Dollar-Cost Averaging Versus Lump-Sum Investing –
Evidence from Sweden

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Abstract

Dollar-Cost Averaging (DCA) is a popular investment strategy for purchasing equity securities. Even though previous research shows that DCA is somehow inefficient, it has remained a default strategy widely recommended by financial advisors worldwide. Using this starting point, this thesis empirically investigates and compares DCA with Lump-Sum Investing (LSI) through a replicative approach. We use a simulation to analyze the strategies performance on the Swedish Equity Market. The evaluation is conducted from both a traditional and behavioral finance framework. In line with Leggio and Lien (2001), whom we replicate, our results indicate LSI being a superior strategy for both mean-variance and loss-averse investors. Hence, we argue that LSI should not be forfeit as a potential strategy when entering the Swedish market. An evaluation of the two strategies should help Swedish investors to make better-informed decisions about whether to use DCA or LSI.

Keywords: Dollar-Cost Averaging; Lump-Sum Investing; Prospect Theory; Utility Theory

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1. Introduction

Dollar-Cost Averaging (DCA) is a popular investment technique for entering the market. Rather than investing all funds at one point in time (Lump-Sum Investing), DCA divides the total amount into equal parts that are regularly invested over a predetermined period. Whether to use a DCA or Lump-Sum Investing (LSI) strategy arises when dealing with a large portion of money that shall be invested. It could be money inherited from a legacy, property and business sale, or any other substantial profit. For the average investor, who invests in stocks and mutual funds, common advice is to use a DCA strategy when entering the market (Statman,1995; Milevsky & Posner, 2003; Leggio & Lien, 2003; Brennan et al., 2005; Hayley, 2010). Although academia provides evidence of DCA being less efficient than other strategies, investors seem prone to implement a DCA strategy (Statman, 1995; Haley, 2010; Merlone & Pilotto, 2015). The discrepancy between practice and studies in the field, therefore, opens room for further investigation. Thus, this study aims to extend the existing literature by comparing the performance of DCA and LSI on the Swedish market, where prior research is currently absent.

The two strategies compared, DCA and LSI, are by nature fundamentally different. In the popular view, Dichtl & Drobetz (2011) argue that DCA has been suggested based on two arguments; first, DCA brings the advantage of reducing the risk of an entire portfolio being purchased at market highs. Second, when investing equal amounts in predetermined periods, an investor buys more shares when prices are low and fewer shares when prices are high. A mathematical result of this, given some downward trend in share price, is that the average paid per share price becomes less than the average price of the share during the investment period. Thus, over an investment period, DCA works as a shock absorber bringing effort to reduce the impact of volatility on the complete purchase (Milevsky & Posner, 2003). In this sense, DCA should not be associated with typical monthly savings since DCA relates to a large sum of invested money over a predetermined period. Hence, in contrast to monthly savings, investors make a conscious decision to phase in capital, which already could have been invested. Opposite to DCA, LSI advocates argue that cash already saved should be invested directly (Haley, 2010). The advantage of LSI is that an investor gains exposure to the market directly. In times of upward trending markets, LSI outperforms by putting money to work right away and thus reaping the benefit of market growth. Since the market experience more periods of upward trends, LSI is expected to generate higher returns on average (Rozeff, 1994). However, a disadvantage of this strategy comparing with DCA is that an investor may inadvertently invest all the cash at a market high (Leggio & Lien, 2003). Thus, for investors who strongly believe a bull market is approaching, it would make sense to use LSI. While DCA being preferable if believing in a future bear market (Grable & Chatterjee, 2015). However, timing the market is no simple task. Thus, this underlines the importance of which strategy on average outperforms and further contextualizes the significance of outcome in performance based on the point of time one historically entered the market.

Due to the wide popularity of DCA in practice, there is extensive literature trying to compare DCA with other strategies.[1] for entering the market. A review of the literature shows an imbalance in popularity between DCA and LSI, where it is evident that LSI holds at least as much support as DCA. In a recent publication, Kowara and Kaplan (2019) argue that the supposed advantages of DCA over LSI are common myths. Nevertheless, the DCA strategy remains popular and frequently advocated by financial advisors and banks (Greenhut, 2006; Merlone & Pilotto, 2015). Milevsky and Posner (2003) and Haley (2010) confirm this occurrence as DCA remains as popular as ever amongst individual investors, despite evidence of LSI outperforming DCA. Thus, the question arises whether investors are potentially underestimating the results from published reports in the field or if other underlying factors may contribute to the wide use of DCA in practice. Although various studies fail to demonstrate the efficiency of DCA empirically, it warrants careful investigation due to its given acceptance in practice.

1.1 Objective

This study aims to contribute to the field of DCA vs. LSI literature in several ways. We aim to add a more profound understanding in this field of study by investigating the Swedish market and further framing this debate to the behaviors of investors. To the best of our knowledge, preceding studies are predominantly made on the American market, with a few exceptions on larger markets in a European setting. By analyzing the Swedish market, this study is the first to do so that we are aware of. Furthermore, since investors tend to allocate a large share of their portfolio to domestic assets (Kilka & Weber, 2000; Bodie et al., 2014), we believe it is relevant to investigate the

[1] Other common strategies include Buy and Hold, Value Averaging (Leggio & Lien, 2001)

performance of DCA vs. LSI on individual domestic markets. Moreover, providing accurate information to Swedish investors could widen the understanding of how using DCA or LSI might differ on their home market. How results from the strategies on the Swedish market will differ in terms of risk and returns compared to previously studied markets is difficult to predict. However, the difference in risk is expected as volatility of stock returns vary across countries (Irvine & Pontiff, 2009). According to Bartram et al. (2012), stocks of U.S. listed firms are more volatile than stocks of comparable non-U.S. listed firms. Moreover, Lindberg and Swanson (2018) report that Swedish firms listed on Nasdaq Stockholm display lower volatility than stocks of comparable European firms. The intended strategies may, therefore, lead to different results on the Swedish market. In this case, lower volatility on the Swedish market could lead to increased performance of LSI.

Further, as Baker (2016) finds evidence of a replicating crisis in published scientific literature, this study is conducted through a replicative approach. We intend to replicate Leggio and Lien (2001) as their study compares the performance of DCA and LSI from both a traditional and behavioral finance perspective. Acknowledging that DCA has been criticized for being inconsistent with traditional finance, aspects of behavioral finance become essential for our study and further research. Thus, an investigation of how DCA and LSI may suit various investors with different behaviors and risk-appetites. According to Hou et al. (2018), financial studies tend to use publication biases, which likely lead to financial studies with false positives that are difficult to replicate. Therefore, we intend to contribute to the literature by trying to verify the findings of Leggio and Lien (2001). Through this aim, our study compares the performance of DCA and LSI on the Swedish market.

This study compares DCA and LSI and rank performance using holding period return (HPR), Sharpe ratio, Sortino ratio, and Value function. Based on the rankings, this study finds LSI being a superior strategy on the Swedish equity market. The remainder of this study proceeds as follows. Section 2 presents the theoretical frameworks used in this study. Section 3 is a thorough literature review with examples of previous studies in the field. Section 4 describes the methodological choices made in this study where the data sample is discussed. Section 5 presents the empirical findings, followed by a discussion of the results. Finally, section 6 presents the conclusions drawn from the results, limitations of the study, and suggestions for future research.

2. Theoretical Framework

2.1 Financial Theories

Behavioral and traditional finance represent two different schools of thought that intend to explain investors' decision-making process (Asab et al., 2014). It is essential to highlight that prior research has tied the framework of both traditional and behavioral finance to the debate of DCA vs. LSI to understand and evaluate the strategies' performance for investors of different nature. While earlier studies have analyzed DCA vs. LSI from a traditional finance perspective,
behavioral finance has increased its attention in later studies. Thus, consistent with prior research, we find the two theories essential for evaluating DCA and LSI.

2.1.1 Traditional Finance and Mean-Variance Investors

Theories of finance are developed from the assumptions that investors are rational and participate in frictionless markets. The Modern Portfolio Theory (MPT) (Markowitz, 1952) and the Efficient Market Hypothesis (EMH) (Fama, 1970) are examples of conventional critical theories within the financial literature, which argue that risk-averse investors make rational choices such as always preferring a lower risk to a higher risk at any given level of return. More importantly, in the debate of DCA and LSI is the concept of expected utility theory and mean-variance investors. The idea of mean-variance investors derives from the well-established MPT (Elton & Gruber, 1999), which was introduced by Markowitz (1952) and further developed through the concept of Capital asset pricing model (CAPM) in studies by Sharpe (1964), Lintner (1965), and Mossin (1966).

Henceforth, choices of traditional finance investors conform to expected utility theory, where investors make choices to maximize expected utility, being a function of wealth (Statman, 1995). The utility theory is based on three principles: First, Dichtl & Drobetz (2011) state that probability-weighted utilities always equal the expected utility. Second, the investor only accepts the choice if resulting in added value to an existing portfolio. The third and final principle assumes that all investors are risk-averse to nature. The definition of risk is within traditional finance measured by variance and captured in the utility function's concavity. The concavity implies that traditional investors always prefer a sure gain over a gamble with an equal expected value (Fisher & Statman, 1999). In practical terms, traditional investors prefer a secured gain of $100 over a 50-50 chance for $200.

Traditional finance assumes that each investor wants to make optimal decisions (Sharpe, 1964). In this context, the mean-variance investor is the most common type of investor with a rational process when entering the market. Previous scholars have tied this concept into the debate of DCA and LSI, which is elaborated further in the literature review.

2.1.2 Behavioral Finance and Loss-Averse Investors

Observations of actual choices demonstrate that investors do not always perceive risk in the setting of what traditional finance suggests. Rather than always being risk-averse, behavioral finance theory argues that investors are risk-averse in some particular settings but not in all (Kahneman & Tversky, 1979). These observations led to the development of prospect theory. The prospect theory of Tversky and Kahneman (1979) argues that individuals react differently between potential losses and gains. The theory expresses outcomes as deviations, both positive and negative, from a reference point and suggests an asymmetric S-shaped Value function. The utility curve is concave for gains and convex for losses, implying risk-averse behavior over gains but risk-seeking behavior over losses. This is opposite to expected utility theory, which assumes that investors are risk-averse over the complete domain of gains and losses, with a concave utility function. Thus, rather than choosing a strategy that satisfies the standard mean-variance model, a behavioral investor aims to maximize his Value function (Kahneman & Tversky, 1979).

An investor's choice of strategy comes from the process of decision-making. According to Bazerman and Moore (2013), this process is heavily influenced by cognitive biases and heuristics. Further, Kahneman and Tversky (1974, 1979, & 1992) argue that behavioral biases can lead to irrational behaviors, which more frequently are observed among participants in financial markets. A person being subject to cognitive biases may line with the prospect theory, consequently finding DCA to be the optimal fit for entering the market. According to Newberry (1995), financial planning literature is often advocating DCA for private investors. In addition, influential experts and credible media channels often support this notion. Hence, one can make a case of availability heuristics being one contradicting factor for this pattern of prospect theory and DCA.

In sum, these properties may imply that a DCA strategy can be appealing to behavioral investors who suffer from cognitive biases and emotional factors.

