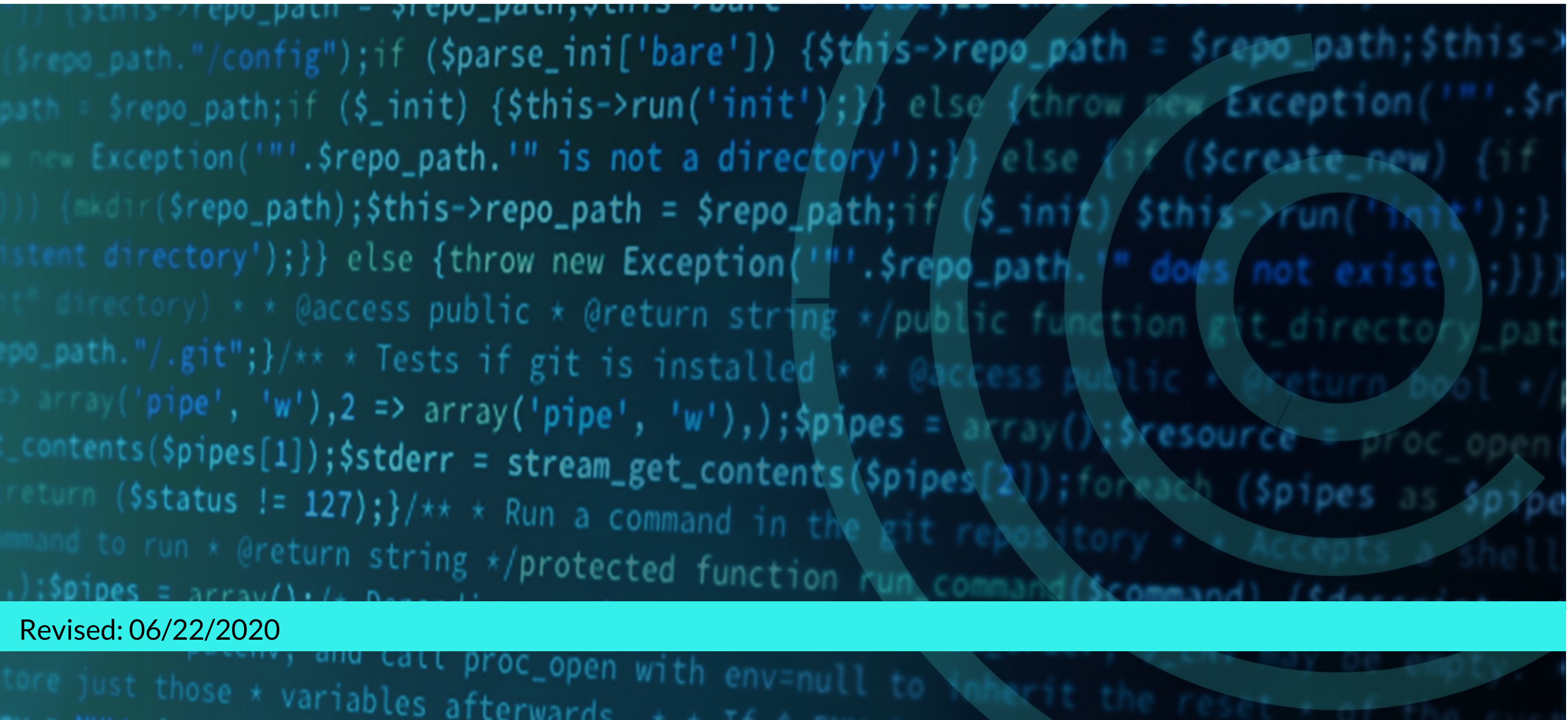
Compiled Notes
Module 1

MScFE 660
Case Studies in Risk Management



Revised: 06/22/2020

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Module 1: The Crash of 1929

This module discusses the 1929 Crash and the subsequent Great Depression that held the world economy captive for over a decade. The module begins by exploring the major macroeconomic trends that led to the crisis through a historical analysis. The module continues by applying several data analysis techniques using Python to model the market conditions during the Great Depression. Historical and economic contexts as well as financial and political trends during those times are discussed to explain how both government and individuals reacted to risks on the Stock Exchange. The module concludes with an overview of the financial crisis that hit Europe in 1931 and initiatives taken globally to rebuild trust in the markets and recover from the economic crisis.

Unit 1: A Storm Brewing: The Build-Up and Crash of 1929

The Wall Street Crash of 1929 occurred in late October 1929 at the **New York Stock Exchange** (NYSE). In the course of a single week, stock market share values collapsed. The events known as 'Black Thursday' and 'Black Tuesday' triggered a decade of extreme economic decline both in the U.S. and around the world, which came to be known as the Great Depression both in America and across the world. What is important to understand from the lead-up to and events of the crash is how *laissez-faire* approaches to market speculation and the situations of panic-selling created the circumstances for the greatest economic collapse in the modern world economy.

The Roaring Twenties

Following the end of World War 1 in 1918, the United States experienced a major boost in the economy as urbanization, industrialization and financial investment in consumer goods industries saw the expansion of the younger, richer, urban population that had money to spare. The new era of the Flapper, dance hall music and a growing automobile market facilitated the growth of American prestige and economic pride. This urbanization, however, came at the cost of the rural agricultural communities that saw major shortages in employable, skilled workers. As a result, agricultural output and farming communities suffered substantial losses during this period.

The 1920s are perhaps best characterized by the extravagance of urban populations who enjoyed lavish lifestyles and were willing to invest in highly speculative offerings on the NYSE. This speculation reflected the hope that the value of stocks would increase unabated as it had since the end of the First World War (1914-1918). The major problem with speculation is that poorly-placed confidence may lead to investor panic. When stocks experience short-term losses, investors will be inclined to sell, which in turn floods the market with available shares, further lowering their values. This panic carries over to other stocks, weakening confidence in the market and resulting in overall decline.

The *laissez-faire* financial policy, marked by minimal regulation and control, embraced by the federal government compounded the swiftness and scope of decline. The Hoover administration, despite the declining gross domestic product and the ongoing decline in agriculture and rural economics, remained steadfast in its non-interventionist approach. This created an economic bubble whereby confidence was not based on rational methods of understanding stock fluctuations, but rather on the personal confidence that investors had in the pathway of the stock exchange.

As the largest economic power of the time, the U.S. experienced the brunt of the initial crash. However, the economic impacts soon spread to Europe, which was still recovering from World War 1 and the Russian Revolution.

