Dimensional

RESEARCH

Global Trading Advantages of Flexible Equity Portfolios

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Equity strategies allowing for a flexible approach to trading generally provide price advantages over strategies that demand immediacy in trading. In this paper, we measure the price advantage Dimensional's equity approach provides relative to several liquidity-seeking benchmarks.

INTRODUCTION

Dimensional's approach to portfolio design produces broadly diversified portfolios. We seek to increase expected returns by capturing company size, relative price, and profitability premiums. Broad diversification and continual monitoring of aggregate portfolio characteristics allows us to consider securities with similar expected returns as close substitutes for one another. This, combined with the ability to spread turnover over time, creates flexibility in portfolio implementation, which in turn allows for flexibility and patience when trading.

In this paper, we measure the benefit of our flexible approach to trading by simulating two different types of liquidity-seeking trading algorithms. We compare the average execution prices of these algorithms to Dimensional's actual execution prices. Examining the data over three years and across more than 40 countries of exposure, we find that Dimensional's trading price advantage averages 40 basis points. Cross-sectional price advantages range from 8 to 100 basis points and can increase in times of volatility by as much as 50% of their average value.

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BACKGROUND

The global equities market is a vast network spanning more than 100 exchanges in 75 countries with approximately $66 trillion in equity outstanding as of December 2013. Turnover in global equities markets during 2013 was about 118%, which generated approximately $78 trillion in nominal traded value.[1] Nearly all of these trades, along with price quotes, are recorded and distributed by exchanges globally. Dimensional has built an infrastructure to collect, process, and analyze these data.

The value of Dimensional's trades, categorized by various regions and cap sizes, are shown in **Exhibit 1**. From January 2010 to December 2012, Dimensional traded nearly $160 billion of equities across more than 40 countries of exposure. Buy and sell trades for Dimensional in the United States, developed ex US, and emerging markets totaled $68.8 billion, $56.6 billion, and $33.9 billion, respectively. Dimensional's buy and sell activity in Australia, the UK, Japan, and Canada was also significant, totaling $10.3 billion, $9.1 billion, $10.2 billion, and $7.0 billion, respectively. We use the trade data in Exhibit 1 combined with global exchange data to understand the benefit of our flexible trading approach.

Exhibit 1 DIMENSIONAL'S TOTAL AMOUNT TRADED
January 1, 2010–December 31, 2012 (US$ billions)

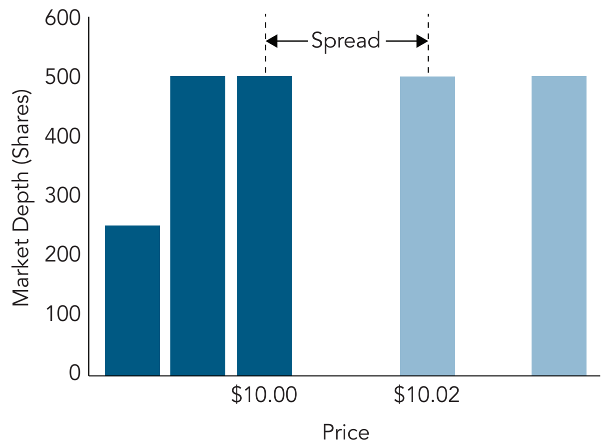
	BUY	SELL	TOTAL
GLOBAL			
Large	53.5	35.8	89.2
Small	48.2	21.9	70.1
Total	**101.6**	**57.7**	**159.3**
UNITED STATES			
Large	25.8	20.0	45.9
Small	14.4	8.5	22.9
Total	**40.2**	**28.6**	**68.8**
DEVELOPED EX US			
Large	16.5	11.6	28.1
Small	19.1	9.3	28.5
Total	**35.7**	**21.0**	**56.6**
EMERGING			
Large	11.1	4.1	15.2
Small	14.6	4.0	18.7
Total	**25.8**	**8.1**	**33.9**

Source: Dimensional Fund Advisors

THE COST OF DEMANDING IMMEDIACY

In equities, trading between buyers and sellers is facilitated through a price–time priority queue called the limit order book, illustrated in **Exhibit 2**. This allows traders to publicly express their interest in buying or selling a specific number of shares of stock at a specific price—called a limit order. Collections of buy- and sell-side limit orders (shown in dark blue and light blue respectively) in the book represent market supply curves at a specific price and point in time.

