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Essays on Modeling of Blind Principal Bid Basket Trading Cost

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ESSAYS ON MODELING OF BLIND PRINCIPAL BID BASKET TRADING COST

by

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Abstract

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Adviser: Professor Christos Giannikos

The following is an executive summary of three essays on the modeling of the blind principal bid (BPB) basket trading cost, each focusing on different issues. The first essay, “How does a liquidity provider price a blind principal bid basket – An empirical perspective,” investigates various determinants of the blind principal bid basket trading cost. I extend Kavajecz and Keim’s (2005) model by identifying the price determinants based on the liquidity provider’s behavior. The model developed in the first essay, however, is not a structural model because it is not based on any theoretical framework. That is addressed in the second essay, “Two theoretical models for blind principal bid basket trading cost.” Both structural models in the second essay are based on well-defined theoretical frameworks for modeling the trading cost of blind principal basket. The key insight in the second essay is the similarity between a dealer’s spread and the trading cost of blind principal bid. I extend the two dealer’s spread model developed by Stoll (1978a, 1978b) and Bollen, Smith and Whaley (2004) to model blind principal bid basket trading cost.

The third essay, “Manager’s Decision to Trade Blind Principal Bid Basket – a behavioral perspective,” investigates an asset manager’s choice between traditional agency trade and blind principal bid for executing a basket of stocks. I look at a manager’s choice based on decision theory, with a behavioral perspective. I test both prospect theory and expected utility theory in modeling a manager’s choice. The results indicate stronger empirical support for prospect theory than for expected utility theory and show that prospect theory provides a better explanation of the observed decisions made by managers.

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Chapter 1

Institutional Description of Trading Blind Principal Bid Baskets

1.1. Institutional Description of Trading Blind Principal Bid Basket

This chapter provides a detail institutional description of trading blind principal bid (BPB[1]) basket since many people may not familiar with this special kind of trading mechanism. It also provides a background for the questions that I am going to investigate in chapter 2, chapter 3 and chapter 4. BPB[2] is a form of basket trading. It is a mechanism that brings together the liquidity demander (i.e., buy side money managers[3]) and the liquidity provider (i.e., sell side BPB brokers). Traditionally, basket trading is related to index arbitrage and the basket of stocks being traded usually tracks a given index (e.g., S&P 500). BPB is often used by quantitative money managers to rebalance their portfolio regularly and execute simultaneously the sell and buy trades in one basket as a single transaction. Unlike the case of index arbitrage, BPB basket usually does not track a particular index. We can describe BPB from two perspectives: first as an auction; second

[1] I shall use BPB as an abbreviation of blind principal bid for the rest of the document.

[2] Often referred to loosely as basket trading, program trading, risk trading.

[3] We use liquidity demander and buy side money managers interchangeably throughout this dissertation.

as a price discovery process, which defines execution price for each stock in a basket. Additional institutional descriptions of BPB can be found in Almgren and Chriss (2003) and Kissell and Glantz (2003, chapter 10).

1.1.1. BPB as an auction

As its name indicates, BPB is basically an auction. The bid submitted by a competing broker to a money manager for consideration is a *liquidity risk premium* that a broker charges a manager for trading a whole basket of stocks as a single transaction. This premium compensates the broker for providing two services. First, the broker provides liquidity to the manager so that all the trades in the basket will be executed simultaneously in a timely manner as a single transaction. Second, the broker commits his own capital in order to provide the liquidity. Such commitment exposes the capital to the risk of stock price movement. Prices of some of the stocks inside the basket may move adversely against the winning broker. Capital commitment makes this type of trade a principal trade rather than an agency trade (which does not require capital commitment from a broker). A bid submitted by a broker is usually quoted as cents per share. For example, if a broker submits a bid of 6 cents per share for a basket with 1 million shares, the money manager will pay $60,000 for trading the whole basket of stocks. In most biddings (auctions), there are several competing brokers, a broker with the lowest bid will win and execute all the trades in a basket. The number of competing brokers may range from 3 to 8. The auction is *blind* since the (stock) names inside the basket are not provided to competing brokers during the auction. Money managers do not want brokers to front-run some of the trades in a basket. Competing brokers, however, are given some overall information or description related to the basket under consideration. This is one of the inputs that competing brokers use in formulating their bids. The money manager decides how much information he will make available to competing brokers, and such decisions can be tricky. If too little information is provided, brokers will submit higher bids reflecting higher (information asymmetry) risk involved. If too much information is given, brokers can potentially perform a reverse engineering and deduce some of the names in a basket[4]. In this event, the broker will charge an additional premium for if he wins the trade then other brokers may front-run him for some of the names in the basket. We shall describe below several possible bidding procedures that the money manager can use to minimize the risk of brokers front-running his trade. The following are some typical basket characteristics provided to bidding brokers. It is entirely possible that the manager might decide to distribute more or less information relative to the list below:

- Dollar value of a basket (buy and sell)
- Number of shares in a basket (buy and sell)
- Number of names in a basket (buy and sell)
- How well the basket tracks the S&P 500 index (buy basket, sell basket)
- How well the buy basket tracks the sell basket
- The volatility of the buy basket, sell basket, and the whole basket
- The top 5 weights in a basket
- Distribution of weight and number of names in various market capitalization buckets (buy and sell). For example, buy 10 names (with total weight of 4%) whose market capitalization is between $1 billion and $5 billion, sell 8 names (with total weight of 4.5%) whose market capitalization is between 1 billion and 5

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[4] On 12/16/2004, the Wall Street Journal published a front-page article, "Client Comes First? On Wall Street, It Isn't Always So", reporting the risk of front-running in BPB.

billion, buy 15 names (with total weight of 9%) whose market capitalization is more than $5 billion but less than $10 billion, etc.

- Distribution of weight and number of names in various percentages of ADV[5] buckets (buy and sell). For example, buy 20 names (with total weight of 15%) whose percentage of ADV is less than 10%, sell 22 names (with total weight of 19%) whose percentage of ADV is less than 10%, buy 5 names (with total weight of 11%) whose percentage of ADV is equal to or larger than 10% but less than 20%, etc.
- The weight, number of names, and weighted average percentage of ADV in each sector (buy and sell).

There are some commonly used standard reports that can be used to provide basket information to bidding brokers[6].

1.1.2. Price discovery process

Price discovery process for the execution prices is relatively simple in BPB. For an agency trade, execution price is unknown before a trade is executed. However, this is not the case in BPB. Execution price for each name in a basket is contractual. Unlike an agency trade, the money manager and bidding brokers have agreed on what will be the execution price for each stock in a basket. There are many possible agreements. One of the agreements is known as *post-close bidding*. Basket characteristics are distributed to bidding brokers right after the market closes, and the agreed upon execution prices are

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[5] Percentage of ADV refers to the dollar value of a trade expressed as a percentage of the average daily dollar (trading) volume. A trade that has a high percentage of ADV generally requires more liquidity and, hence, it is more difficult to trade.

[6] The most commonly used is StockFacts developed by Citigroup.

the same day closing prices. Another example is known as *pre-open bidding*. Basket characteristics are distributed to competing brokers before the market opens, and the agreed upon execution prices are the previous business day's closing prices[7]. In both instances, execution prices are stale prices, and this prevents brokers from front-running the money manager. There is one possible agreement under which the contractual execution prices are not stale prices[8]. Basket characteristics are distributed to competing brokers when the market is open. Execution prices for the stocks in the basket will be the mid-quote at the time when the basket is awarded to the winning bidder. In this case, the execution prices are "fresh", and it is difficult for the winning bidder to front-run the money manager. However, if competing brokers who lost the auction can reverse engineer some of the names in a basket, the winning broker will still be exposed to some potential front-running risk. Another possible agreement, which is no longer popular, is to distribute the basket characteristics while the market is open and the agreed upon execution prices are the same day closing prices. In this case, the money manager may have the risk that the broker might front-run the manager's trade. The following is a typical sequence of events for a bidding process:

1. Basket characteristics report is sent to competing brokers.
2. After reviewing the report, competing brokers submit their best bid (usually quoted as cents per share).

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[7] There is a variant for this post-close and pre-open bidding scheme. Assuming the winning bid is 5 cents per share, the contractual execution price can be booked as: (1) closing price + 5 cents for buy trade, or (2) closing price – 5 cents for sell trade. If we look at the winning bid in this manner, it resembles the half spread of a dealer's stock quotes. We shall discuss this variant in chapter 2 and chapter 3 of this dissertation.

[8] The BPB basket data we collected for this dissertation does not include this type of agreement.

3. Typically, the basket is awarded to the broker with the lowest bid.
4. Names within the basket and the corresponding trades are provided to the winning broker.
5. At this point the money manager can regard trading of the basket completed or executed (i.e., manger's portfolio is re-balanced). From a manager's perspective, there is practically no non-execution risk, and opportunity costs (of trades that are not done at manager's desired time) are minimal.
6. The winning broker will add all trades in a basket into his inventory and may start unwinding the trades he just got from winning the basket. Potentially, he can also cross some of these trades with his existing inventory.

In summary, BPB is a special trading mechanism for specific managers whose profiles match some of the preceding criteria. For managers whose trades have no immediacy, then, BPB may not be appropriate. A broker charges a liquidity risk premium because he is exposed to various kinds of risk when providing liquidity. At the same time, the broker has a competitive advantage in managing some of these risk exposures.

Chapter 2

How does a liquidity provider price a blind principal bid basket – An empirical perspective

2.1. Introduction

According to a report by Greenwich Associates (2005), the total volume of portfolio trading executed by 128 of some of the largest and most active equity trading institutions in the United States in 2005 was approximately $1.03 trillion. About 13% of this volume (i.e., $133.9 billion) was traded using BPB. Academic research in this area, however, has been limited. One contribution of this dissertation is to increase our understanding of the pricing aspect of this type of trading mechanism. We collected data for two hundred and eighty baskets that were traded using BPB. Using regression analysis, we identified a set of determinants related to the cost of trading using BPB. By modeling the behavior of the liquidity provider, we are able to identify a set of determinants related to the pricing of a BPB basket.

This study differs from the well-known study by Kavajecz and Keim (2005) in one major aspect. Our study identifies a new set of pricing determinants based on how the liquidity provider perceives his risk exposure. Determinants from Kavajecz and Keim (2005) are based solely on the characteristics of a blind principal bid basket. Some of our determinants come from the trading environment (for example, trading during earnings announcements season) and are unrelated to the characteristics of a basket. Moreover, our study focuses on a much larger sample. Another contribution of this study is the argument that the role of liquidity provider in BPB is very similar to the role of market maker (or specialist). This leads to an important conclusion that modeling a market maker's quoted spread should be very similar to the modeling of BPB pricing. The quoted stock spread is market maker's compensation in taking inventory risk and adverse selection risk. In fact, the BPB pricing determinants identified in this study are all fall into these two risk categories.

This chapter is organized as follows: Section 2.2 consists of a brief review of the literature. Sections 2.3 and 2.4 describe the methodology and data used in this study. Section 2.5 presents a discussion of the result highlighting both the similarities and differences of our results with those documented in Kavajecz and Keim (2005). Section 2.6 concludes the chapter.

2.2. Literature Review

Since data related to blind principal bids is usually proprietary and, hence, difficult for researchers to obtain, there are not many empirical studies on this trading mechanism. However, Kavajecz and Keim (2005) managed to obtain one set of BPB data (provided by a money manager who uses BPB regularly). There are some similarities and differences between their study and ours. They argue that using BPB results in a transaction efficiency gain and the estimated transaction cost saving is about 62 basis points. Both their paper and this paper have the same dependent variable in the regression analysis – the winning bid. However, in Kavajecz and Keim's study, their independent variables are limited to the basket's characteristics. The independent variables we investigate relate to several categories of risk exposure faced by the liquidity provider, and we try to model these exposures. We shall elaborate this point in more detail in Section 2.3 on methodology. Our sample size is bigger than that in Kavajecz and Keim (2005). In their study, they collected 83 observations (baskets) from one money manager. We collected 280 observations from two money managers. Our sample includes both large-cap baskets and small-cap baskets.

There are many similarities between the role of a dealer and a BPB broker. One of the most important roles is to provide liquidity to the market participants (e.g., money managers) so that their immediacy is satisfied. In the case of a dealer, the immediacy is just for one single name; while for a BPB broker, the immediacy is for a basket of names. A stock's spread is the dealer's fee for providing liquidity, and a BPB basket's liquidity risk premium is the BPB broker's fee for providing liquidity. Conceptually, spread and liquidity risk premium are similar. Both dealer and BPB broker face similar issues in pricing their service of providing liquidity. Studies have shown that a stock's spread can be decomposed into various components: Roll (1984), Choi et al. (1988), Glosten and Harris (1988), Stoll (1989), George et al. (1991), Lin et al. (1995), Madhavan et al. (1995), and Huang and Stoll (1997). Two of the components, inventory and information asymmetry, have received much attention in market microstructure literature. Many models have been developed to analyze the inventory component, for example: Garman (1976), Stoll (1978a, 1978b), Amihud and Mendelson (1980), Ho and Stoll (1981, 1983), O'Hara and Oldfield (1986), and Laux (1995). Many models have also been developed to investigate the information asymmetry component, for example: Kyle (1985), Copeland

and Galai (1983), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admati and Pfleiderer (1988). In essence, a dealer and a BPB broker face similar issues when they try to price the spread and liquidity risk premium respectively, in particular, the issue of inventory risk and information asymmetry risk. We will incorporate this insight into our research methodology as described in the next section.

2.3. Methodology

In this section, we describe the methodology used for investigating the pricing determinants of BPB basket. First, we define the dependent variable. Second, we discuss how to identify the set of pricing determinants that we are going to test. Our methodology is similar to the one used in Kavajecz and Keim (2005), but, the rationale for identifying various independent variables is quite different. Independent variables used in this study are proxies for inventory risk and information asymmetry risk faced by a BPB broker. Examples of sources of inventory risk are stock volatility and time needed to unwind the inventory. Since BPB brokers do not know exactly what is in a basket during bidding, this is an example of information asymmetry between manager and broker. Moreover, if a manager is going to add value, some of his trades in a basket are, by definition, informed trades. As discussed in the section on literature review, when a BPB broker provides liquidity (to satisfy immediacy), he is also exposed to these two sources of risk. Naturally, we would expect a BPB broker to ask for compensation. Our methodology is also similar to that used by Stoll (2000) to identify a list of determinants related to price of immediacy when trading a single name. In this study, we try to identify a list of determinants related to price of immediacy when trading a basket of names. Cross-sectional regression is used by Kavajecz and Keim (2005), Stoll (2000), as well as by this study to perform the analysis.

2.3.1. Dependent variables

The dependent variable of our regression analysis is the winning bid of a BPB basket. The winning bid is defined as a ratio: $\frac{\text{Total cost paid to a broker}}{\text{Total dollar trade size of a basket}}$. Total cost paid equals the winning bid (quoted in cents per shares) times total number of shares in the basket plus a fixed commission per share (if any). Total trade size is evaluated using the latest available closing prices (relative to the bidding date). The ratio is expressed in basis points. This definition is conceptually similar to a stock's proportional quoted half-spread, which is the dependent variable for the price of immediacy regression conducted by Stoll (2000).

2.3.2. Independent variables

We try to identify potential determinants by modeling brokers' behavior. We put ourselves in their position of pricing a basket and try to identify various sources of risk that a winning broker will be exposed to. The winning bid is a function of how these various risk exposures are compensated. We classify various sources of risk in four categories:

1. Market liquidity risk,
2. Idiosyncratic stock risk,
3. Basket characteristics risk,
4. Bidding procedure risk.

Even as we use different risk labels, all these risk exposures can be reconciled back to two basic categories: (1) inventory risk and (2) information asymmetry risk. As mentioned above, these two types of risks are fundamental in explaining a stock's spread. We will show that these two types of risk can also explain a basket's winning bid. All the determinants and proxies described below can also be regarded as proxies for inventory risk or information asymmetry risk or both. We decided to use this new set of labels because they are more descriptive and more intuitive for identifying price determinants in the context of pricing a BPB basket.

2.3.2.1. Market liquidity risk

We tested one determinant in this category – the market-wide liquidity. The proxy for market-wide liquidity is defined as[9]:

$$\begin{aligned}&\text{Market Liquidity Proxy} = \\ &(\text{Total trade weight for NYSE listed stocks } \times 20 \text{ days moving average of NYSE volume}) + \\ &(\text{Total trade weight for NASDAQ listed stocks } \times 20 \text{ days moving average of NASDAQ volume})\end{aligned} \tag{2.1}$$

The expected sign of the estimated coefficient for this proxy should be negative. If the market is more liquid, there will be less risk for the winning broker (and vice versa). This is because the broker will need less time to unwind the trades in a basket. One can also regard this determinant as a proxy for inventory risk.

2.3.2.2. Idiosyncratic stock risk

If a basket is not well diversified or news appears relevant for some of the stocks in a basket, the broker will face a higher stock idiosyncratic risk. We tested two determinants in this category: (1) basket lumpiness and (2) earnings announcement season.

Basket lumpiness

[9] Total trade weights refer to the sum of sell and buy trade weights. NYSE volume data is from Bloomberg, and the corresponding Bloomberg ticker is MVOLNE. NASDAQ volume data is from Bloomberg, and the corresponding Bloomberg ticker is MVOLQE.

