TRB (50)		22.33	63.17	53.23	9.94
TRB (100)		15.50	69.99	63.62	6.37
TRB (150)		11.81	73.68	67.58	6.10
TRB (200)		14.80	70.69	64.96	5.73
TSMOM (50)		24.39	61.10	52.06	9.05
TSMOM (100)		17.49	68.00	61.35	6.65
TSMOM (150)		16.51	68.98	61.42	7.57
TSMOM (200)		15.95	69.55	63.12	6.43
SL (1%)		37.82	47.67	40.14	7.53
SL (3%)		35.55	49.94	37.02	12.91
SL (5%)		36.36	49.13	38.88	10.25
SL (10%)		37.08	48.42	39.92	8.50
SL (20%)		35.33	50.16	42.10	8.06

This table compares the sell savings of stop rules with those of a perfect strategy across NBER business cycles. *Perfect* refers to the saving or excess (T-bill return – stock index) return from a perfect strategy, which always correctly signals out of the stock market on days of market declines. *Missed* is the excess return missed by each stop rule due to it not signaling to be out of the market on days of index declines. *Correct* is the excess return on days that a stop rule signals to be out of the market and the index declines. *Incorrect* is the excess return on days a stopping rule signals to be out of the market and the index increases. The sample period is from 1926 to 2018. Panel A and B contain the results for expansion and recession, respectively. All results are in basis point.

Appendix C.4: Signals proportions across business cycles

Rules	Correct signal	Perfect sells captured
	Panel A: Expansion	
MA (50)	0.505	0.499
MA (100)	0.501	0.494
MA (150)	0.498	0.478
MA (200)	0.495	0.462
TRB (50)	0.501	0.501
TRB (100)	0.491	0.470
TRB (150)	0.483	0.450
TRB (200)	0.488	0.471
TSMOM (50)	0.503	0.497
TSMOM (100)	0.494	0.468
TSMOM (150)	0.487	0.437
TSMOM (200)	0.489	0.428
SL (1%)	0.487	0.461
SL (3%)	0.500	0.459
SL (5%)	0.496	0.431
SL (10%)	0.508	0.441
SL (20%)	0.493	0.315
	Panel B: Recession	
MA (50)	0.545	0.632
MA (100)	0.532	0.697
MA (150)	0.531	0.748
MA (200)	0.528	0.787
TRB (50)	0.532	0.676
TRB (100)	0.525	0.777
TRB (150)	0.522	0.848
TRB (200)	0.520	0.820
TSMOM (50)	0.534	0.644
TSMOM (100)	0.524	0.748
TSMOM (150)	0.528	0.784
TSMOM (200)	0.524	0.793
SL (1%)	0.543	0.525
SL (3%)	0.556	0.506
SL (5%)	0.558	0.490
SL (10%)	0.553	0.503
SL (20%)	0.534	0.563

This table decomposes the sell signals into two proportions across NBER business cycles. *Correct signals* are the proportion of total days when the stop rule signals to be out of the market that the index declines. *Perfect sells captured* the ratio of days the index falls that the stop rule signals to be out of the market. The sample period is from 1926 to 2018. Panel A and B contain the results for expansion and recession, respectively.

Appendix C.5: Transactions across business cycles

Rules	Sell trades	BE TC (%)	Sell trades	BE TC (%)
	Expansion		Recession	
MA (50)	503	0.7	91	2.5
MA (100)	338	0.9	56	3.1
MA (150)	256	0.8	34	4.2
MA (200)	256	0.5	24	5.5
TRB (50)	113	2.4	17	10
TRB (100)	64	2.1	7	13.3
TRB (150)	50	-1.1	4	20.3
TRB (200)	27	4.5	4	19.7
TSMOM (50)	423	0.7	86	1.9
TSMOM (100)	291	0.6	40	2.5
TSMOM (150)	261	0.2	36	3.1
TSMOM (200)	235	0.2	26	3.5
SL (1%)	1652	0.1	413	0.4
SL (3%)	645	0.5	196	1.6
SL (5%)	366	0.8	126	2
SL (10%)	146	2.2	61	3.3
SL (20%)	59	1.9	25	6.6

This table displays the number of sell transactions and the BE (break-even) transaction cost of stop rules across NBER business cycles. *Sell trades* are the number of transactions that the stop rule suggests to be out of the market. The BE TC (break-even transaction cost) is the return reduction to those of the buy-and-hold strategy set as the benchmark. The sample period is from 1926 to 2018.