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Stock Returns with Price Impact

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Abstract

In this paper, we study the stock returns for large trades with price impact. We use the daily changes in volume-weighted average price (VWAP) as a proxy of the returns for institutional investors. This return is then compared statistically to the daily return using closing price. Using a panel data of NYSE/AMEX stocks, we find a fixed effect contributing to the spread between them and it can be interpreted as an unbiased *ex post* estimate of price impact.

JEL classification number: G10, G11, G12 **Keywords:** Volume-Weighted Average Price, Price impact, Stock Returns

1 Introduction

All transactions incur costs, which can be classified as explicit or implicit. Explicit costs include all direct costs of trading, e.g. brokerage commission, taxes and duties, and etc. Explicit transaction costs are in general easy to measure and find a benchmark for reference. Implicit costs, on the other

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hand, are much more difficult to measure and there is no obvious benchmark for reference. [26] categorizes the implicit transaction costs into the execution cost and the opportunity cost. While the opportunity cost is affected by the non-executed position relative to the target position, the execution cost is mainly affected by the execution price.

There are attempts to quantify price impact which is the major part of the implicit execution cost using various techniques in the literature. [21] summarize various techniques for measuring trading costs. [1] present a calibration procedure to estimate pre-trade price impact for equity trades on large-cap stocks. [6] propose two methods to forecast market impact costs and identify expensive trades before actual trading. [16] show that buyer trades primarily affect the ask price and seller trades move the bid price. Also a trade of either type temporarily increased the spread. [8] use net buy-sell turnover to explain short horizon market price movements [18] suggest a vector autoregression model to examine trade informativeness, and conclude that several factors such as trade size, market bid-ask spread, market value of the firm, will influence a trade's price impact. [15] extend Hasbrouck's model to investigate the role of waiting time between consecutive transactions and find that the price impact is larger when trades are more frequent. [13] find this effect of time interval is stronger for stocks with higher probability of information-based trading. [9] note that the identity of the management firm behind the trade also plays a role in market impact and trading cost.

In addition, [22] have shown that the immediate market impact is a concave function of market capitalization and transaction volume for US stocks. Similarly, [7] discover the concave impact function, and serial correlation of trade types. They also show that the seemingly random walk behavior of price changes results from competition between liquidity takers and liquidity providers. On international markets, [11] study the price formation process on the Hong Kong Stock Exchange and found that unlike US stocks, price impacts in HKSE display U-shape pattern during the trading day. [23] study the immediate price impact of a single trade executed in the Australian Stock Exchange and find that stocks with higher capitalization experience lower price impact. [12] study institutional trading in international market and find underlying market condition affects the asymmetry between price impacts of buy and sell orders. We take a different approach to estimating a benchmark for the price impact. Making use of daily volume-weighted average price (VWAP), this approach attempts to provide an *ex post* estimation of price impact. VWAP is widely used as a benchmark for evaluating the execution of large trades that is unbiased estimation of the price at which any randomly selected trader could execute [4, 3]. To isolate the portion of the opportunity cost as stated in [26], we define the benchmark of return facing institutional investors as the daily change of VWAP. We compare this benchmark with the return computed using closing price and according to [2], this is the return without any liquidity effect. As [5] points out, it is difficult to infer from the data that what order was initiated by a buyer or a seller. Unlike [19], our approach is not based on market microstructure.

In our approach, we assume that both the buyer and seller can execute at VWAP. It is further justified by the growing of the popularity of using VWAP as a benchmark and many VWAP strategies have been developed for daily execution of large orders [24]. Institutional investors usually execute large trades by giving the order to traders and evaluate the performance using VWAP as a benchmark. It is then reasonable to assume that an average trader is able to execute at VWAP. Therefore, in the context of portfolio management, the return computed using VWAP instead of closing price is more relevant.

Some related research have been done on the two stock prices. [28] initiate some of the empirical studies on VWAP and suggest that daily VWAP is smoother than the closing price. In fact, [14] suggest that the variation of stock price at the last few minutes of a trading day is disproportionally high. This may contribute to more extreme closing price returns and hence, leptokurtosis. The main contribution of this study is to empirically show that there is a spread between the daily returns calculated using closing price and VWAP. The spread can then be interpreted as an *ex post* estimation of implicit trading costs.

