UNIVERSITÄT BERN

Faculty of Business, Economics and Social Sciences

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Money and Credit: A Long-Term View

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18-11

June 2018

DISCUSSION PAPERS

Schanzeneckstrasse 1
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Money and Credit: A Long-Term View*

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Abstract

Schularick and Taylor (2012) documented a sizeable increase in the ratio between credit and broad money since the end of WWII, which they interpreted in terms of a progressive disconnect between the two aggregates. I show that this interpretation is incorrect, since, as I demonstrate mathematically, this evidence is uninformative for the issue at hand. In fact, Jordà, Schularick and Taylor's (JST) data show that, since the XIX century, fluctuations in broad money and credit have exhibited an extraordinarily strong correlation *within each single country* in the dataset, to the point that (e.g.) either Shin's (1994) or Wright's (2000) test consistently detects *cointegration* between the multipliers of the two aggregates. I also show that, after WWII, there has been *no change* in the relative prediction power of credit and broad money for financial crises compared to the pre-WWII period, and that the change in the multiplier of either aggregate has been more powerful than credit growth, the variable considered by Schularick and Taylor.

My results imply that (1) for the 'traditional' banking sector there has been *no change*, since WWI, in the relationship between its monetary liabilities, and the amount of credit it extends to the private non-financial sector; and (2) only the comparatively recent ascent of the 'shadow' banking sector—which is not covered by either JST's, or the *Bank for International Settlements*' data—introduced a 'wedge' between broad money and credit. Contrary to Schularick and Taylor's interpretation, the ascent of 'shadow banking' is the *only* reason why, today, we live in the 'Age of Credit'.

*I wish to thank Robert Lucas for useful suggestions, Peter Ireland for helpful discussions on money multipliers, and Edward Nelson for comments. Thanks to Alberto Musso and Athanassios Boudalis for kindly providing data for the Euro area and Greece, respectively. Usual disclaimers apply.

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1 Introduction

Since the outbreak of the financial crisis, the evolution of the structure of the financial system over the last several decades has been one of the most intensely investigated issues in macroeconomics. Moritz Schularick and Alan M. Taylor (2012; henceforth ST) have documented a significant increase in the ratio between credit and broad money since the end of WWII, which they have interpreted in terms of a progressive *disconnect* between the two aggregates over the last seven decades:

> 'The first important fact that emerges from the data is the presence of two distinct "eras of finance capitalism" [...]. [T]he first financial era lasted from 1870 to WW2. In this era, money and credit were volatile but over the long run they maintained a roughly stable relationship to each other [...]. Thus, during the first era of finance capitalism, up to 1939, the era studied by canonical monetarists like Friedman and Schwartz, the "money view" of the world looks entirely reasonable. Banks' liabilities were first and foremost monetary, and exhibited a fairly stable relationship to total credit. [...] The relationships changed dramatically in the post-1945 period. [...] [C]redit not only grew strongly relative to GDP, but also relative to broad money after WW2, via a combination of higher leverage and (after the 1970s) through the use of new sources of funding, mainly debt securities, creating more and more nonmonetary bank liabilities.' [1]

Very similar evidence has subsequently been produced in a series of joint papers with Oscar Jordà,[2] based on an expanded version of ST's original dataset. Since Jordà, Schularick and Taylor's (JST) data only cover the 'traditional' (i.e., non 'market-based', or 'shadow') banking sector, their results should be thought of—under their interpretation—as understating the true extent of disconnect between broad money and credit since the end of WWII.[3]

1.1 Main results

This paper contains three main results:

First, I show that ST's interpretation of the evolution of the ratio between credit and broad money is incorrect, since—as I demonstrate mathematically—this evidence is *uninformative* for the issue of whether, since WWII, credit has, or has not become disconnected from broad money. The intuition is straightforward. Assume, just for the sake of the argument, that the logarithm of broad money, m_t, is a random-walk with drift,[4] and that log credit, c_t, is cointegrated with log money, $c_t = \alpha + \beta m_t + \theta_t$,

[1] See Schularick and Taylor (2012, pp. 1034-1036).

[2] See in particular Jordà, Schularick and Taylor (2015, 2017).

[3] This is, e.g., ST's (2012) interpretation: see their footnote 7, p. 1036.

[4] The argument also holds if m_t features a deterministic time trend.

