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Determining the validity of Common Factor models in a non-synchronous market

An empirical test to examine the impact of the time differences

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PREFACE AND ACKNOWLEDGEMENTS

This study is the conclusion of my education at the Erasmus University, which has certainly been interesting. The past few years have been a valuable experience in terms of knowledge and personal development.

A thesis process is always challenging, but health problems have made this personal challenge just a little bit harder. I am thankful that the process is now completed. My gratitude goes out to my supervisors, which have helped tremendously. Without their valuable and patient advice, I could have never finished this task. A. van Geen has given great advice at the start and Gosse Alserda has given excellent guidance during the rest of the writing process.

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ABSTRACT

The validity of the Common Factor models in a non-synchronous situation is examined by comparing them to a Weighted Price Contribution model. The models are tested on shares that are listed at the New York and Taiwanese Stock Exchange, which receive a large amount of price discovery from the American market. This is the opposite situation to the study of Su and Chong (2006), thus giving more information about the validity in different market situations. The analysis shows that the Common Factor models are biased towards the last series in time, after testing all the possible input combination in the non-synchronous markets. Most time combinations result in large bounds for the Information Share model, which makes their economic interpretation meaningless. None of the time combinations are equal to the Weighted Price Contribution that is used as a benchmark for valid results in this situation.

Keywords:

Price discovery; Information share; component share; weighted price contribution; foreign listing

JEL classification: G14, G15

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1. Introduction

Globalization in the financial markets allows companies to list their stocks at multiple exchanges. The different listings still represent the same underlying assets, as such, the law of one price states that these stocks should trade at the same price. In practice, these prices do not move perfectly together, as they are influenced by trading activity on their local exchange. However, these price deviations are relatively small on average, as observed by Karolyi and Gagnon (2010). These differences in trading activity allow researchers to examine the price discovery process of the different markets, because new information is incorporated into the latest price via trading activity. Price discovery research analyzes the speed at which different markets incorporate this new information into the market price. This study examines the validity of two intraday price discovery models in situations without overlapping market hours. The specific models are the Common Factor models, which have been used in this specific situation by Su and Chong (2006). They mentioned a possible bias towards the last market in time, thus this study takes a further look at this possible bias and how it affects the validity.

The Common Factor models assume an unobserved efficient price that is followed by all markets and calculate the price contribution of each market by their respective influence on this unobserved efficient price. The Common Factor models are the Information Share model of Hasbrouck (1995) and the Component Share model of Gonzalo and Granger (1995), which have been created to examine shares that trade simultaneous on multiple exchanges. However, these models have also been used on daily data by Hales (2014) and on non-overlapping markets by Su and Chong (2007). This study examines the validity of the models for non-overlapping markets by comparing the Common Factor models to a Weighted Price Contribution model from Barclay and Hendershott (2003). This Weighted Price Contribution model is made specifically for non-overlapping markets and has been proven to be accurate by Bommel (2009). This means that the results of the Weighted Price Contribution model can be used as a benchmark to test if the Common Factor models produce valid results in a non-overlapping market.

The Weighted Price Contribution method examines the price contribution of trades with certain characteristics, such as trade size or specific time periods. The price contribution of a time period is measured by the weighted return relative to the full period. For markets that have no overlapping trading periods, the intraday trading period falls within the overnight period of the other market, this allows the Weighted Price Contribution model to calculate the influence of the daily return on the overnight return of the other market. The importance of a market corresponds with the value of the Weighted Price Contribution model, as the measure calculates the impact of the daily return on the opening price of the other market. A market that implements no new information will have a resulting measure close to zero, while a market that implements only new information has a result close to unity. A measure of zero means only noise trading, while a market with a measure of unity has only trades based on new information. The most important market in the price discovery process is the market that has the highest model outcome.

The markets on which to compare the two types of models have to adhere to some restriction for an optimal analysis. The combination of markets must have non-synchronous trading hours, as the validity of the Common Factor models is tested in this specific scenario. A secondary restriction is that both markets have to be liquid, as this has a different impact on both types of models. The Weighted Price Contribution model will have an result of zero for the days without price changes, while the Common Factor models will have a lower contribution for low markets with low liquidity. A third restriction is the influence of the market abroad, as most studies show that firms with a local focus have their price discovery in their home market. This indicates that the results of the study of Su and Chong (2007) are valid, as the firms in their study are based in the same time zone as the home market. However, to examine the general validity of the Common Factor models in non-overlapping markets both market situations have to analyzed, as the price point of the foreign market lies further ahead in time. As Common Factor models analyze the speed of price discovery, it is necessary to test if the models are biased towards the first or last market in the analysis. In terms of markets that comply with the above restrictions, the combination of New York and Taiwan stands out. The New York stock exchange is a very liquid market which can be combined with all Asian markets due to the time differences. In terms of the third restriction a study from Wang (2013) found that the Taiwanese market has the most influence from the market abroad in comparison to the other main Asian markets. This can be explained by the large semiconductor industry, which mainly exports to America. Both markets are liquid, which avoids biases arising from low liquidity. Following these restrictions all the stocks that list at both markets are chosen, which are the underlying shares at Taiwan and the Depository[1] Receipts at the New York Stock Exchange. The Depository Receipt is a listing at a foreign market that can be converted to the underlying share.

As the market hours in this analysis are non-overlapping, there are a limited number of time points that can be compared in the Common Factor models. Each of those combinations has a certain time difference between the two series. The combinations with the smallest time difference are shown in table 1. Each combination has a different amount of data and characteristics. The combinations with only closing prices have a relatively large daily time gap, but the dataset itself has almost no gaps. Combinations that use the opening and closing prices have a smaller time gap, but have less available information. The underlying reason is that there is less available data of opening prices in comparison to closing prices. This means that the combinations with two opening prices have less available data than their closing prices counterparts, while having relatively similar time differences. For this reason, these combinations are excluded from further analysis. In the original use of Common Factor models

[1] Or Depositary Receipt depending on the choice of spelling.

the time differences are non-existent, as the series are analyzed at the same interval. By comparing the different combinations, it becomes clear if smaller time differences increase the accuracy.

Table 1 All possible input combinations for the Common Factor models

First series	Second series	Time difference
Taiwan close	New York close	14.5
New York open (t-1)	Taiwan open	12,5
Taiwan open	New York open	11,5
New York close (t-1)	Taiwan close	9.5
Taiwan close	New York open	7
New York close (t-1)	Taiwan open	5

The Common Factor models have two time series as input in their models. During a day the trading hours of Taiwan are first, followed by the New York trading hours. Taiwanese exchange stops earlier during the day than the New York exchange, which means that the gap between the Taiwan opening price and New York closing price of the previous day is the smallest. The time difference is measured in hours.

The research question asks if Common Factor models produce valid results in non-synchronous markets, which is done by examining two components. The first component is the time difference between the two input series for the Common Factor models. This comparison analyses if smaller gaps produce more accurate results, as the time combination from table 1 moves closer to the original models that have no time gaps. This comparison also shows if the models have bias towards the last series of the time combination. The second component is the comparison of the accurate results from the first test to the benchmark model. The analysis of these two elements gives empirical information about the validity of the results and the consistency of these models in this specific situation. To determine the validity and consistency, the following hypotheses are tested.

Hypothesis 1: All different time combinations for the Common Factor models produce the same results.

Hypothesis 2: The Common Factor models and Weighted Price Contribution model produce the same results for all shares.

If both hypothesis are rejected the conclusion is that these Common Factor models don't produce valid results in this specific situation. As the Taiwanese market is representative of the non-synchronous markets, the conclusion can be generalized to similar markets. The first hypothesis gives information about the impact of different input combinations, a rejection of this hypothesis creates uncertainty about the validity. If both hypotheses are not rejected it gives an indication that the Common Factor models produce valid results in this type of market.

The reason to examine the validity of the Common Factor models in this situation is twofold. For the academic research it increases the knowledge about the situations in which the Common Factor models can be used. For the intraday use of the models there is a strong theoretical and empirical foundation. However, the use of the models in non-overlapping markets is not supported. The models have been used in a study of non-overlapping markets by Su and Chong (2007), with a comment by the authors that the models are possibly biased in non-overlapping markets. This study takes a further look at this bias to examine if the earlier study was right to use the model. In practical terms, the possible addition of the Common Factor models in the non-synchronous environment adds a well-supported model to the toolkit of analysts. The models are already in use for intraday situation, which means that only the input data has to change.