2.2 Financial Volatility and Market Valuation

Markets where equities are traded are constantly subjected to a degree of fluctuations in financial terms referred to as volatility. In the debate of DCA vs. LSI, one must discuss the role of market volatility. The two strategies have different exposure to volatility and are therefore considered of different risk. LSI is traditionally considered riskier than DCA since a DCA strategy holds more cash and makes several purchases over time. Therefore, DCA becomes less subjected to volatility and thus experience less risk (Dubil, 2005; Kitces, 2016). Additionally, as a DCA strategy divides an investment into several purchases, it reduces the timing risk when entering the market. Therefore, a natural result of this is that DCA reduces the impact of volatility on the purchase of assets by potentially smoothing out the average price paid. Thus, in theory, DCA performance should correlate with volatility, working better in highly fluctuating markets.

Moreover, the valuation of the market can be tied to volatility, and the debate of DCA vs. LSI. The empirical results of Kane et al. (1996) suggest that the market multiple P/E is sensitive to volatility. Their results show that a permanent one percentage point increase in volatility can reduce the market multiple by 1.8. Based on their results, Kane et al. (1996) argue that the impact of volatility has to be acknowledged in all assessments of market valuation. Additionally, multiple studies test the efficient-market hypothesis by investigating the relationship between P/E ratios and equity performance. Evidence from Basu (1977) suggests P/E ratios being an indicator of future security performance. Empirical results from 1957-1971 indicate that portfolios of stocks with lower P/E valuations seem to have earned higher risk-adjusted returns on average than portfolios consisting of stocks with high P/E ratios. In support, Liem and Basana (2012) report P/E ratios to be negatively correlated with stock returns as they observe significantly higher risk-adjusted returns for stocks with a lower P/E ratio than stocks with higher P/E ratios. Thus, some evidence suggests that in times where stocks trade at higher valuations, returns could potentially be expected to decrease. If such predictions hold, DCA and LSI performance may correlate with valuations in the market.

3. Literature Review

3.1 Traditional Finance and Mean-Variance Investors

Investors who focus solely on superior returns are much in line with traditional finance, which advocates utility maximization (Dichtl & Drobetz, 2011). Weston (1949) was one of the first scholars arguing that the practice of DCA is inconsistent with traditional finance. Further, even though acknowledging the ability of DCA to reduce the risk of investing, Constantinides (1979) finds evidence of DCA being theoretically sub-optimal from the perspective of a mean-variance investor. In other research, Knight and Mandell (1993) present analytical, numerical, and new empirical proof that DCA should be considered unfavorable as LSI generates higher mean utility values over all risk aversion levels, although differences are not statistically significant. Knight and Mandell (1993) brought a new dimension to the debate when empirically testing DCA and LSI using historical monthly returns on the New York Stock exchange from 1962 to 1992. As the DCA strategy yields the lowest annualized returns and mean utility, Knight and Mandell (1993) argue it has no justification due to its poor performance in testing risk and returns compared to the LSI strategy. Furthermore, Rozeff (1994) finds LSI always superior to a DCA strategy in a stock market with a positive risk premium, making sense as LSI is bringing money to work right away. Similar to Knight and Mandell (1993), Leggio and Lien (2001) conduct an empirical study on the American market, where data on large-company stocks (S&P 500 composite) and small company stocks (Ibbotson Small-Company stocks[2]) over the period 1970-1999 is used. In their study, LSI results in the largest annual excess returns, 9.28% for Large-Cap, and 13.72% for Small-Cap, compared with a 4.97% return for a twelve-month DCA strategy on Large-Cap and 4.24% on Small-Cap. Further, they present a Sharpe ratio of 0.456 and 0.403 for LSI on Large-Cap and Small-Cap, respectively 0.386 and 0.216 for DCA. Thus, providing evidence of LSI yielding higher risk-adjusted returns.

In opposition to previous notes, Brennan et al. (2005) consider the benefits of DCA from a rational investor's viewpoint with a concave utility function and find that DCA is dominant when applied to the purchase of securities added to portfolios that are already diversified. Further, Israelsen

[2] Ibbotson Associates Valuation Edition 2000 Yearbook.

(1999) finds DCA being a superior strategy for low-volatile funds over the ten-year period 1988 to 1998. The study investigates annual holding period returns for 35 large equity funds and finds DCA leading to higher returns for 19 of the funds.

Despite some contradicting evidence, there are a significant number of researchers finding LSI being efficient for mean-variance investors. Simply, from the perspective of a rational mean-variance investor, LSI is found to be the superior strategy due to its deliverance of higher risk-adjusted returns (see, e.g., Constantinides, 1979; Rozeff, 1994; Leggio & Lien, 2001).

3.2 Behavioral Finance and Loss-Averse Investors

After the criticism towards DCA from a traditional finance point of view, researchers introduced a behavioral rationale to prove the existence of DCA. Statman (1995) was one of the first scholars who used prospect theory, where potential losses weigh more than potential gains as a reason for why DCA is superior to LSI for loss-averse investors. He argues that the conversion from cash to equity may be optimal. However, such conversion is unappealing for investors who fear the regret that they will experience if the market were to crash immediately after the cash is converted. Thus, arguing that DCA can help alleviate regret and responsibility. Further, Brennan et al. (2005) argue that DCA is consistent with the positive framework of behavioral finance, as investors use frames and react differently to gains and losses. Moreover, Brennan et al. (2005) suggest that DCA can be appealing for investors that lack self-control and attempt to minimize regret of buying in at market highs. Thus, the impact of cognitive biases can be decisive factors explaining the popularity of DCA. In support, Dubil (2004) argues that the advantages of DCA become evident from the perspective of prospect theory as he finds DCA to offer significant risk reduction relative to non-average alternatives, especially for more volatile securities. The findings propose that DCA does not only lower standard deviation but also always lower the probability of expected shortfall by up to as much as 30%. Thus, giving evidence of DCA benefiting people suffering from loss-aversion[3]. However, Leggio and Lien (2001) add to the support of LSI, as their study fails to confirm Statman's (1995) hypothesis of how loss-aversion can explain DCA from a prospect theory point of view. Leggio and Lien (2001) conclude that loss-aversion still does not explain the

[3] Given the same variation in absolute value away from the reference point, there is a bigger impact of losses than of gains. Gains and losses of the same amount are valued asymmetrically, and investors care more about potential losses than potential gains (Kahneman & Tversky, 1979).

existence of DCA as LSI produces a higher Value function than DCA for both Large-Cap and Small-Cap stocks. Interestingly, for Small-Cap stocks, DCA is the only strategy generating a negative value function (-2.91), compared to a positive value of 5.00 for LSI, statistically significant at a 1% level. Based on their results, Leggio and Lien (2001) find DCA being a suboptimal investment strategy for volatile assets such as Small-Cap stocks, which can be considered surprising as financial advisors advocate DCA for being a better risk-reductive method for the purchase of volatile securities (Merlone & Pilotto, 2015).

Further, there are published material in more recent years: Dichtl and Drobetz (2011), Merlone and Pilotto (2015), who are two recent studies on the European market that focus on DCA and its contributing factors for risk-averse investors. Dichtl and Drobetz (2011) test the performance of DCA on the German stock market. While LSI simulated higher mean returns and Sharpe ratios, Dichtl and Drobetz (2011) still argue that DCA remains the attractive strategy for loss-averse investors. This is due to DCA generating a higher mean prospect value than LSI when incorporating loss-aversion in a Monte-Carlo simulation (2.96 vs. 2.34). Further, consistent with their Monte-Carlo simulation results, DCA dominates LSI in cumulative prospect values when simulating on historical data from DAX.[4] (−0.61 vs. −2.94). Their findings conclude that an LSI strategy always delivers higher returns than DCA while also having a higher Sharpe ratio. Therefore, Dichtl and Drobetz (2011) argue that DCA is not a rational strategy for mean-variance investors. However, when taking behavioral aspects into account, loss-aversion is considered the dominant factor leading to their stated inferiority of LSI. Furthermore, Merlone and Pilotto (2015) simulate the Italian market. Their comparison of DCA vs. LSI conducted on 30 funds and stocks showed that DCA outperforms LSI only 35.97% of the times for funds while 53.38% for stocks. Their results indicate that DCA might be a better fit for stock investments than funds. However, their result does not give a scientific reason behind DCA's popularity domestically.

In addition, Frühwirth and Mikula (2014) elaborate on previous research as they extend the findings of Leggio and Lien (2001) and Dichtl and Drobetz (2011). Based on their results, on a multinational sample, Frühwirth and Mikula (2014) argue that DCA is inferior to LSI in the eyes of a prospect theory investor. This is consistent with the findings of Leggio and Lien (2001).

[4] Stock Index of the 30 largest companies traded on the German Stock market.

3.3 Financial Volatility and Market Valuation

In the debate of investment strategies to use, evidence differs on the volatility parameter. Merlone and Pilotto (2015) claim that domestic banks advocate DCA as a volatility-averse strategy to alleviate market volatility. Abeysekera and Rosenbloom (2000) support this by stating that DCA performance is positively correlating with volatility. Thus, a higher volatile market indicates favorable results for DCA over LSI. In addition, Dichtl and Drobetz (2011) argue that volatility is related to an individual's loss-averse approach. Their paper uses prospect theory to conclude why the popularity of DCA increases with volatility. Unlike most research, Israelsen (1999) reveals surprising results by going against the anecdotal assumption of DCA performance, increasing positively with volatility. Israelsen, in fact, has a challenging view to Abeysekera and Rosenbloom (2000). The paper reports DCA being the high yielding method in a lower rather than higher volatile market by highlighting evidence from low-volatile funds. Israelsen (1999) is found to be the lone researcher finding this evidence for DCA. Furthermore, Kowara and Kaplan (2019) say LSI is less risky than DCA due to lower volatility exposure. Dubil (2004) and Greenhut (2006) bring another perspective by stating that DCA and LSI are equal in performance in times with lower expected return and high volatility. The final take is that most scholars find increasing volatility to result in better DCA performances.

Luskin (2017) adds another approach. He argues that the intended CAPE[5] ratio is a determining factor for when to implement DCA or LSI. The study finds a correlation of 0.43 between the chance of DCA outperformance and the starting CAPE ratio. At times when the CAPE ratio exceeds 18.6, DCA is likely to outperform LSI. More specifically, in such scenarios, DCA generates a higher annualized return of 0.45%. However, LSI yields a higher annual return by 1.44% for periods starting with a CAPE ratio below 18.6. Thus, Luskin (2017) adds perspective by how the choice of investment strategy is dependent on external factors such as market valuation rather than one being universally superior in all cases. Thus, it becomes relevant to investigate if DCA vs. LSI performance has fluctuated over time, along with different levels of volatility and valuations on the Swedish market.

[5] Also known as the Shiller P/E or PE 10 Ratio, is an acronym for the Cyclically Adjusted Price-to-Earnings Ratio. The ratio is calculated by dividing a company's stock price by the average of the company's earnings for the last ten years, adjusted for inflation (Luskin, 2017).

3.3.1 Market Dynamics and Seasonality

Rather than arguing which strategy is superior to the other, some researchers stand more neutral. Thus, arguing that internal and external factors primarily influence the performance of DCA and LSI. Abeysekera and Rosenbloom (2000) present an interesting simple rule stating that one strategy cannot be universally superior to the other. Thus, one who expresses contradicting claims would be misleading. The researchers find the relative superiority of the alternative strategies to depend on market dynamics, including the expected rate of return on the stock and the opportunity cost of capital represented by the risk-free rate. Hence, the study argues that the choice of DCA vs. LSI should be based on the distributional properties of the outcome expected by the investor at the initial time of investment. According to Abeysekera and Rosenbloom (2000), investors who believe LSI to be superior to DCA seem to focus solely on marginally superior returns, thus ignoring potential risks.