2 Model and Empirical Results

The daily volume-weighted average price (VWAP) is defined as

$$VWAP_{it} = \sum_{j=1}^{N} \frac{Volume_{itj} \times Price_{itj}}{Volume_{it}},$$
(1)

where Volume_{it} denotes the number of shares in the *i*th stock on day *t*, while Price_{itj} and Volume_{itj} are the price and the number of shares at which the *j*th transaction in the *i*th stock on day *t* was done. As suggested by [4], VWAP is the price an average trader can execute a large order at, we consider the daily simple return that an average trader execute large orders both at VWAP on the consecutive days denoted by ν_{it} , i.e.,

$$\nu_{it} = \frac{\text{VWAP}_{it} - \text{VWAP}_{it-1}}{\text{VWAP}_{it-1}}.$$
(2)

If we let r_{it} to denote the daily simple return computed using closing prices, it is then natural to study the statistical properties of the difference between the two returns. This difference is analogous to the that in [20] where in this approach the buyer-initiated and seller-initiated trades are no longer differentiated but they are combined into one single return. This is also similar to the estimation of round-trip execution costs in [10].

3 Data

The study involves two major sets of data, namely daily closing price and daily VWAP. As daily VWAP is not readily available in common database, the VWAP data set was calculated from intra-day transaction record of all NYSE stocks from January 1993 to December 2005. These transaction details were available from the Trade and Quotes (TAQ) database. On the other hand, closing price data was obtained from the Center for Research in Security Prices (CRSP) for the same period of time.

The Committee on Uniform Security Identification Procedures (CUSIP) number of each stock acts as a primary key across the two data sets. In order to the most consistent and accurate result, some criteria were imposed on the stocks before they are included in the study list. First, the stock needs to have a capitilization greater than 2 billion (by equity value as of July 1999). This criterion is to ensure the liquidity of the stock as institutional traders usually trade more liquid stocks. This leaves 885 stocks in the sample. Each stock is further required to have both closing price and VWAP data for each of their trading days. After these procedures, the total number of stocks included in the study list was 764.

3.1 Descriptive statistics

Table 1 shows the descriptive statistics for 764 stocks with the comparison of the results across various percentiles of all the stocks. The mean of closing return is consistently higher than the VWAP return in every percentile. The same is observed in the standard deviation which is consistent with [28]. Skewness and kurtosis further confirm that neither closing nor vwap return is normally distributed.

3.2 Simple Linear Model

As observed from the descriptive statistics of the two returns, we hypothesize that there will be a spread between ν_{it} and r_{it} . We first assume that the spread is fixed for all the stocks and all the time.

$$r_{it} - \nu_{it} = \alpha + \varepsilon_{it},\tag{3}$$

where ε_{it} are independent error terms. Table 2 shows the estimate of α as well as various standard error summarized in [27]. The implicit cost is significant for each standard error to use.

The spread α can be interpreted as the benchmark for the implicit transaction costs for an institutional trade. From the point of view of a portfolio manager and by the linearity of the simple returns among various stocks, the VWAP portfolio return ν_t can be expressed as

$$\sum_{i} w_i \nu_t = \sum_{i} w_i \left(r_t - \alpha \right) = \sum_{i} w_i r_t - \alpha, \tag{4}$$

Kurtosi	Skewnes	σ	μ	VWAP	Kurtosi	Skewnes	σ	μ	Closing	$\mathbf{D}\mathbf{ays}$		This table return for	
s 110.94	s -3.88	42.30%	9.30%		3 80.91	s -2.81	47.09%	11.92%		2442	Mean	each ncusi	Table 1:
131.76	4.73	21.73%	22.89%		102.11	3.95	24.85%	22.08%		910	Std	es the desc p. Mean a	Summay
1.42	-16.51	16.61%	-61.91%		1.33	-13.02	19.05%	-50.59%		289	1^{st} per	riptive star nd standare	Statistics
3.21	-12.58	20.85%	-9.39%		2.88	-9.71	23.98%	-5.92%		609	5^{th} per	tistics, nam d deviation	of Annua
4.88	-10.43	23.93%	-1.66%		3.97	-8.05	27.18%	-0.00%		1012	10^{th} per	nely, mean, of returns	lized Dail
14.06	-6.98	28.94%	3.88%		11.31	-5.18	32.05%	4.97%		1786	25^{th} per	standard o are both a	y Simple I
56.94	-2.71	35.29%	8.19%		41.36	-1.92	38.74%	9.90%		2649	50^{th} per	deviation, s nnualized a	Return Us
167.61	-0.17	48.65%	14.71%		117.34	-0.02	53.98%	17.10%		3275	75^{th} per	skewness, k ssuming th	ing VWAJ
290.99	0.43	67.23%	23.61%		207.65	0.55	74.03%	28.06%		3275	90^{th} per	urtosis of c here are 252	and Clo
366.96	1.10	88.28%	33.22%		273.07	1.30	97.91%	37.48%		3275	95^{th} per	losing retu 2 trading da	sing Prices
598.38	3.47	125.23%	83.25%		448.40	3.78	141.39%	88.63%		3275	99^{th} per	ırn and vwap ays in a year.	J.