Exhibit 2 LIMIT ORDER BOOK AND SPREAD
The price difference (spread) between the supply and demand sides of the market is the difference between the highest bid price and the lowest ask price.



The difference between the most competitive (highest) bid price and the most competitive (lowest) ask price in the limit order book is referred to as the *spread*. The spread can be thought of as the execution price difference between supplying and demanding immediacy.

A trade can occur when an order is placed at a price that is equivalent to, or less competitive than, the best price on the opposite side of the market.[2] This is a realization of supply and demand curves intersecting. In Exhibit 2, if a sell limit order of 500 shares were placed at a price of $10.00, it would be matched with the pre-existing buy limit order shown at $10.00 resulting in a trade of 500 shares at $10.00. This trade would remove the 500 shares of the buy-side quantity shown at $10.00 from the limit order book. The sell limit order and the pre-existing buy limit order are the demand and supply sides of the market respectively. Traders on the

1. World Exchange Statistics. (n.d.). Retrieved February 1, 2014, from World Federation of Exchanges: http://www.world-exchanges.org/statistics

2. There are a wide variety of order types that have subtle differences in their execution rules. We focus on the basic concept of order execution and avoid going into further detail on more advanced order types.

demand side pay a premium—the spread in this example—in return for execution immediacy. The demander (seller) forgoes placing a limit order at $10.02, which would require them to *patiently* wait for a buyer to execute against them, in favor of *immediately* selling to a pre-existing buyer at $10.00. Conversely, the supplier (represented by the buy-limit order at $10.00) received this premium in return for patiently waiting for the seller to transact against them. The price advantage (cost) in this case, for the supplier (demander), is $0.02 per share, which is equal to the magnitude of the spread ($10.02 - $10.00).

In practice, the cost of demanding immediacy depends on more than just the spread. The order book is dynamic and quickly reacts to information about expected supply and demand. Spreads, prices, and depth (how many shares at each price level) can change throughout the day in response to changes in supply and demand. These quantities are related to the cost of demanding immediacy. For example, market participants may cross the spread and push prices in the same direction as their orders in an effort to complete trades quickly. This type of price impact can represent a large component of the cost of such trades.

FLEXIBLE TRADING

Broad portfolio diversification, minimizing unnecessary turnover, balancing competing premiums, and continual portfolio monitoring all allow for a flexible and patient approach to trading. When trading, Dimensional uses that flexibility to attempt to maintain supply-side rather than demand-side positions in the limit order book.

For example, suppose we need to invest a cash flow or adjust a portfolio's holdings. For each size, price-to-book, and direct profitability range within a given market, there will be many stocks with similar expected returns that can be considered substitutes for each other over short periods of time. Thus, our portfolio managers can provide our trading process real-time flexibility to enable an efficient execution from a daily list of candidate buy and sell orders. For example, suppose stocks A and B are substitutable buy candidates on a given day and there is more sell-side demand in stock A than in stock B. Our trading process can choose to trade stock A over stock B, seeking to interact with motivated sellers of stock A to achieve a better price. By being patient and not demanding immediacy, Dimensional can execute at better prices (buying lower and selling higher) than liquidity seekers.

This short-term interchangeability among securities with similar expected returns creates trade price advantages over portfolios that are required to trade specific securities within tight timeframes—that is, liquidity-demanding portfolios. In the next section, we outline an experiment designed to quantify this price advantage by comparing the price of Dimensional's trades to trades executed by simulated immediacy-demanding algorithms.