If a basket is concentrated in a handful of stocks, the winning broker will face higher idiosyncratic stock risk. The broker will incur great loss if prices for these concentrated stocks move adversely against the broker. Moreover, high concentration may also imply potentially a longer time to unload these names. From a broker's perspective, lumpiness translates into higher risk and, therefore, higher bid for a lumpier basket. We define basket lumpiness as:

$$\text{Basket Lumpiness} = \frac{\sum_{i=1}^{TopThree} (\text{Total Trade Weight})_i \times \text{Total Trade Size of the Basket}}{\text{Average Share Price}} \tag{2.2}$$

This determinant is defined as an estimated number of shares for the top three names[10] (in terms of weight) in a basket. Although the names in a basket are not given to competing brokers, they can use the formula above to gauge the lumpiness of a basket. The reason to define lumpiness in this particular way is to simulate brokers' thinking and analysis. The estimated coefficient for this determinant should be positive. One can also regard this determinant as a proxy for the information asymmetry risk. If a basket is lumpy, it may imply that a manager is making a bigger bet in some of his stocks and is trying to buy (or sell) these names aggressively. If a manager's bet is going to be correct (i.e., informed), it will translate into a big information asymmetry risk from a broker's perspective.

Earnings Announcement Season

After a stock reports its earnings, it is not uncommon for its price to have a big jump (up or down). Therefore, during earnings announcement season, the broker is potentially

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[10] Managers and brokers also refer to these names in a basket as the most prominent issues (or the prominent trades). Usually trade weight for these names is provided to competing brokers by the manager.

exposed to higher idiosyncratic stock risk. Hence, brokers charge more for the liquidity risk premium during earnings announcement season[11]. The proxy for earnings season is defined as a dummy variable whose value is set to one if one of the following criteria is true, otherwise, it is set to zero.

- The date of bidding is in February.
- The date of bidding is within the last 7 calendar days before the end of April, July, or October.
- The date of bidding is within first 14 calendar days after the end of April, July, or October.

The proxy is constructed on the observation that most companies end their fiscal year in December. A company whose fiscal year ends in December typically reports its (audited) earnings during February. For interim quarterly (i.e., end of March, June, and September) earnings report, an announcement typically comes three to six weeks after each (calendar) quarter end. The estimated coefficient for this dummy variable should be positive. One can also think of this dummy variable as a proxy for information asymmetry risk. If a manager is informed, then he will buy stocks with positive earnings surprise expecting the stocks' prices to go up after the stocks' earnings announcement, and he will sell (or short) stocks with negative earnings surprise expecting the stocks' prices to go down after earning announcements.

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[11] Yohn (1998) finds that bid-ask spread gradually increase prior earnings announcements.

2.3.2.3. Basket characteristics risk

Basket characteristics risk refers to the fact that brokers find some baskets easier to trade than others, and some baskets less risky than others. Therefore, the winning bid is a function of these basket characteristics. We tested four determinants in this category:

1. Count of high percentage of ADV from top 3 prominent trades,
2. Small-cap trades,
3. Sector imbalance,
4. High percentage of ADV concentration.

Count of high percentage of ADV from top 3 prominent trades

This determinant is defined as the number of names among the top three biggest positions (in terms of trade weight) whose trade size (in dollars) is more than 50% of ADV. ADV is defined as the average daily volume (in dollars) for the last 10 trading days. By definition, the range for this determinant is from 0 to 3. A prominent trade combined with high percentage of ADV means higher risk for a broker. Therefore the estimated coefficient for this determinant should be positive.

Brokers cannot know the exact value of this determinant, but they have some information that will allow them to make an educated guess. For example, they know the total weight of trades that are more than 50% of ADV[12]. If this weight is less than the weight of any one of three prominent trades, then they know that none of the three prominent trades in the basket is more than 50% of ADV (which means less risk from a broker's perspective). If the total weight of the trades that are more than 50% of ADV is larger than any three of

[12] This information is provided to brokers through, say, a StockFacts report.

the prominent issues, then it is possible that some of the prominent trades are also a high percentage of ADV trade.

We think that this determinant is a proxy for both inventory risk and information asymmetry risk. The prominent names may be due to an informed manager. Even if the prominent names do not imply an informed manager, high ADV alone will translate into higher inventory risk for these prominent names. This is because longer time is needed to unwind these prominent names from a dealer's inventory.

Small-cap trades

As a rule of thumb, small-cap stocks are more difficult to trade since they tend to be less liquid than large-cap stocks. More trades coming from small-cap stocks mean that a broker needs more time to unwind these trades. Longer trading time means higher risk and, therefore, a higher bid. The proxy for this determinant is defined as: total number of shares traded coming from companies whose market capitalization is less than $500 million. Typically, this information is given to the brokers. The estimated coefficient for this determinant should be positive. This proxy is also a proxy for inventory risk, since more time is needed to trade small-cap stocks while, which tend to be more volatile, as well.

Sector imbalance

If there is a net buy (or net sell) for a sector, then there is a directional bet in that sector. From a broker's perspective this translates into a sector imbalance risk. On the other hand, if buys and sells (in terms of trade weights) are about the same, then the buy and the sell provide an internal built-in hedge against a sector movement. If this is the case, a broker perceives it as a less risky exposure. The sector imbalance risk is a particular concern if the manager performs a sector rotation in his portfolio. Such rotation creates a BPB basket that has a net buy in several sectors and a net sell in other sectors. We model this sector imbalance risk by the following proxy: [13]

Net Trade weight for sector i = Buy weight – Sell weight,

Max. net trade weight = maximum net trade weight among the sectors,

Min. net trade weight = minimum net trade weight among the sectors,

Proxy for the sector imbalance risk =

$$\text{Max. net trade weight} - \text{Min. net trade weight.} \tag{2.3}$$

We expect the estimated coefficient for this determinant to be positive. This proxy is also a proxy for information asymmetry risk. If a manger's sector bet turns out to be correct (i.e., informed), then the winning broker will likely suffer.

High percentage of ADV concentration

Typically competing brokers are given total weights and the number of names distributed across various percentage ADV buckets. If high percentage ADV trades are concentrated among fewer names, then this is considered more risky from a broker's perspective. We use the following three proxies for this determinant:

$$\begin{aligned}
\text{Concentration 1} &= \frac{\text{Total trade weight with percentage of ADV between 50\% and 100\%}}{\text{Number of stocks that contribute the total trade weight}} \\
\text{Concentration 2} &= \frac{\text{Total trade weight with percentage of ADV between 100\% and 200\%}}{\text{Number of stocks that contribute the total trade weight}} \\
\text{Concentration 3} &= \frac{\text{Total trade weight with percentage of ADV above 200\%}}{\text{Number of stocks that contribute the total trade weight}}
\end{aligned} \tag{2.4}$$

[13] Barra sector classification is used for the calculation of the proxy, and there are 13 sectors in this classification.

The estimated coefficient for these proxies should be positive. In a relative sense, Concentration 3 indicates the highest risk. Therefore, we expect the following property for the estimated coefficients: coefficient for Concentration 3 > coefficient for Concentration 2 > coefficient for Concentration 1.

These three proxies can also be proxies for inventory risk or information asymmetry risk or both. If the concentration is due to trading illiquid stocks, then it is a proxy for inventory risk (since more time is needed for unwinding). If the concentration is due to trading liquid stocks but the number of shares traded is large, then it is a proxy for information asymmetry risk (since the manager may be informed). If the concentration is due to trading illiquid stocks and the number of shares traded is large, then it is a proxy for both inventory risk and information asymmetry risk.

2.3.2.4. Bidding procedure risk

The BPB basket data we have collected used the following three bidding procedures:

- Pre-open bidding
- Post-close bidding
- Intra-day bidding[14]

In a relative sense, intra-day bidding has the lowest risk, since the winning broker can perform some hedging[15] while the market is open. Pre-open bidding and post-closing

[14] Bidding information is distributed to brokers when the market is open, and the agreed execution prices are the same day closing prices. The winning broker is identified when the equity market is open, but the winning broker will get names in a basket only after market is closed. This procedure was used by one of the managers in our sample before August 2003. In fact, this procedure is no longer popular among users of BPB.

bidding have very different types of risk. With pre-open bidding, a money manager has learned news and information since the previous day's close. It is possible that a manager may package a basket in such a way to take advantage of the overnight news. For example, if there is news about a stock (in a basket) or a sector after the market closed the day before; the manager can decide whether to keep the stock (or stocks in that sector) in the basket depending on the expected price movement of the stock (or sector) due to the news. In this instance, competing brokers will charge more for their disadvantage due to the information asymmetry (the broker does not know the names in a basket[16]). Therefore pre-open bidding is also a proxy for information asymmetry risk. If it is a post-close bidding, it is more difficult for a manager to perform selective packaging. However, the winning broker cannot do much hedging against the basket he just won (because the market is closed). News can come out after the market closes, which may impact some stocks in the basket. Some brokers call this the *overnight risk*. In this case, the post-close biding is a proxy for inventory risk. We have conducted an informal survey with four major BPB brokers asking them the pricing difference between pre-open and post-close bidding. One broker responded that it does not matter. Another said that pre-open bidding is more expensive. The two remaining brokers said that post-closing bidding is more expensive. It is an empirical issue to investigate how the bidding procedure risk is priced.

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[15] The winning broker does not know the names in a basket after the market closes. But he has enough sector level information to perform some sector level hedging.

[16] To mitigate this information asymmetry, most bidding procedures include a force majeure clause, which automatically eliminates individual names from a basket if a stock moves more than 5% (at the open) form the previous day's close. Moreover, if the manager performs selective packaging regularly, brokers will learn about it. Brokers will increase their bid accordingly or not bid on a basket from this manager.

We used two proxies (dummy variables) for this determinant. If it is a pre-open bidding, the pre-open dummy variable is set to one and the post-close dummy is set to zero. If it is a post-close bidding, the pre-open dummy variable is set to zero and the post-close dummy is set to one. The estimated coefficients for these two dummy variables should be positive, but it is ambiguous which coefficient has a bigger value. We shall return to this discussion below.

We have summarized the expected sign of estimated coefficients and risk category for each of the proxies or determinants in Table I.

2.4. BPB data and basket characteristics

By filtering through transaction records from two money managers[17] who are known to trade BPB baskets regularly, we were able to extract 280 baskets during the period from August 2001 to September 2005. For each basket, we extracted the following data items:

- Stock identifier (cusip or ticker)
- Trade type – buy or sell
- Number of shares traded for each stock in a basket
- Date of trade / bidding
- Bidding procedure (pre-open, post-close, intra-day)
- Winning bid (cents / share)
- Commission (cents / share, if any)

[17] A consulting firm specialized in securities transactions provided the transaction records for one of the managers. We thank them for providing the data for this research project. Due to confidentiality, the name of the money managers and those of the winning brokers were excluded from the records before we received the data. We were able to obtain a second set of transaction records from another asset manager. We shall refer to these two managers as manager A and manager B.

With this set of basket data and other data sources (e.g., Barra sector classification, closing prices, trading volume), we were able to construct all determinants and proxies as described in Section 2.3.

There are few differences between our sample and the one used by Kavajecz and Keim (2005). First, there is no overlap in terms of time span. In their study, data is from July 1998 to July 2000. In our study, data is from August 2001 to September 2005. Second, all baskets used pre-open biding in their study. In our sample, there are three different bidding procedures. Manager A used only pre-open bidding. Manager B used both pre-open and post-close bidding from August 2003 to September 2005. Before August 2003, manager B used intra-day bidding. Third, the mean market capitalization of the stocks in a basket is more than $10 billion in their study, which implies that these are large-cap baskets. In our sample, there are 31 small-cap baskets. Fourth, the sample size of our study is larger (280 vs 83). However, there are some data items we do not have. First, we have data only for baskets that are awarded to winning brokers, and not for baskets that are passed over by the manager (i.e., baskets not awarded to any broker after bidding). Second, we do not have data on bids submitted by all competing brokers. We have data only on the winning bids. Table II provides some summary statistics for the basket data used in our study.

By comparing data summary statistics from Kavajecz and Keim (2005) with our full sample shown in Table II, we note the following observations. First, baskets in our sample tend to be bigger in terms of the:

number of stocks being traded in a basket (231 vs 163),

total trade size (329 million vs 89 million), and

mean shares traded per stock (53,781 shares vs 20,651 shares).

Second, stocks traded in our sample have a larger market capitalization than that of Kavajecz and Keim (2005) ($18 billion vs $13 billion). Third, our baskets may be slightly easier to trade. The mean of percentage of ADV is 7.87% vs 10.81%. Fourth, there are three basket characteristics that are very similar:

percentage of names are NASDAQ stocks (23.01% vs 23.30%),

mean price inverse of stocks in a basket (0.0402 vs 0.0379),

percentage of stocks that are buys (45.59% vs 50.80%).

In summary, there is no significant difference in basket characteristics between our sample and that used by Kavajecz and Keim (2005) except for the time span of our sample.

2.5. Result and analysis

We conducted our analysis by running different regressions using various combinations of determinants and proxies discussed in Section 2.3. We also tested the five determinants suggested by Kavajecz and Keim (2005). Table III summarizes the results of these regressions. The first row of the table identifies the different version of regression. The first column on the left contains the determinants (or proxies of the determinants). Each table cell contains three numbers: the top number is the estimated coefficient. The middle number is the T-statistic. The bottom number is the p-value.

2.5.1. Testing the pricing determinants suggested by Kavajecz and Keim (Regression #1)

Kavajecz and Keim (2005) suggested the following five determinants in their study:

1. Number of stocks (names) in a basket,
2. Mean number of shares traded per stock in a basket,
3. Skewness of the distribution of percentage of ADV[18] for stocks in a basket,
4. Percentage of stocks in a basket that trade on NASDAQ,
5. Mean of the ratio ($\frac{1}{\text{Price}}$) for stocks in a basket.

We tested these determinants using our data, and the results are shown as regression #1 in Table III. There are some differences between our results and the one reported by Kavajecz and Keim (2005). First, the adjusted R-sq for their determinants is much smaller in our sample. The adjusted R-sq in their paper is 72.1% (Kavajecz and Keim (2005), p.476). The adjusted R-sq in our sample is 41.16%. The sign of the estimated coefficients for four of the determinants is consistent with Kavajecz and Keim (2005)'s prediction and statistically significant. However, for skewness of the distribution of percentage of ADV for stocks in a basket, it has a negative sign rather than a positive sign suggested by Kavajecz and Keim (2005). On the other hand, this determinant is not significant in this sample.

2.5.2. Determinants based on broker's behavior (Regression #2)

As discussed in Section 2.3, we have proposed a set of determinants based on how a broker perceives his various risk exposures. The performance of these determinants is shown as regression #2 in table III. Adjusted R-sq is comparable to the one reported by Kavajecz and Keim (2005) (71.48% vs 72.1%). The sign of all estimated coefficients matches with our prediction shown in Table I. The only exception is the post-close

[18] Kavajecz and Keim (2005) use the term VolRatio for "percentage of ADV" in their paper.

dummy. All estimated coefficients are significant with three exceptions: earnings announcement dummy, high percentage of ADV concentration 1, and post-close bidding dummy. It is not surprising that the earnings announcement dummy only gets a marginally significant t-statistic. It is because this proxy (for the earnings announcement) is defined in a simple and primitive way. The proxy of high percentage of ADV concentration 1 also records a marginally significant t-statistic. This may indicate that BPB brokers may have higher risk tolerance than we expect. However, based on our discussion with BPB brokers, many mentioned that they would be "very concerned" if they saw stocks in a basket that traded more than 50% of ADV. On the one hand, the estimated coefficient for the post-close dummy has the wrong sign; on the other hand, the t-statistic for the estimation is also small. In Section 2.3.2.3, we predict that the estimated coefficient for Concentration 3 > coefficient for Concentration 2 > coefficient for Concentration 1. Empirical results support this prediction. The coefficient for Concentration 3, Concentration 2, and Concentration 1 are 193.03, 128.75, and 35.19, respectively. Overall, our set of determinants performs quite well in explaining the pricing of BPB.

2.5.3. A hybrid model (Regression #3)

To test the relative performance of these two sets of pricing determinants, we ran a regression using both determinants from Kavajecz and Keim (2005) and those suggested by us. The result is shown as regression #3 in Table III. Adjusted R-sq is now 73.22%, which is only a slight improvement when compared with regression #2 (71.48%). There are some interesting observations regarding the performance of Kavajecz and Keim (2005)'s pricing determinants and our proposed determinants. The significance for skewness of percentage of ADV increases, but it still has a negative sign. The significance for the other four Kavajecz and Keim (2005) determinants is all reduced relative to regression #1. The only Kavajecz and Keim (2005)'s determinant that remains statistically significant is the percentage of stocks that are listed in NASDAQ. For our suggested determinants, those that are significant in regression #2 continue to be significant. Surprisingly, the significance for earnings announcements, and high percentage of ADV concentration 1, improves slightly.