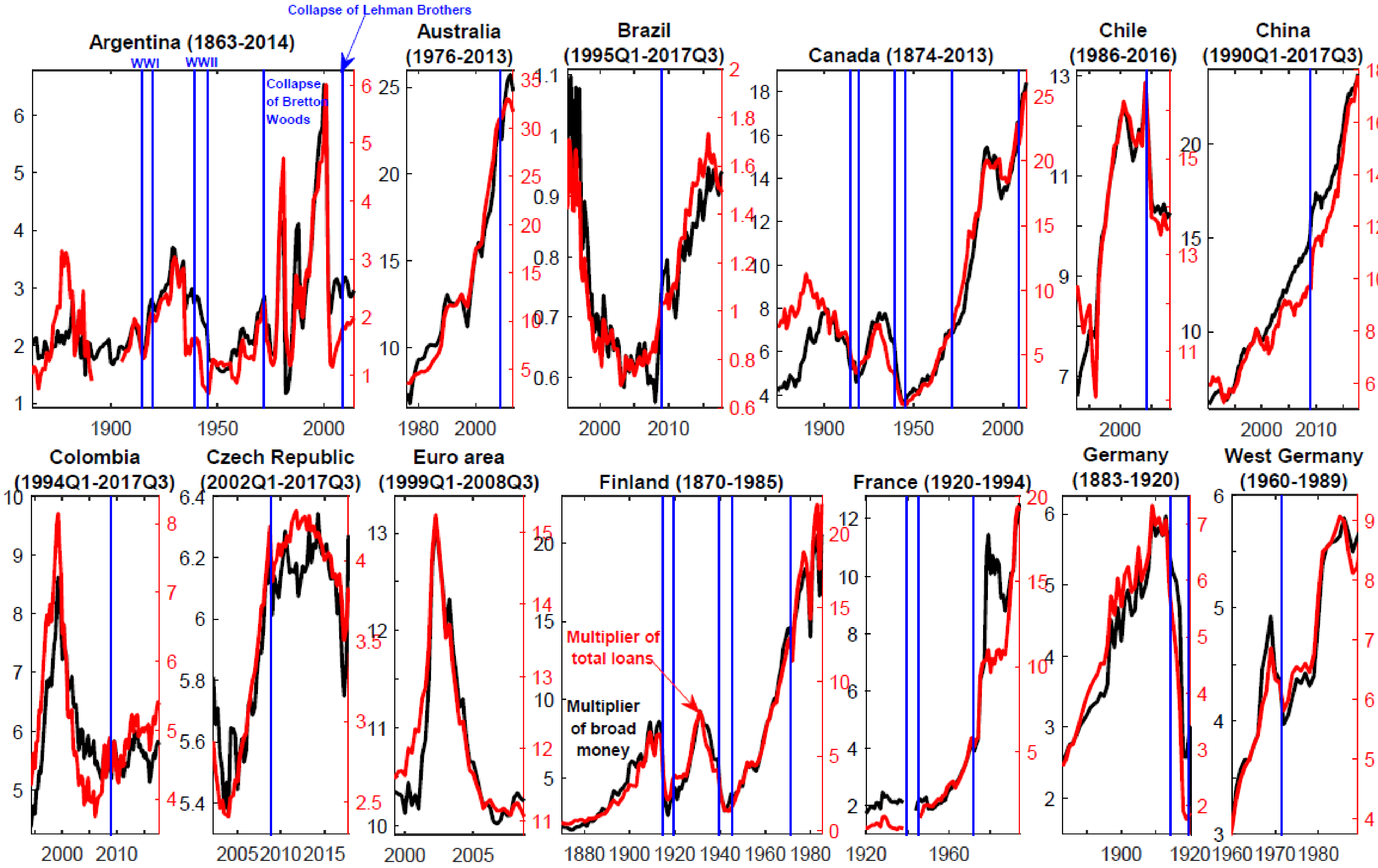

Figure 1a Multipliers of total loans and broad money for individual countries

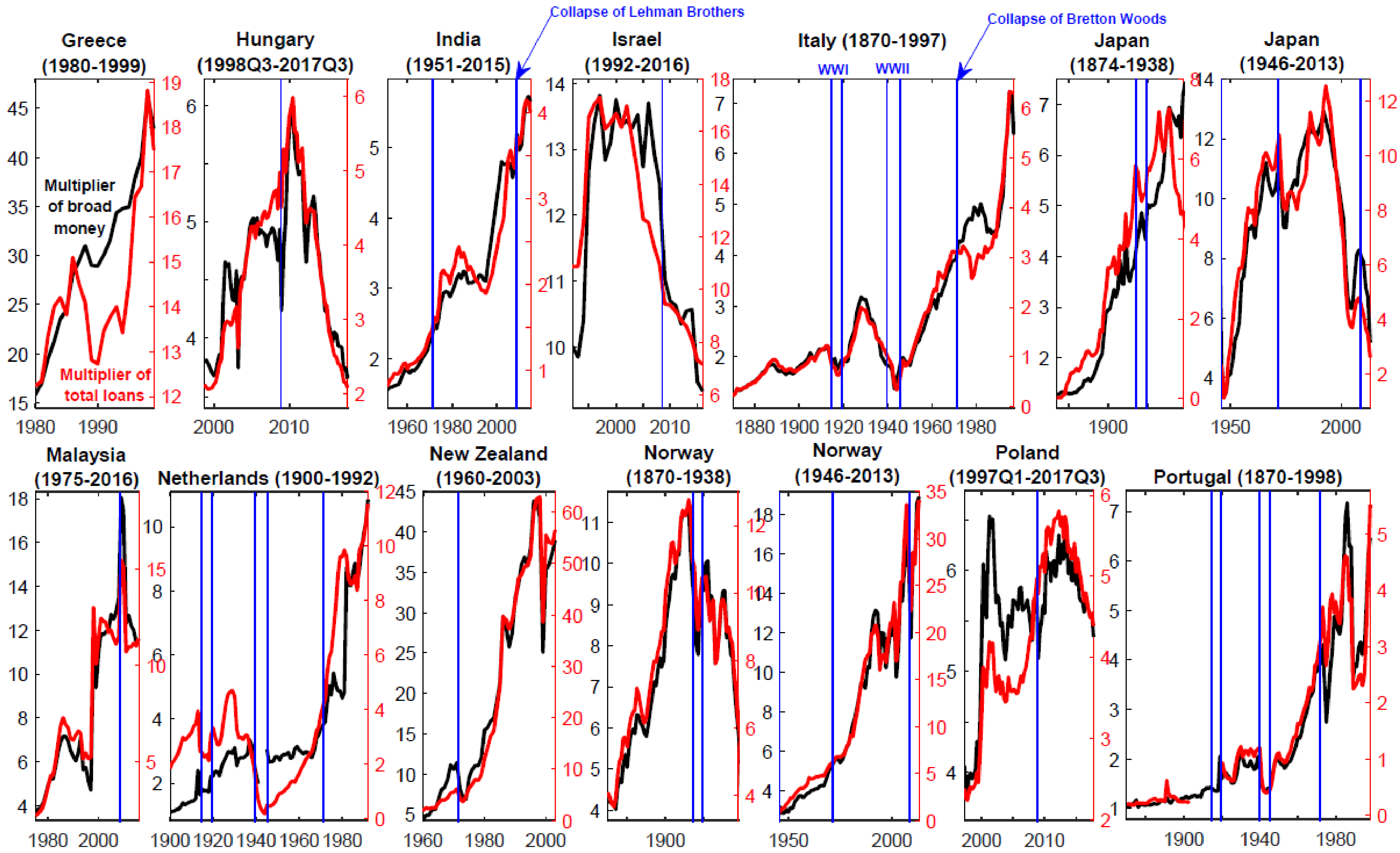

Figure 1b Multipliers of total loans and broad money for individual countries

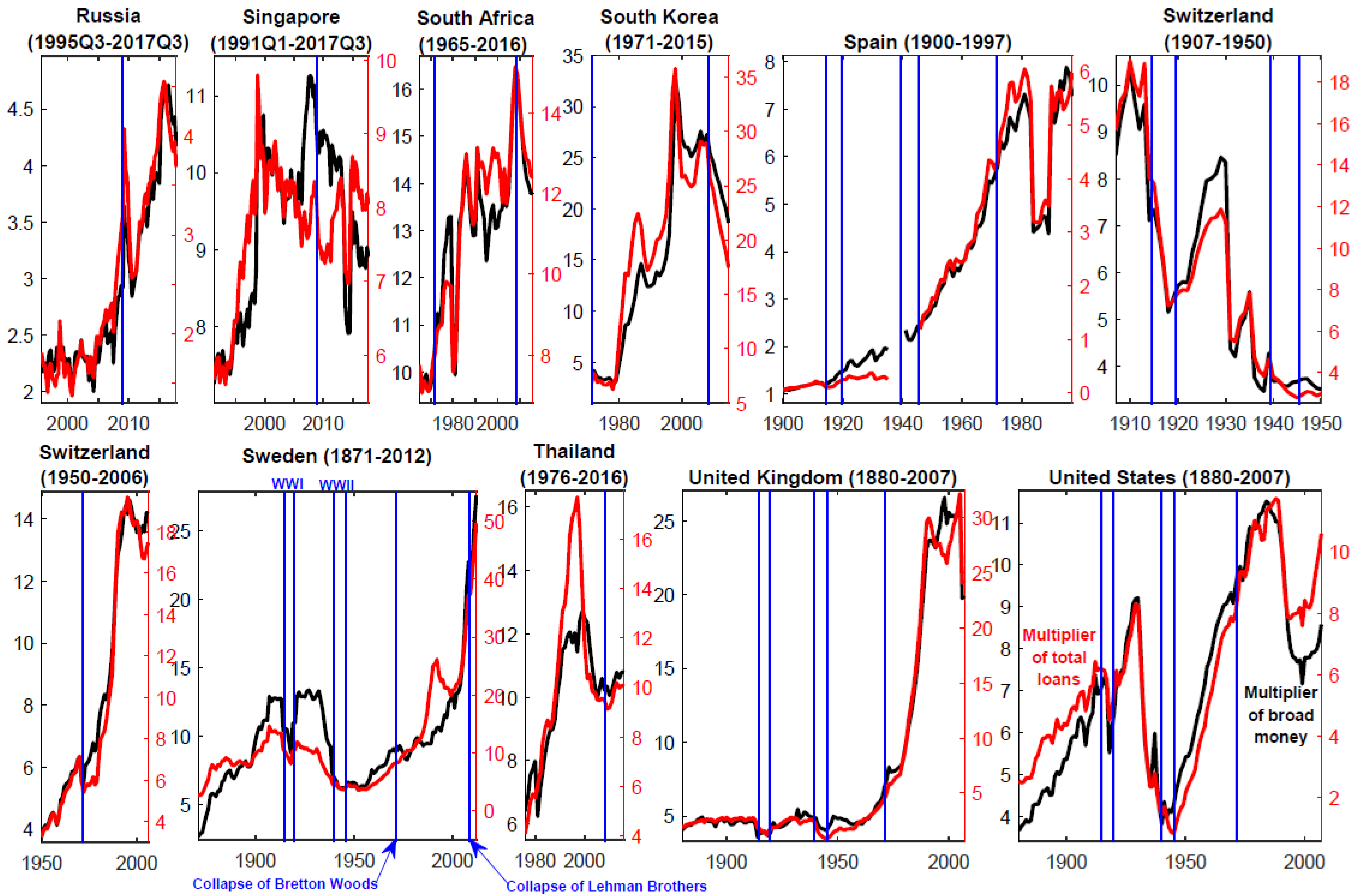

Figure 1c Multipliers of total loans and broad money for individual countries

where the notation is obvious, and θ_t is I(0). Unless $\beta = 1$, the logarithm of the ratio between credit and money, $c_t - m_t = \alpha + (\beta - 1)m_t + \theta_t$, will have a unit root, thus pointing—under ST's interpretation—towards a 'disconnect' between the two aggregates. The implication is that ST's evidence bears no implication for the issue at hand, and it therefore cannot be taken to imply a decoupling, since WWII, between the traditional banking system's monetary liabilities and the amount of loans it extends to the private non-financial sector.

Second, working with JST's dataset I show that, since the Gold Standard era, fluctuations in broad money and credit have exhibited an extraordinarily strong correlation *within each single country*. The correlation between the two aggregates' fluctuations is so strong, especially at the low frequencies, that (e.g.) either Shin's (1994) or Wright's (2000) test consistently detects *cointegration* between their multipliers, defined as the ratio between either aggregate and the monetary base.[5]. Crucially, this has held not only up until WWII, but also over the entire post-WWII period. For nineteen countries not featured in JST's dataset I produce qualitatively the same evidence based on credit data from the *Bank for International Settlements* (*BIS*).[6] The simplest and most powerful illustration of the strength of the relationship between fluctuations in broad money and credit since the second half of the XIX century is provided by the joint evolution of either the multipliers, or the rates of growth of the two aggregates, in the 36 countries I consider, which is shown in Figures 1*a*-1*c*, and in Figures A.1*a*-A.1*c* in the online Appendix,[7] respectively. The evidence speaks for itself: the notion that, after WWII, credit may have become 'disconnected' from broad money is manifestly incorrect. Statistical analysis—based on either country-and-year fixed-effects regressions, frequency-domain methods, or cointegration tests—will simply confirm what the visual evidence so starkly suggests.

Third, I show that based on the same metric used by ST—i.e., the area under the Receiver Operating Characteristic (ROC) curve—after WWII (*i*) changes in the multipliers of either credit or broad money have been more powerful at predicting financial crises than credit growth (the variable originally studied by ST); and (*ii*) there has been *no change* in the *relative* prediction power of the two aggregates, compared to the pre-WWII period. Both before, and after WWII credit had, and has exhibited a slightly greater prediction power than broad money for financial crisis. However, although after WWII the prediction power of *both* aggregates has increased compared to the pre-WWII period, their relative prediction power has remained unchanged.

[5] See e.g. Brunner and Meltzer (1990) and Modigliani and Papademos (1990).

[6] The *BIS* data, like JST's data, only cover the traditional banking sector. As I discuss in Section 1.2.1, the fact that neither dataset covers the 'market-based' banking sector has important implications for the interpretation of my evidence, as well as of JST's.

[7] The online appendix is available at: https://sites.google.com/site/lucabenatiswebpage.

1.2 Implications

My results have two main substantive implications, and a methodological one.

1.2.1 Traditional banks, the ascent of 'shadow banks', and the transition from the 'Age of Money' to the 'Age of Credit'

A first implication is that ST's characterization of the transition from the 'Age of Money' to the 'Age of Credit' is fundamentally incorrect. In contrast with ST's conclusions, my evidence clearly demonstrates that, for the traditional banking sector covered by JST's and the *BIS*' data, there has been *no material change since the Gold Standard era* in the relationship between broad money and credit. In turn, this implies that *only* the comparatively recent, and dramatic ascent of the market-based banking sector—which has been analyzed, e.g., by Adrian and Shin (2008, 2009, 2010, 2011), and is not covered by either JST's or the *BIS*' credit data—has introduced a 'wedge' between broad money and credit. Since shadow banks finance the loans they create not by taking deposits from the public, but rather borrowing on capital markets, such loans feature no corresponding monetary liability which could be counted as part of broad money.[8] As a result, every time shadow banks create a loan, they automatically introduce a wedge between broad money and credit. As shown by Adrian and Shin (2008, 2011), the assets of specific shadow-banking intermediaries—in particular, brokers-dealers—do indeed possess a superior informational content for macroeconomic fluctuations, compared to the assets of traditional banks. *This* is the true reason why, today, we live in the 'Age of Credit', rather than the one given by ST.

To sum up my own position, the ascent of shadow banking is the *only* reason why, today, we live in the 'Age of Credit': if it were for the traditional banking sector—for which the creation of broad money and credit has proceeded in lockstep since the Gold Standard era—we would still be living in the 'Age of Money', and the 'money view' would still be perfectly relevant. Another way of saying this is that, contrary to ST's position, the fundamental distinction is *not* between the two periods before and after WWII, but rather between the traditional and the 'market-based' banking sectors: the former still lives in the 'Age of Money', whereas the ascent of the latter is the only reason why we live in the 'Age of Credit'.

1.2.2 Interpreting the relationship between aggregate financial leverage and macroeconomic stylized facts

My evidence also has implications for the interpretation of several results produced by JST, pertaining to the relationship between aggregate financial leverage—which they measure by the ratio between nominal loans and nominal GDP—and macro-

[8] If these data were systematically collected, which currently is not the case.

economic stylized facts. In their *NBER Macro Annuals* paper,[9] for example, JST document how, since the second half of the XIX century, and especially since WWII, leverage has been negatively correlated with the mean, skewness, and 10th percentile of the distribution of real GDP growth *per capita*, thus implying that, e.g., higher leverage has been associated with systematically deeper recessions. JST interpret these findings as suggesting that more highly leveraged economies tend to experience wider 'boom and bust' fluctuations, which result in comparatively deeper slumps.

JST's interpretation is intuitively sensible, and might well be correct, but it is not the only possible one. In the light of the extraordinarily strong correlation I document between fluctuations in broad money and credit since the second half of the XIX century, an alternative, and equally plausible interpretation is in terms of *monetary instability*. This interpretation is in line with the old Monetarist literature—exemplified, first and foremost, by Milton Friedman and Anna J. Schwartz's (1963) *Monetary History of the United States*—stressing the broad *stability of monetary relationships*, and the dangers originating from instability in the monetary regime. Under this interpretation, the changes in the properties of real GDP growth *per capita* since the end of WWII (e.g., the fact that recessions have been systematically deeper) has nothing to do with financial leverage *per se*, and it rather originates from the fact that the very nature of post-WWII monetary regimes has caused broad money growth to be higher, and more volatile than in the previous era.

My objective here is not to advocate in favor of either interpretation, but rather to make the simple point that, based on this kind of evidence, either of them is equally plausible.

1.2.3 On the relevance of money-multiplier analysis

As discussed (e.g.) by Brunner and Meltzer (1990) and Modigliani and Papademos (1990), since the monetary base is under the control of the central bank, the multipliers of broad money and credit fully characterize the amounts of the two aggregates which are created by the interaction between the financial system and the public, for a given 'input' of base money provided by the monetary authority.[10] To put it differently, the multipliers characterize an economy's 'technology' for the 'production' of broad money and credit starting from a given 'input' of base money.

Money-multiplier analysis played a central role, first and foremost, in Friedman and Schwartz's *Monetary History*,[11] but over subsequent years and decades it was progressively abandoned, to the point that the money multiplier has almost faded

[9] See Jordà, Schularick, and Taylor (2017).

[10] A small, but important qualification to this statement is that the monetary base can be defined even in the absence of a monetary authority (e.g., for the United States before the creation of the Federal Reserve system, see Friedman and Schwartz (1963)). This is why, throughout this paper, I also report a few results for samples during which a specific country did not have a central bank.

[11] See, first and foremost, Chapter 7 ('The Great Contraction').

from frontier research,[12] and the very concept has fallen into near-oblivion.[13]

My results show that the abandonment of money-multiplier analysis was unwarranted, and that this approach still has quite a lot to say. A key issue to stress is the previously mentioned superior prediction power for financial crises, over the post-WWII period, of changes in the multipliers of either broad money or credit, compared to the two aggregates' growth rates.

1.3 Outline of the paper

The paper is organized as follows. The next section provides a brief overview of the data, which are described in detail in online Appendix A. In section 3 I discuss the main stylized facts pertaining to the evolution of broad money and credit since the second half of the XIX century. In Section 4 I show mathematically that ST's interpretation of the increase in the ratio between credit and broad money since WWII is incorrect. In Section 5 I explore the prediction power of broad money and credit for financial crises. Section 6 concludes, and outlines directions for further research.

2 The Data

Throughout the entire paper I report results based on two alternative datasets: a 'narrow' one only comprises the seventeen countries featured in JST's dataset,[14] whereas a 'broader' one also features nineteen additional countries.[15] All of the data and their sources are described in detail in online Appendix A. In this section I provide a brief overview of the main features of the two datasets, and of the data sources.

For the seventeen countries in the narrow dataset, data on broad money, total loans (i.e., credit), nominal GDP, and the price level are all from JST's dataset.[16]

[12] Among the very few recent theoretical analyses of models featuring a money multiplier, see Freeman and Kydland (2000) and Henriksen and Kydland (2010).

[13] E.g., whereas the 1990 *Handbook of Monetary Economics* featured extensive discussions of the money multiplier—see Brunner and Meltzer (1990) and Modigliani and Papademos (1990)—neither the subsequent 2011 edition, nor any edition of the *Handbook of Macroeconomics* even *mentioned* it. To the very best of my knowledge, the only paper to have ever analyzed the money multiplier based on modern time-series methods is Benati and Ireland (2017).

[14] The dataset is available from the internet at: http://www.macrohistory.net/data/. The 17 countries are Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Italy, Japan, the Netherlands, Norway, Portugal, Sweden, and the United States.

[15] The additional countries are Argentina, Chile, South Korea, South Africa, New Zealand, the Euro area, Russia, Brazil, India, Poland, Israel, Hungary, China, Czech Republic, Colombia, Malaysia, Singapore, Greece, and Thailand.

[16] Baker, Lopez-Salido, and Nelson (2018) document how ST's broad money data are sometimes sub-optimal. In order to make this paper's points as clear as possible, for the 17 countries in JST's dataset I exclusively use JST's broad money data. In a previous version of the paper, however, I considered an alternative set of monetary data, for which the sources are the same as Benati *et*

As for the monetary base, the narrow monetary aggregate featured in JST's dataset (i.e., the series labelled as 'narrowm') is equal to the monetary base only for Norway, Sweden, and the United States, whereas it is equal to M1 for all other countries—see the description of JST's data in Jordà *et al.* (2016). For Norway, Sweden, and the United States I have therefore taken the monetary base from JST's dataset, whereas for the remaining fourteen countries I have taken it from national central banks' websites or statistical publications (for details, see online Appendix A). For Belgium and Denmark I was not able to find long-run series for the monetary base.[17] For these two countries I therefore only report results based on either the two aggregates' growth rates, or their ratios with nominal GDP.

