

The value of stop loss strategies

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Abstract

Stop loss strategies can prevent investors from holding their losing investments too long by automatically prompting the sales of losing investments. We examine the impacts of stop loss strategies on the return and risk of individual common stocks. Our results indicate that these strategies neither reduce nor increase investors' losses relative to a buy-and-hold strategy once we extend security returns from past realizations to possible future paths. One unique stop loss mechanism, nevertheless, helps investors to reduce investment risk. These findings suggest that the value of stop loss strategies may come largely from risk reduction rather than return improvement. © 2009 Academy of Financial Services. All rights reserved.

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1. Introduction

Investors tend to hold their losing investments too long and sell their winning investments too soon (i.e., the disposition effect; see Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Odean, 1998). Shefrin and Statman (1985) suggest that this tendency arises from behavioral biases such as mental accounting, pride seeking, regret avoidance, and the lack of self-control. One possible remedy for this behavioral tendency is to use stop loss strategies that prompt the sales of losing investments. A stop loss strategy allows an investor to specify a condition under which a losing investment is automatically sold. Because investors do not have to make contemporaneous selling decisions, stop loss strategies can possibly prevent

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the behavioral biases and help investors to realize their losses sooner. Stop loss strategies are also touted in practice to improve investment returns.

Stop loss strategies, on the other hand, may not be efficient. If security returns are predictable, stop loss strategies fail to incorporate relevant information from the time a strategy is set to the time the contingent sell order is executed. When security returns are unpredictable, selling a losing investment before the end of a holding period does not guarantee that an investor will be better off at the end of this holding period. Although the investor will not incur any further loss on the specific investment, he also gives up the opportunity that this investment may recover during the rest of his holding period. Gollier (1997) and Dybvig (1988) also shows that stop loss strategies are inefficient relative to other possible dominating strategies.

In this article we examine the impacts of stop loss strategies on the return and risk of individual common stocks. In particular, we investigate whether investors using stop loss strategies to sell their (losing) investments would be better off relative to a buy-and-hold strategy. We consider two stop loss strategies on ordinary common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) from 1970 to 2005. Under a stop loss strategy, an investor holds the underlying stock until the specified stop loss condition is met. The investor then reinvests his proceeds in either the S&P 500 index (the SP strategy) or the risk-free asset (one-month T-Bill; the RF strategy) until the end of his holding period. Under the buy-and-hold strategy (the BH strategy), the investor holds the underlying stock for the entire holding period. We examine the holding periods of three months, six months, and one year. We also consider two alternative stop loss mechanisms: The traditional stop loss with a fixed stop price, and the trailing stop loss with a stop price that adjusts upwards automatically with the security price but not downwards.

Using historical return paths and random starting dates for a given holding period, the results show that stop loss strategies can indeed reduce investors' effective holding periods on losing investments. Traditional stop loss strategies have been able to reduce investors' losses on certain stocks but not the others. This loss reduction effect, however, is not stable over time: Although traditional stop loss strategies can reduce investors' losses in general in the 1980s and in the 2000s, this loss reduction effect exists largely for stocks with high past return volatility in the 1970s and in the 1990s. In addition, there seems to be a decreasing ability of stock characteristics including share price, market capitalization, and the book-to-market ratio to explain the effects of traditional stop loss strategies. In the 1970s and in the 1980s, these stock characteristics explain whether the SP strategy outperforms the BH strategy with an adjusted- R^2 ranging from 3% to 19%. In the 1990s and in the 2000s, the adjusted- R^2 ranges from 1% to 4%. Trailing stop loss strategies, on the other hand, show the effect of reducing investment risk rather than reducing investment losses from 1970 to 2005.

We next extend security returns from past realizations to possible future paths. We use bootstrapping techniques to simulate stock returns and evaluate the effects of these stop loss strategies. The results indicate that traditional and trailing stop loss strategies neither reduce nor increase investors' losses relative to the buy-and-hold strategy. These findings are in sharp contrast to the common belief that using stop loss strategies can improve investment returns, and the results are robust whether future returns are independent, autocorrelated, or from momentum samples, and whether we consider transaction costs or use alternative data

intervals. These results also confirm our previous finding that trailing stop loss strategies can help investors to reduce investment risk. For instance, we document a risk reduction effect ranging from 28.66% to 47.08% for median and high-volatility stocks and for median and high-past return stocks under the SP strategy, when the trailing stop price is initially set at five daily return standard deviations below the purchase price. Collectively these findings suggest that realizing losses sooner by certain stop loss strategies can be of value to investors. This value, however, may come largely from risk reduction rather than return improvement.

This research also sheds light on the efficiency of stop loss strategies. Gollier (1997) and Dybvig (1988) both show that stop loss strategies are inefficient. Dybvig (1988) further suggests that the efficiency loss can be large. Yet practitioners use such strategies frequently. To our best knowledge, no empirical analysis has addressed either this inconsistency or the effects of stop loss strategies in general on individual stocks. Our results show that stop loss strategies do not hurt investors on their investment performance. There is no identifiable efficiency loss on the realized returns or the investment risk under these stop loss strategies. Because these strategies may provide investors with disciplines and the potential to reduce investment risk, our findings suggest a possible explanation for the widespread use of stop loss strategies in practice.

The remainder of this paper is organized as follows: In the following section we review the related literature and specify the stop loss strategies we examine. We describe the samples and illustrate the empirical methods in Section 3. The results and robustness checks are presented in Section 4. Section 5 discusses several possible explanations for our results, the tax effects of stop loss strategies, and future extensions. Section 6 concludes this paper.

2. The disposition effect and stop loss strategies

2.1. Evidence on the disposition effect and using stop loss strategies as a possible solution

The disposition effect, the tendency of investors to hold their losing investments too long and winning investments too short, has been documented in several stock markets around the world. Ferris, Haugen and Makhija (1988), Odean (1998), Barber and Odean (1999), and Statman, Thorley and Vorkink (2006) provide the empirical evidence in the United States. Grinblatt and Keloharju (2001) show that Finnish investors reveal the same behavioral pattern. Shapira and Venezia (2001) document this effect in Israel, and Barber, Lee, Liu, and Odean (2007) document this effect in Taiwan. Shapira and Venezia (2001) further show that this effect is stronger for independent investors than for professional investors. Using U.S. data, Dhar and Zhu (2006) report that individuals less literate about investment products are influenced by the disposition effect to a greater extent. Wong, Carducci and White (2006) find that personal characteristics such as gender, marital status, risk tolerance, and education level do not affect the disposition effect in an experimental setting.

Given that the disposition effect adversely affects investors' investment performance (e.g., Odean, 1998), Wong, Carducci and White (2006) suggest the use of mechanical rules to determine when to sell a losing investment. Thaler and Shefrin (1981) provide the theoretical justification. In their two-self model, an individual is characterized by both a farsighted

planner and a myopic doer. Imposed rules can alter the opportunities available to the myopic doer and prevent the doer from reducing the planner's long-run utility. Similarly, a stop loss strategy can serve as a self-imposed rule for investors. To implement a stop loss strategy, an investor places a traditional stop loss order or a trailing stop loss order. A traditional stop loss order is a contingent sell order that allows an investor to specify a fixed stop price on a security.¹ Once the security price falls below the stop price, the sell order becomes effective. A trailing stop loss order, on the other hand, is a contingent sell order in which the stop price adjusts upwards automatically when the security price moves up. If the security price drops, there is no downward adjustment in the stop price. One of the most important features of stop loss strategies is that investors do not have to make contemporaneous selling decisions. Because a stop loss strategy allows the sale of a security to be automatic when the security price drops, this feature can possibly prevent investors from behavioral biases that may otherwise cause them to hold their losing investments too long.

2.2. The efficiency of (traditional) stop loss strategies

Gollier (1997) and Dybvig (1998) show that (traditional) stop loss strategies are inefficient. In Gollier (1997), a static strategy of investing fixed proportions of funds in two assets second-order stochastically dominates a dynamic strategy of switching funds between these two assets. In Dybvig (1998), the path-dependent nature of the performance under stop loss strategies renders these strategies costly relative to other strategies that can achieve the same distribution of terminal wealth. The path dependence also renders stop loss strategies imperfect for portfolio insurance purposes (e.g., Rubinstein, 1985; Bird, Dennis and Tippett, 1988). Empirically, Annaert, Van Osselaer and Verstraeta (2008) find that stop loss strategies do not stochastically dominate a buy-and-hold strategy and other portfolio insurance strategies using index returns from the United States, the United Kingdom, Japan, Australia, and Canada.

2.3. The use and impacts of stop loss strategies

Few studies have addressed the use and impacts of stop loss strategies in practice, and virtually none has examined comprehensively the effects of stop loss strategies on the investment performance of individual stocks. Kaminski and Lo (2008) shows theoretically that stop loss strategies can generate positive return premia under momentum and regime-switching models, but a negative premium when the return generating process follows a random walk. Their simulated evidence using aggregate stock and bond index returns suggests that stop loss strategies may provide positive premia and lower investment risk for investors holding the equity market portfolio. Focusing on a technical moving average trading system, Balsara (2003) finds that using traditional stops supplements the moving average system and improves investment profits for 15 Dow Jones Industrial Average stocks from 1986 to 2001. On investigating QQQ option strategies from 2001 to 2004, Simon (2007) finds that positions closed because of traditional stop loss orders incur larger losses than if the positions remain open, an indication that some losses recover if the positions are not closed. Osler (2003) finds evidence that stop loss orders on currency markets lead to price

cascades, consistent with the notions that widespread uses of stop loss strategies may cause elevated volatility on the marketplace (e.g., Grossman, 1988; Grossman and Zhou, 1996; Osler, 2005), and that they may fuel market crashes (e.g., Shiller, 1987; Shiller, 1990).