There is body of research with Common Factor models, as they started in 1995 which results in a framework of theoretical expectations. The dominance of Taiwan in terms of trading activity compared to New York, implies a higher contribution of Taiwan. As Sabherwal *et al.* (2003) and Hales (2014) find that improved liquidity correlates with a higher contribution. In terms of market regulations the Taiwanese exchange is stricter, which can hinder price discovery. In terms of economic development both countries fall within the same category of the Worldbank. As the characteristics of the Taiwanese market are similar to most developed markets, the contribution is expected to fall in line with the general findings of other price discovery studies. However, Weighted Price Contribution studies find opposing results for the Taiwanese market, this makes it possible to test the validity of the Common Factor models in a contested market situation. The previous non-synchronous Common Factor study of Su and Chong (2007) applied the test in a market with a clear market leader. The results in this study without a clear market leader show that the Common Factor models produce different results than the Weighted Price Contribution model, which indicates that the Common Factor models are not useful for non-overlapping markets.

The rest of the study is organized as follows. Section 2 summarizes the literature about depository receipts and price discovery research. In section 3 the methods of the different tests are discussed. Section 4 examines the data, while section 5 includes the results and the discussion. Section 6 finishes with the conclusions and future research.

2. Literature review

2.1 Depository receipts

The price discovery analysis of dual listed assets is possible because managers decide to list their firm at a foreign exchange. In a survey from Mittoo *et al* (1992) the costs and benefits of foreign listings are discussed by managers of companies with a foreign listing. The main arguments for foreign listings are (1) access to foreign capital markets (2) a larger shareholder base (3) improved liquidity (4) increased exposure for firm (5) appeal to foreign and institutional investors. The validity of the first and second argument depends on the type of depository receipt that is used. There are different types of depository receipts in America with different levels of regulations as Karolyi (1998) describes. The lowest level of depository receipt trades over the counter, which results in a low amount of available price data. Higher levels are listed at exchanges, but have to comply with stricter regulations. Evidence for the third argument is given by Chan *et al.* (1995), Domowitz *et al.* (1995) and Noronha *et al* (1996), which studies show that foreign listings lead to improved liquidity. An increase in exposure for companies with foreign listings is observed by Lang *et al*. (2003) and Baker *et al.* (2002), as they find that a greater amount of analysts is following these companies. The last argument corresponds to the restrictions of large institutional investors, as some governments restrict institutions in investing into foreign assets (OECD, 2015). An increase in institutional investors and analysts will impact the price discovery process as these agents have more means available to analyze company information than amateur investors.

2.2 Valuation

The valuation of the underlying share can be determined by different models, the two main types of models are multiples and fundamental analysis. The multiple method compares ratios, for example price/earnings, to the prices of other firms. This method is relative in nature, as it calculates the company value by comparing it to other firms. These ratios are commonly used as they are easy to calculate, studies like Liu *et al.* (2002) conclude that these methods also produce relatively accurate results. Fundamental methods look at properties of a single company, such as the cash flows or the growth rate. The models in this category range from a simple Dividend-discount model to a more intricate discounted Free Cash Flow model. The Dividend-discount model discounts future dividend payments with the interest rate. In the Discounted Free Cash Flow model the total cash flows are adjusted for investment and debt payments before being discounted with the Weighted Average Cost of Capital. This Weighted Average Cost of Capital takes into account the financial composition of the firm. There are several variants of these models to correct for specific firm or market situations, but the main point for this study is that the valuation of those models will be the same for both the underlying share and the depository receipt. The valuation is the same, as both securities refer to the same cash flows and underlying assets. This means that the calculations of the valuation models produce equal results. As the securities are the same, the law of one price applies. This law states that an asset should be traded at the same price across all markets, adjusted for any exchange rates. In theory any differences between the two assets are corrected with arbitrage actions from market participants, but there are factors that could create legitimate differences in valuation. Different types of regulation can create differences in valuation, as government regulations can put restrictions on ownership of a share. In countries such as China and India there are rules that prevent foreign ownership of shares, which are implemented via different methods of regulation. In China there are local and foreign shares, while India works with a maximum amount of foreign ownership. If the maximum amount is reached any further demand from foreign investors does not increase the price, as they are not able to buy the asset in question. In China the foreign type of shares trade at a premium relative to the local shares, as observed by Chen *et al.* (2001). In markets that have no foreign ownership regulations there are no barriers to prevent arbitrage.

2.3 Arbitrage

Arbitrage is possible when two equal tradeable assets have different prices at the same time, without legitimate reason. In the case of depository receipts the earlier mentioned government regulations are an example of a legitimate reason that equal assets are price differently. There are different strategies to gain arbitrage profits in the depository receipt market. If the assets are directly convertible, a strategy is to buy in one market and sell in the other. This is profitable if the ask price is lower than the bid price, adjusted for transaction costs. American Depository Receipts are only convertible from the receipt to the underlying share, which means that overpricing of the depository receipt is not corrected with this method. Another strategy is to take a long position in the lowest valued asset and a short position in the assets with the highest value until the prices converge back together. Karolyi and Gagnon (2010) analyze the factors that prevent arbitrage in the depository receipt market, the most important factor are the holding cost. Holding cost are a combination of opportunity costs, which are a lack of interest rates on short sales and idiosyncratic risk. The speed at which the market corrects itself influences the arbitrage profits, as the total opportunity cost of missed interest rates on the short sale increases over time. The other main factor is the idiosyncratic risk, which is the risk from a position that cannot be diversified. If one asset moves in the opposite direction due to noise trading, the disparity between the two positions might become larger. These factors mean that the difference between the underlying asset and the depository receipt has to be large enough to compensate for the risk that an arbitrageur faces. Pontiff (2006) shows that in case of holding costs arbitrageurs do not correct the full mispricing, which results in a band that is known as the no-arbitrage band. There is a large body of research regarding the arbitrage opportunities in the American Depository market, such as Rosenthal (1983) that proves that depository receipts are weak form efficient. Kato *et al.* (2008) find that the law of one price holds, as they find no arbitrage opportunities in the daily returns of a sample of American Depository Receipts. Jong *et al.* (2009) find evidence for arbitrage profits in dual listed firms, but they note that arbitrage is risky due to substantial idiosyncratic risk. If the markets overlap there are also arbitrage opportunities, as Suarez (2011) finds arbitrage opportunities in the overlapping market hours of France and American stocks. The largest study of arbitrage opportunities at the daily level is the study of Karolyi and Gagnon (2010) that analyses 504 depository receipts at the daily level and finds that the average difference from parity is an economically small 5 basis points. Their analysis also confirms the importance of holding cost in preventing arbitrage.

2.4 Weighted Price Contribution model

The Weighted Price Contribution model is used to assign price contributions to the different trading periods. In contrast to the Information and Component Share models, it has no assumption about an underlying efficient price. The theoretical validation can be derived from the definition, as it simply measures the weighted average return of a subsection relative to the total return in each period. This simplicity allows it to examine the contribution of different markets, different sizes of trades, different periods of trade and other characteristics that can be linked to trades. The amount of return that trades with a certain characteristic contribute to the total return can be seen as its price contribution. Barclay and Warner (1993) created the model to examine the information that comes from different trade sizes. Cao *et al.* (2000) adapt it to examine price discovery for the pre-opening period of the New York Stock Exhange. Barclay and Hendershott (2003) use the model for daily and overnight returns. Bommel (2009) proves that the model produces valid results if there is no autocorrelation or drift in the data. The model is also used as a complementary analysis to strengthen results, such as in Agarwal (2007). The Weighted Price Contribution analysis shows that the Hong Kong market is dominant in terms of price discovery for companies that are listed at Hong Kong and London. The Weighted Price Contribution was part of a study by Wang and Wu (2014) on dual listed shares from Taiwan and America that found a high influence of the depository return on the opening price in the Taiwanese market. Another finding from this study is that this influence has decreased over time, which they attribute to a shift in export volume from America to China. New information from the Chinese markets arises during the trading period of the Taiwanese market, which results in a higher price contribution of the Taiwanese market. A study by Wang (2013) analyzes the Korean, Hong Kong and Taiwanese markets with the Weighted Price Contribution method, it shows that the results change significantly over time, depending on the economic conditions. The Taiwanese market had a lower price contribution in comparison to the American market in most of the periods.

2.5 Common factor models

There are multiple variants of Common Factor models. In this section, the main differences will be explained. The Information Share model by Hasbrouck (1995) and the Permanent Transitory model by and Gonzalo and Granger (1995) are the most widely used. Both models rely on the assumption that there is an unobserved underlying efficient price that can be seen as the true value of the firm. The model of Hasbrouck measures the variance of the efficient price innovations and attributes this to the different markets. The model of Gonzalo and Granger (1995) takes a look at the price innovations itself and calculates the contribution that each market makes to the price innovations of the efficient price. Both models are built on a Vector Error Correction model and require unit root and cointegration of the time series. De Jong (2002) shows that the models are closely related, but that the Information Share focusses more on variance. The models are similar in structure, Baillie *et al.* (2002) show that the models have similar outcomes if the errors are uncorrelated. If the errors are correlated the models have different outcomes, as the Permanent Transitory model does not take the correlation into account. Considering that correlation increases with longer time frames, it means that the studies with high frequency data result in similar outcomes for both models. Yan and Zivot (2010) find that both models have some biases due to liquidity and noise trading shocks, but using both in conjunction solves that problem. The research done with Common Factor methods is diverse and can be divided into subsections based on the specific market conditions.