2.5.4. A hybrid model (Regression #4)

We built another hybrid model by including only some of the determinants suggested by Kavajecz and Keim (2005) and dropping two of their determinants: (1) skewness of percentage of ADV and (2) number of stocks in a basket, due to their weak performance. The result of this hybrid model is shown as regression #4 in Table III. The coefficients for (1) Mean shares traded per stock and (2) Mean price inverse of stocks in a basket are only marginally significant.

2.5.5. A hybrid model (Regression #5)

For reference, we also provided the result for a hybrid model that includes only one determinant, the percentage of stocks that are listed in NASDAQ, from Kavajecz and Keim (2005)'s model. The result is shown as regression #5 in Table III. The result is very similar to that of regression #2 though slightly better (Adjusted R-sq: 72.68 vs 71.48). In summary, determinants proposed in this paper continue to do well in all hybrid models.

2.5.6. Pricing of BPB basket and option premium (Regression #6)

We also explored the idea of applying option pricing theory to the pricing of a BPB basket[19]. Our hypothesis is that the pricing of BPB basket is positively correlated with BPB broker's hedging cost. It is because the hedging cost is a BPB broker's overhead while providing liquidity service to a manager. One way to model or measure a BPB broker's hedging cost is by the premium of at-the-money option. Imagine a BPB broker buys a put option for each sell[20] transaction in a basket. The strike price and stock price in the put option premium calculation are both set to the closing price used for executing the BPB basket. Basically, a BPB broker buys an at-the-money option that protects him from any potential loss if the stock price goes down. Similarly, the BPB broker can use at-the-money call option to hedge each buy transaction in a BPB basket. These call options protects the BPB broker from any potential loss if the stock price goes up. We do not imply that a BPB broker really buys these options for his hedging purpose. However, the cost of buying these options provides a convenient and analytical way to measure a BPB broker's hedging cost.[21] We used the Black-Scholes formula to calculate the call (or put) option premium for each stock in a BPB basket. We make one more assumption in the option premium calculation. We assume that the time to expiration is four trading days[22]. It is the time a BPB broker needs to unload all the stocks in a BPB basket.

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[19] Copeland and Galai (1983) model bid and ask as call and put options provided by a dealer. However, our argument is different from theirs. We use option price as a measure of BPB broker's hedging cost.

[20] If a manager sells a stock in a basket then the winning BPB will have a long position for that stock. He needs a put option to hedge against decreasing stock price.

[21] Bollen et al. (2004) use similar hedging cost argument for modeling a dealer's spread.

[22] It is based on our discussion with several BPB brokers.

To test our hypothesis, we included the price of these at-the-money options as a new independent variable. The result is shown as regression #6 in table III. The estimated coefficient for this new independent variable is positive (0.17) and statistically significant. The result is also consistent with our expectation. This indicates that further research in studying potential application of option theory in BPB pricing might be fruitful. Chapter 3 will further explore this insight.

2.6. Conclusion

By modeling how BPB brokers perceive various risk exposures, we are able to improve and extend the BPB pricing determinants identified by Kavajecz and Keim (2005). Our larger data set enables us to investigate the effect of trading small-cap baskets. Moreover, by having data on BPB baskets that are executed using different bidding procedures, we are able to test the difference in pricing among bidding procedures. We also show that market-wide liquidity and earnings announcements can impact the pricing of BPB. In other words, BPB pricing determinants are not necessary limited to the trading characteristics of a basket. Other factors, for example, market-wide liquidity, can potentially impact the pricing of BPB. Our analysis shows that the newly proposed pricing determinants perform better than those initially identified by Kavajecz and Keim (2005), at least in this sample. We also conducted a preliminary test on applying option pricing methodology in the context of pricing BPB. Furthermore, our results provide evidence that there might be a possible link between option pricing and BPB pricing. Chapter 3 explores this linkage further.

Table I

Summary of the expected sign of estimated coefficients in regression analysis

The dependent variable in the regression analysis is the winning bid of a BPB basket. The independent variables are listed below under BPB Pricing Determinants. These determinants are based on various risk exposures perceived by a BPB broker. The expected sign of estimated coefficients is listed in the second column. The third column notes the risk category (i.e., inventory risk and information asymmetry risk) for corresponding determinants.

BPB broker Risk Category	**BPB Pricing Determinants**	**Expected Sign**	**Market Microstructure Risk Category**
Market liquidity risk	Market liquidity	Negative	Inventory
Idiosyncratic stock risk	Basket lumpiness	Positive	Information Asymmetry
	Earning announcement season	Positive	Information Asymmetry
Basket characteristics Risk	Percentage of ADV from the top 3 prominent trades	Positive	Inventory and /or Information Asymmetry
	Small-cap trade	Positive	Inventory
	Sector Imbalance	Positive	Information Asymmetry
	High percentage of ADV concentration 1	Positive	Inventory and /or Information Asymmetry
	High percentage of ADV concentration 2	Positive	Inventory and /or Information Asymmetry
	High percentage of ADV concentration 3	Positive	Inventory and /or Information Asymmetry
Bidding procedure Risk	Pre-open bidding	Positive	Information Asymmetry
	Post-close bidding	Positive	Inventory

Table II

BPB Basket data summary statistics

The total number of baskets is 280. The time period is from August 2001 to September 2005. An item with an asterisk is determinant identified by Kavajecz and Keim (2005). We include these items for comparison purposes. For items with two rows of data, the bottom numbers are from Table 2 Panel A of Kavajecz and Keim (2005), which are the characteristics of completed basket in their study. (note: summary statistics are not available for Skewness of percentages of ADV in Kavajecz and Keim (2005))

Data Items / proxy / determinants	Mean	Std Dev	Min	25th	Med	75th	Max
Number of stocks in a basket*	231 163	117 101	41 30	121 82	242 129	320 243	609 396
Total trade size ($ million)	328.57 88.97	225.49 73.33	20.89 16.36	150.48 39.03	285.77 58.08	455.77 122.36	1,188.14 323.25
Total number of shares (shares in million)	11.70	7.87	0.60	5.32	10.10	17.04	45.06
% of stock that are buys	45.59 50.80	9.57 14.00	13.14 15.80	40.13 44.10	46.19 50.00	50.85 53.30	100 100
Winning bids (basis point)	48.90	36.47	7.94	21.67	34.15	67.29	186.64
Mean of % of ADV for stocks in a basket	7.87 10.81	7.64 6.24	0.60 1.00	2.54 5.66	5.04 10.40	11.84 14.36	64.09 26.69
Mean market cap ($ million) of stocks in a basket	17,817 13,359	9,287 11,275	502 1,403	11,303 6,086	18,200 9,584	25.039 13,065	41,677 40,443
Mean shares traded per stocks*	53,781 20,651	30,917 12,910	9,592 3,289	31,510 11,743	47,072 18,526	70,239 27,690	228,201 66,655
Skewness of % of ADV*	4.84	2.80	1.77	3.29	4.20	5.41	18.60
% name of stocks that are NASDAQ*	23.01 23.3	11.44 7.6	0.00 6.8	16.32 19.1	19.53 24.2	23.83 28.2	57.24 37.4
Mean price inverse of stocks in basket *	0.0402 0.0379	0.0132 0.0082	0.0210 0.0205	0.0317 0.0327	0.0359 0.0388	0.0454 0.0430	0.1019 0.0580
Total trade weight in NASDAQ stocks (%)	22.11	13.86	0.00	11.66	18.52	29.72	59.34

Market liquidity ($ million)	1,487	140	1,167	1,400	1,477	1,578	1,982
Basket lumpiness (shares in million)	2.03	1.38	0.19	1.05	1.70	2.55	7.34
Earnings Announcement (dummy)	0.24	0.43	0	0	0	0	1
Count of high % of ADV from top 3 prominent trades	0.71	0.95	0	0	0	1	3
Small-Cap trades (shares in million)	0.55	0.74	0	0	0.01	0.09	14.57
Sector Imbalance risk (%)	13.34	9.27	2.04	6.71	10.28	18.47	51.10
High % of ADV concentration 1	0.03	0.05	0	0	0.01	0.04	0.39
High % of ADV concentration 2	0.02	0.04	0	0	0	0.01	0.39
High % of ADV concentration 3	0.01	0.03	0	0	0	0	0.22
Pre-open dummy	0.62	0.49	0	0	1	1	1
Post-close dummy	0.08	0.28	0	0	0	0	1

Table III

Regression result using various blind principal bid pricing determinants

The dependent variable in the regression analysis is the winning bid of a basket. Independent variables are determinants listed in the first column. Regression #1 uses determinants identified by Kavajecz and Keim (2005). Regression #2 uses determinants suggested in this study based on various risk exposures perceived by a BPB broker. Regression #3, #4 and #5 are hybrid models that combine determinants from Kavajecz and Keim (2005) and those suggested by our analysis. Regression #6 shows the use of option pricing theory in blind principal bid pricing. Each cell in the table contains three numbers: the top number is the estimated coefficient; the middle number is the t-statistic; the bottom number is the p-value.

Determinants	Regression #		
	1	2	3
Number of stocks in a basket*	-0.14 -7.81 <0.0001		-0.02 -0.91 0.3662
Mean shares traded per stocks*	0.0004 6.69 <0.0001		0.000083 1.10 0.2706
Skewness of % of ADV*	-0.41 -0.67 0.5031		-0.84 -1.91 0.0577
% of stocks that are NASDAQ*	197.76 9.87 <0.0001		59.11 3.16 0.0017
Mean price inverse of stocks in basket (%)*	521.27 2.85 0.0047		255.56 1.56 0.1193
Market liquidity		-0.03 -3.02 0.0028	-0.03 -3.43 0.0007
Basket lumpiness (10^{-6})		4.69 4.20 <0.0001	4.04 2.22 0.0272

Earning Announcement (dummy)		3.39 1.19 0.2352	4.86 1.73 0.0853
Count of high % of ADV from top 3 prominent trades		7.17 3.63 0.0003	7.00 3.61 0.0004
Small-cap trades (10^{-6})		12.62 14.23 <0.0001	9.14 7.39 <0.0001
Sector Imbalance		44.54 2.56 0.0112	53.46 2.65 0.0086
High % of ADV concentration 1		35.10 1.02 0.3100	39.34 1.17 0.2419
High % of ADV concentration 2		128.75 3.83 0.0002	134.32 4.06 <0.0001
High % of ADV concentration 3		193.03 4.26 <0.0001	196.97 4.35 <0.0001
Pre-open dummy		15.38 5.15 <0.0001	13.41 3.68 0.0003
Post-close dummy		-4.47 -0.85 0.3985	1.51 0.27 0.7892
option price			
Intercept	-5.32 -0.68 0.4960	47.86 3.55 0.0004	34.81 2.23 0.0266
N	280	280	280
Adj R-sq (%)	41.16	71.48	73.22

Table III (continued)

Regression result using various blind principal bid pricing determinants

Determinants	Regression # 4	5	6
Number of stocks in a basket*			
Mean shares traded per stocks*	0.000106 1.43 0.1534		
Skewness of % of ADV*			
% of stocks that are NASDAQ*	51.61 2.91 0.0039	57.82 3.58 0.0004	30.19 1.78 0.0766
Mean price inverse of stocks in basket (%)*	232.58 1.42 0.1577		
Market liquidity	-0.03 -3.47 0.0006	-0.03 -3.43 0.0007	-004 -3.97 <0.0001
Basket lumpiness (10^{-6})	3.26 1.87 0.0626	5.09 4.63 <0.0001	5.52 5.15 <0.0001
Earning Announcement (dummy)	3.93 1.41 0.1606	4.11 1.47 0.1435	4.43 1.63 0.1041
Count of high % of ADV from top 3 prominent trades	7.39 3.81 0.0002	7.32 3.79 0.0002	8.00 4.25 <0.0001
Small-cap trades (10^{-6})	9.30 7.53 <0.0001	9.92 8.63 <0.0001	9.58 8.56 <0.0001
Sector Imbalance	63.17 3.58 0.0004	57.46 3.30 0.0011	62.16 3.67 0.0003
High % of ADV concentration 1	37.61 1.12 0.2648	37.23 1.10 0.2713	21.25 0.64 0.5202
High % of ADV concentration 2	136.94 4.16 <0.0001	133.92 4.06 <0.0001	130.51 4.08 <0.0001
High % of ADV concentration 3	185.92 4.14 <0.0001	198.91 4.48 <0.0001	189.52 4.39 <0.0001
Pre-open dummy	13.85 3.88	12.26 4.02	22.36 5.86

	0.0001	<0.0001	<0.0001
Post-close dummy	0.06 0.01 0.9916	-3.73 -0.72 0.4716	8.48 1.46 0.1453
option price			0.17 4.19 <0.0001
Intercept	29.12 1.90 0.0586	39.67 2.97 0.0033	11.81 0.81 0.4185
N	280	280	280
Adj R-sq (%)	72.88	72.68	74.28

Chapter 3

Two Theoretical Models for Blind Principal Bid Basket Trading Cost

3.1. Introduction

The market microstructure models for a stock dealer's[23] spread in a quote-driven market are based on trading a single stock. In this chapter, we estimate two different structural models for a liquidity provider's spread when trading a basket of stocks simultaneously and immediately using a market mechanism called blind principal bid (BPB).[24] The spread is a liquidity demander's cost for immediacy. Two previous studies by Kavajecz and Keim (2005) and Chapter 2 of this dissertation investigate a similar question. Neither study, however, is based on any structural models. A considerable body of market microstructure research has attempted explicitly to model a dealer's spread for trading a single stock in a quote-driven market. In this chapter we apply two structural spread models, developed by Stoll (1978a, 1978b) and Bollen, Smith, and Whaley (2004), respectively, in the context of trading a basket of stocks simultaneously. Whereas they use trade data on an individual stock, our model estimation is done using data on trading a basket of stocks simultaneously. This is one of the most important features of this study. Our data come from two active equity asset managers who trade stock baskets and regularly use BPB. The liquidity providers, typically major sell-side firms, are

[23] We use the term dealer and market maker interchangeably throughout this chapter.

[24] For the remainder of this chapter, we use BPB as the abbreviation for blind principal bid. The institutional description of BPB can be found in chapter 1.

customarily called blind principal bid brokers. BPB brokers commit their own capital to provide liquidity by being the counter party for each of the trades within a basket of stocks.

The motivation for this study is based on our observation that the role and function of a BPB broker is very similar to that of a dealer in a quote-driven market, especially with respect to the risk exposure faced by a dealer.[25] Both dealers and BPB brokers facilitate trading by providing immediate liquidity using their own capital. Their capital is exposed to certain risks while providing a liquidity service (e.g., adverse price movement or the other party is informed). Therefore, they will certainly request compensation for their risk exposure: for dealers, in the form of a spread; for BPB brokers, a fee (or trading cost[26]) paid by an asset manager. Our hypothesis involves using the two dealer's spread models mentioned above, subject to some minor extensions, to model the trading cost paid by users of BPB. Our insight is that a BPB broker's fee and a dealer's spread are conceptually equivalent. We found that both extended models perform quite well, explaining a liquidity provider's spread for trading a basket of stocks. Using Bollen, Smith, and Whaley's (2004) methodology, we are able to decompose the spread into various fundamental and structural cost components and rank their relative magnitude. The inventory-holding costs are found to be the largest cost component. We empirically

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[25] The term "blind principal bid dealers" (rather than "blind principal bid brokers") may be a better term for this type of liquidity providers, since their roles and functions are similar to a dealer (who bears risk) in a quote-driven market. Strictly speaking, a broker does not face the same risk as a dealer. Nevertheless, we shall continue to use the industry norm, blind principal broker, for the remainder of the chapter.

[26] In Chapter 1, we refer to this type of trading cost as a "liquidity risk premium."

deduce an implied trading rate used by a liquidity provider to unload shares in a basket after accepting a basket. For trades within a basket, we also analyze an empirical relation between informed trades and their (dollar) trade size (expressed in percentage of average daily dollar volume). One of the potential applications of this study is to help asset managers develop a benchmark trading cost when trading a basket of stocks using blind principal bids.

The remainder of this chapter is organized as follows. Section 3.2 reviews the literature on modeling spread and the various components of a spread. Section 3.3 describes the basket trading data used in this study. Section 3.4 and 3.5 describe how we estimate Stoll's (1978a, 1978b) model and Bollen, Smith, and Whaley's (2004) model, respectively. Section 3.6 concludes the chapter.

3.2. Literature Review

Since Garman (1976) coined the term "market microstructure," there has been an explosive growth of research in this field. This section provides a very brief overview of various research topics relevant to this paper.[27]

One early approach to modeling a dealer's spread was to tackle the problem as an inventory management problem from the dealer perspective. This approach is commonly referred as the inventory model in the market microstructure literature (e.g. O'Hara (1997)). Several studies take this approach. Garman (1976) models the spread as an

[27] Several excellent survey papers and books offer a more detailed and comprehensive treatment; see, for example, Coughenour and Shastri (1999), Madhavan (2000), Stoll (2003), Biais et al. (2005), O'Hara (1997), and Hasbrouck (2006).

optimization problem in which the dealer chooses an optimal bid and ask price. The broker sets bid and ask prices only once at the beginning of time. The objective function is to maximize the dealer's expected profit while taking into consideration the problem of running out of cash or inventory and when the arrival of trade orders is stochastic. Stoll (1978a) also solved the inventory management problem as an optimization problem, but models the compensation for a dealer who holds a sub-optimal portfolio while providing liquidity. Holding sub-optimal portfolio means extra risk exposure that generates a dealer's compensation. Stoll (1978a, 1978b) also analyzes various fundamental cost components in a dealer's spread. Amihud and Mendelson (1980) began with framework similar to that of Garman (1976), but allow bid and ask prices to change when inventory changes. Ho and Stoll (1980), Ho and Stoll (1981), and Ho and Stoll (1983) are extensions and enhancement to Stoll (1978a). O'Hara and Oldfield (1986) tried to address some of the restrictions in Ho and Stoll's (1981) model, for example, by employing an infinite time horizon rather than the finite time horizon in Ho and Stoll (1981).