Assuming that stock returns follow an exponential distribution, Barnes (1970) suggests setting trailing stop prices based on predetermined probability cutoffs. Shyy (1989) shows the existence of an optimal traditional stop price using a simple probability model and provides supporting evidence using CBOT T-bond futures. Zhang (2001) considers setting traditional stop prices under the assumption that stock prices follow geometric Brownian motions coupled by a finite-state Markov chain. Schalow (1996) suggests setting traditional stop prices based on the return standard deviations of individual stocks. Because setting stop prices on return standard deviations avoids the need to make strong distributional assumptions and accounts for the differences in volatility across stocks, we follow Schalow's (1996) suggestion in this paper.

2.4. Stop loss strategies examined

Stop loss strategies can possibly prevent behavioral biases on one hand, but may lead to efficiency losses on the other hand. Whether these strategies will improve or hurt investment performance is therefore an empirical question. To answer this question, we consider two stop loss strategies that allow an investor to set the stop price at a percentage lower than the initial purchase price. Under the SP strategy, if the stop price is hit before the end of an investor's holding period, the investor sells his holdings at the end of the day and reinvests his proceeds in the S&P 500 index. Under the RF strategy, the investor reinvests his proceeds in the risk-free asset, i.e., the one-month T-Bill. Both the S&P 500 index and the one-month T-Bill represent liquid securities that investors can easily purchase with minimum transaction costs. Because trading volume at market close is typically larger than intraday trading volume (e.g., Jain and Joh, 1988), our strategies using market sell orders at close allow our results to be generalized to investment positions of different sizes and reduce the likelihood of non-execution.²

To evaluate the effects of these stop loss strategies on investment performance, we use the performance under a buy-and-hold strategy (the BH strategy) as the benchmark. Under the BH strategy, an investor holds a security until the end of his holding period. We compare the investment performance under the SP and the RF strategies with that under the BH strategy over the holding periods of three months (63 trading days), six months (126 trading days), and one year (252 trading days). These holding periods reflect the fact that, in practice, investors usually can specify contingent orders valid for a few months.

3. Data and methods

3.1. Data

Our sample includes ordinary common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) from January 1970 to December 2005.

For ease of presentation and to allow for time-varying stock returns, we divide the entire sample period into three decade-long subperiods and one subperiod that uses the most recent data: From 1970 to 1979, from 1980 to 1989, from 1990 to 1999, and from 2000 to 2005. We exclude certificates, American depository receipts, shares of beneficial interest, units, Americus trust components, closed-end funds, real estate investment trusts, and stocks of companies incorporated outside the United States. We also exclude stocks with prices below \$5 or above \$1,000 at the beginning of each subperiod. We exclude stocks that do not have at least a one-and-half year trading history right before a subperiod, and stocks that do not have at least two-year valid return data right after the start of that subperiod. We obtain the daily stock return data from the Center for Research in Security Prices (CRSP) database. The daily risk-free return is defined as the simple daily rate that, over the number of trading days in a given month, compounds to the one-month T-Bill rate from Ibbotson and Associates.

3.2. Past return sample

We start our analyses with historical stock returns from 1970 to 2005. For each sample stock in a subperiod, e.g., from 1970 to 1979, we randomly select with replacement 500 starting dates for each holding period of three months, six months, and one year. We implement the BH, SP, and RF strategies on the return series starting on the selected dates. This sampling technique is similar to the block bootstrapping method used in Hansson and Persson (2000), Sanfilippo (2003), and Annaert, Van Osselaer and Verstraeta (2008). It allows us to generate simulated return series without distributional assumptions and keep the distribution of the simulated returns the same as the unknown distribution implied by the original data. This technique also allows the simulated return series to retain the time-series dependence in the original return series. Following Schalow (1996), we set the stop price at five, 10, or 20 daily return standard deviations (based on the one-year daily returns before the subperiod) below the initial purchase price at the beginning of a holding period.

Because the BH, SP, and RF strategies provide investors the same returns if the stop price is not hit, we evaluate their return performance differences given a hit under the stop loss strategies.³ Under the null hypothesis that these strategies provide investors the same returns, the SP and the RF strategies should not outperform the BH strategy consistently. We define the bootstrapped p -value as the probability that the realized return under the SP (RF) strategy is lower than the realized return under the BH strategy. Unlike in parametric tests, the bootstrapped p -value allows statistical inferences without a specified test statistics. We then evaluate this probability across the individual stocks. A p -value of 1% (99%) thus indicates that, for a randomly picked stock, the stop loss strategy outperforms (underperforms) the BH strategy on the level of returns at the 1% significance level. To assess the impact of stop loss strategies on the risk of investments, we compare the unconditional standard deviation of holding period returns under a stop loss strategy with that under the BH strategy. Under the null hypothesis that the stop loss strategy and the BH strategy have the same impact on investment risk, one strategy should not consistently provide a lower standard deviation than the other strategy. We define the bootstrapped p -value as the probability that the standard deviation under the SP (RF) strategy is larger than the standard deviation under the BH strategy. A p -value of 1% (99%) thus indicates that, for a randomly picked stock, the stop

loss strategy outperforms (underperforms) the BH strategy on the risk of investments at the 1% significance level.

3.3. Simulated return samples

The past return sample uses the realized return series in each subperiod. Future returns, however, may not follow the same paths as past realizations. We therefore consider three alternative scenarios: When future returns are independent, when future returns are autocorrelated, and when future returns are from momentum samples. To obtain these samples, we use the same data resampling and residual resampling, i.e., bootstrapping, techniques as in Lei and Li (2007). Similar to the block bootstrapping method used for the past return sample, these techniques can generate simulated returns without distributional assumptions. Unlike the block bootstrapping method, these techniques do not require the simulated return series to follow the same paths as past realizations.

3.3.1. Independent sample

For each sample stock in a subperiod, we generate 500 simulated return series by sampling with replacement from the pool of its daily returns in that subperiod. We draw together with the individual stock returns the corresponding daily S&P 500 index returns and the risk-free returns to preserve their cross-sectional correlations. This data resampling technique provides a simulated sample without the need to specify a unique return distribution or a return generating process. In addition, it eliminates from the simulated return series any return autocorrelation implied in the original return series. We then implement the BH, SP, and RF strategies on the simulated return series and evaluate the performance of stop loss strategies with bootstrapped p -values.

3.3.2. Autocorrelated sample

Because under a stop loss strategy whether and when a stop price will be hit depend on the specific return path, we extend our analyses with autocorrelated returns. We use the residual resampling technique to simulate the sample with autocorrelations implied by the original return series. As in Lei and Li (2007), we estimate an AR(1) model for each sample stock with its original return series in a subperiod:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t \quad (1)$$

where r_t is the stock return on day t . β_0 represents the mean return after considering the first-order return autocorrelation, and β_1 represents the first-order return autocorrelation coefficient. ε_t is the return residual on day t . We record the coefficient estimates ($\hat{\beta}_0$ and $\hat{\beta}_1$) and the return residuals (e_t).

We generate the autocorrelated sample iteratively by Eq. (1). For each sample stock, we input a seed of $r_{t-1} = r_0 = \hat{\beta}_0$ and return residuals (e_t) sampled with replacement from the recorded residual pool. We use the 101th observation as the first daily return for a holding period to obtain a stabilized series. The entire process is then repeated 500 times for each sample stock in a subperiod.⁴

3.3.3. Momentum sample

Jegadeesh and Titman (1993) document the stock return momentum. Specifically, past losers (winners) in the previous year tend to remain losers (winners) in the following 12 months. This return continuity adversely affects investors who hold their losing investments too long (e.g., Kaminski and Lo, 2008). We use momentum samples to investigate the effects of stop loss strategies on investment performance under such return continuity.

We define the momentum sample as follows: We exclude any sample stocks with missing daily returns in the year before a subperiod and rank the remaining stocks by their annual returns in the same year. As in Jegadeesh and Titman (1993), stocks with annual returns above the 90 percentile are the momentum winners. Stocks with annual returns below the 10 percentile are the momentum losers. In between are median stocks. We then use only the daily returns of the sample stocks in the first year of the subperiod for data resampling. Resampling from the daily returns in the first year after the momentum classification allows the simulated return series to carry the characteristics of returns of winner and loser stocks.

4. Empirical results

4.1. Past return sample

Table 1 presents the summary statistics on the sample stocks in the four subperiods. The sample stocks are grouped by their daily return standard deviations in the year before a subperiod. A stock with a standard deviation below (above) the 30 (70) percentile is in the low- (high-) Return STD group. Otherwise the stock is in the median-Return STD group. The rows share price (*Price*), firm size (*Size*), and return standard deviation (*Return STD*) show the cross-sectional statistics of the sample stocks at the beginning of the subperiod. The row *Future Return STD* shows the cross-sectional statistics on the return standard deviations of individual stocks, defined over their daily returns in the subperiod.

