Online Appendix for "Stock Market Co-movement, Domestic Economic Policy, and the Macroeconomic Trilemma: The Case of the UK (1922-2016)"

A1. Stock market data series

UK stock market

To construct the stock market index series for the UK, I obtained a monthly market-wide, capitalisation-weighted nominal stock market index from the Bank of England's (BoE) database "A millennium of macroeconomic data" (Series M13) which is available online at https://www.bankofengland.co.uk/statistics/research-datasets. The series is a spliced construction from different sources as shown in Table A1. They all exclude dividend reinvestment, and consequently, growth rates only reflect capital gains.

Table A1: Sources used by the Bank of England to build the UK stock price index

Start date	End date	Series
Jan-1917	Nov-1921	Morgan (1952) index of industrial share prices derived from Banker's Magazine 1914-1925. June 1914=100
Dec-1921	Sep-1950	Bankers Magazine - 278 variable dividend securities. December 1921=100
Oct-1950	Dec-1951	Actuaries' Investment index of ordinary industrial shares, from Monthly Digest of Statistics (various issues). December 1938=100
Jan-1952	Mar-1962	Actuaries' Investment index of ordinary industrial shares, from Monthly Digest of Statistics (various issues). December 1950=100
Apr-1962	Dec-2016	Financial times - FTSE All-share index 10th April 1962=100

Note: Sources are taken from the Bank of England database "A millennium of macroeconomic data" (Series M13) available online at https://www.bankofengland.co.uk/statistics/research-datasets.

The Banker's Magazine indices, used from January 1917 until September 1950, were the first capitalisation weighted indices calculated in Britain. While they were introduced in 1887 and the methodology was revised in 1895, for this paper the first relevant change in methodology was done in 1907 when the components of the indices were changed, and new companies were added. For this period, the index contains all fixed and variable dividend stocks for industrial companies. A second major revision came in 1921. In it, among the 278 variable dividend securities for industrial companies, some rail and utility companies remained after being nationalised in 1946.

This raises doubts about whether the index correctly reflects the behaviour of the stock market for the late 1940s.[1]

This explains why, for the period starting on October 1950, the Bank of England changes the source series to the Actuaries Investment Index of Industrial shares. According to Haycocks & Plymen (1956), the index reflects the "largest and most reputable companies in each industry" (p. 348). In table 4 they indicate 19 different industries, covering capital and consumption goods, which are included in the industrial index: Paper, oil, chemicals, household goods, stores, electrical, engineering, building, rayon, motors, boots and shoes, food, newspapers, shipping, shipbuilding, tobacco, cotton, breweries, and wool. The index covers 124 securities which, to remain in the index, must fulfil requirements of minimum market capitalisation and dividend payment frequency. The components of the index are revised every 5 years. While the general index described in footnote 1 was equally weighted, the sector indices, particularly the industrial share index used by the BoE, is weighted according to the market capitalisation of each company within the sector using a weighted arithmetic mean.

From April 1962, the BoE starts using the FTSE Actuaries All-share index described by Haycocks & Plymen (1964). It is a capitalisation weighted index which covers 594 companies with market capitalisation of over 4 million pounds and jointly represent close to 60% of the total market value.[2] In line with the Actuaries' Investment Index of industrial shares, the FTSE index is also calculated using a capitalisation-weighted mean. In this index, different broad groups are represented: "capital goods, consumer durables, consumer non-durables, chemicals, oil, shipping, financial and miscellaneous" (Haycocks & Plymen, 1964, p. 269).

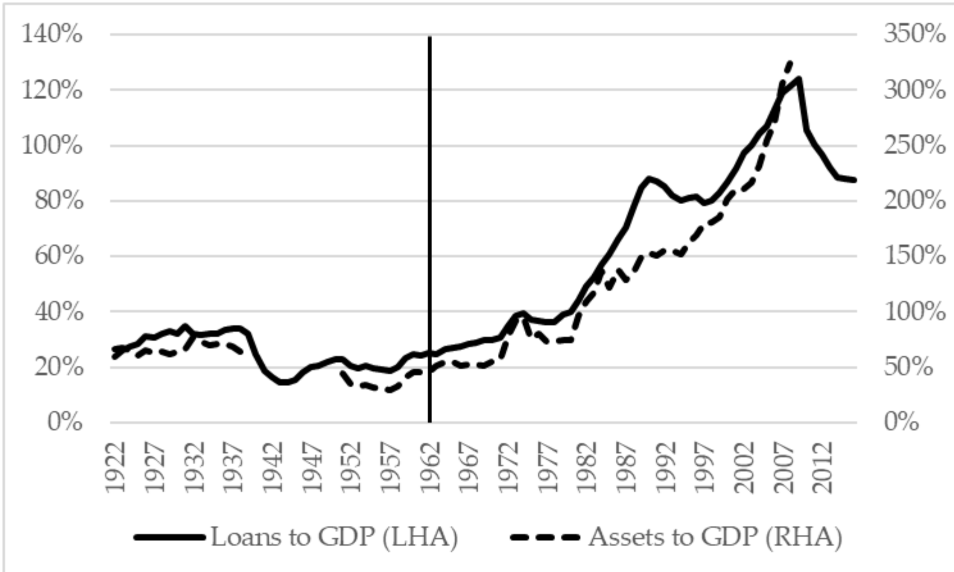
While it would be desirable that the stock market index included the evolution of the financial sector throughout the whole period, neither the Actuaries Investment Index nor the Banker's Magazine indices include the financial sector. According to Haycocks & Plymen (1964), starting in 1962, the Financial Times index, provided by the Bank of England, does include stocks from financial sector companies. Figure A1 presents the evolution of total loans to GDP and bank

[1] To correct for the caveats discussed for the Banker's Magazine series, a possibility would be to replace the series with the Actuaries General Index that was available at the time since 1923. However, in the description of the series provided by Douglas (1929), I find two arguments that prevent us from going down this road. First, the Actuaries' General Investment Index is calculated as an equally weighted and not as a capitalization-weighted index, which can overweight small companies and underweight large participants in the stock market. Second, the general index included, 51 debentures, 23 preferential stocks, and 26 ordinary shares, rendering it incomparable to the other indices which are exclusively focused on industrial company shares in the stock market.

[2] The initial definition of the index covered 650 companies which represented 90% of market value. However, the number of investment trusts in the index was unduly high, overrepresenting the sector. Consequently, the minimum market capitalization for financial companies was set in 16 million pounds. Additionally, for sectors that were underrepresented, companies with market capitalization below 4 million pounds were included in the index.

assets to GDP for the UK. The first series is calculated from the Jordà, Schularick & Taylor (2017) Macrohistory Database while the second series is calculated using the online appendix to Schularick & Taylor (2012).[3]

Figure A1: Loans and bank assets to GDP for the UK



Note: The series of Loans to GDP, from Jordà, Schularick & Taylor (2017) is the ratio of the series *tloans* which contains total loans to the private non-financial sector, to nominal GDP. The series of bank assets to GDP, from Schularick & Taylor (2012) is the ratio of the series *bassets2* which is defined as the year-end sum of all assets in the balance sheets of banks with national residency to nominal GDP.

While a second-best, the inclusion of the financial system starting in 1962 is timely since the expansion of the financial sector in relation to total output exploded concurrently with the financial deregulation of the late 1970s and early 1980s. In that sense, the stock market series employed reflects the evolution of the financial system when it matters most.

Finally, to express the BoE series in real terms, I have used the spliced monthly consumer price index in the database "A millennium of macroeconomic data" (series M6). The index takes the value of 100 in 2015. The index is expressed in real terms where 100 = December 31st, 2015.

US stock market

Data for the US stock market is taken from Robert Shiller's database, available online at http://www.econ.yale.edu/~shiller/data.htm. It is a monthly series of the Standard and Poor Composite Stock Price index which goes back to January 1871 and has been updated until September 2018. The series, which has been used in the different editions of Shiller's (2000) "Irrational Exhuberance", is thoroughly described in Shiller (1989, p. 444) "The series was taken

[3] At the time of writing the third release of the Macrohistory database is available online at http://www.macrohistory.net/data/.

from Standard and Poor's Statistical Service Security Price Index Record, various issues, from tables entitled 'Monthly Stock Price Indexes Long Term'".

The earliest part of the series (1917-1925), has been spliced from the Cowles' "common stock index" series as the Standard and Poor composite was calculated starting in 1926. The index covered 90 companies between 1926 and 1957. From then on, the S&P500 index was introduced. Both the S&P90 and the S&P500 covered companies from a broad array of sectors aiming at representing the broad behaviour of the stock market. As technological change took place, some sectors were dropped, like the railroad sector which was replaced by the transportation sector in 1976. Similarly, new sectors were included, like the financial sector in 1976.

To express the series in real terms, I have used the Consumer Price Index-All Urban Consumers provided by Shiller and taken from the U.S. Bureau of Labor Statistics. It takes a value of 100 in 1983. The index is expressed in real terms where 100 = December 31st, 2015.

A2. Statistical characterisation of stock market series

The following tables include a statistical characterisation of the original time series discussed in Section I of the paper and part A1 of the online appendix. A first section of the left column describes the different series by type, frequency, country, number of observations, start and end date, and source. Two graphs, one for the logarithmic transformation of the series and another for the first differences in the series are included. The following panel in the left section includes descriptive statistics for the series in levels, its logarithmic transformation, the first differences of the log or level series, and the one-period growth rate. The bottom panel of the left column includes a Daniels' trend test for the series in logarithms or levels and first differences, using the rank (Spearman) correlation between the series and a linear time trend (Daniels, 1950). For series of monthly frequency, I include a seasonality test, in levels and growth rates, which tests the statistical significance of the coefficient in the autocorrelation function (ACF) to 12 lags and 24 lags both independently and jointly in the series in logarithms and first differences. Statistically insignificant coefficients allow rejection of the seasonality hypothesis.

In the right column, the first section performs structural breaks tests. To test the logarithmic transformation of the series I employ the test in Perron & Yabu (2009) which is specifically designed to be run on a non-stationary time series. To test the first differences in the series in logarithms, I follow Bai & Perron (1998, 2003) since this test is designed for I(0) series. I present the statistic for the test where the null hypothesis is the absence of breaks against the alternative of one break. Conclusions are based on this test, while the sequential breaks suggested following the Akaike Information Criterion (AIC) are also included (Akaike, 1969, 1974).

The second panel in the column includes stationarity tests for the logarithmic transformations of the series and their first differences. I include the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979, 1981) and the ADF-GLS test (Elliot, Rothenberg & Stock, 1996) on the logarithmic transformation of the series and its first differences. The ADF-GLS tests performs the same ADF test on a series that has been previously detrended using a generalised least squares (GLS) regression. Additionally, I include the Kwiatkowski, Phillips, Schmidt, & Shin (1992) tests (KPSS) which, instead of testing for a unit root, tests for trend stationarity leaving the unit root as the alternative hypothesis.

I also run specific seasonal unit root tests for the series of monthly frequency. The first is the Hylleberg, Engle, Granger & Yoo (HEGY) (1990) test for seasonal integration. Similar to the ADF, the null is that there are some if not all seasonal unit roots in the data. The second seasonal unit root test I include is the one designed by Canova & Hansen (CH) (1995). This test, in the same spirit as KPSS, reverses the hypothesis in HEGY, setting as a null that all seasonal roots are below unity.

Additionally, only for the annual series, I include the Phillips & Perron (1988) test (PP) which runs the ADF test on the first differences of the series rather than on the levels to make it robust to unspecified autocorrelation and heteroskedasticity. I include the Phillips-Perron t-statistic (PP [z(t)]), and the Phillips-Perron normalised bias statistic (PP [z(rho)]). Note that numbers in brackets ([]) represent critical values and not p-values. Whenever the statistic exceeds the critical value, the alternative hypothesis cannot be rejected.

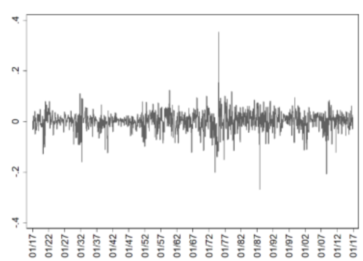
In the third panel, I perform tests to identify the stochastic structure of each time series. I present the statistics of the ARIMA process which best fits the data. Standard errors are included in parenthesis underneath the coefficients. The final panel includes a list of the outliers detected with respect to the best-fitting ARIMA process. These outliers can take three different forms: the additive outlier (AO) which reflects a single jump that immediately reverts to the process; the temporary change (TC) which indicates a jump that reverts slowly towards the identified process; and the level shift (LS) which represents a jump that never reverts to the original process.

Series:	Stocks	**Frequency:**	Monthly
Country:	United Kingdom	**Observations:**	1200
Period:	Jan/1917 - Dec/2016	**Source:**	BoE

Graphs

Logarithmic transformation

First logarithmic differences



Descriptive Statistics	*Level*	*Log*	*Diff Log*	*Gr. Rate*
Mean	1,740.16	7.33	0.10%	0.18%
Median	1,389.46	7.24	0.35%	0.35%
Standard. Dev.	949.67	0.49	4.03%	4.03%
Skewness	1.12	0.48	-0.32	0.37
Kurtosis	3.07	2.24	11.21	15.24
Minimum	423.11	6.05	-26.80%	-23.51%
Maximum	4,347.93	8.38	35.39%	42.45%
Range	3,924.83	2.33	62.18%	65.96%
IQ Range	1,072.47	0.70	4.03%	4.04%

Trend Test

	Log			*Diff log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
Daniels test	20.6801	0.0000	Trend	1.4284	0.1532	No trend

Seasonality Test

	Log			*Diff log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
ACF(12)	2.2932	0.0218	Seas.	0.5646	0.5723	No seas.
ACF(24)	0.6582	0.5104	No seas.	-0.5335	0.5937	No seas.
joint test	0.4869	0.7839	No seas.	0.1877	0.9104	No seas.

Structural Breaks Tests

	Log		*Diff log*			
	PY test	Date	F(0/1)	Conclusion	BIC	Date
1st break	29.8021	Oct-85	1.9021	No breaks	0	
2nd break	5.4452	Jul-59				
3rd break	9.3511	Jan-38				

PY corresponds to the F test in Perron and Yabu (2009), with 5% significance
F(0/1) corresponds to the test in Bai and Perron (2003) of zero breaks againts at least one break
BIC indicates the number of breaks according to the BIC criterion (Bai and Perron, 2003)

Stationarity Tests

	Log			*Diff Log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
ADF	-1.3924	0.5877	I(1)	14.5623	0.0000	I(0)
ADF-GLS	-0.9487	0.3061	I(1)	-9.5445	0.0000	I(0)
KPSS	7.8828	[0.462]	I(1)	0.0784	[0.462]	I(0)
HEGY	-1.5900	0.4867	I(1)	-9.4500	0.0000	I(0)
CH	0.9206	0.9978	I(0)	0.9458	0.9973	I(0)

ARIMA process: ARIMA(0.1.1)

Estimates	ϕ_1	ϕ_2	θ_1	θ_2	σ^2	*ll*	AIC
			0,2384		0.0046	4654.94	-4556.57
			(0.0000)				

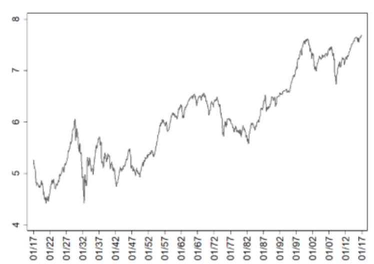
Outliers detected in the estimated ARIMA

Type	Date	Estimate	Type	Date	Estimate
LS	Feb-75	0.0515	LS	Oct-08	-0.0235
LS	Nov-87	-0.0321	AO	Sep-31	-0.0131
AO	Dec-74	-0.0196	AO	Oct-20	-0.0128
AO	May-32	0.0195	LS	Aug-74	-0.0172
LS	Dec-73	-0.026	LS	Oct-59	0.0179
TC	Oct-76	-0.0217			

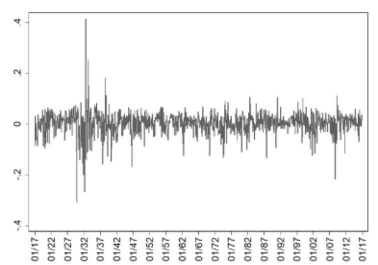
Series:	Stocks	**Frequency:**	Monthly
Country:	United States	**Observations:**	1200
Period:	Jan/1917 - Dec/2016	**Source:**	Shiller

Graphs

Logarithmic transformation



First logarithmic differences



Descriptive Statistics

	Level	*Log*	*Diff Log*	*Gr. Rate*
Mean	599.95	6.04	0.20%	0.30%
Median	400.07	5.99	0.73%	0.73%
Standard. Dev.	529.62	0.85	4.44%	4.45%
Skewness	1.32	0.19	-0.36	0.67
Kurtosis	3.66	2.03	14.43	21.39
Minimum	82.96	4.42	-30.75%	-26.47%
Maximum	2,200.97	7.70	41.48%	51.41%
Range	2,118.01	3.28	72.24%	77.89%
IQ Range	494.57	1.25	4.35%	4.37%

Trend Test

	Log			*Diff log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
Daniels test	31.3486	0.0000	Trend	0.1864	0.8517	No trend

Seasonality Test

	Log			*Diff log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
ACF(12)	-0.4850	0.6277	No seas.	0.7482	0.4543	No seas.
ACF(24)	0.3741	0.7083	No seas.	-0.6339	0.5261	No seas.
joint test	0.0233	0.9884	No seas.	0.0998	0.9513	No seas.

