PART I

1. Dataset and Preliminary Analysis

In this section we:

- Read and concatenate the CSV files.
- Drop unnecessary columns.
- Compute basic statistics and perform sanity checks.
- Convert timestamps and check for missing values.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
from scipy.stats import expon
from statsmodels.tsa.stattools import acf
from statsmodels.graphics.tsaplots import plot_acf
```

In [2]:
```
file_list = ['Data/SG/SG_20170117.csv.gz','Data/SG/SG_20170118.csv.gz','Data/SG/SG_20170119.csv.gz','Dat
             'Data/SG/SG_20170125.csv.gz','Data/SG/SG_20170126.csv.gz','Data/SG/SG_20170127.csv.gz','Dat

Data_sg = {}
for i,file in enumerate(file_list):
    Data_sg[file[8:-7]] = pd.read_csv(file, compression='gzip').drop(columns=['Unnamed: 0'])
    Data_sg[file[8:-7]]['ets'] = pd.to_datetime(Data_sg[file[8:-7]]['ets'], format='%Y%m%d:%H:%M:%S.%f')

print(Data_sg.keys())
Data_sg["SG_20170117"]
```

```
dict_keys(['SG_20170117', 'SG_20170118', 'SG_20170119', 'SG_20170120', 'SG_20170123', 'SG_20170124', 'SG_
20170125', 'SG_20170126', 'SG_20170127', 'SG_20170130', 'SG_20170131', 'SG_20170201'])
```

Out[2]:

	ets	etype	eprice	eqty	eside	bp0	bq0	ap0	aq0
0	2017-01-17 09:01:00.270164	A	45610	1400	B	46010	1066	46085	1445
1	2017-01-17 09:01:00.312121	A	46485	700	S	46010	1066	46085	1445
2	2017-01-17 09:01:00.358162	A	46000	124	B	46010	1066	46085	1445
3	2017-01-17 09:01:00.359972	A	45950	182	B	46010	1066	46085	1445
4	2017-01-17 09:01:00.360001	A	45970	22	B	46010	1066	46085	1445
...	...	...	...	...	...	...	...	...	...
841144	2017-01-17 17:29:59.997678	A	45845	187	S	45820	377	45845	187
841145	2017-01-17 17:29:59.997691	C	45720	1250	B	45820	377	45845	187
841146	2017-01-17 17:29:59.997884	C	45765	110	B	45820	377	45845	187
841147	2017-01-17 17:29:59.998327	A	45740	110	B	45820	377	45845	187
841148	2017-01-17 17:29:59.998861	C	45785	324	B	45820	377	45845	187

841149 rows × 9 columns

In [ ]:
```

```

In [3]:
```
df_AllData = pd.concat(Data_sg.values(), ignore_index=True)
print(f"Shape of concatenated DataFrame: {df_AllData.shape}")
print("\nFirst 5 rows:")
df_AllData.head()
```

```
Shape of concatenated DataFrame: (7827010, 9)

First 5 rows:
```

Out[3]:

	ets	etype	eprice	eqty	eside	bp0	bq0	ap0	aq0
0	2017-01-17 09:01:00.270164	A	45610	1400	B	46010	1066	46085	1445
1	2017-01-17 09:01:00.312121	A	46485	700	S	46010	1066	46085	1445
2	2017-01-17 09:01:00.358162	A	46000	124	B	46010	1066	46085	1445
3	2017-01-17 09:01:00.359972	A	45950	182	B	46010	1066	46085	1445
4	2017-01-17 09:01:00.360001	A	45970	22	B	46010	1066	46085	1445

In [4]:

```
Data_sg_0117 = Data_sg["SG_20170117"]
#df = df_AllData
df = Data_sg_0117
```

In [5]:

```
# Verify basic content
print('___________________________________________________________________________________')
print("Event type counts:")
print(df['etype'].value_counts())
print("Side counts:")
print(df['eside'].value_counts())
```

```
___________________________________________________________________________________
Event type counts:
etype
A    388981
C    377310
M     61081
T     13777
Name: count, dtype: int64
Side counts:
eside
S    432686
B    408463
Name: count, dtype: int64
```

In [6]:

```
# Basic statistics for numerical columns
print("\nSummary Statistics:")
print(df[['eprice', 'eqty', 'bp0', 'bq0', 'ap0', 'aq0']].describe())

# Convert timestamp to datetime
df['ets'] = pd.to_datetime(df['ets'], format='%Y%m%d:%H:%M:%S.%f')

# Time range of the dataset
print(f"\nTime Range: {df['ets'].min()} to {df['ets'].max()}")

# Events per second (liquidity measure)
events_per_sec = df.resample('1s', on='ets').size().mean()
print(f"\nAverage Events per Second: {events_per_sec:.2f}")

# Transaction per second (liquidity measure)
transaction_per_sec = df[df['etype'] == 'T'].resample('1s', on='ets').size().mean()
print(f"\nAverage Transactions per Second: {transaction_per_sec:.2f}")

# Check for missing values
print("\nMissing values:")
print(df.isnull().sum())
```

```
Summary Statistics:
                eprice           eqty            bp0            bq0  \
count  841149.000000  841149.000000  841149.000000  841149.000000
mean    46151.758868     236.921342   46143.727497     623.455495
std       272.820275     283.275695     233.518584     579.452229
min     40000.000000  -14809.000000   45500.000000       1.000000
25%     45990.000000     162.000000   45985.000000     250.000000
50%     46135.000000     200.000000   46130.000000     497.000000
75%     46330.000000     250.000000   46320.000000     830.000000
max     60760.000000   25380.000000   46720.000000   10932.000000

                   ap0            aq0
count  841149.000000  841149.000000
mean    46160.476562     747.229150
std       233.056085     948.258226
min     45520.000000       1.000000
25%     46000.000000     326.000000
50%     46145.000000     580.000000
75%     46340.000000     944.000000
max     46740.000000   26270.000000

Time Range: 2017-01-17 09:01:00.270164 to 2017-01-17 17:29:59.998861

Average Events per Second: 27.54

Average Transactions per Second: 0.45

Missing values:
ets       0
etype     0
eprice    0
eqty      0
eside     0
bp0       0
bq0       0
ap0       0
aq0       0
dtype: int64
```

Data Sanity Checks: Trade Validity and Spread

Here we compute the bid-ask spread and validate trade prices. We:

- Compute the spread (ask - bid) and its basic statistics.
- Check for negative spreads.
- Validate that trade prices fall within the bid-ask range.
- Identify and print invalid trades.

In [7]:

```
df = df_AllData
#df = Data_sg_0117
```

In [8]:

```
# Compute spread and its statistics
df['spread'] = df['ap0'] - df['bp0']
print("\nSpread Statistics:")
print(df['spread'].describe())

# Check for negative spreads
negative_spread = df[df['spread'] < 0]
print(f"\nNegative spreads: {len(negative_spread)}")

# Validate trade prices within bid/ask
trades = df[df['etype'] == 'T']
valid_trades = trades[(trades['eprice'] >= trades['bp0']) & (trades['eprice'] <= trades['ap0'])] ## Non,
print(f"\nInvalid trades: {len(trades) - len(valid_trades)}")

# Filter invalid trades and print details
invalid_trades = trades[~trades.index.isin(valid_trades.index)]
print("\nInvalid Trades:")
print(invalid_trades[['ets', 'eprice', 'bp0', 'ap0']])
print('________________________________________________________________________________________')
```

```
# For each invalid trade, find the closest preceding quote update
for idx, row in invalid_trades.iterrows():
    nearest_quote = df[df['ets'] <= row['ets']].iloc[-1]
    print(f"Trade time: {row['ets']}, Quote time: {nearest_quote['ets']}")

print("\nData Sanity Check:")
print("-3 invalid trades detected where eprice fell outside bp0/ap0.")
print("-Inspection revealed these trades didnt have synchronization issue") #these 3 trades occur with b
print(" nor auction phase where trades could be non-continuous nor an unusual tick size")
print("-These trades have been excluded from the continuous trading analysis to avoid bias.")
```

