

Compiled Notes

Module 2

MScFE 660

Case Studies in Risk Management

```

)) {$this->repo_path = $repo_path;$this->repo_path = $repo_path;$this->
($repo_path."/config");if ($parse_ini['bare']) {$this->repo_path = $repo_path;$this->
path = $repo_path;if ($_init) {$this->run('init');}} else {throw new Exception('"' . $r
* new Exception('"' . $repo_path . '"' is not a directory');}} else {if ($create_new) {if
))) {mkdir($repo_path);$this->repo_path = $repo_path;if ($_init) $this->run('init');}
istent directory');}} else {throw new Exception('"' . $repo_path . '"' does not exist');}}
it" directory) * * @access public * @return string */public function git_directory_pat
repo_path."/ .git");/** * Tests if git is installed * * @access public * @return bool */
-> array('pipe', 'w'),2 => array('pipe', 'w'),);$pipes = array();$resource = proc_open(
t_contents($pipes[1]);$stderr = stream_get_contents($pipes[2]);foreach ($pipes as $pipe
return ($status != 127));}/** * Run a command in the git repository * * Accepts a shell
):$pipes = array();

```

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Module 2: The 1987 Crash and its Regulatory Implications

Module 2 explores the historical context of the 1987 crash, where Thatcher and Reagan's policies of neoliberalism and deregulation resulted in the largest stock market crunch since the Great Depression. A thorough understanding of this context and the monetarist policies approach is used to explain the broader economic implications of the crash and the global repercussions. The module begins by discussing the macroeconomic factors and the political context which led to the crisis and by explaining the Aggregate Supply – Aggregate Demand (AS-AD model) as it applies to the 1987 crisis. Then it continues by introducing the validation, interpretation, and implication steps to analyze the economic model of the crisis. At the end of the module, the contribution of computerized trading, which started in the early 1980's, to the 1987 crash and lack of proper market regulation are discussed.



Unit 1: The 1980s: Boom to Bust

On October 19th, 1987, known as ‘Black Monday’, stock exchanges across the world collapsed, causing massive devaluation and fears of another Depression. The **Dow Jones Industrial Average** (DJIA), the stock exchange indicator charting the biggest 30 companies in America, broke records for its sharpest drop in its history, falling over 500 points in one day – a move of around 22%. To fully understand the crash, it is important first to understand the culture of money and spending in the 1980s, and how the bull market that had developed out of the early 1980s recession influenced the crash. As with the 1929 crash, no singular event caused the crash, and in the case of 1987, it is important to assess the monetary and financial policies of major powers at the time and how the ripple effects caused the crash. Similarly, the procedures and trading mechanisms in the financial system informed how the crash would play out.

The era of growth

The 1980s saw a time of major financial growth and stability amongst many countries, most notably the United Kingdom (UK) and the United States of America (USA). A recession in the late 1970s and early 1980s was of concern to the major leaders of the global economy, causing sharp increases in unemployment and economic instability across the developed world. The recession was coupled with major increases in oil prices which highlighted the reliance of developed economies, like those of the UK and the US on oil. In 1973 and 1979, the **Organization of Petroleum Exporting Countries** (OPEC) introduced embargoes as punitive measures against Western countries that supported Israel and were, from OPEC’s point of view, undermining Islamic governments in the Middle East. These embargoes prompted an ‘oil shock’, causing energy and fuel costs to skyrocket, sparking a recession in these economies.

What is important to note from the recession that persisted until 1985 in some countries, is how it prompted many states to vote in neoliberal leaders and political parties. Neoliberalism, as a political and economic ideology, relies heavily on *laissez-faire* approaches to market regulation, with the idea that less regulation, less government intervention in the market, and lower taxation on the highest earners spur economic growth. This, coupled with privatization of state industries or state-owned companies, a decrease in the size of government and cuts in government spending would, in theory, allow economy could grow more ‘naturally’. Cutting taxes for the wealthy, it was believed, could spur a “trickle-down” effect to the rest of the economy, leading to increased spending and



thus stimulation of the economy as a whole. Neoliberalism was a reaction to the many quasi-socialist approaches adopted by developing economies during the 1960s and 1970s that saw major changes in welfare spending, economic regulation and the privatization of major industries like transportation, telecommunications, power and mining companies, and increased taxation of big business.

The British and the Americans

Challenging this, both the UK and the USA voted in prominent neoliberal, conservative governments. In the UK, the Conservative Party under Margaret Thatcher formed a government in 1979 as a reaction to the ongoing economic decline of the former colonial power. During the preceding two decades, the UK had lost an empire suffered economic instability. Increasingly powerful trade unions coupled with increased government spending on its welfare system worked to create a growing national deficit. The so-called 'Winter of Discontent' in 1978 and 1979 – which saw rolling protests and service shutdowns prompted by public sector trade unions demanding an increase in pay – caused serious damage to economic stability, and the need for change was imminent. Thatcher, hoping to recover British economic prestige and prevent further rolling power blackouts and increased oil prices from the OPEC embargo and the ongoing strikes, implemented policies that sold off government-owned enterprises, cut taxes and rolled back Britain's welfare state in unprecedented ways. A lack of direction in monetary policy in the previous Labor government had prompted Thatcher's government to embrace monetarism. The basic tenet of monetarism is that by restricting the money supply in the economy, inflation is reduced. This was seen to tackle growing financial uncertainty, prompting more investment from the London Stock Exchange. Though there were closures in banks, shipyards, factories and other economic hubs, the economy recovered, and inflation dropped dramatically during the 1980s. Unemployment, however, only fell in the latter half of the decade towards the end of Thatcher's tenure in 1990.

In the U.S., high inflation and restricted growth of the supply of money prompted limited growth during the 1970s. This was worsened by the increased pressure from the OPEC embargo/ Though the U.S. was able to exit the recession fairly early, there were long-lasting effects, including the reactionary election of Ronald Reagan, who was ideologically similar to Britain's Margaret Thatcher. As a neoliberal Republican, Reagan embraced the policies mentioned above: tax cuts for the wealthy, decreased regulation, and cuts to government spending on environmental and social welfare programs. His specific approach to economics became known as 'Reaganomics'. During



Reagan's eight-year tenure, gas regulations and prices were cut and the **gross domestic product** (GDP) rose sharply. Aiming to stimulate the consumer market and create more capital for investment, the government cut income taxes for the wealthy. Though he had guaranteed to cut public spending, Reagan maintained a growth in the defense budget, escalating Cold War proxy conflicts against the Soviet Union in places such as Nicaragua, El Salvador, Angola, and Afghanistan.