Further, Atra and Mann (2001) compare DCA vs. LSI performance on international indices, using monthly data from 1970-1998 with an emphasis on seasonality. The paper examined whether DCA performance is dependent on the month when to enter the market. Hence, factoring the concept of seasonality of securities into the comparison. The study compared annual returns and Sharpe ratios, where the results indicate that DCA provides slightly higher, albeit not significantly higher returns for all indices. Looking at seasonality, they find DCA working better from January to September, while LSI being a superior strategy between October and January. For the entire period, LSI is a better risk-adjusted strategy for most indices studied, which contradicts the claim that DCA is a risk-reducing strategy (Atra & Mann, 2001). Their study believes LSI reduces risk since the entire amount invested experiences more independent return realizations leading to lower risk. This is similar to the conclusions of Rozeff (1994).

3.4 Hypothesis development

From the literature review in the subjects, it becomes clear that a rational investor is in line with traditional finance, while an irrational investor is in line with prospect theory and behavioral finance. Interestingly, the irrational investor seems to be more affected by heuristics, while the rational investor would ignore cognitive biases and solely focus on maximizing expected utility.

The choice of investment strategy is hence a result of investors' processed information available, and further if being subject to behavioral biases or not. Additionally, previous research argues that market volatility plays a role in that advisors recommend DCA because it is more useful in a highly volatile market, while academic results seem mixed.

Thus far, we have established through prior research that; (1) DCA and LSI are two strategies of different nature used for entering the market, (2) DCA is more frequently used in practice and advocated by financial advisors and bankers. However, (3) various studies find LSI being optimal for both mean-variance and loss-averse investors. If these findings hold, one may argue that the popularity of DCA is disproportionate when compared with LSI. Given the relatively limited period of scientific study on behavioral finance and since decisions regarding investments frequently are grounded on beliefs concerning the probability of uncertain events, one should not be surprised to find a substantial amount of financial practice still being governed by cognitive biases. This would suggest that the impact caused by cognitive biases might lead to the popularity of DCA in practice. Therefore, this study intends to compare DCA and LSI performance to provide definite evidence for Swedish investors regarding what strategy to use.

Based on the literature review, we predict LSI to outperform DCA from the perspective of both traditional and behavioral finance. However, it may be considered likely that DCA will perform better when bringing the concept of loss-aversion into account. Further, we expect volatility to affect DCA and LSI performance, where increased volatility may benefit DCA.

4. Methodology

The purpose of this study is to compare the performance of DCA and LSI on the Swedish market. In similar studies, prior research has employed slightly different methods. Some earlier studies have used a Monte-Carlo simulation for this purpose (See, e.g., Abeysekera & Rosenbloom, 2000; Dubil, 2004; Brennan et al., 2005). The method, which makes it possible to examine different economic scenarios, has the shortcoming that it is not based on real financial market data (Dichtl & Drobetz, 2011). The shortcoming of not using real financial data is that such simulations can become unrealistic. Real historical financial data can be autocorrelated, heteroskedastic, and non-normally distributed, which may result in different outcomes and conclusions than studies done through a Monte-Carlo simulation with predetermined values. In opposite, other studies analyze through simulations on historical financial markets data (See, e.g., Israelsen, 1999; Atra & Mann, 2001; Leggio & Lien, 2001; Grable & Chatterjee, 2015). To assure that the right conditions are met for a complete replication of Leggio and Lien (2001), this study relies on historical data for its methodological approach.

The replication of Leggio and Lien (2001) is made through a scientific replication[6] method. Hamermesh (2007) distinguishes three categories of replication: Pure, statistical, and scientific replication. A pure replication is defined as redoing a prior study in the exact same method as preceding publications. A statistical replication differs as it uses the same empirical model but on a different sample from the same underlying population. A scientific replication, which this study conducts, is defined as a study with a different sample and population; however, it uses a similar but not identical statistical model. Hamermesh (2007) argues that scientific replication appears better suited towards our study’s approach of analysis and, indeed, contains most of what economists view as replication. Different from natural sciences, finance and economics are mostly observational in nature. Therefore, it is essential to evaluate the reliability of published results against equivalent, but not identical, observations (Hamermesh, 2007).

[6] A replication study with a different sample and population, which uses a similar but not identical statistical model (Hamermesh, 2007)

4.1 Data and Sample

Table 1: *Selection of Securities*	Data sample
Initial sample of stocks listed on Nasdaq OMX	368
Rejected due to lack of data	223
Final sample of stocks available	145
Stocks used after random selection	50
Market benchmark: SIXRX	1
Final sample:	**51**

Note: The table is a summary of data sampling and processing.

Empirical study data is retrieved from Refinitiv Datastream where monthly Total Return Index data for 2000-2019 are used. The risky assets considered are companies listed on Nasdaq Stockholm (Large-Cap, Mid-Cap, and Small-Cap) and the Swedish Stock Market Index SIXRX[7]. The risk-free asset considered is the Swedish 30-day Treasury bill. Previous studies differ on using the 90 or 30-day Treasury bill as a proxy (See, e.g., Abeysekera & Rosenbloom, 2000; Atra & Mann, 2001; Brennan et al., 2005). In line with previous research, we use a benchmark Index to represent the overall domestic market. The SIXRX included in our study reflects the Stockholm Stock Exchange performance adjusted for dividends and is thus considered appropriate. Further, this study retrieved data on the five-year Schiller P/E ratio from Refinitiv Datastream.

Additionally, even though being aware of the "inefficiency of a single security portfolio" (Brennan et al., 2005), we extend the analysis by conducting the study on stocks listed on Nasdaq Stockholm. As companies listed on Nasdaq Stockholm compose a majority share of Swedish listed firms (Sveriges Riksbank, 2016), Nasdaq Stockholm is considered relevant for our Swedish orientated study. Moreover, since studies in the field address volatility as an effect on the outcome of the performance between DCA vs. LSI, it becomes essential to test the strategies on segments including firms of different market capitalization, trading frequency, and various levels of volatility. Historical volatility data on the three segments over our time span shows that the average 5-year historical volatility for the respective segments is 30%, 37%, and 45%. Thus, on average, increased volatility as the market capitalization decreases. In support, Leggio and Lien (2001) argue that Small-Cap stocks are more volatile and thus interesting to analyze. Another study that

[7] One of the leading indices on the Swedish mutual fund market.

addresses the effect of equities with different levels of volatility on the performance of DCA vs. LSI is Israelsen (1999). He compares DCA vs. LSI performance on mutual funds with high, respectively, low standard deviations and finds a correlation between DCA performance and volatility. Therefore, we find it appropriate to provide more detailed and specific evidence on securities with different market characteristics on Nasdaq Stockholm. This should help investors who are interested in buying individual companies of varying market capitalization. The complete list of companies included in the final sample is presented in Table 4 in the Appendix.

According to Refinitiv Datastream, 368 firms are listed on Nasdaq Stockholm (Large-Cap, Mid-Cap, and Small-Cap). Due to limitations in time and resources, the number of companies analyzed in this study is restricted to 50. The stocks included in the research result from a random selection from a pool of available companies. Out of 368 firms, 223 companies were rejected from the sampling due to the twenty-year time span of our study. Thus, a company needs to have trading data from at least 2000-01-01 to be an acceptable equity in our sample. By excluding all stocks with a lack of data, results may suffer from survivorship bias, which could favor LSI. We, therefore, limit our conclusions to the stocks in our sample. From this pool of 145 available companies, this study limits its sample to 50 randomly selected companies. This sampling is coherent with Leggio and Lien (2001), who conduct their study on a similar sample size. In this sampling, the three segments (Large-Cap, Mid-Cap, and Small-Cap) are used to create a stratified sampling where the weighted percentages give a fair representation of total stocks from each group. Three distinguished sample sizes are determined through a weighted percentage from a total population, being Large, Mid, and Small-Cap. The stratified sampling results in the sample consisting of 17 Large-Cap, 18 Mid-Cap, and 15 Small-Cap stocks currently listed in each segment. As one should be aware of, the segments of which shares are traded are constantly dynamic. Over the 20-year period, securities in the sample have been in different classes. This could influence the results, which must be addressed. We are, however, confident that any consequences are of minor relevance. Further, we consistently choose the B-share when a company offers dual-class shares.

4.2 Evaluation of Investment Strategies

To evaluate DCA and LSI, we use performance measures applicable to both traditional and behavioral investors. Following previous research, holding period return (HPR) and Sharpe ratio will verify the intended strategies from a mean-variance perspective. On the other hand, the Sortino ratio and Value-function will test the strategies from a prospect theory standpoint. The HPR on each security and investment strategy is calculated and then applied to the Sharpe ratio, Sortino ratio, and Value function. As we compare DCA and LSI on four horizons (6, 12, 24, 36 months), there are 234 measuring periods for DCA_6, 229 for DCA_{12}, 217 for DCA_{24}, and 205 for DCA_{36}. Further, this study calculates the standard deviation for the returns on each security for the strategies on all horizons. There is no consideration for inflation or excess returns. All measured returns are nominal. The following sub-heading 4.2.1 introduces essential information regarding the performance measures applied to evaluate DCA and LSI.

4.2.1 Performance Measures

The risk-free rate is applied when calculating the Sharpe and Sortino ratios on all returns in our sample. Leggio and Lien (2001), among other previous studies, use the Sharpe ratio as their risk-adjusted performance measure:

$$Sharpe\ Ratio$$
$$\frac{(Rp - Rf)}{\sigma p} \quad [1]$$

Where:
Rp = holding period return;
Rf = risk-free rate;
σp = standard deviation of holding period return;

Although introduced decades ago, the Sharpe ratio (Sharpe, 1966; Sharpe, 1994; Miller & Modigliani, 1997) is still one of the most used investment measures of performance and used to help investors measure the return of an investment compared to its risk.