There are several empirical studies as well. Stoll (1978b) is the empirical test for Stoll (1978a). Ho and Macris (1984) use transaction prices and dealer inventory of some American Stock Exchange options and find some empirical evidence supporting Ho and Stoll (1981). They show that dealers' spread is positively correlated to asset risk and dealers adjust their quotes in response to their inventory position. Hasbrouck and Sofianos (1993) find that dealers have a preferred level inventory, adjusting the bid and ask prices to bring inventory to a preferred level. Hansch et al. (1998) conduct direct tests of Ho and Stoll's (1983) inventory model using London Stock Exchange data. One of their findings is that relative inventory position is significantly related to the ability to execute large trades, which supports the inventory model of dealer's spread. Naik and Yadav (2003) test Ho and Stoll's inventory model and also investigate a particular question where dealer firms manage inventory on a stock-by-stock or portfolio basis. They find that individual dealers manages their own inventory but do not focus on the overall inventory of their firms.

Another approach to model a dealer's spread is from an information asymmetry perspective, based on adverse selection theory. This class of models takes into consideration that a dealer may be disadvantaged when trading with an informed trader. Some of the literature, e.g. O'Hara (1997), refers to this as the information asymmetry model. Bagehot (1971) is thought to be the first study of this information asymmetry. Copeland and Galai (1983) model a dealer's spread as maximum expected profit, balancing losses from trading with informed traders and gains from trading with uninformed (liquidity) traders. Glosten and Milgrom's (1985) model incorporates an additional element not included in Copeland and Galai's model, namely, that informed traders' trades have information content. Even a dealer cannot distinguish an informed from an uninformed trader; a dealer alters his expectation of a stock's true price conditional on the trades he receives. Easley and O'Hara's (1987) model differs from Glosten and Milgrom's (1985) model in one major aspect: they explicitly consider the effect of trade size executed by traders on stock prices, motivated by empirical observation that large trades are executed at worse prices.

Since the spread can be modeled as a function of inventory holding and information asymmetry, researchers have investigated whether one can decompose the spread into these two components. A broader issue is the estimation of various components (e.g. order processing costs, inventory costs, and information asymmetry costs) that contribute to the bid-ask spread. Empirical studies along these lines include Roll (1984), Choi et al. (1988), Glosten and Harris (1988), Stoll (1989), George et al. (1991), Madhavan et al. (1997), and Huang and Stoll (1997). Huang and Stoll manage to generalize all these works. Coughenour and Shastri (1999) provide a concise survey of this topic, wherein most papers are based on time series analysis. There are, however, some studies that use a cross-sectional approach, for example, Stoll (1978b) and Bollen et al. (2004). Since time series data do not exist for a BPB basket, Stoll and Bollen et al.'s cross-sectional approach makes estimation of various trading cost components feasible for the BPB basket. We discuss these two studies in more detail in Section 3.4 and 3.5.

Some literature also investigates the empirical evidence of the various determinants of a dealer's spread. Demsetz (1986), Tinic (1972), Tinic and West (1972, 1974), Benston and Hagerman (1974) and Branch and Freed (1977). Bollen, Smith and Whaley et al. (2004) provide a concise summary and comparison of these studies. Two studies, Kavajecz and Keim (2005) and chapter 2 of this dissertation, are particularly relevant to this chapter. Both investigate the empirical determinants of BPB trading cost.

3.3. Historical BPB Data

The following is a description of the BPB basket data used in this study. We have gathered 196 BPB baskets executed regularly by two active asset managers.[28] These baskets were traded during the period from January 2002 to September 2005. The trading activities are quite evenly distributed throughout the sample period.[29] Manager A uses only pre-open bidding, while Manager B uses both pre-open and post-close bidding. For each basket executed, we gathered the following data items. (Data items specific to Stoll's (1978) model and Bollen, Smith, and Whaley's (2004) model are discussed in the next two sections.)

1. Stock identifier (CUSIP or ticker) for each name in a basket,
2. Transaction type for each name (buy or sell) in a basket,
3. Number of shares traded for each name in a basket,
4. Execution price[30] for each name in a basket,
5. Lowest (winning) bid (cents per share).

The BPB trading cost (in dollars) paid by the manager for trading a BPB basket can be computed as the total number of shares in a basket times the lowest bid (i.e. winning bid). In some cases, it is convenient to express the cost in basis points. It can be computed by

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[28] We would like to thank a consulting firm specializing in securities transactions for providing transaction records for one of its managers. Due to issues of confidentiality, the names of the money managers and the winning brokers were excluded from the records before we received the data. We obtained a second set of transaction records from another asset manager. We refer to these two managers, both of whom specialize in quantitative investment strategies, as Managers A and B.

[29] The trading frequency is about once a week.

[30] For pre-open bidding, the execution price is the previous day's closing price. For post-close bidding, the execution price is the same- day closing price. Please refer to chapter 1 for more detail.

dividing the cost (in dollars) by the total dollar value of a basket. When a BPB trading cost is expressed in basis points, it is conceptually similar to the relative spread or percentage spread (i.e. Spread / Price) in the market microstructure literature. Table IV provides descriptive statistics of some basket characteristics.

3.4. Estimating Stoll's (1978a, 1978b) model

In this section, we describe how to estimate Stoll's (1978a, 1978b) model using the BPB basket trading data. Stoll (1978a) focuses on developing a theoretical model for the holding cost component in a dealer's spread based on inventory modeling and, to a lesser extent, other cost components. Stoll (1978b) is the empirical counterpart of the structural model developed by Stoll (1978a). Moreover, Stoll (1978b) tried to estimate a structural model in which the spread consists of three cost components (holding cost, order cost, and information cost). As mentioned in the original paper, Stoll sought to "develop a more explicit and rigorous model of the individual dealer's spread." This point is again emphasized by Bollen, Smith and Whaley (2004), who are concerned with the structural form of a spread model because many models are based on economic reasoning rather than formal mathematical modeling. This leads to the criticism of ad hoc model specification and variable selection.

The original model is a spread model for a single stock name, but our description emphasizes the issues that are more relevant in the context of trading a basket of stocks simultaneously. Our model estimation basically follows the Stoll's (1978b) approach. However, we have a slightly different model specification. In the original model, Stoll included a factor for competition (number of dealers). We cannot include this competition factor in our model because we do not have data on the number of BPB brokers that were bidding on each basket.

3.4.1. Model overview

In the following we describe the dependent and independent variables in our cross-sectional regression. As in Stoll's original paper, the natural logarithms of the variables are used when conducting the regression. We also borrow the variable symbols from the original paper to facilitate the cross-reference between two papers.

Basket trading cost (expressed in basis points[31]), s_i, is the dependent variable. In the original paper, s_i is the percentage spread. i is the BPB basket identifier (i.e. $i = 1, 2, 3, \ldots, 196$). All other variables given below are independent variables.

Basket variance, σ^2_i. It is a direct measurement of the risk for a basket.[32] The sign of the estimated coefficient for σ^2_i is expected to be positive. A BPB broker will charge more for a more risky basket.

Basket weighted-average volume, V_i, is the weighted average of dollar volume for a basket. For each stock in a basket, we compute its average daily dollar trading volume during the last 10 trading days (before the date of basket bidding). The weight used in calculating V_i is the dollar value of a trade for a stock (within a BPB basket) divided by

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[31] The BPB trading cost = (cost per share × total number shares traded) / (total BPB basket dollar value traded)

[32] The basket variance is estimated using the MSCI Barra U.S. risk model.

the total dollar value of a basket. Basket volume is used as a proxy for the holding period in Stoll's model. The greater the volume, the shorter time (i.e. less risk) taken by a BPB broker to unload (or reverse) positions in a basket. The sign of the estimated coefficient for V_i is expected to be negative.

Basket weighted-average turnover, $(V/T)_i$. The turnover for each stock within a BPB basket is defined as the 10-day average dollar volume divided by its market capitalization.[33] The weight used in calculating $(V/T)_i$ is the dollar value of a trade for a stock (within a basket) divided by the total dollar value of a basket. Basket turnover is used as a proxy for adverse selection in Stoll's model. Based on Stoll's original argument, if a trade is driven by liquidity need (i.e. it originated from an uninformed trader), the traded volume tends to be proportional to market capitalization. However, if a trade for a stock originates from an informed trader, volume tends to be out of proportion to the stock's market capitalization. The sign of the estimated coefficient for turnover is expected to be positive.

Basket weighted-average stock price, P_i, is a proxy for minimum cost in the original model. For each stock in a BPB basket, we gather the stock's latest closing price (see the footnote for computing stock's market capitalization). As with other variables, the weight used in calculating the basket weighted-average stock price is the dollar value of a trade for a stock (within a basket) divided by the total dollar value of a basket. Stoll argues that there is no prior expectation for the sign of the estimated coefficient.

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[33] Market capitalization is calculated based on the latest available closing price for a stock when basket bidding (auction) occurs.

In the original paper, Stoll also models the effect of dealer competition on the size of a spread. Due to the lack of data on the number of BPB brokers bidding for each historical basket, we do not include this particular independent variable in this study. Table V provides some descriptive statistics for the variables used in the estimation.

3.4.2. Model estimation result and analysis

Table VI summarized the result of estimating Stoll's (1978b) model. Overall, Stoll's model performs quite well to explain BPB basket trading cost. The R-square of the OLS regression is approximately 74%, which is similar to that of Kavajecz and Keim (2005) and chapter 2 of this dissertation. All estimated coefficients are highly significant with the exception of "basket weighted-average stock price." In the original paper by Stoll (1978b), the stock price is used as a proxy for minimum cost. Since the estimated coefficient for basket weighted-average stock price is not significant, it may indicate that we need another proxy for minimum cost in the context of BPB basket trading. All the signs for the estimated coefficients are consistent with our expectation, as shown in Table V.

A larger data sample that includes data from two different assets managers (rather than one manager, as in Kavajecz and Keim's (2005) study), as well as a more parsimonious model specification than the one we studied in chapter 2, are not the only improvements in this chapter. A key feature that distinguishes this study from the two earlier studies is our use of a theoretical framework for the trading cost of a BPB basket and estimation of the structural trading cost model. The structure of our model is not based on ad hoc economic reasoning, but is well defined.

There is, however, one limitation when applying Stoll's model directly in the context of a BPB basket trading. In Stoll's original model, the inventory holding cost component reflects a single period model and the variance of a stock is assumed to be stationary during the period. This assumption may not be true when a BPB broker tries to unload a BPB basket. Our discussions with BPB brokers reveal that they usually unload stocks within a basket at different speeds. Therefore, the basket variance is unlikely to remain stationary during the period when a BPB broker is unloading stocks from a basket. Our second structural model can address this limitation.

3.5. Estimating Bollen, Smith, and Whaley's (2004) model

In this section, we describe and estimate a spread model based on the methodology developed by Bollen, Smith and Whaley (2004). As we have emphasized earlier, this spread model provides a theoretically grounded functional form of the relationship between the spread and its determinants. Their original model is for trading a single stock; a straightforward extension allows us to apply their model in the context of trading BPB baskets. An additional benefit is that this model can compute various components of a spread. Thus, we can compare the distribution of various cost components within a BPB basket spread with some other studies (which tend to analyze the cost categorization of a stock spread). A unique feature is that this model is one of the few that does not use time series data; as mentioned in the literature review, many previous studies do utilize time series data to estimate various cost components in a spread. Since there are no time series data available for BPB baskets, Bollen, Smith and Whaley's (2004) methodology becomes attractive in studying trading cost components for BPB baskets. To facilitate discussion of our study, we provide a very brief overview of Bollen, Smith, and Whaley (2004). Followings the model overview, we present our results on the model estimation and analysis.

3.5.1. Model overview

To minimize potential confusion and facilitate cross-reference between their paper and ours, we follow the terminology and original notation of Bollen, Smith and Whaley (2004). Moreover, the assumptions of their paper are directly applicable: (1) risk-free rate and dividend yield are ignored, and (2) the BPB broker has no existing inventory. Bollen, Smith and Whaley (2004) use the following functional form for a (stock) spread:

$$SPRD_i = f(OPC_i, IHC_i, ASC_i, COMP_i), \tag{3.1}$$

where[34]

i = identifier for a stock,

OPC_i = order-processing costs,

IHC_i = inventory-holding costs,

ASC_i = adverse selection costs,

[34] The following are the descriptions for each cost component as given by Bollen, Smith and Whaley (2004). *Order-processing costs* are those directly associated with providing the market making service and include items such as the exchange seat, floor space rent, computer costs, informational service costs, labor costs, and the opportunity cost of the market maker's time. *Inventory-holding costs* are those a market maker incurs while carrying positions acquired in supplying investors with liquidity. *Adverse selection costs* arise from the fact that market makers, in supplying immediacy, may trade with individuals who are better informed about the expected price movement of the underlying security. *Degree of competition* is likely to affect the level of the market maker's bid/ask spread, particularly in an environment where barriers to entry are being slowly eliminated.

$COMP_i$ = degree of competition.

As discussed in Section 3.4, Stoll (1978b) uses a similar functional form given by (3.1). For this paper, we are unable to model the effect of competition on the trading cost of BPB baskets due to a lack of competition data. We have argued that the cost faced by a dealer is very similar to that of a BPB broker; therefore, we adopt the following functional form for the cost of trading a BPB basket:

$$(BPB\ basket\ trading\ Cost)_i = f(OPC_i, IHC_i, ASC_i), \tag{3.2}$$

where

i = identifier for each BPB basket in our data sample.

Value inventory-holding premium using at-the-money option

Bollen, Smith and Whaley (2004) argue that a dealer's spread "needs to include a premium to cover expected inventory-holding costs, independent of whether the trade is initiated by an informed or uninformed customer." In the context of a BPB basket, an analogous interpretation is that some trades within a BPB basket are liquidity-driven[35] and some others are information-driven.[36] If a basket's trades are purely liquidity-driven, (e.g. subscription or redemption of a S&P 500 index fund), the trade can be hedged easily using S&P 500 future contracts. A blind principal bid is unlikely to be used for this type of trading. Bollen, Smith and Whaley (2004) call this the inventory-holding premium (*IHP*). By using a European style at-the-money option to hedge stock price movement, they show that a dealer's expected *IHP* is equal to the following:

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[35] One examples of a liquidity-driven trade is trades that trim back aggressive over-weight or under-weight positions (relative to a manager's benchmark) that are hitting the allowable upper or lower bound mandated by a portfolio owner.

[36] Since our data are from active asset managers, some of their trades are by definition supposed to be informed so that they can add value for their clients.

$$E(IHP) = S\left[2N\left(0.5\sigma E\left(\sqrt{t}\right)\right) - 1\right], \tag{3.3}$$

where

S = true stock price,

σ = standard deviation of security return,

t = time until next offsetting order,

$N(\cdot)$ = cumulative unit normal density function.

Equation (3.3) is, in fact, the value of an at-the-money option based on the Black-Scholes formula (with the risk-free rate equal to zero). The strike price is equal to the true stock price. The intuition of Bollen, Smith and Whaley's (2004) argument is that the value of the at-the-money option can be thought as the BPB broker's hedging cost so that he is protected from adverse stock price movements while he is holding a basket in his inventory.[37]

The following is an analogous interpretation of equation (3.3) in the context of trading BPB basket. S is the latest closing price[38] for each stock in a BPB basket. From a BPB broker's perspective, his profit or loss is calculated based on the closing prices. Therefore, closing price is the appropriate reference price for hedging purpose. σ is the standard deviation of rate of return for each stock in a basket. t is the time taken by a BPB broker to unload (a.k.a. unwind) a stock from a BPB basket. We introduce an extra variable that helps us model t. The new variable, unloading rate, g, is defined as the

[37] Please refer to the original paper for a more formal and mathematical argument for valuing the inventory-holding premium.