SIMULATING DEMANDING IMMEDIACY

To simulate demanding liquidity from the limit order book, we begin by generating lists of quantities to be bought and sold in specific securities on a daily basis. The quantity of each security for a given day is the total number of shares that were actually bought or sold by Dimensional on that day. These lists are then passed to simulated liquidity-seeking execution algorithms that are designed to buy or sell smaller portions of these quantities repeatedly over the course of the day, until the entire amount has been traded. Thus, while controlling for the quantity traded and the date that quantity was traded on, we can compare the performance of Dimensional's intraday flexible trading approach[3] to algorithms that demand immediacy.

We used the following execution algorithms:

1) **Quote based:** At random times throughout the course of the day, this algorithm simulates extracting the available displayed liquidity from the order book until the daily demand has been met.
2) **Trade based:** This algorithm begins by determining the liquidity-demanding party, "signing" all trades[4] as buyer- or seller-initiated. At random times throughout the day, it uses the buyer-initiated trades to fill buy orders and seller-initiated to fill sell orders until the specified demand has been met.

3. The additional benefit of flexibility across trading days is not quantified by this experiment.

4. We use the Lee-Ready trade signing algorithm, a technique for determining whether a trade was initiated on the buy or sell side. Signing trades allows us to use them to satisfy the demand for a specific side (buy/sell) of the market.

For example, consider a case where the demand is to buy 10,000 shares of company XYZ. If there are 100 shares displayed at the ask price, the quote-based algorithm would purchase those 100 shares, implying it has 9,900 shares of XYZ left to purchase on that day. It waits a random time interval, checks to see how many shares are available at the ask price, and purchases those. It continues in this fashion until all 10,000 shares have been purchased.

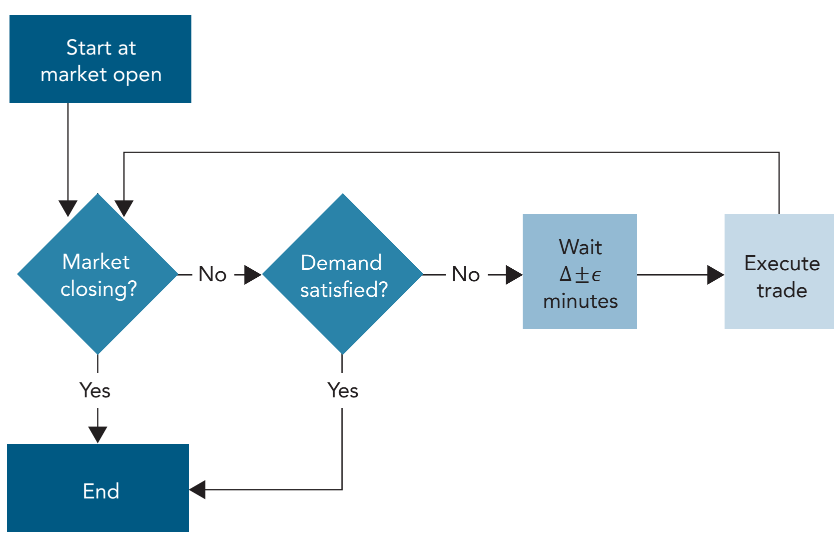
The trade-based algorithm, however, uses actual trades and traded quantities rather than displayed quotes. It signs all trades in company XYZ as buyer- or seller-initiated. To simulate purchasing 10,000 shares of XYZ, it randomly selects buyer-initiated trades sequentially throughout the trading day and assumes it could have traded the entire quantity associated with each trade. For example, if the first randomly selected actual trade was for 1,000 shares, the trade-based algorithm would purchase those 1,000 shares and have 9,000 shares left to purchase on that day. It continues in this fashion until all 10,000 shares have been purchased.

