```
In [43]: import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
          import statsmodels.api as sm
          from statsmodels.tsa.stattools import acf, pacf
          from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
          from datetime import datetime, timedelta
          from bisect import bisect_left
          from copy import deepcopy
          import warnings
          warnings.filterwarnings("ignore")
In [44]: order_currency = pd.read_csv('/Users/rashimohta/Documents/UCB MFE/Semester 3/230X/Homework/Data Currency/ORDER CURRENCY.csv')
          trade_currency = pd.read_csv('/Users/rashimohta/Documents/UCB MFE/Semester 3/230X/Homework/Data Currency/TRADE CURRENCY.csv')
          order_currency['Time'] = pd.to_datetime(order_currency['Time'])
          trade_currency['Time'] = pd.to_datetime(trade_currency['Time'])
In [45]: # Orderbook creation
          def create_orderbook(df, currency_pair):
              orderbook = {}
              current orderbook = {"bid": [], "ask": []}
              current_time = datetime(2012, 1, 25, 9, 30, 0)
              end_time = datetime(2012, 1, 25, 16, 0, 0)
              relevant_columns = [x for x in df.columns if currency_pair in x and
                                   not any(term in x for term in ['DELETED', 'NUM_PARTCP', 'TICK_STATUS', 'RECORD_TYPE', 'OMDSEQ'])]
              for ts, bs, price, amt in df[['Time'] + relevant_columns].dropna().values:
                  while current time < ts:
                       orderbook[current\_time.strftime("\%Y/\%m/\%d \%H:\%M:\%S")] = deepcopy(current\_orderbook)
                       current_time += timedelta(seconds=1)
                  side = 'ask' if bs else 'bid'
                  price = -price if side == 'bid' else price
                  idx = bisect_left(current_orderbook[side], [price, 0])
                  if amt == 0:
                       del current_orderbook[side][idx]
                   \label{eq:current_orderbook} \textbf{elif} \  \, \textbf{idx} \, \, \textbf{<} \, \, \textbf{len}(\textbf{current\_orderbook[side]}) \  \, \textbf{and} \  \, \textbf{current\_orderbook[side][idx][0]} \, == \, \textbf{price:}
                      current_orderbook[side][idx][1] = amt
                   else:
                       current_orderbook[side].insert(idx, [price, amt])
              while current time < end time:
                  orderbook[current\_time.strftime("%Y/%m/%d %H:%M:%S")] = deepcopy(current\_orderbook)
                   current_time += timedelta(seconds=1)
                  orderbook[k]['bid'] = [[abs(x[\emptyset]), \ x[1]] \ \ \textbf{for} \ \ x \ \ in \ \ orderbook[k]['bid']]
              return orderbook
In [46]: # Data processing
          def process_currency_data(order_currency):
              currency_pairs = ['EUR/USD', 'USD/JPY', 'EUR/JPY']
              currency_orderbook = {pair: create_orderbook(order_currency, pair) for pair in currency_pairs}
              dfs_order_curr = {}
              for pair in currency_pairs:
                  df = []
                   for t, book in currency_orderbook[pair].items():
                       bid, ask = book['bid'], book['ask']
                       for i in range(max(len(bid), len(ask))):
                           df.append({
                                "Time": t.
                                "BID_PRICE": bid[i][0] if i < len(bid) else None,
                               "BID_SIZE": bid[i][1] if i < len(bid) else None,</pre>
                               "ASK_PRICE": ask[i][0] if i < len(ask) else None,
                               "ASK_SIZE": ask[i][1] if i < len(ask) else None,
                                "LEVEL": i+1
                           })
                  dfs_order_curr[pair] = pd.DataFrame(df)
dfs_order_curr[pair]['Time'] = pd.to_datetime(dfs_order_curr[pair]["Time"])
                  dfs_order_curr[pair].set_index('Time', inplace=True)
              return currency_orderbook, dfs_order_curr
In [47]: # Data cleaning
          def clean_and_split_data(df, tickers, header):
              df.columns = [x.replace(header, "").replace("..Price", "") for x in df.columns]
return {tick: df.loc[:, ['Time'] + [item for item in df.columns if tick in item]]
                            .rename(columns=lambda x: x.replace(f'{tick}.', ""))
                            set_index('Time')
                       for tick in tickers}
          dfs_trade_curr = clean_and_split_data(trade_currency,['EUR/USD','USD/JPY','EUR/JPY'],"EBS_BOOK::")
```

```
In [48]: def calculate_dollar_volume(trade_df, ticker):
