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When Credit Bites Back *

Abstract

This paper studies the role of credit in the business cycle, with a focus on private credit overhang. Based on a study of the universe of over 200 recession episodes in 14 advanced countries between 1870 and 2008, we document two key facts of the modern business cycle: financial-crisis recessions are more costly than normal recessions in terms of lost output; and for both types of recession, more credit-intensive expansions tend to be followed by deeper recessions and slower recoveries. In addition to unconditional analysis, we use local projection methods to condition on a broad set of macroeconomic controls and their lags. Then we study how past credit accumulation impacts the behavior of not only output, but also other key macroeconomic variables such as investment, lending, interest rates, and inflation. The facts that we uncover lend support to the idea that financial factors play an important role in the modern business cycle.

Keywords: leverage, booms, recessions, financial crises, business cycles, local projections.

JEL Codes: C14, C52, E51, F32, F42, N10, N20.

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Almost all major landmark events in modern macroeconomic history have been associated with a financial crisis. Students of such disasters have often identified excess credit, as the "Achilles heel of capitalism," as James Tobin (1989) described it in his review of Hyman Minsky's book *Stabilizing an Unstable Economy.* Ironically, as the largest credit boom in history engulfed Western economies, the notion that financial factors influence the real economy no longer played a central role in macroeconomic thinking. The warning signs of increased leverage in the run-up to the crisis of 2008 were largely ignored.

Researchers and policymakers alike have been left searching for clearer insights. In 2008, when prevailing research and policy thinking seemed to offer little guidance, the authorities often found themselves turning to economic history. According to a former Governor of the Federal Reserve, Milton Friedman's and Anna Schwartz' seminal work on the Great Depression became "the single most important piece of economic research that provided guidance to Federal Reserve Board members during the crisis" (Kroszner 2010, p. 1). This paper uses the lens of macroeconomic history and builds on our earlier work to present a sharper picture of the role of credit in the business cycle. Since the crisis, financial factors have come back to the forefront of macroeconomic research and history has a great deal to say about such issues.

Just as Reinhart and Rogoff (2009ab) cataloged the history of public debt and its links to crises and economic performance, we examine how private bank lending may contribute to economic instability by drawing on a new panel database of private bank credit creation (Schularick and Taylor 2012). The results have broad resonance. A primary challenge going forward is to redesign monetary and financial regimes, and a key question is how macro-finance interactions need to be integrated into a broader macroprudential policy framework that can mitigate systemic crises.[1] Our results also add clarity at a time when it is still being argued that "[e]mpirically, the profession has not settled the question of how fast recovery occurs after financial recessions" (Brunnermeier and Sannikov 2012) and when, beyond academe, political debate rages over what the recovery "ought" to look like. Thus we engage a broad new agenda in empirical macroeconomics and history that seeks to better understand the role of financial factors in macroeconomic outcomes.[2]

[1] For example, see Turner (2009).

[2] See, e.g., Bordo et al. 2001; Cerra and Saxena 2008; Mendoza and Terrones 2008; Hume and Sentance 2009; Reinhart and Rogoff 2009ab; Bordo and Haubrich 2010; Reinhart and Reinhart 2010; Teulings and Zubanov 2010; Claessens, Kose, and Terrones 2011; Kollman and Zeugner 2012; Schularick and Taylor 2012. Our paper also connects with previous research on stylized facts for the business cycle, e.g., Romer 1986; Sheffrin 1988; Backus and Kehoe 1992; Basu and Taylor 1999).

In line with this research, our main aim is to "let the data speak." We document historical facts about the links between credit and the business cycle without forcing them into a tight theoretical structure.

We will argue that credit plays an important role in shaping the business cycle, in particular the intensity of recessions as well as the likelihood of financial crisis. This is consistent with the aftermath of the Great Recession: countries with larger credit booms in the run-up to the 2008 collapse (such as the United Kingdom, Spain, the United States, the Baltic States, and Ireland) saw more sluggish recoveries in the aftermath of the crisis than economies that went into the crisis with smaller credit booms (like Germany, Switzerland, and the Emerging Markets).[3]

The data support the idea that financial factors play an important role in the modern business cycle, as exemplified in the work of Fisher (1933) and Minsky (1986)—or more recently, Battacharya, Goodhart, Tsomocos, and Vardoulakis (2011), Adrian and Shin (2012), Eggertsson and Krugman (2012), or Brunnermeier et al. (2012), for example. Increased leverage raises the vulnerability of economies to shocks. With more nominal debts outstanding, a procyclical behavior of prices can lead to greater debt-deflation pressures. Rising leverage can also lead to more pronounced confidence shocks and expectational swings, as conjectured by Minsky. Financial accelerator effects (Bernanke and Gertler 1990) are also likely to be stronger when balance sheets are larger and thus more vulnerable to weakening. Such effects could be more pronounced when leverage "explodes" in a systemic crisis. Additional monetary effects may arise from banking failures and asset price declines and confidence shocks could also be bigger and expectational shifts more "coordinated." Disentangling all of these potential propagation mechanisms is beyond the scope of this paper. As a first pass, our focus is on the large-scale empirical regularities.

We begin by presenting descriptive statistics for 140 years of business cycle history across 14 countries. Our first task is to date business cycle upswings and downswings consistently across countries, for which we use the Bry and Boschan (1971) algorithm. We then look at the behavior of real and financial aggregates across these episodes. To allow comparisons over different historical epochs, we differentiate between four eras of financial development, echoing the analysis of trends in financial development in the past 140 years presented in Schularick and Taylor (2012).

[3] These differences in post-crisis economic performance mirror the findings by Mian and Sufi (2010) on the impact of pre-crisis household leveraging on post-crisis recovery at the county level within the United States, and the earlier work of King (1994) on the impacts of 1980s housing debt overhangs on the depth of subsequent recessions in the early 1990s.