As for the remaining nineteen countries, data on total loans are from the *BIS*,[18] and they almost uniformly only cover the post-WWII period. Only for Argentina, I was able to extend the loans series back to 1863 based on the data featured in Ferreres (2005).[19] Data on broad money, nominal GDP, the price level, and the monetary base are all from either national central banks' websites and statistical publications, or from national statistical agencies' websites.

As for the sample periods, for each country I consider the longest available sample, with the single exception that, when working with the multipliers, for the United States, the United Kingdom, and the Euro area—whose monetary policies following the financial crisis have led to dramatic expansions in the monetary base—I end the sample period in 2007. The reason for doing so is that including the subsequent period would distort the inference, since the explosion in the monetary base mechanically caused a simultaneous collapse in the two multipliers, thus artificially 'blowing up' the strength of their correlation. On the other hand, for Japan I do not exclude the period of quantitative easing (QE) which started in early 2001, since the expansion in the monetary base was manifestly much more gradual. Also, since within the European Monetary Union (EMU) the monetary base for individual countries is not defined, when I work with money multipliers I necessarily end the samples for these countries in 1998 (at the latest).

Whereas for the countries in JST's dataset the sample periods typically start in 1870,[20] and for Argentina it starts in 1863, for several countries in the broader dataset the samples are quite short. This is the case, e.g., for Brazil, Colombia, and Russia, for which they start around the mid-1990s, whereas for China the sample starts in

al. (2018). My main findings—in particular, the strong correlation betweeen broad money and credit—were qualitatively the same. (These results are available upon request.)

[17] For Denmark, a series for the monetary base cannot literally be computed due to the lack of data on commercial banks' reserves. I wish to thank Kim Abildgren, of the Danish central bank, for confirming this to me.

[18] See at: https://www.bis.org/statistics/totcredit.htm

[19] Over the period of overlapping (1941-2004) the series from the *BIS* dataset is near-identical to that from Ferreres (2005).

[20] I say 'typically' because, in a few cases, data for the monetary base start much later—e.g., for Australia in 1976—thus compelling me to use shorter samples when working with the multipliers.

1990. In what follows, *all econometric work* for the broader dataset will be based on countries whose samples start at least in 1995 (or, when I use frequency-domain methods, even before that), whereas I will use the countries with shorter samples *only* for 'plotting' purposes, i.e. to visually illustrate the joint dynamics of the two multipliers over the most recent years. Although the samples starting after 1995 are, in fact, quite short, for this paper's purposes the evidence they provide is invaluable, because they clearly show that—contrary to ST's claim of a disconnect between broad money and credit after WWII—in countries such as the Czech Republic, the Euro area, Hungary, and Poland, fluctuations in the two aggregates have proceeded in lockstep even in recent years.

For West Germany I restrict the sample to 1960-1989. The reason is discussed in detail in the Online Appendix A.12.2 of Benati, Lucas, Nicolini, and Weber (2018), and it is summarized in the online data Appendix A to the present paper.[21] As for Switzerland, since, as discussed in the online data Appendix A, the two series for the monetary base for the periods 1907-1950 and 1950-2006 cannot be linked (because they are slightly different in 1950), I consider the two periods separately.

I now turn to the evidence.

3 Evidence

In building up my argument that, since the second half of the XIX century, fluctuations in broad money have exhibited an extraordinarily strong correlation with fluctuations in the total amount of loans granted by the traditional banking sector, I start from the simplest kind of evidence—the raw data—and I then move to progressively more sophisticated methods: the country-and-year fixed-effects regressions used by ST; frequency-domain techniques; and cointegration tests.

3.1 A look at the raw data

3.1.1 The evolution of money and credit multipliers within individual countries

Figures 1*a*-1*c*, and Figures A.1*a*-A.1*c* in the online Appendix, show the joint evolution of the two aggregates' multipliers, and of their growth rates, respectively, for each of the 36 countries in the dataset. Since the evidence in the two sets of figures is qualitatively the same, in what follows I exclusively focus on the multipliers.

The evidence in Figures 1*a*-1*c* clearly points towards a remarkably strong, and almost uniformly stable correlation between fluctuations in the two multipliers since the second half of the XIX century. In particular, contrary to ST's claim about a progressive disconnect between broad money and credit since the end of WWII, it is

[21] In short, the data before 1960 did not include West Berlin and the Saarland, which, in 1960, jointly accounted for about 6 per cent of overall GDP.

manifestly apparent how, even after 1945, the 'production' of the two aggregates for a given 'input' of base money has systematically proceeded in lockstep, especially at the very low frequencies.

Rather than discussing in detail the strength and stability of the correlation for individual countries, it is worth mentioning the few cases in which the two multipliers either temporarily diverge, or exhibit a somehow weak correlation. Two interesting examples of the former are provided by France and Italy during the Great Inflation episode. Whereas, for either country, the two multipliers have evolved in lockstep over the entire rest of the sample, in both cases the Great Inflation has been characterized by a temporary, sizeable increase in the money multiplier compared to the credit multiplier. Although I have no explanation for such temporary divergence, the similarity between the two episodes, for two countries which had similar overall macroeconomic experiences during those years, naturally suggests that they might have been driven by the same mechanism. By the same token, an interesting feature common to both Argentina and Canada is that the two multipliers' fluctuations have been more strongly correlated after WWI than before, with the correlation becoming remarkably strong after WWII: this is exactly the *opposite* of ST's claim about the disconnect between money and credit since WWII. For Thailand the credit multiplier exhibits a large transitory increase, compared to the money multiplier, around the time of the 1997 Asian crisis. The same holds for Sweden around the time of the financial crisis of the early 1990s, and for the United States during the years leading up to the recent financial crisis. By the same token, Singapore exhibits a short-lived deviation between the two multipliers around the time of the recent financial crisis. Greece and Poland exhibit transitory deviations between the multipliers between the mid-1980s and the mid-1990s, and during the years leading up to the financial crisis, respectively, for which I have no explanation. Finally, the Netherlands is the *only* country for which divergences between the two multipliers appear to have been quite frequent, and long-lasting. From a close analysis of the evidence in Figure 1*b* it is however quite apparent how this is partly an illusion originating from the sizeable fall in the loans multiplier, compared to the money multiplier, during WWII. In fact, analyzing separately the two sub-samples before and after WWII, the correlation between the multipliers appears quite strong in both of them.

Summing up The evidence in Figures 1*a*-1*c* shows that, since the second half of the XIX century, fluctuations in the multipliers of broad money and credit have consistently exhibited a very strong correlation within *each* of the 36 countries I analyze. It is important to stress that

(*i*) by no means the correlation between the two multipliers appears to have weakened after WWII: rather, in several cases—notably, Argentina and Canada—it appears to have become stronger.

(*ii*) This stylized fact has consistently held for both the advanced countries featured in JST's dataset, and comparatively less developed countries such Argentina,

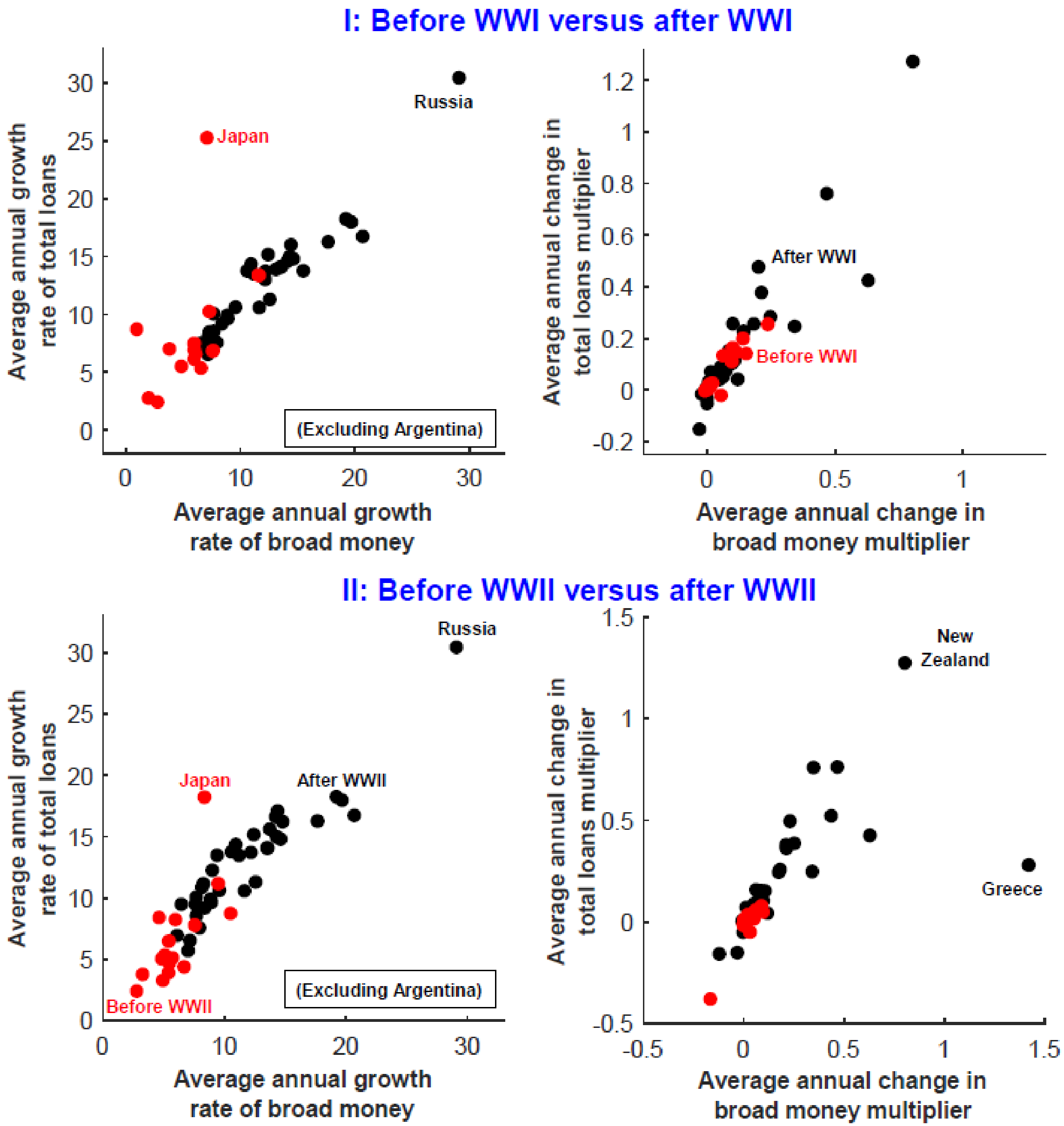

Figure 2 Average rates of growth of broad money and total loans, and average changes in the multipliers, since the Gold Standard era (all countries)

Brazil, Colombia, India, Malaysia, Russia, and China.[22]

(*iii*) By the same token, the strength of the correlation has held equally for low-inflation countries such as Germany, Japan, and Switzerland; for countries which experienced sizeable inflation fluctuations during the Great Inflation episode, such as (e.g.) the United Kingdom; and for very high-inflation countries such as Argentina, Brazil, and Israel.

I now turn to cross-section evidence.

3.1.2 Average growth rates, and average changes in the multipliers, within the countries' cross-section

Figure 2 shows scatterplots of either the average annual growth rates of broad money and total loans, or the average annual changes in the two aggregates' multipliers,[23] based on the broader dataset.[24] In the top row I label with different colors the observations pertaining to the two periods before and after WWI, whereas in the bottom row I do the same for the periods before and after WWII. The scatterplots for the growth rates exclude Argentina, for which the rates of growth of both money and credit have been so large, after WWI, that including it would make the figures difficult to read.[25]

In line with the time-series evidence in Figures 1*a*-1*c*, the cross-section evidence in Figure 2 provides no support to the notion that the relationship between broad money and credit may have changed, and become weaker, after WWII. On the contrary, based on either the changes in the multipliers, or the rates of growth, the relationship between the two aggregates appears to have been broadly similar during either period. The key distinguishing feature of the post-WWII era, compared to the pre-WWII period, simply appears to have been that, after WWII, *both* money *and* credit have been increasing at a substantially faster pace, whereas the relationship between them appears to have remained essentially unchanged.

At first sight, this would appear to contradict ST's figures. In discussing the statistics reported in their Table I (p. 1034) for the pre- and post-WWII periods, ST (p. 1033) state that:

> '[...] it is clear that annual growth rates of broad money (3.65 percent), loans (4.16 percent), and assets (4.33 percent) were fairly similar in the pre-WW2

[22] Which was significantly less developed in the early part of the sample.

[23] For countries for which the data are available at the quarterly frequency, annual growth rates, and annual changes in the multipliers, have been computed after converting the data to the annual frequency by taking averages within the year.

[24] Figure A.2 in the online appendix shows the corresponding evidence for the countries in JST's dataset, which is qualitatively the same as that in Figure 2.

[25] Argentina's average annual growth rates of broad money and credit have been equal to 98.1 and 124.2 per cent since WWI, and to 133.4 and 170.2 per cent since WWII. In fact, the observations for Argentina are *exactly* in line with those for the other countries (this evidence is available upon request), so that this country is nothing but an extreme example of the general pattern.

period; in contrast, after WW2 average broad money growth (8.57 percent) was much smaller than loan growth (10.94 percent) and asset growth (10.48 percent).'