                trade_df['Dollar_Volume_TradCurr'] = trade_df['PRICE'] * trade_df['SIZE']
                if ticker == 'USD/JPY':
                     trade_df['Dollar_Volume_USD'] = trade_df['SIZE']
                 elif ticker == 'EUR/JPY':
                     temp = dfs_order_curr['USD/JPY'][['BID_PRICE', 'ASK_PRICE']]
temp['midquote'] = (temp['BID_PRICE'] + temp['ASK_PRICE']) / 2
                     trade_df = pd.merge_asof(trade_df, temp[['midquote']], on='Time', direction='backward').dropna()
trade_df['Dollar_Volume_USD'] = trade_df['SIZE'] * trade_df['PRICE'] / trade_df['midquote']
                     trade_df.set_index('Time', inplace=True)
                else:
                     trade_df['Dollar_Volume_USD'] = trade_df['Dollar_Volume_TradCurr']
                return trade_df
In [49]: def analyze_trading_activity(trade_df, order_df):
                numTrade = trade_df['SIZE'].resample('T').count().rename('numTrade')
                 tradedShares = trade_df['SIZE'].resample('T').sum().rename('numTrade_shares')
                orderShares = order_df.resample('5s')[['BID_SIZE', 'ASK_SIZE']].sum()
                orderShares['bid_diff'] = orderShares['BID_SIZE'].diff(1)
                orderShares['ask_diff'] = orderShares['ASK_SIZE'].diff(1)
                orderShares['numOrder_Shares'] = orderShares['bid_diff'].abs() + orderShares['ask_diff'].abs()
                orderShares = orderShares['numOrder_Shares'].resample('T').sum()
                \textbf{return} \  \, \texttt{pd.concat}([\texttt{numTrade}, \ \texttt{tradedShares}, \ \texttt{orderShares}], \ \texttt{axis=1})
In [50]: def calculate_ohlc(trade_df):
                return pd.DataFrame({
                     'open': [trade_df['PRICE'].iloc[0]],
                     'close': [trade_df['PRICE'].iloc[-1]],
'high': [trade_df['PRICE'].max()],
                      'low': [trade_df['PRICE'].min()]
In [51]: def calculate_vwap(trade_df):
                dollar_volume = (trade_df['PRICE'] * trade_df['SIZE']).resample('T').sum()
volume = trade_df['SIZE'].resample('T').sum()
                return (dollar_volume / volume).rename('VWAP')
In [52]: def analyze_bbo(order_df):
                bbo = order_df[order_df['LEVEL'] == 1].copy()
bbo['spread'] = bbo['ASK_PRICE'] - bbo['BID_PRICE']
                return bbo.resample('T')[['spread', 'BID_SIZE', 'ASK_SIZE', 'ASK_PRICE', 'BID_PRICE']].mean()
In [53]: def calculate_depth_at_twice_spread(order_df, bbo_df):
    bbo_df["midquote"] = (bbo_df["ASK_PRICE"] + bbo_df["BID_PRICE"])/2
    order_df = order_df.merge(bbo_df[['midquote', 'spread']], on='Time')
                daily_spread = bbo_df['spread'].mean()
                order_df['bid_depth_within_range'] = order_df.apply(
                     lambda x: x['BID_SIZE'] if x['BID_PRICE'] >= x['midquote'] - daily_spread else 0, axis=1)
                order_df['ask_depth_within_range'] = order_df.apply(
                     lambda x: x['ASK_SIZE'] if x['ASK_PRICE'] <= x['midquote'] + daily_spread else 0, axis=1)</pre>
                return order_df[['bid_depth_within_range', 'ask_depth_within_range']].resample('T').mean()
In [54]: def calculate_price_impact(trade_df, order_df):
                PI = 2 * trade_df["BUY_SELL_FLAG"] - 1
                 level1_order = order_df[order_df['LEVEL'] == 1]
                level1_order['midquote'] = level1_order[['BID_PRICE', 'ASK_PRICE']].mean(axis=1)
return_midquote = level1_order['midquote'].pct_change()
                \label{eq:merged_df} merge\_asof(PI, return\_midquote.to\_frame(), on=' \\ \begin{subarray}{c} Time', direction='backward'). dropna() \\ \end{subarray}
                model = sm.OLS(merged_df['midquote'], merged_df['BUY_SELL_FLAG']).fit()
                return model.summary(), merged_df
In [55]: def calculate returns(order df, trade df):
                level1_order = order_df[order_df['LEVEL'] == 1]
                level1_order['midquote'] = level1_order[['BID_PRICE', 'ASK_PRICE']].mean(axis=1)
                quote_price = pd.DataFrame()
                quote_price['1min midquote'] = level1_order['midquote'].resample('T').last()
                quote_price['1s midquote'] = level1_order['midquote'].resample('1s').last()
                quote_price['1min transaction price'] = trade_df.resample('T')['PRICE'].last().to_frame()
quote_price['1s transaction price'] =trade_df.resample('1s')['PRICE'].last().to_frame()
                for col in quote_price.columns:
                      quote_price[f'return {col}'] = np.log(quote_price[col]).diff()
                return quote_price
```