[38] For pre-open bidding, the latest closing price is the previous business day closing price. For post-close bidding the latest closing price is the same-day closing price.

percentage of average daily (dollar) volume (ADV[39]) a BPB broker would like to trade (to unload a stock in a basket) during one trading day. For example, if average daily volume for a stock j (within a BPB basket) is \$1,000,000 and if g = 25% of ADV per day, then a BPB plans to trade \$250,000 worth of a stock each day to unload stock j. Further assume that the dollar trade size for stock j is \$500,000. Hence, it will take the BPB broker about two days to unloaded stock j from a BPB basket. Therefore, we have the following relation between t and g:

$$t = \frac{\left(\dfrac{\text{dollar tradesize for a stock in a basket}}{\text{stock's average daily volume}}\right)}{g}. \tag{3.4}$$

So, it takes two days for the BPB broker to unload this particular stock from a BPB basket. For half of all the shares for stock j, he needs options that expire in one day. For the other half, he needs options that expire in two days. For simplicity, we use the following definition of t in computing *IHP*:

$$t = 0.5 \times \frac{\left(\dfrac{\text{dollar tradesize for a stock in a basket}}{\text{stock's average daily volume}}\right)}{g}. \tag{3.5}$$

By computing *IHP* stock by stock (rather than *IHP* for a BPB basket as a whole), we do not require the unloading process to be done in a proportionally manner, so that the dollar weight for each stock within a basket remains stationary. As mentioned in the previous section, Stoll (1978b) does have this implicit limitation in the case of trading BPB basket. Therefore, Bollen, Smith and Whaley's (2004) methodology has an advantage in

[39] For the rest of the paper, we use the abbreviation ADV to stand for average daily (dollar) volume.

modeling the BPB basket trading cost. In summary, the expected *basket IHP* is the summation of each stock's *IHP* and for each stock its t is given by equation (3.5):

$$E(basketIHP) = \sum S_j \left[2N\left(0.5\sigma_j E\left(\sqrt{t_j}\right)\right) - 1 \right], \tag{3.6}$$

where j = 1, 2, ... , number of stocks in a BPB basket.

Bollen, Smith and Whaley (2004) have the following regression model specification for a dealer's spread:

$$SPRD_i = \alpha_0 + \alpha_1 InvTV_i + \alpha_2 MHI_i + \alpha_3 IHP_i + \varepsilon_i, \tag{3.7}$$

where

$InvTV_i$ = inverse of trading volume = 1/number of shares traded,

MHI_i = modified Herfindahl index,

IHP_i = inventory-holding premium.

As we mentioned in the preceding section, we do not have the necessary data to model competition among BPB brokers. It is unfortunate that we are forced to omit *MHI* in our BPB basket trading cost model specification. *InvTVi* is used to model order-processing cost. Bollen, Smith and Whaley (2004) argue that order-processing costs are largely fixed; hence, the order processing cost per shares goes down when share volume rises. However, the number of shares transacted in BPB baskets is much larger than that transacted by a dealer for a single stock.[40] Therefore, we define *InvTVi* slightly differently and re-define *InvTVi = 1 / sqrt(Total shares in a BPB basket)*. The following is a regression model specification for the BPB basket trading cost:

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvTV_i + \alpha_2 (Basket\ IHP)_i + \varepsilon_i, \tag{3.8}$$

[40] In Table 3 of Bollen, Smith and Whaley (2004), the mean number of shares traded in a day for a stock is between 250,000 and 600,000 during three different sampling periods. However, the mean number shares traded for a BPB basket is about 11 million shares.

where

i = identifier for each BPB basket in our data sample

$(BPB\ basket\ trading\ cost)_i$ = fee (in dollars) paid by manager to BPB broker,

$InvTVi$ = 1 / sqrt(Total shares in a BPB basket),

$(Basket\ IHP)_i$ = Basket IHP given by equation (3.6).

However, in the case of a BPB basket, there are two dimensions for order-processing cost. The first dimension is the total number of shares traded in a basket. The second dimension is the number of names in a basket. Another possible alternative regression model specification for BPB basket trading cost is:

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2 (Basket\ IHP)_i + \varepsilon_i, \tag{3.9}$$

where

$InvNumofNames_i$ = 1 / Number of names being traded in a BPB basket.

In the next section, we compare the estimation results for these two specifications (equation (3.8) and equation (3.9)). Since the number of shares and the number of names are positively correlated,[41] we prefer not to include both proxies in a single model specification. Including both proxies may introduce multicollinearity. Moreover, we prefer a more parsimonious model.

[41] In our data sample, the correlation between the two is 0.77.

Bollen, Smith and Whaley (2004) argue that α_2 in equation 3.8 (or α_2 in equation 3.9 or α_3 in equation 3.7) should be equal to one.[42] They also prove that the expected *IHP* defined in equation (3.3) is approximately linear in the square root of *t*. Therefore, by adjusting the value of *g*, the unloading rate variable, we are able to have the following regression model specification for the BPB basket trading cost:

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvTV_i + (Basket\ IHP(g))_i + \varepsilon_i. \qquad (3.10)$$

In summary, equation (3.10) is a regression model specification which uses an at-the-money option to value inventory-holding premium. The coefficient of $(Basket\ IHP(g))_i$ is calibrated to be equal to one. The estimation results for this model specification are given in next section. There is also some special interpretation of α_0. Bollen, Smith and Whaley (2004) argue that the intercept term represents the minimum tick size. In the case of trading a BPB basket, there is no minimum tick size. A BPB broker is free to submit any bid during a basket auction. Therefore, our prior is that α_0 will not be significantly different from zero.

Informed and uninformed trades in a BPB basket

Bollen, Smith and Whaley (2004) also proposed the following interesting way of interpreting the inventory-holding premium. The major benefit and contribution of this interpretation is that it allows the decomposition of the inventory-holding premium into two components: (1) premium for uninformed trades and (2) premium for informed trades.

$$IHP = IHP_U + p_I(IHP_I - IHP_U) \qquad (3.11)$$

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[42] If we regard the *IHP* as hedging cost, there is no obvious reason for a BPB broker to over-hedge or under-hedge.

where

IHP_U = inventory-holding premium for uninformed trades,

IHP_I = inventory-holding premium for informed trades,

p_I = probability of an informed trade.

Similar to Bollen, Smith and Whaley's (2004) methodology, we use the following Black-Scholes formula to compute the value of IHP_U and IHP_I when a name in a basket is a buy.[43] Basically the value of IHP_U and IHP_I is equal to the value of two slightly different call options.

$$IHP_{k,j} = S_{k,j} N\left(\frac{\ln(S_{k,j} / X_j)}{\delta_j \sqrt{t_j}} + 0.5\delta_j \sqrt{t_j} \right) - X_j N\left(\frac{\ln(S_{k,j} / X_j)}{\delta_j \sqrt{t_j}} - 0.5\delta_j \sqrt{t_j} \right) \tag{3.12}$$

where

j = 1, 2, 3, …. , number of stocks that are purchased in a BPB basket,

k = U or I. U stands for uninformed trade and I stands for informed trade,

σ_j = standard deviation of security return,

t_j = time for unloading a stock from a BPB basket,

X_j = latest closing price for stock j + per share cost of BPB basket trading cost,[44]

$S_{U,j}$ = latest closing price[45] for stock j,

[43] Equation (3.12) is the *IHP* calculation for one share. To calculate the *IHP* for a stock's trade within a basket, one needs to multiply equation (3.12) by the number of shares traded for that stock in a basket.

[44] During a BPB basket auction, competing BPB brokers usually submit their best bid in term of cents per share. Please refer to Section 3 for a numeric example. Conceptually, X_i can be viewed as the ask price quoted by a stock dealer in the case of a manager buying a single stock name.

[45] In the original argument in formulating IHP_U, $S_{U,I}$ is the stock's true price. However, in the context of BPB basket trading, a stock's latest closing price is used to calculate a

$S_{I,j} = (1 + q) \times X_j$[46] and $q > 0$,

$N(\cdot)$ = cumulative unit normal density function.

The following is a brief description of the intuition of $IHP_{U,j}$ and $IHP_{I,j}$. First, consider a uninformed buy of stock j ordered by an asset manager (i.e. a BPB broker is shorting stock j and needs to hedge the upward price movement of stock j), which corresponds to $IHP_{U,j}$. A manager buys stock j at price X_j. Since the trade is uninformed, we argue that the stock price will not significantly deviate from $S_{U,j}$. $IHP_{U,j}$ is the value of a slightly out-of-money call option that provides to the BPB broker protection when the price of stock j goes above X_j. One can think of $IHP_{U,j}$ as a hedging cost. In the case of an uninformed trade, the BPB broker is likely to obtain a profit under the assumption that the price of stock j is very unlikely to rise above X_j. The premium for an informed buy is $IHP_{I,j}$. Similarly, a manager buys stock j at price X_j. However, since the buy is informed, one can imagine the price of stock j jumping to $S_{I,j}$, which is above X_j, right after a BPB broker wins a basket. Therefore, the BPB broker is going to incur a loss on this informed trade. One can imagine the hedging cost ($IHP_{I,j}$) to be an in-the-money call option with strike price = X_j and stock price = $S_{I,j}$.

To calculate the $IHP_{k,j}$ for a stock in a BPB basket whose trade is a sell, $IHP_{k,j}$ is equal to the value of a put option where:

BPB's profit and lost. Therefore, we assume the latest closing price as the stock's true price.

[46] We do not know the real stock price in the case of an informed trade. Like Bollen et al. (2004), we assume that the true price is q percentage above X_i.

X_j = latest closing price - per share cost of BPB basket trading cost,

$S_{I,j} = (1 - q) \times X_j$ and $q > 0$.

To calculate the IHP_U or IHP_I for a BPB basket, we sum up stock level IHP_U and IHP_I. Using Bollen, Smith and Whaley's (2004) methodology, we have the following regression model specification to estimate the probability that a trade is informed:

$$\begin{aligned}(BPB\ basket\ trading\ cost)_i = \\ &\alpha_0 + \alpha_1 InvTV_i + \alpha_2(Basket\ IHP_{U,i}(g))_i \\ &+ \alpha_3(Basket\ IHP_{I,i}(g,q) - Basket\ IHP_{U,i}(g))_i + \varepsilon_i, \qquad (3.13)\end{aligned}$$

where

g = unloading rate that we used in estimating the model given by equation (3.10),

q = a factor that links $S_{I,j}$ and X_j[47],

α_3 = probability of an informed trade.

We chose a value of g such that the estimated coefficient for the *Basket IHP(g)* in equation (3.8) (or equation (3.9)) is equal to one. We need to make some empirical assumption about the value of q. It is because we do not know the true price of a stock (it is assumed only the informed know the true price). For the model given by equation (3.13) to make sense, the estimated value of α_2 must not be significantly different from one and the value of α_3 must not be outside the range between zero and one (since α_3 is the estimated probability of an informed trade).

[47] In Bollen, Smith and Whaley's (2004) paper, they use symbol k and we use symbol q in this paper.

However, there is one consideration unique in the context of trading a BPB basket. It is very difficult to argue that every stock being traded in a basket is an informed trade. In terms of dollar trade size within a BPB basket, it is common that there are small trades that are uninformed (or at least that contribute relatively lower risk to the BPB brokers). This type of trade size distribution is often due to the fact that the trade list (i.e. a BPB basket) is generated by a portfolio optimizer.[48] For example, if a manager's portfolio is out of bounds for certain industry exposures then the optimizer tries to bring the exposures within a pre-specified lower or upper bound. We argue that IHP_I is equal to IHP_U for this type of trade. Otherwise, IHP_I for a BPB basket is overstated. Therefore, we introduce a new parameter, c, called uninformed trade cutoff. This parameter is expressed in units of percentage of ADV. If the dollar trade size of a trade expressed as percentage of ADV is less than c, the IHP_I is set equal to IHP_U (i.e. these type of trades are assumed to be uninformed). Otherwise, IHP_I is computed based on equation (3.12).

We will use the following regression model specification for our empirical analysis:

$$\begin{aligned}(BPB\ basket\ trading\ cost)_i = \\ \alpha_0 + \alpha_1 InvTV_i + \alpha_2(Basket\ IHP_{U,i}(g))_i \\ + \alpha_3(Basket\ IHP_{I,i}(g,q,c) - Basket\ IHP_{U,i}(g)\ )_i + \varepsilon_i, \qquad (3.14)\end{aligned}$$

where

c = uninformed trade cutoff.

[48] A trade list generated by traditional fundamental active manager usually has a lower number of names and the distribution of the dollar trade size is more concentrated.

3.5.2. Model estimation result and analysis

In this section, we discuss various estimation results of the Bollen, Smith and Whaley (2004) model using historical BPB basket trading data.

3.5.2.1. Choosing the proxy for order-processing cost

The first analysis is of the selection of proxy for order-processing cost. In the model overview, we suggested two possible proxies for order-processing cost:

1. *InvTVi* = 1 / sqrt(Total shares in a BPB basket *i*),
2. $InvNumofNames_i$ = 1 / Number of names being traded in a BPB basket *i*.

To begin with, we arbitrarily set the unloading rate variable, *g*, to 25% of average daily volume per day[49] to calculate *t* (time taken to unload a stock from a basket) for each stock in a basket. We need *t* to compute the expected basket *IHP*. The estimation result for modeling the specification given by equation (3.8) and equation (3.9) is summarized in Panel A of Table VII. Panel B is a summary of descriptive statistics for the variables. Panel C is the correlation matrix. When taken separately, both proxy definitions perform quite well. Both have an expected positive sign and their estimated coefficients are significant. The estimation result when including both proxies in a single regression is shown at the bottom of Panel A. In this case, *InvTVi* becomes insignificant while

[49] The value of *g* affects only the estimated coefficient of E(*basket IHP*). The two proxies for order-processing cost are independent of *g*.

$InvNumofNames_i$ continues to be significant. Therefore, we use $InvNumofNames_i$ as the proxy for the order-processing cost for the remainder of the analysis.[50]

3.5.2.2. Calibrating the unloading rate (g) and IHP as at-the-money options

The next step in our analysis is to calibrate the value of variable *g*, the unloading rate, for the regression model specification given by equation (3.15). This specification is based on equation (3.9) and the method of calibration is to choose a value of *g* such that the estimated coefficient α_2 is one (or not significant different from one).

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2 (Basket\ IHP(g))_i + \varepsilon_i. \qquad (3.15)$$

Bollen, Smith and Whaley (2004) show that *IHP* varies in an approximately linear fashion as the square root of *t* varies. As for specification (2) in Panel A of Table VII shows, the estimated value of α_2 is 0.9647, which is slightly lower than one. To make α_2 equal to one requires a reduction the expected value of *Basket IHP(g)* by reducing *t* or increasing *g*. Equation (3.5) shows that *t* and *g* are inversely related. By adjusting the value of *g* from 25% of ADV to 26.86% of ADV[51], the estimated value of α_2 is calibrated to one. Alternatively, we can estimate α_2 together with other model parameters (rather than assuming that α_2 is equal to one) then the value of α_2 can tell us whether the BPB brokers are over / under hedged. Unfortunately, one cannot separately identify α and *g* in

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[50] Analysis results using *InvTVi* as order-processing cost proxy are also available from us. We do not report these results here because $InvNumofNames_i$ continues to perform better in all other analysis.

[51] Since $26.86 = 25/(0.9647 \times 0.9647)$

the model.[52] Therefore, we continue to assume that α_2 is equal to one. Table VIII shows the estimation result of equation (3.15). There is an empirical interpretation of g. The sample data implies that the BPB broker is unloading shares (of a stock) at a rate about 27% of ADV per day. If a dollar trade size of a stock in a BPB basket is less than 27% of ADV, the BPB broker will finish unloading that particular stock in the first day of trading after winning a BPB basket. Similar, if the trade size is 100% of ADV, BPB broker is going to take more than four days to unload the stock.

As Table VIII shows, the estimated value of α_2 is 0.9999 and is highly significant. The estimated coefficient for *InvNumofNames*, α_1, is positive and significant. These observations are consistent with our prior as described earlier. The R^2 of this regression is 74.91% and is comparable to that reported by Bollen, Smith and Whaley (2004).[53]

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[52] As we have discussed earlier, the *Basket IHP(g)* can be computed as $\sum_j S_j \left[2N\left(0.5\sigma_j \sqrt{0.5\left(\frac{tradesize_j}{volume_j}\right)\left(\frac{1}{g}\right)}\right) - 1\right]$. Using an linear approximation for $N(\cdot)$ developed by Bollen, Smith, and Whaley (2004), we have $N\left(0.5\sigma_j \sqrt{0.5\left(\frac{tradesize_j}{volume_j}\right)\left(\frac{1}{g}\right)}\right) \approx \frac{1}{2} + \frac{\sigma_j}{4}\sqrt{\frac{tradesize_j}{\pi \times volume_j}}\left(\sqrt{\frac{1}{g}}\right)$. Then we can express the model that we are going to estimate as: *(BPB basket trading cost)*$_i$ = α_0 + α_1*InvNumofNames*$_i$ + $\alpha_2\left(\frac{1}{\sqrt{g}}\right)\left(\sum_j \frac{S_j\sigma_j}{2}\sqrt{\frac{tradesize_j}{\pi \times volume_j}}\right)_i$ + ε_i. Clearly, since $\left(\sum_j \frac{S_j\sigma_j}{2}\sqrt{\frac{tradesize_j}{\pi \times volume_j}}\right)_i$ is observable, we can identify the term $\alpha_2(1/\sqrt{g})$. But without further information, we cannot separately identify α_2 and g.

[53] R^2 reported by them ranges from about 50% to 80% during three different sample time periods.