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Table 2: Estimate of standard error using different approaches This table shows the simple linear model's estimate of daily spread between closing return and vwap return, and standard errors using different methods as suggested in [27]¹. An asterisk indicates significance at the ten percent level, and two asterisks indicate significance at the five percent level.

	Estimate	Std	<i>t</i> -value
OLS	8.3523×10^{-5}	1.2488×10^{-5}	6.6881**
White	8.3523×10^{-5}	1.2488×10^{-5}	6.6881**
Cluster by neusip	8.3523×10^{-5}	3.1128×10^{-6}	26.833**
Cluster by year	8.3523×10^{-5}	1.3643×10^{-5}	6.1218**

i.e., α can be interpreted as the premium a portfolio manager needs to pay for managing a large portfolio. As a result, an *ex post* estimate of the benchmark of the implicit cost is approximately 2.1% per annum for this period of time.

3.3 Multilevel Linear Model

In view of [27], panel data should be handled cautiously. We follow the standard multilevel analysis [17] and propose a multilevel model for the panel data set. We first consider a random effect at the stock level.

$$r_{it} - \nu_{it} = \alpha_i + \varepsilon_{it},$$

$$\alpha_i = \mu_\alpha + \eta_i,$$
(5)

where ε_{it} and η_i are error terms with variance σ^2 and σ^2_{α} respectively.

Table 3 shows multilevel linear model's estimates of daily spread between closing returns and vwap returns, and the standard error and corresponding t-values for each stock across various quantiles. It is clear that the spread and standard error are relatively close among different stocks, and similar to the results obtained from the simple linear model described above. The spread estimates are significant on the 10 percent level across all quantiles.

We then consider random effect at time level.

$$r_{it} - \nu_{it} = \beta_{u[t]} + \varepsilon_{it},$$

$$\beta_u = \mu_\beta + \zeta_u,$$
 (6)

	significance at	t 5% level.			
	1^{st} per	5^{th} per	10^{th} per	25^{th} per	50^{th} per
$\operatorname{Estimate}(\alpha_i)$	$8.1898{\times}10^{-5}$	8.2105×10^{-5}	8.2280×10^{-5}	$8.2589\!\times\!10^{-5}$	8.3076×10^{-5}
Std	$4.9879{\times}10^{-5}$	4.9879×10^{-5}	4.9879×10^{-5}	$4.9879\!\times\!10^{-5}$	5.0013×10^{-5}
<i>t</i> -value	1.6403^{*}	1.6448^{*}	1.6471^{*}	1.6518^{*}	1.6578^{*}
	75^{th} per	90^{th} per	95^{th} per	99^{th} per	
$\operatorname{Estimate}(\alpha_i)$	$8.4034{\times}10^{-5}$	$8.6159{\times}10^{-5}$	8.7668×10^{-5}	9.0484×10^{-5}	
Std	$5.0120 imes 10^{-5}$	5.0368×10^{-5}	5.0457×10^{-5}	5.0528×10^{-5}	
t-value	1.6778^{*}	1.7233^{*}	1.7541*	1 8009*	

This table summarizes results of the multilevel linear model with random effect at stock level. Quantiles of estimate of α_i , its Table 3: Multilevel Linear Model – random effect at stock level

where ζ_u are error terms with variance σ_{β}^2 . We consider u[t] in two cases. First, u[t] is the calendar month for daily return at time t. Second, u[t] is the calendar year for daily return at time t.

Table 4 shows the result of the multilevel model's estimate of the spread, standard deviation and t-values, with random effect at month level. 10 out of 12 months have a positive spread between closing and vwap returns, and in 7 out of these 10 months, this spread is significant at 5% level. While 2 months give negative spread estimates, none of them is significant.

Table 4: Multilevel Linear Model – random effect at month level This table summarizes results of the multilevel linear model with random effect at month level. Estimate of $\beta_{u[t]}$, its standard deviation and *t*-value are displayed. An asterisk indicates significance at 10% level, and two asterisks indicate significance at 5% level.