Visualization functions

```
In [56]: def plot_liquidity_metrics(bbo_df):
    fig, axes = plt.subplots(3, 1, figsize=(10, 15))
```

```
temp = bbo_df.resample('5T').mean()
                               temp['spread'].plot(ax=axes[0], title='BBO Spread')
temp['BID_SIZE'].plot(ax=axes[1], title='BBO Bid Depth')
                                temp['ASK_SIZE'].plot(ax=axes[2], title='BBO Ask Depth')
                                plt.tight_layout()
                                return fig
In [57]: def plot_price_impact(merged_df):
                                def group_price_impact(group):
                                          if len(group) <= 1:</pre>
                                                  return None
                                         model = sm.OLS(group['midquote'], group['BUY_SELL_FLAG']).fit()
                                         return model.params[0]
                                fig, ax = plt.subplots(figsize=(10, 5))
                                merged_df.set_index('Time').resample('5T').apply(group_price_impact).plot(ax=ax, title='Price Impact (5min Regression)')
                                return fig
In [58]: def plot_return_metrics(quote_price):
                                fig, axes = plt.subplots(2, 1, figsize=(10, 10))
                                quote_price['return 1min transaction price'].dropna().resample('30T').var().plot(ax=axes[0], title='Variance')
                                def group_acf(group):
                                         acf_computed = acf(group['return 1min transaction price'].dropna())
                                          return acf_computed[1] if len(acf_computed) > 1 else None
                                quote_price[['return 1min transaction price']].dropna().resample('30T').apply(group_acf).plot(ax=axes[1], title='1st ACF')
                                plt.tight_layout()
                                return fig
In [59]: def plot_acf_pacf(quote_price):
                                fig, axes = plt.subplots(2, 2, figsize=(15, 15))
                                plot_acf(quote_price['return 1min transaction price'].dropna(), ax=axes[0, 0], title="Trade ACF - 1 Min", lags=np.arange(1, 20))
plot_pacf(quote_price['return 1min transaction price'].dropna(), ax=axes[0, 1], title="Trade PACF - 1 Min", lags=np.arange(1, 20))
                                plot_acf(quote_price['return 1min midquote'].dropna(), ax=axes[1, 0], title="Mid-quote ACF - 1 Min", lags=np.arange(1, 20))
                                plot_pacf(quote_price['return 1min midquote'].dropna(), ax=axes[1, 1], title="Mid-quote PACF - 1 Min", lags=np.arange(1, 20))
                                plt.tight_layout()
                                return fig
In [60]: # Analyze arbitrage opportunities
                      def analyze_arbitrage(currency_orderbook):
                               current_time = datetime(2012, 1, 25, 9, 30, 0)
                                end_time = datetime(2012, 1, 25, 16, 0, 0)
                                arbitrage_data = []
                                while current_time < end_time:</pre>
                                          time_str = current_time.strftime("%Y/%m/%d %H:%M:%S")
                                         eurusd = currency_orderbook['EUR/USD'][time_str]
usdjpy = currency_orderbook['USD/JPY'][time_str]
                                          eurjpy = currency_orderbook['EUR/JPY'][time_str]
                                         if eurusd['ask'] and eurjpy['bid'] and usdjpy['ask']:
    arbi_long_eur = 1 / eurusd['ask'][0][0] * eurjpy['bid'][0][0] / usdjpy['ask'][0][0]
                                                   amt_long_eur = min(eurusd['ask'][0][1], usdjpy['ask'][0][1]/usdjpy['ask'][0][0], eurjpy['bid'][0][1]/usdjpy['ask'][0][0]) if arbi_long_eur > 1 els
                                         else:
                                                  arbi_long_eur = None
                                                   amt_long_eur = None
                                          if eurusd['bid'] and eurjpy['ask'] and usdjpy['bid']:
                                                   arbi_short_eur = eurusd['bid'][0][0] / eurjpy['ask'][0][0] * usdjpy['bid'][0][0]
                                                   amt_short_eur = min(eurusd['bid'][0][1], usdjpy['bid'][0][1]/usdjpy['bid'][0][0], eurjpy['ask'][0][1]/usdjpy['bid'][0][0]) if arbi_short_eur > 1 e
                                                   arbi short eur = None
                                                   \verb"amt_short_eur = None"
                                          arbitrage_data.append({
                                                    'time': time_str,
                                                    'arbi_by_long_eur': arbi_long_eur,
                                                    'arbi_by_long_eur_amt': amt_long_eur,
                                                    'arbi_by_short_eur': arbi_short_eur,
                                                    'arbi_by_short_eur_amt': amt_short_eur
                                         })
                                         current_time += timedelta(seconds=1)
                                arbitrage = pd.DataFrame(arbitrage_data)
                                arbitrage['time'] = pd.to_datetime(arbitrage['time'])
                                arbitrage.set_index('time', inplace=True)