2.5.1 High Frequency

Markets with overlapping trading hours can be analyzed via the simultaneous prices during the shared market hours. This is called an intraday study or a high frequency study. Intraday, because it analyzes data from within the day and high frequency as it uses quotes with a short interval. All high frequency studies show that on average price discovery takes place at the home market with a smaller role for the secondary market. In a study of cross-listed stocks on the Toronto Stock Exchange and the New York Stock Exchange, Eun and Sabherwal (2003) find that the U.S. market contributes on average 38% to the price discovery using the Permanent Transitory model. However, at the individual share level there is a huge variance and the majority of price discovery can happen in either the U.S. or Canada. A study of Spanish cross-listed stocks by Pascual *et al.* (2006) found a negligible role for the New York Stock Exchange compared to the Spanish exchange. Their model was a modified version of Hasbrouck’s information shares method. Another price discovery study on a non-U.S. market from Ding *et al.* (1999) finds that the home market is also more important for stocks listed at the Malaysia and Singapore Exchange.

2.5.2 Exchange rate models

The study of Grammig *et al.* (2005) found a relatively small role for the New York Stock Exchange when they analyzed the price discovery process between stocks on the German XETRA exchange and the New York Stock Exchange. The role of the home market was in line with the other studies, but the interesting result is that 5% of the price discovery is caused by exchange rate shocks. It indicates that models that ignore exchange rates show an incomplete picture. However, the author suggest that this is only relevant for studies on high frequency data. This study uses an adjusted price discovery model, that models the exchange rate endogenously. The original Information Share model does not work with the extra time series, thus they created the Conditional Information Share measure. Frijns *et al.* (2010) use Grammig’s model for both Australian and New Zealand shares that are listed at each market. They find that cross listed stocks have the majority of the price discovery at their home market. The study uses both exogenous and endogenous model and finds that the Australia becomes less important after including the exchange rates as an endogenous variable. Their findings are the opposite of Grammig *et al.* (2005), because they find that the stocks returns influence the exchange rates. The explanation of this phenomenon might be linked to the fact that the Australian and New Zealand exchange rate is a “commodity currency”. Exchange rates are influenced by changes in the relative prices of commodities, which are probably linked to the developments on the stock markets. Dassanayake *et al.* (2015) revisit the Australian and New Zealand markets and confirm that the majority of the price discovery happens in the home markets.

2.5.3 Daily data

The daily data research focuses mostly on non-synchronous markets Kadapakkam *et al.* (2003) show that cross-listed Indian stocks on the London Stock Exchange had equal price discovery from both markets. There are multiple possible explanations, as India is a developing country and has capital restrictions that could influence the result. Su and Chong (2007) study a sample of Chinese cross-listed Hong Kong stocks on the New York Stock Exchange. They employ a combination of the Component Share and Information Share models to examine the price discovery on this non-synchronous markets. Their results show that a majority of the price discovery takes place at the Hong Kong Exchange. Another study by Liebermann *et al.* (1999) about Israeli stocks listed on the New York Stock Exchange find that most stocks have the majority of price discovery at the home market. The model is a vector error correction model similar to the Common Factor models. A secondary discovery of this study is that the model works better for liquid shares.

2.6 Cross-sectional studies

Boehmer and Woe (2013) show that short selling improves the efficiency of the prices on the stock markets after analyzing a large number of announcements of New York listed shares with intraday data. This is an indication that markets that allow short selling have an improved price discovery process. For emerging markets in South America Hales (2014) uses a cross sectional analysis of price discovery results to determine the effect of liquidity on price discovery. The study finds that low domestic liquidity correlates with the market abroad having a bigger impact on price discovery. Eun and Sabherwal (2003) examine the determinant for price discovery in their study about New York and Toronto. One of the findings is that the share of the total trading that takes place abroad correlates with the amount of price discovery abroad.

3 Methodology

3.1 Weighted Price Contribution

The Weighted Price Contribution model is proposed by Barclay and Warner (1993), but Cao *et al.* (2000) are the first to apply the model to different trading periods between the markets. The general model for the price contribution of period i over the sample period is specified as

$$WPC_i = \sum_{1}^{t} \left(\frac{|R_t|}{\sum_{S=1}^{T} |R_s|} \right) \frac{R_{i,t}}{R_t} \tag{1}$$

Where i stands for the different segments of day t. The ratio of $R_{i,t}$ / R_t calculates the percentage of return in day t that is attributed to period i. R_t is the sum of the individual returns of all periods at day t, such that the total price contribution is divided between them. The part between brackets assigns value to an observation depending on the size of the return. This part prevents extreme movements from having a large impact on the outcome. For the Taiwanese market the specification is converted to a model with two periods, an overnight and an intraday return. The trading hours of the New York (Taiwan) market fall within the overnight period of the Taiwanese (New York) market, this means that the trading period can be seen as a segment within the overnight period of the other market. The influence of daily depository receipt return on the overnight return of the underlying share is measured with the following formula

$$WPC = \sum_{t=1}^{T} \left(\frac{|RN_{i,t+1}|}{\sum_{t=1}^{T} |RN_{i,t+1}|} \right) \frac{RD_{i,t}^{A}}{RN_{i,t+1}} \tag{2}$$

De Weighted Price Contribution of the New York market is calculated with the overnight return of the underlying share $RN_{i,t+1}$ and the intraday return of the depository receipt $RD_{i,t}^{A}$. This measures the effect of the daily depository receipt return on the opening of the Taiwanese market. The weighting part of the formula is estimated with absolute values of the overnight returns of the Taiwanese market $|RN_{i,t+1}|$.The formula for the Taiwanese market is created by changing the overnight and daily returns to the opposing market.

$$WPC = \sum_{t=1}^{T} \left(\frac{|RN_{i,t}^{A}|}{\sum_{t=1}^{T} |RN_{i,t}^{A}|} \right) \frac{RD_{i,t}}{RN_{i,t}^{A}} \tag{3}$$

Where RN^A is the overnight return of the depository receipt at time t and RD is the daily return of the underlying share at time t. This formula returns the percentage that the Taiwanese return influences the overnight return of the depository receipt.

A visual representation of the elements within the model is useful to show the validity of the model. The Weighted Price Contribution model reveals the contribution of the intraday period (RDa and RD) within the overnight period of the other market (RN and RNa). The overnight period can be seen as the total period in the general model and the intraday period is the segment of interest. As the Taiwanese and American markets occur sequentially during the day, the night returns have to be calculated toward the previous and next day. The calculations for the contribution of the depository receipt uses the night returns of the next day (t+1) as the American market is last market. The calculation of the contribution of the home share has to use the night return of the day itself, as the Taiwanese market is the first market during day t.

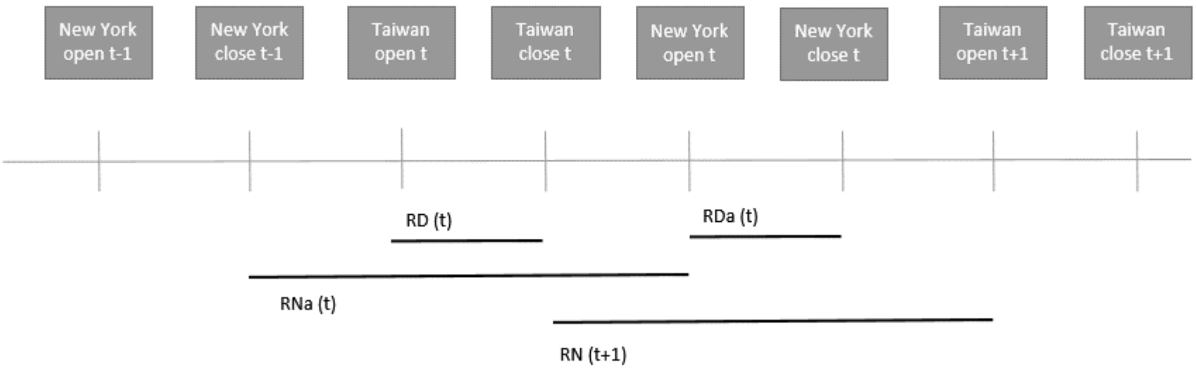

Figure 1 The names in the figure refer to the respective markets and open and close refer to the opening and closing prices of those markets. The price contribution of Taiwan is calculated by measuring the impact of the Taiwanese day return RD(t) on the night return of depository receipt RNa(t). For the opposing market the impact of the day return of the depository receipt RDa(t) is measured on the overnight return of the Taiwanese share RN(t+1).