However, as standard deviation is a two-sided measure, any deviation from the mean regardless of direction is not differentiated by the Sharpe ratio. Therefore, it does not comply with the notion of risk perceived by individuals according to the prospect theory (Leggio & Lien, 2003). The loss-averse investor adopted in Prospect theory became a starting point for questioning the traditional way of measuring risk as Sortino and Price (1994) noted downside deviation as an alternative method. Unlike standard deviation, downside deviation only accounts for negative price fluctuations and is, according to Sortino and Price (1994), defined as:

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Min(0, x_i - T)\right)^2}$$

[2]

Where:
N= total number of returns
x_i= i^{th} return
T= target return
Min= function picking the minimum value of 0 and x_i-T

Sortino and price (1994) argue that positive outcomes should not be associated with risk; instead, it should be viewed as a premium/reward. Thus, as investors do not see a sharp upside in share price as necessarily bad, it should not be penalized in the formula when calculating risk. One can relate the relevance of downside deviation to the prospect theory of Kahneman and Tversky (1979) and individuals' loss-averse consciousness weighing losses more than gains. Chen (2016), therefore, argues that downside deviation better fits financial markets where investors behave irrationally. In support, Markowitz (1991) noted that downside risk is a more appropriate measure of risk than volatility. Markowitz (1991) mainly mentions two reasons why: First, only downside risk is relevant to individual investors, and secondly, returns may not be normally distributed. In support, Rollinger and Hoffman (2013) argue that the "one-sided" risk gives a more accurate result, especially if returns are skewly distributed. When volatility is measured, returns are assumed to be normally distributed. However, such assumptions may not always hold. Results could, therefore, become misleading if volatility caused by positive returns is being included in the risk. Downside risk, therefore, captures this potential asymmetric distribution by only measuring the negative deviations (Rollinger & Hoffman, 2013). The Sortino ratio, which only factors in downside deviation, can thus be seen as a complement or substitute to the Sharpe ratio when analyzing investment performance. Therefore, this study uses the Sortino ratio as an additional risk-adjusted performance measure:

$$Sortino\ Ratio$$
$$\frac{(Rp - Rf)}{\sigma p}$$
[3]

Where:
Rp = holding period return;
Rf = risk-free rate;
σp = standard deviation of negative asset return;

Moreover, in line with the framework of prospect theory, this study adds the Value function to measure performance from the perspective of behavioral investors. According to Kahneman and Tversky (1979), the goal of a behavioral investor is to pick a strategy that maximizes the value function rather than one that satisfies the traditional mean-variance model. The function is, therefore, essential when making an appropriate evaluation of DCA vs. LSI for behavioral investors. The S-shaped value function captures the notion that people react differently between gains and losses by being convex in the domain of losses and concave in the domain of gains. Further, as investor response is more extreme to a loss than a gain, the Value function is steeper for losses than gains. Thus, the formula accounts for the way people perceive risk according to behavioral finance theory, and therefore appropriate for evaluating DCA vs. LSI from such standpoint. The function is by far the most popular approach used for estimating money value (Dichtl & Drobetz, 2011), and is further used in previous research when investigating DCA vs. LSI performance (See, e.g., Leggio & Lien, 2001; Dichtl & Drobetz, 2011). Therefore, this study applies the following two-part valuation function by Kahneman & Tversky (1979):

$$Value\ function$$
[4]
$$V(x) = X_{\alpha}\ ,\ if\ X \geq 0$$
$$V(x) = -\lambda(-X)_{\alpha}\ , if\ X < 0$$

Where:
X = holding period return
α (risk aversion) ≈ 0.88;
λ (loss aversion) ≈ 2.25;

The parameter λ captures the elaborated shortsighted loss aversion and assumes that investors consider losses more than twice as important as gains. To ensure an adequate replication is conducted, we follow Leggio and Lien (2001) by applying the same value for α (0.88) and λ (2.25), which are parameter estimates for a median decision-maker.

4.3 Application of Investment Strategies

To assess the relative merits of DCA and LSI, simulations covering the years 2000-2019 are run for the purchases of the securities in our sample. The following sections discuss the important choices associated with the application of comparing DCA and LSI. The next heading starts by acknowledging the assumptions made, followed by a discussion of time span and installment periodicity. At last, essential steps of the application method are presented.

For the purpose of this study, investors are presumed to have received a large sum of money and chosen an asset of interest in which to invest; in this case, all securities in our sample. Further, this study follows previous studies by assuming that the investor is not interested in implementing any tactical or strategic framework (see, e.g., Grable & Chatterjee, 2015). Thus, the investor seeks to invest money for a long-term goal, such as pension. Further, we assume that the residual not yet invested for the DCA strategies are kept on a savings account with zero interest rate, consistent with the current Swedish bank situation for small private investors. However, given the time frame of our study, as interest rates historically have been higher than currently, this may underestimate the returns of DCA and thus favor the LSI strategy for the earlier periods.

4.3.2 Time span

This study considers Total Return Index quotations from January 2000 through December 2019, i.e., twenty years. By doing so, we examine whether recent actual performances in the market support the still popular suggestion to use DCA. We follow Grable and Chatterjee (2015) by starting our study in 2000. This also marks the beginning of the Dot-Com crash. Further, by conducting our study over 20 years, this study ensures economic cycles featuring downturns, economic booms, and recessions are all included.

4.3.3 Installment periodicity

The installment periodicity differs in previous research. Some studies only consider one installment period while others conduct their analyses on multiple horizons (See, e.g., Williams & Bacon 1993; Knight & Mandell,1993; Marshall, 2000; Leggio & Lien, 2001). Longer installment periods are likely to favor an LSI strategy due to the positive equity risk premium and must be discussed (Samuelson, 1994). Existing studies do not however express a consensus for an appropriate installment period, but most previous research uses a one-year period (see, e.g., Williams & Bacon 1993; Leggio & Lien, 2001). This study follows Leggio and Lien (2001) by applying a 12-month installment period. To extend our analysis, this study adds installment periods of 6, 24, and 36 months.

Further, most literature assumes that shares are purchased monthly. Exceptions can be found in Williams and Bacon (1993) and Marshall (2000), who consider quarterly and bi-yearly installments. However, due to the superiority of monthly investment intervals in prior research, this study employs the same standard, assuming that shares are purchased on the 1st of each month (See, e.g., Leggio & Lien, 2001; Brennan, 2005; Luskin, 2017).

4.3.4 Application

This study assumes investors to have a fixed initial wealth available to invest at time zero (T=0). Since all results are expressed in percentages, the invested amount does not have any impact. With LSI, the entire fixed sum is invested in a risky asset and held for the same length as the corresponding DCA installment period (6, 12, 24, 36 months). With a DCA_6 strategy, the investor chooses to invest ⅙ of the initial wealth at T0, and the remaining ⅚ is set aside in cash until the next month where an additional ⅙ is invested. Each month, an additional ⅙ of the investor's wealth is transferred into the market until being fully invested at T=6. Similarly, the DCA_{12} investor would invest $^1/_{12}$ every month until being fully invested in the risky asset at T=12. To make a fair assessment of LSI against different DCA installment periodicities, this study looks at the total return difference over the multiple horizons. Thus, if a DCA strategy results in an HPR of 8% over six months while LSI generating a 10% HPR over the same time, we report the 2% difference. We then apply this structure across all 6, 12, 24, 36-month periods. As this study considers quotations from 2000, the first investments for all strategies are made on January 1st, 2000, and subsequently compared with each other on July 1st, 2000, January 1st, 2001, 2002, and 2003 depending on installment periodicity. Since anomalous situations exist in monthly returns (i.e., the January effect) and superiority in strategy seem dependent on when it is implemented (Atra & Mann, 2001), returns are also calculated for periods beginning in February, March, etc. followed by new investments every month until the last possible investment period.

5. Results

5.1 LSI vs. DCA - Relative Performance in HPR and Sharpe Ratio

Table 2: *LSI Outperformance*

Averages	HPR (%)				Sharpe (%)			
	LSI_6>DCA_6	LSI_{12}>DCA_{12}	LSI_{24}>DCA_{24}	LSI_{36}>DCA_{36}	LSI_6>DCA_6	LSI_{12}>DCA_{12}	LSI_{24}>DCA_{24}	LSI_{36}>DCA_{36}
SIXRX	65	68	70	72	56	58	64	61
Large-Cap	68	72	77	76	66	67	71	68
Mid-Cap	67	69	70	73	67	67	69	67
Small-Cap	56	56	50	51	58	58	65	65

Notes: Table 2 illustrates the percentage of times where LSI generates a higher HPR and Sharpe ratio over DCA for the various installment periods. These are presented for each respective segment, where the average is the summarized mean for all the individual securities within each segment. Values above 50 indicate that LSI, on average, outperforms DCA while values below 50 indicate that DCA outperforms LSI. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205. The time-period studied is 2000-2019.

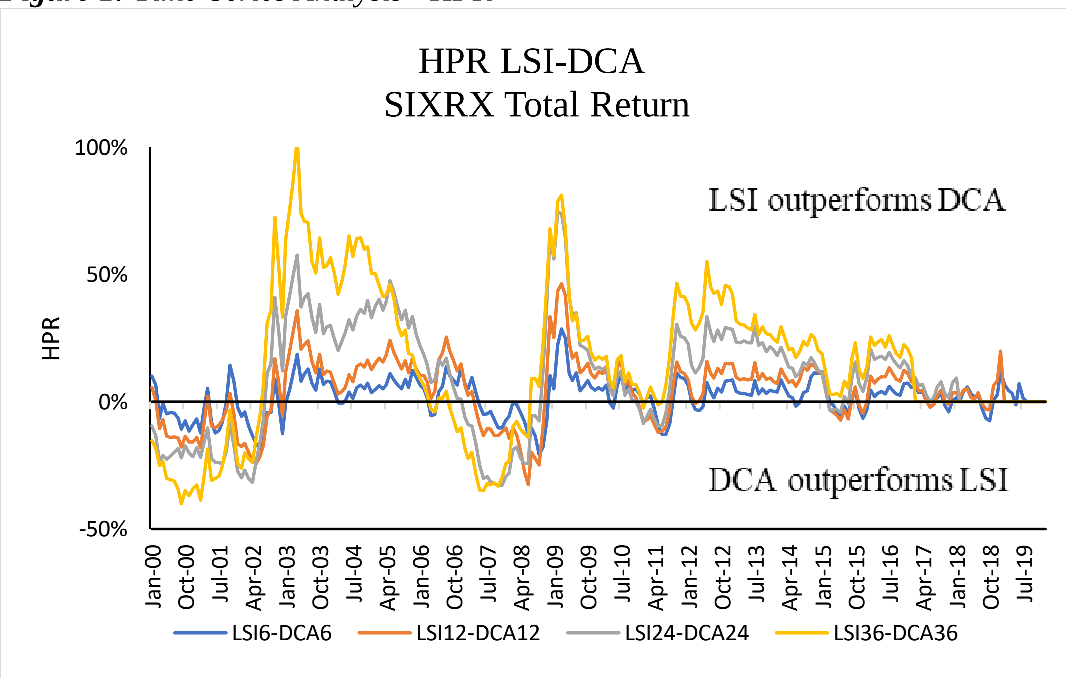
Table 2 demonstrates that LSI, on average, outperforms DCA in both HPR and Sharpe ratio over all installment periodicities and segments analyzed over the period 2000-2019. For the SIXRX, LSI_{36} generates the highest outperformance percentage in HPR on average, while LSI_6 generates the lowest. Historically, the Swedish equity markets have experienced more extended bull periods than bear. Hence, these empirics presented conform to previous research and what can be expected. When taking risk into account, Sharpe ratios indicate that LSI, on average, outperforms DCA in risk-adjusted returns on all installment periodicities and segments. Moreover, Table 2 indicates that the performance of LSI increases with installment periodicity as longer periods generate higher outperformance percentages for both HPR's and Sharpe ratios.

In sum, these results may imply that LSI, on average, is a better investment strategy on the Swedish Market. The Sharpe ratio outperformance rate in Table 2 indicates that LSI is a preferable strategy for mean-variance investors. The outperformance rate is especially evident for longer installment periodicities on Large-Cap and Mid-Cap. The results from Small-Cap securities, which are volatile (Leggio & Lien, 2001), may indicate that volatility plays a role where increased volatility could correlate with DCA performance. For instance, Table 2 shows that for riskier assets, such as Small-Cap stocks, DCA performance appears to increase.

The results are coherent with Merlone and Pilotto (2015), who present similar tables for Italian stocks and mutual funds over a ten-year time-period from 2003-2012. In their study, LSI outperforms DCA 64% of the time for funds and 47% of the time for stocks in HPR. Hence, there is a similarity where LSI appears to outperform on both the Italian and Swedish markets. However, our results indicate a higher outperformance percent for stocks than Merlone and Pilotto (2015). This could be explained by the higher performance of the Swedish stocks, comparing the Swedish and Italian stock samples.