                                arbitrage['duration'] = ((arbitrage['arbi\_by\_long\_eur'] > 1) \mid (arbitrage['arbi\_by\_short\_eur'] > 1)). astype(int) \mid (arbitrage['duration'] = ((arbitrage['arbi\_by\_long\_eur'] > 1) \mid (arbitrage['duration'] = ((arbitrage['duration'] =
                                arbitrage['group'] = (arbitrage['duration'] == 0).cumsum()
                                arbitrage['arbi\_amt'] = arbitrage['arbi\_by\_long\_eur\_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur\_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + arbitrage['arbi\_by\_short\_eur_amt'].fillna(\emptyset) + 
                                arbitrage['arbi_ret'] = arbitrage.apply(lambda x: max(x['arbi_by_long_eur'] or 0, x['arbi_by_short_eur'] or 0), axis=1)
                                arbitrage_summary = arbitrage[arbitrage['duration'] == 1].groupby('group').agg({
                                           'duration': 'sum',
'arbi_amt': 'mean'
                                           'arbi_ret': 'mean'
                                return arbitrage, arbitrage summary
```

```
In [61]: def analyze_ticker(trade_df, order_df, ticker):
             results = {}
             # Calculate dollar volume
             trade_df = calculate_dollar_volume(trade_df, ticker)
             \verb|dollar_volume| = trade_df.resample('T')[['Dollar_Volume_TradCurr', 'Dollar_Volume_USD']].sum()| \\
             results['dollar_volume'] = dollar_volume.describe()
             # Analyze trading activity
             results['trading_activity'] = analyze_trading_activity(trade_df, order_df).describe()
             # Calculate OHIC
             results['ohlc'] = calculate_ohlc(trade_df).describe()
             # Calculate VWAP
             results['vwap'] = calculate_vwap(trade_df).describe()
             # Analyze BBO
             bbo_df = analyze_bbo(order_df)
             results['bbo'] = bbo_df.describe()
             # Plot liquidity metrics
             results['liquidity_plot'] = plot_liquidity_metrics(bbo_df)
             # Calculate depth at twice spread
             results['depth_at_twice_spread'] = calculate_depth_at_twice_spread(order_df, bbo_df).describe()
             results['price_impact_summary'], merged_df = calculate_price_impact(trade_df, order_df)
             results['price_impact_plot'] = plot_price_impact(merged_df)
             # Calculate returns
             quote_price = calculate_returns(order_df, trade_df)
             results['returns'] = quote_price.describe()
             # Calculate realized variance
             results['realized_variance'] = {
                  'midquote': (quote_price['return 1min midquote']**2).sum(),
                  'transaction_price': (quote_price['return 1min transaction price']**2).sum()
             # PLot ACF and PACF
             results['acf_pacf_plot'] = plot_acf_pacf(quote_price)
             # Return distribution
             fig, axes = plt.subplots(2, 1, figsize=(12, 10))
             sns.histplot(quote_price['return 1min midquote'].dropna(), kde=True, ax=axes[0])
             axes[0].set_title('Distribution of 1-minute Midquote Returns')
             sns.histplot(quote_price['return 1min transaction price'].dropna(), kde=True, ax=axes[1])
             axes[1].set_title('Distribution of 1-minute Transaction Price Returns')
             plt.tight_layout()
             results['return_distribution_plot'] = fig
             return results
In [63]: # Process currency data
         currency_orderbook, dfs_order_curr = process_currency_data(order_currency)
         dfs_trade_curr = clean_and_split_data(trade_currency, ['EUR/USD', 'USD/JPY', 'EUR/JPY'], "EBS_BOOK::")
         # Analyze tickers
         tickers = ['EUR/USD', 'USD/JPY', 'EUR/JPY']
         results = {}
          for ticker in tickers:
             results[ticker] = analyze_ticker(dfs_trade_curr[ticker], dfs_order_curr[ticker], ticker)
          # Analyze arbitrage opportunities
         arbitrage, arbitrage_summary = analyze_arbitrage(currency_orderbook)
         # Display results
         for ticker, result in results.items():
             print(f"\n{'='*50}\nResults for {ticker}\n{'='*50}")
             print("\nDollar Volume Statistics:")
             print(result['dollar volume'])
             print("\nTrading Activity Statistics:")
             print(result['trading_activity'])
             print("\nOHLC Statistics:")
             print(result['ohlc'])
             print("\nVWAP Statistics:")
             print(result['vwap'])
             print("\nBBO Statistics:")
             print(result['bbo'])
             print("\nDepth at Twice Spread Statistics:")
             print(result['depth_at_twice_spread'])
             print("\nRealized Variance:")
             print(result['realized_variance'])
             print("\nPrice Impact Summary:")
             print(result['price_impact_summary'])
```

```
# Display plots
    result['liquidity_plot'].show()
result['price_impact_plot'].show()
result['acf_pacf_plot'].show()
    result['return_distribution_plot'].show()
print("\n{'='*50}\nArbitrage Summary\n{'='*50}")
print(arbitrage_summary.describe())
# Plot arbitrage opportunities
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(arbitrage.index, arbitrage['arbi_ret'])
ax.set_title('Arbitrage Returns Over Time')
ax.set_xlabel('Time')
ax.set_ylabel('Arbitrage Return')
plt.show()
# Plot arbitrage amount
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(arbitrage.index, arbitrage['arbi_amt'])
ax.set_title('Arbitrage Amount Over Time')
ax.set_xlabel('Time')
ax.set_ylabel('Arbitrage Amount')
plt.show()
```