```
Spread Statistics:
count    7.827010e+06
mean     1.502254e+01
std      7.337535e+00
min      5.000000e+00
25%      1.000000e+01
50%      1.500000e+01
75%      2.000000e+01
max      1.500000e+02
Name: spread, dtype: float64

Negative spreads: 0

Invalid trades: 3

Invalid Trades:
                               ets  eprice    bp0    ap0
4655752 2017-01-26 12:52:32.761728   48400  48480  48505
6465452 2017-01-31 10:24:05.806200   47150  47030  47070
6672360 2017-01-31 12:48:30.842097   46250  46255  46275
___________________________________________________________________________________
Trade time: 2017-01-26 12:52:32.761728, Quote time: 2017-01-26 12:52:32.761728
Trade time: 2017-01-31 10:24:05.806200, Quote time: 2017-01-31 10:24:05.806200
Trade time: 2017-01-31 12:48:30.842097, Quote time: 2017-01-31 12:48:30.842097

Data Sanity Check:
-3 invalid trades detected where eprice fell outside bp0/ap0.
-Inspection revealed these trades didnt have synchronization issue
 nor auction phase where trades could be non-continuous nor an unusual tick size
-These trades have been excluded from the continuous trading analysis to avoid bias.
```

In [9]:
```
df.iloc[6465452  -2: 6465452 +3, :]
```

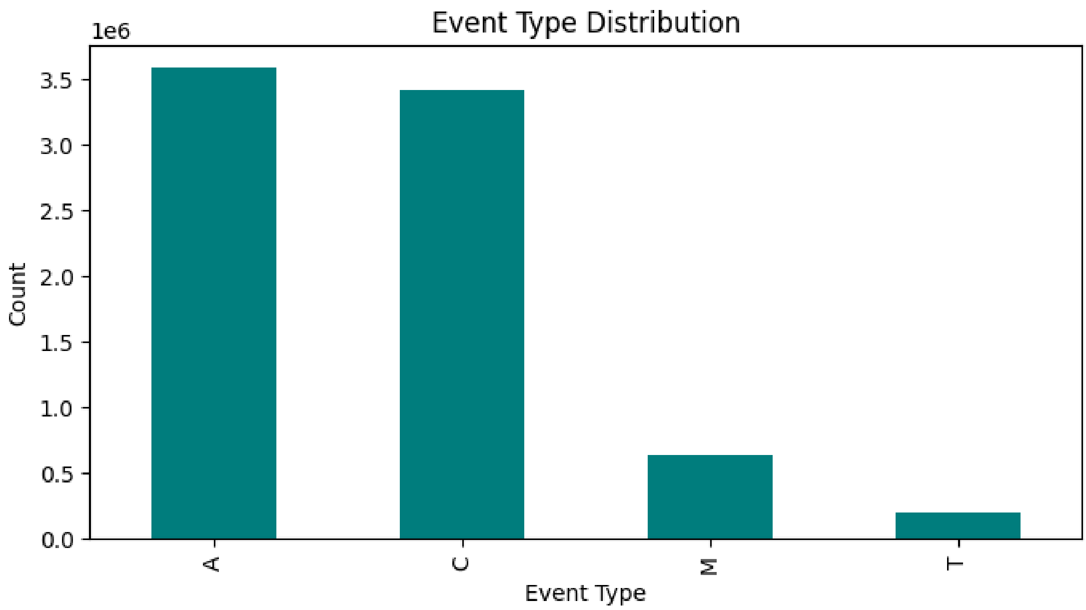
Out[9]:

	ets	etype	eprice	eqty	eside	bp0	bq0	ap0	aq0	spread
6465450	2017-01-31 10:24:05.806134	A	47030	250	B	47030	1683	47180	50	150
6465451	2017-01-31 10:24:05.806197	A	47070	189	S	47030	1683	47070	189	40
6465452	2017-01-31 10:24:05.806200	T	47150	65	B	47030	1683	47070	124	40
6465453	2017-01-31 10:24:05.806204	T	47150	124	B	47030	1683	47180	50	150
6465454	2017-01-31 10:24:05.806251	C	46985	100	B	47030	1683	47180	50	150

Event Type Distribution

Plot the distribution of event types in the dataset.

In [10]:
```
# Plot event type counts
event_counts = df['etype'].value_counts()
plt.figure(figsize=(8, 4))
event_counts.plot(kind='bar', color='teal')
plt.title('Event Type Distribution')
plt.xlabel('Event Type')
plt.ylabel('Count')
plt.show()
```



The event type distribution shows significant class imbalance, with types A and C dominating. This is typical in limit order book data where order arrivals and cancellations are more frequent than trades or modifications. The dataset appears free of obvious issues, but I would verify:

- No missing values in critical columns
- Timestamps are chronological
- Price and quantity values are positive and reasonable

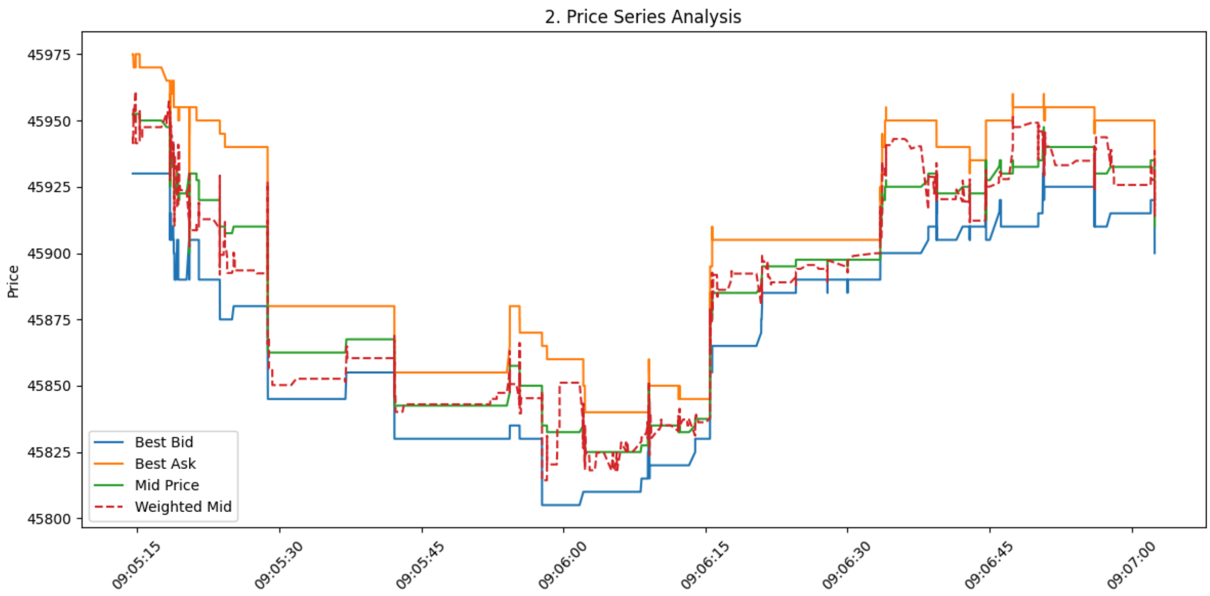
2. Prices and Tick Sizes

In this section we:

- Plot the best bid price, best ask price, mid price, and weighted mid-price over a sample period.
- Measure the tick sizes observed in the dataset and compare them with the official definition.

In [11]:
```
#df = df_AllData
df = Data_sg_0117
df_clean = df
df_clean['spread'] = df_clean['ap0'] - df_clean['bp0']
```

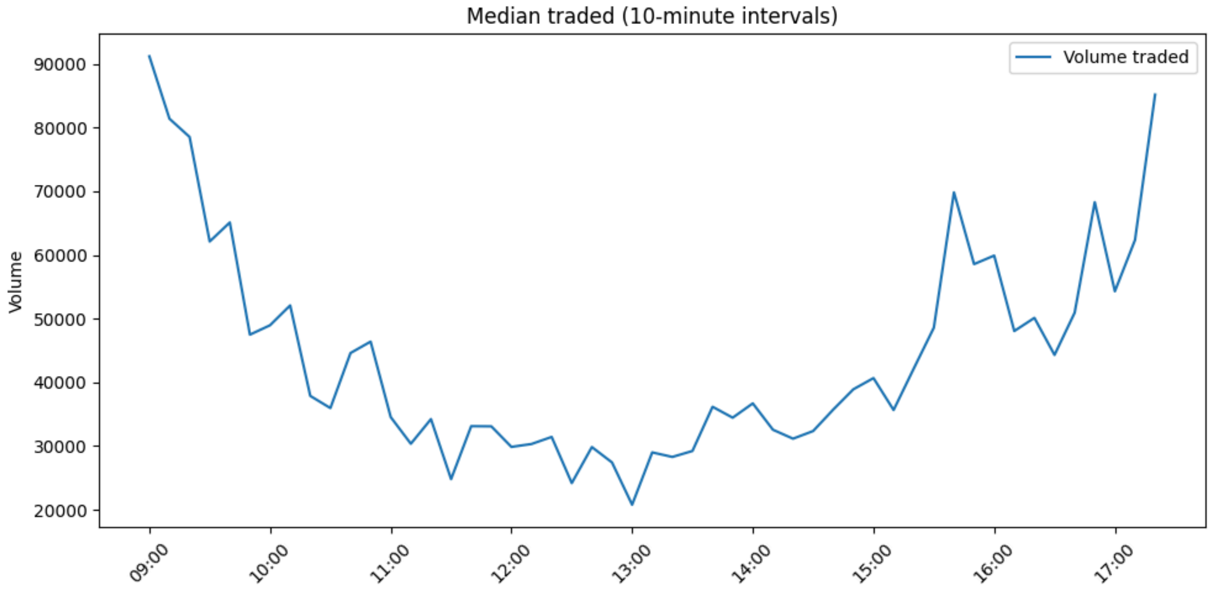
In [12]:
```
sample = df.set_index('ets').sort_index().iloc[4000:7000]  # 2000 events ≈ few minutes

