Pricing Determinants of Blind Principal Bidding
and
Liquidity Provider Behavior

December 2006

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Abstract

By modeling the behavior of the liquidity provider, we are able to identify a set of determinants related to the pricing of a blind principal bid basket. Blind principal bidding is a mechanism for trading a basket of stock simultaneously. This study is different from the well known study by Kavajecz and Keim (2005) in one major aspect. Our study identifies a new set of pricing determinants that are based on how the liquidity provider perceives his risk exposure. Determinants from Kavajecz and Keim 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 not related 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 blind principal bidding is very similar to the role of market maker (or specialist). This leads to an important conclusion that modeling market maker's quoted spread should be very similar to the modeling of blind principal bid pricing. The quoted stock spread is market maker's compensation in taking inventory risk and adverse selection risk. In fact, the blind principal bidding pricing determinants identified in this study are all fall into these two risk categories.

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Introduction

This paper is a study of the pricing aspect of *blind principal bid (BPB)*. BPB is one of the mechanisms for trading a basket of stocks and, thus, a form of portfolio trading. 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 U.S. in 2005 was approximately $1.03 trillion. About 13% of the volume (i.e., $133.9 billion) was traded using BPB. Academic research in this area however is limited. One of the contributions of this paper 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 that is related to the cost of trading using BPB. The set of determinants is identified by modeling various risk exposures faced by the liquidity provider (the BPB broker) and by assuming that the liquidity provider requires compensation for the risk borne.

The paper is organized as follows: Section I provides an institutional description of BPB. Section II consists of a brief review of the literature. Sections III and IV describe the methodology and data used in the study. Section V presents a discussion of the result highlighting both the similarities and differences of our results with those documented in Kavajecz and Keim (2005). Section VI concludes the paper.

I. Institutional description of blind principal bid[1]

Blind principal bid[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 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).

A. 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

[1] Readers who are familiar with BPB can skip this section and go directly to section II.
[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 paper.

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:

[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.

- 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 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)

[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.

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

B. 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 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 is difficult for the winning bidder to front-run the money manager. However, if competing brokers who lost the auction can reverse

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

[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 sections II and III of this study.

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

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).
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.

II. 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 III 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.

III. Methodology

In this section, we describe the methodology used for investigating the pricing determinants of BPB. 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.

A. 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).

B. 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.

B.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]:

[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.

$$\begin{aligned}&\text{Market Liquidity Proxy} = \\ &(\text{Total trade weight for NYSE listed stocks} \times 20 \text{ days moving average of NYSE volume}) + \\ &(\text{Total trade weight for NASDAQ listed stocks} \times 20 \text{ days moving average of NASDAQ volume})\end{aligned} \quad (1)$$

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.

B.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

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:

$$\text{Basket Lumpiness} = \frac{\sum_{i=1}^{TopThree} (\text{Total Trade Weight})_i \times \text{Total Trade Size of the Basket}}{\text{Average Share Price}} \quad (2)$$

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

[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.

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 exposed to higher idiosyncratic stock risk. Hence, brokers charge more for the liquidity risk premium during earnings announcement season. 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.

B.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[11]. 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 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

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

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: [12]

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 = Max. net trade weight – Min. net trade weight (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

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

among fewer names, then this is considered more risky from a broker's perspective. We use the following three proxies for this determinant:

$$\begin{aligned}
&\text{Concentration 1} = \frac{\text{Total trade weight with percentage of ADV between 50\% and 100\%}}{\text{Number of stocks that contribute the total trade weight}} \\
&\text{Concentration 2} = \frac{\text{Total trade weight with percentage of ADV between 100\% and 200\%}}{\text{Number of stocks that contribute the total trade weight}} \qquad (4) \\
&\text{Concentration 3} = \frac{\text{Total trade weight with percentage of ADV above 200\%}}{\text{Number of stocks that contribute the total trade weight}}
\end{aligned}$$

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.

B.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[13]

In a relative sense, intra-day bidding has the lowest risk, since the winning broker can perform some hedging[14] while the market is open. Pre-open bidding and post-closing 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[15]). 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

[13] 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.

[14] 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.

[15] 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.

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.

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.

IV. BPB data and basket characteristics

By filtering through transaction records from two money managers[16] 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

[16] 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.

- Date of trade / bidding
- Bidding procedure (pre-open, post-close, intra-day)
- Winning bid (cents / share)
- Commission (cents / share, if any)

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 III.

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.

V. Result and analysis

We conducted our analysis by running different regressions using various combinations of determinants and proxies discussed in Section III. 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.

A. Testing the pricing determinants suggested by Kavajecz and Keim (Regression #1 in Table III)

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[17] 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.

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

B. Determinants based on broker's behavior (Regression #2 in Table III)

As discussed in Section III, 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 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 III, 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.

C. A hybrid model (Regression #3 in Table III)

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.

D. A hybrid model (Regression #4 in Table III)

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 shares and (2) Mean price inverse of stocks in a basket are only marginally significant.

E. A hybrid model (Regression #5 in Table III)

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.