Despite growing speculation and overvaluation of stocks, post-recession deregulation allowed banks and financial institutions to relax their credit and lending policies, thus mirroring the deregulation that followed the 1929 crash. Legislation like the Depository Institutions Deregulation and Monetary Control Act gave the banking sector broader powers to engage in different financial activities. Similar legislation followed up until the 1987 crash, hailing an era of banks growing in strength and becoming 'too big to fail'.

Elsewhere in the world, economic recovery from the early 1980s recession was gradual. The U.S.'s Cold War allies in Japan, Canada and parts of Western Europe all began to adopt quasi-neoliberal policies. At the same time, economic decline and defeat in Afghanistan (largely a result of U.S. military support in the region) led to the unravelling of the Soviet Union in 1991. Out of this, Western capitalist states took strength from the failure of Soviet socialism and the end of Cold War hostilities.



Unit 2: The Price is Wrong?

The monetarist's hand

One introductory macroeconomic model presented in most Macroeconomics courses discusses an important model, known as the AS-AD Model, or **Aggregate Demand-Aggregate Supply Model**. Similar to the concept of supply and demand in Microeconomics, the AS-AD model considers the relationships between suppliers and consumers, which respond to price in producing or consuming an output. Unlike the microeconomic model, the AS-AD model tried to consider all markets in aggregate, rather than any particular market like, for example, the market for bread, oil, labor or credit.

A key characteristic of the 1987 crash was the range of global macroeconomic factors which triggered changes in inflation and monetary policy. In the first note-pack of this module, we outlined the events surrounding the OPEC oil embargo, neoliberalization and changing banking legislation. Beyond this is freeing up the monopoly and monopsony markets, characterized particularly in the UK by large state industries, increasing prices of raw material prices, and changes in money supply – a canonical example of Cost-Push Inflation, which we will explore both graphically and through data.

The AS-AD model utilizes two important equations representing Aggregate Demand and Aggregate Supply, shown below:

Aggregate demand

$$Y = Y^d\left(\frac{M}{P}, G, T, Z_1\right)$$

where Y represents real GDP or real output, Y^d represents aggregate demand as a function of $\frac{M}{P}$, where M represents money supply and P represents price-level – which can be thought of as a measure of purchasing power – G represents government spending, T represents real taxes and Z_1 represents a range of exogenous factors such as natural disasters, political events and changes in market structure.



Aggregate supply

$$Y = Y^s\left(\frac{W}{P}, \frac{P}{P^e}, Z_2\right)$$

where Y represents real GDP or real output, Y^s represents aggregate supply, as a function of $\frac{W}{P}$, representing nominal wages over price-level- or real wages, $\frac{P}{P^e}$, which aims to account for changes in the anticipated (expected) price level by suppliers and Z_2 , which is a vector of exogenous variables such as levels of technology, capital stock or elements of labor demand.

Below are a set of interactive graphs, that can be used to visualize changes in Z_1 and Z_2 on Aggregate Supply (AS) and Aggregate Demand (AD). These graphs represent short-run AS and AD, as in the long-run, the AS-AD model treats AS as perfectly inelastic in the long run – i.e., a vertical line. Using the sliders, you can begin to understand the effects of various inputs of these graphs.

Again, we will be using a number of libraries introduced in the previous module, such as NumPy, SciPy, HoloViews and Pandas. It is important that you follow the code through this assignment for the peer review at the end of the module. You are encouraged to make changes to explore characteristics on your own.

```
In [1]: import numpy as np
        from scipy.optimize import fsolve
        from scipy.stats import iqr
        import pandas as pd

        import holoviews as hv
        import hvplot.pandas
```

```
In [2]: # There is a compatibility issue with this library \
        #and newer versions of Pandas, this is short fix to the problem, \
        #if you have issues at this chunk comment it out and you should be fine.
        pd.core.common.is_list_like = pd.api.types.is_list_like
        import pandas_datareader.wb as wb
```

```
In [3]: hv.extension('bokeh')
        np.random.seed(42)
```




```
In [4]: def P(*args, **kwargs):
    P = np.linspace(-10, 10, 100).reshape(-1,1)
    P = P[P!=0]
    return P

    def AS(P=P(), W=0, P_e=1, Z_2=0):
        return P-Z_2

    def AD(P=P(), M=0, G=0, T=0, Z_1=0):
        return -P+Z_1
```

```
In [5]: def findIntersection(fun1,fun2,x0):
    return fsolve(lambda x : fun1(x) - fun2(x),x0)
```

```
In [6]: def curves(z_2=0, z_1=0):
    as_eq = pd.DataFrame([P(), AS(P=P(), Z_2=z_2)], index=['Price-Level','Real Output']).T
    ad_eq = pd.DataFrame([P(), AD(P=P(), Z_1=z_1)], index=['Price-Level','Real Output']).T

    as_shock = pd.DataFrame([P(), AS(P=P(), Z_2=z_2+10)], index=['Price-Level','Real Output']).T
    ad_shock = pd.DataFrame([P(), AD(P=P(), Z_1=z_1+10)], index=['Price-Level','Real Output']).T

    result = findIntersection(lambda x: AS(P=x, Z_2=z_2+10), lambda x: AD(P=x, Z_1=z_1+10), 0.0)
    r = result + 1e-4 if result==0 else result

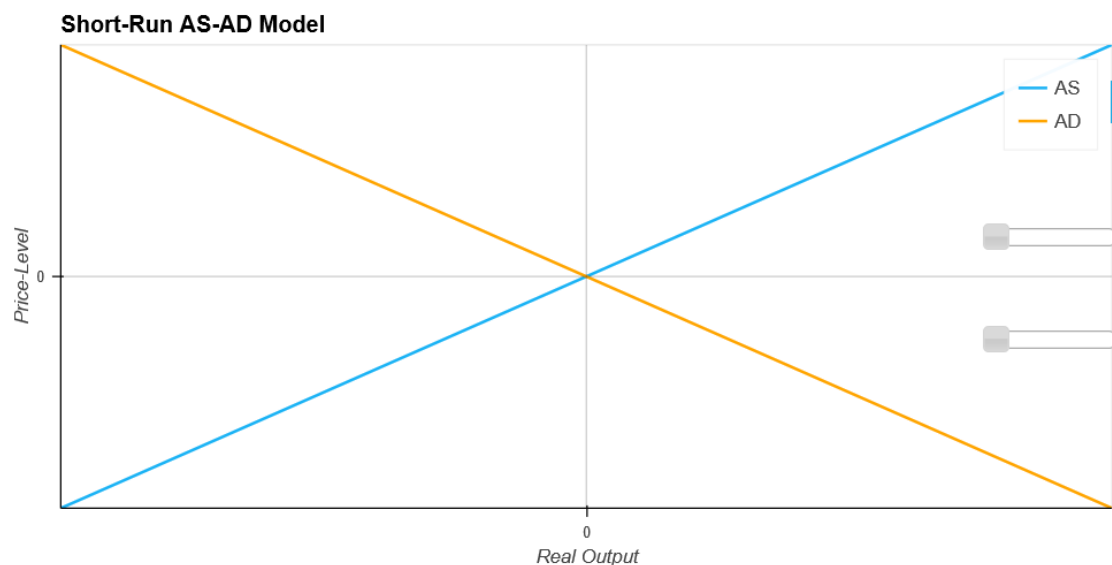
    plot = hv.Curve(as_eq, vdims='Price-Level',kdims='Real Output').options(alpha=0.2, color='#1BB3F5') *\
        hv.Curve(ad_eq, vdims='Price-Level',kdims='Real Output').options(alpha=0.2, color='orange') *\
        hv.Curve(as_shock, vdims='Price-Level',kdims='Real Output', label='AS').options(alpha=1, color='#1BB3F5') *\
        hv.Curve(ad_shock, vdims='Price-Level',kdims='Real Output', label='AD').options(alpha=1, color='orange') *\
        hv.VLine(-result[0]).options(color='black', alpha=0.2, line_width=1) *\
        hv.HLine(AD(P=-r[0], Z_1=z_1+10)).options(color='black', alpha=0.2, line_width=1)

    return plot.options(xticks=[0], yticks=[0], title_format="Short-Run AS-AD Model")
```

```
In [7]: %%opts Curve [width=800, height=400]

    hv.DynamicMap(curves, kdims=['z_2', 'z_1'], label="Short-Run AS-AD Model")\
        .redim.range(z_2=(-10,10), z_1=(-10,10))
```