Table 1 shows that stocks with lower return standard deviations tend to be larger firms with higher share prices. For instance, the average prices of low-, median-, and high-Return STD stocks at the beginning of 1970 are \$38.73, \$26.67, and \$15.19, respectively. The average sizes are \$821.53 million, \$194.46 million, and \$45.96 million, respectively. The average standard deviation of 1.41% of low-Return STD stocks implies that the average stop price based on five (10 and 20) standard deviations is set at 7.05% (14.10% and 28.20%) below the initial purchase price. For median- (high-) Return STD stocks, the average stop prices based on five standard deviations is set at 11.00% (17.25%) below the initial purchase price. The statistics on the future return standard deviation suggest that low- (high-) Return STD stocks continue to have lower (higher) volatility than median-Return STD stocks. For instance, the average standard deviation of low-Return STD stocks from 1970 to 1979 is 1.80%. The average standard deviation is 2.69% for median-Return STD stocks and 4.07% for high-Return STD stocks. These observations support Schalow's (1996) suggestion that investors should set stop prices in terms of return standard deviations. The results from the other subperiods are largely consistent with the results from 1970 to 1979, except that the

Table 1 Summary statistics on sample stocks

Return STD	Variable	1970–1979			1980–1989		
		Mean	Standard deviation	Number of stocks	Mean	Standard deviation	Number of stocks
Low	Price (\$)	38.73	29.44	513	29.88	15.51	501
	Size (\$ million)	821.53	2,662.52		1,121.37	2,951.37	
	Return STD (%)	1.41	0.23		1.26	0.20	
	Future return STD (%)	1.80	0.48		1.79	0.50	
Median	Price (\$)	26.67	15.72	685	23.75	15.06	668
	Size (\$ million)	194.46	370.26		375.26	864.79	
	Return STD (%)	2.20	0.29		2.03	0.28	
	Future return STD (%)	2.69	0.81		2.35	0.66	
High	Price (\$)	15.19	11.33	514	15.67	10.65	501
	Size (\$ million)	45.96	83.18		101.04	172.33	
	Return STD (%)	3.45	0.56		3.28	0.71	
	Future return STD (%)	4.07	1.24		3.19	1.24	
Return STD	Variable	1990–1999			2000–2005		
		Mean	Standard deviation	Number of stocks	Mean	Standard deviation	Number of stocks
Low	Price (\$)	42.24	39.81	403	34.46	40.48	417
	Size (\$ million)	3,044.58	6,800.50		6,392.73	31,941.02	
	Return STD (%)	1.08	0.22		1.65	0.31	
	Future return STD (%)	1.64	0.73		1.95	0.73	
Median	Price (\$)	28.60	17.57	537	31.48	34.41	557
	Size (\$ million)	2,108.84	4,511.98		9,239.62	28,131.04	
	Return STD (%)	1.67	0.19		2.52	0.26	
	Future return STD (%)	2.30	1.22		2.63	1.01	
High	Price (\$)	14.76	14.05	404	20.58	19.39	418
	Size (\$ million)	433.35	1,077.67		3,359.82	12,928.42	
	Return STD (%)	2.75	0.97		3.95	1.13	
	Future return STD (%)	3.70	2.18		3.78	1.77	

This table reports the summary statistics on the ordinary common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) from January 1970 to December 2005. We divide the entire sample period into four subperiods: From 1970 to 1979, from 1980 to 1989, from 1990 to 1999, and from 2000 to 2005. For a stock to be included in a subperiod, it needs to (1) have a price between \$5 and \$1,000 at the beginning of the subperiod, (2) have at least a one-and-a-half year trading history right before the subperiod, and (3) have at least two-year valid return data right after the start of the subperiod. In each subperiod, the sample stocks are grouped by their daily return standard deviations in the year before the subperiod. A stock with a return standard deviation below (above) the 30 (70) percentile is in the low- (high-) Return STD group. Otherwise the stock is in the median-Return STD group. The rows share price (*Price*), firm size (*Size*), and return standard deviation (*Return STD*) show the cross-sectional statistics of the sample stocks at the beginning of a subperiod. The row *Future Return STD* shows the cross-sectional statistics on the return standard deviations of individual stocks, defined over their daily returns in a subperiod.

Table 2 Stop loss strategies on investment returns

Panel A: Traditional stop loss strategies												
Return STD	Stop Price	Hit Rate	Hit Day	BH Return	1970–1979		1980–1989		1990–1999		2000–2005	
					$p(SP)$	$p(RF)$	$p(SP)$	$p(RF)$	$p(SP)$	$p(RF)$	$p(SP)$	$p(RF)$
Low	5 STD	0.52	35.68	0.98	0.59	0.53	0.59	0.61	0.48	0.58	0.64	0.66
	10	0.29	52.39	0.90	0.59	0.55	0.58	0.62	0.48	0.57	0.62	0.66
	20	0.15	62.44	0.83	0.60	0.55	0.58	0.64	0.48	0.56	0.58	0.62
Median	5	0.52	39.90	0.93	0.53	0.50	0.54	0.56	0.47	0.55	0.58	0.59
	10	0.27	58.04	0.82	0.54	0.53	0.55	0.59	0.48	0.55	0.56	0.59
	20	0.13	68.97	0.71	0.57	0.56	0.56	0.61	0.49	0.55	0.55	0.58
High	5	0.51	44.04	0.85	0.50	0.48	0.48	0.50	0.42	0.48	0.52	0.51
	10	0.23	64.06	0.70	0.59	0.57	0.53	0.56	0.43	0.47	0.51	0.51
	20	0.09	75.83	0.56	0.66	0.66	0.57	0.59	0.47	0.50	0.50	0.50
Panel B: Trailing stop loss strategies												
Low	5 STD	0.94	33.49	1.08	0.50	0.44	0.52	0.52	0.41	0.52	0.57	0.53
	10	0.65	57.43	1.04	0.47	0.43	0.48	0.47	0.39	0.47	0.52	0.51
	20	0.36	68.65	0.99	0.45	0.41	0.46	0.44	0.37	0.43	0.48	0.49
Median	5	0.93	37.16	1.07	0.44	0.42	0.46	0.46	0.40	0.47	0.50	0.47
	10	0.59	61.91	1.01	0.40	0.39	0.42	0.42	0.36	0.42	0.45	0.44
	20	0.30	73.44	0.93	0.39	0.38	0.39	0.40	0.34	0.39	0.40	0.41
High	5	0.89	40.91	1.05	0.38	0.37	0.39	0.40	0.35	0.40	0.43	0.41
	10	0.51	65.46	0.96	0.36	0.36	0.35	0.36	0.31	0.35	0.37	0.36
	20	0.24	77.34	0.90	0.37	0.37	0.34	0.35	0.29	0.31	0.35	0.35

This table reports the effects of stop loss strategies on investment returns for the holding period of six months. The column *Hit Rate* shows the average probability across the subperiods that a stop price is hit. The stop price is set at either five, 10, or 20 one-year return standard deviations below the initial purchase price of a stock. The column *Hit Day* shows the average length of time in days before the stop price is hit. The column *BH Return* shows the average end-of-period dollar value of a one-dollar initial investment under the buy-and-hold strategy. The SP (RF) strategy is a stop loss strategy under which an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. The column $p(SP)$ ($p(RF)$) shows the probability, i.e., the bootstrapped p -value, that the realized return under the SP (RF) strategy is lower than the realized return under the BH strategy.

average firm size of median-Return STD stocks at the beginning of 2000 is larger than that of low-Return STD stocks.

4.1.1. Level of investment returns

Table 2 reports the effects of stop loss strategies on investors' realized returns for the holding period of six months. The findings are similar for the three-month and the one-year holding periods. Panel A (B) shows the results under the traditional (trailing) stop loss strategies. The column *Hit Rate* shows the average probability across the subperiods that a stop price is hit. The column *Hit Day* shows the average length of time in days before the stop price is hit. In the column *BH Return* is the average end-of-period dollar value of a one-dollar initial investment under the buy-and-hold strategy. The column $p(SP)$ ($p(RF)$) shows the probability, i.e., the bootstrapped p -value, that the realized return under the SP (RF) strategy is lower than the realized return under the BH strategy. The sample stocks are grouped by their daily return standard deviations in the year before the start of a subperiod.

The results in Table 2 indicate that as the stop price is set further below the initial purchase price, the stop loss condition becomes less likely and takes longer to be met. For instance, Panel A shows that low-Return STD stocks have a 52% hit rate (average hit on the 35.68 day) when the stop price is set at five standard deviations. When the stop price is set at 20 standard deviations, the hit rate is 15% (average hit on the 62.44 day). These results suggest that stop loss strategies reduce the effective holding periods on losing investments. On the other hand, Panel A also shows that the realized returns under the SP and the RF strategies are statistically indistinguishable from the realized returns under the BH strategy. None of the bootstrapped p -values indicates a significant return difference at the 10% level. This finding holds across the subperiods and suggests that these traditional stop loss strategies neither reduce nor increase investors' losses relative to the buy-and-hold strategy for a randomly picked stock. Similar to the results in Panel A, the results in Panel B suggest that although the trailing stop loss strategies reduce the effective holding periods on losing investments, they neither reduce nor increase investors' losses relative to the buy-and-hold strategy.

Comparing across Panel A and Panel B, we find that the trailing stop loss strategies have much higher hit rates than the tradition stop loss strategies (e.g., 94% vs. 52% for low-Return STD stocks when the stop price is set at five standard deviations).⁵ The trailing stop loss strategies also seem to have slightly shorter lengths of time before a hit than the tradition stop loss strategies when the stop price is set at five standard deviations, but have longer lengths of time before a hit when the stop price is set at 10 or 20 standard deviations.

