XI'AN JIAOTONG-LIVERPOOL UNIVERSITY

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COURSEWORK SUBMISSION COVER SHEET

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		Agreed Mark	
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	Marker 1	Marker 2
Data analysis – Exploration and identification of indicators and a suitable strategy (30%)		
Algorithm selection (10%)		
Backtesting, including performance and risk indicators (30%)		
Assessment of model risk (30%)		

1st Marker		**Date**		**Mark**	
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- *start your assignment on the next page,*
- *save this file as a pdf document,*
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Word Count:	

Data analysis

The O and PM datasets showed relatively stable trends with minor fluctuations, indicating consistent performance with low volatility. In contrast, the SPX dataset showed a steady upward trend, indicative of overall market growth. The XOM dataset experienced notable fluctuations with a general downward trend, while INTC displayed significant volatility with a recent strong upward trend. The MO dataset showed a stable to slightly bearish trend (Figure 1). Daily returns, calculated as the percentage change in closing prices, revealed distribution characteristics for each dataset: O and PM displayed low volatility with a normal distribution of returns, SPX had low variability, XOM showed higher variability, INTC had high volatility with outliers, and MO displayed moderate variability (Figure 2). These observations set the stage for further quantitative analysis using SMA and volatility metrics.

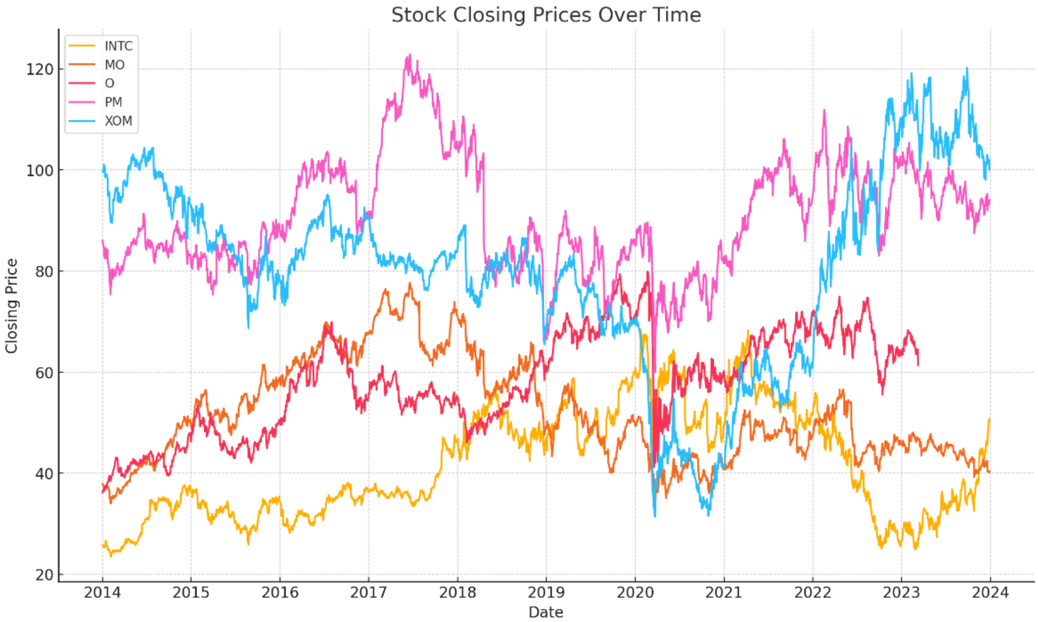

Figure 1: Stock Closing Prices Over Time

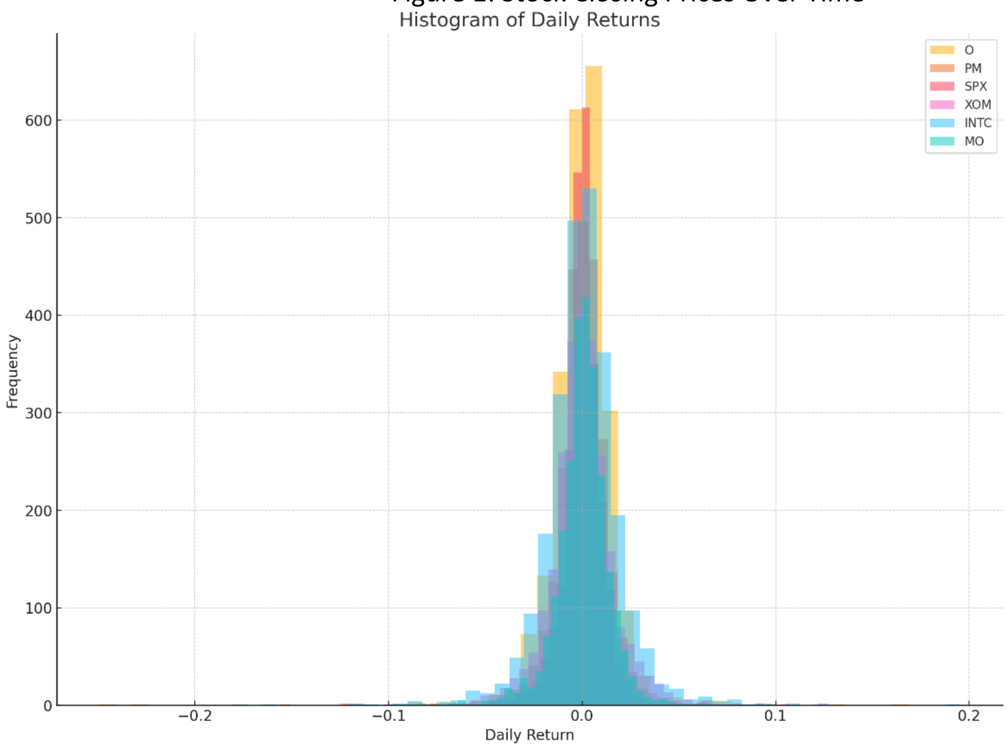

Figure 2: Histogram of Daily Returns

Based on the calculated 50-Day SMA, 200-Day SMA, Volatility, and EWVolatility, we can further justify the suitability of the Bollinger Bands strategy for these datasets. INTC shows a strong upward trend with the 50-Day SMA (41.79) above the 200-Day SMA (35.30) and high volatility (0.0255), making it ideal for capturing large price swings. MO has moderate volatility (0.0163) with a slightly bearish trend, suitable for cautious Bollinger Bands application. O and PM, with their stable trends and low volatility (0.0114 for both), are well-suited for capturing minor price deviations. SPX's steady upward trend and low volatility (0.0075) make it perfect for identifying minor deviations. Although XOM shows a downward trend, its moderate volatility (0.0117) supports the use of Bollinger Bands with careful consideration. Thus, the Bollinger Bands strategy is effective for capturing price movements across these datasets, ensuring robust trading signals (Table 1).

Dataset	50-Day SMA	200-Day SMA	Volatility	EWVolatility