Next, we turn to the much-debated question: Are recessions following financial crises different? Cerra and Saxena (2008) found that financial crises lead to output losses in the range of 7.5% of GDP over ten years. Reinhart and Rogoff (2009ab) calculate that the historical average of peak-to-trough output declines following crises are about 9%. Our results are similar. After 5 years, the financial recession path of real GDP per capita is about 5% lower than the normal recession path. But we go further and show how a large build-up of credit makes matters worse, in normal as well as financial recessions.

We construct a measure of "excess credit" build-up during the previous boom. We define this measure as the rate of change in the ratio of aggregate bank credit (domestic bank loans to the nonfinancial sector) to GDP, in deviation from its mean, and calculated from the previous trough to the subsequent peak. Then we correlate this measure with output declines in the recession and recovery phases for up to 5 years, and test if the credit-intensity of the upswing is systemically related to the severity of the subsequent downturn controlling for whether the recession is normal or a financial-crisis recession. We document, to our knowledge for the first time, that throughout a century or more of modern economic history in advanced countries, a close relationship has existed between the build-up of credit during an expansion and the severity of the subsequent recession. The economic costs of financial crises can vary considerably depending on the credit built up during the previous expansion phase. These findings of meaningful and systematic differences among "unconditional" output-path forecasts provide our first set of benchmark results.

These unconditional calculations raise the question: Are the observed effects of credit on outcomes proxying for omitted information about the economy as it enters the recession? Answering this question requires a more formal approach. Using the local projection methods pioneered in Jordà (2005), we are able to track the effects of excess credit on the path of 7 key macroeconomic variables for up to 5 years after the beginning of the recession. This richer dynamic specification allows us to study whether our main findings are robust to the inclusion of additional control variables and to determine how excess credit shapes the recovery path responses of other macroeconomic variables such as investment, interest rates, prices, and bank lending. Indeed, we find large and systematic variations in outcomes such as output, investment, and lending. These effects are somewhat stronger in recession episodes that coincide with financial crises, but remain clearly visible in garden-variety recessions. A variety of robustness checks lend support to these findings.

To put the results to use, we examine what our estimated models predict following the increase in credit that the U.S. economy saw in the expansion years after the 2001 recession until 2007. The subsequent predicted financial crisis recession path largely coincides with the actual observed path. Both are far below that of a normal recession, but consistent with the historical pattern of previous financial crises that followed similar credit build ups.

Summarizing, the two important stylized facts about the modern business cycle that emerge are: first, financial-crisis recessions are more painful than normal recessions; and second, the credit-intensity of the expansion phase is closely associated with the severity of the recession phase for both types of recessions. As the title of our paper suggests—credit bites back. Even though this relationship between credit intensity and the severity of the recession is strongest when the recession coincides with a systemic financial crisis, it can also be detected in "normal" business cycles, suggesting a deeper and more pervasive empirical regularity.

1 The Business Cycle in Historical Context

1.1 The Data

The dataset used in this paper covers 14 advanced economies over the years 1870–2008 at annual frequency. The countries included are the United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. The share of global GDP accounted for by these countries was around 50% in the year 2000 (Maddison 2005).

For each country, we have assembled national accounts data on nominal GDP and real GDP per capita. We have also collated data on price levels and inflation, investment and the current account, as well as financial data on outstanding private bank loans (domestic bank loans), and short- and long-term interest rates on government securities (usually 3 months tenor at the short end, and 5 years at the long end).

For most indicators, we relied on data from Schularick and Taylor (2012), as well as the extensions in Jordà, Schularick, and Taylor (2011). The latter is also the source for the definition of financial crises which we use to differentiate between "normal recessions" and recessions that coincided with financial crises, or "financial-crisis recessions". (For brevity, we may just refer to these two cases as "normal" and "financial.") Our classification of such episodes of systemic financial instability for the 1870 to 1960 period follows the same definition of "systemic" banking crisis in the database compiled by Laeven and Valencia (2008) for the post-1960 period, maintaining consistency with contemporary approaches.

1.2 The Chronology of Turning Points in Economic Activity

Most countries do not have agencies that determine turning points in economic activity and even those that do have not kept records that reach back to the nineteenth century. Jordà, Schularick, and Taylor (2011) as well as Claessens, Kose, and Terrones (2011) experimented with the Bry and Boschan (1971) algorithm—the closest algorithmic interpretation of the NBER's definition of recession.[4] The algorithm for yearly frequency data is simple to explain. Using *real GDP per capita* data in levels, a variable that generally trends upward over time, the algorithm looks for local minima. Each minimum is labeled as a trough and the preceding local maximum as a peak. Then recessions are the period from peak-to-trough and expansions from trough-to-peak. In Jordà, Schularick, and Taylor (2011) we drew a comparison of the dates obtained with this algorithm for the U.S. against those provided by the NBER. Each method produced similar dates, which is not surprising since the data used are only at a yearly frequency.[5]

In addition, we sorted recessions into two types, those associated with financial crises and those which were not, as described above. The resulting chronology of business cycle peaks is shown in Table 1, where "N" denotes a normal peak, and "F" denotes a peak associated with a systemic financial crisis. There are 298 peaks identified in this table over the years 1870 to 2008 in the 14 country sample. However, in later empirical analysis the usable sample size will be curtailed somewhat, in part because we shall exclude the two world wars, and still more on some occasions because of the limited available span for relevant covariates.

1.3 Four Eras of Financial Development and the Business Cycle

In order to better understand the role of credit and its effects on the depth and recovery patterns of recessions, we first examine the cyclical properties of the economies in our sample. We differentiate between four eras of financial development, following the documentation of long-run trends in financial development in Schularick and Taylor (2012).

[4] See www.nber.org/cycle/.

[5] See Harding and Pagan (2002) for suitable smoothing methods in higher frequency applications of the Bry and Boschan (1971) algorithm.

Table 1: Business Cycle Peaks

"N" denotes a normal business cycle peak; "F" denotes a peak associated with a systemic financial crisis.