The lead-up

Despite the issues arising from speculation (and how the climate of investor confidence kept the NYSE on a tightrope at all times), throughout the 1920s there was an overarching belief that the American economy would continue to grow. However, by 1929, the potential for major financial meltdown was bubbling just beneath the surface. Steel production, construction and agricultural output were slowing down, while easy credit meant that the housing, consumer goods and automobile markets were expanding at an unsustainable rate.

On March 29th, 1929, a minor slide happened on the NYSE after the Federal Reserve sent a warning about excessive speculation in equities. Spurred by the desire to protect their investments, many investors tried to pull out, causing a decline in share prices. Some high profile market participants – like the National City Bank – stepped in to try to stem the losses, and after a minor dip in prices, trading resumed its upward climb until September.

The slip revealed a critical problem with the NYSE: while there was some scope for high-profile investment groups to step in and fix the single issues, the underlying economic problems remained. The slightest hint of crisis could steer the market into trouble and no measures had been put in place by the government or by investment regulatory bodies to prevent this from happening. The stability of the financial market was, at this stage, controlled by human emotion and sentiment.

The beginning of the end started with the crash of the London Stock Exchange in September 1929, after Clarence Hatry, a high-profile British investor, was jailed for fraud and stock market manipulation. Hatry had been placing highly speculative gambles on the London Stock Exchange, despite his extensive debts and minimal assets. Having given fraudulent credit and stock certificates to different banks, Hatry's attempt to cover his own financial issues plunged the stock exchange into turmoil and caused a serious loss of confidence in foreign investment from the NYSE.

The crash

On October 24th the market lost 11% on a day of trading that was so heavy in volume that some investors lost track of their investment values. This was largely due to the inability of the brokerage firms to keep up with the number of sales made on the floor. It was only late in the day that the extent of the losses was fully realized, which resulted in a further rush in sales. Crisis meetings between prominent business and investment leaders saw them elect Richard Whitney, vice president of the NYSE, as the person most able to respond to the crisis.

Backed by the resources of the major banks, Whitney predicted a rise in steel prices, and other blue-chip stocks, which mirrored the approach taken in response to the 1907 stock market panic, wherein major investors stabilized the market by pledging large sums of money. While Whitney managed to stem the short-term crisis, as with the situation in March, it did not address the underlying problems, and the downward slide continued over the next three days.

On October 28th, many investors decided to leave the market as confidence began to slip in the declining Dow Jones Industrial Index and the overall health of the NYSE. The stock exchange slipped by a further 13% and newspapers reported the losses across the country, furthering the decline in financial confidence. On October 29th, panic-selling hit its high mark and the market collapsed as investors refused to buy stocks and dumped their remaining investments wherever they could.

The same methods used by Whitney were adopted by other prominent investors like the Rockefeller family, but this could not shake the decline or the failure in speculative confidence. In the space of two days, more than $14 billion dollars disappeared from the market, requiring financial institutions to call in creditors and recoup assets. This resulted in the Great Depression both in the U.S. and across the world.

Unit 2: Charting the Build-Up and Crash

Volumes, regimes and liquidity

Data analysis will be an important part of many of our modules, including this one. These sections make intensive use of various statistical and data-analysis packages in Python. While these sections include a great deal of code, the aim is not to teach coding or its implementation, as you are expected to come in with those skills.

This section, in particular, will make use of base-packages, such as OS and requests, incorporating data-analysis and plotting using Pandas, NumPy, HoloViews and HvPlot. While many of you are familiar with Pandas and NumPy from previous exposures to Python, there are many online resources to help develop these skills. One package we will use, which may not be familiar to you, is HoloViews and HvPlot. For additional resources on these packages, we recommend using PyViz Tutorials. If you are a bit rusty, I recommend keeping a cheat sheet handy.

The code has been integrated into these sections so students can reproduce and explore it within other parameters or use it in other datasets. It can also guide students on some of the math and help individuals implement their own code in the future.

For the most part, this course will make use of publicly available datasets. In some cases, we will download them programmatically into the code ourselves or integrate numerous data-sources in order to produce our analysis. Much of this course looks at historical data, which can be difficult to come by and oftentimes require a large amount of cleaning. It is crucial that analysts are able to source, clean, integrate and develop data into hypotheses and findings.

Some notes include cells with comments like this:

```
In [1]: ### Fill in some code here to print to console "Financial Engineering"
```

This provides students with the opportunity to better follow the code and extract some of their own findings. This will require you to download the files and run them on your own machine, providing valuable insight into both the code being run and the data being analyzed, as shown below:

In [2]:

```
### Fill in some code here to print to console "Financial Engineering"
print("Financial Engineering")
```

```
Financial Engineering
```

We will start by importing a number of packages. If your environment is set up correctly from the setup notes, it should execute without any issues.

In [1]:

```
# Import Libraries
import os
import requests

import pandas as pd
import numpy as np

import holoviews as hv
import hvplot.pandas
```

In [4]:

```
# Import Plotting Backend
hv.extension('bokeh')
```

The data used for these notes is included if you would like to run this code yourself and analyze the output. You may find it in the course room Compiled Content M1 folder, or download it here:

https://masters.wqu.org/pluginfile.php/177904/mod_folder/content/0/WQU_CSRM_Module%201_Notebooks.zip?forcedownload=1

Code has been included to scrape data directly from the NYSE website – however, this should not be necessary. In long-term historical data, it is often challenging to find consistent information on prices – however, volumes are readily recorded. In order to gain insight into the effects of the crash and the history of these markets, we will observe this datapoint overtime in order to develop an understanding of evolving market regimes.

```
In [5]: date_ranges = [[1970, 1979, 'dat'],
                       [1960, 1969, 'dat'],
                       [1950, 1959, 'dat'],
                       [1940, 1949, 'dat'],
                       [1930, 1939, 'dat'],
                       [1920, 1929, 'prn'],
                       [1900, 1919, 'dat'],
                       [1888, 1899, 'dat']][::-1]
```

```
In [6]: # # Download Data

        # def get_decade(start = 1920, end = 1929, extension='prn'):
        #     "Specify the sparting year of the decade eg. 1900, 2010, 2009"
        #     try:
        #         link = requests.get(f'https://www.nyse.com/publicdocs/nyse/data/Daily_Share_Volume_{start}-{end}.{extension}')
        #         file = os.path.join("..","Data",f"Daily_Share_Volume_{start}-{end}.{extension}")

        #         if link.status_code == 404:
        #             raise
        #         else:
        #             with open(file, 'w') as temp_file:
        #                 temp_file.write(str(link.content.decode("utf-8")))

        #             print(f"Successfully downloaded {start}-{end}")

        #     except:
        #         print("There was an issue with the download. \n\
        # You may need a different date range or file extension. \n\
        # Check out https://www.nyse.com/data/transactions-statistics-data-library")

        # download_history = [get_decade(decade[0], decade[1], decade[2]) for decade in date_ranges]
```