5.2 Performance Comparison over Time

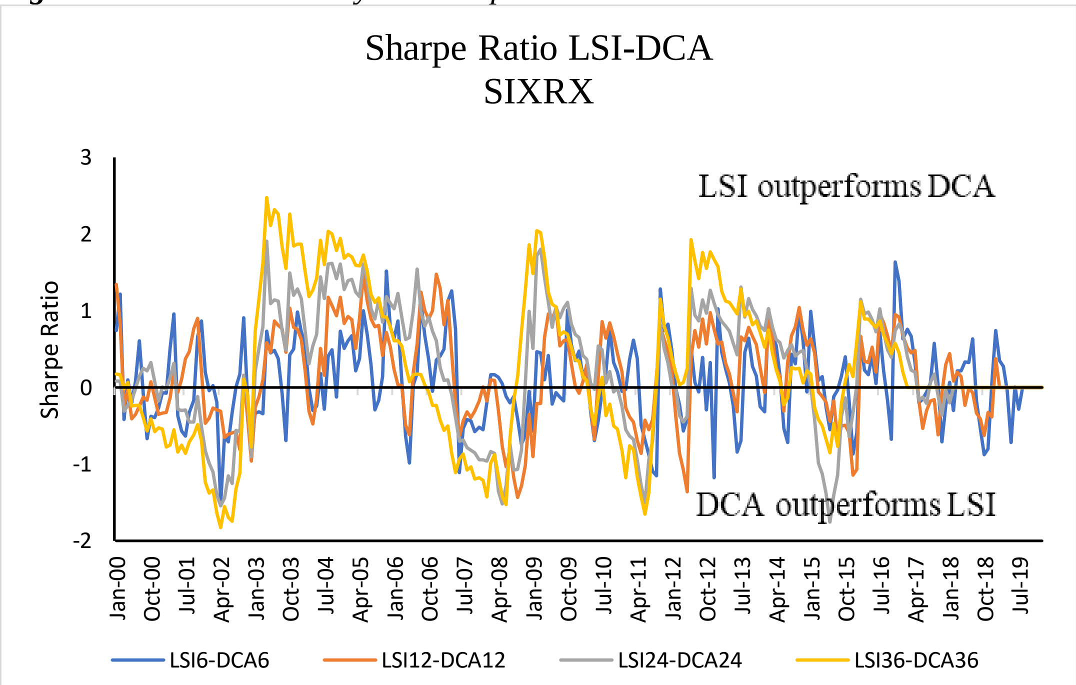
Figure 1: *Time-Series Analysis - HPR*



Notes: Figure 1 illustrates the difference in HPR between LSI and DCA on the various installment periods over the time-period 2000-2019 invested into SIXRX. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205.

Figure 1 illustrates the relative performance of DCA vs. LSI in HPR over the twenty-year period studied. Positive values indicate that LSI generates a higher HPR while negative values indicate that DCA generates a higher HPR. In line with Table 2, Figure 1 shows that LSI, on average, generates a higher HPR than DCA for all installment periodicities. Moreover, the longer the installment periodicity, the greater the difference in HPR. The only periods where DCA substantially outperforms LSI can be found during 2000-2003, and 2007-2008, which coincide with macroeconomic events such as the IT-bubble and the Great Recession of 2007-2008. This is expected because when DCA buys into a declining market, it gets a lower average price than LSI. Additional figures illustrating separate HPR's for the different installment periods are presented in the Appendix.

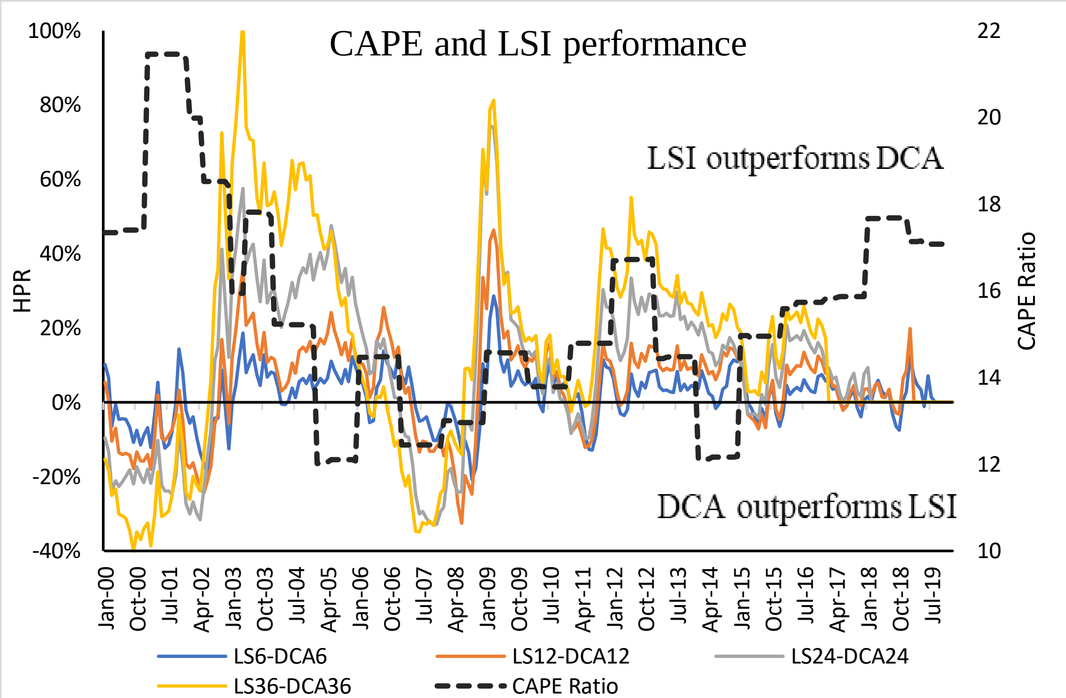
Figure 2: *Time-Series Analysis - Sharpe Ratio*



Note: Figure 2 illustrates the difference in Holding Sharpe Ratio calculated as in equation [1] between LSI and DCA on the various installment periods over the time-period 2000-2019 invested in SIXRX. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205.

Figure 2 illustrates the relative performance of DCA vs. LSI in risk-adjusted returns over the twenty-year period studied. Positive values indicate that LSI generates a higher Sharpe ratio while negative values indicate that DCA produces a higher Sharpe ratio. Compared with Figure 1, we find longer and more frequent periods in Figure 2, where DCA outperforms LSI, which is in line with results from Table 2. However, similar to Figure 1, the longer the installment periodicity, the greater the difference between LSI and DCA performance. This may indicate that the length of installment periodicity matters for investors. Similar to Figure 1, DCA_{36} seems to work well in turbulent markets. For example, during 2000-2003 DCA substantially outperforms LSI_{36}. On the contrary, we note the same difference when the market is trending upwards. Furthermore, figures illustrating the difference in Sortino ratio and Value function performance for the strategies on SIXRX can be found in the Appendix.

Figure 3: *Time-Series Analysis - CAPE Ratio*



Note: Figure 3 illustrates the correlation between the difference in HPR between LSI and DCA on the various installment periods over the time-period 2000-2019 invested into SIXRX with the Schiller price-to-earnings (CAPE) ratio. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months - 217; 36 months -205.

Moreover, this study analyzes the correlation between DCA and LSI performance with the Shiller price-to-earnings (CAPE) ratio on the Swedish market over the timespan studied. Including this market valuation adds another perspective by analyzing whether there is a common underlying factor that may influence the relative performance of DCA and LSI (Luskin, 2017). Further, providing evidence for investors on how to potentially recognize and capitalize on market conditions when deciding on what strategy to use. However, even though the CAPE ratio adjusts for inflation (i.e., it is normalized), one should be careful with the ratio and how it fluctuates over time. Since accounting standards, corporate taxations, and techniques for measuring inflation are frequently being reshaped, so does the denominator of the P/E-ratio. Conclusions should, therefore, be taken with caution (Wilcox, 2011).

Figure 3 indicates that there is a smaller correlation existing between the starting CAPE ratio and strategy performance. When the CAPE ratio exhibits higher values, such as during 2000-2002, Figure 3 indicates that DCA outperforms LSI. Further, during lower market valuations, such as

2005, LSI outperformance increases. However, in contrast to Luskin (2017), who finds a positive correlation of 0.43 between DCA outperformance and the starting CAPE ratio on the American market, we report a weaker correlation of 0.21. Therefore, this study does not argue that market valuations can be a determinant factor in implementing DCA or LSI. Moreover, evidence suggests that the likelihood of DCA outperformance being a function of the starting CAPE ratio is higher on the American than the Swedish market. Taken together, it appears that only during times with extreme CAPE ratio environments, investors could potentially use the ratio as a factor for when to implement DCA or LSI.

5.3 Results Tested for Significance

Table 3 reports the results for the full sample tested for significance. The reported results are presented as the differences in performance between the strategies for the different installment periodicities. Thus, Table 3 presents the difference in mean HPR's, Sharpe ratios, Sortino ratios, and Value functions for LSI_6-DCA_6, LSI_{12}-DCA_{12}, LSI_{24}-DCA_{24}, LSI_{36}-DCA_{36} on SIXRX, Large, Mid, and Small-Cap. Additionally, Table 3 presents the number of observations and the individual mean HPR's for both LSI and DCA.

Regardless of segment and horizon considered, LSI generates the highest mean HPR's. The differences are statistically significant at a 1% level over all segments and horizons except for LSI_6-DCA_6 on Small-Cap stocks, having a significance level of 5%. Moreover, Table 3 indicates that an LSI strategy, on average, results in a 1.87% higher HPR than a DCA strategy for a 6-month installment periodicity on the SIXRX, respectively 4.33%, 10.13%, and 16.73% for a 12, 24, and 36-month window. It is no surprise that DCA generates a lower mean HPR than LSI for all installment periodicities and segments since a DCA strategy forces the investor to hold money outside the capital market, not earning excess returns. These results align with previous studies and are consistent with the positive risk premium of being in the market (See, e.g., Rozeff, 1994; Leggio & Lien, 2001; Brennan, 2005). Further, as LSI requires the investor to invest all the initial wealth at one point in time, there is also no surprise that the variability of those HPR's, measured by standard deviation, are the highest compared with DCA over all segments. These results are found coherent with Leggio and Lien’s (2001) results.

The results in Table 3 show that LSI generates higher Sharpe Ratios over all segments, where the difference is statistically significant at a 1% level for all horizons and segments except for LSI_6-DCA_6 on Small-Cap stocks, having a significance level of 5%. Therefore, in line with previous research, this study argues that LSI should be the preferred investing strategy for mean-variance investors (See, e.g., Constantinides, 1979; Knight & Mandell, 1993; Williams & Bacon, 1993; Abeysekera & Rosenbloom, 2000). The LSI strategy primarily benefits investors on SIXRX, Large-Cap, and Mid-Cap, while on the other hand, having less superiority on Swedish Small-Cap stocks. Even though LSI generates higher HPR's and Sharpe ratios over DCA for Small-Cap stocks, there are lower significances in those results. These results can be compared with Leggio and Lien (2001), who find LSI to generate significantly higher Sharpe-ratios on Small-Cap stocks than DCA.