More formally, for each day/security/trade side combination, both algorithms are given the same dollar quantity of demand (the amount traded by Dimensional). They are required to satisfy this demand over the course of the day, from market open to market close, by transacting in the market. These transactions are broken into smaller pieces and simulated by decrementing the assigned total demand by prevailing market quote or trade dollar quantities[5] at random periods throughout the day. Algorithm decision logic for this is shown in **Exhibit 3**. Starting at market open, algorithms extract liquidity at randomized time intervals, $\Delta+\epsilon$ minutes. Δ is the constant component of the delay that varies from security to security based on average market inter-trade times, and ϵ is a random number between -1 and 1. This timing controls the pace of trades made by the algorithms throughout the course of the day, ensuring that the algorithm finishes all executions by the time the market closes.

These algorithms effectively pose the following question: If a trader were instructed to trade a given amount (represented by the number of shares we actually traded), at what price could the trader reasonably have delivered those shares?

The quote-based algorithm assumes the supply of shares is unchanged after it extracts liquidity. This is unlikely. After

Exhibit 3 DECISION LOGIC USED BY TRADE- AND QUOTE-BASED LIQUIDITY-TAKING ALGORITHMS
Executes trades throughout the course of the day for a specific security/date/trade-side combination until the quantity Dimensional actually traded is reached.



5. Dollar quantity of a trade or quote is the price times corresponding size (in shares)

a trader extracts liquidity, the price of liquidity can go up. Prices can move away (price impact) from the trader or the quantity supplied at the bid or ask can decline. The trade-based algorithm alleviates this issue by using realized intersections of the supply and demand curve.

The trading cost estimates from the quote-based algorithm are also reflective of cases where there is no liquidity available between the bid-ask spread. In this circumstance, a trader must extract liquidity from the top of the order book, incurring the full cost of the spread. The trade-based approach relaxes this assumption. It allows for execution at more competitive prices than the best bid/ask. One example of these price-improving executions are off-exchange matching engines that execute trades at midpoint prices.[6] Together, the simulated quote- and trade-based algorithms allow us to measure a wide range of liquidity-taking behavior.

Once the algorithms have completed their simulated trades in each date/security/side combination, trade-value weighted average prices are computed. Each day, securities are grouped by country, region and size characteristics. The percent difference between the algorithms' prices and Dimensional's actual transaction prices are computed for each group on that day. This can be thought of as the price difference between the immediacy-demanding algorithms and Dimensional's trade algorithms for a group of stocks. This is done for every trading day in the three-year study range, providing a daily time series of price differences for each group. Averages and standard errors are computed from these time series.

CROSS-SECTIONAL PRICE ADVANTAGES OF PATIENT TRADING

Price differences by market capitalization for various regions are shown in **Exhibit 4**. We can see that benefits from the flexible trading approach are pervasive regardless of market cap, although there are important cross sectional differences in our price advantage when trades are grouped by company size. Since company size is highly correlated to bid-ask spreads and total trading volume, demanding immediacy "costs" more when transacting in smaller-cap securities. For example, our purchase prices in the US were, on average, 9.6 basis points lower than the quote-based algorithm for large caps and 27.9 basis points lower for small caps. Similarly, for developed markets ex US and emerging markets, our purchase prices were, on average, 23.6 and 26.2 basis points lower than the quote-based algorithm for large caps and 45.6 and 44.2 basis points lower for small caps.

Exhibit 4 AVERAGE TRADING PRICE DIFFERENCES BETWEEN DIMENSIONAL AND LIQUIDITY-DEMANDING ALGORITHMS (IN BASIS POINTS)

	BUY		SELL	
	ALGORITHM TYPE			
REGION	Quote	Trade	Quote	Trade
UNITED STATES				
Large	9.6	6.7	6.0	5.7
Small	27.9	23.0	26.5	21.9
Marketwide	**20.7**	**17.8**	**20.6**	**20.1**
DEVELOPED EX US				
Large	23.2	17.2	22.7	15.8
Small	45.6	29.0	31.3	21.5
Marketwide	**39.1**	**25.6**	**28.6**	**19.7**
EMERGING				
Large	26.2	17.3	34.2	25.2
Small	44.2	30.6	38.3	27.3
Marketwide	**39.2**	**27.0**	**37.1**	**26.7**