To start exploring this data, we are going to import it into a Pandas DataFrame. Using this DataFrame, we can then import it into HoloViews in order to track specific datapoints over time and interact with them as needed.

```
In [7]: # Read and format the data
        def load_data(start = 1920, end = 1929, extension='prn'):
            path = os.path.join("..","Data",f"Daily_Share_Volume_{start}-{end}.{extension}")

            if extension=='prn':
                data = pd.read_csv(path , sep='   ', parse_dates=['Date'], engine='python').iloc[2:,0:2]
                data.loc[:,"  Stock U.S Gov't"] = pd.to_numeric(data.loc[:,"  Stock U.S Gov't"], errors='coerce')
                data.Date = pd.to_datetime(data.Date, format='%Y%m%d', errors='coerce')
                data.columns = ['Date','Volume']
                return data
            else:
                data = pd.read_csv(path)
                data.iloc[:,0] = data.iloc[:,0].apply(lambda x: str(x).strip(' '))
                data = data.iloc[:,0].str.split(' ', 1, expand=True)
                data.columns = ['Date','Volume']
                data.loc[:,"Volume"] = pd.to_numeric(data.loc[:,"Volume"], errors='coerce')
                data.Date = pd.to_datetime(data.Date, format='%Y%m%d', errors='coerce')
                return data
```

```
In [8]: data = pd.concat([load_data(decade[0], decade[1], decade[2]) for decade in date_ranges], axis=0)
```

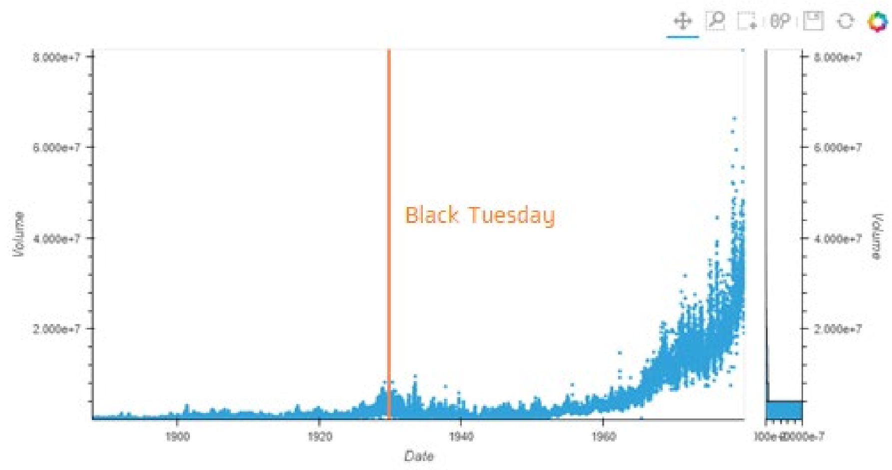
Markets are complex systems made up of multiple agents that not only respond to external information, but to the market itself. These agents learn over time and develop complex behavior through their interactions. As these markets evolve, characteristics can change, requiring new strategies to keep up with market trends. Markets are dynamic and can be made up of a number of states. Markets often respond and behave dramatically differently during a crisis, as happens in bull or bear markets. While price is a major concern for investor performance, so too is liquidity. In venture capital, a key question is around an investment's exit strategy, and for market investors the ability to rapidly liquidate investments can be the difference between bankruptcy and success. As market information changes, we can often observe the market forces of supply and demand push and pull, as investors rapidly move to buy and sell off holdings based on their own investment strategies and fast changing market information. While liquidity, as a concept, is something difficult to directly quantify, for many investors, volume can provide interesting insight into changes to market information, supply and demand, and liquidity. When volumes are lower than normal, it often signals that there are few changes occurring in the market information. When volumes are high, information can be changing dramatically, forcing investors to alter their portfolios and investment strategies.

In the diagram below, we plot volume for the NYSE from 1888 to 1979. During this time, volume, volatility, and kurtosis have all increased dramatically. While we may speculate about the effects of increased market size, computerized trading and even high-frequency trading, it is interesting to note the dramatic changes markets experience during crisis situations.

We see that immediately before and after Black Tuesday, volumes became increasingly volatile as traders sought to price in the drama of new information. The feature of leverage, new to this market crash, forced many traders to alter their positions in the market in hopes of settling margin accounts and holding onto trades.

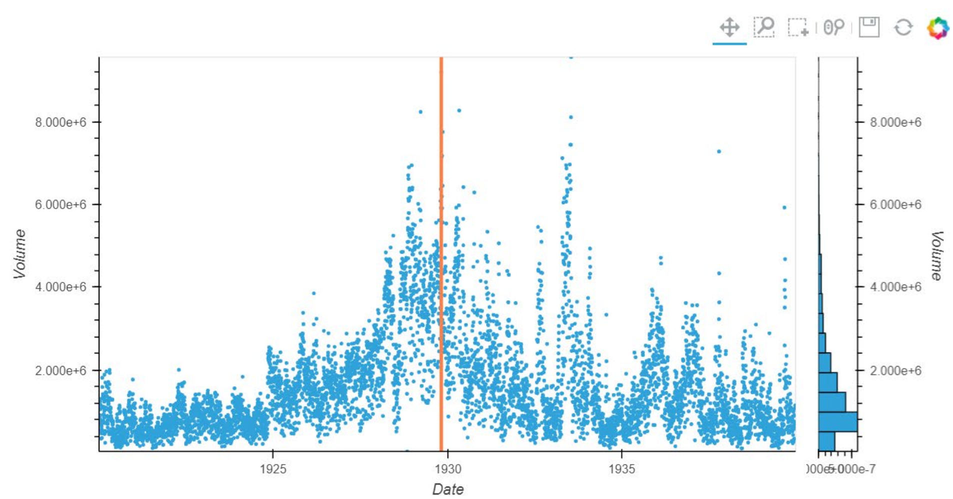
```
In [4]: # Create plotting object
        plot_data = hv.Dataset(data, kdims=['Date'], vdims=['Volume'])

        # Create scatter plot

        black_Tuesday= pd.to_datetime('1929-10-29')

        vline = hv.VLine(black_Tuesday ).options(color='#FF7E47')

        m = hv.Scatter(plot_data).options(width=700, height=400).redim('NYSE Share Trading Volume').hist() * vline * \
            hv.Text(black_ Tuesday+ pd.DateOffset(months=10), 4e7, "Black  Tuesday " , halign='left').options(color='#FF7E47') ')
        m
```

Out[10]:



In [9]:
```
# Create plotting object
plot_data = hv.Dataset(data, kdims=['Date'], vdims=['Volume'])

# Create scatter plot

black_Tuesday = pd.to_datetime('1929-10-29')

vlir= hv.VLine(black_Tuesday )opt.options(color='#FF7E47')

m = hv.Scatter(plot_data).options(width=700, height=400).redim('NYSE Share Trading Volume').hist() * vline * \
    hv.Text(black_Tuesday + pd.DateOffset(months=10), 4e' "Black Tuesday" halign='left').options(color='#FF7E47')
m
```

Out[22]:

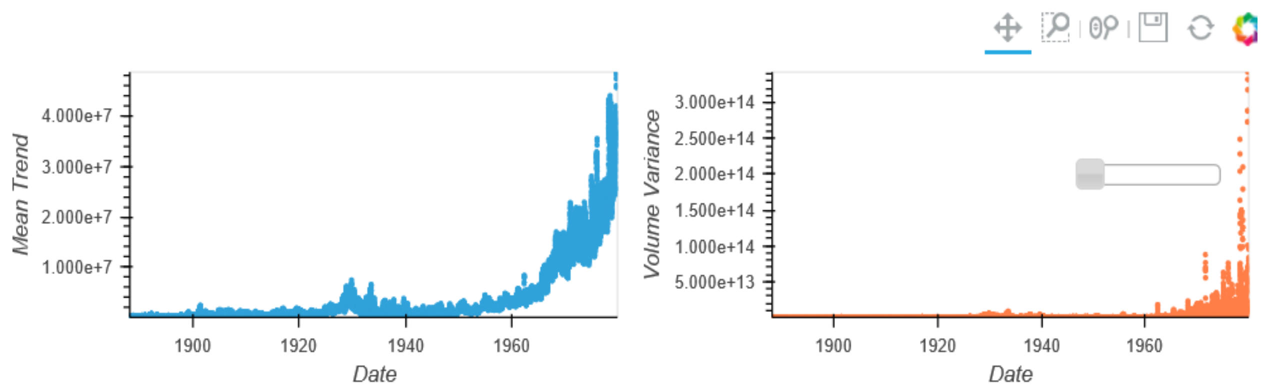


When you implement the code, you can use the slider below to adjust the moving average smoothing. We can apply to this data and the window of volatility in order to better comprehend changing market properties.

In [11]:
```
%%opts Scatter [width=400 height=200]

data['Quarter'] = data.Date.dt.quarter

def second_order(days_window):
    data_imputed = data
    data_imputed.Volume = data_imputed.Volume.interpolate()

    return hv.Scatter(pd.concat([data_imputed.Date, data_imputed.Volume.rolling(days_window).mean()],
                                names=['Date', 'Volumne Trend'], axis=1)
                      .dropna()).redim(Volume='Mean Trend') + \
    hv.Scatter(pd.concat([data_imputed.Date, data_imputed.Volume.rolling(days_window).cov()],
                         names=['Date', 'Volumne Variance'], axis=1)
               .dropna()).redim(Volume='Volume Variance').options(color='#FF7E47')

hv.DynamicMap(second_order,kdims=['days_window']).redim.range(days_window=(7,1000))
```

Out[11]:

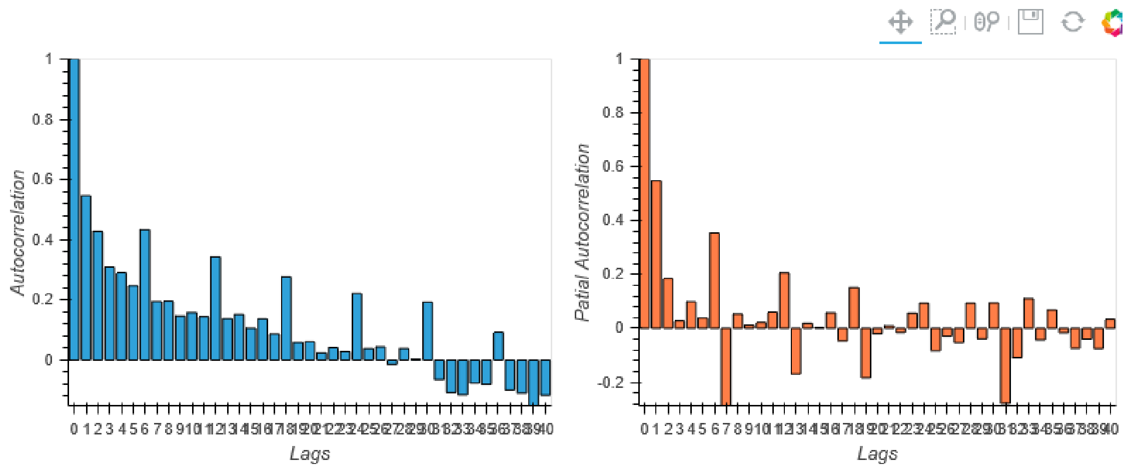
days_window: 7



In [12]:
```
%%opts Bars [width=400 height=300]
from statsmodels.tsa.stattools import acf, pacf

def auto_correlations(start_year, window_years):
    start_year  = pd.to_datetime(f'{start_year}-01-01')
    window_years = pd.DateOffset(years=window_years)

    data_window = data
    data_window = data_window.loc[((data_window.Date>=start_year)
                                  &(data_window.Date<=(start_year+window_years))),:]

    return hv.Bars(acf(data_window.Volume.interpolate().dropna()))\
              .redim(y='Autocorrelation', x='Lags') +\
           hv.Bars(pacf(data_window.Volume.interpolate().dropna()))\
              .redim(y='Patial Autocorrelation', x='Lags').options(color='#FF7E47')

hv.DynamicMap(auto_correlations,kdims=['start_year', 'window_years']
             ).redim.range(start_year=(data.Date.min().year,data.Date.max().year), window_years=(1,25))
```

Out[12]:

start_year: 1888,
window_years: 1



We can model this data in a rudimentary fashion, looking at the partial auto-correlation and auto-correlation present in this data. These properties can vary dramatically over time and provide insight into the variance, efficiency and responsiveness of the market. Many markets in developing economies feature low levels of liquidity, even for large stocks. With large public investment companies and retail investors, changes in investment strategy can subsume liquidity in the market, as large volumes of trades look to be executed. These trades force the price to increase over many days and may result in increases in one- or two-day auto-correlation, depending on the characteristics of market liquidity. These characteristics of momentum can also form part of investor strategy, or describe some element of market micro-structure, but from the plots above it is interesting to note that in recent years auto-correlation of volumes has seen radical changes from the historical norms. In the plots above, we observe some inkling of these properties in the partial auto-correlation plot, which displays a regular two-day correlation indicative of momentum and liquidity.