3.2 Common Factor model requirements

The home share and the depository receipt represent the same underlying asset, this means that there is a direct relationship between the shares. Considering that the rule of one price applies and that arbitrage takes place, the two price series are expected to be roughly equal. Small differences can occur through the exchange rate or the time difference. The first equation describes the expected relationship between the two assets in an ideal situation.

$$p_t^H \approx p_t^B \tag{4}$$

In the model the price of the depository receipts is converted to the home currency. The converted depository receipt p_t^B should then be equal to the home share p_t^H. There are two requirements for the price discovery models. Firstly, the individual time series should have unit root, which is also known as a random walk. Secondly the price series should be co-integrated. Both requirement are necessary to avoid any spurious regressions with the Information Share and Permanent Transitory model.

3.2.1 Augmented Dickey Fuller

The Augmented Dickey Fuller test is used to test the returns of the price series for a variant of non-stationarity, known as unit root. Unit Root is defined as integration of the first order I(1).

$$\Delta y_t = a_0 + a_1 t + \gamma y_{t-1} \sum_{i=1}^{p} \beta_t \Delta y_{t-i} + \varepsilon_t \tag{5}$$

The Δy_t represents the price difference in each individual time series, where t is the time unit. a_0 is a constant factor and $a_1 t$ is a trend factor, those are added to the test if the time series itself has either a constant or a trend. The null hypothesis of the test is unit root (γ =0), if this test is rejected it means that the series is stationary. Considering that stock prices usually follow a random walk it is expected that the null hypothesis will not be rejected. The amount of lags that are included in this model are determined by the Schwartz Bayesian Criterion.

3.2.2 Johansson Integration test

As earlier mentioned both common price discovery models assume the existence of an underlying stochastic trend that links to both the home stock and the depository receipt. A cointegration test can be used to determine the existence of this process. In other words, the cointegration test determines the existence of a cointegrating vector that forms a stationary linear relation between the different stochastic series. The test from Johansen (1988) is chosen because it can be used for both models. This Johansen test transforms the time series into a Vector AutoRegressive Model.

$$\Delta y_t = \Pi \, y_{t-1} + \sum_{i=1}^{p-1} \Pi_i \, \Delta y_{t-i} + \varepsilon_t \tag{6}$$

y_t is a vector of both log prices of the non-stationary price series. Π is a matrix containing $\alpha\beta'$, where α is a vector of adjustment variables and β is the cointegration vector. The α term distributes any movement of to the different series, in terms of the model this is called the speed of adjustment. The cointegration vector β shows the variables for the long term equilibrium between the price series. After modelling the price series, the Trace statistics are analyzed to determine the existence of cointegration and the amount of existing cointegrating relationships. A cointegration vector close to β = (1,-1)' is expected, as the two series should move towards each other.

After determining that the price series are co-integrated and exhibit unit root, the Hasbrouck Information Share and the Permanent Transitory model can be used to show the contributions to price discovery. The basis of these models is a Vector Error Correction Model, which converts the different Error Correction equations into a matrix form. The model shows the return equations of both the home share and the converted depository receipt in an Error Correction Model as specified by Engle and Granger (1987).

$$\Delta p^H = \gamma_0 + \alpha^H z_{t-1} + \sum_{i=1}^{p} \gamma_{1i} \, \Delta p^H{}_{t-i} + \sum_{i=1}^{p} \gamma_{2i} \, \Delta p^A{}_{t-i} + \varepsilon_{1t} \tag{7}$$

$$\Delta p^B = \gamma_0 + \alpha^B z_{t-1} + \sum_{i=1}^{p} \gamma_{1i} \Delta p^H{}_{t-i} + \sum_{i=1}^{p} \gamma_{2i} \Delta p^A{}_{t-i} + \varepsilon_{2t} \tag{8}$$

p^H and p^B are the log prices of the home share and the converted depository receipt. The error correction term of this model is $Z_{t-1} = P_{t-1}^H - P_{t-1}^B$, which is the long term relationship between both assets. α^H and $\alpha^B$are the adjustment variables, these determine the reaction of both series as they move away from the long term equilibrium. The γ_0 is the constant and γ_{1i} and γ_{2i} are the lagged effects of both time series. The ε_t stands for the error term of each individual series.

3.3 Permanent Transitory model

The permanent transitory model estimates the two equations of the error correction model simultaneously. The following vector error correction model of the price series $y_t = (y_{1,t}, y_{2,t})'$ is estimated. The y_1 an y_2 stand for the p^H and p^B within the error correction model.

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \mathrm{A}_i \Delta y_{t-i} + \varepsilon_t \tag{9}$$

The α is the error correction vector, the β is the cointegration vector and the error term is a zero mean vector of the serially uncorrelated innovations. The covariance matrix includes the variances and correlations of the errors.

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \tag{10}$$

$\sigma_{i,t}^2$ is the variance of $\varepsilon_{i,t}$ and ρ is the correlation between the two error terms. The long run relationship dynamics of the model are shown by $\alpha\beta'$ y_{t-1} and the short term dynamics are are represented by the $\sum_{i=1}^{p-1} \mathrm{A}_i \Delta y_{t-i}$ part of the vector error correction model.

Baillie *et al.* (2002) show that the Permanent Transitory model can be written as a the Stock and Watson (1988) common trend representation. Which has a long term and a short term component.

$$y_t = f_t + G_t$$

The common factor (permanent) is ft and the transitory component is Gt (short term). The common factor is a combination of $y_t = (y_{1,t}, y_{2,t})$, whereby ft equals Γy_t as shown by Gonzalo and Granger (1995). The Γ is a 1x2 common factor coefficient vector (γ_1, γ_2), which is orthogonal to α'. The factors are normalized such that γ_1 and y_2 sum to one. The normalization is necessary to assign a percentage based price discovery contribution to both markets. The contribution of the different markets are measured by γ_1 and γ_2 respectively. A more extensive explanation of these calculations can be found in Baillie *et al.* (2002)

3.4 Information Share model

For the Information Share method the error correction model is transformed into a vector moving average specification. This is called the Wold representation.

$$\Delta y_t = \Psi(1) \sum_{s=1}^{t} \varepsilon_s + \Psi^*(\mathrm{L})\varepsilon_t \tag{11}$$

Which can be converted to an integrated form.

$$Y_t = i\psi \left(\sum_{s=1}^{t} \varepsilon_s \right) + \Psi^*(\mathrm{L})\varepsilon_t \tag{12}$$

In this representation $\psi = (\psi_1, \psi_2)$ denotes the row vector of Ψ(1). The i is a vector of ones (1,1)'. Both Ψ(1) and Ψ(L) are polynomials in the lag operator. The Ψ(1) contains information about the size of permanent effects, as it is the sum of the moving average coefficients. T is the number of moving average lags. Matrix $\Psi(1)\ \varepsilon_t$ contains the permanent effect of new information on each time series. Ψ^* is a matrix of polynomials. The combined $\Psi^*(\mathrm{L})\varepsilon_t$ is the transitory part in the lag operator

The product of each row represents the long term component of the different time series that are listed in the error term. This matrix is used to compute the information share, which uses the long term variances. These can be found in the matrix of the variances var($\psi\varepsilon_t$) = $\psi\Omega\psi'$.

Baillie *et al.* (2002) show that the Information Share can be directly estimated without estimating the vector moving average specification. Johansen (1991) notes that $\Psi(1)$ can be estimated from the orthogonalized α and β from the vector error correction model. The calculations are as following

$$\Pi = (\alpha'_\perp (I - \sum_{j=1}^{k} A_j) \beta_\perp)^{-1} \tag{13}$$

$$\Psi(1) = \beta_\perp \Pi \alpha'_\perp \tag{14}$$

The variables are retrieved from the estimated vector error correction model from the permanent transitory approach. The $\alpha'_\perp$ is the inverted orthogonal error correction vector and $\beta_\perp$ the orthogonal cointegrating vector. I is the identity matrix. Further calculations for the Information Share use these variables combined with the covariance matrix from the same estimation. The combination of covariance matrix and the elements from the from the Ψ(1) matrix are used to calculate the information share. Considering that the matrix $\Psi(1) = (\psi, \psi)'$ includes the terms used in the information share, every part of the calculation can be done with these vector error correction model calculations.

$$S_j = \frac{\psi_j^2 \sigma_j^2}{\psi\Omega\psi'} \tag{15}$$

The Information share consist of the ψ of the market multiplied by the variance σ^2 of market j, divided by the total variance $\psi\Omega\psi'$. This calculation is only valid if the variances of the errors are uncorrelated.