	$\operatorname{Estimate}(\beta_{u[t]})$	Std	<i>t</i> -value
January	1.7701×10^{-4}	3.8100×10^{-5}	4.6460**
February	-9.0490×10^{-6}	$3.9071{\times}10^{-5}$	-0.2316
March	9.4032×10^{-4}	3.7077×10^{-5}	2.5361^{**}
April	1.1120×10^{-4}	3.8007×10^{-5}	2.9257^{**}
May	9.1600×10^{-5}	3.7665×10^{-5}	2.4320**
June	3.2468×10^{-5}	3.7408×10^{-5}	0.8679
July	5.3124×10^{-5}	3.7593×10^{-5}	1.4131
August	$2.2053{\times}10^{-5}$	3.6919×10^{-5}	0.5973
September	1.7555×10^{-4}	3.8249×10^{-5}	4.5896^{**}
October	1.1811×10^{-4}	3.7046×10^{-5}	3.1882^{**}
November	-1.4997×10^{-5}	3.8124×10^{-5}	-0.3934
December	1.4860×10^{-4}	3.7579×10^{-5}	3.9544^{**}

Table 5 shows the result of the multilevel model's estimate of the spread, standard deviation and t-values, with random effect at year level. In all 13 years covered in the sample, every year shows a positive spread estimate between closing return and vwap return. And in 11 out of 13 years, the spread estimate is significant at least at 10% level.

Table 6 summarizes the fixed effects observed from the three multilevel

Table 5: Multilevel Linear Model – random effect at year level This table summarizes results of the multilevel linear model with random effect at year level. Estimate of $\beta_{u[t]}$, its standard deviation and *t*-value are displayed. An asterisk indicates significance at 10% level, and two asterisks

	Estimate $(\beta_{u[t]})$	Std	<i>t</i> -value
1993	6.4045×10^{-5}	3.5418×10^{-5}	1.8083*
1994	6.1757×10^{-5}	3.4982×10^{-5}	1.7654^{*}
1995	6.7135×10^{-5}	3.4426×10^{-5}	1.9501^{*}
1996	4.7993×10^{-5}	$3.3697{ imes}10^{-5}$	1.4242
1997	7.7077×10^{-5}	3.2975×10^{-5}	2.3374^{**}
1998	9.7436×10^{-5}	3.2047×10^{-5}	3.0404^{**}
1999	9.5287×10^{-4}	3.1207×10^{-5}	3.0534^{**}
2000	1.1719×10^{-4}	3.1982×10^{-5}	3.6643^{**}
2001	1.1403×10^{-4}	3.3281×10^{-5}	3.4264^{**}
2002	1.3307×10^{-5}	3.3970×10^{-5}	3.9172^{**}
2003	6.7688×10^{-5}	3.4412×10^{-5}	1.9670^{**}
2004	5.5932×10^{-5}	3.4713×10^{-5}	1.6112
2005	6.0159×10^{-5}	3.5123×10^{-5}	1.7128^{*}

indicate significance at 5% level.

linear models described above. Estimates of the spread from the three models are very close to each other, and all are significant on the 5% level. The estimated spread is approximately equal to 2% per annum.

Table 6: Multilevel Linear Model – Summary of fixed effects This table summarizes the fixed effects of the three multilevel models described above. Estimate of the spread, standard deviation and corresponding *t*-values are given. An asterisk indicates significance at 10% level, and two asterisks indicate significance at 5% level.

	Estimate	Std	<i>t</i> -value
By month (μ_{β})	8.3308×10^{-5}	$2.5515{ imes}10^{-5}$	3.2651^{**}
By year (μ_{β})	8.1447×10^{-5}	1.8828×10^{-5}	4.3257^{**}
By neusip (μ_{α})	8.3698×10^{-5}	1.2640×10^{-5}	6.6217^{**}

[17] use intraclass correlation to distinguish whether the grouping in multilevel analysis conveys information. Intraclass correlation is defined as the relative values of individual-level and group-level variances, i.e., $\frac{\sigma_{\alpha}^2}{\sigma_{\alpha}^2 + \sigma_y^2}$. This value ranges from 0 to 1, where 0 denotes the grouping conveys no information and 1 denotes that all members of a group are identical.

Table 7 shows the intraclass correlation for each of the three multilevel models described above. All three intraclass correlation are very close to zero, indicating that the grouping conveys minimal information, and that the spread between closing return and vwap return is more a fixed effect, rather than an effect from grouping of certain characteristics.