However, we have a significant negative intercept in our model estimation. We mentioned earlier that we expect the intercept not to be significantly different from zero. There are two possible explanations for a negative intercept. The first is that the *IHP* is overstated when *IHP* is valued as at-the-money options in equation (3.15). It is because these at-the-money options protect against unfavorable price movement (e.g. an asset manager sold a stock to a BPB broker and the price of the stock subsequently goes down) and a BPB broker can profit from favorable price movement. Bollen, Smith and Whaley (2004) argue that such profit is capped at a certain level due to competition. This explanation is testable if we compute *IHP* as an option collar. Based on option collar approach, the value of *IHP* is the value of an at-the-money option minus the value of a slightly out-of-money option.[54] We report the test result for this explanation in the next section. The second possible explanation is that some of the trades within a basket are crossed with existing inventory carried by a BPB broker. *IHP* for crossed trades should be zero. Testing the second explanation is a more difficult task because data on BPB broker's inventory are usually not publicly available.

3.5.2.3. Inventory Holding Premium (IHP) as option collars

Following is the test result related to explaining the negative intercept described above. When computing the out-of-money option, we assume the strike price is 0.5% away from

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[54] For a buy trade ordered by a manager, *IHP* = value of at-the-money call – value of slightly out-of-money put. In this case, *IHP* is modeled as buying a call and selling a put. Similarly, for a sell trade ordered by a manager, *IHP* = value of at-the-money put – value of slight out-of-money call. In this case, *IHP* is modeled as buying a put and selling a call.

the stock price.[55] The model specification is also based on equation (3.15), but here the inventory-holding premium is modeled as an option collar. Table IX shows the estimation result. The estimated coefficients for *InvNumofNames* and *Basket IHP* are both positive and significant. The result continues to be consistent with our prior belief. However, the intercept is still significantly negative. Therefore, the negative intercept may be due to the internal-crossing between stocks in a basket and a BPB broker's existing inventory. There appears, however, to be a weak point in this argument, as the R^2 of the regression is reduced. In summary, there is some weak evidence that the negative intercept might be attributed to internal crossing.

3.5.2.4. Probability of informed trades and distribution of various trading components

As discussed in the earlier section on an overview of the model, it is possible to estimate the probability that a trade is an informed trade. In this case, the model we estimate is given by equation (3.16), which is modified from equation (3.14).

$$
\begin{aligned}
&(\mathit{BPB\ basket\ trading\ cost})_i = \\
&\quad \alpha_0 + \alpha_1 \mathit{InvNumofNames}_i + \alpha_2(\mathit{Basket\ IHP}_{U,i}(g))_i \\
&\qquad + \alpha_3(\mathit{Basket\ IHP}_{I,i}(g,q,c) - \mathit{Basket\ IHP}_{U,i}(g))_i + \varepsilon_i. \qquad (3.16)
\end{aligned}
$$

When we estimate the model, we need to make some assumptions about the values of *q* and *c*. We assume *q* takes the following values: 0.5%, 1%, 2%, and 3%, while *c* takes the following values: 3% of ADV, 4% of ADV, and 5% of ADV. Table X gives the estimation results for twelve different combinations of *q* and *c*. Panels A, B, and C of Table X correspond to three different values of *c*. The four rows of the sub-table

[55] The 0.5% is an arbitrary number. Bollen, Smith and Whaley (2004) also use 0.5% for calculating the value of the out-of-money option.

represent four different values of q in each panel. There are twelve sub-tables in total. The estimated result will only have economic (and mathematic) interpretations if both of the following conditions are satisfied:

1. The estimated value of α_2 is not significantly different from one.
2. The estimated value of α_3 is not significantly outside the range between zero and one.

Many of our results are similar to those reported by Bollen, Smith and Whaley (2004). The estimated values of α_1, α_2, and α_3 are positive and significant. As q increases (i.e. going down a panel), the probability of informed trades (i.e. the estimated value of α_3) decreases. When q changes, the R^2 of the regression remains quite stable. This implies that the adverse selection component of the BPB basket trading cost appears to be relatively constant. The T-stat for α_2 is always the highest and most significant. This implies that inventory-holding cost is the most significant component of the trading cost.

However, there are some results that differ from those of Bollen, Smith and Whaley (2004). Using their argument, the intercept terms should not be significantly different from zero, because the intercept can be interpreted as minimum tick size. However, there is no such concept of minimum tick size in a BPB basket trading. Our result shows that the intercepts are not significantly different from zero in the usual statistical sense. However, the values of intercept are always negative. A possible explanation may be the possibility of internal crossing between trades in a basket and the existing inventory held by BPB broker. The lack of data on a broker's inventory makes further investigation of this explanation impossible. Due to a lack of data on BPB competition, we are unable to model the effect of competition among BPB brokers on the trading cost of BPB baskets.

Several results are unique in this study. When q is between 0.5% and 3%, BPB brokers begin to assume that a trade is informed when it reaches 3% or 4% of ADV. When q increases, c tends to increase as well. Therefore, when a BPB broker assumes a manager is informed, the broker would expect that informed trades are those with higher percentage of ADV. For a manager with higher skill, the BPB broker expects informed trades are likely to be those with a higher percentage of ADV. Based on Panel A and B, we can compute an average distribution of various cost components for the BPB basket trading cost. The average percentage of trading cost attributed to inventory-holding cost is about 61%, to adverse-selection about 34%, and to order-processing cost is about 23%. We are unable to find any other studies that analyze the distribution of various cost components when trading a basket of stocks. Therefore, it is difficult to compare other results to ours. Alternatively, we may compare our cost distribution with the cost distribution for trading a single stock name. However, the cost distribution for trading a single stock varies significantly among different studies. Stoll (1989) reports order-processing cost as the largest component (47%), followed by adverse-selection cost (43%) and inventory-holding (10%). Stoll's (1989) ranking of various cost components is exactly the opposite of our findings. Bollen, Smith and Whaley (2004) find that inventory-holding cost is the largest component, which corresponds to our results. But they find that adverse-selection cost is the smallest, which differs from our results. Huang and Stoll (1997) report that the biggest cost component is order-processing (62%)

followed by inventory-holding (29%). The smallest cost component is adverse-selection (9%). Their ranking is also different from ours.

In an overall sense, inventory-holding cost and adverse-selection cost are more important in the case of trading a BPB basket. The rationale might be that a BPB broker commits relatively more capital than that in market-making for a single stock, and each BPB basket always has some informed trades. However, one might argue that the relative ranking of various cost components can change over time. For example, during a period of higher risk (i.e. in a market with higher cross-sectional dispersion), adverse selection cost may become the biggest cost component. We leave this question for further research.

3.6. Conclusion

In this study, we estimate two structural spread models for trading BPB baskets. We extend and improve upon the work done by both Kavajecz and Keim (2005) and chapter 2 of this dissertation by providing a formal framework to model the trading cost of BPB baskets. This modeling involves using two spread models developed by Stoll (1978a and 1978b) and Bollen, Smith and Whaley (2004). The main contribution of this study is the successful application of these models in estimating the cost of immediacy (i.e. spread) for trading a basket of stocks. We are also able to characterize some empirical behavior of BPB brokers. Based on our data sample, the unloading rate used by a BPB broker is about 27% of ADV. The more a broker thinks a manager’s trade is informed, the bigger the mis-pricing and the bigger the (dollar) size for that trade in terms of higher percentage of ADV. The largest cost component when trading a BPB basket is found to be inventory-holding cost, followed by adverse-selection cost and order-processing cost. We also find some weak evidence that internal crossing used by the BPB broker who won a basket[56] helps reduce the overall BPB basket trading cost. However, we cannot model this effect of internal crossing formally due to a lack of data. For the same reason, we cannot model the effect of competition on the trading cost of BPB baskets. These are potential future research.

One possible application of this paper is to help asset managers establish a benchmark trading cost when trading BPB baskets. Managers can use this benchmark trading cost to judge the fairness of bids submitted by BPB brokers.

[56] Based on our informal discussion with BPB brokers, the range of crossing can range from 0% and may up to 30% of a basket.

Table IV

Descriptive statistics for some blind principal bid (BPB) basket characteristics

There are 196 baskets used in this study.

Basket Characteristics	Mean	Std. Dev.	Min.	25th	Median	75th	Max.
Number of names in a basket	199	113	41	93	193	294	609
Total trade size ($ million)	333.99	239.56	20.09	146.20	268.09	487.05	1,188.14
Total number of shares (million)	11.26	8.27	0.60	5.05	8.95	16.29	45.06
Names that are buys (%)	45.59	9.34	13.14	40.06	46.24	50.73	100.00
Lowest bid (basis points)	53.57	33.00	8.95	26.90	44.79	73.42	164.75

Table V

Descriptive statistics for the variables in Stoll's (1978a, 1978b) model

The following table lists the variables we used in estimating Stoll's (1978a, 1978b) model. The table also summarizes the expected sign of the estimated coefficient for the independent variables. The sample size is 196. Following Stoll's original approach, the natural logarithm version of all variables is used in the model estimation. The descriptive statistics are based on the natural logarithm version of the variables. s_i = Basket trading cost which is the dependent variable. σ^2_i = Basket variance. V_i = Basket weighted-average (dollar) volume. $(V/T)_i$ = Basket weighted-average turnover. P_i = Basket weighted-average stock price.

Variable	**Mean**	**Std. Dev.**	**Min.**	**25th**	**Median**	**75th**	**Max.**	**Expected Coefficient sign**
s_i	-5.42	0.63	-7.02	-5.91	-5.41	-4.92	-4.11	Dep. Var.
σ^2_i	-4.34	0.86	-5.62	-5.02	-4.39	-3.85	-1.78	+
V_i	18.40	0.90	16.04	18.20	18.48	19.04	20.02	-
$(V/T)_i$	-6.45	0.88	-9.73	-7.02	-6.46	-5.80	-4.49	+
P_i	3.37	0.21	2.94	3.58	3.68	3.82	4.17	Ambiguous

Table VI

Stoll's (1978a, 1978b) model estimation result

The following table summarizes Stoll's (1978a, 1978b) model estimation result. The sample size (N) is 196. Following Stoll's original approach, a natural logarithm version of all variables is used in the model estimation. s_i = Basket trading cost, which is the dependent variable. $\sigma^2{}_i$ = Basket variance. V_i = Basket weighted-average (dollar) volume. $(V/T)_i$ = Basket weighted-average turnover. P_i = Basket weighted-average stock price.

	s_i	$\sigma^2{}_i$	V_i	$(V/T)_i$	P_i	intercept	N	R-sq
Coefficient	Dep. Var.	0.1347	-0.1660	0.4528	0.0565	0.9330	196	74.32
T-stat		4.49	-4.35	14.21	0.37	1.90		
p value		0.0000	0.0000	0.0000	0.7140	0.0587		

Table VII

Proxy for order-processing cost in Bollen, Smith and Whaley's (2004) framework.

Table IV has three panels. Panel A summarizes the model estimation result for the three different model specifications given below. Panel B shows the descriptive statistics of the variables. Panel C shows the correlation among variables. The unloading rate, *g*, is set at 25% of ADV when calculating basket IHP.

(1) $(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvTV_i + \alpha_2 (Basket\ IHP)_i + \varepsilon_i$,

(2) $(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2 (Basket\ IHP)_i + \varepsilon_i$,

(3) $(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvTV_i + \alpha_2 InvNumofNames_i + \alpha_3 (Basket\ IHP)_i + \varepsilon_i$,

where

i = 1, 2, 3, …, sample size of traded BPB baskets (identifier for each BPB basket),

$(BPB\ basket\ trading\ cost)_i$ = fee (in dollars) paid by manager to BPB broker,

$InvTV_i$ = 1 / sqrt(Total shares (expressed in million of share) in a BPB basket *i*),

$InvNumofNames_i$ = 1 / Number of names being traded in a BPB basket *i*,

$(Basket\ IHP)_i = \sum_j S_j[2N(0.5\sigma_j E(\sqrt{t_j})) - 1]$,

j = 1, 2, 3, …, number of stock names in BPB basket *i*,

S_j = latest closing price for stock *j*,

σ_j = standard deviation of return for stock *j*,

t_j = time taken to unload stock *j* from basket *i* which is a function of *g*,

$N(\cdot)$ = cumulative unit normal density function.

Table VII (continued)

Proxy for order-processing cost in Bollen, Smith and Whaley's (2004) framework.

Panel A – Regression Results

	(BPB basket trading cost)$_i$	*$InvTV_i$*	*Inv Numof Names$_i$*	*(Basket IHP)$_i$*	intercept	**N**	R-sq
Model estimation for specification (1)							
Coeff	Dep. Var.	840,475.75		0.9789	-429,215.56	196	74.26
T-stat		1.97		20.51	-1.83		
p value		0.0499		0.0000	0.0683		
Model estimation for specification (2)							
Coeff	Dep. Var.		41,081,072.62	0.9647	-389,989.57	196	74.91
T-stat			3.01	23.55	-2.45		
p value			0.0030	0.0000	0.0152		
Model estimation for specification (3)							
Coeff	Dep. Var.	-300,690.52	48,528,485.53	0.9528	-308,924.29	196	74.94
T-stat		-0.46	2.29	19.62	-1.30		
p value		0.6451	0.0229	0.0000	0.1947		

Panel B – Descriptive Statistics

	Mean	**St. Dev.**	**Min.**	**25%**	**Median**	**75%**	**Max.**
(BPB basket trading cost)$_i$	1,672,477	1,857,896	45,777	608,587	1,217,757	2,060,929	15,557,582
$InvTV_i$	0.3835	0.1931	0.1490	0.2478	0.3835	0.4448	1.2890
Inv Numof Names$_i$	0.0075	0.0052	0.0016	0.0034	0.0052	0.0107	0.0244
(Basket IHP)$_i$	1,753,570	1,662,649	55,917	636,578	1,366,715	2,297,742	13,058,043

Panel C – Correlation Matrix

	(BPB basket trading cost)$_i$	*$InvTV_i$*	*$InvNumofNames_i$*
$InvTV_i$	-0.43		
$InvNumofNames_i$	-0.16	0.77	
(Basket IHP)$_i$	0.85	-0.56	-0.34

Table VIII

Calibrating the value of *g*

By setting the value of g, the unloading rate, to 26.86% of ADV, the estimated value of α_2 in the following model specification is calibrated to one.

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2(Basket\ IHP(g))_i + \varepsilon_i,$$

where

i = 1, 2, 3, …, sample size of traded BPB baskets (i.e. identifier for each BPB basket),

$(BPB\ basket\ trading\ cost)_i$ = fee (in dollars) paid by manager to BPB broker,

$InvNumofNames_i$ = 1 / Number of names being traded in a BPB basket i,

$(Basket\ IHP(g))_i = \sum_j S_j[2\mathrm{N}(0.5\sigma_j \mathrm{E}(\sqrt{t_j})) - 1]$,

j = 1, 2, 3, …, number of stock names in BPB basket i,

S_j = latest closing price for stock j,

σ_j = standard deviation of return for stock j,

t_j = time taken to unload stock j from basket i which is a function of g,

$N(\cdot)$ = cumulative unit normal density function.

	(BPB basket trading cost)$_i$	*Inv Numof Names$_i$*	*(Basket IHP)$_i$*	intercept	**N**	R-sq
Coeff	Dep. Var.	41,078,664.54	0.9999	-389,918.73	196	74.91
T-stat		3.01	23.55	-2.45		
p value		0.0030	0.0000	0.0152		

Table IX

Model inventory-holding premium as option collars

In this model estimation, we model the inventory-holding premium, $IHP^C(g)$, as an option collar rather than an at-the-money option. When calculating the value of the out-of-money option, we assume the strike price (X) is 0.5% away from the latest closing price (S). The unloading rate, g, continues to be 26.86% of ADV.

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2 (Basket\ IHP^C(g))_i + \varepsilon_i,$$

where

i = 1, 2, 3, …, sample size of traded BPB baskets (i.e. identifier for each BPB basket),

$(BPB\ basket\ trading\ cost)_i$ = fee (in dollars) paid by manager to BPB broker,

$InvNumofNames_i$ = 1 / Number of names being traded in a BPB basket i,

$(Basket\ IHP^C)_i = \sum_j S_j[2N(0.5\sigma_j E(\sqrt{t_j})) - 1] - \sum_j$ (out of money option with X_j is 0.5% away from S_j),

j = 1, 2, 3, …, number of stock names in BPB basket i,

S_j = latest closing price for stock j,

σ_j = standard deviation of return for stock j,

t_j = time taken to unload stock j from basket i which is a function of g,

$N(\cdot)$ = cumulative unit normal density function,

X_j = strike price for the out of money option for stock j.

	(BPB basket trading cost)$_i$	*Inv Numof Names$_i$*	*(Basket IHP^C)$_i$*	intercept	**N**	R-sq
Coeff	Dep. Var.	82,245,474.84	5.4516	-887152.88	196	45.43
T-stat		3.68	12.27	-2.95		
p value		0.0003	0.0000	0.0036		

Table X

Estimating the probability of informed trades and distribution of various trading cost components

This table summaries the estimation result of the following regression model specification given by equation (3.16):

$$(BPB\ basket\ trading\ cost)_i = \alpha_0 + \alpha_1 InvNumofNames_i + \alpha_2(Basket\ IHP_{U,i}(g))_i$$

$$+ \alpha_3(Basket\ IHP_{I,i}(g,q,c) - Basket\ IHP_{U,i}(g)\ )_i + \varepsilon_i,$$

where

$InvNumofNames_i$ = 1 / (Number of names being traded in a BPB basket *i*),

$IHP_{U,i}(g))_i$ = inventory-holding premium for uninformed trades,

$IHP_{I,i}(g,q,c)$ = inventory-holding premium for informed trades,

g = unloading rate defined in equation (3.10),

c = uninformed trade cutoff for $IHP_{I,i}$ defined in equation (3.14),

q is defined in equation (3.13).