Table 3*: Summary of Performance Tested for Significance*

Strategy:	N	Mean HPR	HPR	Std Dev	Sharpe	Sortino	Value Function
SIXRX							
LSI_6-DCA_6	235	(4.31 vs. 2.44)	1.87**	4.14	0.09**	0.13**	-0.11
LSI_{12}-DCA_{12}	229	(9.34 vs. 5.01)	4.32**	6.62	0.16**	0.18**	1.04
LSI_{24}-DCA_{24}	217	(21.75 vs. 11.62)	10.13**	10.11	0.26**	0.24**	6.59**
LSI_{36}-DCA_{36}	205	(36.34 vs. 19.61)	16.73**	13.10	0.28**	0.28**	12.24**
Large-Cap							
LSI_6-DCA_6	235	(7.37 vs. 4.25)	3.12**	6.72	0.12**	0.15**	0.93
LSI_{12}-DCA_{12}	229	(16.10 vs. 8.55)	7.55**	10.61	0.16**	0.23**	4.29**
LSI_{24}-DCA_{24}	217	(35.87 vs. 18.19)	17.68**	15.97	0.25**	0.41**	13.43**
LSI_{36}-DCA_{36}	205	(58.51 vs. 29.32)	29.19**	22.17	0.32**	0.53**	23.35**
Mid-Cap							
LSI_6-DCA_6	235	(10.18 vs. 5.58)	4.60**	9.73	0.09**	0.17**	0.64
LSI_{12}-DCA_{12}	229	(23.17 vs. 11.79)	11.38**	15.69	0.14**	0.20**	5.09**
LSI_{24}-DCA_{24}	217	(51.62 vs. 26.52)	25.10**	23.71	0.22**	0.33**	15.01**
LSI_{36}-DCA_{36}	205	(93.01 vs. 43.87)	49.14**	30.37	0.34**	0.41**	31.43**
Small-Cap							
LSI_6-DCA_6	235	(3.52 vs. 1.94)	1.58*	11.27	0.03*	0.06	-4.64**
LSI_{12}-DCA_{12}	229	(6.97 vs. 3.96)	3.01**	18.66	0.07**	0.07	-6.15**
LSI_{24}-DCA_{24}	217	(13.54 vs. 8.56)	4.98**	27.81	0.10**	-0,01	-7.13**
LSI_{36}-DCA_{36}	205	(23.75 vs. 14.34)	9.41**	34.75	0.14**	-0.06	-6.05**

Notes: The Table presents individual mean HPR, mean difference in HPR, Standard Deviation, Sharpe ratio, Sortino ratio and Value functions on the SIXRX, Large-Cap, Mid-Cap, and Small-Cap for installment periodicities of 6,12,24, and 36 months. The time-period studied is 2000-2019. N is the number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205.
$^{*}p<0,05$ Test Statistic of a paired t-test
$^{**}p<0,01$ Test Statistic of a paired t-test
Standard Deviation values derived from mean returns are not tested for statistical significance.

To evaluate if the inefficiency of DCA disappears when taking loss-aversion into account, the Sortino ratio and Value function is computed. Table 3 indicates that investors subject to behavioral biases maximize value with LSI rather than DCA on all segments except Small-Cap. As discussed earlier, DCA performance decreases with the length of installment periods. Prior research finds DCA performance to decrease with longer periods due to increasing installments periodicities holding more money outside the capital market. This pattern is confirmed when observing the results from Table 3 for the Sortino ratio and Value function. Table 3 illustrates that the superiority of LSI is greater for longer installment periodicities on the SIXRX, Large-Cap, and Mid-Cap, where both the Sortino ratio and Value function are significantly higher for LSI. Additionally, DCA_6 is the only window that, on average, generates a higher value function than LSI on the SIXRX. Therefore, investors should prefer a shorter installment period over longer ones if insisting on following financial advisors' advice of phasing capital to the equity market. This is in line with Bisceglia and Zola (2018), who also find shorter installments being favorable.

Moreover, Table 3 indicates that DCA performance is superior for behavioral investors on Small-Cap stocks as DCA generates a higher Value function over LSI, statistically significant at 1%. Interestingly, however, is that all strategies generate a negative Value function for Small-Cap stocks on average. This could be explained by Small-Cap being considered the riskiest segment in our sample and further experiencing more negative returns than the other segments during the period studied. The results differ from Leggio and Lien (2001), as they find DCA being the only strategy generating a negative Value function, while LSI being significantly superior and generating positive values on Small-Cap. The difference between our results is likely to be explained by the lower performance of the Small-Cap stocks in our sample compared with the sample of Leggio and Lien (2001). Therefore, as the asymmetric Value function captures these low and partial negative annual returns, this should explain our studies' different results. However, the overall negative Value functions on Small-Cap may indicate that choice of strategy could be of lower importance for loss-averse investors. Instead, one may argue that loss-averse investors should avoid buying individual securities listed on Small-Cap. The overall reduced superiority of LSI on Small-Cap compared to the other segments is likely a result of the high volatility of Small-Cap stocks and the overall negative trend in Total Return Index over time for some of the Small-Cap stocks in our sample.

Considering all factors, results from Table 3 conform with Leggio and Lien (2001), who find that DCA can be penalizing for investors seeking upside potential. This is due to DCA delaying the transfer from cash into stocks, resulting in lower HPR's and Sharpe ratios for DCA. For financial advisors, our results may question the value of DCA as an efficient investment strategy for entering the Swedish stock market. The proposed advantage of DCA reducing the risk of an entire portfolio being purchased at market highs does not, based on the results, seem as valid as suggested by its advocates. Thus, the fear of buying in at a market high may do more harm than good.

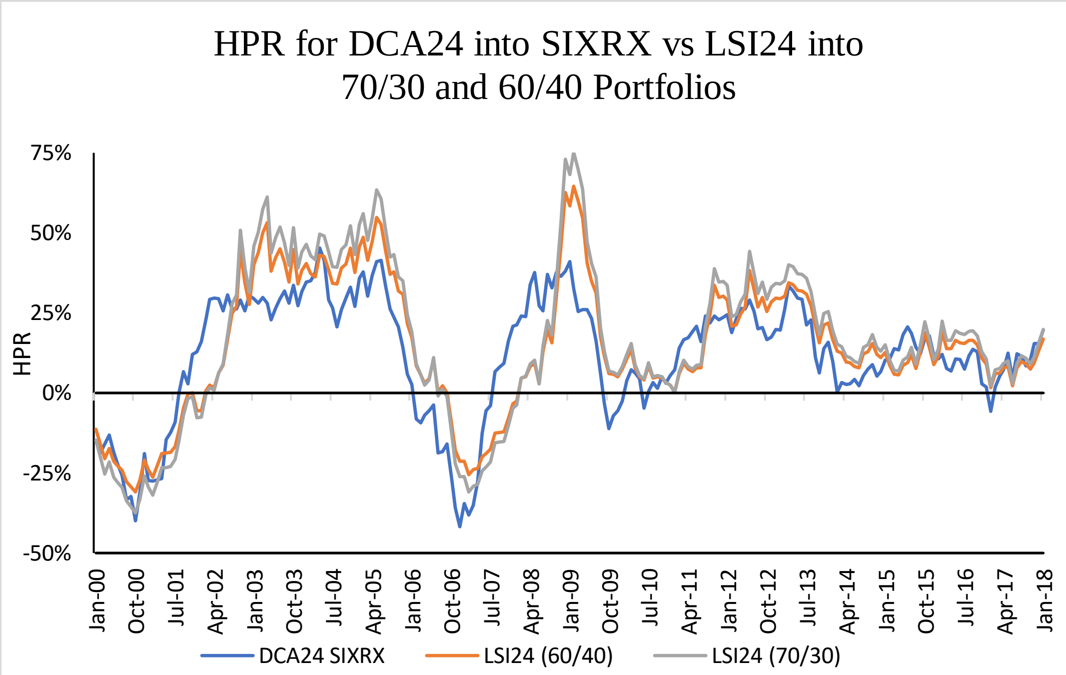
Moreover, as LSI generates the highest Value functions and Sortino ratios on most segments and installment periodicities, our results indicate that loss-aversion does not justify the popularity of DCA. In contrast to Dichtl & Drobetz (2011), we, therefore, argue that LSI remains as the attractive strategy for loss-averse investors due to generating higher cumulative prospect values than DCA. Thus, our results indicate LSI being the superior strategy for loss-averse investors on the Swedish market. We argue that LSI should be considered at least an equally legitimized strategy for loss-averse investors entering the Swedish market. This is comparable with the findings of Leggio and Lien (2001) and Frühwirth and Mikula (2014), who contradict Statman's (1995) claim of DCA being an appropriate strategy for loss-averse investors.

5.4 Performance on Mixed Asset Portfolios

Since most investors choose to invest in a portfolio of mixed assets instead of investing all their wealth in a single asset, this study extends the analysis by creating two portfolios with allocation into the SIXRX and Swedish Government bonds. As discussed above, our results indicate that LSI, on average, outperforms DCA when investing in the same securities. By running simulations on the two portfolios, we compare using an LSI strategy when investing in a lower risk portfolio with averaging-in into a riskier. Thus, analyzing how conservatively one can invest through an LSI strategy and still outperform DCA.

Figure 4 presents an LSI strategy's performance into a more conservative (70/30) and (60/40) stock/bond portfolio compared with a DCA strategy into the SIXRX using rolling 24-month installment periodicities. We do not claim that either of the two portfolios presented contains the optimal mix of assets and are further aware that other allocation levels could have been used. However, we are confident that the two portfolios are appropriate for the purpose of this analysis.

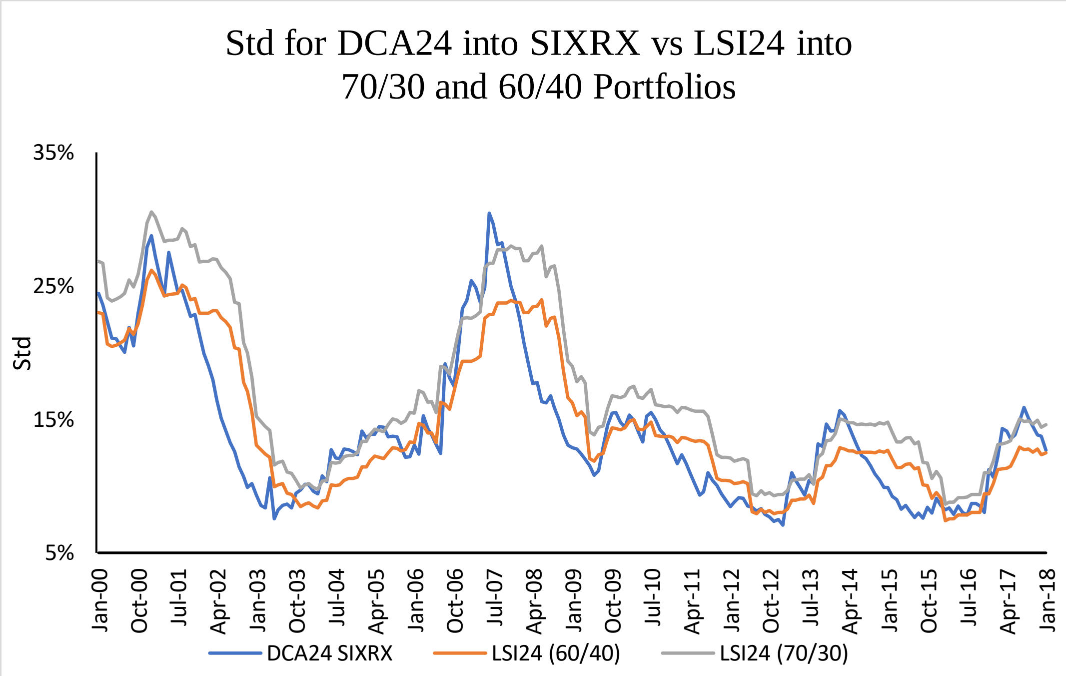
Figure 4: *Time-Series Analysis - HPR*



Notes: Figure 4 illustrates HPR for a DCA_{24} strategy into the SIXRX, compared with an LSI_{24} strategy invested in a 70/30 and 60/40 stock/bond portfolio over the time-period 2000-2018. The portfolios consist of the SIXRX and Swedish Government bonds. The number of observations are 217.