Structural Breaks Tests

	Log		*Diff log*			
	PY test	Date	F(0/1)	Conclusion	BIC	Date
1st break	40.3577	Jun-74	0.2082	No break	0	
2nd break	34.1195	Oct-54				
3rd break	25.9712	Aug-38				

PY corresponds to the F test in Perron and Yabu (2009), with 5% significance

F(0/1) corresponds to the test in Bai and Perron (2003) of zero breaks againts at least one break

BIC indicates the number of breaks according to the BIC criterion (Bai and Perron, 2003)

Stationarity Tests

	Log			*Diff Log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
ADF	-0.5783	0.8731	I(1)	-8.5866	0.0000	I(0)
ADF-GLS	0.6116	0.8485	I(1)	-1.6354	0.0964	I(0)
KPSS	12.5717	[0.462]	I(1)	0.0893	[0.462]	I(0)
HEGY	-1.0300	0.7473	I(1)	-9.0100	0.0000	I(0)
CH	2.5405	0.0623	I(0)	2.4509	0.0839	I(0)

ARIMA process: ARIMA(0.1.1)

Estimates	ϕ_1	ϕ_2	θ_1	θ_2	σ^2	*ll*	AIC
			0,2973		0.0365	2265.89	-4505.78
			(0.0000)				

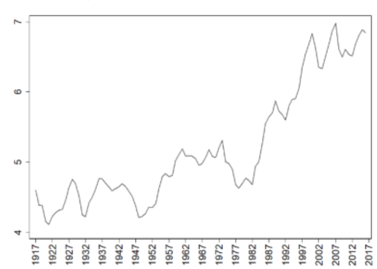
Outliers detected in the estimated ARIMA

Type	Date	Estimate	Type	Date	Estimate
LS	Aug-32	0.3959	LS	Oct-08	-0.1773
TC	Nov-29	-0.256	LS	Jul-38	0.1681
LS	Apr-32	-0.2483	LS	Sep-46	-0.1555
LS	Dec-31	-0.2184	TC	Apr-39	-0.1272
LS	May-33	0.1739	TC	Feb-33	-0.1231
AO	Sep-32	0.1226			

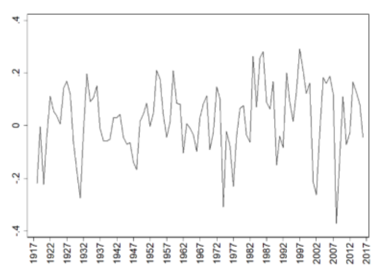
Series:	Stocks	**Frequency:**	Annual
Country:	Other Advanced Economies	**Observations:**	100
Period:	1917 - 2016	**Source:**	JST

Graphs

Logarithmic transformation



First logarithmic differences



Descriptive Statistics

	Level	*Log*	*Diff Log*	*Gr. Rate*
Mean	269.97	5.20	2.26%	3.18%
Median	141.16	4.95	2.94%	2.98%
Standard. Dev.	271.85	0.84	13.43%	13.50%
Skewness	1.50	0.79	-0.46	-0.09
Kurtosis	3.93	2.29	3.17	2.82
Minimum	61.37	4.12	-37.05%	-30.96%
Maximum	1,079.20	6.98	29.17%	33.87%
Range	1,017.83	2.87	66.22%	64.83%
IQ Range	211.53	1.13	17.01%	17.57%

Trend Test

	Log			*Diff log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
Daniel test	87,853	0.0000	Trend	1.8497	0.0644	No trend

Structural Breaks Tests

	Log			*Diff log*			
	PY test		Date	F(0/1)	Conclusion	BIC	Date
1st break	1.2179	No breaks		0.4545	No breaks	3	1954
2nd break							1976
3rd break							1997

PY corresponds to the F test in Perron and Yabu (2009), with 5% significance

F(0/1) corresponds to the test in Bai and Perron (2003) of zero breaks againts at least one break

BIC indicates the number of breaks according to the BIC criterion (Bai and Perron, 2003)

Stationarity Tests

	Log			*Diff Log*		
	Statistic	pvalue	Result	Statistic	pvalue	Result
ADF	-0.3075	0.9215	I(1)	-6.5290	0.0000	I(0)
ADF-GLS	-0.0133	0.6784	I(1)	-3.4415	0.0005	I(0)
KPSS	1.7125	[0.462]	I(1)	0.1775	[0.462]	I(0)

ARIMA process: ARIMA(0.1.1)

Estimates	ϕ_1	ϕ_2	θ_1	θ_2	σ^2	*ll*	AIC
			0,4379		0.0247	225.45	-127.48
			(0.0000)				

Outliers detected in the estimated ARIMA

Type	Date	Estimate		Type	Date	Estimate
-	-	-	-	-	-	-

AO means Additive Outlier; TC means Temporary Change; LS means Level Shift

A3. Trilemma regimes

Trilemma regimes are constructed from the combination of capital control and exchange rate regimes. For the construction of capital control regimes, several sources are exploited. For the period 1922-38, I follow Obstfeld, Shambaugh & Taylor (2010) who have coded capital controls based on documents issued by the League of Nations in 1930 and 1938.[4] For the period 1939-48, I follow OECD (1993) which indicates that Britain had established comprehensive exchange controls at the beginning of the war.[5] For 1949 I use Grilli & Milesi-Ferreti (1995). For 1950-2004 I follow Quinn & Toyoda (2008). For 2005-13 I follow the updated version of Aizenman, Chinn & Ito (2010,2013). For 2014-16 I extend the 2013 observation as Britain has not established capital controls recently.

In the case of exchange rate regimes some papers, like Bernanke & James (1991), offer a complete dating of the period when countries participated in the interwar gold exchange standard and dates for when they abandoned convertibility.[6] However, recent research by Urban & Straumann (2012) has shown that even if the countries eliminated convertibility into gold, they kept a fixed exchange rate. I take this as an invitation to verify directly in the data whether a *de jure* departure from the gold standard coincided with *de facto* flexible exchange rates, and more broadly, whether there may be additional departures from other classifications.

Consequently, I obtained monthly exchange rate series of the British pound against the US dollar, the French franc, the German mark and the euro from the Global Financial Database. To confirm the validity of the series I downloaded the monthly exchange rates of the Swedish Krona and the Norwegian Krone against the five currencies from Edvinsson, Jacobson & Waldenstrom (2008), and Eitrheim, Klovland & Qvigstad (2003) respectively. I then calculated the implied exchange rates of all pairs containing the British pound and verified that the GFD series were consistent.

I follow the methodology by Klein & Shambaugh (2015) to distinguish between hard pegs, soft pegs, and floating exchange rates. In their paper, they calculate monthly devaluations and revaluations of the exchange rate with respect to a base currency from 1973 until 2011.[7] The base currency is that to which the country has historically pegged its currency or the currency to which it is most likely to peg. In this case, I will choose the US dollar as a base currency for Britain in 1922-32, and in 1935-71. During these two periods the price of gold in US dollars was fixed, first at $20.67 per ounce, and later at $35.00 per ounce. As seen in Figure A2, the period 1933-34 was

[4] I thank Alan Taylor for providing access to this data.

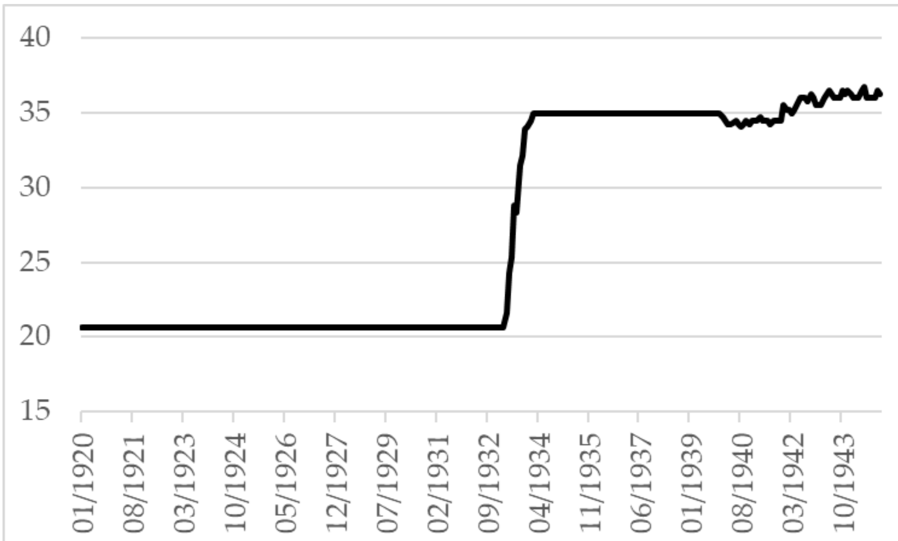
[5] OECD (1993) refers to exchange controls, making no distinction between capital and current account.

[6] Similar characterizations for longer periods are offered by Shambaugh (2004) and Ilzetzki, Reinhart & Rogoff (2017) among others.

[7] In constructing the exchange rate series, they are always expressed in GBP per unit of the base currency. Consequently, a negative (positive) percentage change in the series represents an appreciation (depreciation) of the pound with respect to the base currency.

one of depreciation of the dollar in terms of gold. Therefore, for those two years, I will choose the French Franc as a base currency since France was in the gold standard at the time.[8] Subsequently, for the period 1972-98 the base currency, it is the German mark. During the Economic and Monetary Union (EMU) (1999-2015) the base currency is the euro.

Figure A2: Price of an ounce of gold in US dollars (1920-44)



Note: Data from Global Financial Data. The series corresponds to the gold bullion price per ounce in dollars in New York.

To determine the exchange rate regime for a given country at a given time I follow Shambaugh (2004) and Obstfeld, Shambaugh & Taylor (2010) through the following algorithm. First, using monthly exchange rates against the base currency, hard pegs are those years where the difference of the logarithms of the maximum and minimum value of the exchange rate during a given year is below 0.04. Additionally, hard pegs also occur during those years where, for 11 out of 12 months, the change in the exchange rate is below 1%.[9] As a third step, floats occur on the years where the difference of the logarithms of the maximum and minimum value of the exchange rate during a given year is above 0.1 or when the monthly change for any given month during a year is above 2%. All remaining years are marked as soft pegs. Finally, I use a censoring rule, so that hard pegs occur at least during two successive years, and soft pegs are preceded or followed by either a hard peg or a soft-peg.

Out of 95 observations between 1922 and 2016, 39 correspond to hard pegs, 27 to soft pegs, and 29 to floats. These results are compared with those from Shambaugh (2004) whose database

[8] A similar argument is followed by Urban & Straumann (2012).

[9] The original classification is more stringent and demands that the exchange rate not vary at all during 11 out of 12 months.

is available online and runs uninterruptedly from 1960 until 2014. I find a coincidence between both three-category classifications for 53 out of 55 observations.

There are four possible states of the world, trilemma regimes, according to a binary classification of exchange rates and capital controls: Closed peg, open peg, closed float, and open float. To construct these regimes, however, I need first to shift from the three-way classification of exchange rate regimes, which includes soft pegs, to one where only pegs or non-pegs are established. When following a lax definition of a peg, whereby either soft or hard pegs are considered a fixed exchange rate regime, I find that during 66 out of 95 years the British pound was pegged to some currency. Contrarily, when the strict definition of the peg is followed, and soft pegs are treated as floating regimes, there are only 39 years of a pegged British pound. I compare our results for the strict and lax definitions of a peg with other classifications in the literature such as Ilzetzki, Reinhart & Rogoff (2017) (IRR), and Shambaugh (2004). The former classification runs uninterruptedly from 1925 until 2015, while the latter runs from 1960 until 2014.[10] Table A2 presents the percentage of coincidence between both our classifications, IRR (2017) and Shambaugh (2004).

Table A2: Coincidence between exchange rate regime classifications

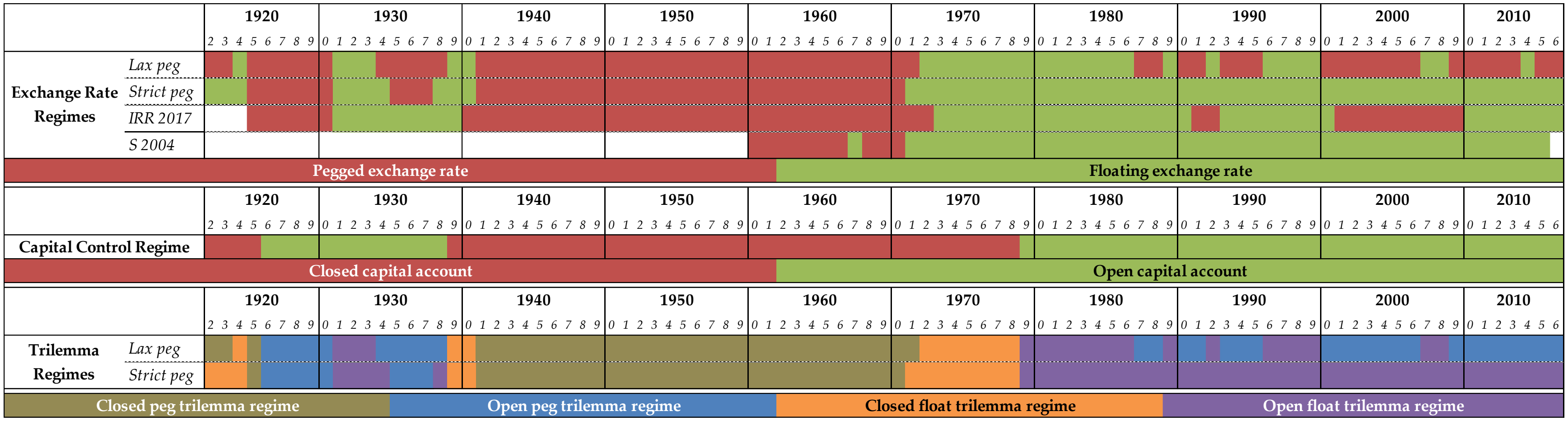
	Coincidence with IRR (2017)	Coincidence with Shambaugh (2004)
Lax peg	74.73%	60.00%
Strict peg	81.32%	98.18%

Note: IRR (2017) refers to the exchange rate regime classification by Ilzetzki, Reinhart & Rogoff (2017). Coincidence is calculated as the number of years where our binary classification coincides with each of the other classifications in the literature over the total number of observations compared.

It is noteworthy that when using a strict definition of the peg, classifying soft pegs as floats, coincidence increases between our classification and both classifications available in the literature. In the following figure, I present the different classification of exchange rates, capital controls and of trilemma regimes using both our lax and strict definitions of the peg. The top panel, dealing with exchange rates, also includes the IRR (2017) and Shambaugh (2004) binary classifications. In the article, our primary specification uses the strict definition of the peg to keep comparability of our results with the literature.