AUS	N	1875	1878	1881	1883	1885	1887	1889	1896	1898	1900	1904	1910
		1913	1926	1938	1943	1951	1956	1961	1973	1976	1981		
	F	1891	1894	1989									
CAN	N	1871	1877	1882	1884	1888	1891	1894	1903	1913	1917	1928	1944
		1947	1953	1956	1981	1989	2007						
	F	1874	1907										
CHE	N	1875	1880	1886	1890	1893	1899	1902	1906	1912	1916	1920	1933
		1939	1947	1951	1957	1974	1981	1990	1994	2001			
	F	1871	1929	2008									
DEU	N	1879	1898	1905	1913	1922	1943	1966	1974	1980	1992	2001	
	F	1875	1890	1908	1928	2008							
DNK	N	1870	1880	1887	1911	1914	1916	1923	1939	1944	1950	1962	1973
		1979	1987	1992									
	F	1872	1876	1883	1920	1931	2007						
ESP	N	1873	1877	1892	1894	1901	1909	1911	1916	1927	1932	1935	1940
		1944	1947	1952	1958	1974	1980	1992					
	F	1883	1889	1913	1925	1929	1978	2007					
FRA	N	1872	1874	1892	1894	1896	1900	1905	1909	1912	1916	1920	1926
		1933	1937	1939	1942	1974	1992						
	F	1882	1907	1929	2007								
GBR	N	1871	1875	1877	1883	1896	1899	1902	1907	1918	1925	1929	1938
		1943	1951	1957	1979								
	F	1873	1889	1973	1990	2007							
ITA	N	1870	1883	1897	1918	1923	1925	1932	1939	1974	1992	2002	2004
	F	1874	1887	1891	1929	2007							
JPN	N	1875	1877	1880	1887	1890	1892	1895	1898	1903	1919	1921	1929
		1933	1940	1973	2001	2007							
	F	1882	1901	1907	1913	1925	1997						
NLD	N	1870	1873	1877	1889	1894	1899	1902	1913	1929	1957	1974	1980
		2001											
	F	1892	1906	1937	1939	2008							
NOR	N	1876	1881	1885	1893	1902	1916	1923	1939	1941	1957	1981	2008
	F	1897	1920	1930	1987								
SWE	N	1873	1876	1881	1883	1885	1888	1890	1899	1901	1904	1913	1916
		1924	1939	1976	1980								
	F	1879	1907	1920	1930	1990	2007						
USA	N	1875	1887	1889	1895	1901	1909	1913	1916	1918	1926	1937	1944
		1948	1953	1957	1969	1973	1979	1981	1990	2000			
	F	1873	1882	1892	1906	1929	2007						

Notes: AUS stands for Australia, CAN Canada, CHE Switzerland, DEU Germany, DNK Denmark, ESP Spain, FRA France, GBR United Kingdom, ITA Italy, JPN Japan, NLD The Netherlands, NOR Norway, SWE Sweden, USA United States. We use crisis dates in Jordà, Schularick, and Taylor (2011) to classify nearby peaks in real GDP per capita identified with the Bry and Boschan (1971) algorithm as either normal or financial. This explains the differences between Table 1 in that paper and the dates reported in this table. See text.

The period before World War II was characterized by a relatively stable ratio of loans to GDP in the advanced countries, with credit and economic growth moving by and large in sync. Within that early period, it is worth separating out the interwar period since, in the aftermath of World War I, countries on both sides of the conflict temporarily suspended convertibility to gold. Despite the synchronicity of lending and economic activity before World War II, both the gold standard and the interwar era saw frequent financial crises, culminating in the Great Depression.[6]

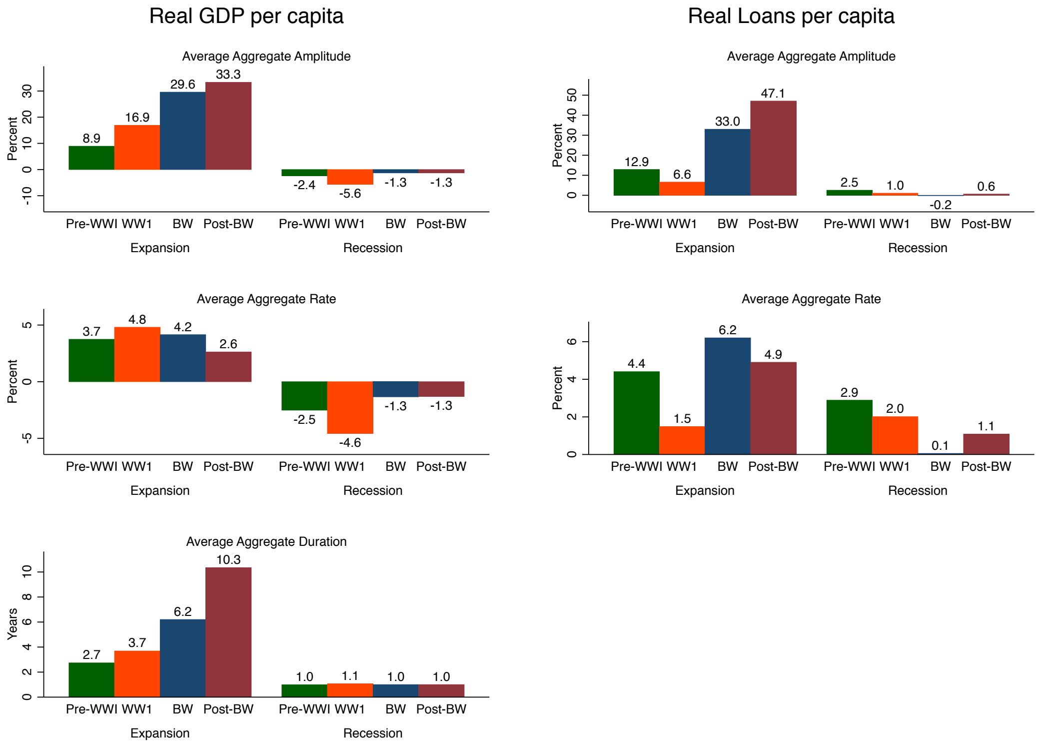
The regulatory architecture of the Depression era, together with the new international monetary order agreed at the 1944 Bretton Woods conference, created an institutional framework that provided financial stability for about three decades. The Bretton Woods era, marked by international capital controls and tight domestic financial regulation, was an oasis of calm. None of the countries in our sample experienced a financial crisis in the three immediate post–World War II decades. After the end of the Bretton Woods system, credit began to explode and crises returned. In 1975, the ratio of financial assets to GDP was 150% in the United States; by 2008 it had reached 350% (Economic Report of the President 2009). In the United Kingdom, the financial sector's balance sheet reached a nadir of 34% of GDP in 1964; by 2007 this ratio had climbed to 500% (Turner 2010). For the 14 countries in our sample, the ratio of bank loans to GDP almost doubled since the 1970s (Schularick and Taylor 2012). Perhaps not surprisingly, financial crises returned, culminating in the 2008 global financial crisis.