3.4.1 Cholesky factorization

If the variances of the errors are uncorrelated the resulting covariance matrix is a diagonal.

$$\Omega = \begin{bmatrix} \sigma_H^2 & 0 \\ 0 & \sigma_B^2 \end{bmatrix} \tag{16}$$

The calculation of the variance of the price innovations would be $\psi\Omega\psi' = \psi_{11}\sigma_H^2 + \psi_{22}\sigma_B^2$ in this case. However, this assumes that the errors are uncorrelated. As the data is measured at a lower frequency the markets are expected to be correlated, which means that Ω_{12} and Ω_{21} are different than zero. This requires the Cholesky factorization of $\Omega = \mathrm{MM}'$ to eliminate this correlation. Choleksy factorization decomposes the covariance matrix into the product of a lower diagonal matrix M and its transpose M'. The lower triangular matrix M that will be used in the Information Share model is visualized below.

$$\Omega = MM' = \begin{bmatrix} m_{11} & 0 \\ m_{21} & m_{22} \end{bmatrix} \begin{bmatrix} m_{11} & m_{12} \\ 0 & m_{22} \end{bmatrix} \tag{17}$$

$$M = \begin{bmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_1(1-\rho^2)^{1/2} \end{bmatrix} \tag{18}$$

The resulting matrix M is used for the Information Share estimation instead of the covariance matrix Ω to take into account the correlation in the non-diagonal part of the covariance matrix.

3.4.2 Information Share

To calculate the contributions of the different markets the Information Share method is employed. The Information Share method calculates the variance of market j relative to the total variance.

$$S_j = \frac{([\psi M]_j)^2}{\psi\Omega\psi'} \tag{19}$$

The $([\psi M]_j)^2$ is the variance of a single market and the $[\psi M]_j$ can be calculated by taking the jth position of the row matrix ψM. The $\psi\Omega\psi'$ matrix is the long run variance. The factorization of M results in different outcomes for the first and last market, such that the market that is listed first in the equation will have a higher contribution. To solve that problem the different permutations are calculated. This means that the ordering of ψ and Ω are changed and the Information Share is recalculated. The different permutations result in an upper and lower bound of the market. The averages of lower and upper bound are seen as an accurate estimate of the markets contribution.

3.5 Model outcomes comparison

As the methods show that the Common Factor models produce a single result for both markets, it is not directly comparable to the Weighted Price Contribution model that produces two individual results. This means that the model outcomes are not expected to be exactly equal, but the direction is expected to be equal as shown in table 2. If one market has a significantly higher contribution than the other market in the Weighted Price Contribution model, the results in the Common Factor models should reflect this. If the models diverge significantly in outcomes, than the models don't measure the same price discovery process. Differences in results can be attributed to biases from the time differences in the Common Factor model inputs or the correlation in the error terms.

Table 2 Expected outcomes if models produce similar results

Weighted Price Contribution	Component Share	Information Share
TW market < NY market	$CS_{TW} < 0.5$, $CS_{NY} > 0.5$	$IS_{TW} < 0.5$, $IS_{NY} > 0.5$
TW market ≈ NY market	$CS_{TW} \approx 0.5$, $CS_{NY} \approx 0.5$	$IS_{TW} \approx 0.5$, $IS_{NY} \approx 0.5$
TW market > NY market	$CS_{TW} > 0.5$, $CS_{NY} < 0.5$	$IS_{TW} > 0.5$, $IS_{NY} < 0.5$

The TW market and NY market in row 1 stand for the price contribution of the Taiwanese and New York market calculated with formula 2 and 3. CS stands for the Component Share model outcomes of both Taiwan (TW) and New York (NY). Similarly, IS stands for the Information Share midpoints of Taiwan (TW) and New York (NY).

4 Data

This study uses data from Taiwan stock exchange listed shares and their New York equivalent Depository Receipts. An American Depository Receipt is a listing of a non-U.S. share on a U.S. stock exchange, created by a sponsoring bank. The price data for both the Taiwanese and New York shares is retrieved from the Datastream database, as well as the Taiwan New Dollar to U.S. dollar exchange rate information. This data is collected on a daily basis, as the markets of New York and Taiwan have no overlapping trading period. The sample data for both models consist of opening and closing prices retrieved at a daily frequency.

As both markets fall in different time zones the local times are converted to the Coordinated Universal Time, so the markets are placed on a 24 hour time frame. The Taiwan market opens first at 1:00 and closes at 5:30, while the New York market opens at 12:30 and closes at 20:00. The daily data of is compared at the smallest intervals between the New York and Taiwanese market, the closest combination is Taiwan at time (t) and New York (t-1).

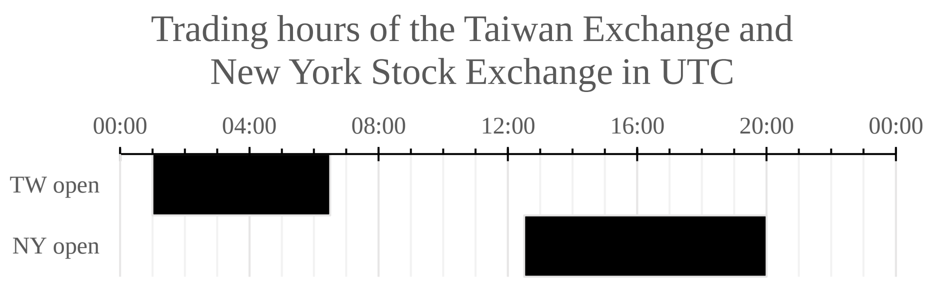

Figure 2 A visualization of the consecutive nature of the trading hours in both markets.

The sample includes all firms that have active stocks listed on both the New York Stock Exchange and the Taiwan Stock Exchange. The sample only includes stocks that are traded on a stock exchange, as stocks that trade over the counter lack liquidity and have a low amount of trading activity. The full sample exist of five stocks, which is the total amount of Taiwanese firms listed in New York. The other Taiwanese dual listed stocks are listed at the London Stock Exchange. Those suffer from low trading activity, which results in the same quotes for multiple days. The choice is made to focus on the stocks with high amount of information over a higher quantity of stocks with a low amount of information.

A possible bias is the industry of the selected firms. Three firms are semiconductor producers and one is a computer hardware manufacturer, which means that the sample is sensitive to the technology sector. The *MSCI ACWI Technology hardware and equipment* index is examined from the first depository receipt listing in the sample until the end of the testing period. Within this period there is one major bubble, which is related to the technology sector. The trading activity and company valuation during this time period is different from the rest of the sample period and creates validity concerns for the models. For the Weighted Price Contribution model this period would have a disproportionate effect, due to the large price movements. For the Common Factor models it creates problems with the requirements of unit root and cointegration. This period can't be estimated separately, as it has not enough observations for an individual analysis. The secondary crash during the financial crisis of 2008 does not directly imply bubble related trading during this period, as the sample has no financial firms. The firms are impacted by the general crisis, but the impact is relatively small relative to dotcom bubble. After removing the bubble period, there are enough observations left to run the Common Factor models, considering that other daily Common Factor studies use less data. The test period start in the middle of 2002 until the end of 2015, which results in at least 3,000 data points per asset.

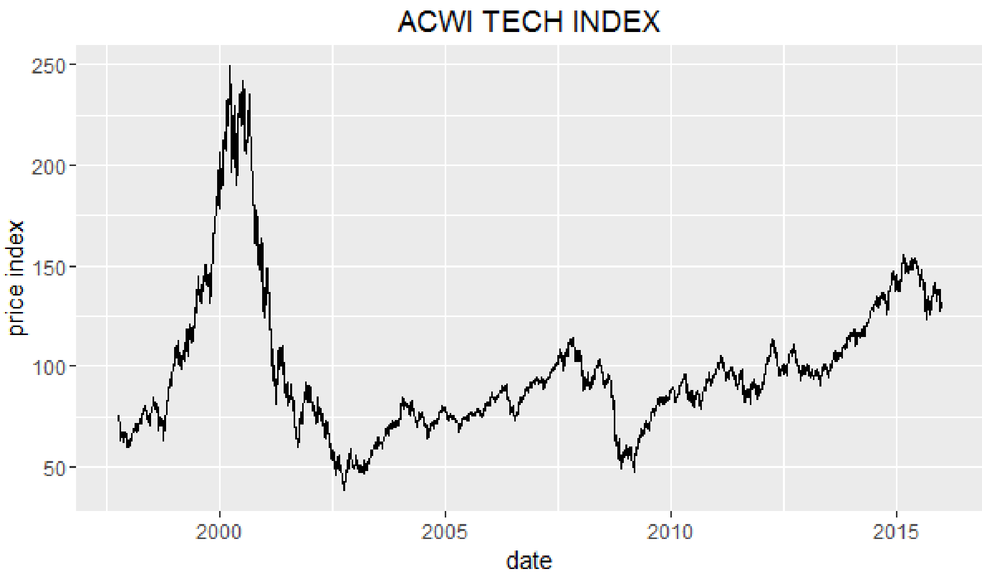

Figure 3

The general statistics in table 3 show that the different companies move in different directions in terms of value. A majority sees an increase in market value, while others lose value during the testing period. The change in local market value in percentages is somewhat different for the underlying share and the depository receipt. This can be cause by two factors, due to a disparity between the underlying share and the depository receipt at the measuring points and by changes in the exchange rate between the start and end of the period. The company codes are used in the further tables if a test statistic refers to either the home share or depository receipt. The TW stands for the Taiwanese home share and the NY for the depository receipt in New York. If a test statistic refers to both assets at the same time the full company name is used.