4.1.2. *Returns of individual stocks*

Table 2 suggests that stop loss strategies neither reduce nor increase investors' losses for a randomly picked stock. It is possible, however, that a stop loss strategy consistently outperforms the buy-and-hold strategy on some stocks but underperforms the buy-and-hold strategy on some other stocks. To investigate this possibility, we report the proportion of individual stocks realizing superior (+) or inferior (–) returns under the stop loss strategies in Table 3. We define a stock as realizing superior (inferior) returns under a stop loss strategy if its realized returns under the strategy are larger (smaller) than the corresponding buy-and-hold returns 90% of the time, i.e., significant at the 10% level.

The results in Panel A of Table 3 indicate that the traditional stop loss strategies consistently outperform the buy-and-hold strategy on certain stocks but not on the others. For instance, Panel A shows that, when the stop price is set at 20 standard deviations in the 1970s, 13% of median-Return STD stocks and 24% of high-Return STD stocks realize superior returns under the SP strategy than under the BH strategy. There was 24% of high-Return STD stocks realize superior returns under the RF strategy. These higher than 10% proportions suggest that these strategies reduce investors' losses on certain stocks for reasons other than pure chance. This loss reduction effect, nevertheless, is not stable over time: Although the traditional stop loss strategies can reduce investors' losses regardless of past stock return volatility in the 1980s and in the 2000s, this loss reduction effect exists largely for stocks with high past return volatility in the 1970s and in the 1990s. The results in Panel B confirm that the trailing stop loss strategies in general neither reduce nor increase

investors' losses. The SP strategy in the 1980s, nevertheless, causes 13% of high-Return STD stocks to experience significant losses relative to the buy-and-hold strategy when the stop price is set at 20 standard deviations.

4.1.3. *Determinants of the performance of traditional stop loss strategies*

Table 3 suggests that the traditional stop loss strategies have been able to reduce investors' losses on certain stocks but not on the others. We next examine the relations between stock characteristics and the performance of traditional stop loss strategies. We identify share price (Price), market capitalization (Size), and the book-to-market ratio (BM; Fama and French, 1992) at the beginning of each subperiod as the possible cross-sectional determinants of the hit rate under the SP strategy and the probability that the SP strategy outperforms the BH strategy.⁶ The information on these stock characteristics is available to most investors, and our conclusions remain similar with the RF strategy. We perform a logit transformation on the hit rate and the probability that the SP strategy outperforms the BH strategy to match them to the real line.⁷ We then regress the natural logarithms of the hit rate and the probability on the natural logarithms of share price, market capitalization, and the book-to-market ratio. Table 4 reports the results on the cross-sectional regressions.

Panel A of Table 4 indicates that only share price has a relatively consistent and positive relation with the hit rate of the SP strategy across the subperiods and across the stop prices. For instance, the coefficient estimates on share price in the 1970 through 1979 subperiod are 0.13 (p -value = 0.00), 0.44 (0.00), and 1.43 (0.00), respectively, when the stop prices are set at five, 10, and 20 return standard deviations. We observe similar positive and significant relations in the other subperiods except when the stop price is set at five standard deviations in the 1990s. On the other hand, the effects of market capitalization and the book-to-market ratio on the hit rate are not stable. For instance, market capitalization has a positive effect on the hit rate in the 1980s but a negative effect in the other subperiods. The book-to-market ratio has a positive effect in the 1990s and in the 2000s but mixed effects in the other subperiods. In addition, the relations between the hit rate under the SP strategies and stock characteristics weaken over time: In the 1970s and in the 1980s, the adjusted R^2 are 18% and 20%, respectively, when the stop price is set at 20 standard deviations. It reduces to 3% in the 1990s and in the 2000s.

The results in Panel B also indicate that the probability that the SP strategy outperforms the BH strategy depends positively on share prices. The effects of market capitalization and the book-to-market ratio on this probability are not stable: They depend on the specific subperiod and the specific stop price. We also observe that the relations between this probability and stock characteristics weaken over time: In the 1970s the adjusted R^2 is 19% when the stop price is set at 20 standard deviations. It reduces to 16% in the 1980s, 3% in the 1990s, and 1% in the 2000s.

4.1.4. *Risk of investments*

Table 5 reports the impacts of stop loss strategies on the risk of investments. The column $p(SP)$ ($p(RF)$) shows the probability, i.e., the bootstrapped p -value, that the standard deviation of the realized returns under the SP (RF) strategy is larger than the standard deviation

Table 4 Stock characteristics and the performance of traditional stop loss strategies

Independent Variable		1970–1979			1980–1989			1990–1999			2000–2005		
		5	10	20	5	10	20	5	10	20	5	10	20
Intercept	0.41 (0.00)	-1.48 (0.00)	-6.04 (0.00)	-1.00 (0.00)	-4.52 (0.00)	-10.66 (0.00)	1.16 (0.00)	-0.13 (0.56)	-1.59 (0.00)	-0.31 (0.12)	-3.18 (0.00)	-5.67 (0.00)	
Price	0.13 (0.00)	0.44 (0.00)	1.43 (0.00)	0.24 (0.00)	0.69 (0.00)	1.51 (0.00)	0.00 (0.92)	0.22 (0.00)	0.53 (0.00)	0.14 (0.01)	0.55 (0.00)	1.11 (0.00)	
Size	-0.05 (0.00)	-0.09 (0.00)	-0.09 (0.06)	0.02 (0.25)	0.08 (0.02)	0.23 (0.00)	-0.07 (0.00)	-0.12 (0.00)	-0.17 (0.00)	-0.02 (0.22)	-0.03 (0.52)	-0.15 (0.02)	
BM	-0.10 (0.00)	-0.10 (0.00)	0.13 (0.09)	-0.11 (0.00)	0.08 (0.21)	0.55 (0.00)	0.04 (0.31)	0.12 (0.02)	0.30 (0.00)	-0.01 (0.82)	0.16 (0.03)	0.28 (0.02)	
Adjusted R ²	0.03	0.09	0.18	0.09	0.13	0.20	0.03	0.02	0.03	0.00	0.03	0.03	

Independent Variable		1970–1979			1980–1989			1990–1999			2000–2005		
		5	10	20	5	10	20	5	10	20	5	10	20
Intercept	-0.58 (0.00)	-2.56 (0.00)	-8.09 (0.00)	-1.87 (0.00)	-5.98 (0.00)	-11.66 (0.00)	0.17 (0.27)	-0.81 (0.00)	-2.62 (0.00)	-2.00 (0.00)	-4.50 (0.00)	-6.31 (0.00)	
Price	0.13 (0.00)	0.63 (0.00)	1.72 (0.00)	0.23 (0.00)	0.88 (0.00)	1.49 (0.00)	0.04 (0.40)	0.26 (0.00)	0.60 (0.00)	0.13 (0.09)	0.54 (0.00)	0.70 (0.00)	
Size	-0.10 (0.00)	-0.16 (0.00)	-0.12 (0.03)	-0.03 (0.29)	0.04 (0.36)	0.18 (0.00)	-0.10 (0.00)	-0.15 (0.00)	-0.19 (0.00)	-0.02 (0.48)	-0.05 (0.31)	-0.13 (0.05)	
BM	-0.19 (0.00)	-0.14 (0.00)	0.07 (0.40)	-0.17 (0.00)	0.12 (0.16)	0.43 (0.00)	0.00 (0.91)	0.16 (0.00)	0.43 (0.00)	-0.10 (0.06)	0.09 (0.33)	0.26 (0.03)	
Adjusted R ²	0.08	0.09	0.19	0.03	0.09	0.16	0.04	0.03	0.03	0.01	0.01	0.01	

This table reports the relations between stock characteristics and the performance of traditional stop loss strategies including the hit rate and the probability that the SP strategy outperforms the BH strategy. Stock characteristics share price (*Price*), market capitalization (*Size*), and the book-to-market ratio (*BM*) are measured at the beginning of each subperiod. We perform a logit transformation on the hit rate and on the probability that the SP strategy outperforms the BH strategy, and regress ln(hit rate) and ln(probability that the SP strategy outperforms the BH strategy) on ln(*Price*), ln(*Size*), and ln(*BM*). The reported numbers are coefficient estimates with corresponding *p*-values in parentheses.