In fact, these numbers are in line with the evidence reported in my Figure 2, as the *ratios* between the rates of growth of loans and broad money for the two periods—being equal to 4.16/3.65=1.14 and 10.94/8.57=1.28, respectively—are not substantially different. So, even based on ST's *own numbers*, there does not seem to have been any material difference in the relationship between the rates of growth of the two aggregates before and after WWII.

Table 1 Estimated slopes from cross-country LAD regressions, and 90 per cent bootstrapped confidence intervals (all countries)

	Before WWI	*After WWI*
Based on the rates of growth	1.048 [-0.282; 1.410]	1.030 [0.841; 1.295]
Based on the changes in the multipliers	0.755 [0.523; 0.959]	0.622 [0.525; 0.732]
	Before WWII	*After WWII*
Based on the rates of growth	1.018 [0.627; 1.608]	1.291 [0.688; 1.300]
Based on the changes in the multipliers	0.486 [0.243; 0.991]	0.621 [0.504; 0.691]

Evidence from LAD regressions In order to go beyond the simple visual impression, Table 1 reports results from Least Absolute Deviations (LAD) regressions based on the data shown in Figure 2.[26] Specifically, the table reports, for each of the four periods, the LAD estimate of the slope coefficient in the regression of average loans growth (the average change in the loans multiplier) on a constant and average broad money growth (the average change in the broad money multiplier). The 90 per cent coverage confidence intervals have been computed *via* resampling techniques.[27]With reference to the main comparison between the two periods before and after WWII, two facts emerge from the table. First, based on either the growth rates,

[26]Table A.1 in the online appendix reports the corresponding results for JST's dataset, which are qualitatively the same as those in Table 1.

[27]Resampling is performed as follows. Consider the cross-country LAD regression of $Y = [Y_1, Y_2, ..., Y_N]'$ on a constant and $X = [X_1, X_2, ..., X_N]'$, where N is the number of countries; Y_i is either average credit growth, or the average change in the credit multiplier, for country i; and X_i is either average broad money growth, or the average change in the money multiplier for country i. Having obtained the simple estimate of the slope coefficient, $\hat{\beta}_{LAD}$, I characterize uncertainty around it as follows. For k = 1, 2, ..., K (with K = 10,000), I randomly draw N indices j from a uniform distribution defined over the integer domain [1, 2, ..., N]', thus building up, for each k, bootstrapped samples (Y_k, X_k). Based on each bootstrapped sample (Y_k, X_k) I then perform the same LAD regression I performed based on the actual data (i.e. Y and X), thus building up the bootstrapped distribution of the LAD regression coefficients. Finally, I rescale the bootstrapped distribution of the slope coefficient in such a way that its median is equal to the simple estimate, $\hat{\beta}_{LAD}$, and I use it to compute the 90 per cent confidence interval reported in Table 1.

or the changes in the multipliers, the simple estimates point towards an increase in the slope after WWII, from 1.02 to 1.29 based on the rates of growth, and from 0.49 to 0.62 based on the multipliers. Second, the extent of uncertainty is however such that neither change is statistically significant: this is clearly shown by the fact that the 90 per cent confidence intervals for the post-WWII period lie strictly inside the corresponding confidence intervals for the pre-WWII period.

I now turn to evidence based on the methodology used by ST.

3.2 Evidence from country-and-year fixed-effects regressions

The first panel of Figure 3 shows, for each country in the broader dataset, the ratio between loans and broad money since the Gold Standard era, whereas the first two panels of Figure 4 show the multipliers of broad money and credit, respectively. The three panels highlight a dramatic extent of cross-country heterogeneity in the evolution of both the ratio between the two aggregates, and either of the two multipliers, since the XIX century. By performing country-and-year fixed-effects regressions based on the data in the first panel of Figure 1,[28] ST extracted the year-specific effects reported as the dark line in their Figure 2, showing a continuous increase, since WWII, in the average ratio between credit and broad money.

3.2.1 Replicating Schularick and Taylor (2012)

The second panel of Figure 3 replicates the just-mentioned evidence in ST's Figure 2 based on either of the two datasets considered herein. The methodology I use is identical to that used by ST:[29] the only difference is that whereas ST perform the regressions based on the *logarithms* of the ratios between loans and broad money, I perform it based on the *levels*. Based on either dataset, the evolution of the estimated year effects in Figure 3 closely replicates the evidence in ST's Figure 2: the year effects exhibit a dramatic collapse between the onset of the Great Depression and the end of WWII; rebound strongly during subsequent years, reaching the previous peaks immediately before the collapse of Bretton Woods; and have significantly increased since then, reaching historically unprecedented levels in the most recent years.

[28] To be precise, based on a previous version of the dataset, featuring only fourteen countries, and slightly shorter sample periods.

[29] ST (p. 1034): '[W]e show the mean of the predicted time effects from fixed country-and-year effects regressions for the dependent variable of interest. That is, for any variable x it we estimate the fixed effects regression $x_{it} = a_i + b_t + e_{it}$ and then plot the estimated year effects b_t to show the average global level of x in year t.'

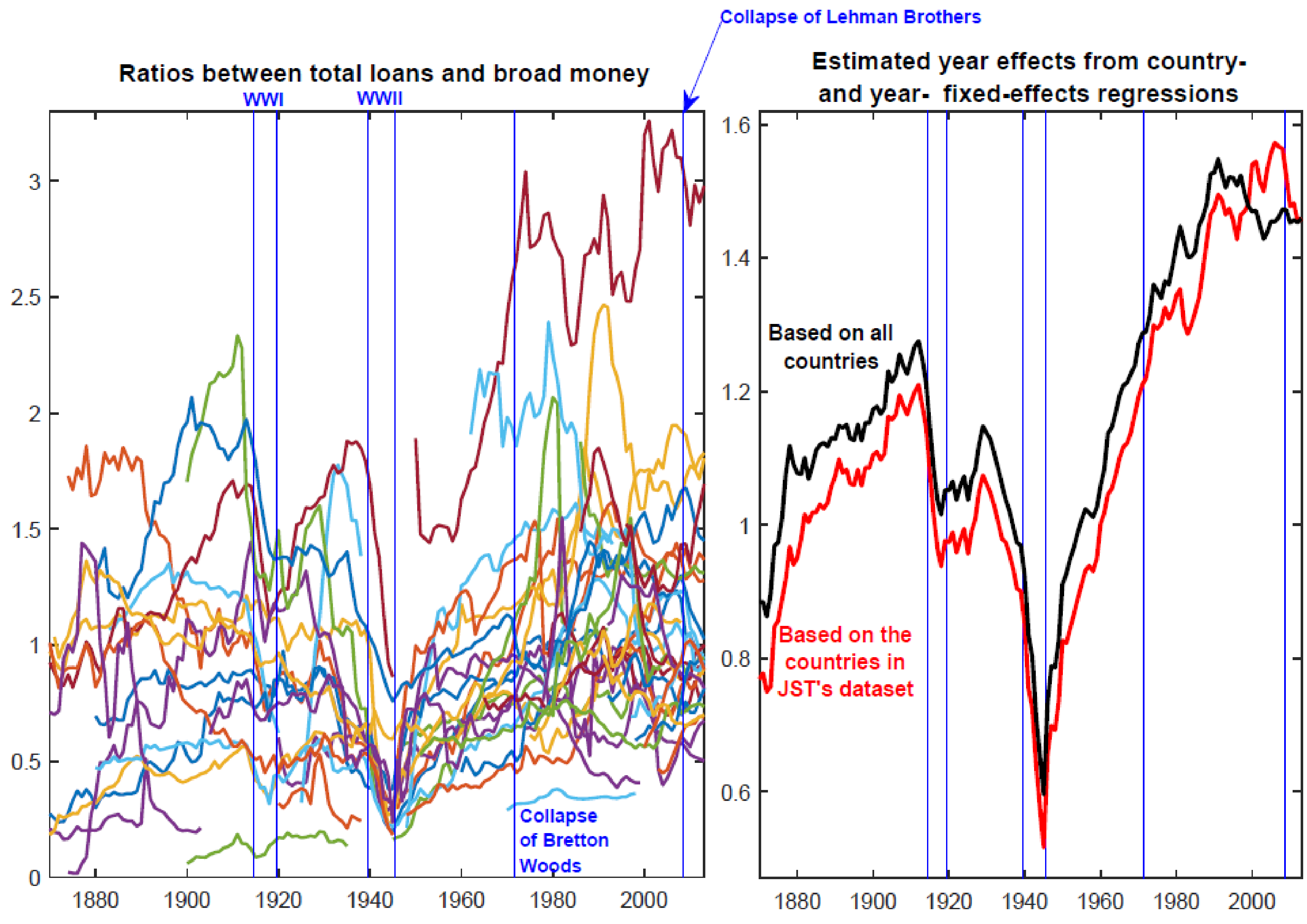

Figure 3 Replicating Schularick and Taylor (2012): Ratios between total loans and broad money, and estimated year effects from country- and year- fixed-effects regressions (1870-2013)

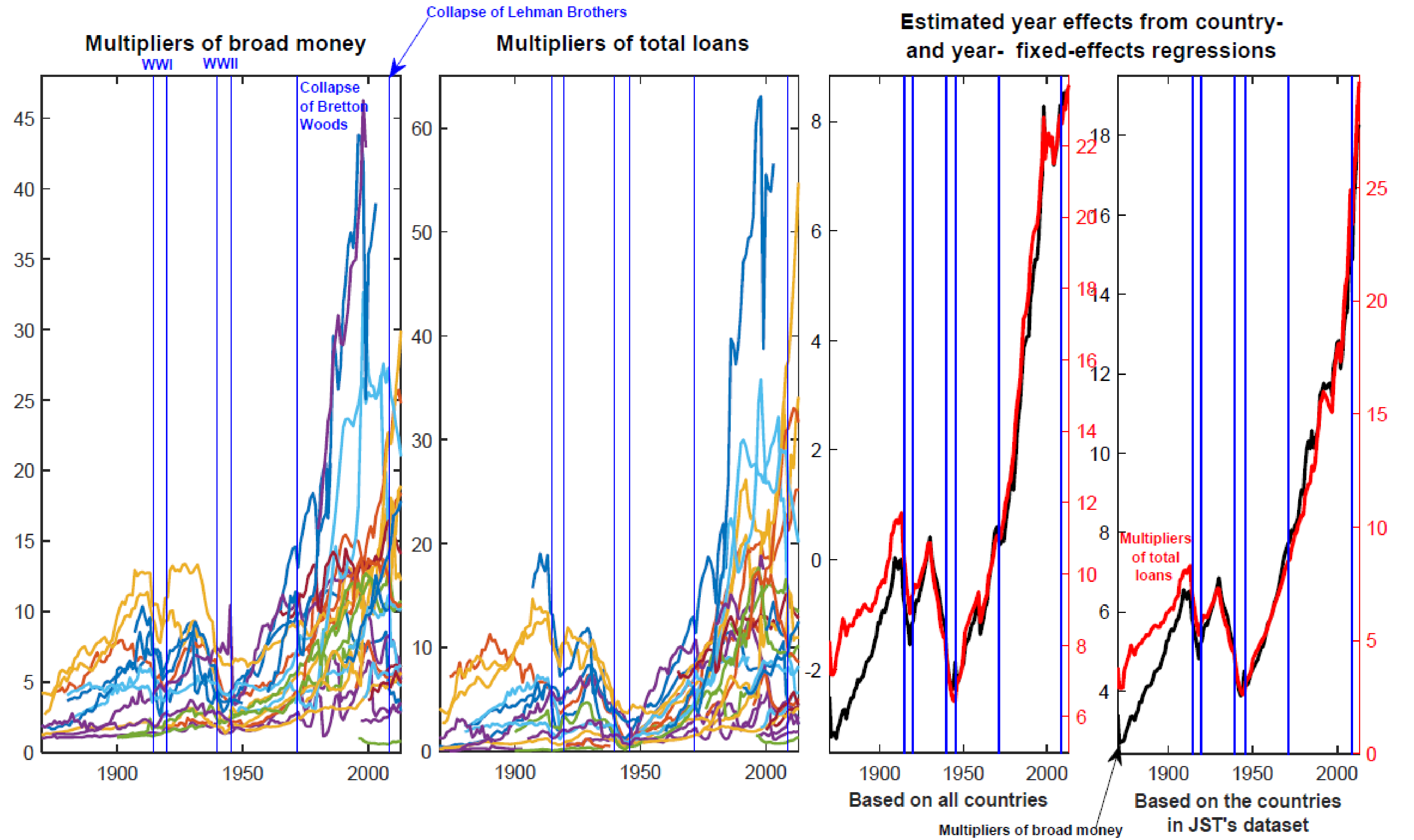

Figure 4 Multipliers of total loans and broad money, and estimated year effects from country- and year- fixed-effects regressions (1870-2013)

3.2.2 Evidence for multipliers, rates of growth, and ratios between either broad money or credit and nominal GDP

The third and fourth panels of Figure 4 show the estimated year effects from the very same country-and-year fixed-effects regressions performed both by ST, and in the previous subsection, but this time for the *multipliers* of either total loans of broad money.[30] Consistent with the evidence in Figures 1*a*-1*c* and Figure 2, based on either JST's or the broader dataset the estimated year effects for the two multipliers have consistently exhibited a remarkably strong correlation over the entire sample, to the point that, over the entire period since WWI, they have been essentially *indistinguishable*.[31] This evidence provides a clear illustration of how, over the entire period since the XIX century, the creation of broad money and credit, starting from a given input of base money, has consistently proceeded in lockstep.

