# Stealth Trading on South African Equities Market

**Degree:** Master of Management in Finance and Investments

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# Abstract

The research examines if there are traders on the Johannesburg Stock Exchange (JSE) with information advantage. By employing high frequency data from 53 securities, the findings show that agents engage in small size trades to camouflage their information advantage. The inverted U-shaped plot was obtained from the dynamic probability of small trades model, which is consistent with the literature. The findings show that stealth trading is more frequent during the middle of the day on the JSE than any other time of the day. About 38% of traders were trading from an information advantage during the period of analysis. This implies that the remaining 62% of the traders engage in uninformed trades.

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## Abbreviations

**ASEA** – Africa Securities Exchange Association

**CEO** – Chief Executive officer

**DPIN** – Dynamic Probability of Informed Trading

**ECM** – Equities Capital Market

**IPO** – Initial Public Offering

**PIN** – Probability of Informed Trading

**NYSE** – New York Stock Exchange

**FO** – Further Offers

**VPIN** – Volume-Synchronized Probability of Informed Trading

**TIB** – Trade Imbalance

# Chapter 1

## 1.1 Introduction

This research builds on the stealth trading hypothesis proposed by Barclay & Warner (1993), which states that informed traders generally spread their trades and break them up through time in order to mask their information. The hypothesis was later tested with data obtained from the NYSE by Chakravarty (2001), who found that the data fits the hypothesis. Furthermore, it has been found that institutions are the basis of the dispoportionate aggregate price change owing to the medium size trades that they perform.

However, according to Ascioglu et.al. (2010), the conclusion that medium size trades solely affect stock prices may be providential as investors during the period before the year 2000 may have favored the medium size trades because of the cumulative high costs of small trades. This criticism is further supported by the study carried out by Hansch & Choe (2007), for the period 1993–2003. These authors found that trades shift to small size from medium size around the year 2000, which can be attributed to costs reduction for transactions due to the reduction in tick-size. In addition, the advent of the internet could have increased the accessibility of information to investors, thus affecting their trades.

An example of the evidence of stealth trading can be reflected in how the CEO of Google, Eric Schmidt, sold his shares. According to Lebedeva et al. (2009), Schmidt sold shares worth $29.3 million between May 24 to May 26 of 2005. These shares were split into 1744 transactions performed in a piecemeal fashion. The number of transactions shows the extent to which traders go in order to conceal the information they have. Such practices of obscuring of information makes it difficult to determine where and when stealth trading has been conducted.

The market microstructure literature categorizes two types of investors: informed and liquidity traders. According to  Chang et al. (2014), informed traders trade on the basis of available information while liquidity traders trade on the basis of meeting the market liquidity needs. The available trade data to a trader does not reflect whether or not the trader is informed or not. Thus, as Easley et al. (1997 a&b) note, most finance experts make inferences from the data and the most used method is the private information (PIN) measure. The weakness of this method, however, is that intraday data must be combined over extended macro horizons in order to apply the PIN model. In  light of this weakness, it is advisable to   follow Chang et al.'s (2014) modified method called dynamic private information (DPIN). The model was modified from the PIN, i.e. it was built on the strengths of the PIN while addressing its weaknesses.

## 1.2 The South African Equities Landscape

According to Huthchinson (2018), the JSE was established to provide a marketplace for shares of the South African financial and mining companies following the discovery of Gold in the Witwatersrand during the last quarter of the 19$^{th}$ century, in 1886 to be precise. It has grown from the colonial days through apatheid until now to be ranked the 19$^{th}$ largest stock exchange by market capitalisation globally and it is the largest on the continent.

The following matrix gives more details of the JSE in accordance with the number of defensive and cyclical shares listed:

| | | | |
|---|---|---|---|
| **Defensive** | **5 Companies**<br>Weight: 6%<br>BAT, ASPEN, BID CORP | **29 Companies**<br>Weight: 12%<br>SHOPRITE, MTN, VODACOM, TIGER BRANDS, CLICKS | **34 Companies**<br>Weight: 18% |
| **Cyclicals** | **47 Companies**<br>Weight: 51%<br>NASPERS, RICHEMONT, BHP, MONDI, INVESTEC | **84 Companies**<br>Weight: 31%<br>STANDARD BANK, IMPERIAL, MR PRICE, BIDVEST | **131 Companies**<br>Weight: 82% |
| | **52 Companies**<br>Weight: 57% | **113 Companies**<br>Weight: 43% | |

*Adopted from Huthchinson (2018).*

**Figure 1.1: Matrix for companies listed on the JSE**

According to Huthchinson (2018), the JSE has more domestic companies listed, however, it is important to note at this stage that their weight is very small as compared to the few big foreign ones. Thus, it is advisable to take note of the fact that the big foreign companies generally move the market on JSE, not the domestic numerous ones. Thus, stealth trading is more likely to be performed by the top 47 companies with over 51% of the market by capitalization. Most of the companies in this category are multinational companies.

Generally, small companies find it difficult to be part of the elite stock exchange on the continent due to systematic barriers of new entrants and the most commonly used is high transactional fees that are sometimes charged. This negatively affects market liquidity on the South African stock exchange and on the African continent as a whole, thereby giving the big players a competitive edge and an indiscriminate advantage to conduct stealth trading. According to Bright Africa (2018), poor liquidity can also upset international investments and may in some instances lead to poor market pricing because only a small volume of shares is traded. This gives big players on the stock to reap huge profits through both stealth equity trading and arbitrage share opportunities. The figure below shows the intraday price volatility on the JSE for the all share index:


**Figure 1.2: The intraday price volatility of the All-Share Index**

## 1.3 Problem Statement

Central to the problem is that the securities' markets are very volatile for very liquid markets, however this is not entirely true for the JSE. The Johannesburg Stock Exchange is partially liquid; thus, the focus of the study is narrowed down to the frequently traded shares. This constant rise and falling, bubbling and bursting of the securities' prices may lead investors to lose large sums of money if they do not have the correct trading strategies to beat the persistently changing market environment. Flowing from the foregoing, this research seeks to quantitatively ascertain if fluctuations in securities' prices are due to inductive methods of trading, such as analyzing charts or whether price movements are due to some traders having private information.

## 1.4 Objectives of Study

- To ascertain the existence and the extent of equities stealth trading on the South African stock exchange.
- To test whether the DPIN model, which is one of the models used to test for stealth trading, fits the data.

## 1.5 Significance of Study

From the reviewed available literature it has been discovered that no studies have been carried out in order to test the stealth trading hypothesis in the emerging markets, notably in Africa. This research is an attempt to fill this apparent intellectual gap by focusing on the South African equities market, specifically focusing of stealth equity trading of JSE.