[10] A version of the classification, updated until December 2014, is available online. It includes bot a binary classification and the identification of soft pegs, hard pegs and periods of floating exchange rates. It can be found at https://www2.gwu.edu/~iiep/about/faculty/jshambaugh/data.cfm

Figure A3: Exchange rate, capital control and trilemma regimes for the UK 1922-2015



Note: Top panel presents exchange rate regimes. Lax peg includes both hard and soft pegs according to Klein and Shambaugh's (2015) classification. Strict peg only refers to hard pegs. IRR 2017 is the binary classification by Ilzetzki, Reinhart and Rogoff (2017), S 2004 is the binary classification by Shambaugh (2004) available online and updated until 2014. Capital control series constructed from several sources: OECD (1993), Grilli & Milesi-Ferreti (1995), Quinn & Toyoda (2008), Obstfeld, Shambaugh & Taylor (2010), and Aizenman, Chinn & Ito (2010,2013). Trilemma regimes are calculated from the interaction of exchange rate and capital control regimes. The primary series in the paper is the one that uses the strict peg, while the series that uses the lax peg is used in a robustness test.

A4. Construction of monthly and annual Local Bull Bear indicators

Let $\mathbf{R}$ be an n-period linear return matrix in which rows will represent time and column vectors $\mathbf{r_n}$ will hold the growth rate from period *t-n* until *t*.[11] Thus, the position $r_{t,n}$ in the matrix can be obtained from $r_{t,n} = (P_t/P_{t-n}) - 1$, where P_t corresponds to the value of the variable at time *t*.[12] The index n represents the different time horizons to which I calculate returns. Following the traditional financial literature, short-run returns cover up to one year, medium-run returns up to three years and long-run returns up to five years (Bodie, Kane & Marcus, 2002).

Figure A4 shows the 3D plots of matrix **R** for the UK monthly real stock market index when n takes all integer values between 1 and 60 months. To exemplify, the series contained in vector $\mathbf{r_{24}}$ contains the two-year returns and vector $\mathbf{r_{60}}$ contains the five-year growth rate. Panel A shows the n period growth rates. However, since the series for two different values of n are not comparable, in Panel B I present each series reexpressed as a compounded annual growth rate (CAGR) to ensure comparability. Note that the axis for the values of n in Panel B is reversed.

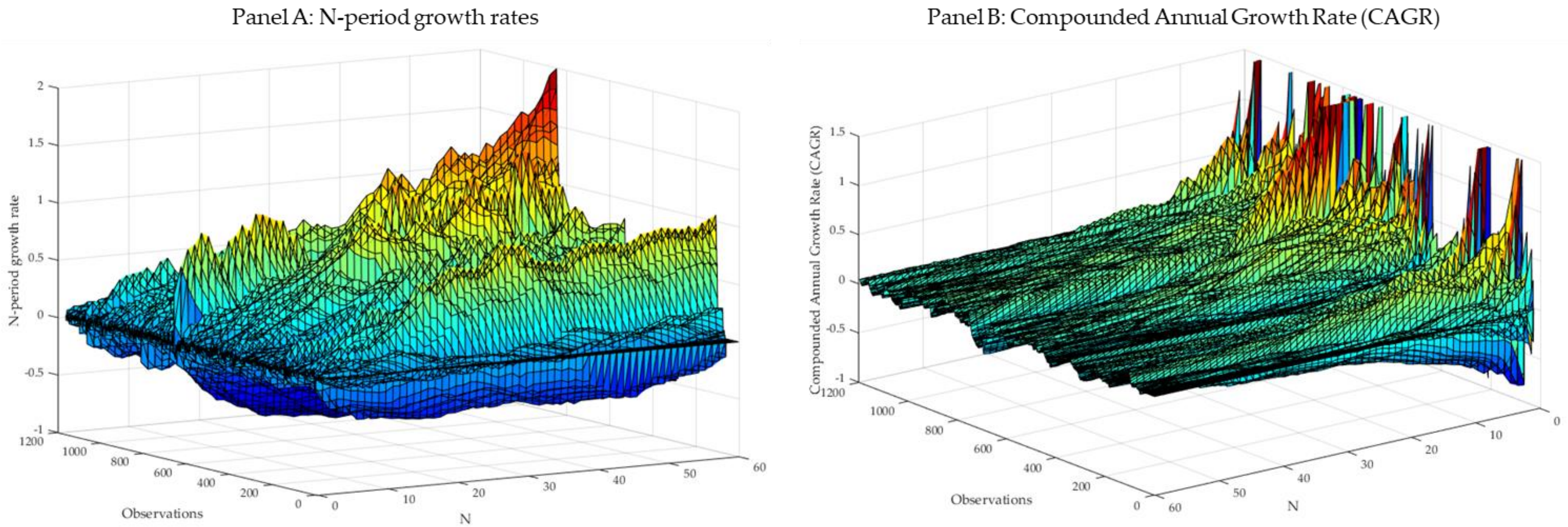
The main takeaway from Panel A in the figure is that returns for the stock market are not only time-varying but that their evolution is contingent on the horizon of observation. Naturally, returns to longer time horizons (larger values of n) are larger than those to short horizons. Additionally, when reexpressed as a compounded annual growth rate (CAGR in Panel B) returns to smaller values of n are noisier than those where n approaches 60.

In that sense, in Panel B one can observe how shocks that affect short-run returns become smoothed out as the lens through which they are observed increases in perspective. This process of increasing the value of n allows us to distinguish between shocks that affect short-run, medium-run and long-run returns. A second issue that shapes the surface in Panel B is the formula employed to calculate the CAGR (See the note to the figure). While monthly returns are exponentiated to the power of 12, 5-year returns are exponentiated to the power of 0.2. It is natural for vectors where n is large to have smaller values and lower variability than vectors where n is small. To exemplify, for an annual rate of return of 10% (25%) when n=1 to persist until n=60 would require the price of the index at time *t+60* to be 61% (204%) larger than the price at time *t*.

[11] Regarding notation, denote matrices in capital letters and in bold. Vectors are noted in lower-case letters and also in bold. Scalars, variables, and constants are italicized.

[12] I prefer to express simple returns as $(P_t/P_{t-1}) - 1$ rather than as $\ln(P_t) - \ln(P_{t-1})$ because, as shown in (SELF CITATION), the logarithmic approximation to returns overestimates losses while it underestimates gains.

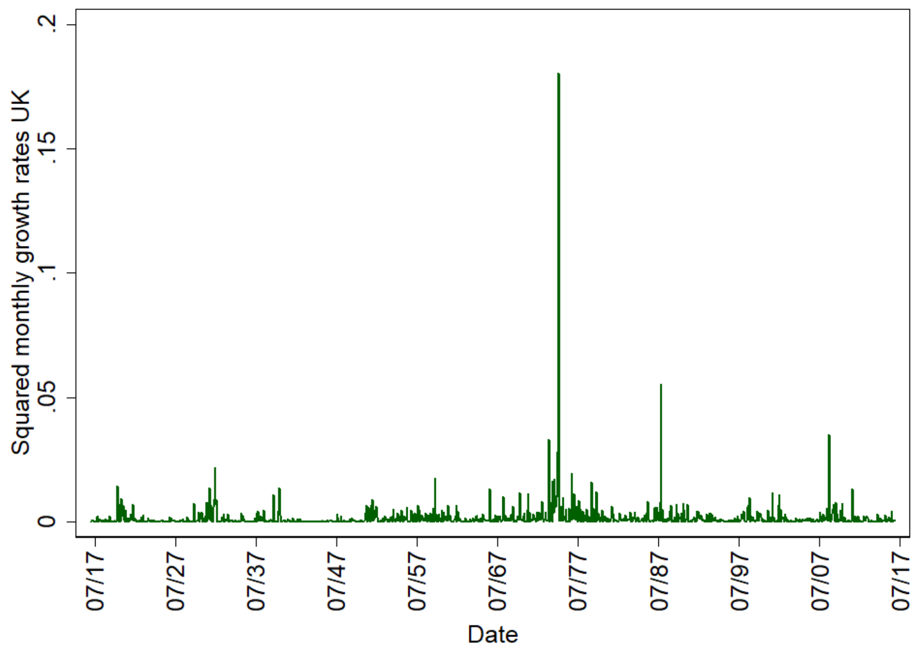
Figure A4: R matrices for the UK stock market index (1922-2016)



Note: Panel A shows the evolution of the period rates of return calculated as $r_{t,n} = (P_t/P_{t-n}) - 1$, where P_t is the value of the index at time t and n takes integer values from 1 to 60 moths. The series where n=12, for example, contains annual returns, while the series where n=28 contains the 28-month growth rates. Panel B shows the same results for matriz **R** expressed as compounded annual growth rates (all are annual return equivalents) which are calculated as $r_{t,CAGR} = \left(1 + r_{t,n}\right)^{12/N} - 1$. In Panel B, note that the axis for n has the values reversed.

A final takeaway from the figure is the evidence of return clustering: a high return at time *t* is usually followed by a high return at time *t+1*. In that same direction, Figure A5 presents the squared monthly growth rate series for the UK index. This series, following Campbell, Lo & MacKinlay (1997), is a quick, back of the envelope calculation of the instantaneous variance in the series. Just as returns, volatility occurs in clusters. Figures for the squared returns to every other time-horizon evidence volatility clustering as well.

Figure A5: Squared monthly returns for the UK stock market index



Note: Calculation performed following Campbell, Lo & MacKinlay (1997). Under the assumption that the mean return is 0, then the squared value of returns is a proxy for the instantaneous variance in the series.

The goal of the LBBI methodology is to exploit the empirical distributions of the data and condense as much of this breadth of information as possible in a few readily-interpretable and intuitive variables. Thus, I construct Local Bull–Bear Indicators (BBIs) for the short-run (from one month to 1 year), medium-run (from 13 months to three years), and long-run (from 37 months to 5 years). The intuition behind the measures is that if growth rates to different time horizons move farther to the right (left) of the distribution the indicators, measured in standard deviations, take larger positive (negative) values. As a thought experiment one can think of the data generating process behind the evolution of a time series as throwing a stone in the centre of a pond, producing waves that move outward towards the shore. LBBIs look at the ripples, distinguishing those that disappear closer to the centre from those that move farther away and from those that reach the shore. Thus, LBBIs discriminate between expansions or contractions that only affect short-run returns from those that affect the medium or long-run.

To avoid using the 60 vectors contained in matrix **R**, I summarise it following the literature on the term structure of interest rates and select the first 12 vectors (corresponding to the short-run or money market horizon), and two equally spaced vectors per subsequent year, corresponding to the 18, 24, 30, 36, month vectors for the medium-run and the 42, 48, 54 and 60 month vectors for the long-run. For annual series, such as the OAE index, n will take integer values from one to five, where the one-year return represents the short-run, the returns for two and three years represent the medium-run, and the returns for four and five years represent the long-run.

As indicated above, by construction, vectors $\mathbf{r_n}$ and $\mathbf{r_m}$ in **R** have different measures since they express n and m period returns respectively. A solution to keep comparability and thus desirable properties such as additivity across vectors with different values of n, is to perform a rolling standardisation of the vectors in matrix **R** such that all vectors are expressed in the same unit of measurement. Doing so generates a new matrix **D** such that:

$$d_{t,n} = \frac{\left(r_{t,n} - \mu_{t,n}\right)}{\sigma_{t,n}} \tag{A1}$$

While $d_{t,n}$ is not a regular z-score, it does measure the distance of a given observation from the time varying mean in terms of the time-varying standard deviation. To obtain a time-varying mean, I use an exponentially weighted five-year moving average (EWMA) such as:

$$\mu_{t,n} = \frac{\sum_{t=0}^{59} \alpha(1-\alpha)^t r_{t,n}}{\sum_{t=0}^{59} \alpha(1-\alpha)^t} \tag{A2}$$

This measure gives more weight to the more recent observations. This is a way of accounting for the clustering of returns evidenced in Figure A4. The weight of the initial observation α is calculated as

$$\alpha = \frac{2}{\text{obs} + 1} \tag{A3}$$

Such that, if for a monthly return vector $\mathbf{r_n}$ I wish to calculate the 60-observation moving average, the weight for the first observation will be 3.28%.

For the time-varying standard deviation, I will use a Generalized Autoregressive Conditional Heteroskedasticity model (GARCH) which has been explicitly designed to tend to the issues of time-varying volatility and volatility clustering (Bollerslev, 1986; Engle & Bollerslev, 1986). The usual GARCH (p,q) model for conditional volatility at time t (h_t) takes the form:

$$h_t = \gamma + \sum_{i=1}^{q} \alpha_i (r_{t-i} - \mu_{t-1})^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{A4}$$

Where parameter p indicates the number of autoregressive lags and parameter q the number of moving average lags that are specified. I specify a GARCH (1,1) conditional volatility model for each vector $\mathbf{r_n}$. This specification

> *"asserts that the best predictor of the variance in the next period is a weighted average of the long-run average variance, the variance predicted for this period, and the new information in this period that is captured by the most recent squared residual"*. (Engle, 2001, pp. 159-160)

The implemented model takes the form:

$$h_t = \gamma + \alpha(r_{t-1} - \mu_{t-1})^2 + \beta h_{t-1} \tag{A5}$$

Where parameter γ is stricty positive and α, and β should move between 0 and 1. It is expected that $\alpha + \beta < 1$ in order for the shocks to have a decaying impact on volatility. The weights assigned to the long-run variance, the moving average component and the aurtoregressive component are $1 - \alpha - \beta$, α, and β respectively. The long-run average variance is obtained from $\sqrt{\gamma/(1 - \alpha - \beta)}$ (Engle, 2001).

When using a GARCH (p,q) model to estimate volatility in the return series, I follow Hansen & Lunde (2005), who indicate that choosing parameters p and q that maximise goodness-of-fit adds little value with respect to the GARCH(1,1) specification.

The values obtained from (A1) refer to the number of sample standard deviations $\sigma_{t,n}$ that a given observation $r_{t,n}$ is away from the sample mean $\mu_{t,n}$ of vector $\mathbf{r_n}$. Since the unit of measurement of all observations $d_{t,n}$ is the same, vectors $\mathbf{d_n}$ and $\mathbf{d_m}$ are comparable within $\mathbf{D}$. In results that are available upon request, all vectors in $\mathbf{R}$ and $\mathbf{D}$ are stationary according to a battery of tests. (A1) can be rewritten as:

$$d_{t,n} = \frac{r_{t,n}}{\sigma_{t,n}} - \frac{\mu_{t,n}}{\sigma_{t,n}} \tag{A6}$$

The expression in (A6) allows for an interpretation of $d_{t,n}$ as the risk-adjusted above-trend return for vector n at time t. It is important to highlight that LBBIs integrate not only measures of return but also of risk into the characterization of expansions and contractions. This will be of paramount importance when I compare LBBIs with the VIX index in part A8.

Since matrix $\mathbf{D}$, in the case of a monthly time series, consists of 20 different vectors a natural next step is to try to aggregate that information into simple indicators. Thus, a Local Bull Bear Indicator (LBBI) is defined as,

$$\text{LBBI} = \omega'\mathbf{D} \tag{A7}$$

Where ω is a vector of weights that add to 1.

Even though the different vectors in **D** have all the same unit of measurement, and thus their linear combinations are interpretable, combining short-run and long-run returns may smooth-out relevant information. To avoid this issue, I construct a short-run LBBI (LBBIS) with the returns from one month up to one year, a medium-run LBBI (LBBIM) with the four vectors from 18 months up to three years, and a long-run LBBI (LBBIL) with the four vectors from 42 months up to five years. To do so, **D** is divided into three corresponding matrices: $\mathbf{D_{short}}$ contains vectors from $\mathbf{d_1}$ to $\mathbf{d_{12}}$, $\mathbf{D_{medium}}$ contains vectors from $\mathbf{d_{18}}$ to $\mathbf{d_{36}}$, and $\mathbf{D_{long}}$ contains vectors from $\mathbf{d_{42}}$ to $\mathbf{d_{60}}$.