Out[784]:



In order to better understand the crash of 1987, let's now apply our understanding of the AS-AD macroeconomic model to predict the effects of global macroeconomic changes on the economy and financial markets.

Before the 1974–1975 recession, there was a particularly sharp rise in the price of energy on world markets, caused by a restriction of oil output by the OPEC – as previously discussed in this module. According to the AS-AD Model, increases in the price of energy services as an exogenous factor, cause a leftward shift to our Aggregate Supply curve. Typically, these Z_i exogenous factors are referred to as exogenous shocks, as they are exogenous to our primary model and serve to disrupt the existing equilibrium in the short-run. This leftward shift takes place as producers respond to the increasing price of raw materials. If we imagine these producers as consumers of oil through trucks, deliveries and energy production, the downward nature of their demand curve suggests that increases in price reduce their demand for a good. Additionally, we can imagine that prices are slow to respond as producers can't change prices immediately. Consumers are resistant to increases in prices and so if producers increase their prices they may lose business to competitors. Increases in the price of raw materials decreases their profits, reducing the investment incentives and produce on aggregate. These serve to shift AS to the left. Using the z_2 slider, you can visualize this shift in the plots above, observing the new price-level and output equilibrium.

With the 1974–1975 recession, the economy also observed a number of secondary effects. Secondary effects are often caused by elements of, as well as the initial shock of, primary effects and as a result, lag behind them. These secondary effects included a reduction in measured productivity (real output), a fall in employment (as producers respond to increasing input prices), a decrease in consumption (as fewer people have jobs and goods are more expensive) and investment expenditures (as consumers have less money after basic expenditure to save). These are all consistent with this recession having been caused by the increase in the price of energy. These can be viewed as a smaller leftward shift in the AD curve but are predominantly captured by the movement of the AS curve along the AD curve.

Typically, Reserve Banks respond to such supply-side shocks by increasing the money supply, lowering interest rates, restoring real output, real income, and employment levels as a way to encourage borrowing on the part of consumers. This serves to further increase the price-level under the AS-AD model, causing inflation, but restoring real GDP. You can observe this effect using the z_1 slider, which allows you to observe an increase in price-level and increase in real output on the



graph. This process of a leftward shift in the AS curve and rightward shift in AD curve is typically referred to as a Cost-Push Inflation and is commonly observed in markets around the world today.

Although the recession of 1981-82 was preceded by an increase in the price of energy, evidence suggests that monetary policy was the primary cause. For this second recession, the energy price increase happened too soon before the recession to have been its principal cause. The major criticism of Monetarist Policy at the time was that it focused primarily on managing inflation as opposed to targeting real output and real income. Inflation had become relatively high in the 1970s in the United States, and by the early 1980s the **Federal Reserve System** (the Fed), took dramatic steps to reduce inflation by restricting growth in the supply of money and driving up interest rates. The idea is that by increasing interest rates you incentivize consumers to save thus limiting the flow of money in the economy. This is known as the money multiplier effect within the Keynesian Cross Macroeconomic Model.

In the next set of notes, we will analyze data from the time of the 1987 crash in order to determine the reliability of the AS-AD model, and whether other data or other models could be incorporated and used to better forecast and understand the evolving risk landscape.



Unit 3: A Market Here, a Market There

Validation, interpretation, implication

Validation, interpretation, and implication are three of the most important steps in analyzing any statistical or economic model. Having introduced the Aggregate Supply-Aggregate Demand Model in the previous notes and the impacts of Cost-Push Inflation, the major question is whether this model serves as an accurate description of the economy and its response to changes in oil prices and Monetarist Policy. In order to evaluate the AS-AD model, we are going to simulate its response to changes in oil prices and broad money supply using real economic data and comparing it to data on real GDP and price-level. Based on our historical discussions earlier in this module, we will compare Reserve Bank responses to economic stagflation brought on by increasing oil prices. In order to identify the effects of Monetarist Policy, we will look at the different approaches taken by Reserve Banks in the US and UK. Much of the data used in this analysis is sourced from the World Bank's World Development Indicators, available through the [pandas datareader API](#). Due to changes in the API and its dependencies, students may need to read through the documentation. A known issue is this API's compatibility with the newer version of the Pandas library. A comment has been added on this in the code and a specific change to one of the Pandas Modules has been made to aid in this compatibility. You will see this across the notes.