We begin by summarizing the salient properties of the economic cycle for the countries in our sample over these four eras of financial development. For this purpose we calculate several cyclical measures which we apply to the time series of real GDP per capita and to lending activity as measured by our (CPI-deflated) real loans per capita variable: (1) the peak-to-trough/ trough-to-peak percent change, which we denominate as the *amplitude* of the recession/expansion cycle; (2) the ratio of amplitude over duration which delivers a per-period rate of change and which we denominate *rate*; and, for real GDP per capita only, (2) the *duration* of recession/expansion episodes in years. Figure 1 summarizes these measures in graphical form.

This analysis of real GDP per capita data in column 1 of the figure reveals several interesting

[6] Major institutional innovations occurred, often in reaction to financial crises. In the United States, this period saw the birth of the Federal Reserve System in 1913, and the Glass-Steagall Act of 1933, which established the Federal Deposit Insurance Corporation (designed to provide a minimum level of deposit insurance and hence reduce the risk of bank runs) and introduced the critical separation of commercial and investment banking. This separation endured for over 60 years until the repeal of the Act in 1999. Similar ebbs and flows in the strictness of financial regulation and supervision were seen across the advanced economies.

Figure 1: Cyclical Properties of Output and Credit in Four Eras of Financial Development



Notes: See text. Peaks and troughs are as defined by the Bry and Boschan (1971) algorithm using real GDP per capita. Expansion is trough to next peak; recession peak to next trough. Duration is time between peak and trough. Amplitude is the log difference between peak and trough levels. Rate is amplitude divided by duration. The four periods are 1870–1913, 1919–1939, 1948–1971, and 1972–2008.

features. The average expansion has become longer lasting, going from a duration of 2.7 years before World War I to about 10 years in the post–Bretton Woods period (row 3, column 1). Because of the longer duration, the cumulative gain in real GDP per capita quadrupled from 9% to 33% (row 1, column 1). However, the average rate at which the economies grew in expansions has slowed down considerably, from a maximum of almost 5% before World War II to 2.6% in more recent times (row 2, column 1). In contrast, recessions last about the same in all four periods but output losses have been considerably more modest in recent times (before the Great Recession, since our dataset ends in 2008). Whereas the cumulative real GDP per capita loss in the interwar period peaked at 5.6%, that loss is now less than half at 1.3% (row 1, column 1). This is also evident if one looks at real GDP per capita growth rates (row 2, column 1).

Looking at loan activity in column 2 of the figure, there are some interesting differences and similarities. The credit story takes form if one looks at the relative amplitude of real loans per capita versus real GDP per capita. Prior to World War II, real GDP per capita grew at a yearly rate of 3.7% and 4.8% (before and after World War I) during expansions, and real loans per capita at a rate of 4.4% and 1.5% respectively; that is, real GDP per capita growth in the interwar period was more than double the rate of loan growth. In the post–Bretton Woods era, a yearly rate of loan per capita growth of 4.9% in expansions was almost double the yearly rate of real GDP per capita growth of just 2.6%, a dramatic reversal.

Interestingly, the positive numbers for recessions in column 2 of the figure indicate that on average, credit continues to grow even in recessions. Yet looking at expansions, the rate of loan growth has stabilized to a degree in recent times, going from 6.2% in the Bretton Woods era to 4.9% in the post–Bretton Woods era (row 2, column 2). However, we must remember that, for some countries, the recent explosion of shadow banking may obscure the true extent of credit-driven leverage in the economy. For example, Pozsar et al. (2010) calculate that the U.S. shadow banking system surpassed the size of the traditional banking system in 2008, and we shall consider such caveats later in an application to the U.S. experience in the Great Recession.

1.4 Credit Intensity of the Boom

The impact of credit on the severity of the recession and on the shape of the recovery is the primary object of interest in what is to come. But the analysis would be incomplete if we did not at least summarize the salient features of expansions when credit intensity varies.

Key to our subsequent analysis will be a measure of "excess credit" in the expansion preceding a recession. We construct an *excess credit variable* (denoted ξ) that measures the excess rate of change per year in the aggregate bank loan to GDP ratio in the expansion, with units being percentage points per year (ppy). Table 2 provides a summary of the average amplitude, duration and rate of expansions broken down by whether excess credit during those expansions was above or below its full-sample historical mean—the simplest way to divide the sample. Summary statistics are provided for the full sample (excluding both world wars) and also over two subsamples split by World War II. The split is motivated by the considerable differences in the behavior of credit highlighted by Schularick and Taylor (2012) before and after this juncture and described above.