The corresponding vectors of weights ω for each **D** are obtained through factor analysis, a technique designed to reduce the dimension of a dataset which includes a large number of variables n into a smaller number m of unobserved factors.[13] The orthogonal factor model takes the following form (Tsay, 2002):

$$\mathbf{D} - \boldsymbol{\mu} = \mathbf{F}\boldsymbol{\Lambda}' + \boldsymbol{\epsilon} \qquad \text{(A8)}$$

Where $\boldsymbol{\mu}$ refers to the mean of vectors in **D**, **F** is a matrix of orthogonal unobserved factors of dimension txm, $\boldsymbol{\Lambda}$ is a matrix of factor loadings of dimensions nxm, and $\boldsymbol{\epsilon}$ is a txn matrix of error terms. Given that I wish to obtain a single LBBI for each specification of **D**, in this particular case m=1, $\boldsymbol{\Lambda}$ is a column vector $\boldsymbol{\lambda}$ of length n and **F** a column vector **f** of length t. (A8) can be rewritten as as:

$$\mathbf{D} - \boldsymbol{\mu} = \mathbf{f}\,\boldsymbol{\lambda}' + \boldsymbol{\epsilon} \qquad \text{(A9)}$$

Each scalar λ_n is the optimal value used to multiply the unobserved factor **f** in order to obtain the corresponding vector $\mathbf{d_n}$. Written in a linear form:

$$d_{t,n} - \mu_n = \lambda_n f_t + \epsilon_{t,n}; n = 1, \dots, N \qquad \text{(A10)}$$

Note that, since each vector in **D** is time series stationary, its mean $\mu_{t,n}$ is time invariant. Consequently, the time subscript is dropped. Thus, to estimate the optimal weight assigned to each vector $\mathbf{d_n}$ to obtain LBBIs, I can solve for $\mathrm{f_t}$ in (A10):

$$\frac{d_{t,n}}{\lambda_n} - \frac{\epsilon_{t,n}}{\lambda_n} = f_t + \frac{\mu_n}{\lambda_n}; n = 1,2, \dots, N \qquad \text{(A11)}$$

In this formulation, the error term contains the part of **D** that cannot be explained by the single vector **f** and is directly related to its explanatory power. From here onward, I will deal with

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[13] To tend to the "curse of dimensionality", factor analysis searches for common underlying factors hidden in the data that explain most of the variations in the covariance or correlation matrix. The orthogonal factor model requires the data to be weakly stationary, which is true for all the vectors in **R** and **D**. An in-depth description of the method can be found in Tsay (2002).

the estimators of the factor loadings ($\widehat{\lambda_n}$) and of the factor ($\widehat{f_t}$). Consequently, the term μ_n/λ_n causes a parallel shift in factor $\widehat{f_t}$ but has no effect on its variance. (A11) can be rewritten as:

$$\frac{d_{t,n}}{\widehat{\lambda_n}} = \widehat{f_t}^*; n = 1,2,\dots,N \qquad \text{(A12)}$$

where $\widehat{f_t}^* = \widehat{f_t}+(\mu_n/\lambda_n)$ The factor loadings, however, do not necessarily add up to 1, so to transform them into weights the following calculation is performed:

$$\omega_{\mathrm{n}}=\frac{1/\widehat{\lambda_n}}{\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(1/\widehat{\lambda_n}\right)} \qquad \text{(113)}$$

The construction of ω in (A13) guarantees that LBBIs mimic the factor with the most significant explanatory power over the original matrix **D** while still being interpretable as standard deviations. (A7) can be rewritten using (A12) and (A13) as follows:

$$\mathrm{LBBI_t}=\frac{d_{t,n}/\widehat{\lambda_n}}{\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(1/\widehat{\lambda_n}\right)}=\frac{\widehat{f_t}^*}{\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(1/\widehat{\lambda_n}\right)};\ n=\left\{\begin{matrix} 1,2,\dots,12 \text{ if } \mathrm{LBBI_{short}} \\ 18, 24, 30, 36 \text{ if } \mathrm{LBBI_{medium}} \\ 42,48,54,60 \text{ if } \mathrm{LBBI_{long}} \end{matrix}\right\} \qquad \text{(A14)}$$

(A14) shows that the short, medium and long-run LBBIs correspond to a rescaled version of the factor that bears the highest explanatory power over the variance-covariance matrices of $\mathbf{D_{short}}$, $\mathbf{D_{medium}}$, and $\mathbf{D_{long}}$. The issue with resolving (A14) in an empirical setting is estimating factor loadings $\widehat{\lambda_n}$. These estimators are obtained through maximum likelihood estimation (MLE).

Following Jöreskog (1967, 1969), if in addition to the model in (A9) $\mathbb{E}(\mathbf{f}) = 0$, $\mathbb{E}(\boldsymbol{\epsilon}) = 0$, $\mathbb{E}(\mathbf{ff}') = \boldsymbol{\Phi}$, and $\mathbb{E}(\boldsymbol{\epsilon\epsilon}') = \boldsymbol{\Psi}$, where $\mathbb{E}$ is the expectations operator, then

$$\boldsymbol{\Sigma} = \mathbb{E}(\mathbf{ZZ}') = \boldsymbol{\lambda\Phi\lambda}' + \boldsymbol{\Psi} \qquad \text{(A15)}$$

The elements $\boldsymbol{\lambda}$, $\boldsymbol{\Phi}$, and $\boldsymbol{\Psi}$ are parameters to be estimated from the data. Johnson & Wichern (2015), indicate that $\boldsymbol{\Phi}$ represents the common variance to all vectors in **D** that is contained in factor **f**, while $\boldsymbol{\Psi}$ can be interpreted as the specific variance not contained in the factor model. Once matrix **S** has been obtained, with the sample variances and covariances estimated from n+1 observations in the data for **D**, Jöreskog (1967) finds that the loglikelihood function of the model in (A15), assuming normality is proportional to:

$$\log \mathrm{L} = -\frac{1}{2}n\left[\log|\boldsymbol{\Sigma}| + \mathrm{tr}\left(\mathbf{S}\boldsymbol{\Sigma}^{-1}\right)\right] \qquad \text{(A16)}$$

The different parameters are calculated by maximising Log L.[14] This maximum likelihood estimation method for the factor loadings offers more tractability than the alternative principal components estimation. While this method also maximises the variance explained by $\mathbf{f}$, the resulting factor loadings, transformed into weights in (A13), allow LBBIs to have both readily-interpretable units of measurement —standard deviations— and economic meaning —risk-adjusted above-average returns.

A final issue to discuss in the construction of LBBIs has to do with the treatment of data to lower frequencies since the OAE index discussed in Section I of the paper has an annual frequency. In this case, the value of n to construct matrix $\mathbf{R}$ will be five. To construct matrix $\mathbf{D}$, I will use a 5 observation EWMA as a time-varying mean, and the GARCH (1,1) volatility (standard deviation) as discussed above. Therefore, $\mathbf{D_{short}}$ will correspond to the one-year return vector, $\mathbf{D_{medium}}$ will contain the vectors for two and three-year returns, and $\mathbf{D_{long}}$ will contain the vectors for four and five-year returns**.** Consequently, using dimensionality reduction techniques to calculate factor loadings is unnecesary. The short-run LBBI will correspond to vector $\mathbf{d_1}$ moreover, the medium and long-run LBBIs will correspond to the simple averages of $\mathbf{d_2}$ and $\mathbf{d_3}$, and $\mathbf{d_4}$ and $\mathbf{d_5}$ respectively. The calculations are presented in (A17)

$$\begin{aligned} \text{LBBIS} &= \mathbf{d_1} \\ \text{LBBIM} &= 0.5(\mathbf{d_2} + \mathbf{d_3}) \\ \text{LBBIL} &= 0.5(\mathbf{d_4} + \mathbf{d_5}) \end{aligned} \qquad \text{(A17)}$$

A5. Comparing LBBIs to other methodologies

In this part, I compare the results using the LBBI methodology with methods such as the Turning Point Algorithm (Bry & Boschan, 1971), the recursive implementation of the Hodrick & Prescott (1997) filter and the Band-Pass filter as in Christiano and Fitzgerald (2003). The comparison is restricted to these methodologies as they are the most frequently used in the literature. A few examples of papers using each methodology follow:

- Turning point algorithm: Bry & Boschan (1971), Hodrick & Prescott (1997), Harding & Pagan (2002a, 2005), Helbling & Terrones (2003), Pagan & Sossounov (2003), Bordo & Wheelock (2006, 2009), Drehmann et al., (2012), Bordo & Landon-Lane (2013), Claessens & Kose (2013), Schüler, Hiebert & Peltonen (2015).
- Band-Pass Filter: Bordo et. al., (2001), Drehmann et al., (2012), Schüler, Hiebert & Peltonen (2015)

[14] The code implemented in MATLAB® has a more sophisticated approach than the one presented in (A16) which I do not elaborate upon as the intuition is clear from the text. For the interested reader, the approach employed follows the factor rotation to maximise the *varimax* criterion presented by Kaiser (1958) and discussed in depth in Johnson & Wichern (2015).

- Hodrick & Prescott (1997) filter: Borio & Lowe (2002, 2004), Borio & White (2004), Schularick & Taylor (2012), Assenmacher-Wesche & Gerlach (2010), Gerdesmeier, Reimers & Roffia (2010), Ng (2011), Shin (2013), Borio (2014a, 2014b).

Turning Point Algorithm (TP)

The turning point algorithm describes local maxima and minima of a time series under a preset group of conditions. The result is a series of dates for peaks and troughs with intermediate sections classified as contractions (bears) or expansions (bulls) (Harding & Pagan, 2005). One of the most frequently used algorithms in business cycle literature is the one developed by Bry & Boschan (1971) to mimic the recession dates found by National Bureau of Economic Research (NBER), which they apply to several economic time series. Three decades later, Pagan & Sossounov (2003) implement these instructions for a long-run monthly index for the US stock market from January 1835 until May 1997 and offer a summary of the rules (Pagan & Sossounov, 2003, pp. 44-45):

I. Determination of initial turning points in data.

I.A. Choice of peaks and troughs in symmetric windows of X months around each price observation.

I.B. Enforcing of alternation.

II. Censoring operations

II.A. Elimination of turns within six months of beginning and end of series

II.B. Elimination of peaks (troughs) at both ends of series which are lower (higher) than values closer to the end

II.C. Elimination of cycles with a shorter duration than Y months both for peak-to-peak and trough-to-trough.

II.D. Elimination of phases (peak-to-trough or trough-to-peak) with a shorter duration than Z months (unless fall/rise exceeds 20%)

III. Statement of final turning points

This simple algorithm produces results that are robust to changes in sample size, although not to window size (Harding & Pagan, 2002a). However, it leaves several choices for researchers allowing for different results using the same inputs. Additionally, the method lacks statistical foundation, difficulting both inference and hypothesis testing (Harding & Pagan, 2002b). For the turning point algorithm, two specifications are performed to obtain starting and ending dates for expansion and contraction phases. First, one for the short-run with a centred observation window of 17 months, a minimum cycle length of 16 months and minimum phase duration of 4 months as in Pagan & Sossounov (2003). An alternative long-run specification uses a centred observation window of 25 months, a minimum cycle length of 24 months and minimum phase duration of 6 months as in Bordo & Wheelock (2009).

The Band-Pass Filter (BP)

The band-pass filter is a two-sided, symmetric filter designed to minimise the adjustment error of a cycle between a preset bandwidth. The central assumption underlying the band-pass filter, as presented by Stock & Watson (1998) and Christiano & Fitzgerald (2003), is that of a minimum and maximum cycle length. Any cycles or information of shorter (longer) frequency than the lower (upper) bound of the bandwidth will be smoothed-out of the time series. A useful characteristic of this method is that it can be used to decompose a time series into as many orthogonal cyclical components as the researcher might need by using different bandwidths. I follow Drehmann et al. (2012) and use the band-pass filter as in Christiano & Fitzgerald (2003) to extract a business cycle with a duration between 18 and 96 months from the logarithmic transformation of the UK stock market index. I follow Bordo et al. (2001), who use the business cycle series to date booms and busts, by extracting peaks and trough using a centred moving window of 25 observations in a process reminiscent of the turning point algorithm.

The HP Filter

The Hodrick & Prescott (1997) filter (HP) is a one-sided high-pass filter designed to decompose a time series in a trend component assumed to vary smoothly over time with a stable second difference, and an independent cyclical component. The HP filter is a parametric approach which depends on the choice of a smoothing parameter λ which penalises the growth component over the cyclical component. Lower values of λ yield models that adapt faster to changes in the data. The filter extracts a trend from an observed time series with a weighted moving average and returns high-frequency component (usually frequencies higher than 40 quarters for quarterly data). It does so with the added benefit that it can be performed on nonstationary time series although the literature has shown that the filter produces artificial long-term cycles if the series is integrated of order 1 (Metz, 2011).

Following Ravn & Uhlig (2002) I use a λ of 129,600.[15] The filter is applied to the stock market indices directly, extracting the last observation for the trend on a rolling window of 120 observations (10 years). The stock market growth gap is calculated as the percentage difference between the expected value of the series and the observed value for a given date.

Dating expansions and contractions by methodology

To compare the results from these three different approaches, I establish starting and ending dates for booms and busts. Both specifications of the turning point algorithm and the band-pass filter produce, as output, such a series.

However, to extract dates from the HP filter and the LBBIs thresholds for what constitutes a boom or a bust need to be established. The choice of a given threshold, however arbitrary, does

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[15] In their paper, Ravn & Uhlig (2002) search for the optimal values of lambda when the frequency of data varies. Their criterion for optimality is that the main properties for the results to one frequency are transferred to other frequencies so that results are not an artifice of the frequency of data used. The monthly equivalent of the optimal quarterly lambda of 1600 found by Hodrick & Prescott (1997) is precisely 129,600.

not imply a loss of information from the series but rather a means of summarising the data. In this case, I follow a simple rule by which if the observation of any given month is above (below) (-)X standard deviations the month is considered to be a boom (bust) month. If two booms (busts) were three or fewer months apart and the value of the gap or LBBI never turned negative (positive), it is treated as a single boom (bust). Additionally, booms (busts) that lasted only one month were kept only if the value of the HP gap or the LBBI was at least (-)2X. I have used a lax threshold of ±0.5 standard deviations and a strict threshold of ±1 standard deviations. The following table shows the percentile of each of the four series that corresponds to each of the thresholds employed.

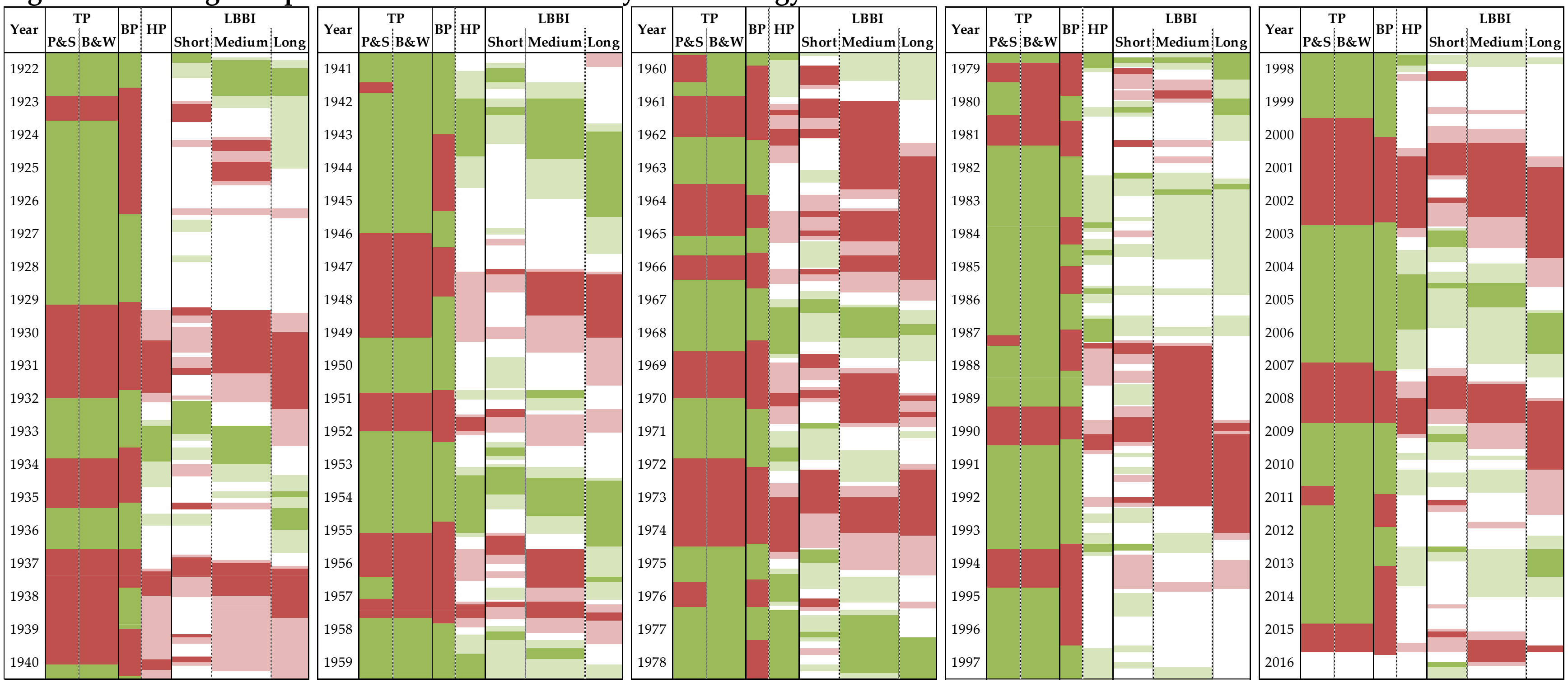
Table A3: Percentiles associated with each threshold by series

Threshold	HP gap	LBBIS	LBBIM	LBBIL
-1 s.d.	11.1	13.0	23.0	21.8
-0.5 s.d.	26.3	27.6	37.9	36.5
0.5 s.d.	67.8	72.7	72.4	71.1
1 s.d.	84.1	90.2	88.6	88.0

Note: Threshold is expressed in standard deviations. For ease of calculation, I have divided the HP gap series by its full sample standard deviation.