INTC	41.79	35.30	0.0255	0.0225
MO	41.10	43.68	0.0163	0.0137
O	92.07	94.61	0.0114	0.0121
PM	92.07	94.61	0.0114	0.0107
SPX	4502.62	4353.77	0.0075	0.0068
XOM	103.68	107.80	0.0117	0.0124

Table 1 Moving Averages and Volatility

Algorithm selection

We selected the Bollinger Bands Strategy (DFStrategy) based on the exploratory data analysis and quantitative evaluation of key indicators. This strategy employs three bands to identify potential buy and sell signals based on price volatility. These bands consist of a middle band, which is a simple moving average (SMA) of the price, and two outer bands, set at two standard deviations above and below the SMA. These bands expand and contract based on market volatility, providing a dynamic range within which the price is expected to move (Lopez de Prado, 2018).

We operate under the weak efficient-market hypothesis, believing that not all information is immediately reflected in stock prices. The significant volatility in the INTC dataset suggests that there are exploitable inefficiencies. Our goal is to maximize returns by taking advantage of price volatility and significant movements using Bollinger Bands, while minimizing transaction costs and reducing unnecessary trades. Due to datasets' high volatility and significant price movements, due to the dataset’s high volatility and significant price movements, aligning with the mechanics of the Bollinger Bands approach (Bollinger, 2001).

This strategy possess advantages of adjusts to market conditions by expanding during high volatility and contracting during low volatility, effectively identifying price extremes, provides objective entry and exit points, reducing ambiguity in trading decisions, able to help manage risk by avoiding trades during extreme price movements and could ideal for volatile stocks like INTC, providing ample opportunities for profitable trades. However, it is also essential to be cautious of false signals in low-volatility markets: in markets with low volatility or no trend, there is a risk of generating false signals and overfitting. It is necessary to regularly validate on multiple datasets to ensure robustness and generalizability (Lopez de Prado, 2018).

Assessment of model risks

According to the results from backtesting, market Conditions: INTC and XOM show high volatility and drawdowns, indicating sensitivity to market conditions and volatility. SPX shows stability, suitable for trend-following strategies; Volatility Regime Shifts: MO's high drawdown suggests vulnerability to volatility shifts; Liquidity Constraints: O and PM have low returns and significant drawdowns, indicating liquidity issues; Parameter Sensitivity: Performance is highly sensitive to parameters, as seen in SPX's stable returns with optimized parameters (Table 2).