The study will:

- Improve knowledge of the sources of stock price volatility and the extent of information asymmetries in the stock market.
- Explain to what extent stealth trading as a strategy is used on the Johannesburg Stock Exchange.
- Shed more light on the market microstructure of the JSE, which is not well studied.

# Chapter 2

## 2.1 Literature Review

### 2.1.1 Stealth Trading Hypothesis

Stealth trading is a term that describes how informed traders indulge in secretive and skillful piecemeal trading of securities in order to disguise their activities and as a way to protect their information advantage (Easley et.al, 1997b). The stealth trading hypothesis as stated by Barclay & Warner (1993) says that information that is privately and asymmetrically held is reflected through trading. Furthermore, privately informed traders prefer medium size trades as opposed to large trades. These authors tested two alternate hypotheses.The first alternate hypothesis; the public information hypothesis, which says the volatility in stock prices is a direct result of the public information. In addition, it predicts that there is a direct proportion between frequency of trades and changes in the stock price. The second alternate hypothesis; the trading volume hypothesis, put forward by Ascioglu et al. (2010). It proposes that changes in stock prices are due to changes in trading volume.

According to a test carried out by Barclay and Warner (1993), in the period 1981-1984 on the NYSE tender offer target, they found that 99.43% of fluctuations in stock prices were due to medium size trades. This was significantly different to the frequency of total trades, which was estimated to be 38.12%. The first alternate hypothesis of public information is rejected due to the disparity in percentages of frequency and cumulative changes in stock prices. The second alternate hypothesis of trading volume was tested and the medium size trades represented 58.18% of total volume but the price change was also significantly different, leading to the rejection of the second alternate hypothesis. Therefore, in light of these results, Barclay & Warner (1993) conclude that there is no evidence to reject the stealth trading hypothesis.

Chakravarty (2001) used the NYSE data to test the stealth trading hypothesis from the period 1990-1999. The limit for the test was securities with a 5% increase in price. The results indicated that cumulative stock price changes were due to medium size trades. Moreover, this disporpotionate price change was mainly due to institutions as opposed to individuals. According to Campbell et al. (2005), institutions prefer smaller or larger trades as opposed to medium trades as stated by the stealth trading hypothesis. However, the authors do not explain why this is the case. However, it may be that institutions prefer larger trades especially in the morning and in the evening because it takes less effort to camourflage private information as markets are very volatile and traders are submitting large trades. Barclay & Warner (1993), further examine the trading behaviour on days of high volatility and high volumes, and they found that institutions have a general inclination towards small to medium size trades.

### 2.1.2 Probability of Informed Trade (PIN) Model

According to Zagaglia (2013), the PIN model is a tool for determining the probability of informed trading as put forward by Easley et al. (1996). The strategic interaction between traders with different information sets is used as a proxy for estimating the model. In particular, the PIN depends on the number of buy and sell trades occurring in the market.

Given intraday trade data, one cannot ascertain absolutely which trades an informed trader carried out. This has led to the development of a number of models that could be used to determine the probability of informed trades with PIN being the most extensively employed model. According to Duarte et al. (2015), the following papers have developed measures of information asymmetry: Easley & O'Hara (1987), Easley et al. (1997) and Easley et al. (1996).

Glosten & Milgrom (1985) argue that huge order flow imbalances can be used as a prediction of informed trading. According to Glosten & Milgrom (1985), the literature has cast some doubt on the ability of the PIN model to determine informed trades because

PINs are usually very low when there is high information assymetry. The following papers; Collin-Dufresne & Fos (2012), Benos & Jochec (2007), Aktas et al. (2008), and Akay et al. (2012). Easley et al. (1997a,b) concede that information is likely to be lost or diluted when analysing macro horizons of trades typically from one month to a year, for PIN determination that aggregates intraday trades data which occurs in intervals as small as five minutes.

Furthermore, the authors agree that for a protracted number of days or months there is a tradeoff between economic reasonableness and approximation accuracy when using the PIN model. Large samples give a better estimation of the model, however, more parameters of estimation for macro horizons affect the stationarity of the data which inevitably dictates the limit of days that can be used in the estimation. This is further reinforced by Duarte & Young (2009) who maintain that PIN can further be disaggregated into two separate components. The first represents the information held privately and the second component due to disturbances in the demand and supply conditions within the stock markets called market illiquidity.

### 2.1.3 Dynamic Probability of Informed Trade (DPIN) Model

The DPIN model is an extension of the trading model proposed by Campbell et al. (1993) used to predict informed selling on the daily stock volatility. According to Chang et al. (2014), the above model is further developed to DPIN by determining the percentage of trades in a given interval that are information based. The following are the advantages of the DPIN model; flexible and it can also be used to make macro comparisons with different models over multiple intervals. In addition to that, it is simultaneously capable of capturing time series and cross sectional variation of probabilities of information based trading at very high intraday frequencies.Furthermore, the DPIN estimation requires no numerical optimisation, which makes it relatively easy to apply (Chang et al., 2014).

Weng et al. (2017) applied the DPIN model to examine the role that information plays when trading futures on the Taiwan futures market. They compared the perfomance of DPIN with the volume-synchronized probability of informed trading (VPIN) and trade imbalance (TIB) in determining the probability of informed trading. They discovered that DPIN model outperforms the other two models that is VPIN and TIB in quantitatively determining information asymmetry. Also, according to Yan & Hongbing (2018) the DPIN has more stable effects in the determination of information asymmetry as compared to the PIN model.

### 2.1.4 The U-Shaped Patterns of Returns

According to Blau (2009), literature has finds an unusual U-shaped pattern of returns in addition to the same pattern for number of trades and volume of trades. Literature has tried to explain this peculiar pattern over the years. According to Copeland, (1976, 1977) the advent of sequantial information is dispersed to a trader during a period that shows positive correlation between the changes in volume and price. The U-shaped pattern in volumes and price is also partially explained by Admati and Pfleiderer (1988). They concluded that information based trading usually occurs during times of high liquidity volumes.This claim was further supported by Foster & Viswanathan (1993) who arrived at the conclusion that higher asymmetry in information is at the beginning and towards the end of day using data from NYSE, further reinforcing the U-shaped pattern of returns.

According to Admati and Pfleiderer (1988), the U-shaped intraday pattern has been found to be consistent with the clustering of uninformed trading and the corresponding strategic informed trading. This further reinforces what was concluded by Barclay and Warner (1993), (Blau, 2009), Chakravarty (2001), and Alexander and Peterson (2007) that small size trades in the form of stealth trading exhibit an inverted U-shaped pattern. However, in this research, the DPIN model is going to be implemented as suggested by

Chang et al. (2014) on the stealth trading hypothesis of Barclay and Warner, (1993) and Chakravarty (2001) on South African equities market.