In [13]:
```
# Try filtering the data and computing
# the skewness and kurtosis over different time periods
# using the .kurtosis() and .skew() functions
```

Unit 3: Modeling the Depression

Modeling market characteristics can be a hard task for historical market events. The lack of data can limit the methods and insights found, while noise and exogenous factors can often obfuscate key insights.

Despite this, simulation is a crucial technique in the understanding of complex systems, which can help us gain insight into the effects different investor-heuristics have on markets. Simulation can come in a number of different forms, many of which you have been exposed to in other courses in finance. These techniques, of which the Monte Carlo Simulation is one, are used extensively in computing Value-at-Risk and expected shortfall for investor portfolios and can be used in pricing a number of complex derivatives and share options schemes.

As per our previous set of notes, we will import a number of libraries in the NumFOCUS ecosystem. In the references section there are a number of links for you to peruse and use as reference guides to help breakdown and understand the code in this section.

In [1]:
```
from functools import reduce
import operator

import os
import requests

import pandas as pd
import numpy as np

import holoviews as hv
import hvplot.pandas
```

In [2]:
```
np.random.seed(42)
```

In [3]:
```
hv.extension('bokeh')
```

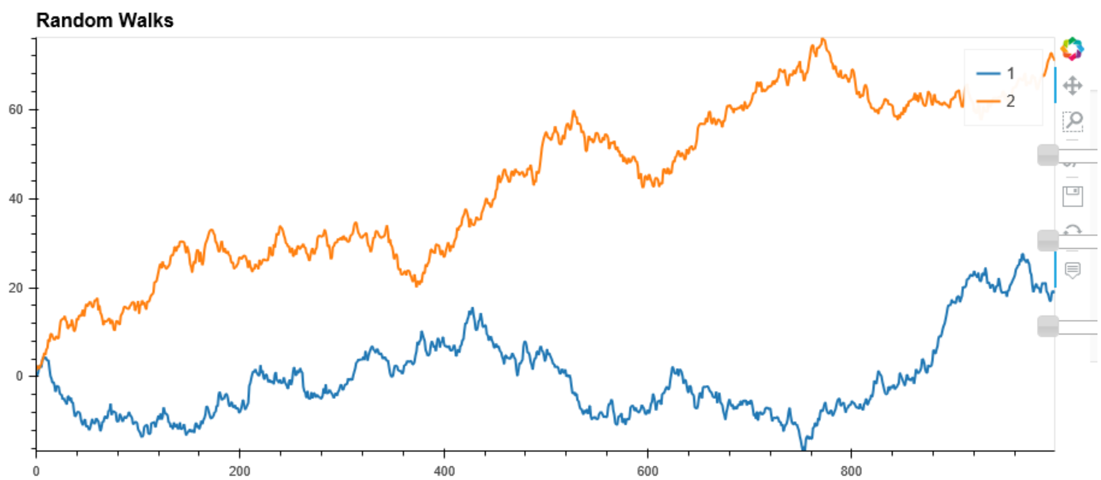
The concept of random walks in prevalent in financial theory. They are used as assumptions in the efficient market hypothesis, the capital asset pricing model and in the Black-Scholes option pricing formula, to name a few. Despite its use, most markets exhibit very different distributional properties – often displaying fatter tails, with far larger jumps and swings.

We can graph these random walks, adjusting their parameters, μ and σ to allow for trend or different levels of volatility. It's important to understand that not all random walks are alike and as you increase the number of walks you sample, you will see clearly how different they can be. A lot of this falls into the realm of statistical arbitrage and can be deeply rooted in our understanding of portfolio theory. While we have not introduced any properties of correlation into these walks, you may try to dissect your own code using this property.

In [4]:
```
def plot(mu, sigma, samples):
    return pd.Series(np.random.normal(mu,sigma, 1000)).cumsum(
    ).hvplot(title='Random Walks', label=f'{samples}')

def prod(mu, sigma, samples):
    return reduce(operator.mul,
                  list(map(lambda x: plot(mu,sigma, x),
                           range(1,samples+1))))
```

In [5]:
```
hv.DynamicMap(prod,kdims=['mu', 'sigma', 'samples']).redim.range(mu=(0,5), sigma=(1,10), samples=(2,10)).options(width=900, heig
ht=400)
```

Out[5]:



These properties are challenging to model, but using rudimentary simulation, we will try our best to capture some of these market dynamics for ourselves. We will create a function that produces a random walk with μ and σ as some function of momentum (affecting μ) and the number of market participants (affecting σ) who get introduced and removed from the market based on activity of their margin accounts. We will initialize a set of 100 with margin accounts, with varying levels of risk. In order for this margin call to affect the market, we will say that if their accounts dip below the margin level, they are ordered to sell and the market μ will be affected with some decay over the next n times steps. As margin accounts are called, the characteristics of our random walk will change and these traders will remain outside the simulation until randomly reintroduced.

Obviously, if many default at the same time, it will take a long time for them to be reintroduced to the market and for prices to stabilize. If few default, they should be reintroduced quickly as new participants arrive to the market to take advantage of mis-pricing. As margin calls affect the μ of our random walk, we should see dramatic pull-downs as this affects other traders in the market. Feel free to change the initialization parameters to see how this affects the graphs below.

After initializing the *accounts* class, the *price* function starts by calculating the % of margin accounts that have been called at a given day and the five-day momentum in the market ($P_t - P_{t-5}$). Using these values and our simulation parameters, these values are used to compute μ and σ for our next market return. The number of accounts called is then updated, given that we now know the returns of the market on the given day. After updating, we randomly reinitialize called accounts, to signify new participants entering or re-entering the market.