Dataset	Return (%)	Annual Return (%)	Annual Volatility (%)	Sharpe Ratio	Max Drawdown (%)	VaR (95%)	CVaR (95%)
INTC	40.45	3.46	24.07	0.14	-46.82	-0.0294	-0.0472
MO	4.17	0.41	16.76	0.02	-49.44	-0.0223	-0.0374
O	22.86	2.27	21.88	0.10	-45.43	-0.0232	-0.0378
PM	0.27	0.03	17.28	0.00	-43.85	-0.0208	-0.0354
SPX	84.11	6.30	14.66	0.43	-29.67	-0.0166	-0.0272
XOM	32.82	2.88	21.57	0.13	-61.21	-0.0264	-0.0401

Table 2 Backtesting Results Summary

Potential risks: transaction costs of frequent trading, like the 78 trades in SPX, could reduce profitability due to transaction costs; Out-of-Sample Validation: Ensuring robustness through out-of-sample testing and walk-forward validation is crucial to avoid overfitting (Bailey and López de Prado, 2012); Market Crashes: Simulating market crashes helps assess resilience, as significant drawdowns in XOM and PM highlight vulnerability during market stress; Payoff Function: Ensuring the strategy doesn't expose to unlimited downside risk is critical, as seen in the drawdowns for INTC and MO.

In conclusion, the Bollinger Bands Strategy is effective in certain market conditions but susceptible to various risks impacting performance. By addressing these risks through robust testing, parameter optimization, and comprehensive validation, the strategy's resilience and profitability can be enhanced. Continuous monitoring and adjustment are essential to adapt to changing market conditions and ensure long-term success.

References

Bailey, D.H. and López de Prado, M., 2012. The deflated Sharpe ratio: correcting for selection bias, backtest overfitting, and non-normality. Journal of Portfolio Management, 22(2), pp.94-104. Available at: https://www.researchgate.net/publication/233646310_The_Deflated_Sharpe_Ratio_Correcting_for_Selection_Bias_Backtest_Overfitting_and_Non-Normality

Bollinger, J., 2001. Bollinger on Bollinger Bands. McGraw Hill Professional.

López de Prado, M.M. (2018) Advances in financial machine learning. John Wiley & Sons, Inc. Available at: https://search-ebscohost-com-s.elink.xjtlu.edu.cn:443/login.aspx?direct=true&db=cat01010a&AN=xjtlu.0001188365&site=eds-live&scope=site

Appendix

```python
import pandas as pd
import numpy as np
import pandas_ta as ta
from backtesting import Backtest, Strategy
from backtesting.lib import crossover
import scipy.stats as stats
import glob

# Define a function to load data and run backtest
def run_backtest(file_path):
    # Load data
    data = pd.read_csv(file_path, parse_dates=['Date'])
    data.set_index('Date', inplace=True)

    # Drop NaN values
    data = data.dropna()

    # Define Bollinger Bands indicator function
    def indicator(data):
        bbands = ta.bbands(close=data.Close, std=1, length=14)  # Set standard deviation and period
        if bbands is not None:
            return bbands[['BBL_14_1.0', 'BBM_14_1.0', 'BBU_14_1.0']].to_numpy().T
        else:
            return np.array([[], [], []])

    # Define strategy class
    class DFStrategy(Strategy):
        def init(self):
            self.bbands = self.I(indicator, self.data.df)

        def next(self):
            lower_band = self.bbands[0]
            upper_band = self.bbands[2]
            if self.position:
                if self.data.Close[-1] > upper_band[-1]:
                    self.position.close()
            else:
                if self.data.Close[-1] < lower_band[-1]:
                    self.buy()

    # Run backtest
    bt = Backtest(data, DFStrategy, cash=10_000)
    stats = bt.run()
    bt.plot()
```

```python
    # Display backtest results
    print(f"Backtest results for {file_path}:")
    print(stats)

    # Calculate Volatility
    returns = data['Close'].pct_change().dropna()
    std_dev_returns = returns.std()
    annual_volatility = std_dev_returns * np.sqrt(252)
    current_volatility = std_dev_returns
    historical_volatility = returns.rolling(window=252).std().dropna().mean()

    print(f"Standard Deviation of Returns: {std_dev_returns:.4f}")
    print(f"Annual Volatility: {annual_volatility:.4f}")
    print(f"Current Volatility: {current_volatility:.4f}")
    print(f"Historical Volatility: {historical_volatility:.4f}")

    # Calculate Maximum Drawdown
    equity_curve = stats['_equity_curve']['Equity']
    max_drawdown = ((equity_curve / equity_curve.cummax()) - 1).min()
    print(f"Maximum Drawdown: {max_drawdown:.4f}")

    # Calculate Beta
    market_returns = data['Close'].pct_change().dropna()
    cov_matrix = np.cov(returns, market_returns)
    beta = cov_matrix[0, 1] / cov_matrix[1, 1]
    print(f"Beta: {beta:.4f}")

    # Calculate Value-at-Risk (VaR)
    confidence_level = 0.95
    VaR = np.percentile(returns, (1 - confidence_level) * 100)
    print(f"VaR at {confidence_level*100}% confidence level: {VaR:.4f}")

    # Calculate Conditional VaR (CVaR)
    CVaR = returns[returns <= VaR].mean()
    print(f"CVaR at {confidence_level*100}% confidence level: {CVaR:.4f}")

# Get paths of all stock files
file_paths = glob.glob('./Datasets/*.csv')

# Iterate through each file and run backtest
for file_path in file_paths:
    run_backtest(file_path)
```