The first two panels of Figure 5 present the corresponding evidence for the annual *growth rates* of either loans or broad money. In order to better highlight the strength of the correlation, I present results for 5-year rolling averages of the estimated year effects. Evidence is qualitatively the same as that based on the multipliers, and I will therefore not discuss it in detail.

Rather, it is of interest to devote a few words to the evidence shown in the last two panels of Figure 5, which plot the year effects from country-and-year fixed-effects regressions for the *ratios* between either broad money, or total loans, and nominal GDP.[32] Based on the countries in JST's dataset, the two ratios had been moving in lockstep between 1870 and the outbreak of WWI. They then significantly diverged during the following six decades, with the ratio for loans first collapsing, reaching a trough around the end of WWII, and then rebounding strongly during subsequent years; and the ratio for money displaying sizeable fluctuations around the level it had reached around WWI. By the time of the collapse of Bretton Woods, the relationship between the two ratios which had characterized the pre-WWI era had fully re-established itself, and during subsequent years the two ratios kept increasing in synch, to the point that, if they had not been shown with different colors, it would be difficult to tell them apart. This evidence illustrates how, in terms of the relationship between the ratios between either broad money or credit and nominal GDP, *there is no difference between the pre-WWI era, and the period following the collapse of Bretton Woods*. As the last panel of Figure 5 shows, during either period the two ratios had, and have been moving in lockstep. This provides a further illustration of the fact that ST's claim of a disconnect between broad money and credit since WWII is incorrect. Finally, evidence based on the broader dataset is in line with that based

[30] Once again, for all countries for which the data are available at the quarterly frequency, I preliminarly convert them to the annual frequency by taking annual averages.

[31] Quite obviously, once appropriately rescaled: notice that in either panel the left hand-side and right hand-side scales are different.

[32] As mentioned in Section 1.2.2, the latter ratio is interpreted by Jordà, Schularick, and Taylor (2017) as a measure of aggregate financial leverage for the whole economy.

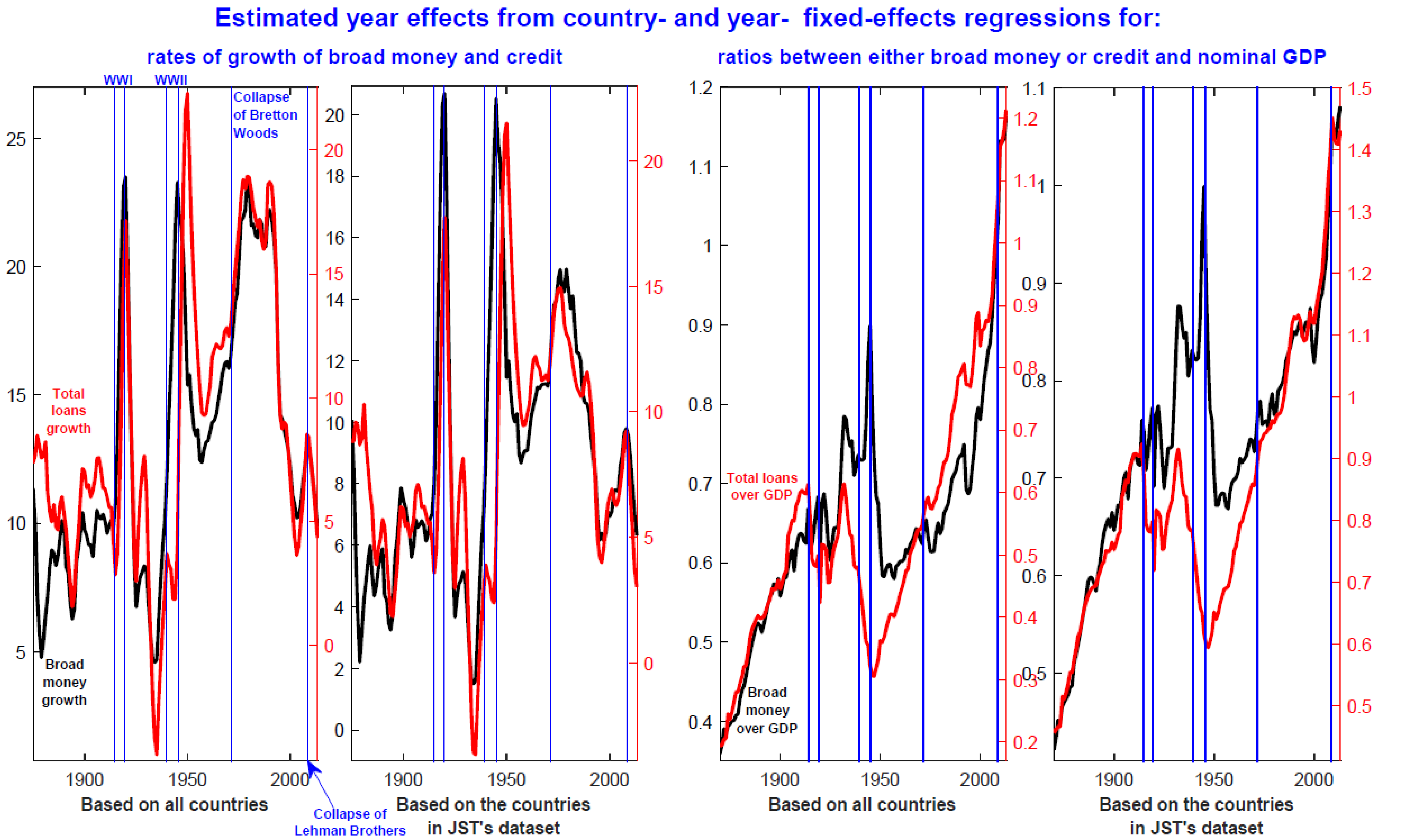

Figure 5 Estimated year effects from country- and year- fixed-effects regressions (1870-2013)

Table 2 Fractions of frequency-0 variance of the first-differences of the multipliers of broad money and of total loans explained by the most powerful common shock, based on the longest continuous available samples

	First difference of:					
	broad money multiplier			*total loans multiplier*		
	Mode	Median	90%-coverage confidence interval	Mode	Median	90%-coverage confidence interval
Argentina (1905-2014)	0.990	0.983	[0.064; 0.997]	0.990	0.983	[0.066; 0.997]
Australia (1976-2013)	0.990	0.964	[0.128; 0.996]	0.990	0.964	[0.100; 0.996]
Canada (1874-2013)	0.990	0.991	[0.116; 0.999]	0.990	0.993	[0.141; 0.999]
Chile (1986-2016)	0.990	0.970	[0.109; 0.997]	0.990	0.974	[0.125; 0.997]
China (1990Q1-2017Q3)	0.990	0.968	[0.052; 0.996]	0.990	0.968	[0.053; 0.996]
Finland (1870-1985)	0.990	0.992	[0.081; 0.999]	0.990	0.992	[0.082; 0.999]
France (1946-1994)	0.929	0.692	[0.053; 0.957]	0.939	0.714	[0.049; 0.959]
West Germany (1960-1989)	0.990	0.963	[0.045; 0.997]	0.990	0.963	[0.043; 0.997]
India (1951-2015)	0.990	0.970	[0.135; 0.996]	0.980	0.970	[0.125; 0.996]
Italy (1870-1997)	0.980	0.939	[0.091; 0.993]	0.980	0.943	[0.098; 0.994]
Japan (1874-2013)	0.990	0.973	[0.063; 0.997]	0.990	0.973	[0.063; 0.997]
Malaysia (1975-2016)	0.990	0.987	[0.098; 0.998]	0.990	0.987	[0.100; 0.998]
Netherlands (1945-1992)	0.929	0.741	[0.134; 0.967]	0.929	0.796	[0.170; 0.972]
New Zealand (1960-2003)	0.990	0.979	[0.084; 0.998]	0.990	0.979	[0.084; 0.998]
Norway (1870-2013)	0.990	0.986	[0.077; 0.999]	0.990	0.986	[0.080; 0.999]
Portugal (1920-1998)	0.990	0.906	[0.039; 0.994]	0.990	0.908	[0.042; 0.994]
Singapore (1991Q1-2017Q3)	0.990	0.820	[0.091; 0.991]	0.990	0.803	[0.093; 0.988]
South Africa (1965-2016)	0.980	0.919	[0.030; 0.990]	0.980	0.921	[0.031; 0.991]
South Korea (1971-2015)	0.990	0.982	[0.052; 0.998]	0.990	0.982	[0.051; 0.998]
Spain (1946-1997)	0.990	0.984	[0.044; 0.998]	0.990	0.985	[0.045; 0.998]
Sweden (1871-2013)	0.990	0.992	[0.143; 0.999]	0.990	0.992	[0.143; 0.999]
Switzerland (1950-2006)	0.990	0.994	[0.162; 0.999]	0.990	0.994	[0.166; 0.999]
Thailand (1976-2016)	0.990	0.964	[0.257; 0.997]	0.990	0.968	[0.253; 0.997]
United Kingdom (1880-2007)	0.990	0.994	[0.683; 0.999]	0.990	0.994	[0.753; 0.999]
United States (1880-2007)	0.990	0.965	[0.023; 0.998]	0.990	0.965	[0.022; 0.998]

[a] Spectral bootstrapping has been implemented *via* Berkowitz and Diebold's (1998) procedure.

on JST's, being just slightly less stark.

I now turn to evidence from cross-spectral methods, which allow to properly characterize the strength of the relationship at the low frequencies.

3.3 Evidence based on the most powerful common shock at the frequency ω=0

In Section 3.4 I will show that either Shin's (1994) or Wright's (2000) test detects cointegration between the multipliers of broad money and total loans. In this section I discuss conceptually related evidence based on a more flexible approach requiring less stringent assumptions.[33]

Table 2 reports, for the longest continuous sample which is available for each country, the fractions of frequency-0 variance of the first-differences[34] of the multipliers of broad money and total loans which are explained by the *most powerful common shock*—to be defined in the next sub-section—whereas Tables 3*a*-3*b* report the same type of evidence for the pre- and post-WWII periods. The spectral density matrix of the data has been estimated based on the fast-Fourier transform (FFT). Smoothing of the periodograms and cross-periodograms has been implemented in the frequency domain based on a Bartlett spectral window, with the spectral bandwidth being selected automatically based on the algorithm proposed by Beltrao and Bloomfield (1987). Finally, spectral bootstrapping has been implemented *via* the procedure proposed by Berkowitz and Diebold (1998), which is a multivatiate generalization of the univariate procedure introduced by Franke and Hardle (1992).

3.3.1 Extracting the most powerful common shock at ω=0

The best way to illustrate the approach used herein is to highlight similarities and differences with identification based on *long-run restrictions* within a structural VAR context, as in (e.g.) Blanchard and Quah (1989). Within this context, a researcher starts by estimating a VAR(p), $Y_t = B_0 + B_1 Y_{t-1} + ... + B_p Y_{t-p} + u_t$, with $E[u_t u_t'] = \Omega$, for the series of interest, thus obtaining (e.g., OLS) estimates for the relevant objects, $\hat{B}_i$, i = 0, 1, 2, ..., p, and $\hat{\Omega}$. Based on these, (s)he computes the estimate of the spectral density matrix of Y_t at the frequency ω=0 as $\hat{S}(0) = \hat{C}\hat{\Omega}\hat{C}'$, where $\hat{C}$ = $[I_N - \hat{B}(1)]^{-1}$, where I_N is the $N \times N$ identity matrix, and $\hat{B}(1) = B_1 + B_2 +$ ... $+ B_p$. Finally, the researcher factors $\hat{S}(0)$ as $\hat{S}(0) = LRI \times LRI'$, where LRI is

[33] Online Appendix B reports additional results based on spectral analysis, pertaining to the cross-spectral coherence and gain between the first differences of the multipliers of broad money and total loans at the very low frequencies. These results are conceptually in line with the evidence reported in this section, and they are therefore not reported or discussed here.

[34] I consider the first differences, rather than the levels, of the multipliers because spectral analysis is predicated on the assumption of stationarity, whereas—as I discuss in Section 3.4.1—the null of a unit root cannot be rejected for any multiplier and any country, with the single exception of Argentina for the period since the early XX century.

the matrix of the structural shocks's long-run impacts, featuring zeros in the relevant positions. There are two differences between this approach and what I am doing here:

(i) rather than extracting $\hat{S}(0)$ from a VAR estimated in the time-domain, I estimate it directly in the frequency domain, based on the FFT of the data. The key advantage of doing this is that I do not have to take a stand on the presence, or absence of cointegration between the two multipliers, as the FFT-based estimator works equally well in both cases.[35]

(ii) The shock I identify maximizes the *conditional cross-spectrum*[36]—i.e., the cross-spectrum computed only conditional on this shock—between the first differences of the two multipliers at ω=0, which is the natural measure of the strength of the co-movement between the two variables in the infinite long-run.[37]

3.3.2 Evidence

Table 2 reports, for the first difference of either multiplier, the mode, median, and 5th and 95th percentiles of the bootstrapped distribution of the fraction of frequency-0 variance of the series explained by the just-defined most powerful common shock. Once again, the evidence speaks for itself, with (e.g.) the modal estimate being equal to 0.99 for the first differences of either multiplier for nearly all countries, with the exceptions of France (0.929 and 0.939), Italy and South Africa (in both cases, 0.98 for both multipliers), and the Nertherlands (0.929 for either multiplier). Both the median estimates, and the confidence intervals, exhibit somehow more heterogeneity, but the main message from Table 2 is very clear: the shock which maximizes the frequency-0 covariation between the first differences of the two multipliers explains very large fractions of the variance of *both* series at ω=0.