Figure A6 summarises the results graphically by identifying the differences in dating across methodologies. For TP and BP bull phases are highlighted in green, and bear phases are highlighted in red. In the case of LBBIs and HP, expansions (contractions) under the strict specification are highlighted in dark green (red) while expansions (contractions) that only show up under the lax specification are highlighted in light green (red).

Figure A6: Dating of expansions and contractions by methodology



Note: TP refers to the Turning point algorithm. P&S refers to the short-run specification by Pagan & Sossounov (2003). B&W refers to the long-run specification by Bordo & Wheelock (2009). BP refers to the business cycle component extracted using the band-pass filter as in Christiano & Fitzgerald (2003). HP refers to the Hodrick & Prescott (1997) filter applied recursively with 10-year observation windows and a lambda of 129,600 as in Ravn & Uhlig (2002). Bull (bear) phases under TP and BP are highlighted in dark green (red). In the case of LBBIs and HP, expansions (contractions) under the strict specification are highlighted in dark green (red) while expansions (contractions) that only show up under the lax specification are highlighted in light green (red).

I then I build coincidence dummies between the different methodologies which take the value of 1 if two indicators show a boom or a bust in the same month and zero otherwise. The value of the coincidence index between both methodologies will be the mean of the respective coincidence dummy expressed as a percentage. The following table contains the coincidence indices for LBBIs (rows) against the usual methodologies (columns). Values above 90% (70%) are highlighted in dark (light) green.

Table A4: Coincidence index between methodologies

	TP (P&S)	TP (B&W)	BP	HP (X=0.5 S.D.)	HP (X=1.0 S.D.)
Short-run LBBI (X=0.5 S.D.)	91%	89%	86%	56%	55%
Short-run LBBI (X=1.0 S.D.)	95%	88%	93%	46%	65%
Medium-run LBBI (X=0.5 S.D.)	70%	75%	63%	79%	59%
Medium-run LBBI (X=1.0 S.D.)	75%	76%	71%	62%	73%
Long-run LBBI (X=0.5 S.D.)	65%	62%	47%	57%	47%
Long-run LBBI (X=1.0 S.D.)	74%	72%	49%	54%	65%

Note: TP refers to the Turning point algorithm. P&S refers to the short-run specification by Pagan & Sossounov (2003). B&W refers to the long-run specification by Bordo & Wheelock (2009). BP refers to the business cycle component extracted using the band-pass filter as in Christiano & Fitzgerald (2003). HP refers to the Hodrick & Prescott (1997) filter applied recursively with 10-year observation windows and a lambda of 129,600 as in Ravn & Uhlig (2002). Values above 90% (70%) are highlighted in dark (light) green.

Coincidence across methodologies is high in general. Interestingly, it is decreasing in the time horizon of the LBBI, as medium and long-run indicators, by design, capture different phenomena than the usual methodologies. From the description above, it is clear that the latter focus on short-run changes in the levels of the indices, while medium and long-run LBBIs are designed to capture the persistence of phases in time and as time-horizon increases, noisier less important phases are filtered out. In what follows we present a narrative of the British and global economic history to frame the expansions and contractions identified in Figure A6 in the broader context.

The interwar years: 1922-1945

A first boom occurs, according to LBBIS and LBBIM, in early 1922 affecting short-run returns until late 1922 and medium-run returns until late 1923. LBBIL dates the boom between mid-1922 until mid-1925. Following Alford (1972), while the boom phases denote the beginning of a recovery after the depression in 1921-22.

Subsequently, LBBIs find bear phases in 1923 (LBBIS), 1924-25 (LBBIS and LBBIM), 1926 and 1929 (all specifications). These bear phases coincide with events like the return to the gold standard at the prewar parity (1925) and the general strike of 1926 (Huberman, 2014). A bust corresponding to the stock market crash of 1929 in the US shows up in all specifications. After the crash, the Great Depression shook the world economy both east and west of the Atlantic, with implications for the British stock market. The short-run indicator shows a small recovery in 1927 and another in 1928. None of them is robust enough to affect the medium or long-run indicators. The interesting issue from this analysis is that LBBIs allow us to nuance the story that would have been told otherwise if only using TP or BC (as in findings by Bordo & Landon-Lane, 2013)

However, the effects of the Great Depression, the pressure on the gold standard, the failure of the Credit Anstalt Bank in Austria (1931), a weakening trade position, and measures such as tax increases and wage cuts to balance the budget coincide with a bear market picked up by LBBIS (1930-31 and 1931-32), LBBIM (1929-32) and LBBIL (1929-33) (Wolf, 2008 and James, 2014). Interestingly, although the acute phase seems to take place only up until late 1931, a few months after the abandonment of gold convertibility, the effects on medium and long-run returns is evidenced by LBBIL until 1933.

After the abandonment of the gold standard in September 1931, LBBIs date a boom that starts between 1932-34 depending on the specification of the indicator. Its short-run effects last until early 1935, while the medium-run indicator dates its end by late 1935 and the long-run indicator found an effect until 1936 when the seeds of the Second World War had already been planted. All LBBIs identify a relevant bust phase during the height of the Second World War, starting in 1937. While the medium and long-run indicators find a single bear phase lasting until 1941, the short-run indicator breaks down the bear phase into three distinct stages. The first stage in 1937-38, coincides with the reoccupation of the Rhineland (1936) and the annexation of Austria (1938). The second phase during a few months during 1939, coincides with the British declaration of war against Germany (September 1939). A final stage lasting a few months by early 1940, coincides with the occupation of France, Belgium, the Netherlands, Luxembourg, Latvia, Estonia, and Lithuania, all of which took place during that year (Hobsbawn, 1994).

For the end of this period, LBBIs find a boom that varies in dating depending on the indicator. LBBIS finds it starts in early-1941 and ends by late-1943. Conversely, LBBIM dates its beginning in late-1941 and its end by early 1945. Finally, LBBIL indicates it begins in 1942 and runs until 1946. This complicated process of recovery and boom could relate to the fact that both output and employment increased due to the war effort even if the public coffers were nearing exhaustion. Both the establishment of exchange controls (1939) and the entry of the US into the conflict (1941) may have supported the stock market by avoiding divestment and pumping investor’s expectations (Milward, 1970).

Bretton Woods: 1945-1971

By late 1947, all LBBI specifications, note the beginning of a bear phase. While LBBIM indicates this phase runs until early-1950, LBBIL dates its end in late 1951 with a small recurrence during 1952. LBBIS, on the other hand, indicates that this bear trend occurred in two different waves (1947-48 and 1949-50). A bull phase, dated only by the short and medium-run indicators, occurs in 1950-51. This boom is illustrative of the communication between short, medium and long-run LBBIs. The bull phase, according to the LBBIS begins in mid-1950, while both LBBIM and LBBIL still indicate the presence of a bust. Short-run risk-adjusted returns improve enough to start affecting medium-run returns and thus moving the LBBIM above the threshold of a bust phase. By mid-1951, short-run returns have been above average for a sustained period, thus passing the medium-run risk-adjusted returns above the threshold for a bull phase. However, this boom is not powerful enough to revert the trend in long run returns, which keep signalling a contraction until early 1952. In that sense, instead of describing this phase as a full-fledged expansion, it can be better thought of as a recovery. A second bust is dated by LBBIS (1951) and LBBIM (1951-52)

The dynamic described throughout the previous paragraph coincides with the ascent of the Labour government after the end of the war (1945), which was accompanied by increased taxes and nationalisation of industries (Dow, 1964). Additionally, the bear phases may be associated with the threatening of British colonial rule, since in July 1947 the UK signed the Indian Independence Act and Kenya and the Federation of Malaya rebelled against British rule in 1951-52 (Austin, 2014). From an exchange rate perspective, it is worthwhile to recall the UK devalued the pound in 1949 as one of the measures to help solve the dollar shortage that troubled the international monetary order at the time (Bordo & Schwartz, 1999; Eichengreen & Sussman, 2000). The other two measures put in place were the European Reconstruction Plan (Marshall Plan) in 1948-52, and the establishment of the European Payments Union in 1950 (Neal, 2015).

The following expansion is dated by LBBIS in 1952-54, while the medium-run indicator dates in 1953-55, and the long-run indicator indicate it runs from 1953 until 1957. This expansion coincides with a wave of European stock market booms (Bordo & Wheelock, 2009). It was an intense expansion since its medium and long-run effects could be identified almost by the end of the decade. Subsequently, a new crash that shows up in all BBIs occurs in 1957-58. The bust shows up in the medium and long-run returns propelled by two explosive a busts registered by BBIS in 1955-56 and 1957-58. The first one roughly coincides with the end of the Bandung conference which continued the decolonisation process, and the Suez Crisis which undermined the perception of a British Empire (Hyam, 2006). The second bear market may be associated with the US recession of 1958 which coincides with the only negative GDP growth in the UK in 1950-70. The decade ends as LBBIS dates a new boom period in 1958-60. Concurrently, LBBIM indicates this boom lasts until early 1961 while LBBIL indicates its long-run effects wane by late 1961. The results for the 1950s coincide with the historiography which points out that the decade was one of unparalleled economic growth in the UK, with low levels of unemployment, a reduction of the national debt, and increasing demand, particularly after the end of the rationing in 1954 (Hobsbawm, 1994; Middleton, 2000).

In general, the decade of the 1960s is one of underperformance in the stock market. LBBIS and LBBIM register a crash in 1961-62 with medium-run effects until 1964. This bust may be related to brief dips in the UK's output at the beginning of the decade, and to a rolling recession that occurred in the US in 1960-61. LBBIS and LBBIM identify a significant crash in 1964-65 which according to LBBIM lasts until 1967. A third crash in 1966-67, shows up both in the short and medium-run indicators. This crash may be associated with the balance of payments and exchange rate problems that characterised the UK economy at the time, and that ended with the devaluation of the pound in November of 1967. The effects of these three explosive and expansive busts compounded to produce a single long crash which registers in the long-run indicator from 1962 until 1967. According to the three specifications of the indicator, a boom takes place in 1967-69. This finding is consistent with those by Bordo & Landon-Lane (2013) who date the boom in 1966-68. Finally, the decade ends with two successive bear phases, as identified by the short-run indicator in 1969 and 1970. LBBIM identifies the effects of this crash until 1971.

Interestingly, this description of relative economic underperformance of the UK during the European Golden Age of economic development is consistent with the findings by Crafts (2012). The Bretton Woods era ends with a short boom in 1971-1972 which quickly affects long-run returns and thus shows up in all three indicators. We associated this boom with a period of rapid UK growth, deregulation of the mortgage market and significant tax cuts that were implemented in 1970-72 (Aldcroft, 2002).

Post Bretton Woods: 1971-2015

The first significant bust in the period occurs under the conservative government of Edward Heath (1970-74) that faced dire economic conditions, with union strikes, increasing unemployment, very high inflation and the first oil shock (1973-74) which led the broadest crash in the series according to the LBBI methodology (Huberman, 2014). This bust starts, according to LBBIS, in mid-1972 and lasts until December 1974. This bust affects medium and long-run returns until late 1975.

A short-run recovery from the oil-shock crash begins in early 1975 and lasts, according to the three indicators, until the second oil shock of 1979. This second shock registers only in the short and medium-run indicators since at that time Britain had become a net oil exporter and the oil hikes did not affect the economy as strongly. The short and medium-run bear phases are not strong enough to revert the positive trend of the long-run indicator which signals a boom until 1981. This mid-1970s boom roughly coincides with a bail-out authorised by the IMF in 1976 aimed to attack the significant budget deficits and the concerns over the value of the pound, which had lost 20% of its value since 1972. After implementing spending cuts, the economy started a recovery period, also aided by a recovery in the balance of payments via oil exports (Aldcroft, 2002).

The 1980s begin with a crash identified only by the short and medium-run indicators in mid-1979 and lasting until May 1980. This bear phase coincides with the second oil shock, a recession characterised by union strikes all around Britain, high inflation, and unemployment (Minford, 2015). LBBIS then identifies six different booms during 1980-87: 1980, 1982-83, 1984, 1984-85, 1986, and 1987. LBBIM and LBBIL identify a single boom during this period starting in mid and late 1982 respectively. This is the lengthiest long-run boom in the series and coincides with a period of high GDP growth, receding inflation, and decreasing unemployment after the first critical years of the Thatcher government. Bordo & Landon-Lane (2013) associate this boom with increasing house prices, growing GDP, low taxes and decreasing interest rates.

However, this expansive era is nuanced by a quick bust that shows up in the short and medium-run indicators during September-October 1981. Subsequently, the expansion of the 1980s comes to an immediate halt with a crash that begins in 1987 (the Black Monday). It is a sudden event that affects simultaneously short and medium-run returns. The short-run phase ends by 1988 but is quickly followed by another contraction during 1990. A third bear phase, which shows up in LBBIS, occurs in July and August 1992. The effects of these three bear phases are compounded and appear in a medium and long-run crash that lasts until 1992 and 1993 respectively. This contractionary phase in the UK stock market coincides with the entrance of the UK in the European Monetary System (EMS) in October 1990, and with episodes of rising inflation and unemployment accompanied by decreasing industrial output and GDP. By the end of the Thatcher government (November 1990) the economy had slid in what would be the most prolonged recession since the Great Depression (1990-93). Additionally, speculative attacks against the British Pound by institutional investors resulted in the abandonment of the EMS in late 1992 (Eichengreen, 2008; Minford, 2015).

By the end of 1992, LBBIS registers an expansive phase that lasts until early 1993. Another short and medium-run expansion appears in late 1993 and early 1994. All indicators show a short contraction in 1994-95. Subsequently, LBBIS shows two expansions in 1995 and a third on in 1997 which also registers in LBBIM and LBBIL until 1998. These booms coincide with the Conservative governments of John Major and the first Labour government of Tony Blair, and occurred during a period of stability, decreasing inflation, and GDP growth after the recession of 1990-93.

By the end of the century, global capital markets started facing severe risks from emerging markets: Asian crisis in 1997, Russian default in 1998, Brazilian crisis in 1999, Argentinean crisis 2001, Dotcom bubble 2001-03 (Kindleberger & Aliber, 2005). All these events coincided with significant corrections in the stock market which show up in the three specifications of BBIs as a long and severe bust in 2000-03 with long-run effects running until 2004.

After this period of turmoil, the three indicators register a boom that occurs between the burst of the technological bubble (2003-04) and the beginning of the Global Financial Crisis (2007).

The period was also one of financial innovation and market deregulation which allowed the stock market to recover. Most of the capital that was fleeing the emerging markets looks for haven either in the US or Europe and with that additional capital inflows the stock market started booming (James, 2014). The length of the boom is nuanced by LBBIM and LBBIL, as they find that the medium and long-run returns only boom starting in 2005 and 2006 respectively. While the short-run indicator dates the end of the boom phase in 2006, the other two indicators date its end in mid to late 2007, coinciding with the first announcements of problems in the subprime market in the US.

The indicators show the bear associated with the GFC beginning in late 2007 or early 2008 and its end in 2008, 2009, or 2011 according to LBBIS, LBBIM, and LBBIL respectively. Its long-lasting effects occur in part because recovery was prolonged (only two bull episodes in the short-run indicator in 2009-10) and because there was a short-run downturn in 2011 that coincided with the peak of the European debt crisis (Neal, 2015).