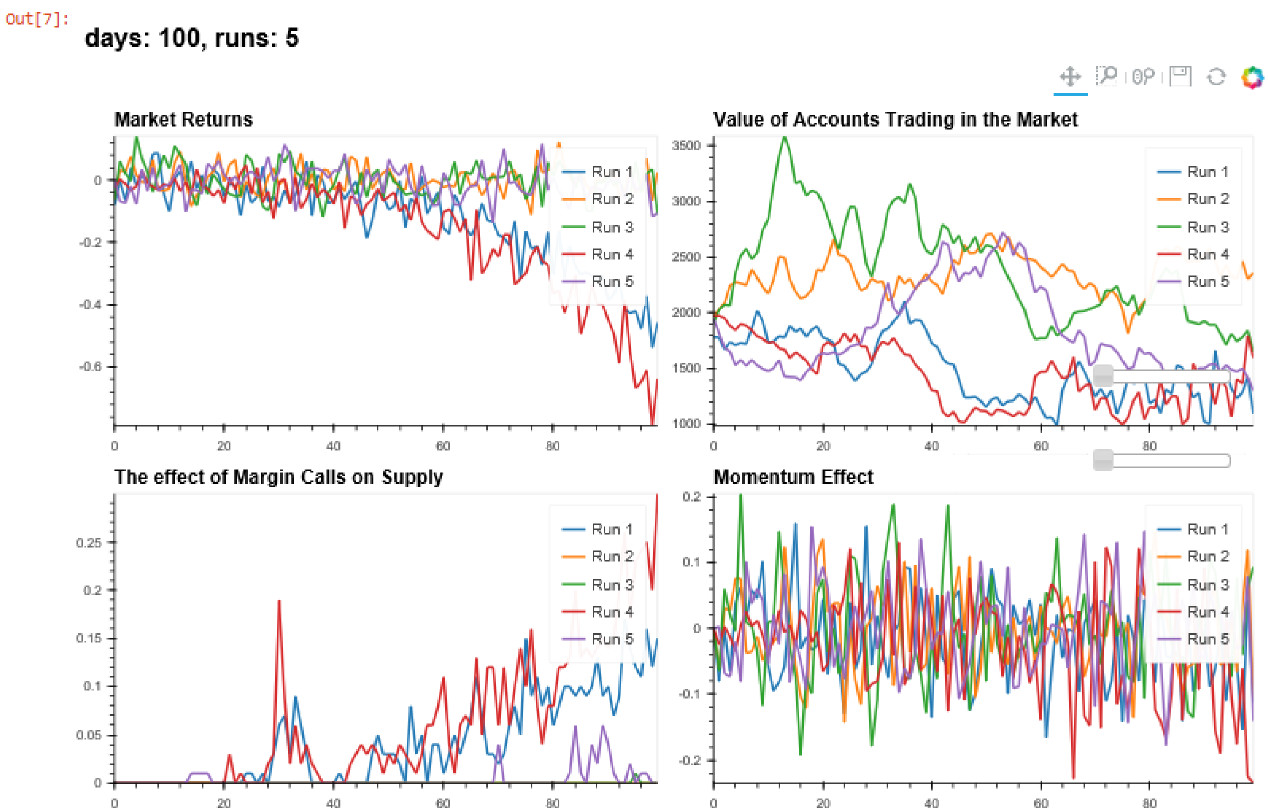
```
In [119]: class Accounts:
    def __init__(self, account_mu=20, account_sigma=5, account_numbers=100, mu=0, sigma=0.05, margin_mu=0.1, momentum_mu=0.025,
margin_sigma=0.001):
        # We initialize paramters for our simulations
        self.account_mu=account_mu
        self.account_sigma = account_sigma
        self.account_numbers = account_numbers

        self.margin_mu=margin_mu
        self.momentum_mu=momentum_mu
        self.margin_sigma=margin_sigma

        self.accounts= np.maximum(np.random.normal(loc=self.account_mu, scale=self.account_sigma, size = self.account_numbers),
0)
        self.call=self.accounts*np.random.uniform(0.5,0.7,self.account_numbers)

        self.mu=mu
        self.sigma=sigma

        self.called_accounts_factor = 0

        self.momentum = 0
        self.history = [0,0,0,0,0]

        return None

    def price(self):
        # Calculate factors
        self.called_accounts_factor =((self.accounts <= self.call).sum())/self.account_numbers
        self.momentum = (self.history[4] - self.history.pop(0))

        # Update paramteres
        self.mu = self.mu - self.margin_mu*self.called_accounts_factor + self.momentum_mu*self.momentum
        self.sigma = self.sigma + self.margin_sigma*self.called_accounts_factor

        # Update accounts
        self.history.append(np.random.normal(loc=self.mu, scale=self.sigma))
        self.accounts = self.accounts*(1+self.history[4]*np.random.uniform(low=0.5,high=1.5,size=self.account_numbers))

        # Reset called accounts
        reset = (np.random.rand(self.account_numbers)>=0.3) * (self.accounts <= self.call)
        self.accounts[reset] = np.random.normal(self.account_mu, self.account_sigma)
        self.call[reset] = self.accounts[reset]*np.random.uniform(0.2,0.5,np.sum(reset))

        return [self.history[4], self.accounts.sum(), self.called_accounts_factor, self.momentum]
```

We will run this simulation over 100 days, and produce five different runs to get an idea of the possible outcomes this simulation produces. We will keep track of the market returns, the average value of our margin accounts, the number of accounts called at a given point in time, and the effect they will have on the distribution of returns. We will also keep track of the momentum effect we will be using to affect the distribution of returns.

```
In [120]: def simulation_plots(days=10000, runs=5):
              run = []

              for _ in range(runs):
                  a = Accounts()
                  prices = pd.DataFrame([a.price() for day in range(days)],
                                        columns=['Market Returns', 'Value of Accounts Trading in the Market', 'The effect of Margin Calls
  on Supply', 'Momentum Effect'])
                  run.append(prices)

              plot = reduce(operator.mul,[i.iloc[:,0].hvplot() for i in run]) +\
                     reduce(operator.mul,[i.iloc[:,1].hvplot() for i in run]) +\
                     reduce(operator.mul,[i.iloc[:,2].hvplot() for i in run]) +\
                     reduce(operator.mul,[i.iloc[:,3].hvplot() for i in run])


              return plot.cols(2)
```

In the graph below, you can adjust the number of runs and the number of days over which the simulation is run. Please take into account that this is not perfectly calibrated to any particular market and so, in real life situations, validation would be crucial to ensuring variables, like days, accurately track real trading days, as opposed to some other unit of time, like weeks or seconds. In these graphs, each line represents a run of the simulation over the intended number of days. These are presented in different colors to aid in readability. The four panes of the plot represent: market returns, value of accounts trading in the market, the effect of margin calls on supply and a momentum effect.

```
In [121]: %%opts Curve [width=500 height=300]
          hv.DynamicMap(simulation_plots, kdims=['days', 'runs']).redim.range(days=(100,500), runs=(5,15)).options(width=900, height=400)
```



From these graphs, you can see how volatile returns appear. Unlike white noise, these feature strong violent trends. Margin calls take place dramatically for almost all participants in the market like a set of dominoes, and momentum tends to carry these effects as traders panic.