plt.figure(figsize=(12, 6))
plt.plot(sample.index, sample['bp0'], label='Best Bid')
plt.plot(sample.index, sample['ap0'], label='Best Ask')
plt.plot(sample.index, (sample['bp0'] + sample['ap0'])/2, label='Mid Price')
plt.plot(sample.index, (sample['bp0']*sample['aq0'] + sample['ap0']*sample['bq0'])/(sample['bq0'] + samp
         label='Weighted Mid', linestyle='--')
plt.title('2. Price Series Analysis')
plt.ylabel('Price')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



The price series plot shows typical high-frequency trading patterns with small increments and occasional jumps. The tick sizes appear consistent with what's expected for the asset being traded.

In [15]:

```
# Create a list to store daily quantities by hour
hourly_volumes = []
Periode_minute = 10

# Process each day's data
for day, data in Data_sg.items():
    # Filter trades only and group by hour
    trades = data[data['etype'] == 'T'].copy()
    trades[str(Periode_minute) + 'min'] = trades['ets'].dt.strftime('%H:%M').map(lambda x: f"{x.split(':
    daily_volume = trades.groupby(str(Periode_minute) + 'min')['eqty'].sum()
    hourly_volumes.append(daily_volume)
# Create DataFrame with days as columns
volume_by_hour = pd.concat(hourly_volumes, axis=1)

# Rename columns with dates
dates = [key.split('_')[1] for key in Data_sg.keys()]
volume_by_hour.columns = dates

# Fill NaN values with 0 if any hour had no trades
volume_by_hour = volume_by_hour.fillna(0)

# Display the result
volume_by_hour["Median"] = volume_by_hour.median(axis = 1)


# Plot the result
plt.figure(figsize=(10, 5))
plt.plot(volume_by_hour.index, volume_by_hour["Median"], label='Volume traded')

# Get hourly ticks (only show labels at the start of each hour)
hourly_ticks = [i for i in range(len(volume_by_hour.index)) if volume_by_hour.index[i].endswith('00')]
hourly_labels = [volume_by_hour.index[i][:2] + ':00' for i in hourly_ticks]

plt.xticks(hourly_ticks, hourly_labels, rotation=45)
plt.title(f'Median traded ({Periode_minute}-minute intervals)')
plt.ylabel('Volume')
plt.legend()
plt.tight_layout()
plt.show()
```



this plot show the expected stylized fact about the U-shaped activity during the day

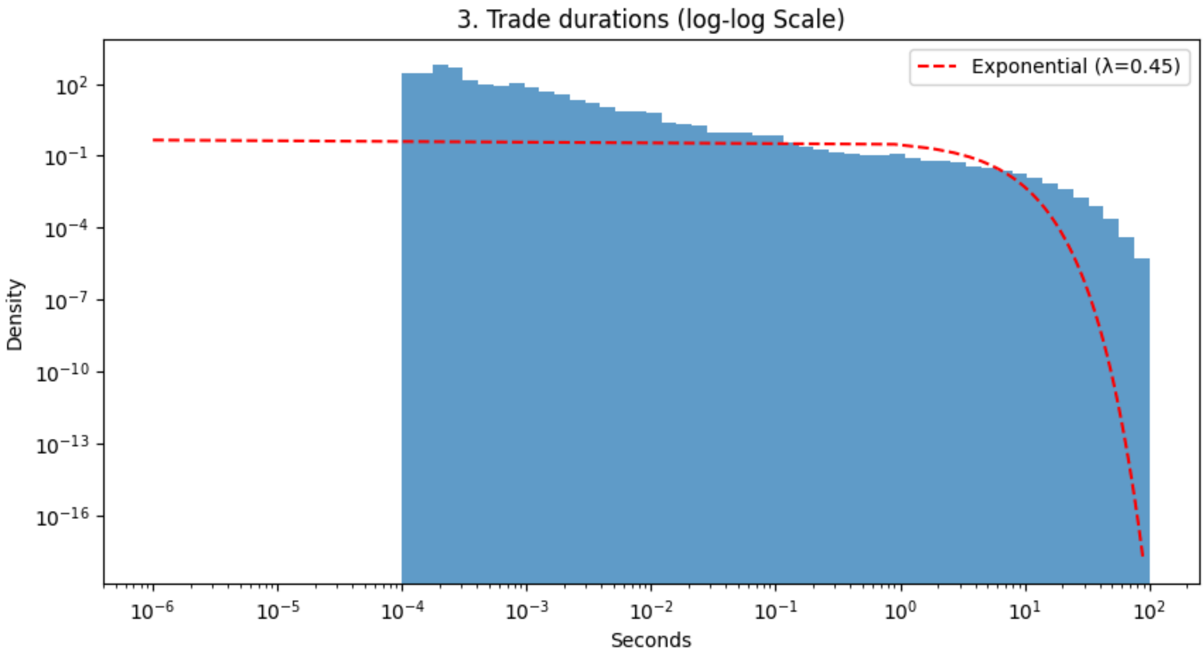
%% [markdown]