Source: Dimensional Fund Advisors

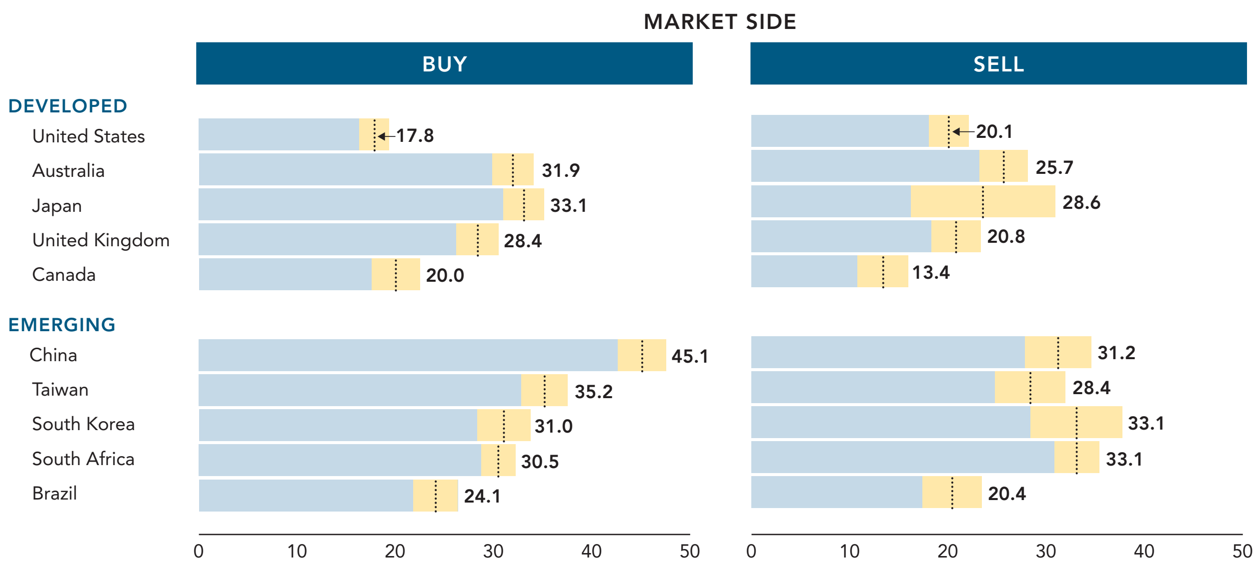
Exhibit 4 also shows that the price differences between Dimensional trades and simulated liquidity- seeking trades were larger in developed markets outside the US. For example, purchases in developed markets excluding the US were $35.7 billion during the study period (as shown in Exhibit 1), and our execution prices were 39.1 basis points lower than the quote-based algorithm, versus 20.7 basis points lower in the US. This may indicate that demanding immediacy was more expensive in those markets over the study's time period. The price advantages for emerging markets collectively were similar to those of developed markets excluding the US.

6. The midpoint price is the average of the best bid and best ask prices.

For a more detailed understanding of the benefits provided by trading flexibility, average price differences between Dimensional's actual transaction prices and those of the trade-based simulated algorithm for the largest five developed and emerging markets by trading volume are shown in **Exhibit 5**. Price differences in Dimensional's favor are shown as positive numbers. The 97.5% confidence intervals, displayed as yellow bands, show these price differences were reliably different from zero. Over the three-year period examined, price differences were positive across all countries, emerging and developed, indicating that there are persistent and pervasive price advantages to using a patient and flexible trading approach. For example, our purchases in the US totaled approximately $40.2 billion from 2010 to 2012. Controlling for the quantity and date of each trade, our execution prices for US buys were, on average, 17.8 basis points lower than the execution prices from a trade-based liquidity-seeking algorithm with a standard error of 0.76 basis points.