Table 3 Summary and descriptive statistics of home shares and depository receipts

Code	Name	Currency	ADR ratio	MV start (x bln)	MV End (x bln)	Average Daily turnover
TW:ASE	ADVANCED SEMICON.ENGR.	TW	-	200.2	297.3	49809
TW:ADT	AU OPTRONICS	TW	-	267.9	93.6	73641
TW:CHG	CHUNGHWA TELECOM	TW	-	713.7	768.8	9853
TW:TSM	TAIWAN SEMICON.MNFG.	TW	-	1842.2	3708.1	62610
TW:UTD	UNITED MICRO ELTN.	TW	-	210.4	154.3	66873
U:ASX	ADVANCED SEMICON.ENGR. SPN.ADR 1:5	U$	1:5	6.9	8.9	824
U:AUO	AU OPTRONICS ADR 1:10	U$	1:10	9.2	2.8	2177
U:CHT	CHUNGHWA TELC.CO.SPN.ADR 1:10	U$	1:10	24.5	23.3	611
U:TSM	TAIWAN SEMICON.SPN.ADR 1:5	U$	1:5	65.2	118.0	10062
U:UMC	UTD.MICRO ELTN.CO.ADR 1:5	U$	1:5	8.2	4.8	3505

SEMICON is short for Semiconductor. ENGR stands for engineering. ELTN stands for electronics. ADR stands for American Depository Receipt. The stock is listed in the currency that is displayed in the currency column, all values in the same row are denoted in the displayed currency. TW stands for the Taiwan New Dollar, the currency that is used in Taiwan. U$ stands for the U.S. Dollar. MV stands for the market value displayed in the local currency. The average turnover is measured in trades per day.

The trading volume on the Taiwanese is exchange is higher than New York for every stock in the sample. In absolute trade volume the New York market is significantly smaller than Taiwan, the New York trade can be expressed in a percentage of the Taiwan trade, respectively 2%, 3%, 6%, 16% and 5%. As the depository receipts represent multiple underlying shares, the daily turnover in market value has a higher relative portion of the total trade. The turnover in dollar volume in New York relative to Taiwan is 8%, 30%, 62%, 80% and 26% for all respective shares. The Taiwanese exchange remains the dominant exchange, although with a smaller margin for Chunghwa telecom and Taiwan Semiconductors .

5. Results

5.1 Weighted Price Contribution

The Weighted Price Contribution results reveal the importance of both markets by a percentage measure. The percentage of each market shows the influence of the day return on the overnight return of the other share. The interpretation of this measure is straight forward, if the first market has no influence on the opening price of the other market the result will be around 0%. A market that is fully responsible for the opening price of the other market will have a result around 100%. This is possible because the official opening price of a market is different than the closing price of the previous day. The Weighted Price Contribution model calculates the influence that a market has on the opening price of the other market.

Table 4 Results from the Weighted Price Contribution model

Company	U.S. daytime - Taiwan overnight	Taiwan daytime - U.S. overnight
ADVANCED SEMICON	60.37	**72.65**
AU OPTRONICS	71.50	**77.60**
CHUNGHWA TELCO	**68.54**	41.32
TAIWAN SEMICON	**83.48**	51.64
UTD.MICRO ELTN	**93.51**	53.59
Market average	**75.48**	59.36

Calculated values are multiplied by 100 to display values as percentages. Results from the U.S. vs Taiwan column are calculated with formula 2, while values in Taiwan vs U.S. are calculated with formula 3

The results show that both markets contribute to the price discovery in the overnight setting. On average the majority of the shares receive more price information from the American market than the Taiwanese market in the overnight setting. This indicates that the American market is more important than the Taiwanese market in terms of price discovery. The Taiwanese market has a higher contribution for the shares of Advanced Semiconductors and AU Optronics. However, the difference is relatively small. This observation coincides with earlier results of Wang and Wu (2014), who found a large difference for Taiwanse Semiconductors and United Micro Electronics and a smaller difference for Advanced Semiconductors and AU Optronics in their total sample period. The averages are relatively similar to the findings of Wang (2013) with respectively 80% and 50% for their full sample period. The sample periods of the earlier studies fall within this research sample period, as such the results are expected to fall in the same region. Individual results from this test are compared to the results of the Common Factor measures.

The weighted average part of the Weighted Price Contribution increases the weight for larger returns. While this is necessary for the validity of the model it also increases the weight of volatile periods. As the total sample period is 12 year, it consists of stable periods and crises. The volatile periods will have a larger impact on the measure than the stable periods, to examine this effect the full sample is divided in subsamples. In the different subsamples the development and consistency of the results are analyzed.

The analysis of the subsamples in table 12 shows that the individual contributions change during the sample period. On average the contributions from the American market decrease over time, while the Taiwanese contributions rise. This matches the observations from Wang and Wu (2014) that the Chinese market becomes more important for Taiwan relative in comparison to the American market. In the first eight years 3/4 of the sets gain most price discovery form the American market, this lowers to just 1/3 in the last six years.

5.2 Unit Root test

The Augmented Dickey Fuller test is performed on each individual time series of the dataset. The log price series of the home share and Taiwanese dollar equivalent of the depository receipt are tested for the exogenous model. Each individual time series is analyzed to examine which Dickey Fuller model has to be used. After examining the price graphs and model choices of similar papers the Unit Root test with drift is chosen. The Unit Root test is done on four price series, as all of the combination from the Common Factor tests can be made with these four series.

Table 5 Augmented Dickey Fuller Unit Root test on all time series

Company	TW open	TW close	NY open	NY close
ADVANCED.SEMICON.ENGR.	-1.77	-1.51	-1.61	-1.57
AU.OPTRONICS	-1.05	-0.95	-0.97	-1.02
CHUNGHWA.TELECOM	-2.43	-2.53	-2.41	-2.63*
TAIWAN.SEMICON.MNFG.	-1.47	-0.80	-0.92	-1.21
UNITED.MICRO.ELTN.	-2.36	-2.12	-1.79	-2.58*

* is the 10% critical value of -2.57, ** is the 5% critical value of -2.87, *** is the 1% critical value of -3.43. The Taiwan Equivalent is the depository receipt converted to Taiwanese New Dollars. If the absolute value of the test statistic is smaller than the critical value in absolute terms the null hypothesis of unit root is rejected.

As none of the series are rejected at the higher critical levels, it is probable that all the time series have unit root. The Chunghwa Telecom and United Micro Electronics closing price series are rejected at the 10% level, but not at the 5% level. This means that the null hypothesis of unit root is not strongly rejected, the series can be used. Considering that the test show that all the time series used in the model exhibit unit root, the cointegrating relationships can be tested.

5.3 Cointegration test

The Johansen test for cointegration is employed for the set of time series of each company in the exogenous model. The Trace statistics and the cointegrating relationship (β) are reported. The Johansen test determines the existence of a linear relation between the different price series, with the expected long run relationship is (1, -1), as the values should remain close to each other. For the validity of the model the actual cointegrating relation has to be close to the expected relationship. Every set of shares is analyzed over the four of the closest possible time series combinations from table 1. to examine if the results are consistent.

Table 6 Results from the Johansen cointegration test

Set	NY close - TW close		TW close - NY close		TW close - NY open		NY close - TW open	
	1	2	1	2	1	2	1	2
ASE	45.00***	1.48	44.34***	1.41	36.77***	1.43	29.32***	1.42
ADT	71.66***	0.92	69.90***	0.92	59.13***	0.86	52.85***	1.02
CHG	42.00***	2.88	42.51***	2.84	35.85***	2.83	25.26***	2.38
TSM	27.35***	1.07	28.47***	0.94	24.54***	0.87	25.62***	0.91
UTD	9.40	2.95	9.74	3.04	8.53	2.8	9.51	2.98
Cointegrating relation								
ASE	-0.981		-1.019		-1.020		-0.981	
ADT	-1.013		-0.987		-0.988		-1.013	
CHG	-0.960		-1.042		-1.039		-0.952	
TSM	-0.927		-1.078		-1.077		-0.926	
UTD	-0.697		-1.427		-1.487		-0.663	

The normalized cointegrating equation is reported for each set of underlying share and depository receipt. The existence of cointegrating relations is tested with trace and eigenvalue statistics. The Trace is reported in this table, as the eigenvalue results were equal to the trace results. The Trace test has the null hypothesis of n amount of cointegrating relations versus alternative of the maximum amount of relations. The first test rejects the hypothesis of zero cointegrating relations, versus the alternative of two cointegrating relations. In the second test the null hypothesis of one cointegrating relation versus the alternative of two cointegrating relations is not rejected. Critical values of the first test are 15.66, 17.95 and 23.52 and of the second test 6.50, 8.18 and 11.65, the 10%/5%/1% confidence levels in the table are given by */**/***.