In some ways, Table 2 echoes some themes from the previous section. In the full sample, excess credit correlates with an extension of the expansion phase by about 2 years (5.6 versus 3.7 years)

Table 2: Real GDP per capita in Expansions and "Excess Credit"

	Amplitude		Duration		Rate	
	Low excess credit	High excess credit	Low excess credit	High excess credit	Low excess credit	High excess credit
Full Sample						
Mean	13.6%	21.2%	3.7	5.6	4.1%	3.5%
Standard Deviation	(12.9)	(33.9)	(3.5)	(6.6)	(2.2)	(2.0)
Observations	83	126	83	126	83	126
Pre–World War II						
Mean	11.9%	9.4%	2.7	2.8	4.8%	3.5%
Standard Deviation	(9.8)	(9.1)	(1.9)	(2.2)	(2.3)	(2.1)
Observations	52	90	52	90	52	90
Post–World War II						
Mean	22.9%	47.8%	6.9	11.8	3.0%	3.5%
Standard Deviation	(21.4)	(55.3)	(5.1)	(9.4)	(1.3)	(1.9)
Observations	35	32	35	32	35	32

Notes: See text. Amplitude is peak to trough change in real GDP per capita. Duration is peak to trough time in years. Rate is peak to trough growth rate per year of real GDP per capita. High (low) "excess credit" means that this measure is above (below) its sample mean during expansions in the given period. The full sample runs from 1870 to 2008 for 14 advanced countries. To cleanse the effects of the two world wars from the analysis, the war windows 1914–18 and 1939–45 are excluded, as are data corresponding to peaks which are within 5 years of the wars looking forwards, or 2 years looking backwards (since these leads and lags are used in the analysis below).

so that accumulated growth is about 7% higher (21% versus 14%), although low excess-credit expansions display faster rates of real GDP per capita growth (4.1% versus 3.5% per year) on a per-period basis. However, there are marked differences between the pre– and post–World War II samples. As we noted earlier, expansions last quite a bit longer in the latter period—in Table 2 the ratio is about 2-to-3 times larger. Not surprisingly, the accumulated growth in the expansion is also about 2-to-3 times larger in the post–World War II sample. Even though excess credit is on average much higher in the post–World War II era, excess credit appears to be associated with longer periods of economic growth whichever way it is measured: cumulated growth from trough to peak between low and high excess-credit expansions is almost 25% larger (48% versus 23%); and expansions last almost 5 years longer in periods of high excess credit (12 versus 7 years).

Naturally, the sample size is rather too short to validate the differences through a formal statistical lens, but at a minimum the data suggest that the explosion of credit after World War II had a small but measurable impact on growth rates in expansion phases. Whether these gains were enough to compensate for what was to happen during downturns is another matter. To answer that question in detail, we now focus on recessions and recoveries.

2 The Credit in the Boom and the Severity of the Recession

We will make use of a data universe consisting of up to 223 business cycles in 14 advanced countries over 140 years. In all cases we exclude cycles which overlap the two world wars.[7] This forms our core sample for all the analysis in the rest of this paper. Most key regressions also exclude those cycles for which loan data are not available. By collating data on the entire universe of modern economic experience under finance capitalism in the advanced countries since 1870, we cannot be said to suffer from a lack of data: this is not a sample, it is very close to the entire population for the question at hand. If inferences are still unclear with this data set, we are unlikely to gain further empirical traction using aggregate macroeconomic data until decades into the future.

Thus the real challenge is formulating hypotheses, and moving on to testing and inference using the historical data we already have. We want to address two key questions:

- Are financial recessions significantly different, i.e., more painful, than normal recessions?
- Is the intensity of credit creation, or leveraging, during the preceding expansion phase systematically related to the adversity of the subsequent recession/recovery phase?

We will follow various empirical strategies to attack these questions, beginning in this section with the simplest unconditional regression approach. For each peak date, a key pre-determined independent "treatment" variable will be the yearly percentage point excess rate of change in aggregate bank loans relative to GDP in the preceding expansion phase (previous trough to peak, where excess is determined relative to the mean). We denote this measure ξ and think of it as the "excess credit" intensity of the boom. That is, we employ this proxy as a way of thinking about how fast the economy was increasing its overall financial leverage according to the loan/GDP ratio metric. (In the aggregate, domestic financial claims net out, and if the capital/output ratio is long-term stable, as per the stylized growth facts, then loan/GDP will reflect how far underlying real assets have been levered into debt.) The only other "treatment" variables will be indicators for whether the peak comes before a normal recession N or a financial recession F.

In what follows, the term treatment refers to a perturbation in the excess credit variable ξ that is pre-determined relative to the recession. That the treatment is pre-determined does not

[7] See the note to Table 2 for an explanation on how we cleanse the effects of the two world wars from the analysis.

Table 3: Summary Statistics for the Treatment Variables

	(1) All recessions		(2) Financial recessions ($F = 1$)		(3) Normal recessions ($N = 1$)	
	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)
Financial recession indicator (F)	0.29		1		0	
Observations	223		50		173	
Normal recession indicator (N)	0.71		0		1	
Observations	223		50		173	
Excess credit measure (ξ), ppy	0.47	(2.17)	1.26	(2.51)	0.24	(2.01)
Observations	154		35		119	

Notes: See text. The annual sample runs from 1870 to 2008 for 14 advanced countries. To cleanse the effects of the two world wars from the analysis here and below, the war windows 1914–18 and 1939–45 are excluded, as are data corresponding to peaks which are within 5 years of the wars looking forwards, or 2 years looking backwards. "ppy" denotes rate of change in percentage points per year (of bank loans relative to GDP).

necessarily imply that the treatment is assigned as if it were random. Hence the response to treatment may or may not reflect a causal link.

Some summary statistics on these treatment variables can be found in Table 3 for the sample of 223 recessions. Of these recessions, 173 are normal recessions, and the 50 others are financial crisis recessions, as described earlier. We also have information on the excess credit variable ξ for a subsample of these recessions, just 154 observations, due to missing data, and covering 119 normal recessions and 35 financial recessions. Averaged over all recessions, the excess credit variable has a mean of 0.47 percentage points per year (ppy) change in the loans to GDP ratio over prior expansions (s.d. = 2.17 ppy). The mean of excess credit for normal recessions is 0.24 ppy (s.d. = 2.01) and is, not surprisingly, quite a bit higher in financial recessions at 1.26 ppy (s.d. = 2.51 ppy). The latter finding meshes with the results in Schularick and Taylor (2012) who use the loan data to show that excess credit is an "early warning signal" that can help predict financial crisis events.