Table 5 Stop loss strategies on investment risk

Panel A: Traditional stop loss strategies									
Return STD	Stop Price	1970–1979		1980–1989		1990–1999		2000–2005	
		$p(\text{SP})$	$p(\text{RF})$	$p(\text{SP})$	$p(\text{RF})$	$p(\text{SP})$	$p(\text{RF})$	$p(\text{SP})$	$p(\text{RF})$
Low	5 STD	0.26	0.02	0.38	0.28	0.10	0.10	0.59	0.47
	10	0.49	0.26	0.56	0.62	0.23	0.36	0.68	0.71
	20	0.63	0.48	0.61	0.77	0.36	0.52	0.61	0.66
Median	5	0.11	0.04	0.26	0.22	0.07	0.14	0.45	0.40
	10	0.42	0.36	0.53	0.61	0.24	0.42	0.64	0.69
	20	0.64	0.64	0.65	0.73	0.40	0.58	0.51	0.55
High	5	0.09	0.05	0.23	0.26	0.05	0.08	0.35	0.31
	10	0.65	0.65	0.51	0.64	0.24	0.34	0.52	0.55
	20	0.71	0.74	0.45	0.51	0.41	0.52	0.40	0.41

Panel B: Trailing stop loss strategies									
Low	5 STD	0.16	0.00	0.17	0.01	0.14	0.00	0.23	0.06
	10	0.22	0.02	0.27	0.07	0.16	0.03	0.36	0.29
	20	0.29	0.10	0.35	0.22	0.18	0.15	0.42	0.46
Median	5	0.03	0.01	0.05	0.02	0.02	0.01	0.11	0.05
	10	0.11	0.05	0.22	0.13	0.05	0.06	0.29	0.28
	20	0.22	0.21	0.30	0.28	0.16	0.19	0.33	0.40
High	5	0.03	0.01	0.07	0.04	0.03	0.02	0.08	0.07
	10	0.22	0.18	0.22	0.24	0.11	0.13	0.21	0.22
	20	0.40	0.40	0.29	0.34	0.22	0.25	0.29	0.33

This table reports the impacts of stop loss strategies on the risk of investments for the holding period of six months. Under the SP (RF) strategy, an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. The column $p(\text{SP})$ ($p(\text{RF})$) shows the probability, i.e., the bootstrapped p -value, that the standard deviation of the realized returns under the SP (RF) strategy is larger than the standard deviation of the realized returns under the BH strategy.

of the realized returns under the BH strategy. The results in Panel A indicate that the traditional stop loss strategies reduce the investment risk in a few instances and the risk reduction is limited in the 1970s and in the 1990s. For example, when the stop price is set at five standard deviations in the 1970s, the SP strategy reduces the investment risk for high-Return STD stocks. The RF strategy reduces the investment risk for the sample stocks regardless of their past return volatility. In the 1980s and in the 2000s, neither the SP strategy nor the RF strategy reduces investment risk.

The results in Panel B indicate that the trailing stop loss strategies consistently reduce investment risk over the subperiods. For instance, when the stop price is set at five standard deviations, the SP strategy reduces investment risk for high-Return STD stocks from 1970 to 2005. It reduces investment risk for median-Return STD stocks from 1970 to 1990. The RF strategy reduces investment risk regardless of the subperiods and past return volatility. These results suggest that the trailing stop loss strategies have been able to reduce investment risk for investors, despite the fact that these strategies do not reduce investment losses. The traditional stop loss strategies, on the other hand, have only period-specific effects on reducing investment risk.

4.2. Simulated return samples

Because future returns may not follow historical paths, we investigate the effects of stop loss strategies on investment performance using simulated returns that do not dictate return paths as past realizations. We report the results based on the most recent subperiod from 2000 to 2005. The results from earlier subperiods are similar unless otherwise mentioned.

4.2.1. Level of investment returns

Table 6 reports the effects of stop loss strategies on realized returns based on the simulated return samples. Consistent with previous results, the results in Table 6 suggest that these stop loss strategies reduce the effective holding periods on losing investments. For instance, when the stop price is set at five standard deviations, the traditional stop loss strategy has a 52% hit rate (average hit on the 38.92 day) on low-Return STD stocks in the independent sample. The hit rate is 12% (average hit on the 69.89 day) when the stop price is set at 20 standard deviations. We observe similar results from the autocorrelated sample and the momentum sample, and in Panel B under the trailing stop loss strategies. Table 6 also indicates that the realized returns of the SP and the RF strategies are statistically indistinguishable from the realized returns of the BH strategy. None of the bootstrapped p -values indicates a significant return difference at the 10% level. These findings suggest that these traditional and trailing stop loss strategies neither reduce nor increase investors' losses relative to the buy-and-hold strategy. We also find in this case that the trailing stop loss strategies have much higher hit rates than the tradition stop loss strategies (e.g., 97% vs. 52% for low-Return STD stocks when the stop price is set at five standard deviations in the independent sample). The trailing stop loss strategies seem to have slightly shorter lengths of time before a hit than the tradition stop loss strategies when the stop price is set at five standard deviations, but have longer lengths of time before a hit when the stop price is set at 10 or 20 standard deviations.

4.2.2. Returns of individual stocks

Table 7 reports the proportion of individual stocks realizing superior (+) or inferior (–) returns under the stop loss strategies based on the simulated return samples. Different from our previous results based on the past return sample, the results in Panel A indicate that the loss reduction effect of the traditional stop loss strategies does not persist in this case. For instance, when the stop price is set at 20 standard deviations in the independent sample, 9% (6%) of high-Return STD stocks realize superior (inferior) returns under the SP strategy than under the BH strategy. These smaller than 10% proportions suggest that the superior and inferior performance of the SP strategy on these stocks may be caused by pure chance. We observe similar results across the autocorrelated sample and the momentum sample. The results in Panel B, on the other hand, confirm our previous finding that the trailing stop loss strategies neither reduce nor increase investors' losses.

4.2.3. Risk of investments

Table 8 reports the impacts of stop loss strategies on the risk of investments based on the simulated return samples. As in Table 5, the column $p(SP)$ ($p(RF)$) shows the probability, i.e., the bootstrapped p -value, that the standard deviation of the realized returns under the SP

Table 6 Stop loss strategies on investment returns: Simulated returns

Panel A: Traditional stop loss strategies														
Return past	STD/price	Independent sample			Autocorrelated sample			Momentum sample			$p(\text{RF})$			
		Hit	Rate	return	Hit	rate	day	Hit	Hit	return				
Low/loser	5	0.52	38.92	0.95	0.60	0.55	38.92	0.95	0.56	0.62	36.77	0.76	0.42	0.37
	10	0.27	58.81	0.85	0.57	0.53	58.08	0.85	0.53	0.38	58.73	0.58	0.37	0.33
	20	0.12	69.89	0.76	0.54	0.51	68.58	0.76	0.54	0.19	72.48	0.44	0.34	0.30
Median	5	0.52	42.49	0.88	0.54	0.51	42.82	0.89	0.55	0.58	37.02	0.88	0.53	0.45
	10	0.24	63.41	0.73	0.51	0.48	63.12	0.74	0.51	0.48	58.77	0.73	0.48	0.41
	20	0.09	74.04	0.58	0.47	0.44	73.24	0.59	0.46	0.16	73.03	0.62	0.45	0.39
High/winner	5	0.49	45.17	0.79	0.49	0.46	45.33	0.79	0.49	0.64	38.52	0.79	0.44	0.39
	10	0.21	64.73	0.58	0.43	0.41	64.42	0.59	0.44	0.36	60.91	0.61	0.42	0.38
	20	0.08	75.56	0.41	0.39	0.37	74.55	0.41	0.39	0.16	75.96	0.49	0.41	0.37

Panel B: Trailing stop loss strategies														
Return past	STD/price	Independent sample			Autocorrelated sample			Momentum sample			$p(\text{RF})$			
		Hit	Rate	return	Hit	rate	day	Hit	Hit	return				
Low/loser	5	0.97	36.19	1.08	0.55	0.48	36.74	1.08	0.49	0.99	30.96	1.06	0.44	0.38
	10	0.62	63.04	1.01	0.48	0.42	62.59	1.02	0.48	0.75	58.89	0.96	0.36	0.31
	20	0.31	74.59	0.94	0.43	0.37	73.42	0.95	0.43	0.43	73.10	0.83	0.30	0.26
Median	5	0.95	40.19	1.07	0.49	0.44	40.67	1.07	0.49	0.98	30.80	1.10	0.53	0.44
	10	0.56	66.77	0.97	0.42	0.38	66.46	0.97	0.42	0.37	60.60	1.03	0.46	0.38
	20	0.25	77.87	0.87	0.36	0.32	77.00	0.88	0.35	0.32	75.48	0.92	0.40	0.33
High/winner	5	0.91	43.26	1.06	0.43	0.39	43.35	1.06	0.43	0.98	30.04	1.09	0.43	0.37
	10	0.50	66.89	0.95	0.35	0.32	66.62	0.94	0.35	0.76	59.03	1.03	0.38	0.33
	20	0.23	76.43	0.88	0.29	0.27	76.50	0.86	0.29	0.44	74.47	0.99	0.34	0.31

This table reports the effects of stop loss strategies on investment returns for the holding period of six months. The simulated returns are based on either stock returns from 2000 to 2005 for the independent and autocorrelated samples, or stock returns in 2000 for the momentum sample. The column *Hit Rate* shows the probability that a stop price is hit. The stop price is set at either five, 10, or 20 one-year return standard deviations below the initial purchase price of a stock. The column *Hit Day* shows the average length of time in days before the stop price is hit. The column *BH Return* shows the average end-of-period dollar value of a one-dollar initial investment under the buy-and-hold strategy. The *SP (RF)* strategy is a stop loss strategy under which an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. The column $p(\text{SP})$ ($p(\text{RF})$) shows the probability, i.e., the bootstrapped p -value, that the realized return under the *SP (RF)* strategy is lower than the realized return under the *BH* strategy.