# Chapter 3

## 3.1 Methodology

### 3.1.1 The Data

The data for all trades for South Africa was obtained from Bloomberg for the period 18/05/2018 to 28/07/2018 in 5 minutes' intervals.

According to Zagaglia (2013), the Lee and Ready (1991) algorithm is used to match the quotes and trades which is standard to empirical microstructure literature, to determine whether or not the trade is seller or buyer initiated. According to Chang et al. (2014), the trading interval is calculated as the total daily trading minutes divided by the 5-minute time interval.

Each trade of buying or selling is assigned to a specific interval depending on the time the trading occurred. Returns are then determined by log differencing the last recorded midpoint price of successive intervals.

### 3.1.2 A Dynamic Intraday Measure of the Probability of Informed Trading (DPIN)

According to Chang et al. (2014) the Avramov et al. (2006) empirical method is employed to model high frequency data. The research carried out by Avramov et al. (2006) focused solely on the impact that sell trades have on volatility. Furthermore, the research wanted to estimate the PIN by first demarcating the buy and the sell trades.

Residuals are used as the unexpected component of returns. This is then used to differentiate between contrarian vs herding trades in the following regression:

$$R_{i,j} = \gamma_0 + \sum_{k=1}^{d} \gamma_{1i,k} D_k^{Day} + \sum_{k=1}^{v} \gamma_{2i,k} D_k^{Int} + \sum_{t=1}^{t} \gamma_{i,t} R_{i,x-t} + \varepsilon_{i,j} \qquad (2)$$

Where $\mathrm{R}_{\mathrm{i,j}}$ is the calculated return on a specific stock I at interval j which ranges from ($j = 1, \dots v$), $D_K Day$ is the day dummy variables for a week day that is Monday to Friday, the variables d, v and t are number of operating days in a week, number of intervals and lag intervals respectively. $D_K^{Int}$ is a dummy variable that is equivalent to the 5-minute interval of returns on a particular day *t*. Chang et al. (2014) further propose that the error term $\varepsilon_{\mathrm{i,x}}$ captures the small changes in returns leftover after accounting for the average time of the day together with the day of the week effects, thus it captures unexpected returns.

The dynamic probability of informed trading base measure ($DPIN_{BASE}$) is put forward as an extension of Avramov et al. (2006), which says that buying in the presence of negative unexpected returns or selling in the presence of positive unexpected returns is classified under informed or contrarian trades. Conversely, buying in the presence of positive unexpected returns or selling in the presence of negative unexpected returns are classified under uninformed or herding trades. The following equation shows the number of buy ( $NB_{i,j}$), the number of sell ( $NS_{i,j}$), and the total number of trades ( $NT_{i,j}$):

$$DPIN_{BASE(i,j)} = \frac{NB_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} < 0\right) + \frac{NS_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} > 0\right) \qquad (3)$$

Where $\varepsilon_{i,x} < 0$ is an indicator variable that should equal one when there are negative unexpected returns and zero otherwise. $\varepsilon_{i,x} > 0$ is also an indicator variable which equals 1 when there are positive unexpected returns and zero otherwise. The logic behind equation (3) above is that buy during declining or selling during rising prices is indicative of informed trading and the opposite is true.

### 3.1.3 The DPIN: Accounting for Disposition Effect and Trend Chasing

The $DPIN_{BASE}$ equation (3) is very broad because buying and selling in the midst of price volatility is important in determining informed or uninformed trading. However, further refinements need to be made on the $DPIN_{BASE}$ model to arrive at such a conclusion.

According to Chang et al. (2014), there is a disposition effect that traders encounter when selling shares and trend chasing when buying shares that has to be accounted for. According to Aramov et al. (2006), the behavioral finance literature shows that unsophisticated investors have cognitive biases and common among them is loss aversion which is the reluctance of investors to realise their losses. This reinforces what the disposition effect puts across that uninformed investors become reluctant to sell their stocks in the presence of price decline and are more susceptible to selling following increases in price. According to Chang et al. (2014), sells that occur in negative unexpected returns with positive past cumuluative returns show both disposition effect and herding, thus are likely as a result of uninformed trading.

According to Chang et al. (2014), the buying side also has behavioral explanations that include; feedback trading and herding, anchoring, overreaction and biases in confirmation. Any of these explanations could be true in a given circumstance. However, the magnitude that investors recognize past increases in prices as a positive signal to which they respond by buying more stocks, and such trades most likely result from herding. Thus, buying following positive unexpected returns as well as positive previous cumulative returns are positive with positive past cumulative returns exhibit both trend chasing and herding which is most likely a result of uninformed trading.

The following equation is an extension of the $DPIN_{DISP}$ accounting for the trend chasing and disposition effect:

$$DPIN_{Disp(i,j)} = \left[\frac{NB_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} < 0\right) + \frac{NS_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} > 0\right)\right]\left(R_{i,j-v;j-1} < 0\right) \qquad (4)$$

Where $\left(\mathrm{R}_{\mathrm{i,j-v;j-1}} < 0\right)$ is used as a variable indicator that should take a value of 1 when there is a negative cumulative return over the last v intervals and zero otherwise. The above equation builds on the *DPIN$_{BASE}$ equation* (3) for classifying informed trades broadly. However, it adds a condition that if past cumulative returns are negative then the investor is more informed. More so, the buying that occurs in declining prices as well as the selling that occurs in rising prices in the presence of negative past cumulative returns show a highly likelihood of informed trading as opposed to trend chasing or the disposition effect for uninformed investors Chang et al. (2014).

### 3.1.4 The DPIN: Accounting for the Size of Trades

A further refinement can be made that takes into consideration the trade size to determine a more polished classification of informed trades. According to Easley and O'Hara (1987), contrarian traders are more inclined to trade in large orders, thus a further condition can be imposed on the *DPIN$_{BASE}$* equation accounting for trade sizes, to the following equation:

$$DPIN_{Size(i,j)} = \left[\frac{NB_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} < 0\right) + \frac{NS_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} > 0\right)\right]\left(LT_{i,j}\right) \qquad (5)$$

Where $\left(\mathrm{LT}_{\mathrm{i,j}}\right)$ is an indicator for "large trades" that should equal 1 when the size of total trades of a stock I over the interval j is larger than that of the stock's median interval trade size for the same trading day and it is zero otherwise. The equation (5) above builds from the *DPIN$_{BASE}$* with an addition of $\left(\mathrm{LT}_{\mathrm{i,j}}\right)$ with the intuition that large trades' contrarian sells or buys are most likely a result of contrarian trading.