 Table 7: Multilevel Linear Model – Intraclass correlation

This table summarizes the individual- and group-level variance, and also intraclass correlation as defined in [17], where intraclass correlation is defined

	as $\frac{\sigma_{\alpha}^2}{\sigma_{\alpha}^2 + \sigma_y^2}$.		
	Individual-level variance (σ_y)	Group-level variance (σ_{α})	Intraclass correlation
By month	1.7061×10^{-2}	7.7061×10^{-5}	0.0020%
By year	1.7062×10^{-2}	5.0592×10^{-5}	0.0009%
By neusip	1.7062×10^{-2}	5.0592×10^{-5}	0.0009%

Finally, we consider the model with random effect at stock and time level.

$$r_{it} - \nu_{it} = \alpha_i + \beta_{u[t]} + \varepsilon_{it},$$

$$\alpha_i = \mu_\alpha + \eta_i,$$

$$\beta_u = \mu_\beta + \zeta_u.$$
(7)

Table 8: Multilevel Linear Model on Multiple Factors– Summary of fixed effectsThis table summarizes the fixed effects of the three multilevel models onmultiple factors: month and neusip, year and neusip, and all three factors.Estimate of the spread, standard deviation and corresponding t-values are

given. An asterisk indicates significance at 10% level, and two asterisks indicates significance at 5% level

indicate significance at 5% level.	
Estimate	Std

	Estimate	Sta	<i>t</i> -value
By month and neusip (μ_{β})	8.3311×10^{-5}	2.5187×10^{-5}	3.3077^{**}
By year and neusip (μ_{β})	8.1447×10^{-5}	1.8828×10^{-5}	4.3257^{**}
By month, year and neusip (μ_{α})	8.2738×10^{-5}	2.5953×10^{-5}	3.1880^{**}

3.4 The effect of implicit transaction costs on portfolio management

While there is a significant difference between the daily closing returns and daily VWAP returns, the impact on the portfolio can still be affected by the investment style [20]. We test a hypothesis on the impact of the implicit transaction costs on the classical mean-variance optimal portfolio [25]. We form a subset of the stocks from our previous selection that are traded over the whole period from 1993 to 2005. There are 318 stocks in total. We perform parameters estimation using the data from 1993 to 1999 and we conduct out-of-sample evaluation of the rolling mean-variance optimal portfolio with daily rebalancing. Explicit transaction costs are ignored. We then test the hypothesis that evaluating the mean-variance optimal portfolio using closing price generates better returns than using VWAP.

Table 9 shows that the return evaluated using VWAP is lower but the result is not significant. It illustrates that even the spread of the two returns

Table 9: Out-of-Sample performance of mean-variance portfolio: evaluate using closing price and VWAP

This table compares the out-of-sample performance of two mean-variance portfolios evaluated using closing price and VWAP, respectively. t-sta and p-val are results from the paired t test.

VW	VAP	Clo	sing		
Mean	Std	Mean	Std	<i>t</i> -sta	p-val
9.9700×10^{-5}	6.7360×10^{-3}	1.3143×10^{-4}	7.7181×10^{-3}	-0.1267	-0.8991

is significant, it may not be significant at the portfolio level, further confirm the findings in [20]. Given that evaluating at VWAP gives worse returns than using closing price. It is of interest to further test the hypothesis that using VWAP for parameters estimation generates better returns than using closing price, given VWAP is to be used as the evaluation of the mean-variance optimal portfolio. Table 10 shows that using VWAP for parameter estimation gives

Table 10: Out-of-Sample performance of mean-variance portfolio: construct using closing price and VWAP

This table compares the out-of-sample performance of two mean-variance portfolios using closing price and VWAP for parameter estimation. Both portfolios use VWAP for evaluation. t-sta and p-val are results from the paired t test.

VW	VAP	Clos			
Mean	Std	Mean	Std	t-sta	p-val
1.0224×10^{-4}	6.7217×10^{-3}	9.9700×10^{-5}	6.7360×10^{-3}	0.0109	0.9913

better return and again the result is not statistically significant.

4 Conclusion

In this paper, we study the statistical properties of the difference between the closing return and VWAP return. Using multilevel analysis, we conclude that there is a spread of approximately 2% per annum. This spread is both statistically and economically significant. We can interpret this spread as an unbiased *ex post* estimate of the market impact. Empirical results also show that this market impact depends on the investment style.

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