0.000000e+00

2.879773e+07

5.100539e+07

8.859964e+07

0.000000e+00

2.879773e+07

5.100539e+07

8.859964e+07

1.166953e+09

max 1.166953e+09

Trading Activity Statistics:						
	numTrade	numTrade_shares	numOrder_Shares			
count	390.000000	3.900000e+02	3.900000e+02			
mean	37.269231	6.089487e+07	4.377487e+08			
std	36.636431	7.571124e+07	5.961196e+08			
min	0.000000	0.000000e+00	9.500000e+07			
25%	16.000000	2.200000e+07	2.335000e+08			
50%	27.000000	3.900000e+07	3.175000e+08			
75%	42.000000	6.800000e+07	4.425000e+08			
max	340.000000	8.920000e+08	8.289000e+09			

OHLC Statistics:

min

25%

50%

75%

	open	close	high	low
count	1.00000	1.0000	1.00000	1.0000
mean	1.29736	1.3113	1.31209	1.2947
std	NaN	NaN	NaN	NaN
min	1.29736	1.3113	1.31209	1.2947
25%	1.29736	1.3113	1.31209	1.2947
50%	1.29736	1.3113	1.31209	1.2947
75%	1.29736	1.3113	1.31209	1.2947
max	1,29736	1.3113	1.31209	1.2947

VWAP Statistics:

count	389.000000
mean	1.302737
std	0.005599
min	1.294987
25%	1.297332
50%	1.303261
75%	1.308151
max	1.311953
Name:	VWAP, dtype: float64

BBO Statistics:

	spread	BID_SIZE	ASK_SIZE	ASK_PRICE	BID_PRICE
count	390.000000	3.900000e+02	3.900000e+02	390.000000	390.000000
mean	0.000113	2.021789e+06	1.967684e+06	1.302776	1.302663
std	0.000017	1.006989e+06	8.623788e+05	0.005592	0.005585
min	0.000067	1.000000e+06	1.016667e+06	1.295006	1.294917
25%	0.000102	1.516667e+06	1.500000e+06	1.297404	1.297320
50%	0.000112	1.758333e+06	1.800000e+06	1.303304	1.303193
75%	0.000124	2.195833e+06	2.166667e+06	1.308172	1.308045
max	0.000166	9.750000e+06	1.191667e+07	1.311959	1.311841

Depth at Twice Spread Statistics:

	bid_depth_within_range	ask_depth_within_range
count	3.890000e+02	3.890000e+02
mean	8.835476e+05	1.163496e+06
std	1.000045e+06	2.454074e+06
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	5.000000e+05	9.000000e+05
75%	1.700000e+06	1.700000e+06
max	4.800000e+06	4.500000e+07

Realized Variance:

{'midquote': 2.9840510862646875e-05, 'transaction_price': 2.9131547122962268e-05}

Price Impact Summary:

OLS Regression Results

Dep. Variable: midquote		R-squared	R-squared (uncentered):		
Model:	OLS	OLS Adj. R-squared (uncentered):		entered):	0.001
Method:	Least Squares	F-statist	ic:	13.97	
Date:	Fri, 30 Aug 2024	Prob (F-s	tatistic):	0.000187	
Time:	16:48:14	Log-Likelihood:			1.2112e+05
No. Observations:	14535	AIC:			-2.422e+05
Df Residuals:	14534	BIC:			-2.422e+05
Df Model:	1				
Covariance Type:	nonrobust				
=======================================					
	coef std err	t	P> t	[0.025	0.975]
BUY_SELL_FLAG 1.804	e-06 4.83e-07	3.737	0.000	8.58e-07	2.75e-06
				========	======
Omnibus:	2842.445	Durbin-Wa			0.550
Prob(Omnibus):	0.000	Jarque-Be	era (JB):	34	1742.290

 Skew:
 0.584
 Prob(JB):
 0.00

 Kurtosis:
 10.483
 Cond. No.
 1.00

Notes

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Results for USD/JPY

Dollar Volume Statistics:

Dollar_Volume_TradCurr Dollar_Volume_USD 3.900000e+02 3.900000e+02 1.932805e+09 2.480256e+07 mean 2.489543e+09 3.194427e+07 std 0.000000e+00 0.000000e+00 min 25% 5.472335e+08 7,000000e+06 50% 1.242494e+09 1.600000e+07 75% 2.268353e+09 2.900000e+07 2.079064e+10 2.670000e+08 max

Trading Activity Statistics:

numTrade numTrade_shares numOrder_Shares count 390,000000 3.900000e+02 3.900000e+02 2.877077e+08 mean 15.489744 2.480256e+07 std 16.853479 3.194427e+07 2.749227e+08 0.000000 0.000000e+00 2.200000e+07 5.000000 7.000000e+06 25% 1.390000e+08 50% 11.000000 1.600000e+07 2.040000e+08 75% 20.000000 2.900000e+07 3.180000e+08 max 155.000000 2.670000e+08 2.133000e+09

OHLC Statistics:

open close high low 1.000 0.0 0.0 1.00 NaN 78.288 77.56 mean NaN std NaN NaN NaN NaN NaN 78.288 77.56 min NaN 25% NaN NaN 78.288 77.56 50% NaN NaN 78.288 77.56 75% NaN NaN 78.288 77.56 NaN NaN 78.288 77.56

VWAP Statistics:

count 377.000000
mean 77.947814
std 0.222758
min 77.582657
25% 77.733250
50% 77.887000
75% 78.172400
max 78.280389
Name: VWAP, dtype: float64

BBO Statistics:

ASK_PRICE BID_PRICE spread BID_SIZE ASK_SIZE count 390.000000 3.900000e+02 3.900000e+02 390.000000 390.000000 0.008005 2.098088e+06 2.215346e+06 77.954397 77.946392 mean 0.001582 1.012986e+06 1.505184e+06 std 0.221191 0.221726 0.004017 1.000000e+06 1.000000e+06 77.585417 min 77.578567 25% 0.006854 1.450000e+06 1.433333e+06 77.745079 77.737112 50% 0.007958 1.833333e+06 1.825000e+06 77.892225 77.884458 75% 0.008917 2.416667e+06 2.316667e+06 78.177571 78.170825 0.014333 7.633333e+06 1.571667e+07 max 78.283483 78.277583