F. Model the BPB using option evaluation (Regression #6 in Table III)

We also explored the idea of applying option pricing theory to the pricing of a BPB basket. We think of the BPB auction as two OTC option contracts written by competing brokers. One of the contracts is a call contract for all the buy transactions in the basket. The other contract is a put contract for all the sell transactions in the basket. The strike prices for these options are the previous day's closing prices for pre-open bidding and the same day closing prices for post-close bidding. Therefore, for a BPB trade, an asset manager buys both contracts from a BPB broker and exercises them. This idea is similar to the one suggested by Copeland and Galai (1983) who looked at bid and ask prices as call and put options provided by a dealer.

We used the Black-Scholes formula to find the call (or put) option premiums for each stock in a BPB basket. The sum of these individual option prices is used as our first crude approximation of the premium of an option on the basket of stocks. We make two assumptions in each option price calculation. First, we assume the option is at the money. Second, we assume the time to expiration is 30 minutes. It is about the time interval between the first submitted bid coming back from one of the competing brokers and the time when an asset manager awards a basket to a winning broker. Since a manager will exercise at expiration (not before), options are calculated as European options. To test the potential application of option theory in pricing BPB, we included the calculated basket option price 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 (1.15) and statistically significant. This indicates that further research in studying potential application of option theory in BPB pricing might be fruitful. Giannikos and Suen (2006) is a study that further explores this insight.

VI. 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. Further research, however, is needed to explore this linkage.

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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 Pricing Determinants	**Expected Sign**	**Risk category**
Market liquidity	Negative	Inventory
Basket lumpiness	Positive	Information Asymmetry
Earning announcement season	Positive	Information Asymmetry
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
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	Median	75th	Max
Number of stocks in a basket*	231	117	41	121	242	320	609
	163	101	30	82	129	243	396
Total trade size ($ million)	328.57	225.49	20.89	150.48	285.77	455.77	1,188.14
	88.97	73.33	16.36	39.03	58.08	122.36	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	9.57	13.14	40.13	46.19	50.85	100
	50.80	14.00	15.80	44.10	50.00	53.30	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	7.64	0.60	2.54	5.04	11.84	64.09
	10.81	6.24	1.00	5.66	10.40	14.36	26.69
Mean market cap ($ million) of stocks in basket	17,817	9,287	502	11,303	18,200	25.039	41,677
	13,359	11,275	1,403	6,086	9,584	13,065	40,443
Mean shares traded per stocks*	53,781	30,917	9,592	31,510	47,072	70,239	228,201
	20,651	12,910	3,289	11,743	18,526	27,690	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	11.44	0.00	16.32	19.53	23.83	57.24
	23.3	7.6	6.8	19.1	24.2	28.2	37.4
Mean price inverse of stocks in basket *	0.0402	0.0132	0.0210	0.0317	0.0359	0.0454	0.1019
	0.0379	0.0082	0.0205	0.0327	0.0388	0.0430	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
Earning 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**	**4**	**5**	**6**
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	0.000106 1.43 0.1534		
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	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 (%)*	521.27 2.85 0.0047		255.56 1.56 0.1193	232.58 1.42 0.1577		
Market liquidity		-0.03 -3.02 0.0028	-0.03 -3.43 0.0007	-0.03 -3.47 0.0006	-0.03 -3.43 0.0007	-004 -3.97 <0.0001
Basket lumpiness (10^{-6})		4.69 4.20 <0.0001	4.04 2.22 0.0272	3.26 1.87 0.0626	5.09 4.63 <0.0001	5.52 5.15 <0.0001
Earning Announcement (dummy)		3.39 1.19 0.2352	4.86 1.73 0.0853	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		7.17 3.63 0.0003	7.00 3.61 0.0004	7.39 3.81 0.0002	7.32 3.79 0.0002	8.00 4.25 <0.0001
Small-cap trades (10^{-6})		12.62 14.23 <0.0001	9.14 7.39 <0.0001	9.30 7.53 <0.0001	9.92 8.63 <0.0001	9.58 8.56 <0.0001
Sector Imbalance		44.54 2.56 0.0112	53.46 2.65 0.0086	63.17 3.58 0.0004	57.46 3.30 0.0011	62.16 3.67 0.0003
High % of ADV concentration 1		35.10 1.02 0.3100	39.34 1.17 0.2419	37.61 1.12 0.2648	37.23 1.10 0.2713	21.25 0.64 0.5202
High % of ADV concentration 2		128.75 3.83 0.0002	134.32 4.06 <0.0001	136.94 4.16 <0.0001	133.92 4.06 <0.0001	130.51 4.08 <0.0001
High % of ADV concentration 3		193.03 4.26 <0.0001	196.97 4.35 <0.0001	185.92 4.14 <0.0001	198.91 4.48 <0.0001	189.52 4.39 <0.0001
Pre-open dummy		15.38	13.41	13.85	12.26	22.36

		5.15 <0.0001	3.68 0.0003	3.88 0.0001	4.02 <0.0001	5.86 <0.0001
Post-close dummy		-4.47 -0.85 0.3985	1.51 0.27 0.7892	0.06 0.01 0.9916	-3.73 -0.72 0.4716	8.48 1.46 0.1453
Basket option price						1.15 4.19 <0.0001
Intercept	-5.32 -0.68 0.4960	47.86 3.55 0.0004	34.81 2.23 0.0266	29.12 1.90 0.0586	39.67 2.97 0.0033	11.81 0.81 0.4185
N	280	280	280	280	280	280
Adj R-sq (%)	41.16	71.48	73.22	72.88	72.68	74.28