Australia, Japan, the UK, and Canada also show positive and large price advantages of 31.9, 33.1, 28.4, and 20.0 basis points, respectively, for purchases during the study period. For the emerging markets countries shown, Dimensional's purchases in China, South Korea and Brazil were 45.1, 31.0, and 24.1 basis points cheaper than trade-based liquidity seekers, with standard errors of 1.22, 1.35, and 1.13, respectively.

Exhibit 5 AVERAGE PRICE DIFFERENCES BETWEEN DIMENSIONAL AND A LIQUIDITY-DEMANDING ALGORITHM
(In basis points)

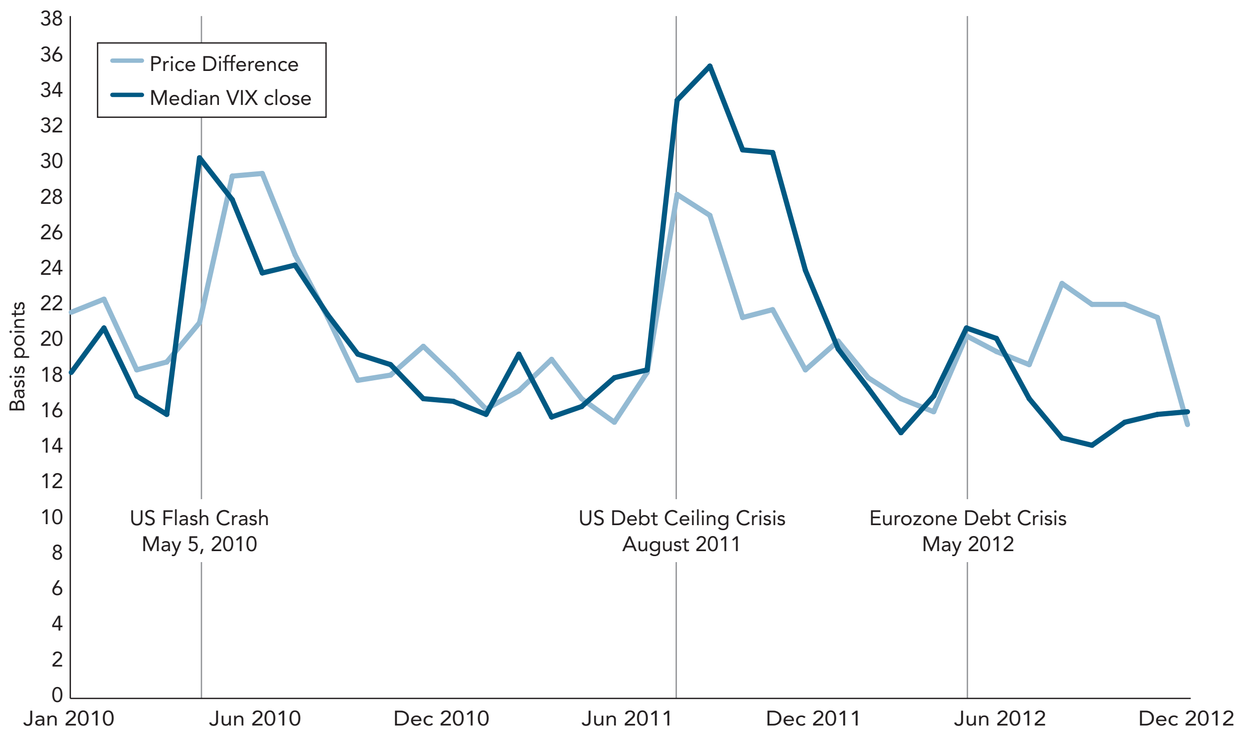


The 97.5% confidence bands defined by yellow bars indicate all differences are reliably different from zero.
Source: Dimensional Fund Advisors