Table 7 Proportions of individual stocks realizing superior/inferior returns under stop loss strategies: Simulated returns

Panel A: Traditional stop loss strategies												
Return STD/ past return	Stop price	Independent sample			Autocorrelated sample			Momentum sample				
		SP strategy		RF strategy	SP strategy		RF strategy	SP strategy		RF strategy		
		+	-	+	-	+	-	+	-	+	-	
Low/loser	5 STD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.01	0.04
	10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03
	20	0.01	0.00	0.01	0.03	0.00	0.01	0.01	0.05	0.05	0.05	0.04
Median	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.01	0.01
	10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.01
	20	0.04	0.02	0.04	0.05	0.02	0.03	0.03	0.04	0.01	0.03	0.01
High/winner	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01
	10	0.01	0.01	0.01	0.02	0.00	0.02	0.00	0.04	0.00	0.02	0.01
	20	0.09	0.06	0.08	0.08	0.06	0.07	0.08	0.05	0.01	0.06	0.00

Panel B: Trailing stop loss strategies												
Return STD/ past return	Stop price	Independent sample			Autocorrelated sample			Momentum sample				
		SP strategy		RF strategy	SP strategy		RF strategy	SP strategy		RF strategy		
		+	-	+	-	+	-	+	-	+	-	
Low/loser	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.09
	10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.07
	20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.04
Median	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.03
	10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02
	20	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.02
High/winner	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.06
	10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.04
	20	0.02	0.05	0.01	0.01	0.05	0.01	0.05	0.00	0.03	0.00	0.02

This table reports the proportion of individual stocks realizing superior (+) or inferior (-) returns under a stop loss strategy for the holding period of six months. The simulated returns are based on either stock returns from 2000 to 2005 for the independent and autocorrelated samples, or stock returns in 2000 for the momentum sample. Under the SP (RF) strategy, an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. A stock realizes superior (inferior) returns under a stop loss strategy if its realized returns under the strategy are larger (smaller) than the corresponding buy-and-hold returns 90% of the time, i.e., significant at the 10% level.

Table 8 Stop loss strategies on investment risk: Simulated returns

Return STD/ Past Return		Independent sample			Autocorrelated sample			Momentum sample			
Stop Price	BH	SP %	p(SP)	BH	SP %	p(SP)	BH	SP %	p(SP)	RF %	p(RF)
Low/loser	5 STD	0.24	96.80	0.50	0.24	96.59	0.54	0.51	90.77	0.34	0.25
	10	0.24	99.94	0.72	0.24	99.46	0.70	0.51	95.96	0.45	0.36
	20	0.24	99.89	0.72	0.24	99.74	0.71	0.51	98.17	0.39	0.31
Median	5	0.32	93.40	0.32	0.33	91.93	0.35	0.37	95.30	0.44	0.25
	10	0.32	98.44	0.57	0.33	98.44	0.59	0.37	98.50	0.56	0.39
	20	0.32	99.31	0.59	0.33	99.00	0.55	0.37	99.18	0.57	0.41
High/winner	5	0.50	92.80	0.29	0.47	92.68	0.31	0.58	91.11	0.27	0.19
	10	0.50	98.17	0.49	0.47	98.00	0.52	0.58	97.59	0.40	0.31
	20	0.50	99.49	0.36	0.47	99.45	0.36	0.58	99.20	0.40	0.30

Return STD/ Past Return		Independent sample			Autocorrelated sample			Momentum sample			
Stop Price	BH	SP %	p(SP)	BH	SP %	p(SP)	BH	SP %	p(SP)	RF %	p(RF)
Low/loser	5 STD	0.24	76.85	0.10	0.24	76.62	0.14	0.50	63.90	0.00	0.00
	10	0.24	90.97	0.25	0.24	89.82	0.26	0.50	86.44	0.09	0.03
	20	0.24	95.18	0.27	0.24	94.57	0.28	0.50	94.89	0.25	0.17
Median	5	0.33	71.34	0.01	0.32	71.32	0.02	0.37	67.40	0.05	0.00
	10	0.33	89.31	0.08	0.32	89.29	0.10	0.37	88.72	0.19	0.04
	20	0.33	95.29	0.11	0.32	94.89	0.14	0.37	95.49	0.28	0.11
High/winner	5	0.49	66.63	0.02	0.48	68.12	0.01	0.63	52.92	0.01	0.00
	10	0.49	86.45	0.08	0.48	88.33	0.08	0.63	74.42	0.08	0.03
	20	0.49	93.88	0.17	0.48	96.63	0.23	0.63	85.32	0.10	0.09

This table reports the impacts of stop loss strategies on the risk of investments for the holding period of six months. The simulated returns are based on either stock returns from 2000 to 2005 for the independent and autocorrelated samples, or stock returns in 2000 for the momentum sample. Under the SP (RF) strategy, an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. The column BH shows the standard deviation of the realized returns under the BH strategy. The column SP % (RF %) shows the return standard deviation under the SP (RF) strategy as a percentage of the return standard deviation under the BH strategy. The column p(SP) (p(RF)) shows the probability, i.e., the bootstrapped p-value, that the return standard deviation under the SP (RF) strategy is larger than the return standard deviation under the BH strategy.

(RF) strategy is larger than the standard deviation of the realized returns under the BH strategy. To provide a closer look at the risk reduction effect of the stop loss strategies, we also show in this table the return standard deviation under the SP (RF) strategy (column *SP % (RF %)*) as a percentage of the return standard deviation under the BH strategy (column *BH*).

The insignificant bootstrapped *p*-values in Panel A suggest that the traditional stop loss strategies do not reduce or increase the risk of investments. For instance, when the stop price is set at five standard deviations, the standard deviation of the realized returns under the SP strategy for low-Return STD stocks in the independent sample is 96.80% of the standard deviation of 0.24 under the BH strategy (*p*-value = 0.50). The *p*-value is 0.32 (0.29) for median- (high-) Return STD stocks. These insignificant *p*-values across the simulated return samples and our previous findings based on the past return sample collectively suggest that these traditional stop loss strategies do not have a reliable effect on reducing investment risk.⁸

The results in Panel B, on the other hand, indicate that the trailing stop loss strategies significantly reduce the risk of investments in many cases. For instance, when the stop price is set at five standard deviations, the SP strategy reduces the return standard deviation for median- and high-Return STD/winner stocks across the samples. The return standard deviation under this SP strategy ranges from 52.92% (winner stocks in the momentum sample) to 71.34% (median-Return STD stocks in the independent sample) of the standard deviation under the corresponding BH strategy, suggesting a risk reduction effect from 28.66% to 47.08%. In the momentum sample, the same SP strategy also reduces the standard deviation for loser stocks. The RF strategy reduces the standard deviation for all the samples when the stop price is set at five standard deviations, and the risk reduction effect ranges from 36.01% (high-Return STD stocks in the autocorrelated sample) to 51.59% (winner stocks in the momentum sample). These findings suggest that although these trailing stop loss strategies neither reduce nor increase investors' losses relative to the buy-and-hold strategy, trailing stop loss strategies with certain stop prices can help investors to reduce the risk of their investments.

4.3. Robustness checks

4.3.1. Transaction costs

Our previous analyses assume no transaction cost on carrying out the stop loss strategies. A switch between the underlying stock and either the S&P 500 index or the one-month T-Bill, however, triggers an extra transaction before the end of a holding period. The associated transaction costs may reduce the investment performance under a stop loss strategy relative to the buy-and-hold benchmark. To examine the effects of transaction costs on the performance of stop loss strategies, we assume a conservative transaction cost estimate of 1%. We impose the transaction cost each time a stop loss condition is met and a switch occurs under a stop loss strategy. Similar to our previous findings, the realized returns under the SP and the RF strategies are statistically indistinguishable from the realized returns under the BH strategy. For brevity, we do not report those insignificant results but report the impacts of stop loss strategies on the risk of investments with the 1% transaction cost in Table 9.

Table 9 Stop loss strategies on investment risk: Simulated returns with a 1% transaction cost

Return STD/ Past return		Panel A: Traditional stop loss strategies														
		Independent sample			Autocorrelated sample			Momentum sample								
Stop Price	BH	SP %	p(SP)	RF %	p(RF)	BH	SP %	p(SP)	RF %	p(RF)	BH	SP %	p(SP)	RF %	p(RF)	
Low/loser	5 STD	0.24	97.99	0.56	90.73	0.18	0.24	97.79	0.60	90.77	0.21	0.51	91.16	0.34	86.78	0.27
	10	0.24	100.80	0.79	98.21	0.53	0.24	100.29	0.77	97.85	0.53	0.51	96.23	0.45	94.59	0.38
Median	5	0.32	94.26	0.38	90.44	0.15	0.33	92.77	0.41	89.06	0.20	0.37	95.95	0.42	97.78	0.33
	10	0.32	98.94	0.66	97.82	0.51	0.33	98.92	0.68	97.84	0.52	0.37	98.98	0.60	95.93	0.43
High/winner	5	0.50	93.26	0.32	91.60	0.22	0.47	93.17	0.36	91.40	0.22	0.58	91.47	0.28	87.83	0.20
	10	0.50	98.38	0.57	97.93	0.47	0.47	98.22	0.60	97.75	0.49	0.58	97.83	0.42	96.45	0.35
	20	0.50	99.55	0.41	99.44	0.40	0.47	99.51	0.39	99.39	0.34	0.58	99.32	0.42	98.90	0.34

Panel B: Trailing stop loss strategies

Low/loser	5 STD	0.24	76.35	0.10	58.37	0.00	0.24	76.14	0.14	58.35	0.00	0.50	63.32	0.00	56.68	0.00
	10	0.24	91.39	0.33	84.40	0.04	0.24	90.24	0.34	83.54	0.05	0.50	86.10	0.09	83.56	0.03
Median	5	0.33	70.91	0.01	61.49	0.00	0.32	70.91	0.02	61.67	0.01	0.37	66.82	0.05	54.45	0.00
	10	0.33	89.47	0.12	86.45	0.02	0.32	89.46	0.16	86.59	0.03	0.37	88.58	0.20	82.92	0.05
High/winner	5	0.49	66.23	0.02	62.30	0.00	0.48	67.71	0.02	63.62	0.00	0.63	52.45	0.01	47.98	0.00
	10	0.49	86.26	0.09	85.40	0.05	0.48	88.14	0.09	87.25	0.05	0.63	74.05	0.09	72.48	0.03
	20	0.49	93.69	0.17	93.65	0.15	0.48	96.42	0.24	96.42	0.21	0.63	85.04	0.11	84.88	0.09

This table reports the impacts of stop loss strategies on the risk of investments for the holding period of six months. The simulated returns are based on either stock returns from 2000 to 2005 for the independent and autocorrelated samples, or stock returns in 2000 for the momentum sample. Under the SP (RF) strategy, an investor incurs a transaction cost of 1% and reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the day once the stop price is hit. The column BH shows the standard deviation of the realized returns under the BH strategy. The column SP % (RF %) shows the return standard deviation under the SP (RF) strategy as a percentage of the return standard deviation under the BH strategy. The column p(SP) (p(RF)) shows the probability, i.e., the bootstrapped p-value, that the return standard deviation under the SP (RF) strategy is larger than the return standard deviation under the BH strategy.