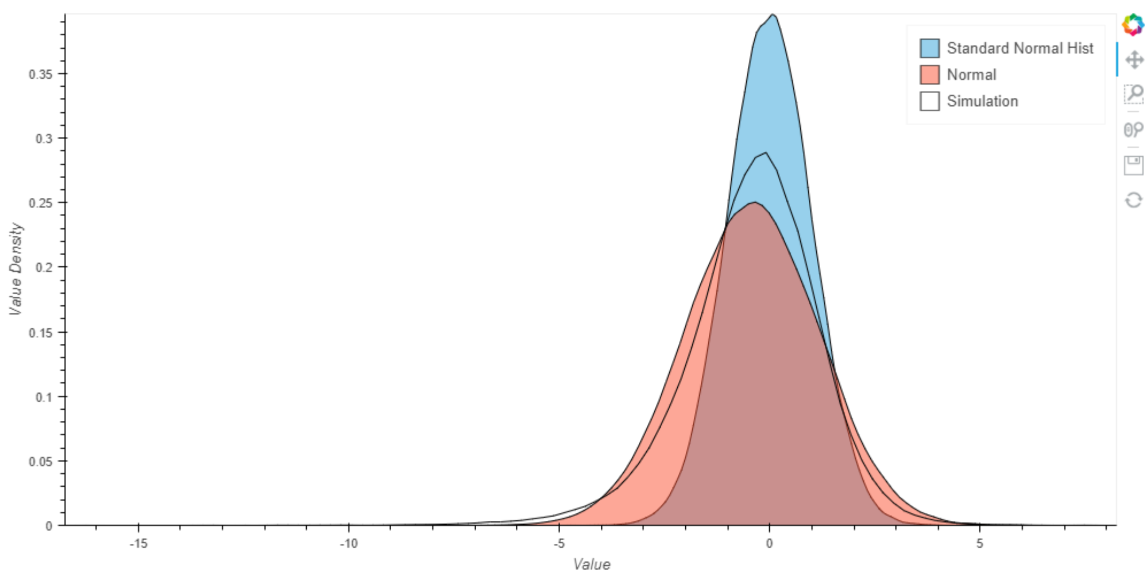
Looking at the next graphs, when we compare this simulation against the standard normal distribution and a normal distribution with equivalent mean and variance properties, we see noticeably different characteristics. Our models appear both skewed and spread out, with far higher probabilities for events well outside the standard normal distribution that we used as our original function. While it still appears approximately normal, if we compare it to a normal distribution with similar mean and variance characteristics, we do appear to have a far higher levels of kurtosis – indicated by the higher mode of the distribution and the longer left tail. This longer left tail seems to indicate additional skewness to the distribution, which may form an interesting characteristic for investors to consider.

In [108]:
```
def simulation_prices(days=100, runs=1000, axis=0):
    run = []

    for _ in range(runs):
        a = Accounts()
        prices = pd.DataFrame([a.price()[0] for day in range(days)],
                              columns=['return'])
        run.append(prices)


    output = pd.concat(run, axis=axis)
    output.columns = [f'Run {i+1}' for i in range(output.shape[1])]

    return output
```

In [109]:
```
simulations = simulation_prices()
```

In [110]:
```
%%opts Overlay [show_title=True] Distribution [height=500, width=1000]
hv.Distribution(np.random.normal(simulations.mean(),simulations.std(),100000), label='Normal') * hv.Distribution(simulations.ilo
c[:,0], label='Simulation').options(fill_alpha=0.0)
```

Out[73]:



In [12]:
```
# Try creating a Q-Q plot for this data youself,
#  to see the differences in these distributions quartiles
```

In [13]:
```
# Use a Kolmogorov-Smirnov or Shapiro Wilks Test
#  and Analyze your hypothesis
```

While the majority of existing research indicates that market returns are not random, using simulations we can begin to observe the effects increased leverage and momentum have in transforming these returns into wider tail distributions, with vastly different market characteristics. In the 1929 Crash, the introduction of cheap and freely available credit is considered a key contributor to the crash – spurring the new approaches to finance and legislation that followed. Markets are perpetually faced with new policies, theories and strategies that affect them in a variety of ways.

While it is difficult to predict the effects new policies may have, using rudimentary assumptions, we can create simulations that try to predict potential outcomes. These predictions can aid in financial risk management.

In the reference list, you will find sources that simulate and discuss the effects of margin on financial markets. While some argue that margin increases risk and amplifies crashes, others argue that it also improves efficiency, allowing traders to better act on market information and structures their portfolios according to the characteristics of market microstructure.

Unit 4: How the World Rebuilt Itself

The Crash of the NYSE in October 1929 hailed the beginning of the Great Depression, which ushered in over a decade of economic, social and political instability in the United States and around the world. What is important to grasp from the Great Depression and the subsequent rebuilding of financial powers, is that important economic, socio-political and financial changes were implemented to restore stability.

The biggest contributor to the Great Depression lay in the misplaced optimism during the early 20th century. After the market crashed and public confidence in the economic system fell, banks and financial institutions found it hard to retain commercial growth and recoup lost funds. Over time, deflation kicked in and the sale of commercial goods went into steep decline, prompting immediate retrenchment across the industrial sector, which was predominantly centered in urban areas. This created a situation of mass unemployment, reducing the tax base and the gross domestic product, which fell by an estimated 40% during the course of the Great Depression.

Global decay and crisis

The spread of the depression from the U.S. to other financial hubs was largely a result of the gold standard, whereby the value of a country's currency was pegged to the units of gold held by the government. The problem with this is that the gold standard disenabled the federal government to inject money into the banking and financial system, as they were constrained by their gold reserves. Expanding the supply of money in circulation therefore first required governments to go off of the gold standard. Because of this, the financial sector needed to increase interest rates and recoup any asset possible to cover their liabilities that were exposed during the crash.

These practices created major instability in a financial market, both locally and globally, that was already unstable because of trade wars created by American and British protectionism. Protectionism in the 1920s referred specifically to how the Western powers created a series of tariffs and custom laws that dissuaded local economies from interacting with foreign powers, in favor of local – or colonial – goods and services. Further instability was created by poor credit regulation and financial oversight, as seen in the Hatley incident in London, and how international trading was being treated with suspicion.

Changes and challenges in Germany, Britain and the United States

In 1931, European markets were hit with a financial crisis. As a carry-over from the NYSE crash, European financial hubs (most notably London and Berlin) suffered similar liability issues. In 1931, several institutions collapsed, prompting widespread financial instability, which increased inflation and devalued currencies.

The German economy was hit especially hard, as it was still paying reparations to France for World War 1 and was struggling to rebuild industries. Despite international negotiations, where the U.S. tried to put a moratorium on German reparations, they persisted at France's insistence. Economic decline in Germany allowed for the rise of the Nazi Party under Adolf Hitler, who was able to capitalize on the anger and economic desperation of the German people.

The British and their empire faced similar strain from the global financial instability as investors pulled assets out of the market and withdrew gold, prompting major currency devaluation and financial deficits across the world. A political crisis occurred as the two opposing parties, Labor and Conservative, fought to fix the problem without defunding the welfare system or raising taxes. The Conservatives eventually won out and removed Britain from the gold standard. This was a consistent trend amongst many countries during the early 1930s.