In order to understand the implications of this result, it is important to recall that if the two multipliers were *cointegrated*, the shock I am identifying would explain, by definition, 100 per cent of the variance of both series at ω=0. This is the reason why,

[35] In the presence of cointegration, $S(0)$ will be reduced-rank, but that's all.

[36] Let $S_{12}(\omega)$ be the (1,2) element of the spectral density matrix of the first differences of the two multipliers at the frequency ω. The cross-spectrum is defined as $[\text{Co}(\omega)^2 + \text{Qu}(0)^2]^{1/2}$, where Co($\omega$) and Qu($\omega$) are the real and the imaginary parts, respectively, of $S_{12}(\omega)$.

[37] From a technical point of view, identification of the shock is straightforward. Starting from an initial factorization of $\hat{S}(0)$ as $\hat{S}(0) = L_{start} \times L'_{start}$, where, e.g., L_{start} is the Cholesky factor of $\hat{S}(0)$, identification boils down to finding a rotation angle ω such that the rotation matrix

$$R = \begin{bmatrix} \cos(\omega) & \sin(\omega) \\ \text{-}\sin(\omega) & \cos(\omega) \end{bmatrix}$$

produces a new factorization $\hat{S}(0) = L \times L'$, with $L = L_{start} \times R$, which maximizes the cross-spectrum *conditional* on the first shock, i.e. the cross-spectrum for

$$\hat{S}_1(0) = L \times \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \times L'.$$

Table 3*a* Fractions of frequency-0 variance of the first-differences of the multipliers of broad money and of total loans explained by the most powerful common shock, based on the longest continuous available samples

	First difference of broad money multiplier:						Fraction of random draws from the two distributions for which the fraction after WWII is smaller than before WWII:
	Before WWII			*After WWII*			
	Mode	Median	90%-coverage confidence interval	Mode	Median	90%-coverage confidence interval	
Argentina	0.980	0.942	[0.043; 0.991]	0.980	0.948	[0.056; 0.992]	0.476
Canada	0.990	0.981	[0.267; 0.997]	0.990	0.971	[0.063; 0.997]	0.584
Finland	0.990	0.959	[0.020; 0.997]	0.970	0.912	[0.043; 0.987]	0.639
Germany	0.990	0.996	[0.916; 0.999]	0.990	0.963	[0.053; 0.997]	0.844
Italy	0.980	0.964	[0.015; 0.995]	0.980	0.866	[0.090; 0.987]	0.709
Japan	0.939	0.859	[0.425; 0.979]	0.990	0.988	[0.111; 0.999]	0.163
Netherlands	0.980	0.887	[0.113; 0.989]	0.950	0.748	[0.131; 0.970]	0.650
Norway	0.990	0.991	[0.074; 0.999]	0.990	0.967	[0.067; 0.996]	0.737
Portugal	0.626	0.564	[0.100; 0.912]	0.980	0.902	[0.051; 0.989]	0.211
Spain	0.970	0.828	[0.067; 0.989]	0.990	0.984	[0.045; 0.998]	0.183
Sweden	0.980	0.924	[0.039; 0.992]	0.980	0.940	[0.056; 0.995]	0.464
Switzerland	0.990	0.989	[0.086; 0.999]	0.990	0.994	[0.216; 0.999]	0.400
United Kingdom	0.980	0.940	[0.081; 0.994]	0.990	0.984	[0.076; 0.998]	0.294
United States	0.990	0.998	[0.885; 0.999]	0.990	0.995	[0.143; 0.999]	0.669

[a] Spectral bootstrapping has been implemented *via* Berkowitz and Diebold's (1998) procedure.

Table 3*b* Fractions of frequency-0 variance of the first-differences of the multipliers of broad money and of total loans explained by the most powerful common shock, based on the longest continuous available samples

	First difference of total loans multiplier:						Fraction of random draws from the two distributions for which the fraction after WWII is smaller than before WWII:
	Before WWII			*After WWII*			
	Mode	Median	90%-coverage confidence interval	Mode	Median	90%-coverage confidence interval	
Argentina	0.980	0.943	[0.043; 0.991]	0.980	0.948	[0.057; 0.992]	0.479
Canada	0.990	0.980	[0.227; 0.997]	0.990	0.974	[0.069; 0.997]	0.569
Finland	0.990	0.959	[0.021; 0.997]	0.970	0.912	[0.041; 0.987]	0.639
Germany	0.990	0.996	[0.936; 0.999]	0.990	0.963	[0.052; 0.997]	0.851
Italy	0.980	0.964	[0.016; 0.995]	0.980	0.866	[0.089; 0.987]	0.713
Japan	0.990	0.859	[0.368; 0.989]	0.990	0.988	[0.109; 0.999]	0.184
Netherlands	0.980	0.938	[0.165; 0.994]	0.889	0.748	[0.136; 0.964]	0.749
Norway	0.990	0.991	[0.074; 0.999]	0.980	0.967	[0.065; 0.996]	0.739
Portugal	0.737	0.777	[0.141; 0.967]	0.980	0.902	[0.053; 0.989]	0.326
Spain	0.970	0.812	[0.065; 0.983]	0.990	0.985	[0.046; 0.998]	0.164
Sweden	0.980	0.940	[0.050; 0.993]	0.980	0.942	[0.054; 0.994]	0.499
Switzerland	0.990	0.989	[0.087; 0.999]	0.990	0.994	[0.219; 0.999]	0.406
United Kingdom	0.980	0.941	[0.083; 0.994]	0.990	0.984	[0.077; 0.998]	0.294
United States	0.990	0.998	[0.910; 0.999]	0.990	0.995	[0.143; 0.999]	0.672

[a] Spectral bootstrapping has been implemented *via* Berkowitz and Diebold's (1998) procedure.

as I mentioned, the present approach is conceptually related to cointegration, but it is also more flexible. The bottom line from Table 2 is that, even if the two multipliers ultimately turned out *not* to be, strictly speaking, cointegrated, nonetheless their relationship is, in fact, remarkably close to that between cointegrated processes.[38] In fact, a key result in Table 2 is that, for each single country, the estimated fractions of variance at ω=0 for the two multipliers are virtually identical (as just mentioned, if the series were cointegrated, their fractions of variance at ω=0 explained by the common shock would be both equal to 100 per cent).

Tables 3*a*-3*b* report the same evidence as in Table 2, but for pre- and post-WWII periods. In either table, the very last column reports the probability that a random draw from the distribution of the fraction of variance at ω=0 explained by the most powerful common shock for the post-WWII period is smaller than a random draw from the corresponding distribution for the pre-WWII period. I will not comment on the results in detail, but what ought to be stressed is that, once again, even through the lenses of this approach, there is no evidence whatsoever that the correlation between the two multipliers may have weakened after WWII.

I now turn to the results from cointegration analysis.

3.4 Evidence from cointegration methods

Tables A.4*a*-A5*c* in the online appendix report bootstrapped p-values[39] for Elliot *et al.* (1996) unit root tests for the multipliers of broad money and credit, either with or without a time trend, and for either the longest available sample, or the two sub-samples before and after WWII. With one single exception—Argentina since 1905—the null hypothesis of a unit root is never rejected for either multiplier.

Tables 4 and 5 report, for the longest available sample, and for the two sub-samples before and after WWII, respectively, bootstrapped p-values for Shin's (1994) tests of the null of cointegration between the two multipliers; and, based on Wright's (2000) test, the 90 per cent coverage bootstrapped confidence interval for β, the second element of the normalized candidate cointegration vector $[1\ \text{-}\beta]'$. Wright's test searches across the parameter space for all of the values of β for which the null hypothesis of stationarity of the candidate cointegration residual $\mu_M - \beta\mu_L$—where μ_M and μ_L are the multipliers of broad money and loans—cannot be rejected. The advantage of Wright's test over Shin's is that it is valid under more general conditions, in particular, when the series under investigation are not I(1), but rather local-to-

[38] To put it differently, the size of the unit root component which is *not* common to the two multipliers is very small.

[39] p-values have been computed by bootstrapping 10,000 times estimated ARIMA(p,1,0) processes. In all cases, the bootstrapped processes are of length equal to the series under investigation. As for the lag order, p, since, as it is well known, results from unit root tests may be sensitive to the specific lag order which is being used, for reasons of robustness I consider two alternative lag orders, either 1 or 2 (with annual data), or 4 and 8 (with quarterly data).

unity (see the discussion in Wright (2000)).[40] I bootstrap both tests as in Cavaliere *et al.* (2012), based on the VECM estimated conditional on one cointegration vector.

Table 4 Testing for cointegration based on the longest available samples[a]

		Shin's tests	*Wright's tests*
Country	*Period*	bootstrapped p-values	90% confidence interval for $\hat{\beta}$
Argentina	1863-1891	0.225	[-0.438; 0.932]
Australia	1976-2013	0.489	[0.354; 0.639]
Canada	1874-2013	0.035	[-0.421; 1.580]
Chile	1986-2016	0.717	[-0.364; 1.637]
China	1990Q1-2017Q3	0.078	[1.197; 2.647]
Finland	1870-1985	0.856	[0.777; 1.082]
France	1946-1994	0.944	[0.310; 1.705]
Germany	1883-1913	0.051	[0.524; 1.139]
	1960-1989	0.705	[0.252; 0.642]
India	1951-2015	0.094	[1.138; 1.868]
Italy	1870-1997	0.892	[0.675; 1.865]
Japan	1874-2013	0.325	[0.873; 2.048]
Malaysia	1975-2016	0.295	[0.724; 1.429]
Netherlands	1946-1992	0.336	[0.443; 0.803]
New Zealand	1960-2003	0.977	[0.549; 0.644]
Norway	1870-2013	0.037	[-0.481; 1.519]
Portugal	1870-1903	0.143	[0.426; 1.726]
	1920-1998	0.629	[0.979; 1.544;]
Singapore	1991Q1-2017Q3	0.407	[-0.653; 1.347]
South Africa	1965-2016	0.315	[0.519; 0.864]
South Korea	1971-2015	0.416	[0.919; 2.119]
Spain	1900-1935	0.816	[2.476; 4.461]
	1946-1997	0.160	[1.033; 1.183]
Sweden	1871-2012	0.302	[-0.626; 1.374]
Switzerland	1907-1950	0.384	[0.280; 0.495]
	1950-2006	0.164	[0.618; 0.803]
Thailand	1976-2016	0.023	[0.529; 1.639]
United Kingdom	1880-2007	0.023	[0.725; 0.805]
United States	1880-2007	0.111	[-0.291; 1.710]

[a] Based on 10,000 bootstrap replications. For details, see text.

[40] The test exploits the duality between testing and the construction of confidence intervals, so that the confidence interval for β at a given significance level is simply the set of all values of β for which stationarity of $\mu_M - \beta\mu_L$ cannot be rejected.

Table 5 Testing for cointegration by sub-samples[a]			
		Shin's tests	*Wright's tests*
Country	*Period*	p-values	90 per cent confidence interval for $\hat{\beta}$
	Post-WWI		
Argentina	1920-2014	0.566	[-0.013; 1.987]
Canada	1920-2013	0.749	[0.453; 0.623]
Finland	1920-1985	0.742	[0.734; 1.189]
Italy	1920-1997	0.691	[0.155; 2.155]
Japan	1920-2013	0.400	[-0.136; 1.864]
Norway	1920-2013	0.246	[0.075; 0.505]
Portugal	1920-1998	0.636	[0.979; 1.544]
Sweden	1920-2012	0.083	[-0.679; 1.321]
United Kingdom	1920-2007	0.769	[0.697; 0.787]
United States	1920-2007	0.353	[-0.374; 1.626]
	Post-WWII		
Argentina	1946-2014	0.183	[0.860; 2.045]
Canada	1946-2013	0.594	[0.531; 0.646]
Finland	1946-1985	0.435	[0.762; 1.047]
Italy	1946-1997	0.166	[0.139; 2.139]
Japan	1946-2013	0.042	[-0.099; 1.901]
Norway	1946-2013	0.079	[0.442; 0.522]
Portugal	1946-1998	0.298	[0.913; 2.118]
Sweden	1946-2012	0.279	[-0.732; 1.268]
United Kingdom	1946-2007	0.943	[0.686; 0.796]
United States	1946-2007	0.030	[-0.369; 1.631]

[a] Based on 10,000 bootstrap replications. For details, see text.

Two main results emerge from the tables:

(i) Wright's test detects cointegration for *all* countries and *all* periods; and

(ii) based on Shin's test, the null of cointegration is rejected, at the 10 per cent level, only in a handful of cases. Based on the full sample, this is the case for Canada, India, Norway, Thailand, and the United Kingdom. Whereas, e.g., rejection for Canada can be rationalized in the light of the evolution of the two multipliers in the XIX century's portion of the sample (see Figure 1a), other rejections are puzzling: this is the case, in particular, for the United Kingdom, for which, as shown in Figure 1c, the two multipliers have been moving in synch over the entire period since 1880. A simple way to rationalize this, and similar rejections of the null is in terms of the 'luck of the draw': even if cointegration were there in all samples, due to the very nature of statistical tests, a certain number of rejections should always be expected.[41]

Overall, I take the evidence from Tables 4 and 5 as providing additional, strong confirmation of this paper's main thesis. I now turn to analyze in more detail an issue I briefly mentioned in the Introduction: the evolution of the ratio between loans and broad money is uniformative for the issue of whether there is, or is not, a stable relationship between the two aggregates.