The Trace statistics reveal the existence of a cointegrating relationship in four of the sets with a high certainty, only United Micro Electronics does not have a cointegrating relationship. The hypothesis of no cointegrating relationship is strongly rejected at the 1% level for the first four sets, while the hypothesis of the last set is clearly accepted. In each case the hypothesis of one cointegrating relationships is not rejected to the alternative of two cointegrating relationships. More than one cointegrating relationship is not expected from this data, which is confirmed by the test. The cointegrating relationship of United Micro Electronics does not hold because of a period of divergence and reversal to parity during 2009-2012. The cause of this divergence is unclear, the start coincides with a listing on an U.S. Hardware index and a stock split. The subsamples before and after this divergence are cointegrated, these results are reported in table 11 in the appendix. There is no valid reason to adjust for this divergence, therefor the subsamples are not included in the main analysis.

The cointegrating relationship of each company is close to the expected long run relationship, except for United Micro Electronics. The resulting values close to 1 imply that the two shares move towards each other in the long run, which is expected for dual listed shares. For each company the cointegrating relationship is reported for the four most logical time combinations. In these combinations the result is normalized to the first market in the series, which is New York in the first and last series. While the second and third combination is normalized to Taiwan, which means that the resulting cointegrating relationship is reversed. After adjusting for this effect the test reveals that the different time combinations yield the same result. These results indicate that different choices of time differences have no considerable effect on the long term relationship of the data. In general these results determine that first four sets contain the correct requirements for valid results in the Common Factor models.

5.4 Component Share

The Permanent Transitory method displays the contributions to price discovery from the different markets with the Component Share measure. The Component Share reveals the relative influence of the different markets on the common factor in the error correction process. This test is done on the combination of time points from table 1 to examine the effect of the different choices on the permanent transitory model.

Table 7 Components share results for each combination

	NY close - TW close	TW close - NY close	TW close - NY open	NY close - TW open
TW:ASE	0.95	0.52	0.96	0.92
TW:ADT	0.80	0.39	0.61	0.91
TW:CHG	0.78	0.53	0.61	0.89
TW:TSM	0.74	0.30	0.54	0.71
TW:UTD	0.88	0.85	0.79	0.77

The component share is normalized, such that that the values of both markets sum to one. The reported values refers to the percentage of price discovery that occurs at the Taiwanese exchange for the individual shares in the analysis. Results for United Micro Electronics are reported, but are not necessarily valid due to the rejection of the cointegration test.

The results show a dominant position for the Taiwanese Exchange for each pair. The New York Stock Exchange is slightly dominant in one combination, but on average the Taiwanese market dominates. According to these results the New York Stock Exchange can be classified as the satellite market. Results are not consistent over the different time combinations, which indicates that the choice of time series changes the results of the permanent transitory model in non-overlapping markets. Differences in results between the time combinations can be attributed to differences in the amount of available data and the differences in time. There is less data available of the opening prices in comparison the closing prices, which results in gaps within the sample. This results in a trade-off in terms of quality of the data in the first combination versus the smaller time gaps in the third and last combination. According to these results the choice of time series influences the outcome of the model, but there is no clear pattern between the different combinations.

The results of the individual companies can be compared with the other models, to examine if the models measure the same price contribution. The results coincide with the trading volume hypothesis of Cheol and Sabherwal (2003), as the majority of the trading activity happens in Taiwan. Results from the Weighted Price Contribution model are different to the Permanent Transitory model in at least three of the cases. The individual Weighted Price Contribution results show either a dominant position for the American market or a relatively equal amount of price discovery for both markets. This results clearly contrasts the Component Share results where the majority of the results show a dominant position for the Taiwanese market.

5.5 Information Share

The Information Share is the second Common Factor method that is used, this model adjust for the correlation. As the data is taken on daily frequency the occurrence of correlation is expected. The two most important parts from the Information Share are the midpoints and upper and lower bounds. The midpoints are a good estimation of the price contribution according to Baillie *et al.* (2002), while the spread between the upper and lower bounds determines the accuracy of the results.

Table 8 Mid points from the Information Share model

	NY close - TW close	TW close - NY close	TW close - NY open	NY close - TW open
TW:ASE	0.94	0.49	0.73	0.70
TW:ADT	0.86	0.42	0.54	0.61
TW:CHG	0.84	0.45	0.55	0.73
TW:TSM	0.71	0.25	0.49	0.64
TW:UTD	0.96	0.76	0.87	0.83
U:ASX	0.06	0.51	0.27	0.30
U:AUO	0.14	0.58	0.46	0.39
U:CHT	0.17	0.55	0.45	0.27
U:TSM	0.29	0.75	0.51	0.36
U:UMC	0.05	0.24	0.13	0.17

The reported midpoints in this table are the averages between the lower and upper bound of each share. The different combinations of time series are taken from table 1, as they represent the different possible time combinations.

Within the Information Share results in table 8, the same pattern occurs as in the Component Share results. Different time combinations produce different outcomes, without any clear pattern. Out of these combinations the set of NY close (t-1) and TW close gives the highest contribution to the Taiwanese market. On the other side the combination of TW close and NY close gives to lowest contribution to the Taiwanese market. In between are the other two combinations that use an opening price. On average the different combinations fall between the Taiwanese market contributing half up to almost all price information, so on average the Taiwanese market is dominating the price discovery. At the level of the individual firm there are some differences. The first three firms gain at least half to all their price information from the Taiwanese market. The fourth company, Taiwan Semiconductors, has varying results from the majority for Taiwan to a majority for the New York market. The last firm, United Micro Electronics, is the only firm which has a large majority for Taiwan in each time combination. However, the series of United Micro Conductors are not cointegrated, so the results of this company have to be treated with caution.

Table 9 Upper and lower bounds from the Information Share model

	NY close - TW close		TW close – NY close		TW close - NY open		NY close - TW open	
	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower
TW:ASE	1.00	0.87	0.85	0.13	1.00	0.45	1.00	0.40
TW:ADT	0.97	0.75	0.78	0.06	0.94	0.13	1.00	0.21
TW:CHG	0.91	0.76	0.69	0.21	0.82	0.28	0.99	0.46
TW:TSM	0.93	0.48	0.46	0.05	0.82	0.16	0.96	0.19
TW:UTD	0.98	0.93	0.96	0.55	0.90	0.85	0.89	0.76
U:ASX	0.13	0.00	0.87	0.15	0.55	0.00	0.60	0.00
U:AUO	0.25	0.03	0.94	0.22	0.87	0.06	0.79	0.00
U:CHT	0.24	0.09	0.79	0.31	0.72	0.18	0.54	0.01
U:TSM	0.52	0.07	0.95	0.54	0.84	0.18	0.81	0.04
U:UMC	0.07	0.02	0.45	0.04	0.15	0.10	0.24	0.11

The Information Share shows the upper and lower bounds for the underlying shares and depository receipts. This result is a range due to the Choleksy factorization, where the first ordering gives a higher contribution than the second ordering. The size of the range determines the accuracy of the results. The price series of the United Micro Electronics shares are not co-integrated and might return biased results.

Midpoints in table 8 are determined by taking the average of the upper and lower bound of each market. Table 9 reports the upper and lower bounds for each firm and time combination. The bound influence the usefulness of the results in two ways. The main problem is the absolute size of the bounds, as the measure only specifies that the actual value lies somewhere in between these two bounds. An example of this problem can be found in table 9 at the TWclose-NYopen combination of

TW:ADT, which measure falls between 13% and 91%. In the results only the time combination of NYclose-TWclose gives small bounds. Other combinations produce large bounds for most companies except United Micro Electronics. This indicates that the results for this company are either very one sided or that the errors are uncorrelated. A second problem with the bounds is overlapping. Larger bounds increase the chance that the lower bound will be below the upper bound of the second market. In that case it is not certain that the midpoints are a good approximation. An example of this is the Advanced semiconductor combination at TWclose-NYopen, where according to the midpoint the Taiwanese market contributes 75% and New York contributes 25% to the price discovery. Due to the lower bound of the Taiwanese market being 45% and the upper bound of New York being 55% percent, it is also possible that each market contributes 50%. The only results that don't overlap are again the ones within the NYclose-TWopen combination.

5.6 Comparison

In determining the validity the Common Factor models are compared in two different ways, following the two hypotheses. First comparison is between the different input combination, which are the different time points from table 1. After running the Common Factor models on the four most logical time combinations, it becomes clear that the first hypothesis is rejected. There is no consistency in the permanent transitory model outcomes, the Information Share midpoints and Information Share bounds. The smaller time differences did not make the models more accurate, as no clear pattern emerged from the different combinations. There is only one combination of time points that produces meaningful results, which is NYclose-TWopen. From the results it is clear that the gaps in data in the combinations with opening prices are not the cause, as the TWclose-NYclose combination uses the same data as NYclose-TWclose, but produces inaccurate results.