2.1 Unconditional Recession Paths

The dependent variables we first examine will be the key characteristic of the subsequent recession and recovery phases that follow the peak: the level in post-peak years 1 through 5 of log real GDP per capita (y) relative to its level in year 0 (the peak year). The data on y are from Barro and

Ursúa (2008) and the peaks and troughs are derived from the Bry and Boschan (1971) algorithm discussed earlier.

We are first interested in characterizing the simple *unconditional path* of the cumulated response of the variable y to a treatment x at time $t(r)$:

$$\begin{aligned} CR(\Delta_h y_{it(r)+h}, \delta) \quad = \quad & E_{it(r)}(\Delta_h y_{it(r)+h} | x_{it(r)} = \overline{x} + \delta) \\ - \quad & E_{it(r)}(\Delta_h y_{it(r)+h} | x_{it(r)} = \overline{x}), \qquad h = 1, \ldots, H, \end{aligned} \tag{1}$$

where $CR(\Delta_h y_{it(r)+h}, \delta)$ denotes the average cumulated response of y across countries and recessions, h periods in the future, given a size δ change in the treatment variable x. In principle, x could be a discrete or continuous treatment. And in general x may be a vector, with perturbations δ permissible in each element. In what follows, we introduce at various times controls for both normal recessions and financial crisis (N, F) recessions into x as a discrete treatment, and we also introduce our "excess credit" variable (ξ) in both discrete and continuous forms.

2.2 Normal v. Financial Bins

Our first results are shown in Table 4 for the simplest of specifications. Here the treatment variable x is a binary indicator for normal/financial recession.

Table 4 shows the unconditional path for the level of log real GDP per capita computed from a set of regressions corresponding to equation (1) at each horizon. The normalization implies that the peak year reference level of log real GDP per capita is set to zero, and deviations from that reference are measured in log points times 100. Hence the intercept coefficients at horizon h (up to 5 years) represent the average path for a recession of each type. The sample is the largest possible given our dataset and covers 223 recessions (173 normal, 50 financial), excluding windows that overlap the two world wars (and excluding the recessions starting in 2007–08 for which the windows do not yet have complete data).

The results reveal that in year 1 there is no significant difference between the two recession paths. The per capita output change is -2.0% in normal recessions and -2.7% in financial recessions, but an F-test cannot reject the null of equality of coefficients. However, at all other horizons out to year 5 the difference between the normal and financial-crisis recession paths is statistically significant (at the 1% level), and the paths accord very well with our intuition.

Table 4: Unconditional Recession Paths, Normal v. Financial Bins

Log real GDP per capita (relative to Year 0, $\times 100$)	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Normal recession (N)	-2.0*	-0.0	2.0*	3.3*	4.5*
	(0.2)	(0.3)	(0.4)	(0.6)	(0.7)
Financial recession (F)	-2.7*	-3.1*	-2.5*	-0.9	1.0
	(0.3)	(0.6)	(0.8)	(1.1)	(1.2)
F-test Equality of coefficients, Normal=Financial (p)	0.11	0.00	0.00	0.00	0.01
Observations, Normal	173	173	173	173	173
Observations, Financial	50	50	50	50	50
Observations	223	223	223	223	223

Dependent variable: $\Delta_h y_{it(r)+h}$ = (Change in log real GDP per capita from Year 0 to Year h)$\times$100.
Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$

Along the recovery path, output relative to peak is more depressed in financial recessions. The difference is about -3% in year 2, -4.4% in year 3, -4.1% in year 4 and -3.5% in year 5. These losses are quantitatively significant, as well as being statistically significant.

2.3 Excess Credit as a Continuous Treatment

Earlier we found that excess credit is higher in financial recessions. A natural way to control for excess credit continuously is as follows. In addition to indicator variables for each type of recession (N, F) to capture an average treatment response in each bin, we also include interaction terms to capture marginal treatment responses due to deviations of excess credit from its specific recession-type mean. In normal recessions the variable is defined as $(N \times (\xi - \overline{\xi_N}))$ and in financial recessions as $(F \times (\xi - \overline{\xi_F}))$. As a result the sample is reduced further to 154 recessions for which the excess credit variable is available in all recessions, 119 of these being normal recessions and 35 being financial recessions.

Table 5 offers a concise look at our hypothesis that "credit bites back": not only are financial crisis recessions on average more painful than normal recessions (row 2 effects are lower than row 1) but within each type a legacy of higher excess credit from the previous expansion creates an ever more painful post-peak trajectory (row 3 and 4 coefficients are negative, all bar one which is zero).

The average treatment responses show that, with controls added, financial recession paths are below normal recession paths. The difference is shown by an F-test to be statistically significant

Table 5: Normal v. Financial Bins with Excess Credit as a Continuous Treatment in Each Bin

Log real GDP per capita (relative to Year 0, ×100)	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Normal recession (N)	-1.9*	0.3	2.2*	3.4*	4.5*
	(0.2)	(0.4)	(0.5)	(0.7)	(0.9)
Financial recession (F)	-3.3*	-3.9*	-3.5*	-1.6	0.7
	(0.4)	(0.7)	(1.0)	(1.4)	(1.6)
Excess credit × normal recession ($N \times (\xi - \overline{\xi_N})$)	0.0	-0.2	-0.0	-0.2	-0.2
	(0.1)	(0.2)	(0.3)	(0.4)	(0.4)
Excess credit × financial recession ($F \times (\xi - \overline{\xi_F})$)	-0.1	-0.7*	-0.4	-0.9+	-1.0
	(0.2)	(0.3)	(0.4)	(0.6)	(0.6)
F-test Equality of coefficients, Normal=Financial (p)	0.01	0.00	0.00	0.00	0.03
F-test Equality of coefficients, interaction terms (p)	0.45	0.13	0.46	0.28	0.31
Observations, Normal	119	119	119	119	119
Observations, Financial	35	35	35	35	35
Observations	154	154	154	154	154

Dependent variable: $\Delta_h y_{it(r)+h}$ = (Change in log real GDP per capita from Year 0 to Year h)×100.
Standard errors in parentheses. $^+$ $p < 0.10$, * $p < 0.05$
Notes: In each bin, recession indicators (N, F) are interacted with demeaned excess credit, $(\xi - \overline{\xi_N}, \xi - \overline{\xi_F})$.

