Finally, the model requires some form of initialization to produce a viable order book before actual trading can begin. This is done in a series of 10 initial Monte Carlo steps, in which liquidity providers place limit orders around an initial price, $p_a = p_b = p_0$, with no liquidity taker activity present. This corresponds to the placement of approximately $\lfloor 10\alpha N_A \rfloor$ limit orders.

C. Liquidity Taker Agent Specification

Each simulation contains N_A liquidity takers, who submit market orders to the LOB at a given frequency, μ. This means that for any given Monte Carlo step, approximately $\lfloor \mu N_A \rfloor$ market orders are placed by liquidity takers. Each of the aforementioned orders is of size 1 and is a buy order with probability $q_{taker}(t)$, with $q_{taker}(0) = \frac{1}{2}$.

A sell market order simply executes and results in the removal of the best bid from the LOB and a buy market order simply executes and results in the removal of the best ask from the LOB, since all orders are of size 1.

Unlike $q_{provider}$, $q_{taker}(t)$ is not fixed, but rather evolves over time. It is implemented as a mean-reverting random walk, with mean $q_{taker}(0)$, increment Δ_S, and a mean reversion probability of $\frac{1}{2} + |q_{taker}(t) - \frac{1}{2}|$.

3. Calibration Experiment Design

A. Data

The dataset used in all calibration experiments is acquired in the TRTH (Thomson Reuters 2016) format, presenting a tick-by-tick series of trades, quotes and auction quotes.

We convert the dataset to a series of one-minute price bars, with each price corresponding to the final quote mid price for each minute, where the mid price of a quote is given as the average of the level 1 bid price and level 1 ask price associated with that quote, as was previously done in Platt and Gebbie (2016). From this series of prices, we may obtain a series of log prices [2], which is the series we attempt to calibrate the model to.

The transaction dataset often presents events occurring outside of standard trading hours, 9:00 to 17:00, but we consider only quotes with a timestamp occurring in the period from 9:10 to 16:50 on any particular trading day. This is a result of the fact that the opening auction occurring from 8:30 to 9:00 tends to produce erroneous data during the first 10 minutes of continuous trading and the fact that the period from 16:50 to 17:00 represents a closing auction.

In all calibration experiments, we investigate a one-week period, corresponding to a total of 2300 one-minute price bars, representing 460 minutes of trading each day from Monday to Friday.

Finally, we consider a single, liquid stock listed on the Johannesburg Stock Exchange, Anglo American PLC, over the period beginning at 9:10 on 1 November 2013 and ending at 16:50 on 5 November 2013. This dataset was also considered in Platt and Gebbie (2016).

B. Calibration Framework

As previously discussed, we apply the calibration framework described by Fabretti (2013) to an intraday ABM approximating a continuous double auction market through the use of realistic order matching procedures, as opposed to a model operating at a daily time scale and using closed-form approximations to market prices.

We make use of the method of simulated moments (Winker et al. 2007) to construct an objective function that measures errors relating to the mean, standard deviation, kurtosis, Kolmogorov-Smirnov (KS) test and generalized Hurst exponent when comparing a log price time series measured from the data and a log price time series simulated using the Preis et al. (2006) model.

We aim to minimize this objective function by employing the Nelder-Mead simplex algorithm combined with the threshold accepting heuristic (Gilli and Winker 2003).

We reproduce the implementation we pre-

[2] This is a technical requirement of the method of Fabretti (2013) and is discussed in detail in Platt and Gebbie (2016).