Depth at Twice Spread Statistics:

 $\verb|bid_depth_within_range| ask_depth_within_range|$ count 3.890000e+02 3.890000e+02 mean 8.326478e+05 9.264781e+05 std 8.959464e+05 1.008696e+06 0.000000e+00 0.000000e+00 25% 0.000000e+00 0.000000e+00 50% 7.000000e+05 6.000000e+05 75% 1.400000e+06 1.500000e+06 9.9000000+06 max 6.700000e+06

Realized Variance:

{'midquote': 2.8758760741247084e-05, 'transaction_price': 2.8341723710336358e-05}

Price Impact Summary:

OLS Regression Results

______ Dep. Variable: midquote R-squared (uncentered): 0.000 Model: Adj. R-squared (uncentered): 0.000 OLS Method: Least Squares F-statistic: 1.641 Date: Fri, 30 Aug 2024 Prob (F-statistic): 0.200 16:48:14 Log-Likelihood: 50370. Time: No. Observations: 6041 AIC: -1.007e+05 Df Residuals: 6040 BIC: -1.007e+05 Df Model:

```
Covariance Type:
                      nonrobust
______
              coef std err t P>|t| [0.025 0.975]
BUY SELL FLAG 9.541e-07 7.45e-07 1.281 0.200 -5.06e-07 2.41e-06
______
                       1260.018 Durbin-Watson:
                       0.000 Jarque-Bera (JB):
Skew:
                          0.021 Prob(JB):
                                                        0.00
                        16.880 Cond. No.
                                                            1.00
Kurtosis:
______
Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
_____
Results for EUR/JPY
_____
Dollar Volume Statistics:
     Dollar_Volume_TradCurr Dollar_Volume_USD
count
             3.880000e+02
                             3.880000e+02
mean
             5.672623e+08
                             7.280163e+06
             8.003334e+08
                             1.027654e+07
std
                             0.000000e+00
             0.0000000+00
min
25%
             1.014078e+08
                             1.297582e+06
50%
             3.040450e+08
                             3.888294e+06
75%
             7.110802e+08
                             9.126341e+06
             5.467697e+09
                             6.999502e+07
max
Trading Activity Statistics:
       numTrade numTrade_shares numOrder_Shares
count 388.000000
                 3.880000e+02
                               3.900000e+02
mean
      3.969072
                 5.587629e+06
                               1.662692e+08
std
       4.953434
                 7.885816e+06
                                8.552759e+07
       0.000000
                 0.000000e+00
                                4.400000e+07
min
25%
      1.000000
                 1.000000e+06
                               1.090000e+08
       2.000000
                 3.000000e+06
                               1.455000e+08
50%
       5.000000
                 7.000000e+06
                               1.997500e+08
75%
max
      37,000000
                 5.400000e+07
                                5.880000e+08
OHLC Statistics:
       open close
                   high
                           low
            1.00 1.000 1.0
count
       1.00
mean 101.22 101.92 101.949 101.2
std
       NaN NaN NaN NaN
     101.22 101.92 101.949 101.2
min
25%
     101.22 101.92 101.949 101.2
50%
     101.22 101.92 101.949 101.2
75%
     101.22 101.92 101.949 101.2
     101.22 101.92 101.949 101.2
max
VWAP Statistics:
count 306,000000
       101.535929
mean
        0.182354
       101.200150
min
25%
       101.401125
50%
       101.500000
75%
       101.679391
       101,940000
max
Name: VWAP, dtype: float64
BBO Statistics:
                           ASK_SIZE ASK_PRICE BID_PRICE
        spread
                  BID_SIZE
count 390.000000 3.900000e+02 3.900000e+02 390.000000 390.000000
      0.018984 1.465155e+06 1.975137e+06 101.555631 101.536648
mean
       0.003303 5.586371e+05 3.714859e+06 0.184550 0.184130
std
min
       0.007717 1.000000e+06 1.000000e+06 101.217633 101.204233
25%
       0.017017 1.133333e+06 1.166667e+06 101.415367 101.395458
50%
       0.019175 1.308333e+06 1.366667e+06 101.509633 101.491542
       0.020917 1.595833e+06 1.716667e+06 101.697329 101.679742
75%
       0.033267 6.800000e+06 5.103333e+07 101.940583 101.923117
max
Depth at Twice Spread Statistics:
     bid_depth_within_range ask_depth_within_range
count
             3.890000e+02
                               3.890000e+02
             6.059126e+05
                                 9.812339e+05
mean
std
             5.736850e+05
                                 1.092091e+06
min
             0.000000e+00
                                 0.000000e+00
             1.000000e+05
                                 3.000000e+05
25%
             5.000000e+05
                                 8.000000e+05
50%
                                 1.300000e+06
75%
             1.000000e+06
max
             2.500000e+06
                                 9.600000e+06
{'midquote': 2.4692265843908004e-05, 'transaction price': 1.920834315567409e-05}
Price Impact Summary:
                          OLS Regression Results
```