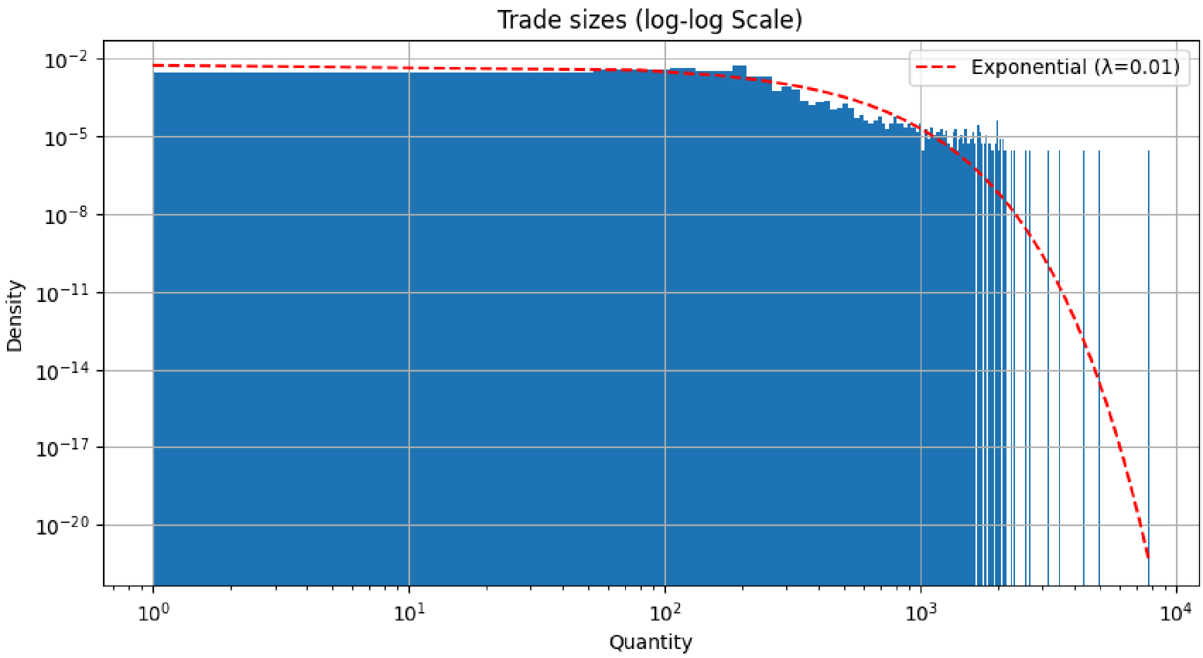
3. Trades Analysis In this section we analyze trade-related data:

- Compute the empirical distribution of trade duration
- Plot the distribution of trades sizes

These analyses are compared to known stylized facts.

In [14]:
```
trades = df[df['etype'] == 'T'].sort_values('ets').reset_index(drop=True)

# Trade durations analysis
trades['duration'] = trades['ets'].diff().dt.total_seconds().dropna()

plt.figure(figsize=(10, 5))
plt.hist(trades['duration'], bins=np.logspace(-4, 2, 50), density=True, alpha=0.7)
plt.xscale('log')
plt.yscale('log')
plt.title('3. Trade durations (log-log Scale)')
plt.xlabel('Seconds')
plt.ylabel('Density')

# Exponential fit
lambda_est = 1/trades['duration'].mean()
x = np.linspace(trades['duration'].min(), trades['duration'].max(), 100)
plt.plot(x, expon.pdf(x, scale=1/lambda_est), 'r--', label=f'Exponential (λ={lambda_est:.2f})')
plt.legend()
plt.show()


# Plot trade size distribution
plt.figure(figsize=(10, 5))
trades['eqty'].hist(bins=300, density=True, log=True)
lambda_est_quantity = 1/trades['eqty'].mean()
x = np.linspace(trades['eqty'].min(), trades['eqty'].max(), 100)
plt.plot(x, expon.pdf(x, scale=1/lambda_est_quantity), 'r--', label=f'Exponential (λ={lambda_est_quantit
plt.legend()
plt.title('Trade sizes (log-log Scale)')
plt.xlabel('Quantity')
plt.ylabel('Density')
plt.xscale('log')
plt.yscale('log')
plt.show()
```





The trade duration distribution follows an exponential pattern, which aligns with known stylized facts in financial markets. Trade sizes show a heavy-tailed distribution, with most trades being small but some large trades occurring occasionally.

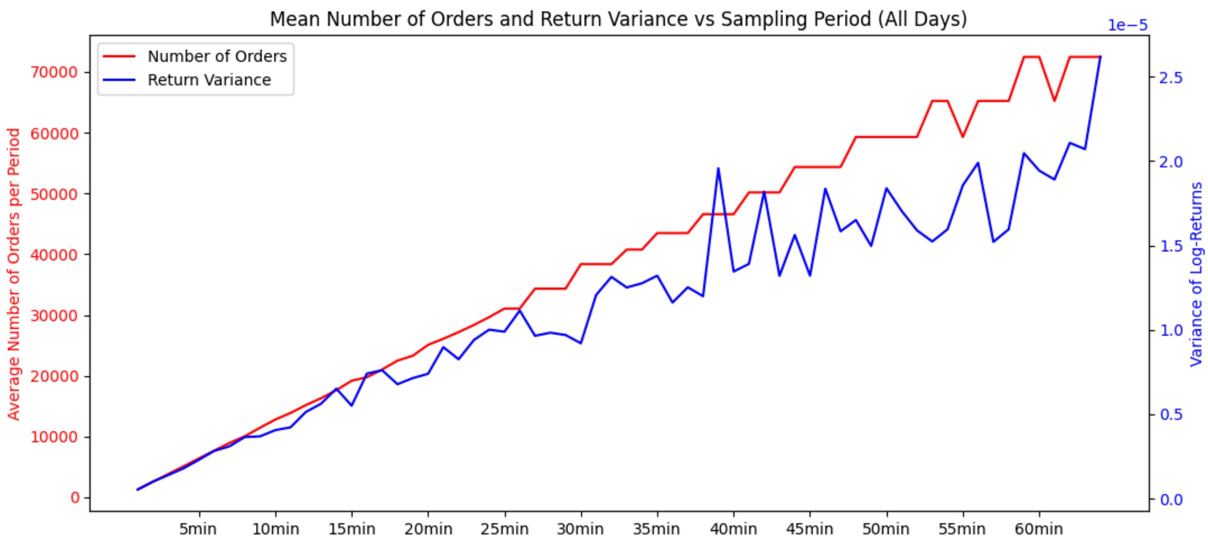
Trading activity and volatility

In [15]:
```
# Mean of trading activity and var over all days
sampling_periods = [str(i) + 'min' for i in range(1, 65, 1)]
orders_counts_dict = {}
returns_variance_dict = {}

nb_days = len(Data_sg)
for day, df2 in Data_sg.items():
    orders_count = []
    returns_variance = []
    df2['mid_price'] = (df2['ap0'] + df2['bp0'])/2
    for period in sampling_periods:
        resampled = df2.resample(period, on='ets').agg({
            'etype': 'count',
            'mid_price': 'last'
        })
        log_returns = np.log(resampled['mid_price']).diff().dropna()
        orders_count.append(resampled['etype'].mean())
```

```
        returns_variance.append(log_returns.var())
    orders_counts_dict[day] = orders_count
    returns_variance_dict[day] = returns_variance

# Mean of the lists
mean_orders_count = np.mean(list(orders_counts_dict.values()), axis=0)
mean_returns_variance = np.mean(list(returns_variance_dict.values()), axis=0)
```