In some cases, data has been scaled in order to aid in interpretability, as we are concerned with the effect and not the specific value for broad money or oil prices. Where possible these changes have been flagged and are crucial for their inclusion in later AS-AD model. Our libraries remain the same as the previous set of notes, using NumPy, SciPy, HoloViews, and Pandas, with much of the code repeated from before.

```
In [1]: import numpy as np
        from scipy.optimize import fsolve
        from scipy.stats import iqr
        import pandas as pd

        import holoviews as hv
        import hvplot.pandas
```

```
In [2]: # There is a compatibility issue with this library \
        #and newer versions of Pandas, this is short fix to the problem, \
        #if you have issues at this chunk comment it out and you should be fine.
        pd.core.common.is_list_like = pd.api.types.is_list_like
        import pandas_datareader.wb as wb
```



```
In [3]: hv.extension('bokeh')
np.random.seed(42)
```

```
In [4]: def P(*args, **kwargs):
P = np.linspace(-10, 10, 100).reshape(-1,1)
P = P[P!=0]
return P

def AS(P=P(), W=0, P_e=1, Z_2=0):
return P-Z_2

def AD(P=P(), M=0, G=0, T=0, Z_1=0):
return -P+Z_1
```

```
In [5]: def findIntersection(fun1,fun2,x0):
return fsolve(lambda x : fun1(x) - fun2(x),x0)
```

```
In [6]: indicators = wb.get_indicators()
indicators.head()
```

Out[6]:

	id	name	source	sourceNote	sourceOrganization	topics	unit
0	1.0.HCount.1.90usd	Poverty Headcount (\$1.90 a day)	LAC Equity Lab	The poverty headcount index measures the propo...	b'LAC Equity Lab tabulations of SEDLAC (CEDLAS...	Poverty	
1	1.0.HCount.2.5usd	Poverty Headcount (\$2.50 a day)	LAC Equity Lab	The poverty headcount index measures the propo...	b'LAC Equity Lab tabulations of SEDLAC (CEDLAS...	Poverty	
2	1.0.HCount.Mid10to50	Middle Class (\$10-50 a day) Headcount	LAC Equity Lab	The poverty headcount index measures the propo...	b'LAC Equity Lab tabulations of SEDLAC (CEDLAS...	Poverty	
3	1.0.HCount.Ofcl	Official Moderate Poverty Rate-National	LAC Equity Lab	The poverty headcount index measures the propo...	b'LAC Equity Lab tabulations of data from Nati...	Poverty	
4	1.0.HCount.Poor4uds	Poverty Headcount (\$4 a day)	LAC Equity Lab	The poverty headcount index measures the propo...	b'LAC Equity Lab tabulations of SEDLAC (CEDLAS...	Poverty	

```
In [7]: indicators.loc[indicators.id == 'NY.GDP.PETR.RT.ZS',:]
```

Out[7]:

	id	name	source	sourceNote	sourceOrganization	topics	unit
7865	NY.GDP.PETR.RT.ZS	Oil rents (% of GDP)	World Development Indicators	Oil rents are the difference between the value...	b'World Bank staff estimates based on sources ...	Energy & Mining ; Environment	

```
In [8]: countries = wb.get_countries()
countries.head()
```

Out[8]:

	adminregion	capitalCity	iso3c	incomeLevel	iso2c	latitude	lendingType	longitude	name	region
0		Oranjestad	ABW	High income	AW	12.51670	Not classified	-70.0167	Aruba	Latin America & Caribbean
1	South Asia	Kabul	AFG	Low income	AF	34.52280	IDA	69.1761	Afghanistan	South Asia
2			AFR	Aggregates	A9	NaN	Aggregates	NaN	Africa	Aggregates
3	Sub-Saharan Africa (excluding high income)	Luanda	AGO	Lower middle income	AO	-8.81155	IBRD	13.2420	Angola	Sub-Saharan Africa
4	Europe & Central Asia (excluding high income)	Tirane	ALB	Upper middle income	AL	41.33170	IBRD	19.8172	Albania	Europe & Central Asia

The World Bank data-portal offers a wide array of data points used to benchmark various interventions, economic growth, prosperity, education, and healthcare. This data is extensive but often inconsistent across countries or years. For this reason, we may need to find appropriate



proxies to capture macroeconomic variables discussed in academia. For tracking the real cost of oil over time, we will use the Reserve Banks measure of 'oil rents (% of GDP)' which is defined as “... the difference between the value of crude oil production at regional prices and total costs of production”. Data was sourced between 1970 to 2017 for use in the analysis in order to get a long run understanding of the events leading up to the crash of 1987 as well as the implication monetary policy and commodity prices may have on markets today.

The graph below shows an accurate measure for the changing economic cost of oil experienced by particular countries over time. The graph details clear spikes in oil rents in both the US and UK, starting at around 1976, at the time of the first recession. These reach their peak for both countries at around 1980 and 1985, before restoring to long-run norms. Zooming and panning through the data, you can observe greater detail in these movements as they changed over time and better understand the events at the time of the crash.

```
In [9]: %%opts Curve [width=800, height=450]
oil = wb.download(indicator='NY.GDP.PETR.RT.ZS', country=['USA','GBR'], start=pd.to_datetime('1970', yearfirst=True), end=pd.to_datetime('2017', yearfirst=True))
oil = oil.reset_index().dropna()

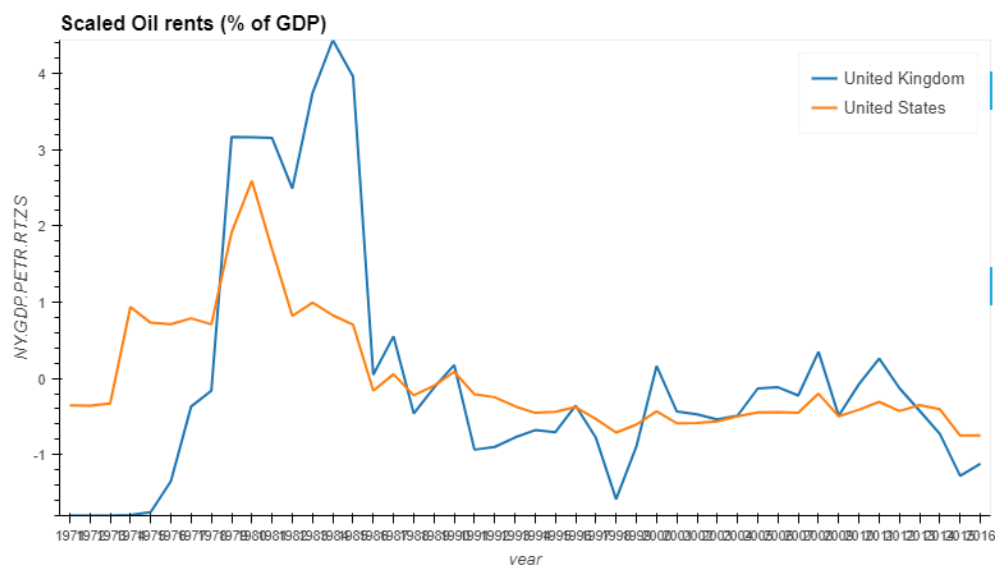
oil_unscaled = oil

oil.loc[oil.country=='United States', 'NY.GDP.PETR.RT.ZS'] = (oil.loc[oil.country=='United States', 'NY.GDP.PETR.RT.ZS'] -
oil.loc[oil.country=='United States', 'NY.GDP.PETR.RT.ZS'].mean
())/ \
iqr(oil.loc[oil.country=='United States', 'NY.GDP.PETR.RT.ZS'])

oil.loc[oil.country=='United Kingdom', 'NY.GDP.PETR.RT.ZS'] = (oil.loc[oil.country=='United Kingdom', 'NY.GDP.PETR.RT.ZS'] -
oil.loc[oil.country=='United Kingdom', 'NY.GDP.PETR.RT.ZS'].mean
())/ \
iqr(oil.loc[oil.country=='United Kingdom', 'NY.GDP.PETR.RT.ZS'])

oil_plot = oil.iloc[:, -1, :].hvplot.line(x='year', y='NY.GDP.PETR.RT.ZS', by='country', title='Scaled Oil rents (% of GDP)')
oil_plot
```