Dep. Variable:	mi	dquote	R-squared (uncentered):			0.	003
Model:		OLS Adj. R-squared (uncen		ntered):	0.	002	
Method:	Least S	quares	F-statistic:			4.	242
Date:	Fri, 30 Au	g 2024	Prob (F-statistic):		0.0	396	
Time:	16	:48:15	Log-Likelihood:			125	72.
No. Observations:		1540	AIC:			-2.514e	+04
Df Residuals:		1539	BIC:			-2.514e	+04
Df Model:		1					
Covariance Type:	nor	robust					
	coef sto	lerr	t	P> t	[0.025	0.975]	
DIV SELL FLAC 2 61	00.06 1.76	. 06	2 060	0.040	1 720 07	7 070 06	
BUY_SELL_FLAG 3.61	96-06 1.76	ie-86	2.000	0.040	1./2e-0/	7.076-06	
Omnibus:	74 076	Donald Nata		=======	1.013		
	4		Durbin-Watson:				
Prob(Omnibus):		0.000	Jarque-Bera (JB):		9389.668		
Skew:	-0.935		Prob(JB):			0.00	
Kurtosis:		14.951	Cond. No.			1.00	

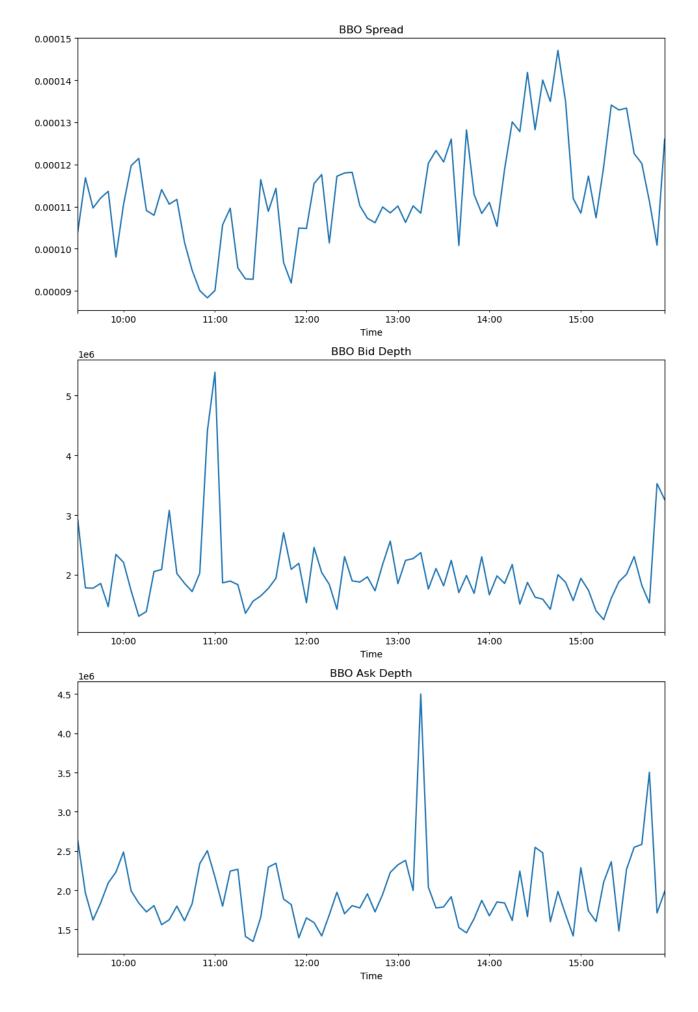
Notes:

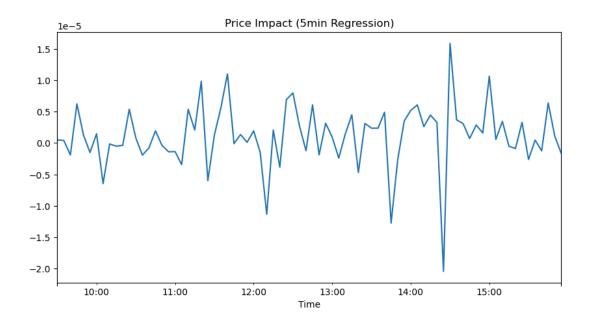
 $[1]\ R^2$ is computed without centering (uncentered) since the model does not contain a constant.