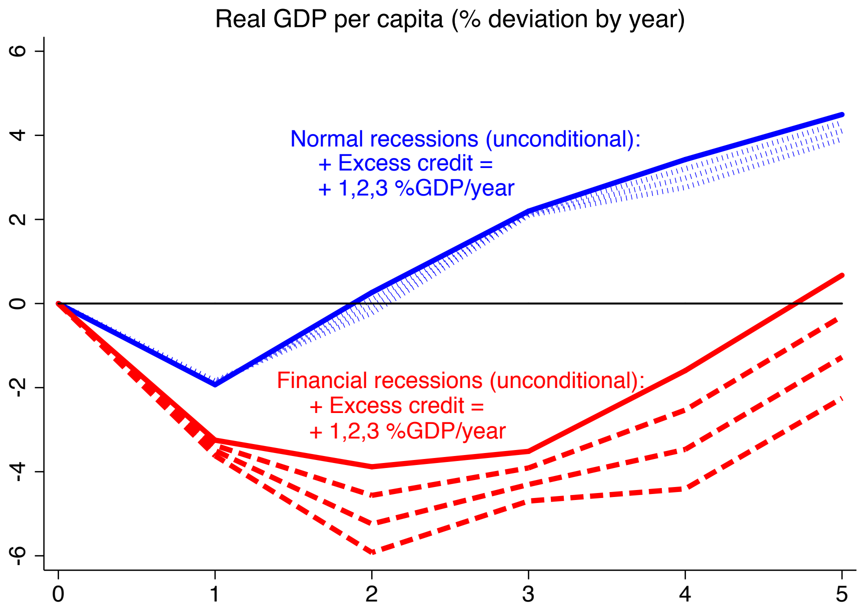
out to 5 years. In a normal recession (with excess credit at its "normal" mean) GDP per capita is typically -2% in year 1 with a bounce back to zero in year 2, trending to about $+4.5\%$ in year 5. In a financial recession (with excess credit at its "financial" mean) GDP per capita drops -3% to -3.8% in years 1 and 2, and is not significantly different from zero in year 5.

As for the marginal treatments associated with excess credit, the coefficient for the normal bin ($N \times (\xi - \overline{\xi_N})$) ranges between 0 and -0.2 over the five horizons, but no single coefficient is statistically significant. But the coefficient for the financial bin ($F \times (\xi - \overline{\xi_F})$) ranges between -0.1 and -1.0, which is to say much larger in quantitative terms, and it does breach statistical significance levels at some horizons (and also does so in a joint test).

2.4 Summary: All Recessions are not Created Equal

In advanced economies, based on a universe of roughly 200 recession episodes over a century and a half, the post-peak recession path is not a random draw but is very much path dependent. First, a recession and recovery path associated with a financial crisis peak is liable to be much prolonged and more painful than that found after a normal peak. Second, what happens to credit during the previous expansion generally matters a great deal for the subsequent recession.

Figure 2: Unconditional Paths Under Continuous Excess Credit Treatment



Notes: See text. Solid lines show coefficient values from Table 5, that is, when the excess credit variable ξ is assume to be at its mean in each bin. The dotted and dashed lines show predicted paths when the excess credit variable ξ is perturbed in 3 increments of +1 percentage points per year in each bin.

Our main argument, to be explored below, is now clearly seen. On the one hand, we already know that financial-crisis events tend to be more likely after credit booms, a chain of association that has been noted before (Schularick and Taylor 2012). In addition, we now see that the subsequent recession is generally more severe when the expansion has been associated with high rates of change in the loans-to-GDP ratio, all else equal.

Figure 2 summarizes the treatment responses derived from Table 5. The figure shows the average treatment response path (when excess credit is at the within-bin mean), along with the predicted paths when the excess credit treatment is perturbed +1, +2 or +3 percentage points per year above its mean. The average paths for the normal/financial bins are solid lines, and perturbations are shown with dotted/dashed lines. Recall from Table 3 that the standard deviation of the excess credit variable is about 2 ppy in normal recessions and about 2.5 ppy in financial recessions. Thus the fan chart reflects deviations in excess credit from average by amounts corresponding to 0.5, 1 and 1.5 standard deviations approximately.

3 The Dynamics of Excess Credit: Recession and Recovery

Using unconditional averaging, we have seen that the evolution of economies from the onset of the recession differs greatly depending on whether the recession is associated with a financial crisis or not. In addition, the more excess credit formation in the preceding expansion, the worse the recession and the slower the subsequent recovery appear to be. These findings are based on a basic event-study approach à la Romer and Romer (1989) that treats every occurrence identically.

One concern might be that economies are complex and dynamic, with numerous feedback loops. Could the results in the previous section be explained by other macroeconomic factors and a richer dynamic specification? Will the prima facie evidence survive more rigorous scrutiny? In this section we explore these questions using more advanced econometric techniques. By enriching the analysis with more variables and more complex dynamics, we make it far less likely that excess credit survives as an independent driver of business cycle fluctuations. And yet this is precisely what we are going find.