The results in Table 9 suggest that the existence of transaction costs lowers slightly the statistical significance but not the magnitude of the risk reduction effect of trailing stop loss strategies. For instance, when the stop price is set at five standard deviations, the SP strategy still reduces the return standard deviation for median- and high-Return STD/winner stocks across the samples. The return standard deviation under this SP strategy ranges from 52.45% (winner stocks in the momentum sample) to 70.91% (median-Return STD stocks in the independent sample and in the autocorrelated sample) of the standard deviation under the corresponding BH strategy, suggesting a risk reduction effect from 29.09% to 47.55%. Our results are thus robust to the inclusion of transaction costs.

4.3.2. *Samples based on weekly returns*

The past return sample and the simulated return samples are based on daily stock returns. To test whether our results are sensitive to the daily interval, we replace daily returns with weekly returns. We redefine the stop loss strategies as follows: Under the SP (RF) strategy, if the stop price is hit before the end of an investor's holding period, the investor sells his holdings at the end of the week and reinvests his proceeds in the S&P 500 index (the one-month T-Bill). We then examine the effects of stop loss strategies on the investment performance of stocks over the holding periods of 13 weeks, 26 weeks, and 52 weeks. The results lead to the same conclusion that these stop loss strategies neither reduce nor increase investors' losses. We report the impacts of stop loss strategies on the risk of investments with the weekly returns in Table 10.

The results in Table 10 still support the risk reduction effect of trailing stop loss strategies. For instance, when the stop price is set at five standard deviations, the SP strategy reduces the standard deviation of realized returns for high-Return STD/winner stocks across the samples, and for median-Return STD stocks in the independent and autocorrelated samples. The magnitude of the risk reduction effect is lower, however, in this case. The return standard deviation under this SP strategy ranges from 71.26% (winner stocks in the momentum sample) to 82.37% (median-Return STD stocks in the autocorrelated sample) of the standard deviation under the corresponding BH strategy, suggesting a risk reduction effect from 17.63% to 28.76%. Given our previous finding of the risk reduction effect from 28.66% to 47.08% using daily returns, these results suggest that investors carrying out these strategies should use the daily interval instead of the longer weekly interval.

5. Discussion

5.1. *Why do trailing stop loss strategies reduce risk?*

Our results based on the simulated return samples suggest that traditional stop loss strategies and trailing stop loss strategies neither reduce nor increase investors' losses relative to a buy-and-hold strategy. Trailing stop loss strategies, on the other hand, consistently reduce investment risk across the samples. In this section, we explore some possible explanations for the risk reduction effect of trailing stop loss strategies.

Table 10 Stop loss strategies on investment risk: Simulated weekly returns

Return STD/ Past return		Independent sample			Autocorrelated sample			Momentum sample								
Stop Price	BH	SP %	p(SP)	RF %	p(RF)	BH	SP %	p(SP)	RF %	p(RF)	BH	SP %	p(SP)	RF %	p(RF)	
Low/loser	5 STD	0.24	97.80	0.57	92.12	0.19	0.23	98.06	0.62	92.52	0.24	0.50	92.45	0.35	88.39	0.28
	10	0.24	100.08	0.74	98.00	0.44	0.23	99.68	0.69	97.76	0.51	0.50	96.38	0.45	94.91	0.35
	20	0.24	100.04	0.71	99.29	0.55	0.23	99.88	0.71	99.21	0.57	0.50	98.46	0.41	97.99	0.33
Median	5	0.32	95.19	0.40	92.12	0.16	0.30	95.61	0.45	92.56	0.23	0.36	96.61	0.48	89.81	0.28
	10	0.32	98.68	0.59	97.77	0.44	0.30	98.80	0.62	97.93	0.45	0.36	98.52	0.57	95.83	0.40
	20	0.32	99.50	0.56	99.24	0.50	0.30	99.50	0.56	99.26	0.48	0.36	99.16	0.53	98.19	0.38
High/winner	5	0.46	94.54	0.33	93.04	0.20	0.45	94.77	0.37	93.31	0.25	0.61	91.09	0.29	88.06	0.21
	10	0.46	98.63	0.51	98.22	0.42	0.45	98.54	0.48	98.17	0.39	0.61	97.96	0.40	96.84	0.32
	20	0.46	99.54	0.33	99.45	0.28	0.45	99.53	0.34	99.43	0.32	0.61	99.37	0.34	99.02	0.31

Panel B: Trailing stop loss strategies

Low/loser	5 STD	0.24	85.01	0.14	72.36	0.00	0.23	84.97	0.21	72.16	0.00	0.50	77.11	0.07	71.95	0.01
	10	0.24	92.25	0.15	86.64	0.00	0.23	92.09	0.20	86.62	0.00	0.50	91.33	0.20	89.53	0.11
	20	0.24	95.27	0.11	92.96	0.01	0.23	94.47	0.14	92.27	0.02	0.50	96.29	0.21	95.96	0.20
Median	5	0.32	81.67	0.02	74.96	0.00	0.31	82.37	0.03	75.33	0.00	0.36	82.54	0.16	71.85	0.02
	10	0.32	91.96	0.05	89.55	0.00	0.31	92.26	0.05	89.75	0.00	0.36	93.53	0.25	88.70	0.07
	20	0.32	96.57	0.08	95.86	0.04	0.31	96.02	0.08	95.33	0.01	0.36	96.61	0.25	94.82	0.12
High/winner	5	0.46	80.67	0.02	77.97	0.01	0.44	81.19	0.02	78.34	0.01	0.58	71.26	0.04	67.38	0.01
	10	0.46	93.75	0.07	93.30	0.07	0.44	93.99	0.09	93.41	0.07	0.58	86.44	0.12	85.50	0.11
	20	0.46	98.17	0.25	98.38	0.25	0.44	98.88	0.25	99.04	0.26	0.58	95.08	0.29	95.24	0.29

This table reports the impacts of stop loss strategies on the risk of investments for the holding period of six months. The simulated returns are based on either weekly stock returns from 2000 to 2005 for the independent and autocorrelated samples, or weekly stock returns in 2000 for the momentum sample. Under the SP (RF) strategy, an investor reinvests his proceeds in the S&P 500 index (the one-month T-Bill) at the end of the week once the stop price is hit. The column BH shows the standard deviation of the realized returns under the BH strategy. The column SP % (RF %) shows the return standard deviation under the SP (RF) strategy as a percentage of the return standard deviation under the BH strategy. The column p(SP) (p(RF)) shows the probability, i.e., the bootstrapped p-value, that the return standard deviation under the SP (RF) strategy is larger than the return standard deviation under the BH strategy.

5.1.1. *Is it information?*

Information is valuable and past prices per se can serve as information. Beaver, Lambert and Morse (1980), for instance, find that stock price changes contain information on future earnings. A trailing stop loss strategy enables the stop price to adjust upwards automatically with the security price but not downwards. It is thus possible that this adjusting mechanism avoids a stale stop price and allows the trailing stop loss strategy to incorporate relevant information from past price changes. However, our evidence from the independent sample suggests that this is not the case. Specifically, in the independent sample we remove any time-series dependence in the return series such that past price changes would contain no information for future returns. Yet the risk reduction effect of the trailing stop loss strategies remains.

5.1.2. *Is it the risk of switching assets?*

It is conceivable that if the switching asset (e.g., the S&P 500 index or the one-month T-Bill) is less risky than the original investment under a stop loss strategy, the holding period returns will be less volatile than the buy-and-hold returns as long as some switches between these two assets occur. However, both the traditional and the trailing stop loss strategies we examine use the same switching assets. Yet we observe the consistent risk reduction effect only under the trailing stop loss strategies. This observation suggests that the risk of switching assets alone does not fully explain the risk reduction effect of the trailing stop loss strategies.

5.1.3. *Dynamic versus static strategies*

In terms of the stop price, a traditional stop loss strategy is a static strategy with a fixed stop price. A trailing stop loss strategy, on the other hand, is a dynamic strategy with an upward-adjusting stop price. Building on the binomial framework from Dybvig (1998), the fixed stop price effectively truncates from below the distribution of the holding period terminal wealth under the buy-and-hold strategy at a fixed level. The upward-adjusting stop price truncates the distribution of the terminal wealth dynamically over time. Because during the holding period the dollar stop price under a trailing stop loss strategy is always no smaller than the fixed dollar stop price under a traditional stop loss strategy, the resulting terminal wealth distribution under the trailing stop loss strategy should be bounded within the distributions under the traditional stop loss strategy and under the buy-and-hold strategy. This analysis predicts that the terminal wealth distribution under the trailing stop loss strategy should have the smallest variance relative to the other two distributions, as long as the switching asset has less total risk than the original investment. Our result that the trailing stop loss strategies significantly reduce investment risk relative to the buy-and-hold strategies is consistent with this prediction.