During model estimation, we assume that *q* takes the values: 0.5%, 1%, 2%, and 3%, and that *c* takes the values 3% of ADV, 4% of ADV, and 5% of ADV. The table contains three vertical panels (A, B, and C), which correspond to three different values of *c*. For each panel, there are four estimation results (four sub-tables) that correspond to the four different values of *q*. Each sub-table has the following six columns:

1. Name of dependent and independent variables. Trade Cost = $(BPB\ basket\ trading\ cost)_i$ which is the dependent variable. InvNames = 1 / (Number of names being

traded in a BPB basket *i*). IHPU = *Basket* $IHP_{U,i}(g)$ and IHPI = *Basket* $IHP_{I,i}(g,q,c)$.

2. Estimated values for the regression intercept and coefficient of the independent variables (i.e. α_0, α_1, α_2, and α_3).
3. T-statistics for each estimated values.
4. Mean value for the dependent and independent variables.
5. Mean trading cost contributed by each of the independent variables.
6. Trading cost contributed by each independent variable expressed as a percentage of the mean BPB basket trading cost.

Table X (continued) – Panel A

Estimating the probability of informed trades and distribution of various trading cost components

In this panel, the uninformed trade cutoff (*c*) is assumed to be 3% of ADV. *q* takes the following values: 0.5%, 1.0%, 2.0%, and 3.0% as one goes down the panel. Each value of *q* corresponds to a sub-table in Table X.

	***c* = uninformed trade cutoff = 3% of ADV**					
	Var.	**Est. Coeff.**	**T-stat**	**Mean Val.**	**Cost Contri.**	
***q* = 0.5%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-333,136.75	-1.21	-333,136.75	-333,136.75	-20%
	InvNames	52,368,942.94	2.48	0.0075209	393,860.17	24%
	IHPU	0.8754	5.44	1,138,439.40	996,589.85	60%
	(IHPI-IHPU)	0.7885	2.48	780,207.93	615,193.95	37%
	R-sq = 51.00					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.77)					
***q* = 1.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-244,106.34	-0.88	-244,106.34	-244,106.34	-15%
	InvNames	47,866,879.42	2.25	0.0075209	360,000.72	22%
	IHPU	0.9656	6.18	1,138,439.40	1,099,277.08	66%
	(IHPI-IHPU)	0.2601	1.89	1,757,715.50	457,181.80	27%
	R-sq = 50.36					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.22)					
***q* = 2.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-209,995.89	-0.75	-209,995.89	-209,995.89	-13%
	InvNames	46,090,009.22	2.16	0.0075209	346,637.11	21%
	IHPU	0.9987	6.49	1,138,439.40	1,136,959.43	68%
	(IHPI-IHPU)	0.0990	1.67	4,029,030.40	398,874.01	24%
	R-sq = 50.16					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.01)					
***q* = 3.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-236,170.57	-0.85	-236,170.57	-236,170.57	-14%
	InvNames	47,405,547.96	2.23	0.0075209	356,531.11	21%
	IHPU	0.9759	6.31	1,138,439.40	1,111,003.01	66%
	(IHPI-IHPU)	0.0679	1.84	6,490,985.30	440,737.90	26%
	R-sq = 50.31					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.16)					

Table X (continued) – Panel B

Estimating the probability of informed trades and distribution of various trading cost components

In this panel, the uninformed trade cutoff (*c*) is assumed to be 4% of ADV. *q* takes the following values: 0.5%, 1.0%, 2.0%, and 3.0% as one goes down the panel. Each value of *q* corresponds to a sub-table in Table X.

	***c* = uninformed trade cutoff = 4% of ADV**					
	Var.	**Est. Coeff.**	**T-stat**	**Mean Val.**	**Cost Contri.**	
***q* = 0.5%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-427,010.19	-1.62	-427,010.19	-427,010.19	-26%
	InvNames	56,661,845.96	2.77	0.0075209	426,146.55	25%
	IHPU	0.7446	4.61	1,138,439.40	847,681.98	51%
	(IHPI-IHPU)	1.1456	3.42	720,777.37	825,722.56	49%
	R-sq = 52.34					
	estimated coefficient for IHPU is not significantly diff from 1 (t=1.58)					
***q* = 1.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-344,589.39	-1.29	-344,589.39	-344,589.39	-21%
	InvNames	52,733,197.83	2.54	0.0075209	396,599.68	24%
	IHPU	0.8466	5.37	1,138,439.40	963,802.80	58%
	(IHPI-IHPU)	0.4055	2.78	1,619,197.90	656,584.75	39%
	R-sq = 51.39					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.97)					
***q* = 2.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-307,699.38	-1.14	-307,699.38	-307,699.38	-18%
	InvNames	50,894,526.69	2.44	0.0075209	382,771.27	23%
	IHPU	0.8904	5.74	1,138,439.40	1,013,666.44	61%
	(IHPI-IHPU)	0.1570	2.50	3,717,798.70	583,694.40	35%
	R-sq = 51.03					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.71)					
***q* = 3.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-329,615.91	-1.23	-329,615.91	-329,615.91	-20%
	InvNames	51,920,671.25	2.50	0.0075209	390,488.77	23%
	IHPU	0.8686	5.58	1,138,439.40	988,848.46	59%
	(IHPI-IHPU)	0.1037	2.66	6,004,184.80	622,633.96	37%
	R-sq = 51.23					
	estimated coefficient for IHPU is not significantly diff from 1 (t=0.84)					

Table X (continued) – Panel C

Estimating the probability of informed trades and distribution of various trading cost components

In this panel, the uninformed trade cutoff (*c*) is assumed to be 5% of ADV. *q* takes the following values: 0.5%, 1.0%, 2.0%, and 3.0% as one goes down the panel. Each value of *q* corresponds to a sub-table in Table X.

	***c* = uninformed trade cutoff = 5% of ADV**					
	Var.	**Est. Coeff.**	**T-stat**	**Mean Val.**	**Cost Contri.**	
***q* = 0.5%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-559,354.83	-2.22	-559,354.83	-559,354.83	-33%
	InvNames	61,969,221.73	3.15	0.0075209	466,062.65	28%
	IHPU	0.5687	3.59	1,138,439.40	647,430.49	39%
	(IHPI-IHPU)	1.6767	4.79	666,984.83	1,118,333.46	67%
	R-sq = 54.83					
	estimated coefficient for IHPU is significantly diff from 1 (t=2.72)					
***q* = 1.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-487,923.43	-1.90	-487,923.43	-487,923.43	-29%
	InvNames	58,964,487.98	2.94	0.0075209	443,464.43	27%
	IHPU	0.6799	4.37	1,138,439.40	774,024.95	46%
	(IHPI-IHPU)	0.6312	4.09	1,493,870.50	942,931.06	56%
	R-sq = 53.48					
	estimated coefficient for IHPU is significantly diff from 1 (t=2.05)					
***q* = 2.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-452,102.41	-1.74	-452,102.41	-452,102.41	-27%
	InvNames	57,333,864.96	2.84	0.0075209	431,200.72	26%
	IHPU	0.7326	4.76	1,138,439.40	834,020.70	50%
	(IHPI-IHPU)	0.2504	3.76	3,431,949.50	859,360.15	51%
	R-sq = 52.89					
	estimated coefficient for IHPU is not significantly diff from 1 (t=1.74)					
***q* = 3.0%**	Trade Cost	Dep. Var.		1,672,476.90		
	Intercept	-469,808.59	-1.82	-469,808.59	-469,808.59	-28%
	InvNames	58,044,440.05	2.89	0.0075209	436,544.86	26%
	IHPU	0.7121	4.62	1,138,439.40	810,682.70	48%
	(IHPI-IHPU)	0.1612	3.91	5,553,416.00	895,210.66	54%
	R-sq = 53.16					
	estimated coefficient for IHPU is not significantly diff from 1 (t=1.87)					

Chapter 4

Decision to Trade Blind Principal Bid Basket – A Behavioral Perspective

4.1. Introduction

Previous studies (Kavajecz and Keim 2005; Chapter 2 and Chapter 3 of this dissertation) focus on how a BPB basket is priced. This chapter looks at a different, but related, question. We investigate how a manager decides to opt for executing a BPB basket rather than going through the traditional agency trade. A key feature of BPB is that a manager knows the trading cost before the basket execution, whereas when using agency trade the actual realized trading cost is unknown before execution. Choosing to use agency trade for execution is a decision under risk and prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992; Wakker and Tversky 1993) might be able to predict a manager's final choice (i.e., BPB vis-à-vis agency trade). We also investigate whether expected utility theory can also be used to model a manager's behavior by estimating that manager's absolute risk aversion.

One contribution of this chapter is our unique data sample, and our results complement other studies that use data generated in an experimental or laboratory setting. In our sample, the trading decision is made by professional quantitative asset managers rather than by game show participants, as other studies have investigated (Gertner 1993; Metrick 1995; Beetsma and Schotman 2001; Fullenkamp et al. 2003). We studied reallife business decisions by managers who should be expected to have a better understanding of risk and reward due to the nature of their investment business than typical game show participants. This makes the analysis of their decisions quite interesting.

Another important feature of our sample is that the monetary stake of a manager's decision is very high. The average trading cost a BPB basket in our sample is $1.8 million. It is very difficult to simulate the effect of such high stakes in an experimental setting.[57] High-stakes decisions are good for studying risk aversion in the framework of expected utility theory; as Rabin (2000a, 2000b) and Rabin and Thaler (2001) have argued, expected utility theory may not characterize the risk aversion properly when stakes are small.

The remainder of the chapter is organized as follows. Section 4.2 describes an implementation shortfall model we use to estimate the expected agency trading cost a manager incurs. In Section 4.3, we describe a simple model to estimate a manager's absolute risk aversion under expected utility theory. Section 4.4 shows that a manager's decision to use BPB for execution rather than agency trade is consistent with prospect theory's prediction. Section 4.5 concludes the chapter.

[57] Kachelmeier and Shehata (1992) tried to simulate the effect of high monetary stakes by conducting experiments in a country with a relatively low cost of living.

4.2. A model for a manager's agency trading cost

Since this chapter investigates a manager's choice between a BPB basket and an agency trade,[58] we need a model to measure the expected trading cost and the variance of the trading cost.

4.2.1. A model for predicting implementation short fall

We use an implementation shortfall model developed by Almgren et al. (2005)[59] to compute the expected implementation shortfall for a stock. Borrowing their notation and results, the implementation shortfall, A, is a normal distribution random variable with its expected value (expressed in dollars), and variance (expressed in dollar squared) can be computed as follows:

$$E[A] = XS_0[\frac{1}{2}\gamma\sigma\frac{X}{V}(\frac{\Theta}{V})^{\delta} + \eta\sigma\,\mathrm{sgn}(X)\left|\frac{X}{VT}\right|^{\beta} + \mathrm{sgn}(X)\varepsilon(\frac{1}{S_0})] \tag{4.1}$$

$$Var(A) = T\left(\frac{\sigma^2}{3}\right)(XS_0)^2 \tag{4.2}$$

where

X = number of shares to be traded, negative for sell and positive for buy,

S_0 = closing price agreed to be used as the execution price for a BPB basket,

γ = model parameter (estimated to be 0.314 ± 0.041),

σ = daily volatility,

V = average daily volume in shares,

δ = model parameter (estimated to be 0.267 ± 0.22),

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58 The agency trading cost is defined as implementation shortfall, as suggested by Perold (1988).

59 One can also use other models as long as the model can provide an estimate of expected implementation shortfall and variance of the implement shortfall.

$\Theta =$ total shares outstanding,

$\eta =$ model parameter (estimated to be 0.142 ± 0.0062),

$sgn(X) =$ +1 if $X > 0$; -1 if $X < 0$,

$\beta =$ model parameter (estimated to be 0.600 ± 0.038),

$T =$ trade duration in days (i.e., time horizon to finish a trade),

$\varepsilon =$ agency trade broker commission (assumed to be 2 cents / share).

For all market impact model parameters (γ, δ, η, and β), we use values estimated by Almgren et al. (2005). It is likely, though, that stocks in a basket have different liquidity requirement and hence take different time, T, to complete their execution. Realistically, a large position in a basket needs a longer time to trade than do smaller positions. Therefore, we introduce an extra variable that help us model T more effectively when dealing with a basket of stocks. The new variable, agency trading rate, g, is the percentage of average daily share volume a manager would like to execute in the agency trade in a given day (the unit for g is a percentage of average daily share volume). For example, if the average daily volume for a stock i in a basket is 1,000,000 shares and g = 25% of average daily volume, then a manager plans to trade 250,000 shares of stock i in a day. Furthermore, if we assume 125,000 shares of stock i in a basket, then the manager is going to finish trading stock i in half a day (i.e. $T = ½$ and $T = \frac{X/V}{g}$). We assume that g is exogenous in this study and that a manager has a trading rate in mind for agency trade execution.[60]

[60] Typically, asset managers have some rule of thumb regarding the agency trading rate.

Both Bertsimas and Lo (1998) and Almgren and Chriss (2000) demonstrate that a implementation shortfall will be minimal if the trajectory for trading a block of shares (for a single name) spreads the shares evenly across a given time horizon, T. Another way to describe this trading trajectory is to trade shares at a constant rate. If a manager chooses a higher g (while all other variables remain the same), the expected implementation shortfall will increase and the variance of implementation shortfall will decrease. Similarly, if g decreases, so too will the expected implementation shortfall but the variance of implementation shortfall will increase.

We also assume that trading a stock affects only the price of that stock and no other stock prices (i.e., it has no cross-impact effect). The expected implementation shortfall for a basket will then be the sum of the expected implementation shortfall for each name in a basket. The variance of implementation shortfall for a basket can be computed in a similar manner. Using this model, the implementation shortfall for executing a basket of stocks as agency trade is a normal random variable with finite expectation and variance.

4.2.2. Historical BPB basket data

We have gathered 196 blind principal bid baskets executed regularly by two asset managers.[61] These baskets were traded between January 2002 and September 2005. One

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[61] We would like to thank a consulting firm specializing in securities transactions for providing transaction records for one of its managers. To ensure confidentiality, the names of the money manager and the winning brokers were excluded from the records before we received the data. We obtained a second set of transaction records from another asset manager. Both managers specialize in quantitative investment strategies.

manager uses only pre-open bidding and the other manager uses both pre-open and post-close bidding. For each basket executed, we gather the following data items:

1. Stock identifier (CUSIP or ticker) for each name in a basket,
2. Transaction type for each name (buy or sell) in a basket,
3. Number of shares traded for each name in a basket,
4. Execution price[62] for each name in a basket,
5. Winning bid (which appears as cents per share in the data).

The cost (in dollars) of trading a BPB basket can be computed as the total number of shares in a basket times the winning bid. Table XI provides descriptive statistics for some of the basket characteristics. For a given agency trading rate, *g*, we can compute the hypothetical expected implementation shortfall and variance of implementation shortfall for each basket in our sample using the method discussed in the previous section.

4.3. Estimating a manager's absolute risk aversion

Expected utility theory provides a good starting point for our investigation to model a manager's decision under risk. If a manager is risk neutral, the use of BPB – which provides a known trade cost before execution – provides no benefit. The maximum cost a risk-neutral manager is willing to pay to a BPB broker is the expected implementation shortfall. However, the cost of trading a BPB basket is typically more expensive than the expected implementation shortfall. If a manager is willing to pay a higher cost in exchange for a known trading cost, it indicates that he is risk averse when executing a basket.

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[62] As Section 4.1 details, the execution price for pre-open bidding is the previous day's closing price, and for post-close bidding it is the same-day closing price.

In this section, we seek to estimate a manager's absolute risk aversion (*ARA*) under the expected utility theory. We impose no assumptions on the shape of the manager's utility function; our estimation is based on observing the manager's behavior (i.e., his decision to trade BPB baskets). Other studies have employed this approach of characterizing risk aversion indirectly based on observations of decisions made by individuals (Beetsma and Schotman 2001; Jullien and Salanie 2000). An alternative approach is to use experimental procedures such as survey questionnaires regarding decision under risk to estimate the risk aversion. Donkers et al. (2001), Binswanger (1980) and Kachelmeier and Shehata (1992) have followed this alternative approach.

4.3.1. A simple model to estimate the absolute risk aversion

We use the following variables in describing the model and methodology:

- *A* is the random variable representing the implementation shortfall when a basket is executed using an agency trade (as described in detail in Section 4.2). Recall that *A* follows a normal distribution with expectation *E[A]* and variance *VAR(A)* and they can be computed by equation (4.1) and (4.2).
- Let σ_A be the standard deviation of the random variable *A*.
- Let *B* be the BPB basket trading cost.

