Time Weighted Price Contribution

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Abstract:

In the era of high frequency trading and the pervasiveness of irregularly spaced trading, we control for the time element in the Modified Weighted Price Contribution (MWPC) model by Jahanshahloo and Spokeviciute (2018). We empirically show that our new modification controls for reaction time (Speed) of market participants to arrival of new information.

Keywords: Market Microstructure; Price Discovery, High Frequency Trading, Irregularly Spaced Data.

JEL classification: G1

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1 Introduction

One of the main functions of financial markets is price discovery (O'Hara, 2003). Different models, such as Information Share by Hasbrouck (1995), Component Share by Gonzalo and Granger (1995), and Weighted Price Contribution by Barclay and Warner (1993), have been used to estimate market participants' contribution to price discovery.

The implicit assumption of these models is that prices arrive at equally spaced intervals, therefore, the time element in these models is ignored.[1] However, one of the fundamental characteristics of high frequency data is that trades/quotes can occur at irregularly spaced intervals (Goodhart and O'Hara, 1997). Thus, the general approach when using these models is sampling at arbitrary intervals to generate equally spaced observations or ignoring the time overall. These methods, however, may cause various issues, such as imputation bias, unobservable information content, occurrence of stale prices as well as over- or underestimation of price discovery (see Section 2).

In this paper we address the issue of *irregular* price arrival time by extending the work of Jahanshahloo and Spokeviciute (2018). Specifically, we incorporate the time element in their model and introduce the Time Weighted Price Contribution (TWPC) model. We provide empirical evidence to demonstrate the validity of our model.

2 The Forgotten Element: Time

Time is an important factor in microstructure models (Engle and Patton, 2004; Furfine, 2007; Frijns and Schotman, 2009) with an impact on volatility, efficiency, and information content of the prices (Dufour and Engle, 2000; Engle, 2000). To understand the implications of time, it is critical for these models to accurately reflect the role that time plays. However, doing so –

[1] Frijns and Schotman (2009) extend the IS model of Hasbrouck (1995) and develop a price discovery measure for tick time data.

especially in the case of the high frequency data, where trades/quotes can occur at varying time intervals (Goodhart and O'Hara, 1997) – is not simple.

One of the methods used to overcome the issue of irregularly spaced time series is sampling data at an arbitrary frequency (Korczak and Phylaktis, 2010; Kehrle and Peter, 2013). While commonly used, this method can induce issues of over- and/or under-sampling. On the one hand, if the chosen interval is small whilst the trading is not frequent (i.e. *oversampling*), there will be periods with no new information and heteroscedasticity of a specific form as well as stale prices may be introduced into the data (Jong and Nijman, 1997; Engle and Russel, 1998). On the other hand, information will be lost if low-frequency sampling (*undersampling*) is chosen. Specifically, individual transactions may be ignored (Jong and Nijman, 1997; Engle and Russel, 1998), and data aggregation may introduce contemporaneous correlation (Frijns and Schotman, 2009). In relatively longer sampling intervals, market participants will have had time to update their prices, and the data on information asymmetries will be hidden (Frijns and Schotman, 2009).

To illustrate the issue of under-sampling, we show in Figure 1 the ask price for EUR:USD currency pair.[2] The dotted line shows the prices at their arrival time, whereas the solid line represents sampling at a one-second frequency.[3] The converted time series omits 43 prices and ignores data of 16 market participants. Furthermore, points A through B suggest there was no new information for 3 seconds. Finally, the calculated standard deviation of the altered data series suggests a 23% lower volatility than the actual one.

[2] We do not provide an illustration for oversampling to preserve space, however, it is available upon request.

[3] Even in this scenario the data points are not equally spaced, as a single price in a one second interval is chosen. The time distances amongst these chosen prices, albeit less, remain irregular.