5.2. *Tax implications*

Our previous analyses do not consider the tax effects of stop loss strategies. Realized losses, however, can provide investors valuable tax deductions. To shed lights on these tax effects, we conduct a scenario analysis using the aggregate estimates in Table 6 from the independent sample. The results using the other samples do not differ much.

Focusing on the low-Return STD stocks under the traditional stop loss strategies first, Table 1 shows an average return standard deviation of 1.65% for these sample stocks. The stop price at five standard deviations thus translates into 8.25% below the initial purchase price. Assuming the 8.25% to be approximately the loss an investor realizes when the stop loss order is executed, the investor has a tax deduction of 8.25% of his initial investment. Because the corresponding buy-and-hold return, which is statistically indistinguishable from the realized return under the stop loss strategy, is $-5%$ ($= 0.95 - 1$), this realized loss provides the investor an incremental tax deduction of 3.25% (assuming negligible time value of money). Given the hit rate of 52%, the expected value of the tax benefit on carrying out this stop loss strategy for an investor in the 10% tax bracket is 0.17% ($= 0.52 \times 3.25\% \times 10\%$). For an investor in the 35% tax bracket, the expected value is 0.59%.

Following similar calculations, we obtain the expected tax benefit of 0.04% (0.14%) for an investor in the 10% (35%) tax bracket when the stop price is set at 10 standard deviations, and 0.11% (0.38%) when the stop price is set at 20 standard deviations. The expected tax benefit for an investor in the 10% (35%) tax bracket ranges from 0.00% to 0.08% (from 0.00% to 0.26%) on median-Return STD stocks, and from 0.00% to 0.16% (0.00% to 0.56%) on high-Return STD stocks. These results are consistent with the intuition that investors in higher tax brackets benefit more from realizing losses and thus from using stop loss strategies. These small tax benefits (less than 0.60%), however, are unlikely to have significant impacts on our results under the traditional stop loss strategies, considering the previous finding that even the inclusion of a 1% transaction cost does not alter our conclusions.

For trailing stop loss strategies, on the other hand, the same scenario analysis cannot be readily applied using the aggregate estimates in Table 6 alone. Because the stop price under a trailing stop loss strategy adjusts upwards automatically with the security price, there is no guarantee that an investor will incur a loss relative to his initial purchase price when the stop price is hit. To address this issue, we estimate for these strategies the probability of loss when the stop price is hit and the conditional loss relative to the loss implied by the initial stop price. For instance, we estimate a loss probability of 57% and a conditional relative loss of 78% for low-Return STD stocks in the independent sample when the stop price is set at five standard deviations.⁹ Using these estimates and the aggregate estimates in Table 6, we obtain the expected tax benefits for an investor in the 10% (35%) tax bracket ranging from 0.36% to 0.49% (from 1.26% to 1.72%) on low-Return STD stocks, from 0.44% to 0.58% (1.53% to 2.04%) on median-Return STD stocks, and from 0.71% to 0.84% (2.50% to 2.92%) on high-Return STD stocks.¹⁰ These larger expected tax benefits than under the traditional stop loss strategies suggest that the higher hit rates and larger incremental tax deductions (because of the smaller tax deductions at the end of a holding period) under the trailing stop loss strategies are more than offsetting the less than 100% loss probabilities and conditional relative losses on providing tax benefits. This result also provides further support to the use of trailing stop loss strategies.

5.3. *Future extensions*

Given the scope of our analyses on effectively the universe of NYSE- and AMEX-listed ordinary common stocks (excluding penny stocks) over more than three decades, we rely

on daily and weekly data in this paper. These data frequencies, however, prevent us from determining the exact time a stop loss condition is met, and limit our focus to those met conditions that also present at the end of a day. One natural extension of our analyses is to use intraday data to pinpoint the time a stop loss order is triggered and investigate the effects of the execution price uncertainty faced by a regular market sell order on the performance of stop loss strategies. For instance, once a stop loss order is triggered, the execution price of a market sell order may be well below the stop price in a fast moving market. Such execution price uncertainty inevitably would depend on the order size, the time of a day, and the specific security examined, and it may adversely affect the performance of stop loss strategies.

Another possible extension of our analyses is on the tax effects of stop loss strategies. Our scenario analysis on such tax effects relies on aggregate estimates and applies to the average stock in our sample. We leave a more detailed analysis on whether the expected tax benefits under the trailing stop loss strategies suffice to improve the investment returns significantly, and on the tax effects of stop loss strategies in general for future research.

6. Conclusion

Stop loss strategies allow investors to limit their losses by automatically prompting the sales of losing investments. They also help investors to avoid holding onto their losing investments too long. These strategies are touted to improve investment returns and are widely used in practice. On the other hand, simple intuition and theoretical evidence suggest that these strategies may not be efficient. In this article, we examine the impacts of stop loss strategies on the return and risk of individual common stocks and identify the value of stop loss strategies.

We consider two stop loss strategies on stocks listed on NYSE and AMEX from 1970 to 2005. Under the SP strategy, an investor reinvests his proceeds in the S&P 500 index once the stop loss condition is met. Under the RF strategy, the investor reinvests his proceeds in the one-month T-Bill. We also consider two alternative stop loss mechanisms: The traditional stop loss with a fixed stop price, and the trailing stop loss with a stop price that adjusts upwards automatically with the security price but not downwards. We use a buy-and-hold strategy as the performance benchmark.

The results based on historical return paths suggest that these stop loss strategies can reduce the effective holding periods on losing investments. Traditional stop loss strategies have been able to reduce investors' losses on certain stocks but not the others. We also find evidence that the relations between stock characteristics and the loss reduction effect of traditional stop loss strategies weaken over time. Trailing stop loss strategies, on the other hand, show the effect of reducing investment risk rather than reducing investment losses.

Using bootstrapping techniques to extend security returns from past realizations to possible future paths, we find that these stop loss strategies neither reduce nor increase investors' losses relative to the buy-and-hold strategy. Trailing stop loss strategies, nonetheless, continue to help investors to reduce their investment risk. These results are robust regardless of whether future returns are independent, autocorrelated, or from momentum

samples, and whether we consider transaction costs or use alternative data intervals. We conclude that realizing losses sooner by certain stop loss strategies can be of value to investors. In contrast to the common belief that using stop loss strategies can improve investment returns, this value may come largely from risk reduction rather than return improvement.

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Notes

1. Strictly speaking, a stop loss order can also be a contingent buy order for investors with short positions. We limit our attention to the more common scenario in which investors hold long positions. In addition, some people may refer to the contingent market sell order as a stop (loss) order and the contingent limit sell order as a stop limit order. We refer to them as stop loss orders.
2. Market orders at close are available through many brokerage accounts. For instance, Fidelity Brokerage, one of the largest brokerage firms in the United States, allows its account holders to specify such orders. Using regular market orders in this case investors would face the execution price uncertainty that depends heavily on the order size and the time the order is executed. Using limit orders, on the other hand, investors would face the risk of non-execution.
3. Our conclusions are strengthened if we use unconditional returns instead of the conditional ones.
4. Using standardized residuals (e.g., Davidson and MacKinnon, 1993; Johnston and DiNardo, 1996) to simulate the autocorrelated returns does not affect our results.
5. Because the dollar stop price under a trailing stop loss strategy is always no smaller than the fixed dollar stop price under a traditional stop loss strategy, the hit rate should be higher under a trailing stop loss strategy. Our results are consistent with this prediction.
6. We borrow these stock characteristics from the literature examining cross-sectional stock returns. We do not include past return standard deviation as an independent variable because the generated dependent variable is mechanically related to the past standard deviation.
7. See, for instance, this transformation in Nagel (2005). We replace values below 0.0001 and above 0.9999 with 0.0001 and 0.9999, respectively, before the transformation.
8. There is some evidence from the simulated samples that, when the stop price is set at

five standard deviations, the traditional stop loss strategies reduce the risk of investments in the 1970s and in the 1990s.

9. The loss probability ranges from 57% to 78%, and the conditional relative loss ranges from 69% to 78% in the independent sample.
10. As an example to illustrate the calculations, consider low-Return STD stocks in the independent sample: Table 1 shows an average return standard deviation of 1.65% for these sample stocks. The stop price at five standard deviations thus translates into 8.25% below the initial purchase price. The conditional relative loss of 78% implies that the average conditional loss is 6.44%, that is, 78% of the 8.25%. Assuming the 6.44% to be approximately the loss an investor realizes when the stop loss order is executed, the investor has a tax deduction of 6.44% of his initial investment. Because the corresponding buy-and-hold return, which is statistically indistinguishable from the realized return under the stop loss strategy, is 8% ($= 1.08 - 1$), this realized loss provides the investor an incremental tax deduction of 6.44% (assuming negligible time value of money). Given the hit rate of 97% and the loss probability of 57%, the expected value of the tax benefit on carrying out this stop loss strategy for an investor in the 10% tax bracket is 0.36% ($= 0.97 \times 0.57 \times 6.44\% \times 10\%$). For an investor in the 35% tax bracket, the expected value is 1.26%.

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