To have a simpler model, we approximate *A* (which is a continuous random variable) by a two-state discrete random variable:

$$\text{Approximated Implementation shortfall} = \begin{Bmatrix} \mathrm{E[A]} + \sigma_{\mathrm{A}} \ \text{ with 0.5 probability} \\ \mathrm{E[A]} - \sigma_{\mathrm{A}} \ \text{ with 0.5 probability} \end{Bmatrix}. \qquad (4.3)$$

We model a manager's implementation shortfall using only two states, with each state equally probable to occur. In the high state, the implementation shortfall is one standard deviation (σ_A) above *E[A]*. In the low state, the implementation shortfall is one standard deviation (σ_A) below *E[A]*. This discrete random variable has the same expectation and variance as the continuous random variable *A*. Let us define $H = E[A] + \sigma_A$ and $L = E[A] - \sigma_A$. In summary, if a manager executes a basket as an agency trade, his implementation shortfall (i.e., agency trading cost) is either *H* or *L*, with equal probability of 0.5.

The following is a simple model we can use to estimate a manager's absolute risk aversion under the expected utility theory framework. The technique used here is similar to that used by Brunello (2002) and Eisenghauer and Ventura (2003). By assuming *B* is the maximum BPB trading cost that a manager will pay such that he is indifferent about using either BPB or agency trade, we have the following equation in which *U(·)* is a manager's utility function and *W* is wealth:

$$U(W-B) = \frac{1}{2}U(W-L) + \frac{1}{2}U(W-H)\ . \tag{4.4}$$

A Taylor series expansion of equation (4.4), ignoring higher order terms, gives the following equations:

$$\begin{aligned} &U(W) + (-B)U^{'}(W) + \frac{1}{2}(-B)^2 U^{''}(W) = \\ &\frac{1}{2}U(W) + \frac{1}{2}(-L)U^{'}(W) + \frac{1}{4}(-L)^2 U^{''}(W) + \frac{1}{2}U(W) + \frac{1}{2}(-H)U^{'}(W) + \frac{1}{4}(-H)^2 U^{''}(W) \end{aligned} \tag{4.5}$$

In expected utility theory, the absolute risk aversion (*ARA*) is defined as $-\frac{U^{''}(W)}{U^{'}(W)}$. By rearranging the terms in equation (4.5), we can express a manager's *ARA* using the following equation:

$$ARA = -\frac{U^{''}(W)}{U^{'}(W)} = \frac{2(2B-L-H)}{L^2+H^2-2B^2}\ . \tag{4.6}$$

Using the BPB basket data described in Section 4.2.2, we can estimate a manager's *ARA* by equation (4.6). The result of the *ARA* estimation is given in the next section.

4.3.2. Result of Absolute Risk Aversion Estimation

For each BPB basket, we can compute one observation of *ARA* based on equation (4.6). The mean of all the *ARA* observations in our sample of BPB baskets is our estimation of a manager's *ARA*. There are 196 observations in our sample. We also conduct the following hypothesis testing:

H_0: Mean of $ARA = 0$

H_1: Mean of $ARA > 0$

If expected utility theory can model a manager's choice about how to execute a basket, then our prior is that the mean of the *ARA* observations should be significantly bigger than zero (i.e., reject the null hypothesis and the value of a manager's *ARA* should be positive and non-zero). Since we assume the trading rate, g, is exogenous and the value of L and H is a function of g, we estimate the *ARA* and conduct the hypothesis testing for various values of g.

Table XII summarizes the estimation of a manager's *ARA* and the result of the hypothesis testing.[63] The overall result is contradictory with our prior. For a trading rate equal to 10%, 20%, and 40%, the estimated *ARA* is not significantly different from zero. For a trading rate equal to 30% and 50%, the estimated *ARA* is significantly negative. In summary, it appears that a zero or negative risk aversion may indicate that expected

[63] In reality, it is very difficult for a manager to have an agency trading rate greater than 30. The results in Table XII where the trading rate is greater than 30 are mainly for reference.

utility theory may be unable to model an asset manager's decision to choose a method for executing a basket of stocks. In the next section, we test an alternative theory.

4.4. Using Prospect Theory to predict a manager's decision to trade a BPB basket.

Prospect theory, invented by Kahneman and Tversky (1979) and further developed (such as the cumulative prospect theory) by Tversky and Kahneman (1992) and Wakker and Tversky (1993), is one of the alternative theories in modeling decision under risk, seeking to account for the discrepancy between individuals' decision and the predictions of expected utility theory. Barberis and Thaler (2003) suggest that prospect theory is the most successful theory at capturing the experimental results in studying how individuals make decision. Expected utility theory is normative: it models how individuals *should* behave when faced with risky choice. Prospect theory, though, is descriptive: it models how individuals *do* behave when faced with risky choice. Trepel et al. (2005) outline some possible neural bases of the various components of prospect theory based on human imaging, lesion, and neuropharmacology. There is considerable evidence showing that people do not follow expected utility theory when making decisions under risk. A famous classic example is the Allais paradox documented by Allais (1953).

In this study, we aim to use prospect theory to show that BPB (rather than agency trade) is indeed the preferred choice for the baskets executed by the managers. One can also view our analysis as a joint test of prospect theory vs. expected utility theory in the context of manager's choice on how to execute a stock basket. In what follows, we describe our testing method and introduce some key features of prospect theory, including reference point, value function, weighting function, and the value of a gamble.

We continue to use the variables defined in Section 4.3 and approximate the implementation shortfall (which is a continuous random variable) by the same two-state discrete random variable.[64]

4.4.1. Framing and reference point

Framing refers to how a problem is posed for a decision maker. In expected utility theory, its *Invariance* assumption (axiom) makes framing irrelevant in decision making. However, Tversky and Kahneman (1986) shows that framing can affect the decision maker's choice. The framing in our analysis is that a manager evaluates whether switching to agency trade is a better choice for executing a basket relative to using BPB. The reference point in a manager's evaluation is the cost of trading a BPB basket (which is known to the manager when he needs to choose either BPB or agency trade for execution). Prospect theory argues that decision is made by evaluating gain or loss respective to a reference point. This argument is different from that of expected utility theory, which argues that decision is made based on the maximization of expected terminal utility. According to prospect theory, a manager will give up BPB and choose to use agency trade for execution only if the agency trade can provide a positive gain.

There are three scenarios for describing the gain or loss of choosing agency trade.[65] First, if $B > H > L$, there is a gain of $(B - H)$ with 0.5 probability and a gain of $(B - L)$ with 0.5 probability. Second, if $H > B > L$, there is a loss of $(H - B)$ with 0.5 probability and a gain

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[64] Equation (4.3) in Section 4.3.1.

[65] We continue to use the two-state discrete model, developed in Section 4.3, for the implementation shortfall of agency trade.

of ($B - L$) with 0.5 probability. Third, if $H > L > B$, there is a loss of ($H - B$) with 0.5 probability and another loss of ($L - B$) with 0.5 probability.

4.4.2. Value Function

The purpose of the value function in prospect theory is to convert a gain or a loss, such as those we discussed in the previous section, to a subjective value. Tversky and Kahneman (1992) suggest the following value function *v(x)*:

$$v(x) = \begin{Bmatrix} x^{\alpha} \text{ if } x \geq 0 \\ -\lambda(-x)^{\beta} \text{ if } x < 0 \end{Bmatrix} \tag{4.7}$$

Both α and β are estimated to be 0.88 in their study; this value has becomes a standard assumption in prospect theory literature. λ is the coefficient of loss aversion, which measures the relative sensitivity to gains and losses and is estimated to be 2.25. Therefore, a decision maker attaches a more negative subjective value than the face value of $(-x)^{\beta}$ in case of a loss.

4.4.3. Weighting Function

The decision weights are weights an individual uses to compute the value of a gamble. In the expected utility theory framework, the decision weights are objective probabilities. In prospect theory, a weighting function performs a nonlinear transformation of the objective probability of a prospect (i.e., outcome in a gamble) to a decision weight.[66] In this study, there are only two prospects (the high state and low state) when agency trade

[66] One may think of the decision weight as subjective probability.

is used for execution. We use the following weighting function suggested by Tversky and Kahneman (1992):[67]

$$w(p) = \begin{cases} \dfrac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}} \text{ if prospect is a gain} \\ \dfrac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{1/\delta}} \text{ if prospect is a loss} \end{cases} \tag{4.8}$$

where p is the objective probability. The estimated values of γ and δ are 0.61 and 0.69, respectively, in Tversky and Kahneman (1992). One of the interesting features of this weighting function is that it overweights small probabilities and underweights moderate and high probabilities. This models the subjective probabilities used by people as they make decisions.

4.4.4. Calculate the value of choosing to use agency trade

The value of a gamble to use agency trade for execution can be calculated by using the (cumulative) prospect theory (Tversky and Kahneman, 1992). The intuition behind the calculation is that the value of a gain (or loss) from a manager's perspective is based on the subjective value of gain and loss weighted by his perceived subjective probabilities. Let V_A be the value of a gamble to choose agency trade for executing a basket. V_A can be computed using the following formula:

$$V_A = \begin{cases} (1 - \dfrac{0.5^{\gamma}}{(2 \times 0.5^{\gamma})^{1/\gamma}})(B-H)^{\alpha} + \dfrac{0.5^{\gamma}}{(2 \times 0.5^{\gamma})^{1/\gamma}}(B-L)^{\alpha} \text{ if B} \geq \text{H} > \text{L} \\ \dfrac{0.5^{\gamma}}{(2 \times 0.5^{\gamma})^{1/\gamma}}(B-L)^{\alpha} - \dfrac{0.5^{\delta}}{(2 \times 0.5^{\delta})^{1/\delta}}\left[\lambda(H-B)^{\beta}\right] \text{ if H} > \text{B} \geq \text{L} \\ -\lambda \dfrac{0.5^{\delta}}{(2 \times 0.5^{\delta})^{1/\delta}}(H-B)^{\beta} - \lambda(1 - \dfrac{0.5^{\delta}}{(2 \times 0.5^{\delta})^{1/\delta}})(L-B)^{\beta} \text{ if H} > \text{L} \geq \text{B} \end{cases} \tag{4.9}$$

[67] There are several other common functional forms for the weighting function (see Goldstein and Einhorn 1987; Lattimore et al. 1992; Tversky and Fox 1995; Prelec 1998).

The ability to compute V_A allows us to conduct a test on prospect theory's prediction. If we compute the V_A for each of BPB baskets in our sample, the mean of V_A should be significantly less than zero. Our hypothesis is that a manager should attach a negative value to the gamble of choosing agency trade for execution (i.e., not switching to use agency trade for execution). Otherwise, the basket should have been executed using agency trade and should not appear in our sample of BPB baskets. Similar to the hypothesis testing conducted in Section 4.3, we conduct the following test for various values of g (trading rate):

H_0: Mean of $V_A = 0$

H_1: Mean of $V_A < 0$

Table XIII summarizes the test results. The mean of V_A is significantly negative in all different values of trading rate. At a low trading rate, a manager experiences a smaller expected implementation shortfall but higher variance of the implementation shortfall. To a loss-averse manager, the higher variance of implementation shortfall makes agency trade less attractive than BPB. Moreover, a lower trading rate means it will take a relatively longer time to complete the execution of a basket. For a BPB basket, the execution is immediate, which in turn makes agency trade less attractive. At a higher trading rate, however, the variance of implementation shortfall is smaller (and there is a shorter time to complete execution), but the higher expected implementation shortfall makes agency trade less attractive than BPB. Our test results are consistent with the prediction based on prospect theory. Since our sample is a set of baskets executed using BPB, we expect that the mean of V_A is negative. The baskets with significant positive V_A should have been executed using agency trade and should not be in our sample.

The concept of loss aversion, λ, in prospect theory captures a key element in a manager's decision making process. A manager is more sensitive to potential loss than to potential gain, which makes a manager more reluctant to switch to agency trade. Regret effect is a related concept to loss aversion and can also strengthen our argument qualitatively. Kahneman and Tversky (1982) argue that one's regret as a result of a loss due to one's decision to act is stronger than the regret associated with one's decision not to act. In the case of a manager's decision, he already knows the exact BPB basket trading cost (i.e., the value of *B* in our model) when he needs to decide whether to give up the BPB basket execution (i.e., abandon the status quo). If he decides to trade a basket using agency trade for execution and incurs a loss, he will feel more regret. Hence, the regret effect tends to guide the manager not to act (i.e., not to switch to use agency trade) and to use BPB basket for execution. Overall, the manager's decision to use BPB basket for execution is consistent with prospect theory.

4.5. Conclusion

This chapter tests expected utility theory and prospect theory in modeling an asset manager's choice between BPB and agency trade for executing a basket of stocks. Both theories can be used to model an individual's decision under risk. If a manager follows expected utility theory, we should be able to estimate a manager's absolute risk aversion (*ARA*). However, our estimation of *ARA* is not significantly different from zero. This result contradicts our expectation, since we know that a manager is risk averse when selecting a trade method for execution. We also test prospect theory as an alternative explanation for the manager's choice. Applying prospect theory, we find that the manager attaches a negative value to the choice of agency trade over BPB basket. This is consistent with the fact that these baskets are being traded using BPB. In summary, the test results indicate stronger empirical support for prospect theory than for expected utility theory in modeling a manager's choice of trade execution method.

Table XI

Descriptive statistics for some blind principal bid (BPB) basket characteristics

There are 196 baskets used in this study.

Basket Characteristics	Mean	Std. Dev.	Min.	25th	Median	75th	Max.
Number of names in a basket	199	113	41	93	193	294	609
Total trade size ($ million)	333.99	239.56	20.09	146.20	268.09	487.05	1,188.14
Total number of shares (million)	11.26	8.27	0.60	5.05	8.95	16.29	45.06
Names that are buys (%)	45.59	9.34	13.14	40.06	46.24	50.73	100.00
Winning bid (basis points)	53.57	33.00	8.95	26.90	44.79	73.42	164.75

Table XII

Estimation of a manager's absolute risk aversion

For each BPB basket, we compute one observation of a manager's absolute risk aversion (*ARA*) using the equation: $ARA = -\frac{U^{''}(W)}{U^{'}(W)} = \frac{2(2B - L - H)}{L^2 + H^2 - 2B^2}$. *L*, *H*, and *B* are defined in Section 4.3.1. The mean of all *ARA* observations in our sample of BPB baskets is our estimation of a manager's *ARA*.

We also test the following hypothesis:

H_0: Mean of *ARA* = 0

H_1: Mean of *ARA* > 0

Since we assume the agency trading rate, *g*, is exogenous and value of *L* and *H* is a function of *g*, we estimate the *ARA* and conduct the hypothesis testing for various values of *g*.

Agency Trading Rate (% of average daily volume per day)	**Mean of ARA (10^{-6})**	**H_0: Mean of ARA = 0** **H_1: Mean of ARA > 0**	**T-stat**	**p value**
10	3.31	Cannot reject H_0	0.88	0.1912
20	-0.45	Cannot reject H_0	-0.65	0.7420
30	-2.27	Mean of ARA Significantly < 0	-1.94	0.9733
40	0.88	Cannot reject H_0	0.40	0.3461
50	-1.51	Mean of ARA Significantly < 0	-1.79	0.9626

Table XIII

Testing Prospect Theory's Prediction

For each of the BPB baskets in our sample, we compute the value of V_A, which is the value of a gamble (from the perspective of a manager) to choose agency trade for execution rather than using BPB basket. The equation for V_A is given below:

$$V_A = \left\{ \begin{array}{l} (1-\frac{0.5^{\gamma}}{(2\times 0.5^{\gamma})^{1/\gamma}})(B-H)^{\alpha} + \frac{0.5^{\gamma}}{(2\times 0.5^{\gamma})^{1/\gamma}}(B-L)^{\alpha} \text{ if B} \geq \text{H} > \text{L} \\ \frac{0.5^{\gamma}}{(2\times 0.5^{\gamma})^{1/\gamma}}(B-L)^{\alpha} - \frac{0.5^{\delta}}{(2\times 0.5^{\delta})^{1/\delta}}\left[\lambda(H-B)^{\beta}\right] \text{ if H} > \text{B} \geq \text{L} \\ -\lambda\frac{0.5^{\delta}}{(2\times 0.5^{\delta})^{1/\delta}}(H-B)^{\beta} - \lambda(1-\frac{0.5^{\delta}}{(2\times 0.5^{\delta})^{1/\delta}})(L-B)^{\beta} \text{ if H} > \text{L} \geq \text{B} \end{array} \right\}$$

Our prior is that the mean of V_A for our sample should be significantly less than zero. In other words, there is no positive gain for switching to agency trade. Otherwise these baskets should have been executed using agency trade and should not appear in our historical sample of BPB baskets. We conduct the following hypothesis testing for various values of *g* (agency trading rate):

H_0: Mean of $V_A = 0$

H_1: Mean of $V_A < 0$

There are 196 BPB baskets in our sample; the result of the testing is given below.

Agency Trading Rate (% of average daily volume per day)	**Mean of V_A**	**H_0: Mean of $V_A = 0$ H_1: Mean of $V_A < 0$**	**T-stat**	**p value**
10	-257,947	Reject H_0; V_A significantly negative	-2.29	0.0116
20	-254,942	Reject H_0; V_A significantly negative	-2.23	0.0133
30	-266,149	Reject H_0; V_A significantly negative	-2.32	0.0108
40	-282,176	Reject H_0; V_A significantly negative	-2.44	0.0077
50	-300,339	Reject H_0; V_A significantly negative	-2.59	0.0051

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