In the U.S., the Hoover administration tried in vain to stem the spread of economic instability. Rising unemployment, industrial sector problems and a sudden environmental crisis in the agricultural heartland saw the American economy decline sharply. After three years, Franklin D. Roosevelt replaced Hoover as president and initiated the New Deal, a widespread series of policies that targeted failing industries, public works projects and financial regulation.

Fixing the system

The attempt to rescue the American economy and prevent further incidents saw regulation practices enhanced under the Hoover and Roosevelt administrations. The New Deal saw a major shift in American social welfare and workers' rights as well as the beginning of more assertive government-led bank reform. Critically, the U.S. pulled out of the gold standard and created a series of laws that protected both investors and the integrity of banks.

Unscrupulous and irrational lending were major problems that caused the crash and the subsequent Great Depression, and the Roosevelt administration sought to hold financial institutions more accountable. Federal resources were placed behind major banks and investment institutions, and only those that covered their liabilities properly were able to reopen. Legislation passed in the early 1930s severely limited speculation on financial markets and assets. Only a few restricted financial institutions could make speculative investments and many created procedures to prevent panic-selling, which was one of the major contributors to the crash. The Securities Act of 1933 regulated securities trading, requiring every security and transaction to be registered with the federal government.

The New Deal also created a series of economic and welfare systems aimed at reducing pressure on the financial systems, which were trying to cover their liabilities. Relief efforts directed at farmers affected by the Dust Bowl environmental disaster and urban commercial and industrial workers increased the ability of farmers, factory workers and urban residents to repay debts. Job stimulation, education programs and agricultural subsidies ensured that money would flow more freely in the financial system, prompting investment and economic expansion comparable to that found in the years leading up to the crash. As public works projects improved infrastructure, goods, services and money moved more freely, prompting financial growth across the United States.

The New Deal continued into the late 1930s. when the outbreak and spread of World War II increased the demand for military supplies across the globe. This sparked industrial development in the U.S., which traded extensively with the Allied powers even before officially entering the war in 1941. After entering the war, the United States finally came out of the Great Depression, as the full mobilization of its war industry created more jobs – both on and off the battlefield – and allowed the country to assert itself as a dominant economic and industrial power.

The 1930s also saw the rise of Keynesian economics throughout the capitalist world. British economist John Maynard Keynes theorized that aggregate demand − the demand produced by all sectors of the economy, from individual consumers to major commercial needs and desires − was critical to rebuilding during short-term declines, as experienced during the Great Depression. Keynes opposed austerity and fiscal management during crisis moments, instead favoring continued spending and economic investment. This macroeconomic framework informed most economic and financial decisions made by the major world powers (such as Britain, the U.S., and Japan) during the early to mid-twentieth century.

Bibliography

Ágnes, P. (2013) "A fekete csütörtök"[Online]. Available at: http://kkghuman.blogspot.com/2013/10/a-fekete-csutortok.html

Diltz, C. (2017) "In 1930s Seattle, homeless residents built eight Hooverville settlements" [Online]. Available at: https://www.seattletimes.com/seattle-news/seattles-hoovervilleswere-depression-era-homeless-camps/

Everett. (2018) "Richard Whitney 1888-1974, President" [Online]. Available at: https://fineartamerica.com/featured/richard-whitney-1888-1974-president-everett.html

"File: DJIA Black Monday 1987.svg" [Online]. Available at: https://en.wikipedia.org/wiki/File:DJIA_Black_Monday_1987.svg

Goldberg, S. (2017) "Black Monday: What I Learned from the 1987 Stock Market Crash" [Online]. Available at: https://www.kiplinger.com/article/investing/T031-C007-S001-black-mondaylessons-from-1987-stock-market-crash.html

Kirilova, V. (2016) "Wall Street's blackest hours: Black Monday revisited" [Online]. Available at: https://www.leaprate.com/news/wall-streets-blackest-hours-black-monday-revisited/

Konkel, L. (2018) "How Did the Gold Standard Contribute to the Great Depression?" [Online]. Available at: https://www.history.com/news/how-did-the-gold-standard-contribute-to-the-great-depression

Kuethe, R. (2016) "Franklin D. Roosevelt (1933 – 1945)" [Online]. Available at: https://www.elsevierweekblad.nl/buitenland/article/2016/08/de-amerikaanse-presidentfranklin-d-roosevelt-342781/

Lockie, A. (2015) "The 5 most bizarre weapons of World War 2" [Online]. Available at: https://www.businessinsider.com/the-5-most-bizarre-weapons-of-world-war-ii-2015-7?IR=T

Neel, A. (1982) "Franklin D. Roosevelt" [Online]. Available at: http://content.time.com/time/covers/0,16641,19820201,00.html

O'Rourke, A. (2016) "12 Scary Photographs of the 1929 Wall Street Crash That Kicked Off The Great Depression" [Online]. Available at: https://www.bustle.com/articles/137485-12-scaryphotographs-of-the-1929-wall-street-crash-that-kicked-off-the-great-depression

Paul, R. (2015) “The History of Central Park’s Hooverville, the Great Depression Pop-Up Shanty Town” [Online]. Available at: https://centralpark2016.wordpress.com/history-of-central-park/

Rappoport, P. and White, E. N. (2016) “Was There a Bubble in the 1929 Stock Market?” Published by : Cambridge University Press on behalf of the Economic History Association. Stable URL: http://www.jstor.org/stable/2122405 ‘Was There a Bubble in the 1929 Stock Market ?’, 53(3), pp. 549–574.

Rice, D. (2013) “Does the Dust Bowl stack up to today’s disasters?” [Online]. Available at: https://www.usatoday.com/story/weather/2012/11/13/dust-bowl-drought/1691507/

Theunredacted. (2015) “Adolf Hitler. Flight of Grey Wolf” [Online]. Available at: https://medium.com/@theunredacted/adolf-hitler-e2715ce5dfb2

Thurner, S., Farmer, J. D. and Geanakoplos, J. (2012) “Leverage causes fat tails and clustered volatility”, Quantitative Finance, 12(5), pp. 695–707. doi: 10.1080/14697688.2012.674301.

Xiong, W. (2001) “Convergence trading with wealth effects: An amplification mechanism in financial markets”, Journal of Financial Economics, 62(2), pp. 247–292. doi: 10.1016/S0304-405X(01)00078-2.

Collaborative Review Task

In this module, you are required to complete a collaborative review task that is designed to test your ability to apply and analyze the knowledge you have learned in the module.

Task

What circumstances led to Richard Whitney's gamble on October 24th 1929 failing, causing the New York Stock Exchange to collapse?

Write a short essay to answer the question. Your answer should be no longer than 300 words.