Out[9]:



In order to track Reserve Bank policy, we need to observe its effect on money markets and on money supply. For use in these notes, we will be looking at M4 or broad money, defined as “the sum of currency outside banks; demand deposits other than those of the central government; the time, savings, and foreign currency deposits of resident sectors other than the central government; bank and traveler’s checks; and other securities such as certificates of deposit and commercial paper”. While for specific Reserve Bank interventions M0 and M1 money may be more appropriate to understanding Reserve Bank policy implication, M4 money will be used to understand its effects through the money multiplier effect. From the graphs below, we can see strongly diverging changes in broad money between these two economies around 1985. While the UK experiences stabilizing and increasing broad money, the US experiences a drastic decline in broad money as a percent of GDP, which continues well into the 1990s.

```
In [10]: %%opts Curve [width=800, height=450]
money = wb.download(indicator='FM.LBL.BMNY.GD.ZS', country=['USA', 'GBR'], start=pd.to_datetime('1970', yearfirst=True), end=pd.to_datetime('2017', yearfirst=True))
money = money.reset_index().dropna()

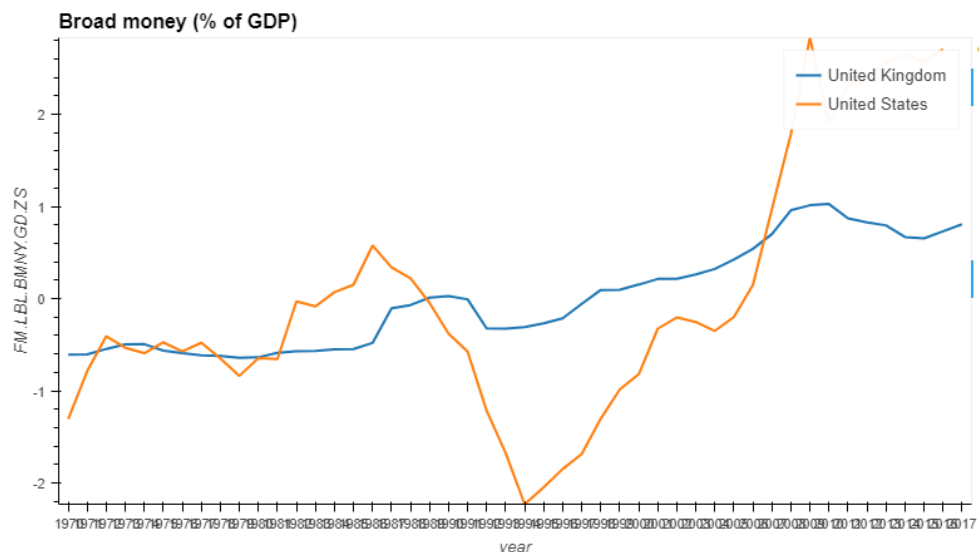
money_unscaled = money

money.loc[money.country=='United States', 'FM.LBL.BMNY.GD.ZS'] = (money.loc[money.country=='United States', 'FM.LBL.BMNY.GD.ZS'] -
                                                                money.loc[money.country=='United States', 'FM.LBL.BMNY.GD.ZS'].mean()) / \
                                                                iqr(money.loc[money.country=='United States', 'FM.LBL.BMNY.GD.ZS'])

money.loc[money.country=='United Kingdom', 'FM.LBL.BMNY.GD.ZS'] = (money.loc[money.country=='United Kingdom', 'FM.LBL.BMNY.GD.ZS'] -
                                                                money.loc[money.country=='United Kingdom', 'FM.LBL.BMNY.GD.ZS'].mean()) / \
                                                                iqr(money.loc[money.country=='United Kingdom', 'FM.LBL.BMNY.GD.ZS'])

money_plot = money.iloc[:, -1:].hvplot.line(x='year', y='FM.LBL.BMNY.GD.ZS', by='country', title='Broad money (% of GDP)')
money_plot
```

Out[10]:



We will compare this variable against real GDP or real output using a constant 2010 USD price-level. Given the relationship between real GDP and our AS-AD model, we will look at real GDP per capita growth due to its scaling and interpretability. From the graphs below, it is clear that a strong correlation exists between these two countries across time, with clear evidence of recessions in 1987 and 1974.

```
In [11]: %%opts Curve [width=800, height=450]
gdp = wb.download(indicator='NY.GDP.PCAP.KD', country=['USA', 'GBR'], start=pd.to_datetime('1970', yearfirst=True), end=pd.to_datetime('2013', yearfirst=True))
gdp = gdp.reset_index()

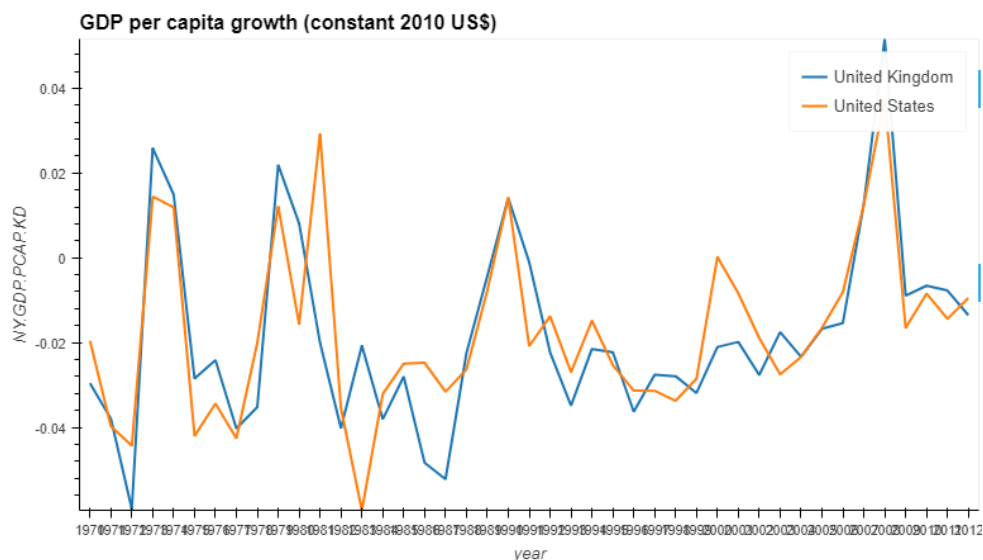
gdp.loc[:, 'NY.GDP.PCAP.KD'] = gdp.loc[:, 'NY.GDP.PCAP.KD'].pct_change()

gdp = gdp.loc[pd.to_numeric(gdp.year) <= 2012, :].dropna()

gdp_plot = gdp.iloc[:, -1, :].hvplot.line(x='year', y='NY.GDP.PCAP.KD', by='country', title='GDP per capita growth (constant 2010 US$)')

gdp_plot
```

Out[11]:



In the interactive plot below, we will use scaled values for broad money and oil rents as values of Z_2 and Z_1 for use in our AS-AD model. Using the slider, we can see more of these exogenous shocks through time, as well as their effect on price-level and real GDP output. Using the real output set at 0 (equilibria) between this price-level, we scale this equilibrium and compare it against our real GDP, shown by the red dot in the right panel of the graph, to analyze the validity of this model for use across a range of applications. We can compare these models for the UK and the US to arrive at a conclusion around the effects of Monetary Policy on the real economy and capital markets. These models do not take into account all variables but aim to approximate an estimate of these models' predictions.



```
In [12]: def curves_data_UK(year=1971):

    oil_z2 = oil.loc[oil.country=='United Kingdom', 'NY.GDP.PETR.RT.ZS'].iloc[:::-1]
    oil_z2 = oil_z2 - oil_z2.iloc[0]

    money_z2 = money.loc[money.country=='United Kingdom', 'FM.LBL.BMNV.GD.ZS'].iloc[:::-1]
    money_z2 = money_z2 - money_z2.iloc[0]

    z_2 = oil_z2.iloc[year-1971] - 10
    z_1 = money_z2.iloc[year-1971] - 10

    as_eq = pd.DataFrame([P(), AS(P=P(), Z_2=z_2)], index=['Price-Level', 'Real Output']).T
    ad_eq = pd.DataFrame([P(), AD(P=P(), Z_1=z_1)], index=['Price-Level', 'Real Output']).T

    as_shock = pd.DataFrame([P(), AS(P=P(), Z_2=z_2+10)], index=['Price-Level', 'Real Output']).T
    ad_shock = pd.DataFrame([P(), AD(P=P(), Z_1=z_1+10)], index=['Price-Level', 'Real Output']).T

    result = findIntersection(lambda x: AS(P=x, Z_2=z_2+10), lambda x: AD(P=x, Z_1=z_1-10), 0.0)
    r = result + 1e-4 if result==0 else result

    plot = hv.Curve(as_eq, vdims='Price-Level', kdims='Real Output').options(alpha=0.2, color='#1B83F5') * \
        hv.Curve(ad_eq, vdims='Price-Level', kdims='Real Output').options(alpha=0.2, color='orange') * \
        hv.Curve(as_shock, vdims='Price-Level', kdims='Real Output', label='AS').options(alpha=1, color='#1B83F5') * \
        hv.Curve(ad_shock, vdims='Price-Level', kdims='Real Output', label='AD').options(alpha=1, color='orange') * \
        hv.VLine(-result[0]).options(color='black', alpha=0.2, line_width=1) * \
        hv.HLine(AS(P=-r[0], Z_2=-z_2-10)).options(color='black', alpha=0.2, line_width=1)

    gdp_mean = gdp.loc[gdp.country=='United Kingdom', 'NY.GDP.PCAP.KD'].iloc[0]
    gdp_iqr = iqr(gdp.loc[gdp.country=='United Kingdom', 'NY.GDP.PCAP.KD'])

    gdp_plot_UK = gdp.loc[gdp.country=='United Kingdom', :].iloc[:::-1].hvplot.line(x='year', y='NY.GDP.PCAP.KD', title='GDP per capita growth (constant 2010 US$)') * \
        hv.VLine(year).options(color='black') * pd.DataFrame([(AD(P=r[0], Z_1=z_1+10)*gdp_iqr*0.35+2.5*gdp_mean), year], columns=['Real Output', 'year']).hvplot.scatter(y='Real Output', x='year', color='red')

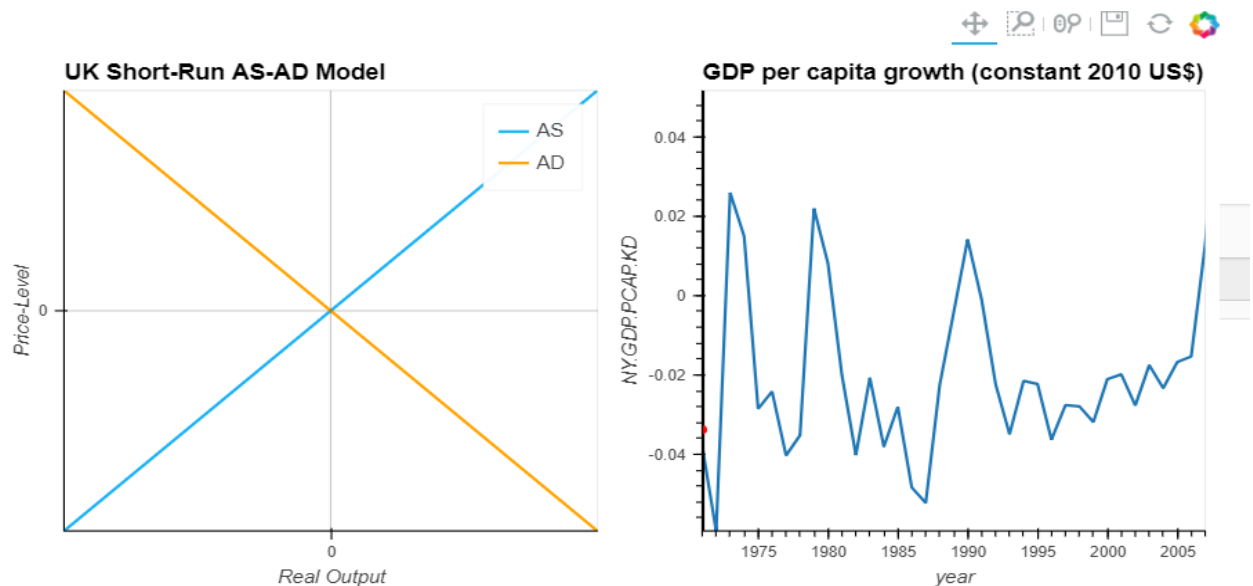
    return plot.options(xticks=[0], yticks=[0], title_format="UK Short-Run AS-AD Model") + gdp_plot_UK

In [13]: %opts Curve [width=400, height=400]

hv.DynamicMap(curves_data_UK, kdims=['year'], label="UK Short-Run AS-AD Model")\
.redim.range(year=(1971,2007))
```