However, according to Chakravarty (2001), for stealth trading the equation (5) above is further refined because traders undergoing stealth trading submit small trades to camouflage their trades so the equation above is further refined to:

$$DPIN_{Size(i,j)} = \left[\frac{NB_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} < 0\right) + \frac{NS_{i,j}}{NT_{i,j}}\left(\varepsilon_{i,j} > 0\right)\right]\left(SM_{i,j}\right) \quad (6)$$

Where $\left(\mathrm{SM}_{\mathrm{i,j}}\right)$ is an indicator for "small trades" that should equal one when the total size of trade for a specific stock $i$ over the interval $j$ is smaller than that of the share's median interval trade size for the same trading day and it is zero otherwise (Chang et al., 2014).

# Chapter 4

## 4.1 Results and Discussion

### 4.1.1 Results from the DPIN_BASE calculation

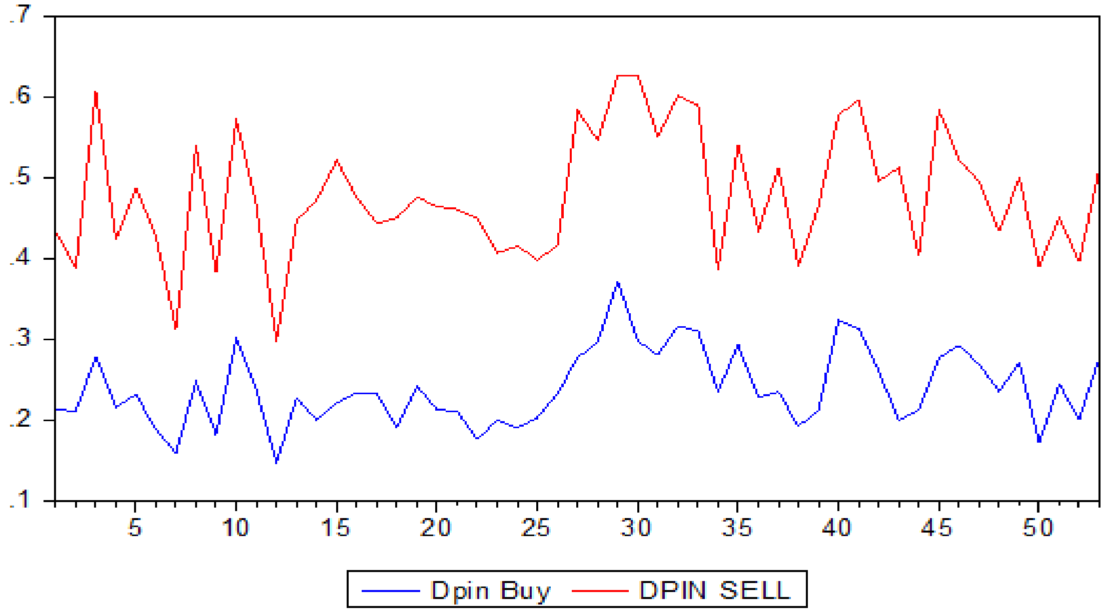
The sells and buys were separated using the sign of the residuals. The residuals capture the unexpected returns after running the regression for equation (2) in chapter 3. The returns were first placed in intervals using equation (1) above. The unexpected returns with a negative sign are given an indicator variable of unit and zero otherwise. The buys and the sells are then separated, the table below shows the descriptive statistics for the $DPIN_{BUY}$, $DPIN_{SELL}$ and the resulting $DPIN_{BASE}$ calculated:

**Table 4.1: The results from the calculation of DPIN_BASE, DPIN_SELL and DPIN_BUY**

| | DPIN_BASE | DPIN_SELL | DPIN_BUY |
|---|---|---|---|
| Mean | 0.4787 | 0.2395 | 0.2392 |
| Median | 0.4646 | 0.2353 | 0.2331 |
| Maximum | 0.6277 | 0.3299 | 0.3723 |
| Minimum | 0.298 | 0.1503 | 0.1465 |
| Std. Dev. | 0.0785 | 0.0436 | 0.0475 |
| Skewness | 0.0758 | 0.0554 | 0.4546 |
| Kurtosis | 2.4459 | 2.5664 | 2.7863 |
| Jarque-Bera | 0.7289 | 0.4424 | 1.9262 |
| Probability | 0.6946 | 0.8016 | 0.3817 |
| Sum | 25.3725 | 12.6934 | 12.6791 |
| Sum Sq. Dev. | 0.3207 | 0.0989 | 0.1173 |

The $DPIN_{BUY}$ and the $DPIN_{SELL}$ over different intervals were plotted as shown on figure 4.1 below:

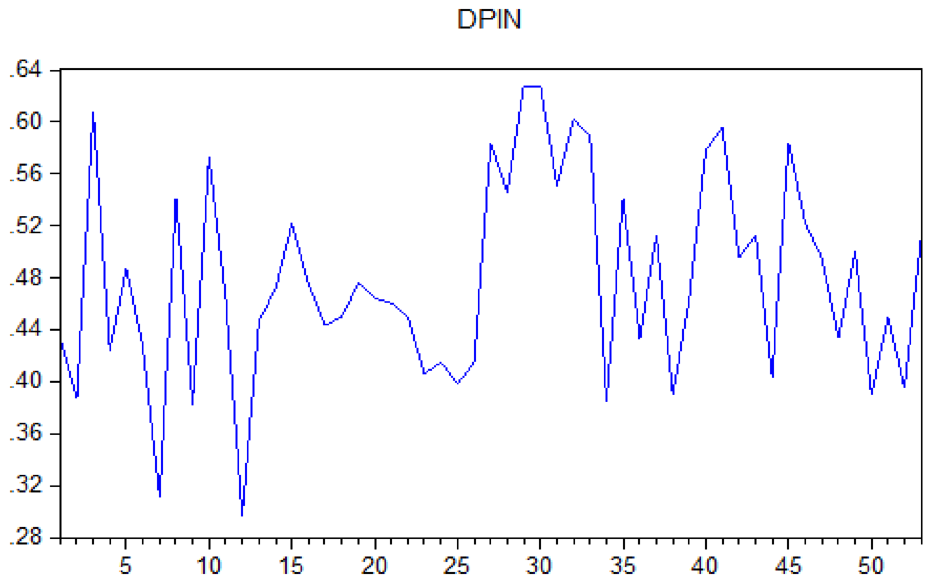
**Figure 4.1: The plot for DPIN_SELL and DPIN_BUY**




The dynamic probability ($DPIN_{BASE}$) is then calculated using equation (3) above in chapter 3. According to Campbell et al. (1993), the rationale behind DPINs is that uninformed trading often exhibits negative serial correlation in share returns while informed trading has no correlation. The above plots show negative serial correlation between intervals 1-16 and from 35-53. This shows more information asymmetry at the beginning and at the end of the day.