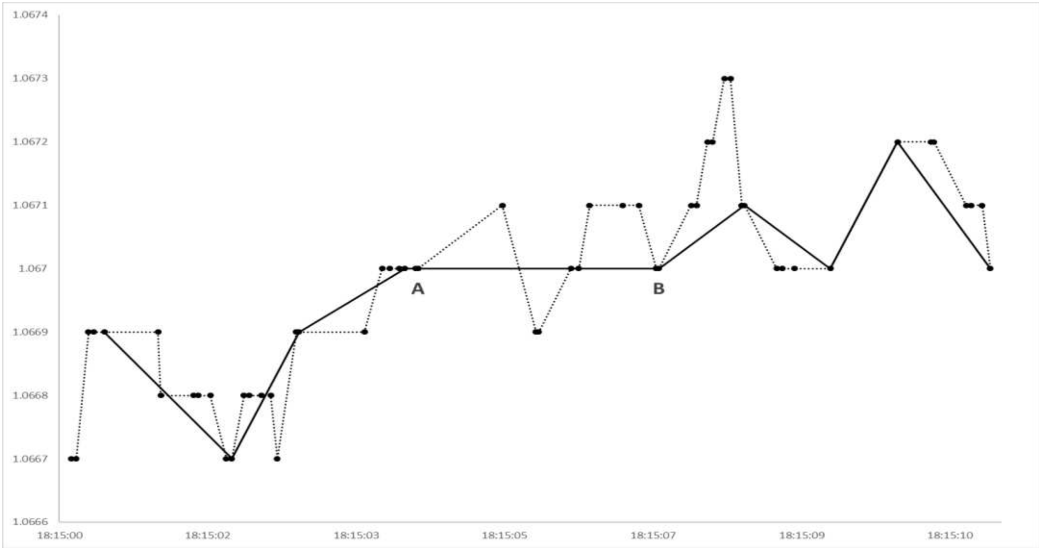

Figure 1. EUR:USD ask price on March 15th, 2017 between 18:15:00.000 and 18:15:10.781.

Another way to deal with unequally spaced data is to ignore the time element and work under the assumption that quotes arrive at equal time intervals. This method, however, undermines the information content that is carried via the varying time distances between prices and ignores the non-trading intervals that contain information about the underlying asset (Goodhart and O'Hara, 1997). In this case, market participants' contribution to price discovery might be incorrectly estimated penalizing or rewarding the market participants regardless of their speed.

Whilst the existing price discovery models mainly focus on the price changes, price discovery is a two-dimensional process that involves not only the magnitude and direction of price change but also the *element of time*. We propose a price discovery model based on these two elements: the relative price and time change as well as the relation between them.

3 The Model

Based on the implicit assumption of equally spaced data, Jahanshahloo and Spokeviciute (2018) define MWPC as follows:

$$MWPC_{i,j} = \sum_{t=1}^{T} \left(\frac{\nabla p_t^{i,j}}{\sum_{t=1}^{T} \left| \Delta p_t^i \right|} \right), \tag{1}$$

$$\nabla p_t^{i,j} = \sum_{n=1}^{N_t} \left(\left| p_{n-1}^i - p_f^i \right| - \left| p_n^{i,j} - p_f^i \right| \right), \tag{2}$$

where $\nabla p_t^{i,j}$ denotes the total price convergence to the final price executed by dealer *j* for asset *i* in time *t*. The current, previous, and final prices are denoted by $p_n^{i,j}$, p_{n-1}^i and p_f^i, respectively, N_t is the number of trades/quotes in time *t* and T is the total number of periods.

To incorporate the time element in the MWPC, we first measure the time distance between the current and the previous price and then use this distance to adjust the value of the price convergence. We do so by dividing the numerator in the MWPC by the measured time distance. This adjustment allows us to introduce market participants' quoting/trading speed into the calculation of the contribution to the price discovery process. The formal expression is as follows:

$$\frac{\nabla p_t^{i,j}}{\Delta t_t^{i,j}} = \sum_{n=1}^{N_t} \frac{\left| p_{n-1}^i - p_f^i \right| - \left| p_n^{i,j} - p_f^i \right|}{t_n^{i,j} - t_{n-1}^i} \tag{3}$$

where t_{n-1}^i and $t_n^{i,j}$ are the respective clock times for prices p_{n-1}^i and $p_n^{i,j}$.

As in the MWPC, the contribution of dealer *j* to asset *i* is expressed as a proportion of all other dealers' contribution combined. We, therefore, define the Time Weighted Price Contribution model (TWPC) as follows[4]:

$$TWPC_{i,j} = \frac{1}{\sum_{t=1}^{T} \frac{\nabla p_t^i}{\Delta t_t^i}} \times \sum_{t=1}^{T} \left(\frac{\nabla p_t^{i,j}}{\Delta t_t^{i,j}} \right) \tag{4}$$

[4] Please note that if the prices arrive at equal intervals, the model would be exactly as expressed by the MWPC. The proof is available upon request from the authors.