A final bear market appears to happen during 2015 and early 2016 in all three indicators. This bust may be associated with the Brexit talks and the current transit that the European Union Referendum Act 2015. This legislation was currently advancing through the UK legislative: it was approved by the House of Commons in June 2015 and would be approved by the House of Lords in December of that same year.

A6. Dating expansions and contractions in the UK stock market under different thresholds

To date expansions and contractions in the British stock market, the rule described in part A5 is followed. To characterise each phase, I include detailed measures. First, duration is the number of months between the start and end date. The starting (ending) date is the first (last) day of the given month. Second, I deal with two measures of amplitude. First, the compounded annual growth rate (CAGR) between the level of the original series at the starting and ending dates. Second, the difference between the 1, 3 and 5-year CAGR for the short, medium and long-run LBBIs respectively between the starting and ending date. Finally, severity is defined as the accumulated value of the indicator between the starting and ending date of a bull or bear phase. This measure can be thought of as the area between the LBBI and the horizontal axis for a set period.

The following tables contain the dating for bull and bear phases in the UK stock market, using the short, medium and long-run LBBIs, under two different values of the threshold. A strict threshold of ±1 standard deviation, and a lax threshold of ±0.5 standard deviations. These are the same thresholds employed in part A5. The additional information contained in this appendix is of interest for researchers, a valuable contribution of this paper, and a precious resource for further research.

Table A5: Dating of bulls and bears using a lax threshold

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Short-run LBBI - 0.5 SD threshold						
Bull	01/22	09/22	9	40.61%	-1.34%	8.41
Bear	07/23	01/24	7	-16.59%	-18.81%	-8.74
Bear	09/24	10/24	2	-22.89%	-4.40%	-1.71
Bear	10/26	11/26	2	-17.56%	-7.32%	-2.27
Bull	02/27	05/27	4	24.94%	6.25%	2.47
Bull	03/28	04/28	2	32.03%	0.10%	1.13
Bear	10/29	02/30	5	-20.81%	-12.63%	-7.17
Bear	05/30	01/31	9	-22.69%	-8.06%	-8.87
Bear	04/31	09/31	6	-42.06%	-16.45%	-6.06
Bear	06/32	06/32	1	-85.30%	-13.75%	-1.52
Bull	08/32	09/33	14	28.78%	36.05%	16.44
Bull	01/34	04/34	4	39.20%	7.10%	3.00
Bear	07/34	10/34	4	-11.88%	-7.58%	-3.08
Bear	09/35	10/35	2	-35.39%	-6.99%	-2.23
Bull	01/36	04/36	4	25.11%	7.18%	3.15
Bear	04/37	06/38	15	-22.54%	-25.42%	-14.60
Bear	09/39	11/39	3	-33.81%	-8.36%	-3.33
Bear	05/40	07/40	3	-62.81%	-19.12%	-3.86
Bull	05/41	01/42	9	10.75%	22.85%	11.32
Bull	06/42	09/43	16	14.45%	11.82%	14.45
Bull	05/46	06/46	2	30.22%	4.82%	1.55
Bear	09/46	10/46	2	-20.53%	-6.99%	-1.59
Bear	08/47	03/48	8	-19.11%	-12.05%	-7.59
Bear	05/49	08/49	4	-23.28%	-6.02%	-3.26
Bull	04/50	02/51	11	7.20%	12.94%	8.01
Bull	04/51	06/51	3	35.55%	4.88%	3.17
Bear	11/51	06/52	8	-41.72%	-33.70%	-8.22
Bull	11/52	04/53	6	6.62%	23.12%	6.25
Bull	07/53	10/54	16	37.67%	24.39%	16.50
Bear	08/55	06/56	11	-19.71%	-36.77%	-12.33
Bear	10/56	11/56	2	-45.63%	-4.93%	-2.72
Bull	04/57	07/57	4	22.36%	2.77%	3.37
Bear	09/57	02/58	6	-38.12%	-21.95%	-7.01
Bull	06/58	01/60	20	42.37%	62.74%	16.96
Bear	06/60	01/61	8	2.03%	-26.82%	-8.35
Bear	06/61	07/62	14	-24.32%	-29.12%	-17.67
Bull	08/63	11/63	4	23.21%	-2.63%	2.96
Bear	05/64	08/65	16	-12.04%	-21.13%	-12.11
Bull	10/65	06/66	9	12.60%	23.62%	5.78
Bear	08/66	11/66	4	-40.44%	-26.18%	-5.38
Bull	04/67	09/68	18	39.71%	53.60%	16.06
Bear	03/69	11/69	9	-28.25%	-47.75%	-12.49
Bear	03/70	07/70	5	-35.70%	5.06%	-5.98
Bull	04/71	04/72	13	47.28%	55.52%	12.20
Bear	09/72	12/74	28	-48.09%	-78.92%	-29.37
Bull	02/75	03/76	14	59.06%	66.23%	15.64
Bear	08/76	11/76	4	-54.07%	-33.02%	-4.89
Phase	**Start date**	**End date**	**Dur.**	**Amplitude Δ price**	**Amplitude Δ CAGR**	**Sev.**
Short-run LBBI - 0.5 SD threshold						
Bull	02/77	10/77	9	40.26%	75.63%	9.42
Bear	02/78	03/78	2	-34.36%	-16.20%	-1.20
Bull	08/78	09/78	2	53.10%	-8.13%	1.45
Bull	03/79	05/79	3	82.93%	10.79%	3.73
Bear	07/79	01/80	7	-21.78%	-15.29%	-7.34
Bear	03/80	05/80	3	-29.27%	-20.95%	-2.23
Bull	07/80	11/80	5	34.80%	32.14%	4.91
Bear	09/81	10/81	2	-60.04%	-18.57%	-3.48
Bull	09/82	04/83	8	39.24%	33.10%	7.83
Bull	01/84	01/84	1	108.58%	3.59%	1.15
Bear	06/84	07/84	2	-37.30%	-12.19%	-1.96
Bull	11/84	02/85	4	49.71%	2.33%	2.62
Bull	02/86	04/86	3	93.12%	20.13%	2.88
Bull	01/87	07/87	7	87.54%	29.29%	5.35
Bear	10/87	05/88	8	-33.84%	-59.34%	-11.26
Bear	09/88	12/88	4	-15.99%	24.10%	-3.73
Bull	02/89	08/89	7	33.98%	16.16%	3.90
Bear	10/89	11/90	14	-20.35%	-40.21%	-15.50
Bull	03/91	03/91	1	164.25%	10.76%	1.15
Bull	08/91	09/91	2	24.86%	21.17%	1.24
Bear	11/91	12/91	2	-37.15%	-11.77%	-1.84
Bear	07/92	09/92	3	-28.63%	-12.52%	-3.77
Bull	11/92	03/93	5	39.93%	19.87%	4.41
Bull	12/93	01/94	2	92.68%	6.46%	2.14
Bear	04/94	03/95	12	-9.12%	-21.08%	-11.13
Bull	06/95	01/96	8	18.48%	16.98%	4.44
Bull	01/97	02/97	2	49.84%	3.90%	1.42
Bull	07/97	08/97	2	34.75%	4.21%	1.19
Bull	02/98	04/98	3	59.80%	12.92%	2.60
Bear	08/98	10/98	3	-53.23%	-26.58%	-5.17
Bear	09/99	10/99	2	-17.82%	8.86%	-1.58
Bear	04/00	10/01	19	-16.12%	-30.06%	-21.11
Bear	06/02	03/03	10	-36.04%	-20.07%	-9.10
Bull	05/03	04/04	12	20.22%	48.04%	12.93
Bull	09/04	04/06	20	20.74%	19.41%	14.62
Bear	08/07	03/09	20	-31.41%	-48.82%	-21.27
Bull	05/09	04/10	12	37.13%	71.05%	11.64
Bull	10/10	02/11	5	17.96%	4.89%	3.44
Bear	08/11	11/11	4	-29.15%	-20.88%	-5.32
Bull	01/13	05/13	5	31.20%	12.95%	4.69
Bear	10/14	10/14	1	-48.63%	-5.86%	-1.84
Bear	07/15	02/16	8	-18.09%	-14.89%	-7.74
Bull	07/16	12/16	6	21.63%	18.36%	4.83
Medium-run LBBI - 0.5 SD threshold						
Bull	03/22	08/23	18	13.60%	21.17%	20.55
Bear	08/24	12/25	17	5.25%	-10.85%	-17.25
Bear	10/26	11/26	2	-17.56%	-0.62%	-1.22

Table A4: Dating of bulls and bears using a lax threshold (continued)

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Medium-run LBBI - 0.5 SD threshold						
Bear	11/29	07/32	33	-15.79%	-24.10%	-50.68
Bull	05/33	12/34	20	7.08%	18.09%	24.58
Bull	05/35	06/35	2	6.99%	2.98%	1.13
Bear	09/35	10/35	2	-35.39%	-3.56%	-1.60
Bear	06/37	09/40	40	-16.92%	-16.96%	-37.12
Bull	12/41	05/45	42	5.41%	17.66%	48.87
Bear	08/47	01/50	30	-9.22%	-10.20%	-30.74
Bull	04/51	10/51	7	4.89%	1.29%	5.95
Bear	01/52	11/52	11	-14.43%	-1.57%	-7.34
Bull	08/53	07/55	24	25.25%	24.89%	27.59
Bear	02/56	07/58	30	-2.47%	-16.73%	-34.15
Bull	11/58	10/60	24	22.86%	21.12%	19.72
Bear	07/61	05/64	35	-3.55%	-25.36%	-63.93
Bear	10/64	03/67	30	-8.05%	-7.12%	-30.46
Bull	09/67	03/69	19	23.80%	14.27%	19.66
Bear	08/69	04/71	21	-4.04%	-11.14%	-30.71
Bull	02/72	12/72	11	3.84%	9.99%	7.78
Bear	03/73	08/75	30	-28.21%	-29.94%	-31.39
Bull	12/75	08/76	9	-15.74%	3.07%	8.22
Bull	12/76	06/79	31	17.86%	29.64%	40.91
Bear	11/79	06/80	8	-8.80%	-12.84%	-6.73
Bear	09/81	10/81	2	-60.04%	-3.99%	-2.14
Bear	03/82	04/82	2	-20.61%	-6.47%	-1.36
Bull	09/82	03/85	31	21.42%	18.39%	22.70
Bull	03/86	04/86	2	96.02%	2.26%	1.12
Bull	05/87	07/87	3	115.49%	12.30%	1.86
Bear	11/87	09/92	59	-3.88%	-28.97%	-96.54
Bull	08/93	02/94	7	36.91%	9.78%	5.51
Bear	02/95	04/95	3	11.22%	1.03%	-2.34
Bull	09/97	05/98	9	26.33%	7.08%	4.65
Bear	10/99	10/99	1	-16.26%	-1.24%	-1.03
Bear	05/00	11/03	43	-10.01%	-23.37%	-65.09
Bull	06/04	05/07	36	13.09%	22.20%	30.83
Bear	01/08	12/09	24	-11.58%	-16.50%	-33.10
Bull	04/10	04/10	1	21.46%	-0.56%	1.19
Bull	09/10	04/11	8	15.79%	5.30%	7.07
Bear	04/12	05/12	2	-37.24%	-8.50%	-1.33
Bull	02/13	06/14	17	6.25%	1.98%	11.48
Bear	08/15	07/16	12	-1.30%	-5.22%	-15.43
Long-run LBBI - 0.5 SD threshold						
Bull	04/22	06/25	39	7.01%	11.76%	32.49
Bear	10/26	12/26	3	-4.26%	-2.06%	-2.74
Bear	12/29	11/33	48	-3.74%	-9.23%	-74.01
Bull	11/34	02/37	28	7.04%	11.92%	27.33
Bear	08/37	05/41	46	-14.07%	-18.41%	-48.96
Bull	03/43	01/47	47	4.11%	10.20%	66.52
Bear	09/47	01/51	41	-4.46%	-7.87%	-46.83

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Long-run LBBI - 0.5 SD threshold						
Bear	11/51	06/52	8	-41.72%	-7.57%	-5.41
Bull	12/53	07/57	44	6.62%	11.93%	53.63
Bear	10/57	11/58	14	10.95%	0.09%	-12.26
Bull	08/59	05/61	22	19.80%	7.55%	14.33
Bear	10/62	06/67	57	-0.36%	-6.27%	-92.33
Bull	11/67	04/69	18	16.25%	2.47%	15.75
Bear	05/70	04/71	12	-3.53%	-1.47%	-10.68
Bull	07/71	08/71	2	54.56%	5.02%	1.05
Bear	07/72	10/75	40	-22.64%	-19.45%	-46.55
Bear	09/76	10/76	2	-73.51%	-3.80%	-1.05
Bull	10/77	08/81	47	-0.52%	17.05%	60.62
Bull	11/82	04/86	42	19.77%	14.33%	28.61
Bull	01/87	07/87	7	87.54%	8.44%	3.74
Bear	03/90	09/93	43	2.50%	-3.83%	-111.09
Bear	06/94	03/95	10	-5.32%	-0.41%	-6.77
Bull	03/98	04/98	2	40.46%	1.48%	1.03
Bear	03/01	01/05	47	-6.32%	-14.43%	-90.47
Bull	11/05	10/07	24	10.56%	14.14%	26.78
Bear	07/08	12/11	42	-4.30%	-10.81%	-52.15
Bull	09/12	06/14	22	8.30%	11.50%	19.45
Bear	01/16	02/16	2	-24.80%	-1.30%	-2.14

Table A6: Dating of bulls and bears using a strict threshold

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Short-run LBBI - 1.0 SD threshold						
Bull	01/22	04/22	4	76.90%	6.56%	5.16
Bear	08/23	01/24	6	-9.73%	-8.67%	-7.96
Bear	10/29	12/29	3	-38.75%	-12.86%	-5.65
Bear	08/31	09/31	2	-62.51%	-11.54%	-2.42
Bull	08/32	07/33	12	33.85%	51.19%	15.06
Bear	09/35	10/35	2	-35.39%	-6.99%	-2.23
Bear	05/37	11/37	7	-30.52%	-21.63%	-9.23
Bear	09/39	09/39	1	-73.45%	-7.37%	-2.25
Bear	05/40	06/40	2	-68.49%	-15.54%	-2.88
Bull	07/41	11/41	5	19.07%	5.45%	7.76
Bull	09/42	11/42	3	39.21%	5.92%	4.54
Bear	08/47	09/47	2	-45.85%	-6.22%	-3.30
Bear	11/51	01/52	3	-56.34%	-18.84%	-4.31
Bull	01/53	03/53	3	19.32%	18.85%	4.23
Bull	08/53	05/54	10	36.64%	27.52%	11.59
Bear	09/55	03/56	7	-25.45%	-15.18%	-9.96
Bear	09/57	10/57	2	-61.47%	-11.69%	-3.20
Bull	08/58	10/58	3	55.18%	32.05%	3.80
Bear	06/60	12/60	7	-5.30%	-30.52%	-7.62
Bear	06/61	12/61	7	-28.70%	-16.78%	-10.44
Bear	05/62	07/62	3	-44.74%	-0.98%	-4.55
Bear	11/64	12/64	2	-43.71%	-10.16%	-3.34
Bear	06/65	07/65	2	-33.50%	-8.02%	-2.06
Bear	08/66	09/66	2	-55.33%	-16.23%	-3.70
Bull	07/67	11/67	5	52.77%	44.42%	5.91
Bear	03/69	07/69	5	-44.38%	-46.22%	-9.17
Bear	04/70	06/70	3	-51.97%	-1.59%	-4.80
Bull	04/71	05/71	2	174.58%	32.97%	3.76
Bear	09/72	12/73	16	-34.66%	-58.26%	-19.15
Bull	02/75	06/75	5	218.84%	58.31%	7.83
Bear	08/76	10/76	3	-68.00%	-31.48%	-4.21
Bull	08/77	09/77	2	144.35%	33.22%	3.25
Bull	03/79	04/79	2	163.12%	17.84%	3.16
Bear	07/79	08/79	2	-36.94%	-15.88%	-2.14
Bull	09/80	10/80	2	29.25%	4.01%	2.12
Bear	09/81	10/81	2	-60.04%	-18.57%	-3.48
Bull	09/82	10/82	2	78.52%	26.94%	3.03
Bear	11/87	02/88	4	-43.73%	-40.86%	-7.72
Bear	02/90	10/90	9	-26.14%	-30.91%	-12.61
Bear	07/92	08/92	2	-50.64%	-14.43%	-3.21
Bull	12/93	01/94	2	92.68%	6.46%	2.14
Bear	08/98	10/98	3	-53.23%	-26.58%	-5.17
Bear	10/00	09/01	12	-25.28%	-32.30%	-16.39
Bear	06/02	07/02	2	-69.11%	-10.54%	-3.60
Bull	06/03	11/03	6	22.53%	31.82%	7.90
Bull	01/05	02/05	2	44.38%	3.75%	2.25
Bear	11/07	10/08	12	-38.93%	-45.25%	-15.51