The mean value of the intraday $DPIN_{BASE}$ obtained in this research is 0.4787 while that reported by Chang et al. (2014) is 0.447. This shows that this research's outcomes are consistent with the findings found by some literature sources. However, the standard deviation obtained in this research is 0.0785 whilst that reported in literature is 0.297. This means the estimated standard deviation is lower than that of literature, which could be attributed to the difference in length of time intervals, used in this research and that used in literature. Chang et al. (2014) used 15-minute intervals whilst a 5-minute interval was used in this research. At higher frequencies, the information dissemination is not expected to be very high on the trading floors compared to 15-minute intervals. Thus, this justifies a higher standard deviation that is expected for relatively lower frequencies because there is time for information to propagate the floor and reflect in the trades submitted. The figure 4.2 below shows the plot of DPIN_BASE:

**Figure 4.2: The plot for DPIN_BASE**




The graph shows high negative serial correlation at the beginning and at the end of the day. This, according to Campbell (1993), shows herding in those periods. These results are consistent with those found by some literature sources such as by Chang et al. (2014) and Easley et al. (2002). In corroborating what the literature found these findings show that traders will most likely to trade based on information during the middle of the day when information has disseminated, thus the plot shows little autocorrelation in the period 16-35.

### 4.1.2 DPIN_BASE with Disposition Effect and Trend Chasing results

The table 4.2 below shows the results of the DPIN_BASE adjusted for the disposition and trend chasing effects. This adjusted DPIN_BASE is called DPIN_DISP. The table shows the descriptive statistics obtained from equation (4). This simply rationalizes the notion that in price declines informed investors are less willing to sell their stocks due to loss aversion.

**Table 4.2: The results for DPIN_BASE accounting for disposition and trend chasing**

| DPIN_DISP | |
|---|---|
| Mean | 0.1203 |
| Median | 0.0000 |
| Maximum | 0.6082 |
| Minimum | 0.0000 |
| Std. Dev. | 0.1714 |
| Skewness | 1.3784 |
| Kurtosis | 3.7548 |
| Jarque-Bera | 18.0416 |
| Probability | 0.0001 |
| Sum | 6.3762 |
| Sum Sq. Dev. | 1.5277 |

The DPIN_DISP mean reported by Chang et al. (2014) for intraday trades is 0.212 which is in agreement with that reported by Easley et al. (2002) of 0.191 from the PIN model. In this research a mean of 0.1203 was obtained. The standard deviation reported in by Chang et al. (2014) is 0.301 whilst that estimated in this research is 0.1714. A possible explanation could be that the frequency values are different which means that the average taken over small cluster movements will be very small and it follows that the standard deviation will be slightly lower than that 15-minute interval.

At this point, some sort of conclusion about contrarian and herding traders can be made on the JSE. This is, however, not conclusive as the DPIN_DISP captures the dynamic probability of informed trading in relation to the cumulative returns over an interval. Therefore, it compares the buys and sells in the presence of positive or negative cumulative returns. Thus, buying that occurs in declining prices when past cumulative returns are negative shows informed trading and the opposite is true. By considering the price movements and past cumulative returns the informed investors are estimated to be 37.7% whilst 62.3% is uninformed investors.

### 4.1.3 Results for DPIN accounting for the size of Trades

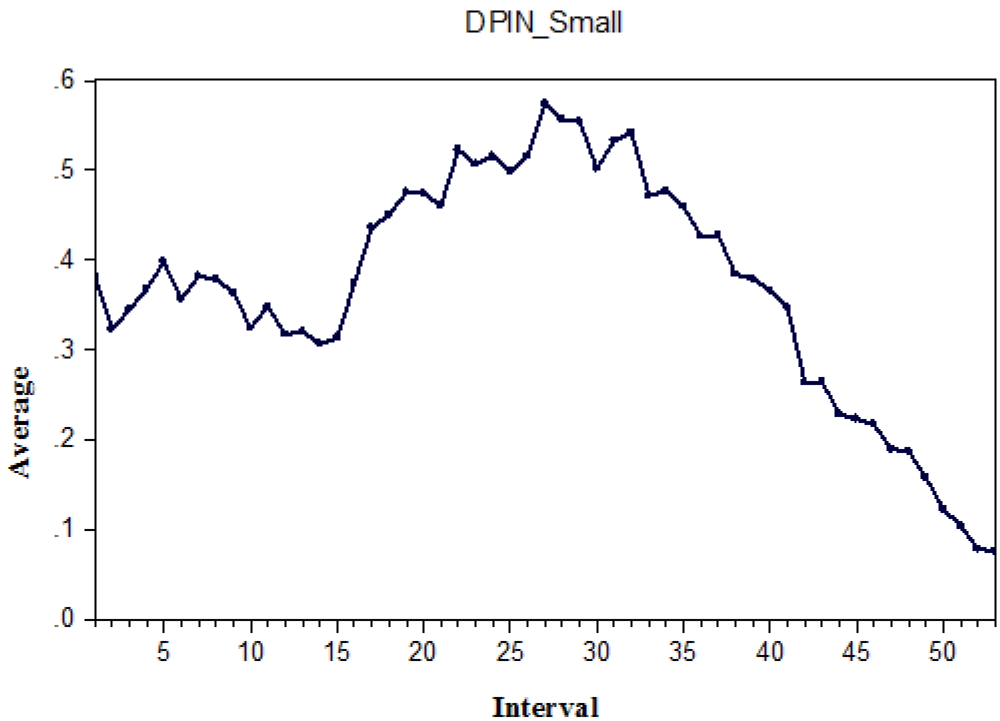
The table above shows the descriptive statistics for dynamic probability accounting for sizes in trades. The rationale in general intraday trading is that traders generally submit large trades in the presence of information. However, stealth trading is the submission of small trades in the presence of information in order to camouflage their position. The adjusted DPIN_BASE for size is DPIN_SMALL. The DPIN_LARGE for intraday analysis has a U-shaped plot whilst stealth trading has an inverted U-shaped pattern for informed trading.