Figure 4 indicates that a DCA_{24} strategy into the Swedish stock market in most cases generates a lower HPR than an initial investment into a 70/30 or 60/40 Swedish stock/bond portfolio over the time-period studied. On average, DCA_{24} generates an HPR of 11.62%, while LSI_{24} (60/40) generates a 14.26% HPR and LSI_{24} (70/30) 16.13%. Thus, results indicate that investors are better off using LSI into a more conservative portfolio if aiming to maximize HPR.

Figure 5: *Time-Series Analysis – Standard Deviation*



Notes: Figure 5 illustrates Standard Deviation for a DCA_{24} strategy into the SIXRX, compared with an LSI_{24} strategy invested in a 70/30 and 60/40 stock/bond portfolio over the time-period 2000-2018. The portfolios consist of the SIXRX and Swedish Government bonds. The number of observations are 217.

Moreover, Figure 5 shows that the risk of an initial investment in the (70/30) and (60/40) portfolios is similar to averaging into the SIXRX. On average, the DCA_{24} strategy has a standard deviation of 14.21%, compared to a standard deviation of 14.56% and 17.01% for LSI_{24} into the (60/40), respectively (70/30) portfolio. These results imply that Swedish investors, on average, are better off investing a lump-sum of money into a more conservative portfolio than using a DCA_{24} strategy for investments into the SIXRX since the risk-adjusted returns are higher for the portfolios. For investors interested in having 100% allocation in the SIXRX but fear the timing of buying in at market high, results suggest investors could put all the capital to work right away through a conservative portfolio, and further over time, shift allocation from bonds to stocks to reach 100% allocation in the SIXRX. However, due to the current nature with low risk-free rates, such a strategy may yield lower risk-adjusted returns today than during the period studied.

Through the result discussed in section five, this study intends to open a discussion for Swedish investors not to forfeit LSI as a possible strategy. Results show clear evidence for LSI being a strategy worth implementing based on risk-adjusted returns for both traditional and behavioral investors.

6. Conclusion

This study aims to compare the performance of DCA and LSI on the Swedish market by simulating security purchases covering a twenty-year period. While profound investors widely advocate DCA, it receives less praise from the academic world. Building on traditional and behavioral finance, this study implements several performance measures to acknowledge the different risk appetites between investors. The results presented earlier indicate that there are no sufficient arguments for using DCA over LSI, independent of theoretical approach. Regardless of horizon and segment considered, this study finds LSI being a superior strategy on most performance measures. Consequently, LSI generates a higher HPR, Sharpe ratio, Sortino ratio, and Value function. However, if choosing between DCA horizons, shorter periods should be preferred. The results are consistent with previous research and Leggio and Lien (2001) findings, which this thesis replicates. Thus, one can argue that this study is an adequate replication of Leggio and Lien (2001). Although almost 20 years separate the studies, both find evidence for LSI being a better investment strategy to implement. However, Leggio and Lien (2001) conclude that DCA is suboptimal for Small-Cap stocks. In contrast, we find DCA to be the optimal strategy for behavioral investors due to lower performance for LSI on Small-Cap. Thus, there is not sufficient evidence to support the statement by Leggio and Lien (2001). The causality of the relationship between volatility and DCA performance is determined where DCA performs better on stocks with higher volatility. Additionally, results indicate a weak correlation between DCA outperformance and market valuation. Further, for investors aiming to reduce purchase risk, we recommend using LSI into conservative portfolios.

Based on the discussed findings, this study succeeds in supporting the existence of LSI as an efficient investment strategy for both mean-variance and loss-averse investors. Thus, we support our hypothesis of LSI yielding overall better performance than DCA. The results provide additional evidence of why LSI should be acknowledged more in the practical world. Further, this study argues that DCA could be a potential financial heuristic where using DCA as a strategy for entering the market has become a rule of thumb taken for granted. Thus, we believe that our results can help Swedish investors make more conscious decisions on market strategies.

6.1 Limitations and Suggestion for Future Research

This study does not take transaction costs into account, which reasonably can be assumed to vary inversely with the size and directly with the investment frequency (Knight & Mandell, 1993). Thus, incorporating such costs into the model may further strengthen the support of LSI (Knight & Mandell, 1993; Bajtelsmith, 2006). Further, as we assume that the residual amount not yet invested was kept on a savings account with no interest, this has reduced the HPR's for the DCA strategies. Furthermore, as equity segments are dynamic, firms with rapid growth may be a Large-Cap equity at the end of the testing period while qualifying in the Small and Mid-segments earlier on. This could potentially influence the comparison between equity segments. Further, our sample suffers from survivorship bias, which may benefit LSI. Additionally, if other securities had been randomly chosen, results may have differed. Thus, we limit our conclusions to the securities observed in our sample. Furthermore, other investment strategies exist than LSI, such as the 50:50 buy and hold strategy and value average strategy, which could have been used (See, e.g., Knight & Mandell, 1993; Brennan et al., 2005; Dichtl & Drobetz, 2014). Further, by adding multiple values to the Value function, rather than just applying the ones from Leggio & Lien (2001), one could analyze the effect of different risk and loss-aversion levels. Finally, our research could be further extended by looking into a broader set of stocks on the Swedish market. Even though being confident that these are minor issues, suggestions for further research are therefore to acknowledge these limitations.

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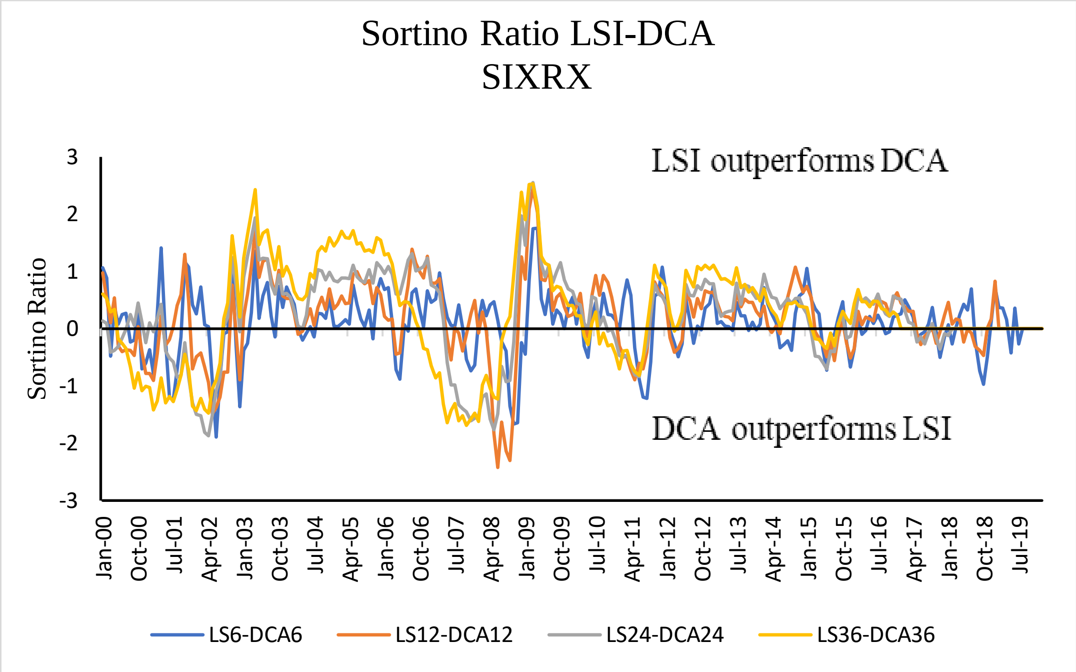
Appendix

Table 4: List of companies included in the final sample

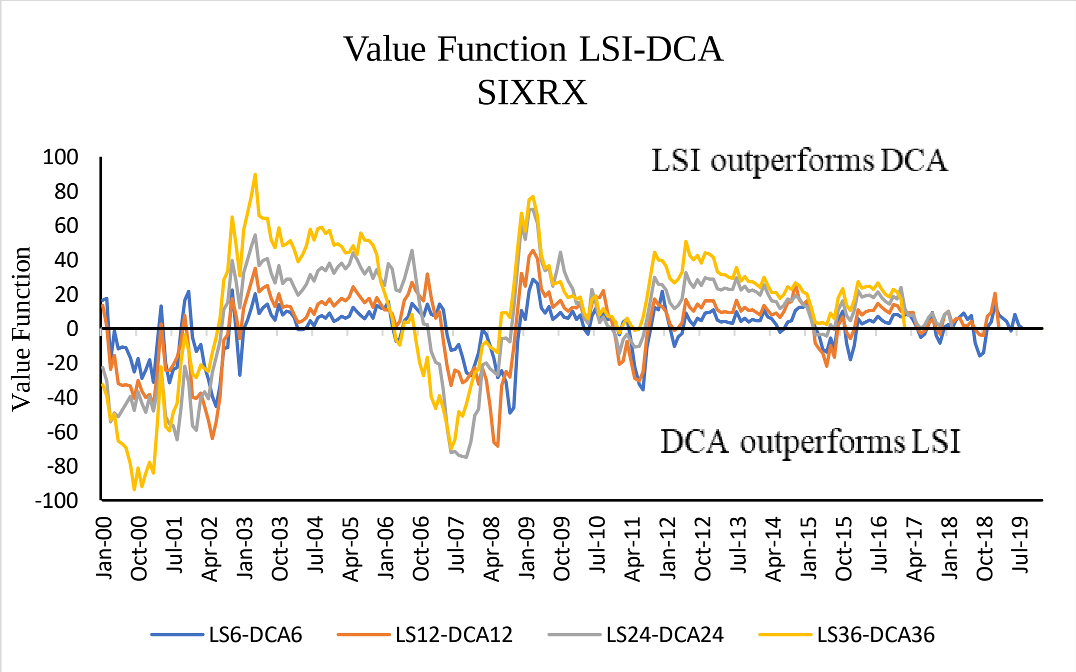
Company Name
Large-Cap
Atlas Copco B
AF Poyry B
ASSA Abloy B
Ericsson B
Investor B
Holmen B
Kinnevik B
NCC B
Sagax
SCA B
Svenska Handelsbanken
Skanska B
Swedish Match
Securitas B
Hennes & Mauritz B
SKF B
Mid-Cap
Beijer Alma B
Biogaia B
Bure Equity
Catella B
Clas Ohlson B
Enea
Fingerprint Cards B
Midsona B
New Wave Group B
OEM International B
Probi
Raysearch B
SAS
Sectra B
Skistar B
Traction B
VBG Group B
Vitec Software Group B
Small-Cap
Bergs Timber B
Concordia Marititme B
CTT Systems
Duroc B
ICTA
Lammhults Design Group B
Net Insight B
Novotek B
Poolia B
Precise Biometrics
Prevas B
Softronic
Empir Group B
Venue RetailGroup B
Viking Supply Ships B