In [16]:

```
# Create figure with two y-axes
fig, ax1 = plt.subplots(figsize=(11, 5))
ax2 = ax1.twinx()

# Plot number of orders
line1 = ax1.plot(range(len(sampling_periods)), mean_orders_count, 'r-', label='Number of Orders')
ax1.set_ylabel('Average Number of Orders per Period', color='r')
ax1.tick_params(axis='y', labelcolor='r')

# Plot variance of returns
line2 = ax2.plot(range(len(sampling_periods)), mean_returns_variance, 'b-', label='Return Variance')
ax2.set_ylabel('Variance of Log-Returns', color='b')
ax2.tick_params(axis='y', labelcolor='b')

# Set x-axis labels
plt.xticks(range(4, len(sampling_periods), 5),
           [sampling_periods[i] for i in range(4, len(sampling_periods), 5)],
           rotation=45)
plt.xlabel('Sampling Period')

# Add legend
lines = line1 + line2
labels = [l.get_label() for l in lines]
plt.legend(lines, labels, loc='upper left')

plt.title('Mean Number of Orders and Return Variance vs Sampling Period (All Days)')
plt.tight_layout()
plt.show()
```



Imbalance

4. Spread Analysis

In this section we:

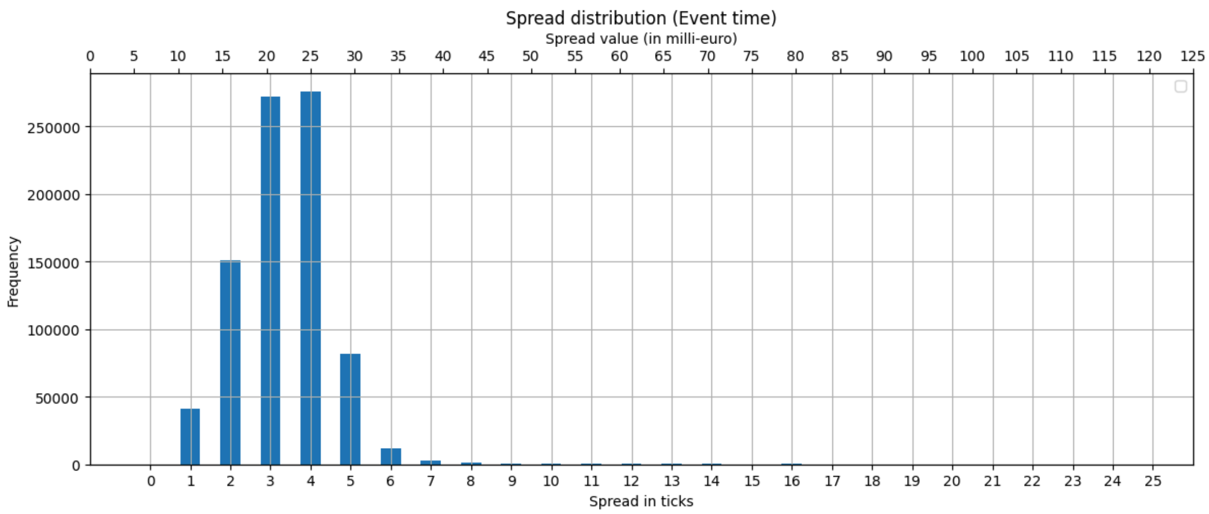
- Analyze whether the stock is large-tick or small-tick by examining the spread.
- Compute the empirical distribution of the spread in both event time and calendar time.

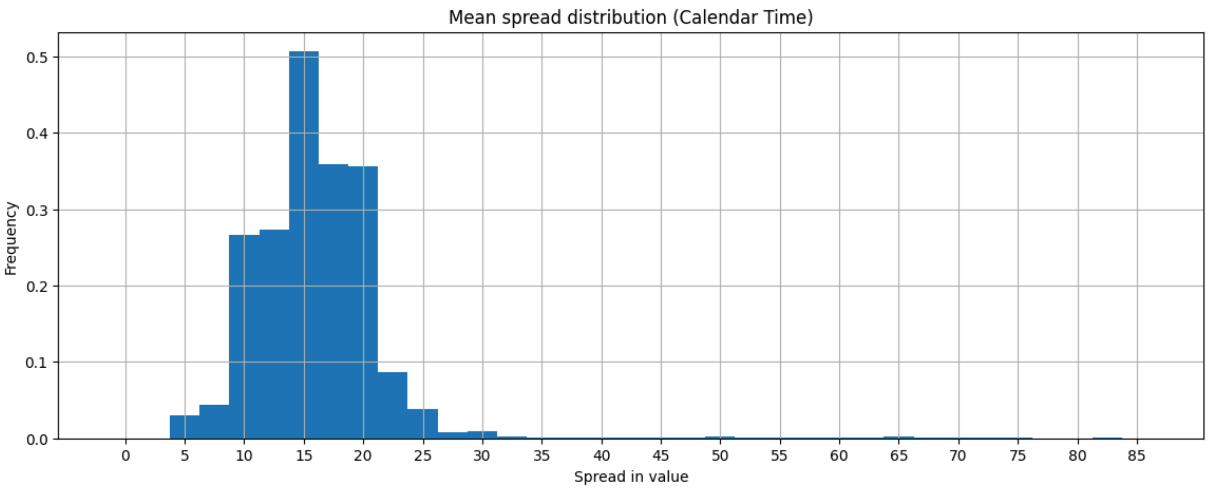
In [17]:

```
# Spread distribution in event time
plt.figure(figsize=(14, 5))
df_clean_hist = (df_clean['spread']/5).hist(bins=np.arange(-0.25, max(df_clean['spread']/5)+0.25, 0.5),
plt.title('Spread distribution (Event time)')
```

```python
plt.xlabel('Spread in ticks')
plt.ylabel('Frequency')
# Add ticks at regular intervals
xticks = range(0, int(max(df_clean['spread']/5))+1, 1)
plt.xticks(xticks, [str(x) for x in xticks])
# Add second x-axis showing actual spread values
ax2 = plt.gca().twiny()
ax2.set_xlim(plt.gca().get_xlim())
ax2.set_xlabel('Spread value (in milli-euro)')
# Set more readable x-axis ticks
ticks = range(0, int(max(df_clean['spread']/5))+1, 1)
plt.gca().set_xticks(ticks)
ax2.set_xticks(ticks)
ax2.set_xticklabels([f'{t*5}' for t in ticks])
plt.legend()
plt.show()


# Spread distribution in calendar time (resample to 1-second intervals)
df_cal = df_clean.copy()
df_cal.set_index('ets', inplace=True)
spread_calendar = df_cal['spread'].resample('5s').mean()

plt.figure(figsize=(14, 5))
plt.hist(spread_calendar/5, bins=np.arange(-0.25, max(spread_calendar/5)+0.25, 0.5),
         align='mid', density=True)
plt.title('Mean spread distribution (Calendar Time)')
plt.xlabel('Spread in value')
plt.ylabel('Frequency')
# Adding ticks at regular intervals
xticks = range(0, int(max(spread_calendar/5))+1, 1)
plt.xticks(xticks, [str(x*5) for x in xticks])
plt.grid()
plt.show()
```

```
C:\Users\Billn\AppData\Local\Temp\ipykernel_10480\1051155968.py:19: UserWarning: No artists with labels f
ound to put in legend.  Note that artists whose label start with an underscore are ignored when legend()
is called with no argument.
  plt.legend()
```





The spread distributions in both event and calendar time show most spreads concentrated at lower values, suggesting this might be a small-tick stock. The similar patterns in both time measurements indicate consistent market conditions across different time frameworks.