**Table 4.3: Results for the DPIN_SMALL accounting for size of trades.**

| DPIN_SMALL | |
|---|---|
| Mean | 0.3696 |
| Median | 0.3789 |
| Maximum | 0.5744 |
| Minimum | 0.0771 |
| Std. Dev. | 0.1302 |
| Skewness | -0.5404 |
| Kurtosis | 2.5683 |
| Jarque-Bera | 2.9916 |
| Probability | 0.2241 |
| Sum | 19.5865 |
| 0Sum Sq. Dev. | 0.8812 |

The average for stealth trading according to the draft report by Abad & Pascaul (2011), in their article "*Revisiting stealth trading hypothesis*" for small size trades to be 0.4503. This is a follow up from the literature envisaged by (Barclay & Warner, 1993, Chakravarty, 2001, Alexander & Peterson, 2007). The method commonly used in these studies is the PIN model of (Easley & O'Hara, 1987) thus for this research the DPIN was used and the value of mean determined is 0.3696. This DPIN_SMALL is close to the value obtained using the PIN model. The figure 4.4, below shows the inverted U-shaped plot for DPIN_BASE with trade size effects:

**Figure 4.4: The inverted U-shaped plot for DPIN_SMALL trades.**



# Chapter 5

## 5.1 Conclusion

The data that has been used is from the largest stock exchange on the continent; the Johannesburg Stock Exchange (JSE). The data was used to test stealth trading, which is the process when informed traders trade strategically engage in small and secretive trades to cover up their information advantage.

One conclusion that can be made from the results is that the DPINs showed negative serial correlation in the morning and in the evening and positive during mid-day. The DPIN_SMALL is very high during mid-day because the frequency of stealth trading is very low during times of high trading activity. This is possibly because traders with information advantage can reduce the time consumed and the costs associated with breaking up trades into smaller ones by submitting larger trades during times of high frequency trading without revealing their information advantage to other sophisticated traders. However, one of the conclusions is that during times of low trades stealth trading is very common as traders want to maintain their information advantage. The inverted U-shaped plot was obtained figure 4.4 in chapter 4.

The results obtained in this research have shown that there is stealth trading on the JSE. It is mostly performed during mid-day and about 38% of the traders on the stock exchange trade based on private information.

# Appendix A

**Table A1: The test for Stationarity and Serial Correlation**

| Ticker Name | Stationarity Test (Augmented Dicky Fuller ) | Serial Correlation( Durbin-Watson test (DWT) and Lagrange Multiplier) |
|---|---|---|
| AIP SJ Equity | Stationary | DWT > 1.7 |
| ADH SJ Equity | Stationary | DWT > 1.7 |
| AFE SJ Equity | Stationary | DWT > 1.7 |
| ARI SJ Equity | Stationary | DWT > 1.7 |
| AMS SJ Equity | Stationary | DWT > 1.7 |
| AGL SJ Equity | Stationary | DWT > 1.7 |
| ANG SJ Equity | Stationary | DWT > 1.7 |
| APN SJ Equity | Stationary | DWT > 1.7 |
| ARL SJ Equity | Stationary | DWT > 1.7 |
| ATT SJ Equity | Stationary | DWT > 1.7 |
| AVI SJ Equity | Stationary | DWT > 1.7 |
| BAW SJ Equity | Stationary | DWT > 1.7 |
| BIL SJ Equity | Stationary | DWT > 1.7 |
| BID SJ Equity | Stationary | DWT > 1.7 |
| BTI SJ Equity | Stationary | DWT > 1.7 |
| CCO SJ Equity | Stationary | DWT > 1.7 |
| CPI SJ Equity | Stationary | DWT > 1.7 |
| CLS SJ Equity | Stationary | DWT > 1.7 |
| CFR SJ Equity | Stationary | DWT > 1.7 |
| CML SJ Equity | Stationary | DWT > 1.7 |
| DTC SJ Equity | Stationary | DWT > 1.7 |
| DCP SJ Equity | Stationary | DWT > 1.7 |
| DSY SJ Equity | Stationary | DWT > 1.7 |
| EMI SJ Equity | Stationary | DWT > 1.7 |
| EXX SJ Equity | Stationary | DWT > 1.7 |
| FSR SJ Equity | Stationary | DWT > 1.7 |
| GLN SJ Equity | Stationary | DWT > 1.7 |
| GFI SJ Equity | Stationary | DWT > 1.7 |
| GRT SJ Equity | Stationary | DWT > 1.7 |
| HAR SJ Equity | Stationary | DWT > 1.7 |
| IMP SJ Equity | Stationary | DWT > 1.7 |
| IPL SJ Equity | Stationary | DWT > 1.7 |
| ITU SJ Equity | Stationary | DWT > 1.7 |
| OML SJ Equity | Stationary | DWT > 1.7 |

| | | |
|---|---|---|
| PIK SJ Equity | Stationary | DWT > 1.7 |
| PFG SJ Equity | Stationary | DWT > 1.7 |
| PPC SJ Equity | Stationary | DWT > 1.7 |
| PSG SJ Equity | Stationary | DWT > 1.7 |
| RDF SJ Equity | Stationary | DWT > 1.7 |
| REM SJ Equity | Stationary | DWT > 1.7 |
| RMH SJ Equity | Stationary | DWT > 1.7 |
| SLM SJ Equity | Stationary | DWT > 1.7 |
| SAP SJ Equity | Stationary | DWT > 1.7 |
| SOL SJ Equity | Stationary | DWT > 1.7 |
| SHP SJ Equity | Stationary | DWT > 1.7 |
| SGL SJ Equity | Stationary | DWT > 1.7 |
| SBK SJ Equity | Stationary | DWT > 1.7 |
| SNH SJ Equity | Stationary | DWT > 1.7 |
| SBK SJ Equity | Stationary | DWT > 1.7 |
| BVT SJ Equity | Stationary | DWT > 1.7 |
| TFG SJ Equity | Stationary | DWT > 1.7 |
| TBS SJ Equity | Stationary | DWT > 1.7 |
| TRU SJ Equity | Stationary | DWT > 1.7 |
| VOD SJ Equity | Stationary | DWT > 1.7 |
| WHL SJ Equity | Stationary | DWT > 1.7 |