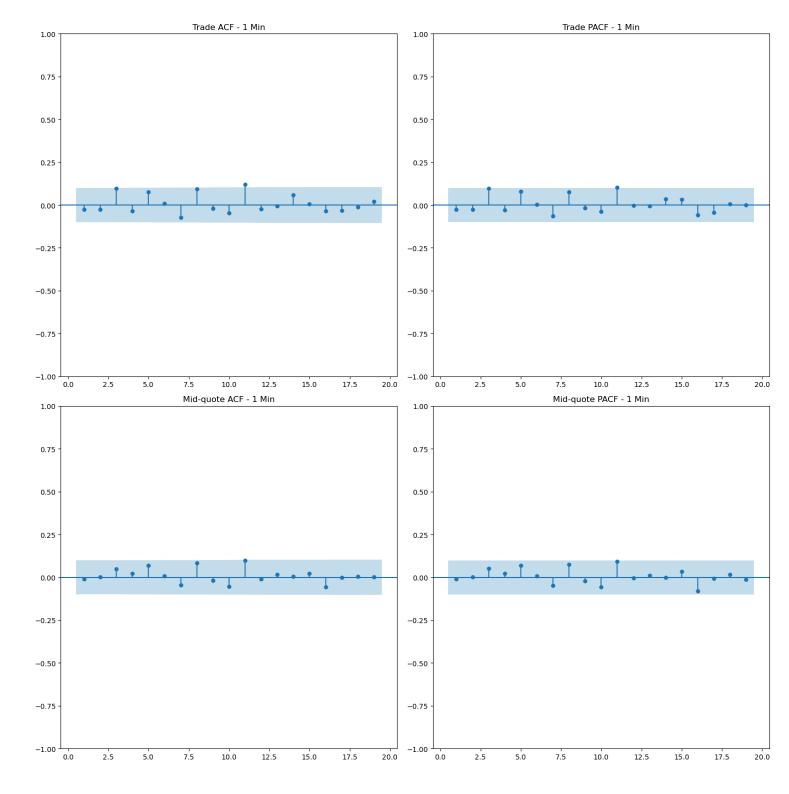
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

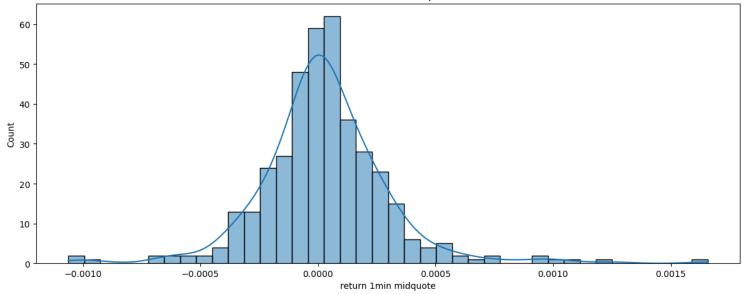
{'='*50} Arbitrage Summary {'='*50}

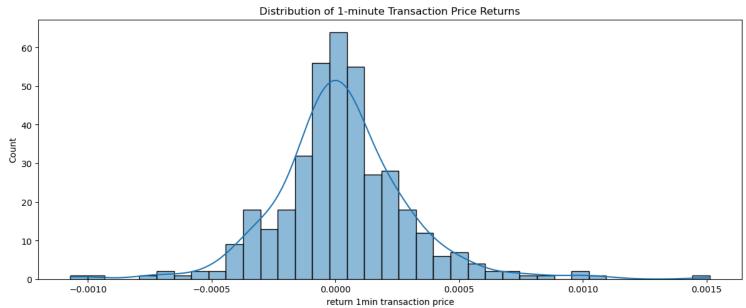
duration arbi_amt arbi_ret
count 22.000000 22.000000 22.000000
mean 1.272727 15251.456549 1.000018
std 1.077113 8934.258804 0.000020
min 1.000000 12787.723785 1.000000
25% 1.000000 12797.870661 1.000003
50% 1.000000 12824.000522 1.000013
75% 1.000000 12871.835163 1.000024
max 6.000000 53350.405463 1.000079

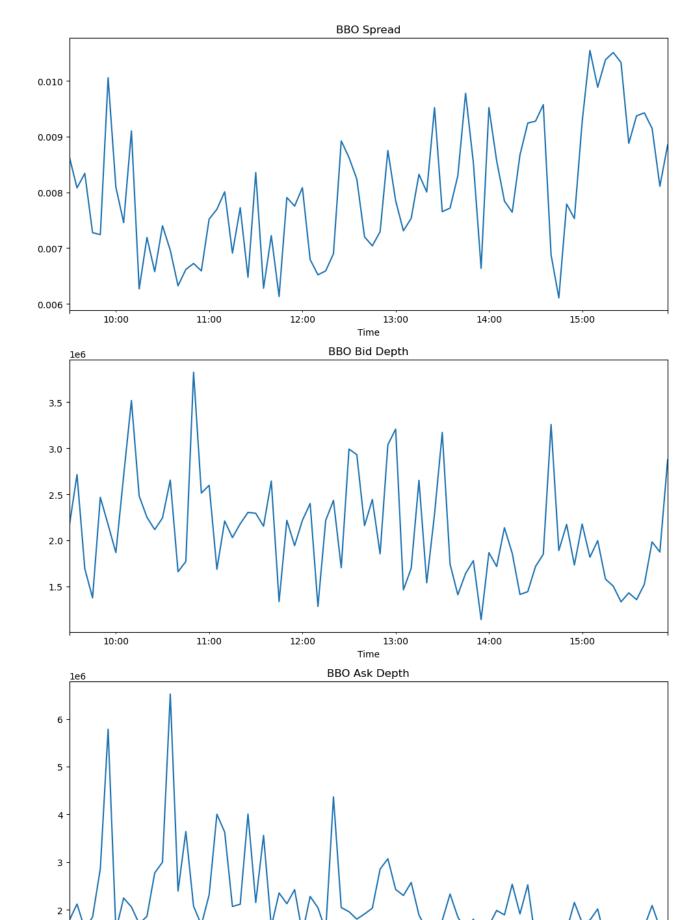












15:00

14:00

11:00

12:00

13:00

Time

10:00