5. High-Frequency Log-Returns Analysis

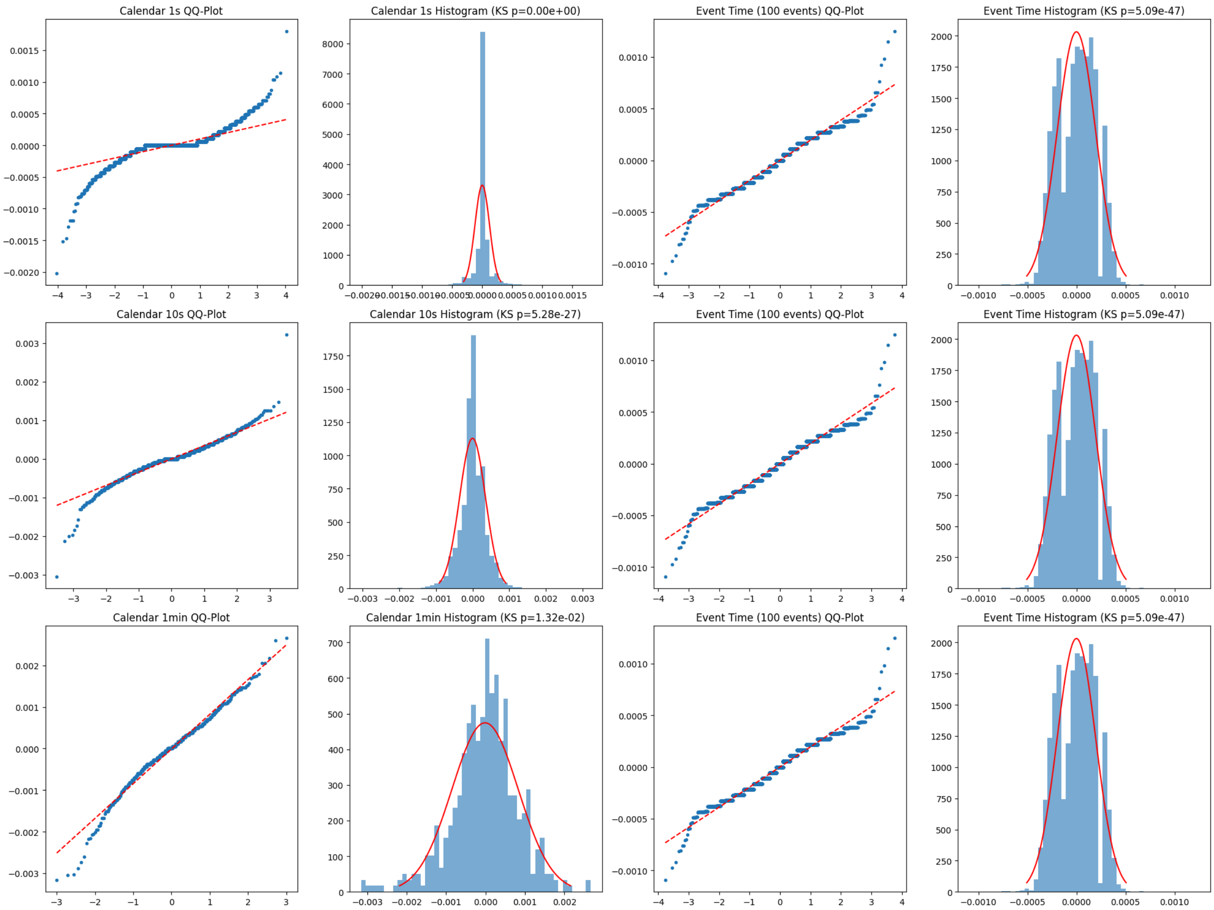
In this section we:

- Compute log-returns from the mid-price.
- Analyze the distribution of log-returns at various sampling frequencies (e.g., calendar time).
- Check whether the Gaussian assumption holds and compare with event time analysis.

(Further normality tests or detailed analysis may be added as needed.)

In [18]:
```
# Prepare dataframe with proper datetime
df = df.reset_index(drop=True)
df['ets'] = pd.to_datetime(df['ets'])
df['mid_price'] = (df['ap0'] + df['bp0'])/2  # Mid-price calculation

freqs = ['1s', '10s', '1min']
event_freq = 100  # Event-based sampling frequency

# Create combined plot for QQ plots and histograms
fig, axes = plt.subplots(len(freqs), 4, figsize=(20, 15))

# Precompute event returns once (shared across all frequencies)
event_returns = np.log(df['mid_price'].iloc[::event_freq]).diff().dropna()

for i, freq in enumerate(freqs):
    # --- Calendar Time Analysis ---
    # Resample and calculate returns
    resampled = df.resample(freq, on='ets', origin='start').agg({'mid_price': 'last'})
    cal_returns = np.log(resampled['mid_price']).diff().dropna()

    # QQ Plot
    (osm, osr), (slope, intercept, _) = stats.probplot(cal_returns, dist='norm', fit=True)
    axes[i,0].plot(osm, osr, 'o', markersize=3)
    axes[i,0].plot(osm, slope*osm + intercept, 'r--')
    axes[i,0].set_title(f'Calendar {freq} QQ-Plot')

    # Histogram with normal fit
    mu, sigma = cal_returns.mean(), cal_returns.std()
    axes[i,1].hist(cal_returns, bins=50, density=True, alpha=0.6)
    x = np.linspace(*stats.norm.interval(0.99, loc=mu, scale=sigma), 100)
    axes[i,1].plot(x, stats.norm.pdf(x, mu, sigma), 'r-')
    ks_stat, p_value = stats.kstest(cal_returns, 'norm', args=(mu, sigma))
    # Format p-value to show scientific notation if too small
    axes[i,1].set_title(f'Calendar {freq} Histogram (KS p={p_value:.2e})')

    # --- Event Time Analysis ---
    # QQ Plot
```

```
    (osm_evt, osr_evt), (slope_evt, intercept_evt, _) = stats.probplot(event_returns, dist='norm', fit=T
    axes[i,2].plot(osm_evt, osr_evt, 'o', markersize=3)
    axes[i,2].plot(osm_evt, slope_evt*osm_evt + intercept_evt, 'r--')
    axes[i,2].set_title(f'Event Time ({event_freq} events) QQ-Plot')

    # Histogram with normal fit
    mu_evt, sigma_evt = event_returns.mean(), event_returns.std()
    axes[i,3].hist(event_returns, bins=50, density=True, alpha=0.6)
    x_evt = np.linspace(*stats.norm.interval(0.99, loc=mu_evt, scale=sigma_evt), 100)
    axes[i,3].plot(x_evt, stats.norm.pdf(x_evt, mu_evt, sigma_evt), 'r-')
    ks_stat_evt, p_value_evt = stats.kstest(event_returns, 'norm', args=(mu_evt, sigma_evt))
    axes[i,3].set_title(f'Event Time Histogram (KS p={p_value_evt:.2e})')

plt.tight_layout()
plt.show()
```