Figure 6: *Time-Series Analysis – Sortino Ratio*



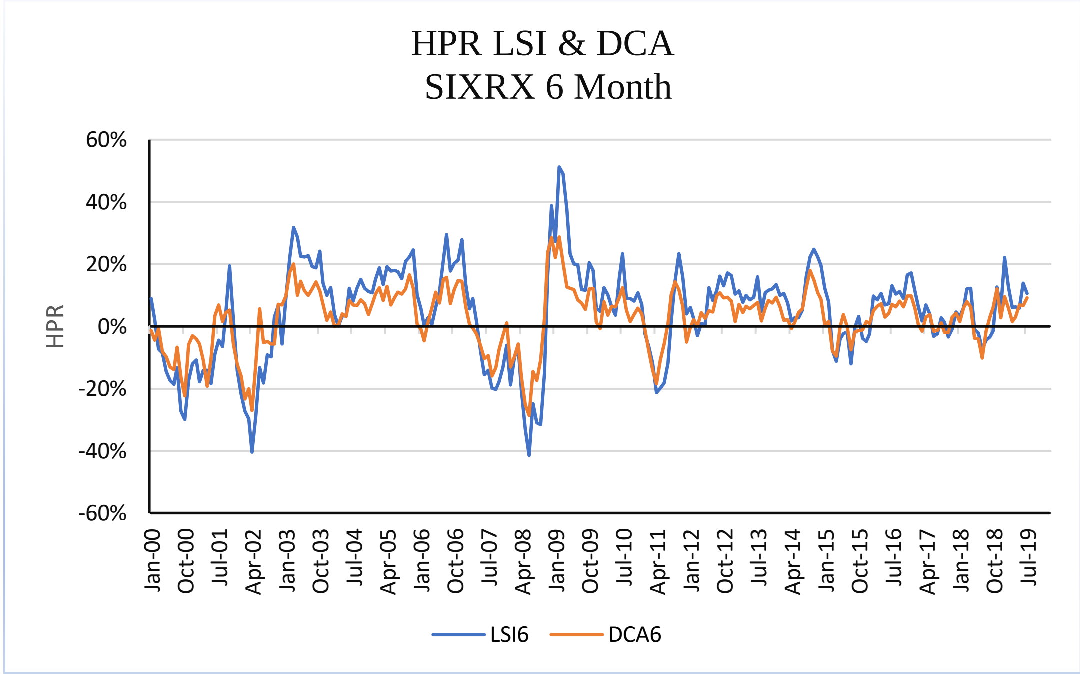
Note: Figure 6 illustrates the difference in Sortino Ratio calculated as in equation [3] between LSI and DCA on the various installment periods over the time-period 2000-2019 invested in SIXRX. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205.

Figure 7: *Time-Series Analysis – Value Function*



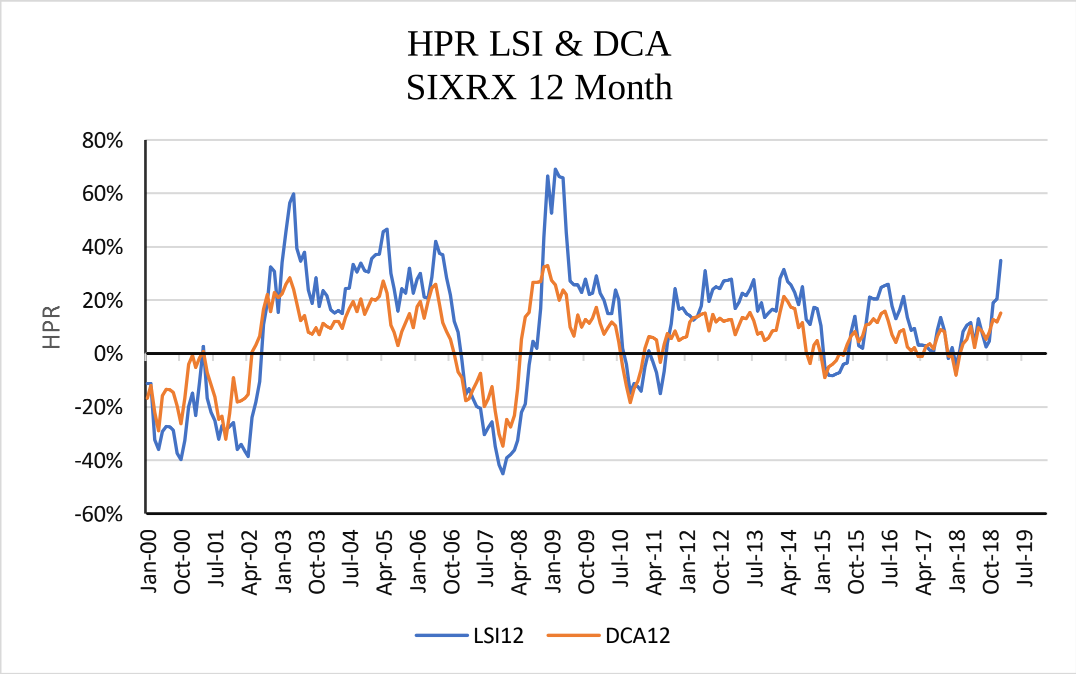
Note: Figure 7 illustrates the difference in Value Function calculated as in equation [4] between LSI and DCA on the various installment periods over the time-period 2000-2019 invested in SIXRX. Number of observations for the different installment periods: 6 months – 235; 12 months - 229; 24 months -217; 36 months -205.

Figure 8: *Time-Series Analysis – HPR*



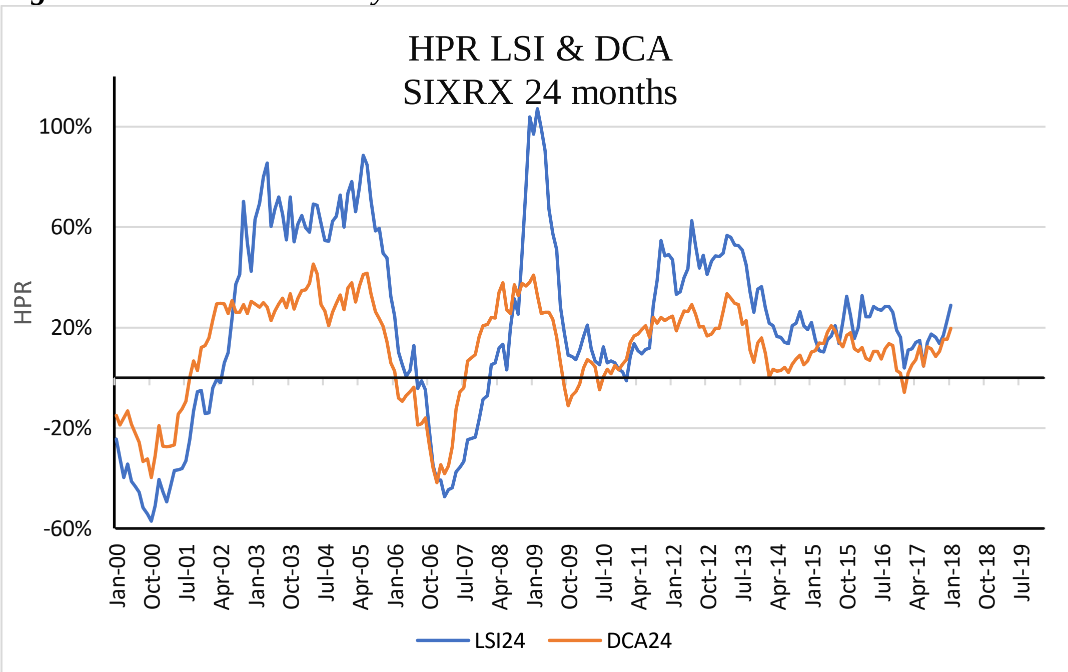
Note: Figure 8 illustrates HPR for LSI and DCA with a 6-month installment periodicity invested into the SIXRX over the time-period 2000-2019. Number of observations are 235.

Figure 9: *Time-Series Analysis – HPR*



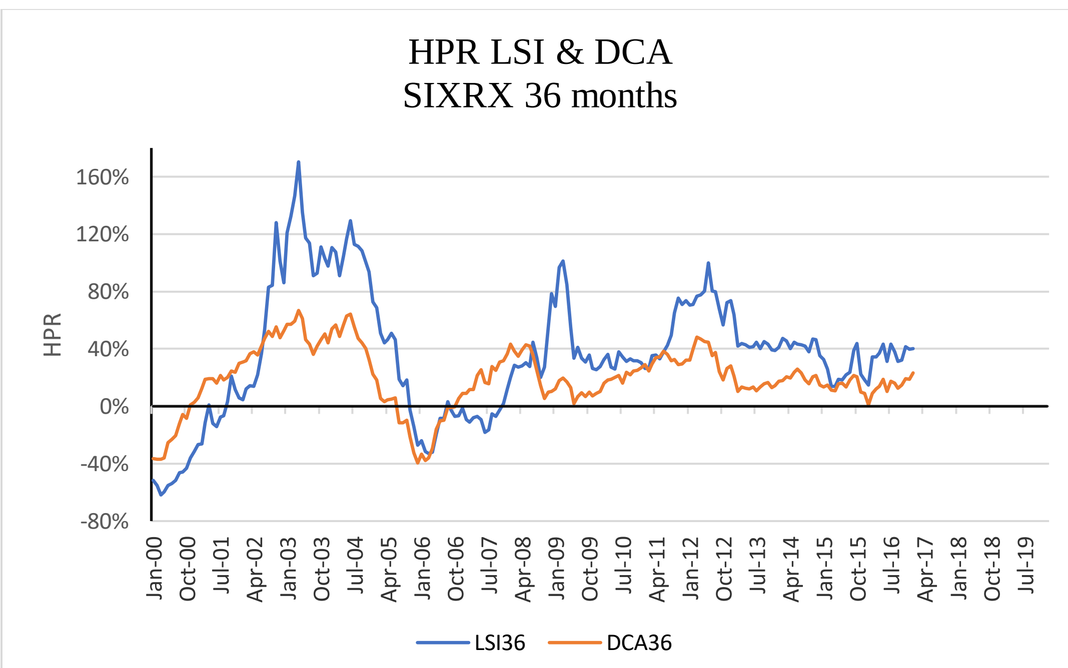
Note: Figure 9 illustrates HPR for LSI and DCA with a 12-month installment periodicity invested into the SIXRX over the time-period 2000-2019. Number of observations are 229.

Figure 10: *Time-Series Analysis – HPR*



Note: Figure 10 illustrates HPR for LSI and DCA with a 24-month installment periodicity invested into the SIXRX over the time-period 2000-2019. Number of observations are 217.

Figure 11: *Time-Series Analysis – HPR*



Note: Figure 11 illustrates HPR for LSI and DCA with a 36-month installment periodicity invested into the SIXRX over the time-period 2000-2019. Number of observations are 205.