The combination of NYclose-TWclose has Taiwan in the last position and has a higher contribution for Taiwan, in contrast to the combination where NYclose is last. To examine if the last market is given a higher contribution by these models, a time combination with a larger time difference is added. This combination of TWclose (t-1) and NYclose uses the same closing price data, but has New York at the last position with a larger time gap. In table 10, the contributions of Taiwan are displayed at the different closing time combinations, a clear pattern is visible. The market that is last in the analysis gives more price contribution according to the models, which is the only factor that changes in this analysis. This confirms the bias towards the last series of the input combination.

Table 10 A comparison of the closing price combinations in the IS and CS model

	NY close(t-1) - TW close		TW close - NY close		TW close(t-1) - NY close	
	CS	IS	CS	IS	CS	IS
TW:ASE	0.95	0.94	0.52	0.49	0.26	0.08
TW:ADT	0.80	0.86	0.39	0.42	0.20	0.03
TW:CHG	0.78	0.84	0.53	0.45	0.41	0.18
TW:TSM	0.74	0.71	0.30	0.25	0.20	0.03
TW:UTD	0.88	0.96	0.85	0.76	0.71	0.63

The different combinations of closing prices are compared to examine a bias towards the last series. Combination are similar to table 7 and 8, except for the new TW close (t-1) – NY close combination. CS stands for the component share outcomes and IS stands for the Information Share midpoints of the contribution of the Taiwanese market.

In the second comparison the Common Factor model outcomes are compared to the Weighted Price Contribution model outcomes. If the models measure the same price contribution process the results should be roughly the same. The Weighted Price Contribution model results in table 4 show that the Taiwanese market is slightly more important for the first two companies in the sample. The last three firms receive more price information from the New York market. Considering that the price series of the last company are not cointegrated, the first four companies are leading in the comparison. In the Component Share results the first two companies also receive more price information from the Taiwanese market, but the dominance of Taiwan is larger in the Component Share results than observed in the Weighted Price Contribution results. The last three companies gain most of their price discovery from the New York market, which is opposed to the Weighted Price Contribution results. The comparison with the Information Share model is slightly more complicated as the previous comparison has shown that only one combination, the NYclose-TWclose has meaningful results. This means that only this input combination is used for the comparison with the Weighted Price Contribution. This combination has similar results to the permanent transitory model, for each share a large majority of the price discovery comes from the Taiwanese market. Which again stands in contrast to the Weighted Price Contribution results, where three firms gain most of their price contribution from the New York stock exchange. For the first four companies the Weighted Price Contribution result fall in the same direction as the Common Factor models twice, but are opposite in two other cases. If the models measured the same price discovery process all the results should have fallen in the same region. Hypothesis 2 is rejected, which is a strong indication that the Common Factor models are not valid in this specific situation.

5.7 Discussion

A limitation is that the sample size is relatively small, as the total amount of Depository Receipts from Taiwan is relatively low. However, it is important for an optimal analysis to find a different situation than the earlier study by Su and Chong (2006). As receiving a large amount price contribution from the American market means that the time bias works in the opposite direction. This bias for the last series is found in the tests for each company. This makes it relatively certain that the effect will occur in a larger sample. This certainty is supported by the fact that only the biased combination of NYclose-TWclose produces small bounds for the Information Share, while all the other time combinations have such large bounds that economic interpretation becomes impossible. The comparison has also a possible problem due to the long timeframe of the sample period, because the price discovery process can change over time. The Weighted Price Contribution model can be divided into subsamples to examine trends, but this is not possible with the Common Factor models as they require a larger number of data points. Normally, the comparison between different models is examined by simulating a large number of sets, however the interaction between the different markets over time is difficult to model.

6. Conclusions

The main question if Common Factor models produce valid results in a non-synchronous market has a clear answer. The tests indicate that the models are not valid in this situation. The results have shown that the Common Factor model are not producing consistent results over the different input combinations, thereby rejected hypothesis 1. The comparison also reveals that the Common Factor models have different outcomes than the Weighted Price Contribution model, which is a rejection of the second hypothesis. In the comparison of the different input combinations only one combination produces meaningful results, which is the NYclose-TWclose combination. This finding goes against the knowledge that smaller intervals for the data input produces more accurate results. Smaller time gaps at the daily level prove to be more correlated, which means that this mechanic does not work for non-synchronous markets.

An important factor for this research is the time difference between the input combinations, it was uncertain if the consecutive nature of the time series would add a bias to the last series. As models examine at which speed the markets implement new information, including a series that comes later in time would intuitively influence the results. In the results there is evidence for a bias towards the last series, as the combinations with Taiwan as the last market give a higher contribution to Taiwan. The strongest evidence for the bias comes from table 10, where only the ordering is changed. However, this effect is not as strong in the combinations in the combinations with opening prices and in the company results of United Micro Electronics. The different ordering does not reverse the outcomes within the United Micro Electronics results, which indicates that the ordering of the time series in the Common Factor models influences the outcome, but does not fully determine it.

The case of United Micro Electronics gives more insight into where these models produce meaningful outcomes. The reason that United Micro Electronics is not cointegrated, is that the price of the depository receipt moves upward for a certain time period before returning back to the price of the underlying share. This strong movement back towards the underlying share results in the models produces a high contribution for the market of the underlying share. A highly asymmetric case decreases the impact of correlation, as shown in Baillie *et al.* (2002). This means that the Information Share method has smaller bounds for non-synchronous markets if one market dominates the price discovery process. If one market dominates the price discovery, the Information Share can produce meaningful results, but the biases still remain.

After testing the different aspects of the Common Factor models in a non-synchronous environment, most evidence points towards the models producing invalid results. While the models can possibly produce accurate results in one sided markets, in this divided market in this study the models produce different results than the benchmark model. The sample size of the comparison is relatively small, but the results are in line with the lack of theoretical foundation for the Common Factor models in this specific situation. This finding is strengthened by the discovery of a bias towards the last series, which explains the higher contributions for Taiwan in the NYclose-TWclose combination. Another aspect that can be seen in the Weighted Price Contribution results in table 12, is that price discovery changes over time, which means that a model with a shorter time span produces more current results. This is not possible with the Common Factor models, as they require a large number of data points. At the daily level this can amount to at least several years of data. This means that shorter trends in price discovery are not revealed by the Common Factor models used at the daily interval. All these observations point out different problems with the use of usage of Common Factor models in this situation, which means researchers are advised to use a different model for this situation.

6.1 Future Research

Future research could focus on comparing other methods to examine if they measure price discovery in non-overlapping markets in the same way. There are different models that measure similar processes, such as the Error Correction model from Lieberman *et al*. (1999) or the impact of the local exchange on the stock returns as in Agarwal *et al*. (2007). A large empirical study can show the relation between the different model outcomes.

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8. Appendix

Table 11 IS and CS results before and after divergence in United Micro Electronics

UNITED.MICRO.ELTN.	Unit Root test	Cointegration test	Cointegrating relation	Component Share	Information Share (mid)
Before divergence	-0.55	46.26***	1, -0.81	0.74, 0.26	0.73, 0.27
After divergence	-0.46	22.49**	1, -1.07	0.84, 0.16	0.97, 0.03

This table combines all tests for the Common Factor models on the sections before and after the divergence in United Micro Electronics in time combination NYclose-TWclose. Results are lower than the results from table 7 and 8, but still in the same area. These parts of the sample are valid in terms of unit root and cointegration.

Table 12 Weighted Price Contribution results in subsamples

Subsample	2002-2003		2004-2005		2006-2007		2008-2009		2010-2011		2012-2013		2014-2015	
	US	TW	US	TW	US	TW	US	TW	US	TW	US	TW	US	TW
ADVANCED SEMICON	69.23	82.24	72.25	78.31	56.23	76.94	67.61	56.87	50.13	74.20	54.65	64.92	45.91	89.09
AU OPTRONICS	74.25	82.27	86.73	74.24	78.91	76.26	73.58	65.24	55.41	74.69	39.74	80.13	51.93	83.88
CHUNGHWA TELCO	72.51	47.66	16.55	35.88	88.36	27.91	84.85	35.51	69.38	52.78	55.35	62.19	45.54	42.33
TAIWAN SEMICON	98.38	36.25	86.43	57.65	98.80	53.99	89.77	44.07	82.87	46.45	58.95	63.98	74.09	72.02
UTD.MICRO ELTN	98.88	44.32	90.37	59.70	113.56	49.55	118.07	41.12	95.24	45.06	41.94	67.92	58.73	81.37

The US stands for the American market and the TW stands for the Taiwanese market. The US results are calculated by formula 2 and TW by formula 3. Each sample starts at the start of the first year and ends at the last date of the second year.