VOLATILITY AND THE VALUE OF FLEXIBILITY

The price of immediacy varies through time. News events can cause higher volatility in prices as new information is incorporated. Volatility risk generally leads to wider spreads, so demanding immediacy becomes even more costly during periods of high uncertainty. **Exhibit 6** overlays three major news events (the "flash crash,"[7] the US debt ceiling crisis, and the Eurozone debt crisis) that contributed to recent periods of high volatility, as measured by the monthly median of the VIX index (dark blue line). We can see that the overall trade price advantage in US securities (light blue line) was highly correlated with volatility and increased by as much as 50 percent during periods of high volatility. This highlights the benefit of continual portfolio monitoring and gradual rebalancing. By spreading portfolio turnover over all the trading days of the year, generating lists of candidate stocks to buy and sell daily, and having real-time flexibility in what stocks from those lists to buy and sell, our trading process can react to events in the marketplace as they unfold and opportunistically execute when it is more efficient to do so. In contrast, for portfolios that do not have this flexibility, demanding immediate execution may come at an even higher price in periods of higher volatility.

Exhibit 6 VOLATILITY AND THE TRADE PRICE ADVANTAGE OVER TIME



7. The "flash crash" refers to the crash and subsequent reversion of stock prices due to a trade algorithm error that took place on May 6, 2010.

CONCLUSION

Portfolio design and trading are mutually dependent. Dimensional's approach to portfolio design allows for patient, flexible trading, which research demonstrates to have provided significant price advantages, both cross-sectionally and over time. The extent of this study—over a period of three years and more than 40 countries, demonstrates the consistency, robustness, and sustainability of this approach.

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APPENDIX - COMPUTATIONS

The price difference between demanding liquidity and patiently trading $c_{i,t}$, in security *i* on day *t* is:

$$c_{i,t} \triangleq s\left(\frac{\bar{p}^a_{i,t} - \bar{p}^D_{i,t}}{\bar{p}^D_{i,t}}\right),$$

where *s* is the buy (1) or sell (-1) side indicator respectively, $\bar{p}^a_{i,t}$ is the trade value weighted average price of the algorithm *a*'s trades and $\bar{p}^D_{i,t}$ is the trade value weighted average price of Dimensional's trades on a given day *t* in security *i*. Differences are computed separately for buys and sells. Note that *s* in the equation makes the percent difference $c_{i,t}$, symmetric for both buy side and sell side. The pre-trade demand used for simulating liquidity taking algorithms is defined to be *exactly equal* to the total value of all trades that Dimensional executed in a security/day combination, represented as:

$$d^a_{i,t} \triangleq \sum_{n=1}^{N} s^D_{i,t,n},$$

where $d^a_{i,t}$ is the quantity in shares that demanders extract within a security over a single day and $s^D_{i,t,n}$ is Dimensional's trade volume in shares. The total trade value for a security/day combination is:

$$v_{i,t} \triangleq \sum_{n=1}^{N} p_{i,t,n} s^D_{i,t,n}$$

$p_{i,t,n}$ is Dimensional's trade price for the n^{th} trade in security *i*, on day *t*. We use this traded value to weight the price differences across securities by $c_t \triangleq \frac{\sum_{i \in I} c_{i,t} v_{i,t}}{v_t}$, where *I* is a collection of securities. Examples of collections are securities grouped by country, portfolio strategy, fund, and market capitalization. v_t is the total trade value of all securities in the collection on day *t*. In this study, we define these collections based on three characteristics of the underlying securities: country, market capitalization (size), and book-to-market (style). Our results are presented using two different groupings: country and region size. Both of these groupings are further split into buy and sell sides. The daily value-weighted average of the cross-section is computed over the three-year time range as

$$c \triangleq \frac{\sum_t c_t v_t}{v}$$

This final weighted average gives the price difference *c* for each group. *v* is the total trade value for that group over the time range of the simulation.