4 Why Is the Evolution of the Ratio Between Credit and Broad Money Uninformative?

Consider a panel of N countries, and assume that, for each individual country $i = 1$, 2, 3, ..., N, the logarithm of the multiplier of broad money follows either a random-walk with drift,

$$\ln \mu_{i,t}^{M} = \ln \mu_{i,t-1}^{M} + \delta_i + \eta_{i,t} \tag{1}$$

or a process with a deterministic time trend,

$$\ln \mu_{i,t}^{M} = \kappa_i + \rho_i \ln \mu_{i,t-1}^{M} + \gamma_i t + \eta_{i,t} \tag{2}$$

where $\mu_{i,t}^{M} \equiv M_{i,t}/M_{0,i,t}$, with $M_{i,t}$ and $M_{0,i,t}$ being broad money and the monetary base for country i; and $\eta_{i,t}$ being a country-specific shock to $\mu_{i,t}^{M}$, with (e.g.) $\eta_{i,t} \sim N(0, \sigma_{i,\eta}^{2})$. In (1) δ_i is a country-specific drift, whereas in (2) κ_i and ρ_i and γ_i are a country-specific intercept, AR coefficient, and time trend, respectively. Since, as documented in Figure 4, since WWII the multipliers of broad money have been increasing across the board, I assume that, for all countries i, δ_i>0 and γ_i>0. Finally, I assume that 0<ρ_i<1—so that (1) is stationary around a determistic time trend—whereas κ_i is unrestricted.

Let us then assume, for the sake of the argument, that for *each* country i the logarithm of the multiplier of total loans is, up to a stationary stochastic process, a linear function of the logarithm of the money multiplier,

$$\ln \mu_{i,t}^{L} = \alpha_i + \beta_i \ln \mu_{i,t}^{M} + \theta_{i,t} \tag{3}$$

where $\mu_{i,t}^{L} \equiv L_{i,t}/M_{0,i,t}$, with $L_{i,t}$ being total loans, and $\theta_{i,t}$ being an I(0) process—e.g., for the sake of the argument, $\theta_{i,t} \sim N(0, \sigma_{i,\theta}^{2})$. Since, as documented in Figure 3, the ratio between loans and broad money has been broadly increasing since WWII, I assume that β_i>1 for all $i = 1$, 2, 3, ..., N.

The implication of (3) is that—conceptually in line with the 'money view'—conditional on the monetary base, fluctuations in broad money are the *only* driver of either permanent or long-horizon fluctuations in bank loans (depending on whether the specification for the money multiplier is either (1) or (2), respectively).

[41] In particular, it the test is correctly size, x per cent incorrect rekections at the x per cent level.

From (3), the logarithm of the ratio between loans and broad money is equal to

$$[\ln \mu_{i,t}^{L} - \ln \mu_{i,t}^{M}] = \alpha_i + (\beta_i - 1) \ln \mu_{i,t}^{M} + \theta_{i,t} \tag{4}$$

For ST's country-and-year fixed-effects regression $x_{it} = a_i + b_t + e_{it}$ based on the panel of N countries, with $x_{it} = [\ln \mu_{i,t}^{C} - \ln \mu_{i,t}^{M}]$, the theoretical value of the estimate of the year effect b_t is equal to

$$\hat{b}_t = \frac{1}{N} \sum_{i=1}^{N} (\beta_i - 1) \ln \mu_{i,t}^{M} \tag{5}$$

which, since $\beta_i > 1$ for all $i = 1, 2, ..., N$, exhibits an upward trend originating from the upward trend (either deterministic, or stochastic) in the broad money multipliers.

This is the result shown by ST in Figure 2 (and in Figure 3 in the present paper) for the ratios between total loans and broad money. The previous discussion suggests that this result is not capturing any disconnect between credit and broad money, and that an interpretation of this evidence along these lines is incorrect.

I finally turn to the predictive power of broad money and credit for financial crises.

5 The Predictive Power of Broad Money and Credit for Financial Crises

In Section V ('Credit Booms and Financial Crises'), ST use both linear and logit probability models in order to explore whether lagged real credit and real broad money growth may help to predict financial crises. Their main claim is that, whereas in the pre-WWII sample credit and money were essentially equally powerful at predicting crises, in the post-WWII period credit has become significantly more powerful than broad money, thus lending further support to their main contention that, since WWII, the world economy has entered the 'Age of Credit'.

In this section I apply ST's methodology in order to reconsider the entire issue, based on either of the two datasets considered herein, and paying special attention to the predicting power of the two multipliers. As anticipated in the Introduction, my two main results are that after WWII, (*i*) changes in the multipliers of either credit or broad money have been more powerful at predicting financial crises than real credit growth; and (*ii*) there has been no change in the relative prediction power of the two aggregates, compared to the pre-WWII period. Both before, and after WWII credit had, and has exhibited a greater prediction power than broad money for financial crisis. However, although after WWII the prediction power of both aggregates has increased compared to the pre-WWII period, their relative prediction power has remained unchanged.

5.1 Methodology

I uniquely focus on ST's preferred specification, based on the logit probability model; featuring country-specific dummies but no year-specific dummy; and featuring no additional regressor beyond five lags of either the rates of growth of real money or credit, the first differences of the multipliers of the two aggregates, or the first differences of their ratios with nominal GDP (so, overall I consider six possible sets of regressors). This is to make my results, and the comparison with ST, as transparent as possible. For the seventeen countries in JST's dataset, the dates of the financial crisis are from the dataset itself,[42] whereas for the other countries (as discussed in the online data Appendix A) they are from either Bordo *et al.* (2001), Cecchetti *et al.* (2009), or Laeven and Valencia (2013).

The dependent variable in the logit specification, Y, is a dummy which takes the value of 1 for the financial crises years, and 0 otherwise. As for the matrix of regressors, X, I consider the just-mentioned six possible specifications. The likelihood function for the sample is given by

$$L(\beta) = \prod_{i=1}^{N} p(x_i)^{y_i} [1 - p(x_i)]^{1-y_i} \tag{6}$$

where N is the sample size, β is the vector of parameters to be estimated, $y_i = 1$ for the financial crises years, and $y_i = 0$ otherwise, and $p(x_i)$ is the probability for observation i, which is a function of the previously mentioned regressors. With

$$\ln \frac{p(x_i)}{1 - p(x_i)} = x_i'\beta \quad \Rightarrow \quad p(x_i) = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}} = \frac{1}{1 + e^{-x_i'\beta}} \tag{7}$$

the log-likelihood is

$$\ln L(\beta) = \sum_{1=1}^{N} y_i(x_i'\beta) - \sum_{1=1}^{N} \ln(1 + e^{x_i'\beta}) \tag{8}$$

I maximize (8) numerically *via* simulated annealing, exactly as in Benati (2008).[43] Having found the parameter vector which maximizes the likelihood, $\hat{\beta}_{MLE}$, rather

[42] Specifically, the file JSTcrisisR2.xlsx.

[43] Specifically, following Goffe *et al.* (1994), I implement simulated annealing *via* the algorithm proposed by Corana *et al.* (1987), setting the key parameters to T_0 =100,000, $r_T = 0.9$, $N_t = 5$, $N_s = 20$, $\epsilon = 10^{-6}$, and $N_\epsilon = 4$, where T_0 is the initial temperature, r_T is the temperature reduction factor, N_t is the number of times the algorithm goes through the N_s loops before the temperature starts being reduced, N_s is the number of times the algorithm goes through the function before adjusting the step size, ϵ is the convergence (tolerance) criterion, and N_ϵ is the number of times convergence is achieved before the algorithm stops. Finally, initial conditions were chosen stochastically by the algorithm itself, whereas the maximum number of functions evaluations, set to 1,000,000, was never achieved.

than relying on asymptotic formulas, I stochastically map the log-likelihood's surface *via* Random-Walk Metropolis (RWM). The *only* difference between the 'standard' RWM algorithm which is routinely used for Bayesian estimation and what I am doing here is that the 'jump' to the new position in the Markov chain is accepted or rejected based on a rule which does not involve any Bayesian priors, as it uniquely involves the likelihood of the data. So, to be clear, the proposal draw for β, $\tilde{\beta}$, is accepted with probability min[1, $r(\beta_{s-1}, \tilde{\beta} \mid Y, X)$], and rejected otherwise, where β_{s-1} is the current position in the Markov chain, and

$$r(\beta_{s-1}, \tilde{\beta} \mid Y, X) = \frac{L(\tilde{\beta} \mid Y, X)}{L(\beta_{s-1} \mid Y, X)} \tag{9}$$

which uniquely involves the likelihood.[44] All other estimation details are identical to Benati (2008), to which the reader is referred to. I use 1,000,000 draws for the burn-in period, and 4,000,000 draws for the ergodic distribution, which I 'thin' by sampling every 2,000 draws in order to reduce the draws' correlation.

Tables A6*a*-A6*c* in the online Appendix report the fractions of accepted draws—which are uniformly very close to the 23 per cent ideal acceptance rate in high dimensions[45]—and two statistics for checking the autocorrelation of the draws:[46] the first autocorrelation, and draws' inefficiency factors.[47] The first autocorrelations are uniformly around 0, whereas the inefficiency factors are typically around one, which is much lower than the 20-25 value which is typically taken as signalling problems in convergence.

5.2 Evidence

Figure 6 reports, based on either JST's or the broader dataset, and for either the full samples, or the two sub-periods before and after WWII, the distributions of the same metric used by ST, i.e., the area under the ROC curve (AUROC). In each case I report results for two sets of regressors, based on either broad money or credit.

[44] With Bayesian priors it would be

$$r(\beta_{s-1}, \tilde{\beta} \mid Y, X) = \frac{L(\tilde{\beta} \mid Y, X)P(\tilde{\beta})}{L(\beta_{s-1} \mid Y, X)P(\beta_{s-1})}$$

where $P(\cdot)$ would encodes the priors about β.

[45] See Gelman, Carlin, Stern, and Rubin (1995).

[46] Specifically, for reasons of space, the tables report statistics for the autocorrelation of the draws for the metric used by ST—i.e., the area under the Receiver Operating Characteristic (ROC) curve—rather than for each individual parameter in the vector β. Results for the parameters in β are qualitatively the same, and are available upon request.

[47] The inefficiency factors are defined as the inverse of the relative numerical efficiency measure of Geweke (1992), $RNE = (2\pi)^{-1}\frac{1}{S(0)}\int_{-\pi}^{\pi} S(\omega)d\omega$, where $S(\omega)$ is the spectral density of the sequence of draws from RWM for the quantity of interest at the frequency ω. I estimate the spectral densities as before, based on the FFT transform.

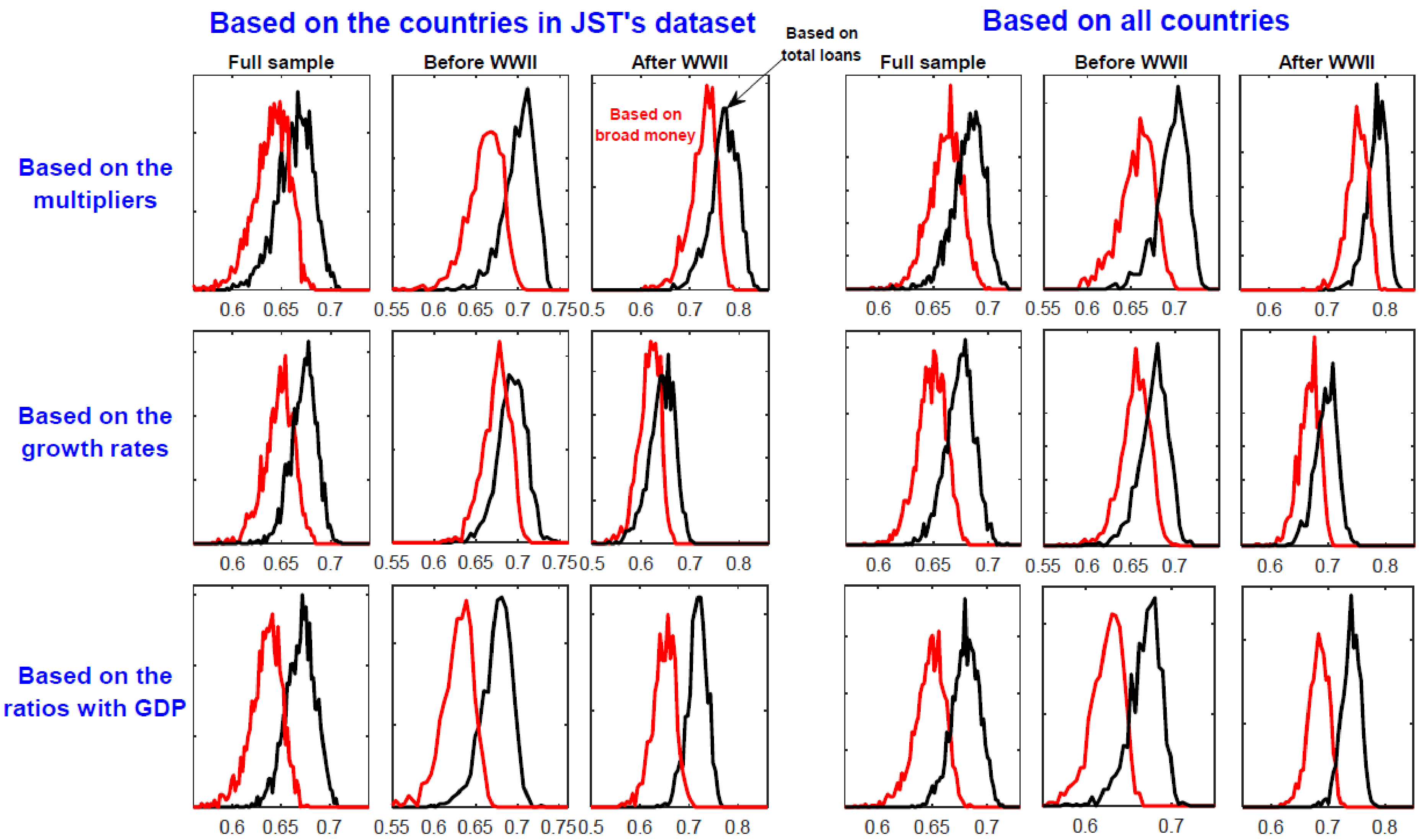

Figure 6 Maximum likelihood estimates of the AUROC: distributions of the AUROC's draws generated via Random-Walk Metropolis