Out[13]:

year: 1971



Looking at the graphs for UK GDP per capita growth and our AS-AD model, it is clear that while our model fails to account for the peaks in GDP per capita growth in 1973 and 1979, it does appear stationary at those points in time, as indicated in our comparison between real GDP and real GDP growth in this graph. Overall the model seems to account well for the overall trend of stationarity in the mid to late 1970s and then growth in 1990 in the mid-2000s.

```
In [14]: def curves_data_US(year=1971):

    oil_z2 = oil.loc[oil.country=='United States', 'NY.GDP.PETR.RT.ZS'].iloc[:::-1]
    oil_z2 = oil_z2 - oil_z2.iloc[0]

    money_z2 = money.loc[money.country=='United States', 'FM.LBL.BMNY.GD.ZS'].iloc[:::-1]
    money_z2 = money_z2 - money_z2.iloc[0]

    z_2 = oil_z2.iloc[year-1971] -10
    z_1= -money_z2.iloc[year-1971]-10

    as_eq = pd.DataFrame([P(), AS(P=P(), Z_2=z_2)], index=['Price-Level', 'Real Output']).T
    ad_eq = pd.DataFrame([P(), AD(P=P(), Z_1=z_1)], index=['Price-Level', 'Real Output']).T

    as_shock = pd.DataFrame([P(), AS(P=P(), Z_2=z_2+10)], index=['Price-Level', 'Real Output']).T
    ad_shock = pd.DataFrame([P(), AD(P=P(), Z_1=z_1+10)], index=['Price-Level', 'Real Output']).T

    result = findIntersection(lambda x: AS(P=x, Z_2=z_2+10), lambda x: AD(P=x, Z_1=-z_1-10), 0.0)
    r = result + 1e-4 if result==0 else result

    plot = hv.Curve(as_eq, vdims='Price-Level', kdims='Real Output').options(alpha=0.2, color='#1B83F5') *\
            hv.Curve(ad_eq, vdims='Price-Level', kdims='Real Output').options(alpha=0.2, color='orange') *\
            hv.Curve(as_shock, vdims='Price-Level', kdims='Real Output', label='AS').options(alpha=1, color='#1B83F5') *\
            hv.Curve(ad_shock, vdims='Price-Level', kdims='Real Output', label='AD').options(alpha=1, color='orange') *\
            hv.VLine(-result[0]).options(color='black', alpha=0.2, line_width=1) *\
            hv.HLine(AD(P=-r[0], Z_1=z_1+10)).options(color='black', alpha=0.2, line_width=1)

    gdp_mean = gdp.loc[gdp.country=='United States', 'NY.GDP.PCAP.KD'].iloc[0]
    gdp_iqr = iqr(gdp.loc[gdp.country=='United States', 'NY.GDP.PCAP.KD'])

    gdp_plot_US = gdp.loc[gdp.country=='United States',:].iloc[:::-1,:].hvplot.line(x='year', y='NY.GDP.PCAP.KD', title='GDP per capita growth (constant 2010 US$)') *\
            hv.VLine(year).options(color='black') * pd.DataFrame([(AD(P=-r[0], Z_1=-z_1-10))*gdp_iqr*0.3+gdp_mean*4, year]), columns=['Real Output', 'year']).hvplot.scatter(y='Real Output', x='year', color='red')

    return plot.options(xticks=[0], yticks=[0], title_format="US Short-Run AS-AD Model") + gdp_plot_US

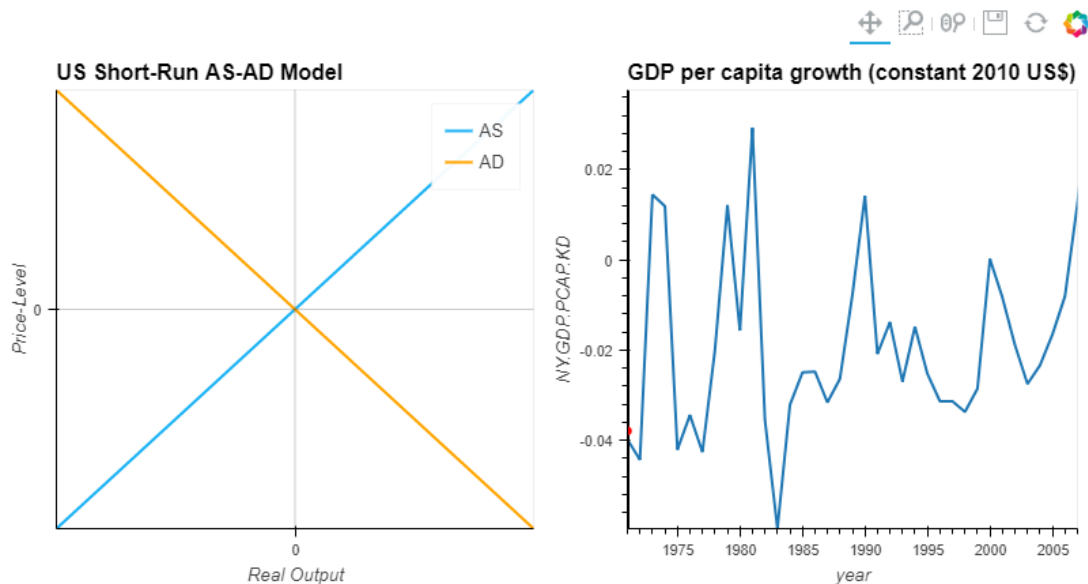
In [15]: %%opts Curve [width=400, height=400]

hv.DynamicMap(curves_data_US, kdims=['year'], label="US Short-Run AS-AD Model")\
    .redim.range(year=(1971,2007))
```