The acquired values from the TWPC assign contribution to price discovery not only based on the direction of the price but also on the speed that the price was disseminated (reaction time). Specifically, higher values are attributed when the convergence to the final price is greater and the time it takes for the trade/quote to be disseminated is shorter. These two elements, i.e., direction and speed are further adjusted in relation to other participants' contribution.[5]

4 Empirical Evidence

To examine whether our modification captures the information content of the time element in dealers' contribution to price discovery, we consider the following OLS regression model:

$$CPD_{j,t} = \beta_0 + \beta_1 ART_{j,t} + \gamma_j + \varepsilon_{j,t} \tag{5}$$

where $CPD_{j,t}$ is the contribution to ask or bid price discovery of dealer *j* at period *t* calculated using WPC, MWPC, and TWPC in 1-minute intervals. $ART_{j,t}$ is the average reaction time (as a proxy of speed[6]) of dealer *j* to price updates in a period *t* and is calculated as the average time difference between the dealer's prices and the previous prices. $ART_{j,t}$ can be formally expressed as follows:

$$ART_{j,t} = \frac{1}{N_{j,t}} \sum_{n=1}^{N_{j,t}} t_n^i - t_{n-1} \tag{6}$$

where $N_{j,t}$ is the number of prices disseminated by dealer *j* in period *t*, t_n^j is the clock time of price *n* by dealer *j* and t_{n-1} is the clock time of the previous price. Following Madureira and Underwood (2008) the model includes dealer fixed effects, γ_j, and is estimated with robust standard errors, $\varepsilon_{j,t}$.

[5] TWPC does not violate the prerequisite of the WPC and MWPC that the sum of all agents' contribution to price is 100%.
[6] Speed is inversely related to reaction time, i.e. the shorter the reaction time, the higher the speed.

We collected real time data on dealers' high frequency bid and ask quotes for EUR:USD with the identity and location of the dealers from the Thomson Reuters. This data allows us to estimate how individual dealers contribute to the price discovery process. The dataset contains 434 days[7] of data from April 24th, 2013 to November 29th, 2017[8].

Table 1

Average Reaction Time Effect

	WPC		MWPC		TWPC	
	(1) CPD (Ask)	(2) CPD (Bid)	(3) CPD (Ask)	(4) CPD (Bid)	(5) CPD (Ask)	(6) CPD (Bid)
ART	0.424***	0.420***	0.278***	0.202***	-0.317***	-0.315***
	(0.0242)	(0.0248)	(0.0205)	(0.0207)	(0.0261)	(0.0260)
Constant	4.045***	4.065***	4.328***	4.396***	4.859***	4.857***
	(0.0478)	(0.0461)	(0.0397)	(0.0382)	(0.0684)	(0.0682)
Dealer FE	Yes					
Observations	9,481,636					
Adj. R-squared	0.30%	0.36%	0.70%	0.80%	0.40%	0.40%

Hubert-White robust standard errors are in parentheses and **, *** indicate statistical significance at the 5% and 1% levels, respectively.

Table 1, Columns (1) through (4) show that when time element is ignored, an increase in ART of a dealer is positively associated with their contribution to price discovery. These results contradict the consensus stemming from empirical findings, such as Brogaard et al. (2014) and Chaboud et al. (2014), that higher frequency traders contribute positively to the price discovery process. Including the element of time via TWPC corrects this issue. Specifically, we show in columns (5) and (6) that higher ART (speed) has a negative (positive) effect on the contribution to price discovery. These results are robust to random sub-sample selections, which we omit to preserve space.

7 We choose these days because data is without interruption.

8 This time span is chosen due to data availability.

5 Conclusion

With the pervasiveness of high frequency and irregularly spaced trading, time has become an increasingly important element in price discovery. Specifically, it has been widely agreed upon that speed, i.e., traders' reaction time, has a significant impact on their contribution to price discovery. However, whilst the markets have learnt to adapt to the changing nature and prevalence of high-frequency trading, little has been done to modify the existing empirical price discovery models to help us understand the implications of time. The ignorance of time element in these models further leads to misestimation of market participants' impact on price discovery and the functioning of financial markets.

We address this issue by incorporating the element of time to the MWPC. With our new model, TWPC, unequally spaced data can be studied, allowing us to unbiasedly estimate different market participants' contribution to price discovery. We employ a unique tick-by-tick real time dataset for the FX market and provide empirical evidence on the validity of the TWPC.

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