## Descriptive Statistics for Each Share:

**Table A2: Descriptive Statistics for Shares**

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | ADH | AFE | AGL | AIP | AMS | ANG | APN |
|---|---|---|---|---|---|---|---|
| Mean | 1.75E-18 | -1.34E-18 | -1.43E-18 | 1.94E-18 | -4.20E-18 | 7.20E-19 | -1.31E-18 |
| Median | -6.30E-05 | 0.000304 | -0.000741 | 0.000264 | -0.000662 | -0.001110 | 0.000269 |
| Maximum | 0.021936 | 0.014084 | 0.019261 | 0.027261 | 0.021611 | 0.021355 | 0.013685 |
| Minimum | -0.013145 | -0.015151 | -0.012185 | -0.020324 | -0.025703 | -0.017096 | -0.017387 |
| Std. Dev. | 0.006606 | 0.005414 | 0.006962 | 0.008237 | 0.008794 | 0.007776 | 0.006523 |
| Skewness | 0.657661 | -0.231621 | 0.673332 | 0.260138 | -0.156680 | 0.697877 | 0.061627 |
| Kurtosis | 4.690241 | 3.173468 | 3.362249 | 4.056646 | 3.528746 | 3.631094 | 2.925811 |
| Jarque-Bera | 11.27634 | 0.601515 | 4.780784 | 3.410171 | 0.928677 | 5.768252 | 0.050876 |
| Probability | 0.003559 | 0.740257 | 0.091594 | 0.181757 | 0.628551 | 0.055904 | 0.974883 |
| Sum | 9.47E-17 | -8.50E-17 | -9.02E-17 | 1.01E-16 | -2.38E-16 | 2.99E-17 | -8.48E-17 |
| Sum Sq. Dev. | 0.002531 | 0.001700 | 0.002812 | 0.003935 | 0.004485 | 0.003507 | 0.002468 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A3: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | ARI | ARL | ATT | AVI | BAW | BID | BIL |
|---|---|---|---|---|---|---|---|
| Mean | -1.03E-18 | -5.85E-18 | -1.40E-18 | 2.49E-19 | 7.06E-19 | -2.03E-18 | 3.90E-19 |
| Median | -0.001534 | -0.000270 | 0.000289 | 6.93E-06 | -0.000165 | 4.17E-05 | -0.000755 |
| Maximum | 0.047165 | 0.028133 | 0.010905 | 0.011839 | 0.026933 | 0.012044 | 0.016084 |
| Minimum | -0.024024 | -0.024822 | -0.009139 | -0.008265 | -0.019574 | -0.014930 | -0.011769 |
| Std. Dev. | 0.012820 | 0.009191 | 0.004576 | 0.004208 | 0.009377 | 0.005256 | 0.006257 |
| Skewness | 1.061460 | 0.129379 | 0.061952 | 0.642240 | 0.237207 | -0.066112 | 0.619762 |
| Kurtosis | 5.154865 | 4.530133 | 2.588794 | 4.013955 | 3.383957 | 3.384510 | 3.218712 |
| Jarque-Bera | 22.49433 | 5.920309 | 0.453421 | 6.583400 | 0.915711 | 0.406438 | 3.894630 |
| Probability | 0.000013 | 0.051811 | 0.797152 | 0.037191 | 0.632639 | 0.816099 | 0.142657 |
| Sum | -6.07E-17 | -3.48E-16 | -7.55E-17 | 1.04E-17 | 5.46E-17 | -1.13E-16 | 1.69E-17 |
| Sum Sq. Dev. | 0.009532 | 0.004899 | 0.001214 | 0.001027 | 0.005100 | 0.001602 | 0.002271 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A4: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | BTI | BVT | CCO | CFR | CLS | CML | CPI |
|---|---|---|---|---|---|---|---|
| Mean | -8.67E-19 | 2.76E-19 | -9.56E-19 | 8.01E-19 | -2.13E-18 | -1.51E-18 | 2.28E-18 |
| Median | -0.000855 | -0.000119 | 0.000194 | -0.000478 | 0.000286 | -0.000394 | -0.000677 |
| Maximum | 0.019825 | 0.012295 | 0.012971 | 0.010971 | 0.011094 | 0.016687 | 0.015259 |
| Minimum | -0.013452 | -0.016233 | -0.019136 | -0.011747 | -0.014573 | -0.012990 | -0.014575 |
| Std. Dev. | 0.006121 | 0.006142 | 0.005570 | 0.004415 | 0.006146 | 0.006175 | 0.006041 |
| Skewness | 0.645536 | -0.524223 | -0.452678 | 0.071297 | -0.115444 | 0.248180 | 0.206719 |
| Kurtosis | 3.552223 | 3.255768 | 4.390732 | 3.435362 | 2.553752 | 3.099021 | 3.103873 |
| Jarque-Bera | 4.847385 | 2.863109 | 6.769775 | 0.515938 | 0.620597 | 0.629770 | 0.446731 |
| Probability | 0.088594 | 0.238937 | 0.033881 | 0.772619 | 0.733228 | 0.729873 | 0.799822 |
| Sum | -4.77E-17 | 1.67E-17 | -5.12E-17 | 5.64E-17 | -1.21E-16 | -9.28E-17 | 1.21E-16 |
| Sum Sq. Dev. | 0.002173 | 0.002188 | 0.001799 | 0.001131 | 0.002191 | 0.002211 | 0.002117 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A5: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | DCP | DSY | DTC | EMI | EXX | FSR | GFI |
|---|---|---|---|---|---|---|---|
| Mean | -1.90E-18 | 4.51E-18 | -2.35E-18 | 2.50E-18 | 1.47E-19 | -2.19E-18 | 1.99E-18 |
| Median | -0.001415 | -0.000244 | -0.000634 | 0.000185 | 0.001255 | -0.000384 | 0.000267 |
| Maximum | 0.029524 | 0.015199 | 0.036382 | 0.021893 | 0.025320 | 0.015144 | 0.019855 |
| Minimum | -0.037553 | -0.013483 | -0.061291 | -0.014198 | -0.023859 | -0.015369 | -0.018461 |
| Std. Dev. | 0.011180 | 0.006275 | 0.015768 | 0.006057 | 0.009214 | 0.006593 | 0.006190 |
| Skewness | -0.016539 | 0.070069 | -0.891594 | 0.301195 | -0.083908 | 0.101855 | 0.077595 |
| Kurtosis | 4.422627 | 2.634055 | 5.698098 | 5.156177 | 3.500058 | 3.265341 | 4.738944 |
| Jarque-Bera | 4.978029 | 0.377489 | 25.71292 | 12.32110 | 0.683959 | 0.275097 | 7.493029 |
| Probability | 0.082992 | 0.827998 | 0.000003 | 0.002111 | 0.710363 | 0.871492 | 0.023600 |
| Sum | -1.21E-16 | 2.73E-16 | -1.45E-16 | 1.47E-16 | 4.77E-18 | -1.28E-16 | 1.08E-16 |
| Sum Sq. Dev. | 0.007250 | 0.002284 | 0.014421 | 0.002128 | 0.004924 | 0.002521 | 0.002222 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A6: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | GLN | GRT | HAR | IMP | IPL | ITU | OML |
|---|---|---|---|---|---|---|---|
| Mean | -2.09E-18 | 2.94E-20 | 6.91E-19 | -4.67E-18 | -1.50E-18 | -2.26E-18 | -2.65E-19 |
| Median | 0.001100 | -5.48E-05 | 5.30E-05 | 0.001064 | 0.001042 | 0.002152 | 0.000192 |
| Maximum | 0.014809 | 0.013280 | 0.020981 | 0.035833 | 0.017241 | 0.013496 | 0.019062 |
| Minimum | -0.045186 | -0.012917 | -0.028155 | -0.055929 | -0.016440 | -0.039590 | -0.016329 |
| Std. Dev. | 0.009484 | 0.004920 | 0.009871 | 0.015356 | 0.007215 | 0.009842 | 0.005602 |
| Skewness | -1.960448 | 0.018221 | -0.362074 | -0.282986 | 0.036417 | -1.935119 | 0.143286 |
| Kurtosis | 10.18332 | 3.232216 | 3.267066 | 5.415810 | 2.728291 | 7.823741 | 5.480800 |
| Jarque-Bera | 164.6432 | 0.135829 | 1.464467 | 15.13463 | 0.194529 | 94.02443 | 15.33138 |
| Probability | 0.000000 | 0.934340 | 0.480834 | 0.000517 | 0.907316 | 0.000000 | 0.000469 |
| Sum | -1.13E-16 | 8.67E-19 | 2.13E-17 | -2.81E-16 | -9.06E-17 | -1.16E-16 | -8.67E-18 |
| Sum Sq. Dev. | 0.005216 | 0.001404 | 0.005651 | 0.013676 | 0.003019 | 0.005618 | 0.001820 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A7: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | PFG | PIK | PPC | PSG | RDF | REM | RMH |
|---|---|---|---|---|---|---|---|
| Mean | 2.06E-18 | -7.94E-19 | -1.79E-18 | -3.59E-18 | -1.76E-19 | 2.69E-18 | -1.54E-19 |
| Median | 0.000849 | -0.000242 | -0.000116 | -0.000458 | 0.000652 | 0.000135 | 0.000287 |
| Maximum | 0.017104 | 0.011659 | 0.026276 | 0.020370 | 0.007038 | 0.014598 | 0.017697 |
| Minimum | -0.023330 | -0.015782 | -0.045746 | -0.012437 | -0.014052 | -0.012132 | -0.015981 |
| Std. Dev. | 0.008149 | 0.005531 | 0.012255 | 0.006360 | 0.004498 | 0.005166 | 0.006885 |
| Skewness | -0.337159 | -0.242029 | -0.801424 | 0.693927 | -1.129269 | 0.271792 | 0.055710 |
| Kurtosis | 3.428086 | 2.911674 | 5.387373 | 3.888766 | 4.471465 | 3.529872 | 3.288557 |
| Jarque-Bera | 1.568325 | 0.595195 | 20.32716 | 6.676934 | 17.86275 | 1.416608 | 0.235212 |
| Probability | 0.456502 | 0.742600 | 0.000039 | 0.035491 | 0.000132 | 0.492479 | 0.889046 |
| Sum | 1.28E-16 | -4.42E-17 | -1.20E-16 | -2.08E-16 | -6.94E-18 | 1.51E-16 | -4.77E-18 |
| Sum Sq. Dev. | 0.003851 | 0.001774 | 0.008710 | 0.002346 | 0.001173 | 0.001548 | 0.002750 |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 | 59 |