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Short-run LBBI - 1.0 SD threshold						
Bull	08/09	10/09	3	93.25%	40.27%	4.82
Bear	08/11	09/11	2	-56.56%	-20.04%	-4.02
Bull	01/13	02/13	2	51.94%	-1.21%	2.30
Bear	08/15	09/15	2	-37.93%	-7.36%	-2.81
Bull	07/16	08/16	2	71.45%	13.29%	2.43
Medium-run LBBI - 1.0 SD threshold						
Bull	04/22	04/23	13	23.50%	12.96%	17.18
Bear	09/24	12/24	4	-0.93%	-4.67%	-5.62
Bear	05/25	11/25	7	3.12%	-1.19%	-7.35
Bear	11/29	09/31	23	-20.75%	-21.83%	-42.04
Bull	05/33	06/34	14	12.28%	14.10%	19.56
Bear	07/37	06/38	12	-21.28%	-7.64%	-17.12
Bull	06/42	03/44	22	10.07%	17.35%	34.41
Bear	09/47	12/48	16	-6.89%	-4.23%	-20.02
Bull	04/51	06/51	3	35.55%	2.12%	3.50
Bull	12/53	01/55	14	30.63%	18.33%	19.73
Bear	02/56	03/57	14	-0.52%	-5.92%	-16.50
Bear	09/57	02/58	6	-38.12%	-7.91%	-9.23
Bull	02/59	05/59	4	46.93%	5.46%	4.68
Bear	07/61	02/64	32	-4.06%	-24.29%	-62.05
Bear	11/64	09/65	11	-13.02%	-1.43%	-14.87
Bear	03/66	08/66	6	-29.42%	-8.04%	-5.93
Bull	10/67	08/68	11	43.10%	17.93%	13.50
Bear	10/69	03/71	18	-9.52%	-15.47%	-28.25
Bear	07/73	07/74	13	-50.87%	-31.57%	-18.65
Bull	02/77	10/78	21	12.73%	16.81%	32.37
Bull	03/79	04/79	2	163.12%	6.62%	2.86
Bear	03/80	05/80	3	-29.27%	-5.93%	-3.45
Bull	03/83	04/83	2	38.56%	5.31%	2.22
Bear	12/87	09/92	58	1.53%	-17.19%	-95.98
Bear	10/00	12/02	27	-20.70%	-24.87%	-54.40
Bull	01/05	09/05	9	16.87%	13.65%	11.07
Bear	02/08	03/09	14	-35.78%	-22.47%	-25.21
Bear	11/15	06/16	8	-4.27%	-3.51%	-11.36
Long-run LBBI - 1.0 SD threshold						
Bull	07/22	04/23	10	21.60%	4.49%	11.56
Bear	07/30	10/32	28	-10.51%	-8.63%	-61.02
Bull	05/35	06/35	2	6.99%	1.82%	2.66
Bull	11/35	06/36	8	18.16%	5.10%	10.65
Bear	09/37	02/39	18	-13.12%	-8.85%	-26.88
Bull	06/43	12/45	31	3.60%	9.14%	54.77
Bear	10/47	08/49	23	-8.53%	-6.78%	-33.03
Bull	01/54	12/55	24	10.64%	5.51%	39.71
Bull	12/56	01/57	2	87.34%	4.68%	2.32
Bear	01/58	03/58	3	-4.33%	-1.13%	-4.09
Bear	03/63	11/66	45	-5.03%	-15.30%	-82.76
Bull	04/68	07/68	4	77.30%	3.69%	5.02

Table A5: Dating of bulls and bears using a strict threshold (continued)

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Long-run LBBI - 1.0 SD threshold						
Bear	06/70	07/70	2	1.34%	1.42%	-3.15
Bear	12/70	01/71	2	3.84%	0.30%	-2.23
Bear	09/72	08/74	24	-42.83%	-24.25%	-35.35
Bull	10/77	10/79	25	-3.28%	23.04%	39.48
Bull	06/80	11/80	6	38.09%	2.91%	8.53
Bull	01/83	02/83	2	45.92%	2.63%	2.23
Bear	04/90	06/90	3	6.97%	0.82%	-4.00

Phase	Start date	End date	Dur.	Amplitude Δ price	Amplitude Δ CAGR	Sev.
Long-run LBBI - 1.0 SD threshold						
Bear	08/90	07/93	36	1.85%	-6.77%	-103.61
Bear	07/01	03/04	33	-8.76%	-12.58%	-78.86
Bull	12/05	02/07	15	13.24%	7.45%	19.45
Bear	08/08	08/10	25	-2.56%	-6.01%	-38.08
Bull	02/13	11/13	10	9.69%	10.12%	11.51
Bear	01/16	02/16	2	-24.80%	-1.30%	-2.14

A7. Statistical characterisation of LBBIs for the three stock market indices

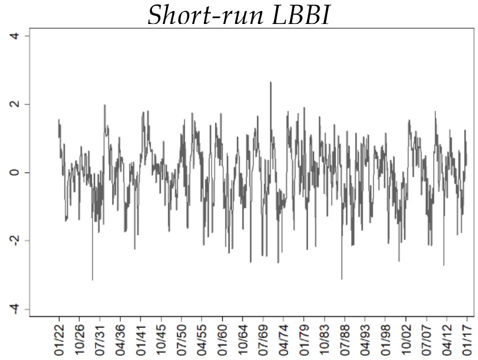
The following tables include a statistical characterisation of the LBBI series calculated in Section II. A first section describes the different series by type, frequency, index, number of observations and starting and ending dates. Then I include a graph for each of the series. The first panel in the right section includes descriptive statistics for the three series.

The right column includes a Daniels' (1950) trend test for the three series. I then follow Bai & Perron (1998, 2003) and perform their test for structural breaks since it is designed explicitly for I(0) series. I present the statistic for the test where the null hypothesis is the absence of breaks against the alternative of one break. Conclusions are based on this test, although I also include the number and dates of sequential breaks suggested following the Bayesian Information Criterion (BIC).

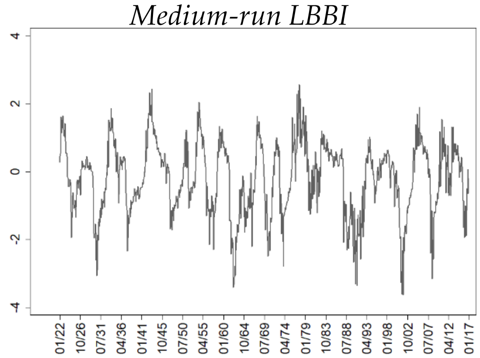
The bottom panel includes stationarity tests for the series in levels. In all cases, I include the ADF, ADF-GLS and KPSS tests. For monthly series, I present the HEGY and CH tests. For annual series, I include the PP test. All of these tests are discussed at length in part A2 of this appendix. Note that numbers in brackets ([]) represent critical values and not p-values. Whenever the statistic exceeds the critical value, the alternative hypothesis cannot be rejected.

LBBI:	Stock market	**Frequency:**	Monthly
Country:	United Kingdom	**Observations:**	1140
Period:	Jan/1922 - Dec/2016		

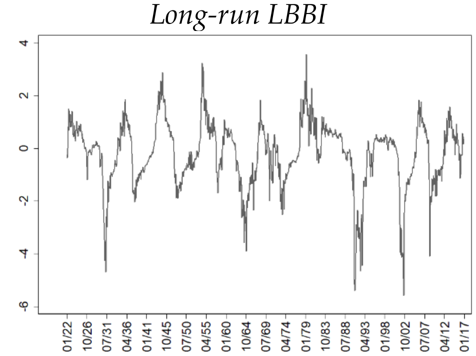
Short-run LBBI



Medium-run LBBI



Long-run LBBI



Descriptive Statistics

	LBBIS	*LBBIM*	*LBBIL*
Mean	-0.05	-0.20	-0.21
Median	0.01	-0.06	-0.07
Standard. Dev.	0.84	1.05	1.23
Skewness	-0.39	-0.39	-0.87
Kurtosis	3.19	2.95	4.87
Minimum	-3.16	-3.64	-5.58
Maximum	2.65	2.56	3.57
Range	5.81	6.20	9.15
IQ Range	1.16	1.48	1.45

Trend Test

Daniels test	*LBBIS*	*LBBIM*	*LBBIL*
Statistic	-0.0090	-0.6050	-2.0573
pvalue	0.9929	0.5452	0.0397
Result	No trend	No trend	Trend

Structural Breaks Tests

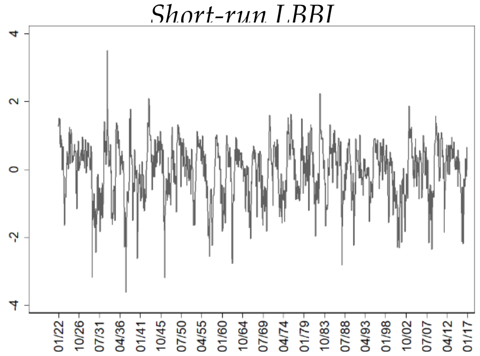
	LBBIS	*LBBIM*	*LBBIL*
F(0/1)	0.6809	0.0165	0.0162
Conclusion	No breaks	No breaks	No breaks
BIC	3	3	3
Date 1	Oct-35	Dec-69	Dec-74
Date 2	Jun-56	Feb-73	Sep-87
Date 3	Aug-37	Sep-72	Nov-87

Stationarity tests

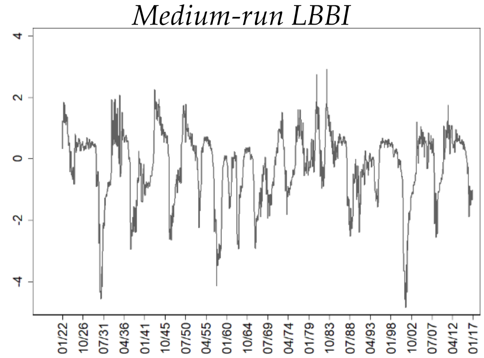
	LBBIS			*LBBIM*			*LBBIL*		
	Statistic	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*
ADF	-10.3069	0.0000	I(0)	-6.7223	0.0000	I(0)	-5.1144	0.0000	I(0)
ADF-GLS	-3.9112	0.0000	I(0)	-5.1532	0.0000	I(0)	-4.4684	0.0000	I(0)
KPSS	0.0399	[0.462]	I(0)	0.1087	[0.462]	I(0)	0.2261	[0.462]	I(0)
HEGY	-8.660	0.0000	I(0)	-6.460	0.0000	I(0)	-5.2300	0.0000	I(0)
CH	1.0392	0.9943	I(0)	1.3666	0.8744	I(0)	1.2779	0.9278	I(0)

LBBI:	Stock market	**Frequency:**	Monthly
Country:	United States	**Observations:**	1140
Period:	Jan/1922 - Dec/2016		

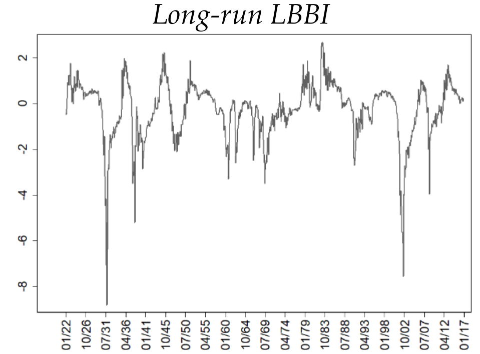
Short-run LBBI



Medium-run LBBI



Long-run LBBI



Descriptive Statistics

	LBBIS	*LBBIM*	*LBBIL*
Mean	-0.06	-0.22	-0.27
Median	0.07	0.03	-0.08
Standard. Dev.	0.84	1.14	1.23
Skewness	-0.52	-0.94	-1.66
Kurtosis	3.63	4.28	9.02
Minimum	-3.62	-4.83	-8.80
Maximum	3.50	2.92	2.68
Range	7.12	7.75	11.48
IQ Range	1.16	1.38	1.31

Trend Test

Daniels test	*LBBIS*	*LBBIM*	*LBBIL*
Statistic	-0.8810	-0.4187	-0.1549
pvalue	0.3783	0.6754	0.8769
Result	No trend	No trend	No trend

Structural Breaks Tests

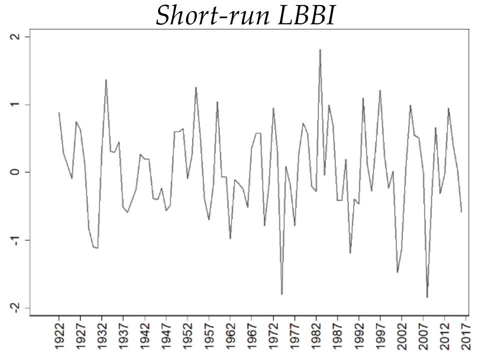
	LBBIS	*LBBIM*	*LBBIL*
F(0/1)	0.0228	0.3630	0.7008
Conclusion	No breaks	No breaks	No breaks
BIC	3	3	3
Date 1	May-37	Dec-69	Dec-74
Date 2	Oct-37	Jan-52	Oct-82
Date 3	Aug-37	Jan-73	Jun-96

Stationarity tests

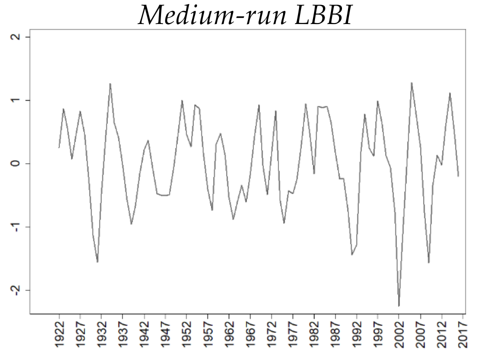
	LBBIS			*LBBIM*			*LBBIL*		
	Statistic	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*
ADF	-9.4948	0.0000	I(0)	-7.6136	0.0000	I(0)	-5.7756	0.0000	I(0)
ADF-GLS	-4.4194	0.0000	I(0)	-5.5413	0.0000	I(0)	-5.1543	0.0000	I(0)
KPSS	0.0498	[0.462]	I(0)	0.1054	[0.462]	I(0)	0.1436	[0.462]	I(0)
HEGY	-9.590	0.0000	I(0)	-6.560	0.0000	I(0)	-5.2900	0.0000	I(0)
CH	1.8456	0.4261	I(0)	1.0311	0.9947	I(0)	0.9548	0.9972	I(0)

LBBI:	Stock market	**Frequency:**	Annual
Country:	Other Advanced Economies	**Observations:**	95
Period:	1922 - 2016		

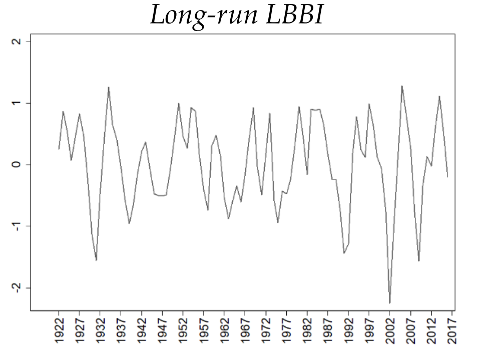
Short-run LBBI



Medium-run LBBI



Long-run LBBI



Descriptive Statistics

	LBBIS	*LBBIM*	*LBBIL*
Mean	0.03	0.01	-0.04
Median	0.02	0.13	0.06
Standard. Dev.	0.68	0.70	0.75
Skewness	-0.22	-0.53	-0.39
Kurtosis	3.42	3.20	3.30
Minimum	-1.85	-2.25	-2.39
Maximum	1.82	1.28	1.61
Range	3.67	3.53	4.00
IQ Range	0.89	0.97	0.89

Trend Test

Daniels test	*LBBIS*	*LBBIM*	*LBBIL*
Statistic	1.3484	1.3386	1.1494
pvalue	0.1775	0.1649	0.2504
Result	No trend	No trend	No trend

Structural Breaks Tests

	LBBIS	*LBBIM*	*LBBIL*
F(0/1)	0.1062	0.1649	0.2504
Conclusion	No breaks	No breaks	No breaks
BIC	0	0	0
Date 1			
Date 2			
Date 3			

Stationarity tests

	LBBIS			*LBBIM*			*LBBIL*		
	Statistic	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*	*Statistic*	*pvalue*	*Result*
ADF	-4.2474	0.0005	I(0)	-6.0822	0.0000	I(0)	-6.5726	0.0000	I(0)
ADF-GLS	-5.1838	0.0000	I(0)	-4.7228	0.0000	I(0)	-3.7574	0.0001	I(0)
KPSS	0.0300	[0.462]	I(0)	0.0337	[0.462]	I(0)	0.0549	[0.462]	I(0)

A8. A Comparison between VIX and LBBIs: Are they related?