Out[15]:

year: 1971



Similarly, for the US, the AS-AD model appears fairly accurate in tracking overall trends in the data, despite particular failures at points in time. Despite its simplicity, the AS-AD model captures the important macroeconomic dynamics providing predictive insight into the effects of global politics and macroeconomic policy on a country's economy. It is clear that while countries respond differently to monetary intervention, such interventions play a crucial role in managing economic crisis which we will explore in greater depth in later modules.

Unit 4: Trying to Run a Better Market

Program trading – or the computerized trade of a group or ‘basket’ of stocks – is often cited as one of the major contributors to the stock market crash of 1987. Though minimally used during the 1970s and early 1980s, by 1987, major institutions like hedge funds, banks and investment firms were all invested in capitalizing on the potential introduced by large-scale computerized trading. What is critical, however, is to assess how the reliance on electronic trading caused havoc and created a climate of panic-selling and financial instability due to a lack of regulation. Furthermore, when coupled with the indecision by governments as to whether they should increase liquidity and respond assertively to the crisis, the 1987 crash could have turned out much worse.

The calm

In the days leading up to the crash, the Dow Jones Industrial Average (DJIA) dropped dramatically as the fears of a bear market surfaced. On October 14th, the DJIA fell steeply by 95.46 points (3.8%) and on the following day fell a further 58 points (2.4%), prompting a surge in selling. Compounding this were two attacks on American oil tankers off the coast of Kuwait by the Iranian military – as part of the ongoing Iran-Iraq War (1980-1988) – on the 15th and 16th. The US Navy retaliated on October 19th by bombarding an Iranian oil platform in the Persian Gulf. A final cause of anxiety on the market, on the 16th, was the Great Storm of 1987 – a major North Atlantic storm that ravaged the British Isles and Scandinavia – causing the London Stock Exchange to close for one day. All of these circumstances saw the DJIA falter and begin to fall, prompting panicked responses across worldwide stock exchanges.

Over the weekend, a sense of panic overcame investors, who hurried into Monday (October 19th) wanting to sell. The crash started in Hong Kong and quickly spread to Western markets as the day progressed. Over half a billion dollars at the New York Stock Exchange (NYSE) changed hands in the first few minutes of trading, causing stocks to rapidly fall in value. The volume overwhelmed the systems used by traders and companies, causing a serious backlog in orders.



The crash

The 1980s market system used to track and carry out orders was known as program trading. Program trading was the digitalization of trading on the markets, using computer algorithms to purchase or sell off securities. Algorithms were fed instructions – for example, purchase a batch of stocks in a specific sector and sell at a specific time later in the same day or week – and carried them out accordingly. Large financial institutions like hedge fund organizations and investor groups used program trading as a means towards faster, more operationalized trading. At the time of the 1987 crash, limited regulations were in place, with no limitations on orders during times of instability, and any program could make orders during downticks in the market or during a time of free-falling indicators.

Thus, on the morning of the 19th when computers acted on sell orders, it required a vast amount of liquidity to prevent severe instability in the market. As mentioned above, the ripple effect began in Hong Kong, as confidence in the previous years of economic growth petered out and caused panic among investors. This soon spread to London and the European markets, and in due time to the NYSE. Panic continued throughout the day, seeing over a billion dollars' worth of stocks sold within the first few hours. Machines were overwhelmed by the volume of sales and stalled, causing a backlog in orders and blurring the real value of shares and the market stability. Between opening and closing on October 19th, the DJIA experienced the biggest drop in its history of 508.32 points (22.61%). The hardest hit exchange was in New Zealand, which fell around 60% by the close of day. This was largely because the Reserve Bank of New Zealand refusing to release liquidity into the market, which was in contrast with West Germany, Japan and the US, who all released short term liquidity. As a result, the New Zealand financial market took a massive beating and took several years to recover to pre-1987 levels.

Given the panic, the US Federal Reserve Bank issued a statement the following day stating it would help fill the void in liquidity in an attempt to prevent a free fall in the market. This, however, was not enough and the market continued to fall. Upon consultation with the Reagan administration and the Federal Reserve, it seemed likely that the NYSE would be closed, which in turn would cause untold chaos in international markets. However, at the Chicago Board of Trade and the Chicago Mercantile Exchange, investors rallied behind a few key stocks. The rally in Chicago was seen in New York and investors sought to replicate their successes. As a result, confidence in the market began to rise and



with this, buybacks occurred and the DJIA regained strength. This began an eventual upswing in the NYSE and the DJIA, and foreign markets followed the trend.

In hindsight, the potential for economic instability introduced by program trading arose from several factors, including the lack of regulation and the inability of existing legislation to properly manage such large-scale banking and financial transactions. Much like in 1929, overvaluation was also a concern, and the crash happened when this overvaluation coupled with unbridled program trading, a reckless public confidence, and lax regulations. Though the digitization of the stock exchange had helped make the financial world more technologically up-to-date, it needed to be regulated to ensure it did increase volatility in times of stress. Though another depression had been avoided due to the response of the American Federal Reserve and Chicago investors, more needed to be done to stem future crashes.



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Collaborative Review Task

In this module, you are required to complete a collaborative review task, in addition to a multiple-choice quiz. The collaborative review task is designed to test your ability to apply and analyze the knowledge you have learned in the module.

Task

Using data from a set of 5 different countries graph the effects of changes in Oil rents and Broad money on an AS-AD Model starting at equilibrium starting in 1970 and ending in 2007. As much data is missing in these records, I would recommend using 'USA','GBR','CAN','ZAF' and 'MEX', denoted by their ISO3 codes. The code provided in notes 2 and 3 should provide a strong starting point for this analysis. Using this data, and controlling for each country, fit a linear model to analyze the covariance between the predictions of our model and Real GDP per Capital, controlling for properties like trend. Comment on the fit of the model and the standard errors to test whether our model presents model significant levels of covariance between our Predicted Real GDP and Real GDP. Discuss the application and insights of this model to Financial Risk Management and our understanding of the macroeconomy.