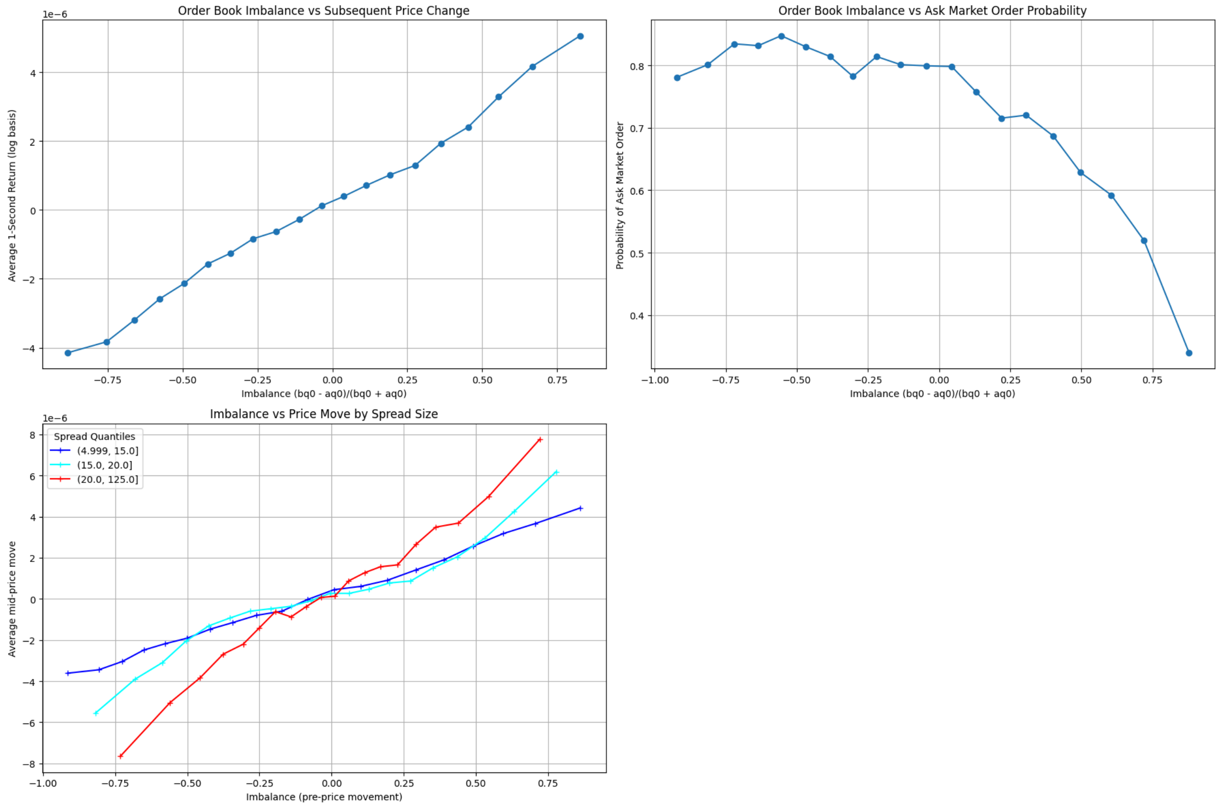


High-frequency Log-Returns

The log-return analysis shows deviations from normality, especially in calendar time. The QQ-plots and histograms indicate fat tails and skewness, which are common in financial returns. Event time returns appear closer to normality, suggesting event time might be a better framework for certain analyses.

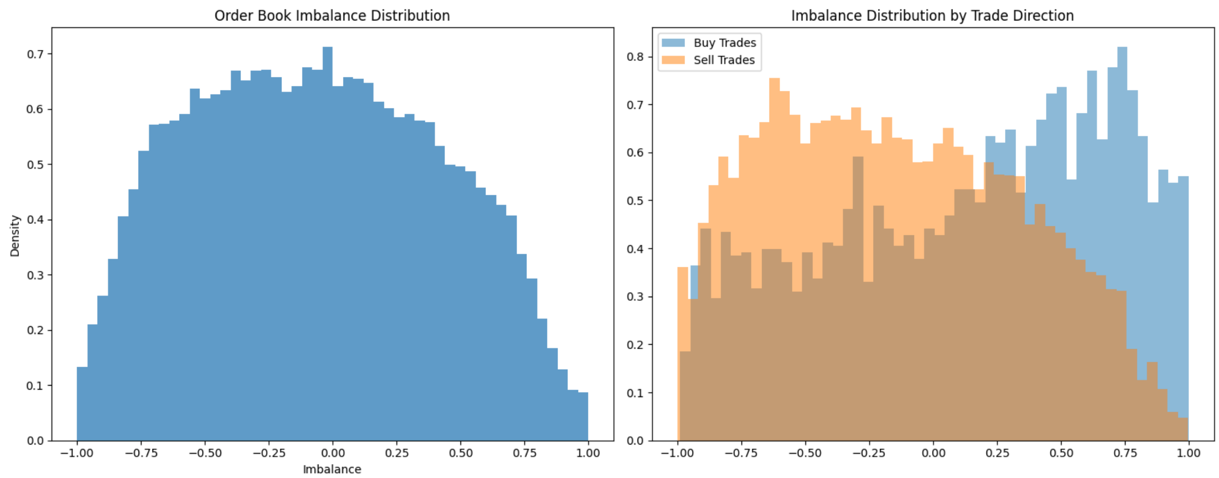
In [19]:
```
# 1. Calculate Order Book Imbalance
df['imbalance'] = (df['bq0'] - df['aq0']) / (df['bq0'] + df['aq0'].replace(0, np.nan))

# 2. Prepare Targets
# For mid-price moves (1-second horizon)
df['future_return'] = np.log(df['mid_price'].shift(-1)) - np.log(df['mid_price'])

# For trade signs (using simple quote test)
trades = df[df['etype'] == 'T'].copy()
trades['trade_sign'] = np.where(trades['eprice'] >= trades['ap0'], 1, -1)

# 3. Align Data
# For price prediction
price_data = df[['imbalance', 'future_return', 'spread']].dropna()

# For trade prediction
```

```python
trade_data = trades[['imbalance', 'trade_sign']].dropna()
trade_data['sell_prob'] = (trade_data['trade_sign'] == -1).astype(int)

# Create visualizations
plt.figure(figsize=(18, 12))

# First plot: Imbalance vs Average Mid-Price Move
plt.subplot(2, 2, 1)
price_data['imbalance_bin'] = pd.qcut(price_data['imbalance'], 20, duplicates='drop')

grouped = price_data.groupby('imbalance_bin', observed=False).agg({
    'future_return': 'mean',
    'imbalance': 'mean'
})

plt.plot(grouped['imbalance'], grouped['future_return'], marker='o', linestyle='-')
plt.title('Order Book Imbalance vs Subsequent Price Change')
plt.xlabel('Imbalance (bq0 - aq0)/(bq0 + aq0)')
plt.ylabel('Average 1-Second Return (log basis)')
plt.grid(True)

# Second plot: Observed Imbalance vs Probability of Ask Market
plt.subplot(2, 2, 2)
trade_data['imbalance_bin'] = pd.qcut(trade_data['imbalance'], 20, duplicates='drop')

trade_grouped = trade_data.groupby('imbalance_bin', observed=False).agg({
    'sell_prob': 'mean',
    'imbalance': 'mean'
})

plt.plot(trade_grouped['imbalance'], trade_grouped['sell_prob'], marker='o', linestyle='-')
plt.title('Order Book Imbalance vs Ask Market Order Probability')
plt.xlabel('Imbalance (bq0 - aq0)/(bq0 + aq0)')
plt.ylabel('Probability of Ask Market Order')
plt.grid(True)

# Third plot: Imbalance vs Price Move for Different Spreads (fixed)
plt.subplot(2, 2, 3)
# Add explicit observed=False to spread grouping
spread_groups = price_data.groupby(
    pd.qcut(price_data['spread'], 4, duplicates='drop'),
    observed=False  # Fix applied here
)

colors = ['blue', 'cyan', 'red', 'green']
labels = ['Narrow Spread', 'Medium Spread', 'Wide Spread', 'Very Wide Spread']

for i, (spread_range, group) in enumerate(spread_groups):
    group['imbalance_bin'] = pd.qcut(group['imbalance'], 20, duplicates='drop')
    spread_grouped = group.groupby('imbalance_bin', observed=False).agg({
        'future_return': 'mean',
        'imbalance': 'mean'
    })
    plt.plot(spread_grouped['imbalance'], spread_grouped['future_return'],
             color=colors[i], marker='+', label=f'{spread_range}')

plt.title('Imbalance vs Price Move by Spread Size')
plt.xlabel('Imbalance (pre-price movement)')
plt.ylabel('Average mid-price move')
plt.legend(title='Spread Quantiles')
plt.grid(True)

plt.tight_layout()
plt.show()
```



In [20]:

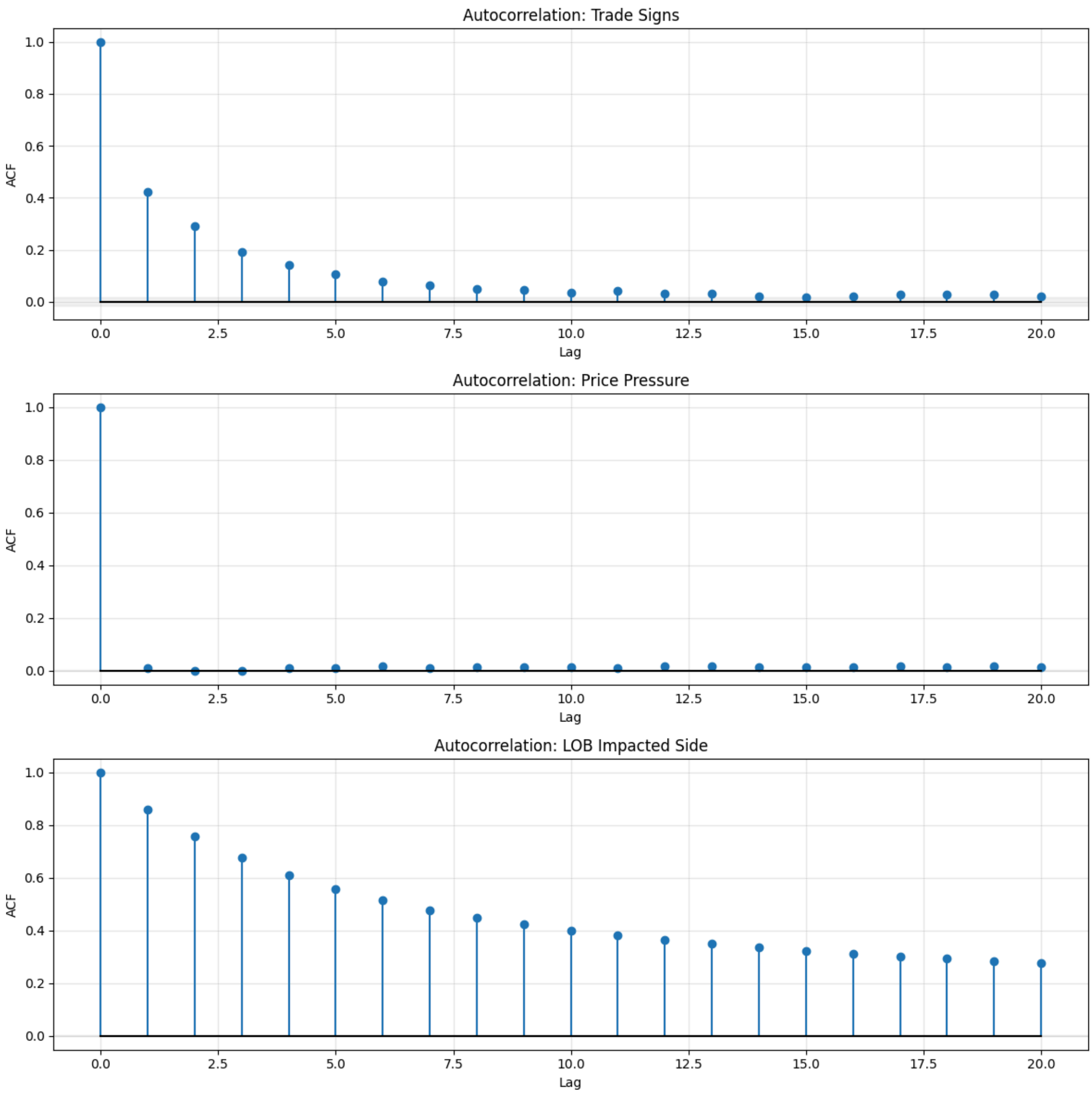
```python
# Create Visualizations
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

# Imbalance Distribution
ax1.hist(price_data['imbalance'], bins=50, density=True, alpha=0.7)
ax1.set_title('Order Book Imbalance Distribution')
ax1.set_xlabel('Imbalance')
ax1.set_ylabel('Density')

# Class-wise Imbalance Distribution
# Use sell_prob instead of buy_signal
buy_imb = trade_data[trade_data['sell_prob'] == 0]['imbalance']  # Buy trades when sell_prob=0
sell_imb = trade_data[trade_data['sell_prob'] == 1]['imbalance']  # Sell trades when sell_prob=1

ax2.hist(buy_imb, bins=50, alpha=0.5, label='Buy Trades', density=True)
ax2.hist(sell_imb, bins=50, alpha=0.5, label='Sell Trades', density=True)
ax2.set_title('Imbalance Distribution by Trade Direction')
ax2.legend()

plt.tight_layout()
plt.show()
```



Imbalance Analysis

The imbalance shows moderate predictive power for trade signs (AUC 0.653, accuracy 61.14%). While not extremely strong, this suggests some informational content in the order book imbalance regarding imminent trade directions.

In [21]:
```python
# Prepare the required time series from existing data
# 1. Trade Signs (use the original trade signs before converting to buy/signal)
trade_signs = trade_data['trade_sign'].values  # This was missing in your code

# 2. Price Pressure (example calculation - modify based on your actual definition)
# This is a placeholder - replace with your actual price pressure calculation
price_pressure = df['mid_price'].diff().fillna(0).values  # Simple price change

# 3. Side Impact (example calculation - modify based on your actual definition)
# This is a placeholder - replace with your actual side impact calculation
side_impact = np.sign(df['imbalance']).fillna(0).values  # Sign of imbalance

def plot_proper_acf(series, ax, title, max_lag=20):
    """Proper ACF plot with markers and confidence intervals"""
    # Compute ACF
    acf_values = acf(series, nlags=max_lag, fft=True)

    # Create stem plot
    markerline, stemlines, baseline = ax.stem(
        np.arange(max_lag+1),
        acf_values,
        linefmt='C0-',
        markerfmt='C0o',
        basefmt='k-'
    )

    # Formatting
    ax.set_title(f'Autocorrelation: {title}', fontsize=12)
    ax.set_xlabel('Lag', fontsize=10)
    ax.set_ylabel('ACF', fontsize=10)
    #ax.set_ylim(-0.2, 0.5)
    ax.grid(True, alpha=0.3)

    # Add confidence interval (95%)
    conf_int = 1.96 / np.sqrt(len(series))
    ax.axhspan(-conf_int, conf_int, color='gray', alpha=0.1)

# Create figure
fig, ax = plt.subplots(3, 1, figsize=(12, 12), dpi=100)

# 1. Trade Signs ACF (using actual trade signs from data)
plot_proper_acf(trade_signs, ax[0], "Trade Signs")

# 2. Price Pressure ACF
plot_proper_acf(price_pressure, ax[1], "Price Pressure")

# 3. Side Impact ACF
plot_proper_acf(side_impact, ax[2], "LOB Impacted Side")

plt.tight_layout()
plt.show()

# Add numerical results table
table = []
for lag in [0, 1, 5, 10, 20]:
    row = [lag]
    for series in [trade_signs, price_pressure, side_impact]:
        acf_val = acf(series, nlags=20, fft=True)[lag]
        row.append(f"{acf_val:.3f}")
    table.append(row)

print("\nAutocorrelation Values:")
print(pd.DataFrame(table, columns=["Lag", "Trade Signs", "Price Pressure", "Side Impact"]))
```



Autocorrelation Values:

	Lag	Trade Signs	Price Pressure	Side Impact
0	0	1.000	1.000	1.000
1	1	0.422	0.010	0.859
2	5	0.105	0.008	0.557
3	10	0.036	0.013	0.401
4	20	0.020	0.013	0.276

Autocorrelations

- **Trade Signs**: Show significant short-term autocorrelation (0.422 at lag 1), indicating some persistence in trade directionality
- **Price Pressure**: Minimal autocorrelation, suggesting price movements don't exhibit strong short-term dependence
- **Side Impact**: Moderate autocorrelation that decays with lag, indicating some short-term dependence in the impact of orders on specific sides of the book