## Table A8: Descriptive Statistics for Shares

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | SAP | SBK | SERIES01 | SGL | SHP | SLM | SNH |
|---|---|---|---|---|---|---|---|
| Mean | -1.79E-18 | 8.67E-19 | 30.50000 | -1.88E-18 | 2.64E-18 | 2.60E-18 | 5.61E-18 |
| Median | -0.000696 | 0.000445 | 30.50000 | -0.000589 | 0.000573 | 0.000969 | 0.001286 |
| Maximum | 0.014829 | 0.018083 | 60.00000 | 0.031262 | 0.012139 | 0.016150 | 0.106948 |
| Minimum | -0.011465 | -0.018964 | 1.000000 | -0.035326 | -0.025091 | -0.031942 | -0.106887 |
| Std. Dev. | 0.006008 | 0.006985 | 17.46425 | 0.012520 | 0.007156 | 0.008074 | 0.036664 |
| Skewness | 0.504169 | -0.299911 | -1.36E-16 | -0.418511 | -1.351872 | -1.474297 | 0.221781 |
| Kurtosis | 2.985017 | 3.545688 | 1.799333 | 3.719140 | 5.666675 | 6.731166 | 4.710408 |
| Jarque-Bera | 2.500054 | 1.616506 | 3.604002 | 2.993681 | 35.45258 | 55.59718 | 7.675514 |
| Probability | 0.286497 | 0.445636 | 0.164968 | 0.223836 | 0.000000 | 0.000000 | 0.021542 |
| Sum | -1.12E-16 | 6.07E-17 | 1830.000 | -1.04E-16 | 1.66E-16 | 1.54E-16 | 3.77E-16 |
| Sum Sq. Dev. | 0.002094 | 0.002830 | 17995.00 | 0.009092 | 0.002970 | 0.003781 | 0.077968 |
| Observations | 59 | 59 | 60 | 59 | 59 | 59 | 59 |

**Table A9: Descriptive Statistics for Shares**

Date: 11/21/18 Time: 11:25
Sample: 1 60

| | SOL | TBS | TRU | VOD | WHL |
|---|---|---|---|---|---|
| Mean | 1.31E-18 | 3.96E-18 | 2.32E-18 | 1.91E-18 | -1.10E-19 |
| Median | 0.001113 | -0.000459 | 0.001474 | 9.57E-05 | 0.000187 |
| Maximum | 0.012158 | 0.014823 | 0.013483 | 0.019560 | 0.005609 |
| Minimum | -0.018688 | -0.013815 | -0.018881 | -0.013047 | -0.010430 |
| Std. Dev. | 0.005615 | 0.004755 | 0.007486 | 0.007696 | 0.002117 |
| Skewness | -0.646067 | 0.054324 | -0.546689 | 0.245909 | -2.001034 |
| Kurtosis | 4.041260 | 4.079328 | 3.137896 | 2.320535 | 12.37663 |
| Jarque-Bera | 6.769844 | 2.892854 | 2.985626 | 1.729580 | 255.5136 |
| Probability | 0.033880 | 0.235410 | 0.224740 | 0.421140 | 0.000000 |
| Sum | 9.02E-17 | 2.41E-16 | 1.38E-16 | 1.18E-16 | -6.94E-18 |
| Sum Sq. Dev. | 0.001829 | 0.001311 | 0.003250 | 0.003435 | 0.000260 |
| Observations | 59 | 59 | 59 | 59 | 59 |

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