Following Wilmott (2006), financial derivatives are contracts signed at a time t_0, which mature at time t_k. The two best-known derivatives contracts are forwards and European options. The forward contract is one in which the issuer of the contract commits him or herself to buy or sell a given asset (the underlying), at a future date (expiration), at a set price that is known at time t_0 (strike price). The beneficiary, the counterparty to the issuer, also commits him or herself to sell or buy the underlying asset under the agreed upon conditions. The strike price of a forward contract is set in such a way that there is no need to exchange cash flows on the date of issuance.

A European option contract is similarly defined, but in this case, while the issuer commits to buying or selling the underlying, the beneficiary of the contract can choose to sell or buy depending on current market conditions.[16] In a call option, the beneficiary of the contract can buy the underlying at the strike price on the maturity date. He or she will only do so if the market price is above the strike price (the option is "in the money"). In a put option, the beneficiary of the contract can sell the underlying at the strike price on the maturity date. He or she will only do so if the market price is below the strike price. On the date of issuance, options are quoted and negotiated out of the money, meaning that for a call (put) option, the strike price must be above (below) the market price (spot price). Since the bearer of the option has no downside in his or her future cash flows, just as in an insurance contract, options have a positive price at the time of issuance (premium) which the beneficiary pays to the issuer. The premium for call and put options on a stock market index are calculated as follows (Wilmott, 2016, V1 pp 116-118):

$$c = Se^{-D(T-t)}N(d_1) - Ke^{-r(T-t)}N(d_2) \tag{A18}$$

$$p = -Se^{-D(T-t)}N(-d_1) + Ke^{-r(T-t)}N(-d_2) \tag{A19}$$

$$d_1 = \frac{log\left(\frac{S}{K}\right) + \left(r - D + \frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} \tag{A20}$$

$$d_2 = \frac{log\left(\frac{S}{K}\right) + \left(r - D - \frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} = d_1 - \sigma\sqrt{T-t} \tag{A21}$$

Where S is the spot value of the index, D is the continuous expected dividend growth rate, $(T-t)$ represents time to maturity, N is the standard normal distribution function, K is the agreed upon strike price, r is the continuous risk-free interest rate between time t and time T, and σ is the volatility of the underlying asset. Several important relationships from equations (A18) and (A19) are relevant:

[16] A relevant characteristic of European options is that they can only be exercised at the maturity date. Conversely, American options can be exercised at any point in time between issuance and maturity.

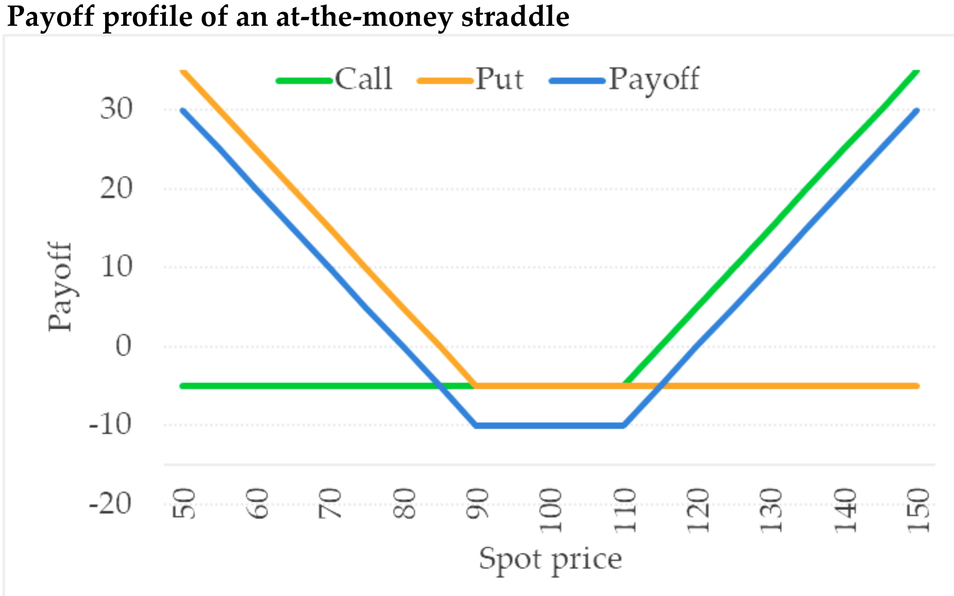
All else equal, if the strike price increases call (put) options become more in the (out of the) money and their price *c* (*p*) increases (decreases). With regards to the payout, higher expected dividend growth rates *D* imply a lower value for both put and call options. On the other hand, higher σ increases the value of both types of contracts. Note that the relationship between expected dividend growth, volatility, and LBBIs mirror their relations to the price of call and put options. When expected dividends increase, the stock price increases and so do LBBIs. When volatility increases the denominator in the LBBI function increases, and thus the LBBI decreases.

According to CBOE (2014, p. 4), the generalised formula for calculating the VIX index is:

$$\frac{VIX}{100} = \sigma^2 = \left(\frac{2}{(T-t)}\sum_i \frac{\Delta K_i}{2_i^2} e^{r(T-t)} Q(K_i)\right) - \left(\frac{1}{(T-t)}\left(\frac{\left(K + e^{r(T-t)}(c-p)\right)}{K_0} - 1\right)\right) \quad \text{(A22)}$$

Where *c* and *p* correspond to the price of the out-of-the-money call and put options centred around an at-the-money strike price K. K_0 is the first traded strike price below strike price K, K_i is the strike price of the *i*-th out-of-the-money option such that for call options $K_i > K_0$ and for put options $K_i < K_0$, and $Q(K_i)$ is the mid-point of the bid-ask spread for each option with strike K_i. According to Wilmott (2006), buying an out-of-the-money call option and selling an out-of-the-money put option is an investment structure called an at-the-money straddle. The payoff structure of that investment strategy at time *T* is depicted in Figure A7.

Figure A7: Payoff profile of an at-the-money straddle



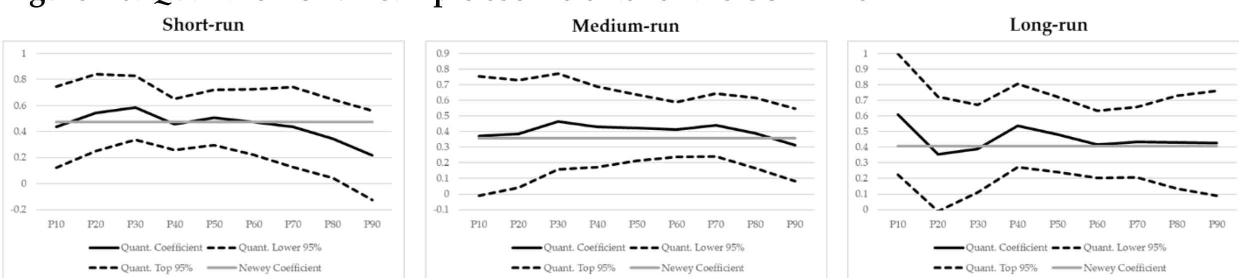
Note: In the payoff structure depicted above the current stock market price is $100. The out-of-the-money call option (green line) has a strike price of $110. The out-of-the-money put option (orange line) has a strike price of $90. To exemplify, the premium paid for each option is $5. The payoff for the portfolio of options is depicted in the blue line.

If the current stock price is $100, such that both options are out-of-the-money, higher expected volatility will increase the probability that the structure has a positive payoff. Consequently, higher volatility will increase the value of the structure and affect the VIX index positively. In the payoff structure shown in Figure A7 I assume there are no dividend payments. If a dividend payment occurs during the life of the contracts, that is a payoff that the beneficiary is not entitled to and thus would cause a parallel downward shift of the payoff structure. Consequently, as the expected dividend growth rate increases the payoff in the structure and the value of the VIX is reduced.

A9. Regressions by deciles

I run quantile regressions by decile of Model II in Table 4 of the paper. We find that the regression coefficient for the US LBBIs under the full sample regression always falls within the confidence intervals of the coefficients under the quantile specification. This indicates that both coefficients are statistically the same. Figure A8 presents the coefficients for the full sample regression (grey) and the quantile regression (black). 95% confidence bands around the latter are marked by dashed lines.

Figure A8: Quantile VS full sample coefficients for the US LBBIs



A10. Breaking down the OAE index

After showing in Section III that the co-movement between the UK and OAE peaks when the former is lagged 1 year, a question that remains is whether this relationship affects developed and developing stock markets in the same way. To test this, we use market capitalisation as a proxy for stock market development. We follow Rajan & Zingales (2003) and Kuvshinov & Zimmermann (2018) to break down the sample of other advanced economies between countries with large or small stock markets relative to GDP.

We take market capitalisation data for 1913 and 1999 from Rajan & Zingales (2003) for the 14 countries that coincide with our database.[17] We then rank the countries from highest to lowest

---

[17] Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Switzerland, Sweden, the United Kingdom and the US.

in both years and calculate the average. Those countries ranked above the United States are treated as the high market capitalisation countries, and those below are treated as the low market capitalisation countries. There is partial or no information for Spain, Finland, and Portugal. After confirming data presented in Kuvshinov & Zimmermann (2018), we assigned these countries the lowest possible ranking. The ranking of countries is presented in Table A7.

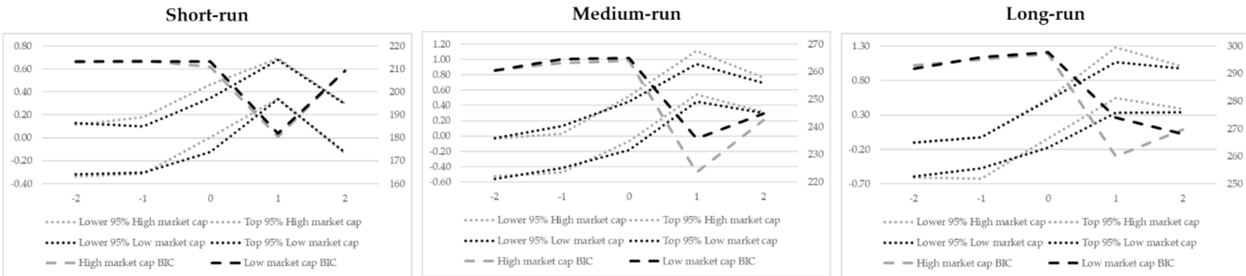
Table A7: Country ranking by market capitalisation to GDP

Country	Rank 1913	Rank 1999	Average Rank
UK	1	2	1.5
Switzerland	5	1	3
Netherlands	6	3	4.5
Canada	4	6	5
France	3	7	5
Belgium	2	10	6
Sweden	8	4	6
US	10	5	7.5
Japan	7	9	8
Australia	11	8	9.5
Germany	9	14	11.5
Norway	14	11	12.5
Italy	13	13	13
Denmark	12	15	13.5
Spain	17*	12	14.5
Finalnd	17*	17*	17
Portugal	17*	17*	17

Note: Data with stars from Kuvshinov & Zimmermann (2018), all other data from Rajan & Zingales (2003).

I build high and low market capitalisation equally weighted OAE indices and run the same lead-and-lag specification as in Section III using each of them separately. Figure A9 presents the 95% confidence intervals for both coefficients and the BIC criterion. Since intervals always share values over the Y-axis, it follows that the relationship identified in Figure 3 of the paper is robust to the level of development in the stock market of advanced economies.

Figure A9: Evolution of confidence bands of high and low capitalisation OAE LBBIs as a function of leads and lags



Note: X-axis indicates the number of leads (positive) or lags (negative) of the variable of interest. High (low) capitalisation confidence bands in grey (black).

A11. Chow tests using the lax definition of the peg

Table A8: Chow test for structural breaks in the US LBBI coefficients by regime

Hypothesis I: There is no break by trilemma regime			
Horizon	*Short*	*Medium*	*Long*
Statistic	**2.92**	1.87	**4.16**
P-value	**0.04**	0.14	**0.01**
Hypothesis II: There is no break by domestic polic regime			
Horizon	*Short*	*Medium*	*Long*
Statistic	1.37	1.38	1.70
P-value	0.24	0.24	0.14
Hypothesis III: There is no joint break by trilemma and domestic policy regime			
Horizon	*Short*	*Medium*	*Long*
Statistic	0.96	1.32	**3.53**
P-value	0.50	0.23	**0.00**

Note: Each panel contains a Chow (1960) test for structural breaks in the coefficient for the LBBI for the US under different regimes. The null hypothesis is there is no break. Hypothesis I tests for breaks by trilemma regime. Hypothesis II tests for breaks by domestic policy regime. Hypothesis III tests for a joint break by trilemma and domestic policy regime.

A12. Regressions including interactions between regimes and LBBIs for the US

Table A9: Regressions including interactions between regimes and LBBIs for the US according to Chow test

UK LBBI to time horizon	Short-run	Medium-run	Long-run
United States LBBIs	0.2068*	0.358***	0.0938
Interactions			
TR 2 - Open peg	0.3572*		
TR 3 - Closed float	0.0141		
TR 4 - Open float	0.4782***		
TR 2 U MBBR			0.6877
TR 3 U MBBR			0.3144
TR 4 U MBBR			-0.0306
TR 1 U WDM			0.7874*
TR 3 U WDM			-8.9040
TR 1 U Keynesianism plus			0.0247
TR 3 U Keynesianism plus			1.275**
TR 4 U Thatcherism			0.9853**
TR 4 U Inflation targeting			0.5786
Controls	Yes	Yes	Yes
Dummies	Yes	Yes	Yes
Newey lags	1	1	1
Observations	93	93	93
Adjusted R2	0.4686	0.4968	0.5955

Note: Regression results using the model that is best adjusted to the Chow (1960) tests presented in Section IV. All regressions contain controls, dummy variables and Newey-West corrected standard errors. Confidence * 90%, ** 95%, *** 99%. In the short-run specification, the omitted variable is the closed peg trilemma regime as it is the most restrictive of all. In the long-run specification, the omitted variable is the interaction between the closed peg trilemma regime and the stop-go policy domestic regime as it is the most restrictive of all. The corresponding dummies are also omitted.

A13. Hausman specification test for endogeneity of the OAE LBBIs

Following Maddala (2001) and Banerjee & Duflo (2003), I applied the Hausman specification test for endogeneity of the OAE LBBIs in models III and IV. The null hypothesis is that the variable is not endogenous (the corresponding LS estimates are consistent) vs the alternative that the variable is endogenous (the corresponding LS estimates are inconsistent). The Hausman statistic is Chi-squared distributed with degrees of freedom equal to the number of parameters estimated in the LS equation (excluding the intercept). Due to problems of (quasi) singularity of the (transformed) covariance matrix in the Hausman test, in some cases, a certain number of parameters have been excluded from the null hypothesis, which reduces the degrees of freedom in the test.

In the absence of a set of instrumental variables properly defined, the framework of testing endogeneity corresponds with the poor man's exogeneity strategy in which lags of the control variables appearing in the corresponding equation have been used as instruments.

As can be seen in the following results, in all the cases the LBBIs for OAE appear as a non-endogenous variable.

Model III

Short-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.69
                Prob>chi2 =      0.9984
```

Medium-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        4.02
                Prob>chi2 =      0.7777
```

Long-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        8.87
                Prob>chi2 =      0.1812
```

Model IV

Short-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        1.58
                Prob>chi2 =      0.6645
```

Medium-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        5.95
                Prob>chi2 =      0.6533
```

Long-run OAE LBBI
```
    Test:  Ho:  difference in coefficients not systematic
                  chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.76
                Prob>chi2 =      0.9979
```

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