Table 6 Predicting financial crises based on total loans and broad money: maximum likelihood estimates of the area under the ROC curve (median, and 5th and 95th percentiles of the distribution generated via Random-Walk Metropolis)			
	Distribution based on:		Difference between random draws from the distributions based on loans and money:
	loans multiplier	*money multiplier*	
	Only JST's countries		
Before WWII	0.706 [0.670; 0.729]	0.665 [0.626; 0.691]	0.041 [-0.004; 0.087]
After WWII	0.774 [0.718; 0.814]	0.733 [0.678; 0.766]	0.044 [-0.020; 0.113]
	All countries		
Before WWII	0.701 [0.666; 0.722]	0.661 [0.620; 0.686]	0.040 [-0.001; 0.083]
After WWII	0.788 [0.754; 0.810]	0.755 [0.721; 0.780]	0.033 [-0.009; 0.076]
	loans growth	*money growth*	
	Only JST's countries		
Before WWII	0.695 [0.665; 0.720]	0.678 [0.646; 0.699]	0.018 [-0.020; 0.058]
After WWII	0.647 [0.596; 0.682]	0.621 [0.580; 0.648]	0.026 [-0.033; 0.080]
	All countries		
Before WWII	0.679 [0.647; 0.702]	0.658 [0.627; 0.681]	0.022 [-0.016; 0.063]
After WWII	0.700 [0.664; 0.727]	0.671 [0.636; 0.695]	0.030 [-0.014; 0.077]
	loans over GDP	*money over GDP*	
	Only JST's countries		
Before WWII	0.680 [0.645; 0.703]	0.633 [0.596; 0.658]	0.047 [0.004; 0.089]
After WWII	0.720 [0.682; 0.749]	0.654 [0.609; 0.685]	0.068 [0.016; 0.118]
	All countries		
Before WWII	0.674 [0.636; 0.697]	0.630 [0.591; 0.653]	0.045 [0.000; 0.091]
After WWII	0.743 [0.714; 0.766]	0.687 [0.654; 0.712]	0.057 [0.017; 0.097]

Table 6 reports the median, and the 5th and 95th percentiles of the distributions for the two periods before and after WWII. The last column also reports statistics in line with those in the last column of Table 3*a*-3*b*, in order to better characterize the comparison between the pre- and post-WWII periods. Specifically, the column reports the median, and the 5th and 95th percentiles of the distributions of the difference between two random draws from the distributions based on total loans and on broad money, in order to chacterize how the relative predictive power of the two aggregates has changed after WWII. So, to be clear, focusing (e.g.) on the results for the pre-WWII period for JST's countries based on the two multipliers—for which the medians of the two distributions based on loans and broad money are 0.706 and 0.665 respectively—the median and the two percentiles reported in the last column, 0.041 [-0.004; 0.087], pertain to the distribution of the difference between one random draw from the distribution based on loans, and one random draw from the distribution based on money. The fact that the median of this distribution is 0.041 points towards a greater predicting power of the first difference of the multiplier of total loans, compared to the first difference of the multiplier of broad money, based JST's countries before WWII.

In order to properly assess this evidence, it is important to recollect that a perfect classifier would have an AUROC equal to 1, whereas by tossing a coin we would get an AUROC of 0.5. The following main results emerge from the evidence in the figure and the table:

(*i*) for the post-WWII period, changes in the *multipliers* of either loans or broad money have been more powerful at predicting financial crises than credit growth, the variable originally studied by ST. In particular, for this period the change in the multiplier of total loans has clearly been the best predictor across the six I consider.

(*ii*) Total loans are uniformly more powerful at predicting financial crises than broad money. So, in spite of the previously documented remarkably strong correlation between *long-run* fluctuations in credit and broad money over the entire sample period since the XIX century, credit exhibits a greater *short-to-medium-run*[48] forecasting power for financial crises than broad money.

(*iii*) Crucially, however, based on the statistics in the last column of Table 6, there is *no evidence* that credit may have become comparatively more powerful at predicting financial crises, compared to broad money, after WWII. Focusing on the first differences of the multipliers, the median of the distribution of the difference between random draws from the two distributions based on loans and on broad money was equal, based on JST's countries, to 0.041 before WWII and it has been equal to 0.044 after WWII, whereas the corresponding figures for the broader dataset are 0.040 and 0.033. Figures for the two inferior predictors—the growth rates, and the ratios with nominal GDP—are qualitatively the same.

(*iv*) With the single exception of the evidence considered by ST—i.e., rates of growth for the sample of JST's countries—*all* other evidence in Table 6 points towards an *increase* in the predicting power of both credit and broad money since WWII. This is especially clear for the multipliers, which, e.g. based on JST's countries, feature increases in the median estimate of the AUROC from 0.706 to 0.774 for loans, and from 0.665 to 0.733 for broad money.

So the bottom line is that both before, and after WWII credit had, and has exhibited a greater prediction power than broad money for financial crises. However, although after WWII the prediction power of both aggregates has increased compared to the pre-WWII period, their relative prediction power has remained unchanged. Once again, there is *no evidence* that, for the traditional banking sector covered by either JST's or the *BIS* data, the post-WWII period has been in any way different from the pre-WWII era (other than the just-mentioned increase in the predicting power for financial crises common to both loans and broad money).

[48] As mentioned, in line with ST, I am using five lags of the regressors.

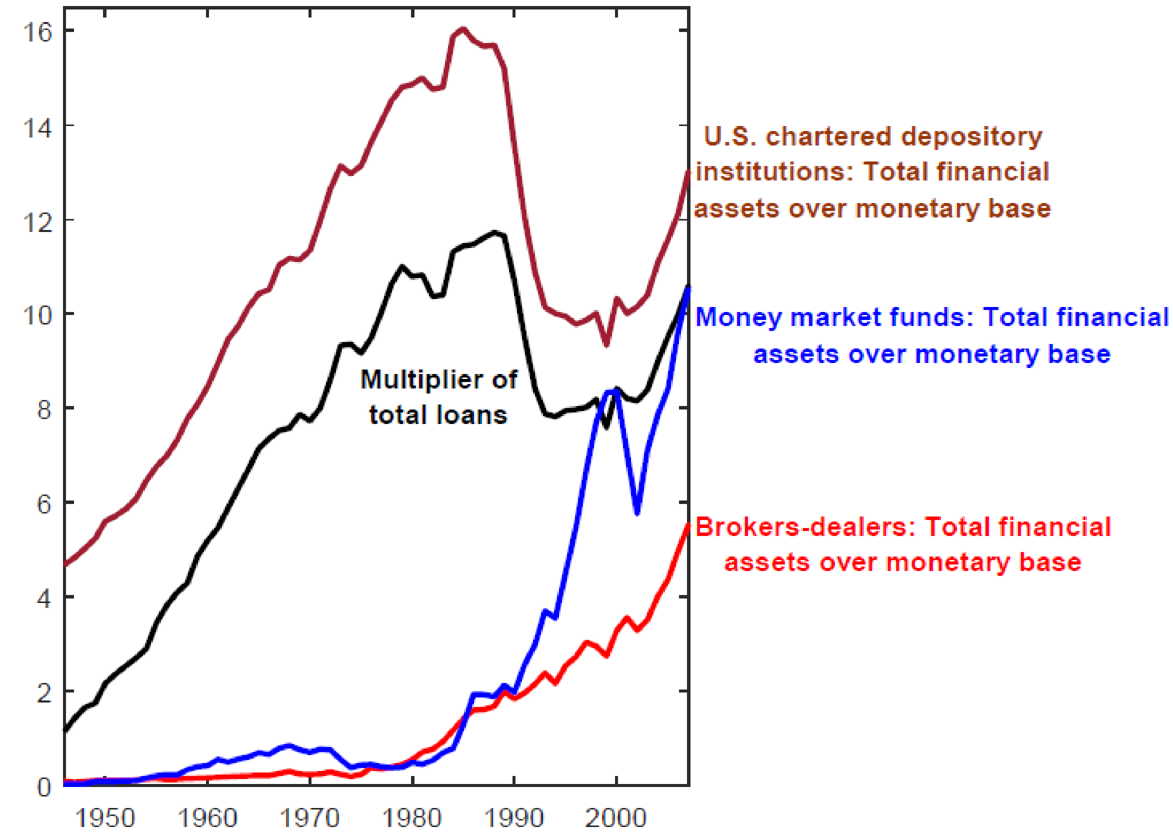

Figure 7 The expansion of the 'market-based' banking system in the United States (1946-2007): ratios between the aggregate assets of financial intermediaries and the monetary base

6 The Ascent of Shadow Banking and the Onset of the Age of Credit

My results demonstrate that ST's claims that, post-WWII, credit has become disconnected from broad money, and more powerful at predicting financial crises, are incorrect. Drawing, from this evidence, the conclusion that nothing has changed since the Gold Standard era,[49] and in particular since WWII, would however be grossly incorrect. What has changed is *what is not in either JST's or the BIS data*, that is, the 'market-based' banking sector which was largely behind the recent financial crisis.

To the very best of my knowledge, data for the shadow-banking sector are not collected either systematically, or with a breadth and extent of detail comparable to that which pertains to the traditional banking sector. In Figure 7 I therefore report some simple evidence for the United States, based on annual data from the *Financial Accounts of the United States* (Z.1 release) from the Federal Reserve Board's website. The figure shows, for the period 1946-2007, the ratios between the aggregate assets of several financial intermediaries and the monetary base. I end the sample in 2007 for the reason I discussed in Section 2, pertaining to the dramatic increase in the monetary base since then. The multiplier of total loans is the same series shown as the red line in the very last panel of Figure 1*c*, and since it pertains to the traditional banking sector, it provides a benchmark in order to put into perspective the *relative* expansion of shadow financial intermediaries compared to traditional banks.

Whereas, as it would be expected based on what we have seen so far, the assets of traditional banks (here, U.S. chartered depository institutions) closely co-moved with the multiplier of total loans, the assets of two market-based intermediaries (brokers-dealers and money-marke funds) literally exploded since the early 1980s, and are now of the same order of magnitude—and, taken together, even greater—than those of traditional banks. As shown by Adrian and Shin (2008, 2011), the assets of brokers-dealers do indeed possess a superior informational content for macroeconomic fluctuations, compared to the assets of traditional banks. This is the true reason why, today, we live in the 'Age of Credit', rather than the one given by ST.

Summing up, the ascent of shadow banking is the *only* reason why, today, we live in the 'Age of Credit': if it were for the traditional banking sector—for which the creation of broad money and credit has proceeded in lockstep since the Gold Standard era—we would still be living in the 'Age of Money', and the 'money view' would still be perfectly relevant. Another way of saying this is that, contrary to ST's position, the fundamental distinction is *not* between the two periods before and after WWII, but rather between the traditional and the 'market-based' banking sectors: the former still lives in the 'Age of Money', whereas the ascent of the latter is the

[49] With the exception of the increase in the predicting power of both loans and broad money for financial crises.

only reason why we live in the 'Age of Credit'.

7 Conclusions

Schularick and Taylor (2012) documented an increase in the ratio between credit and broad money since the end of WWII, which they interpreted in terms of disconnect between the two aggregates. I have demonstrated that this interpretation is incorrect, since, as I have shown mathematically, this evidence is uninformative for the issue at hand. In fact, Jordà, Schularick and Taylor's data show that, since the XIX century, fluctuations in broad money and credit have exhibited an extraordinarily strong correlation within each single country in the dataset. I have also shown that, after WWII, there has been no change in the relative prediction power of credit and broad money for financial crises compared to the pre-WWII period. My results imply that for the 'traditional' banking sector there has been no change, since WWI, in the relationship between its monetary liabilities, and the amount of credit it extends to the private non-financial sector; and only the comparatively recent ascent of the shadow banking sector introduced a wedge between broad money and credit.

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