The statistical toolkit that we favor builds on the local projection (LP) approach introduced in Jordà (2005). The elementary premise is that dynamic multipliers are properties of the data that can be calculated directly, rather than indirectly through a reference model (e.g., a standard VAR). In this respect, our approach can be rightfully called semi-parametric.

There are several advantages to the direct approach. The most obvious is that specification of a reference model is not required. Dynamic multipliers depend only on the quality of the local approximation, and not on whether the model is a good global approximation to the data generating process. Moreover, extending the analysis to account for asymmetries, nonlinearities, and richer data structures (such as time-series, cross-section panels of data) is greatly simplified. We can also sidestep the parametric and numerical demands that richer structures impose on a global reference model and which can often make the problem intractable in practice.

Our treatment variable will still be excess credit ξ, defined as the percentage point per year change in the ratio of loans to GDP in the expansion. Recall that we use the term "treatment" as a pre-determined perturbation to the historical norm. We ask: how different would the path of the economy be, conditional on a rich set of covariates and their lags, if excess credit in the expansion had deviated from its conditional mean? We do not assume that treatment assignment is random.

The mechanics of how this is done require a bit of notation. The dimensions of our panel are as follows. Let N denote the cross-section dimension of 14 countries. Let T denote the time dimension of approximately 140 years. Let K denote the vector of macroeconomic variables, to be described shortly. For any variable $k = 1, ..., K$, we want to characterize the change in that variable from the start of the recession to some distant horizon $h = 1, ..., H$, or from time $t(r)$ to time $t(r) + h$. Here, the time index t denotes calendar time and $t(r)$ denotes the calendar time period associated with the r^{th} recession.

We will use the notation $\Delta_h y^k_{it(r)+h}$ to denote the relevant measure of change h periods ahead in y^k for country $i = 1, ..., N$ from the start of the r^{th} recession where $r = 1, ..., R$. Sometimes the change measure might be the percentage point change, given by the difference in 100 times the logarithm of the variable. An example would be when $y^k_{i,t}$ refers to 100 times the log of real GDP per capita. Other times it may refer to the simple time difference in the raw variable, for example, think of interest rates.

This notation highlights that the analysis is based on the subsample of recessions and what happens in their neighborhood. It does not use data outside those periods. Excess credit may well affect expansions and some of the earlier evidence suggests that this is the case, but it is not the direct object of study here. Their omission eliminates sources of bias and sharpens the focus on recessions and the recovery.

For notational convenience, we collect the K variables y^k_{it} into the vector Y_{it} as follows: $Y_{it} = \begin{bmatrix} \Delta y^1_{it} & ... & \Delta y^J_{it} & y^{J+1}_{it} & ... & y^K_{it} \end{bmatrix}'$. That is, the first J out of the K variables enter in their first differences (appropriate for likely nonstationary variables). An example would be 100 times the logarithm of real GDP per capita so that Δy^{GDP}_{it} would refer to the yearly growth rate in percent. The latter $K - J$ variables enter in the levels (appropriate for likely stationary variables). An example would be an interest rate.

Finally, we will denote by $x_{t(r)}$ our treatment variable ξ when the treatment is excess credit formation in the expansion that preceded the r^{th} recession. In terms of turning points, $t(r)$ refers to a *peak* of economic activity as defined in earlier sections. Therefore $t(r) + h$ for $h = 1, ..., H$ refers to the subsequent H periods, some of which will be recessionary periods (those immediately following $t(r)$), some of which will be expansion periods linked to the recovery from the r^{th} recession.

We are now interested in the following *conditional path* for the cumulated response of each variable in the K-variable system:

$$\begin{aligned} CR(\Delta_h y^k_{it(r)+h}, \delta) \quad = \quad & E_{it(r)}(\Delta_h y^k_{it(r)+h} | x_{it(r)} = \overline{x} + \delta; Y_{it(r)}, Y_{it(r)-1}, ...) \\ & -E_{it(r)}(\Delta_h y^k_{it(r)+h} | x_{it(r)} = \overline{x}; Y_{it(r)}, Y_{it(r)-1}, ...), k = 1, ..., K; h = 1, ..., H. \end{aligned} \tag{2}$$

Here $CR(\Delta_h y^h_{it(r)+h}, \delta)$ denotes the average cumulated response across countries and across recessions of the k^{th} variable in the system, at a horizon h periods in the future, in response to a δ change in the treatment variable, *conditional* on the lagged history of all the variables in the system at the path start time $t(r)$. It is worth noting that this expression (2) for the conditional path differs in one key respect from expression (1) for the unconditional path: it flexibly allows for the feedback dynamics within the system and conditions for them through the inclusion of the controls Y.

Under linearity, the cumulated response in expression (2) is simply the sum of the 1 to h impulse responses:

$$\begin{aligned} IR(\Delta y^k_{it(r)+h}, \delta) \quad = \quad & E_{it(r)}(\Delta y^k_{it(r)+h} | x_{it(r)} = \overline{x} + \delta; Y_{it(r)}, Y_{it(r)-1}, ...) \\ & -E_{it(r)}(\Delta y^k_{it(r)+h} | x_{it(r)} = \overline{x}; Y_{it(r)}, Y_{it(r)-1}, ...), k = 1, ..., K; \quad h = 1, ..., H. \end{aligned} \tag{3}$$

That is,

$$CR(\Delta_h y^k_{it(r)+h}, \delta) = \sum_{j=1}^{h} IR(\Delta y^k_{it(r)+j}, \delta). \tag{4}$$

Expression (3) will be recognized as the definition of an impulse response in Jordà (2005). There are several advantages to calculating the cumulated response directly from expression (2) rather than with expression (4). First, it can be used to display the paths that the economy would follow in normal versus financial recessions for different assumptions on the treatment level in a manner similar to that in Figure 2. Second, it provides a direct estimate of the marginal accumulated effect that is more convenient for inference.

In this paper we calculate the cumulated response in (2) with a fixed-effects panel specification, and at each horizon we allow a discrete treatment depending on whether the recession is financial or not (N, F), and a continuous treatment, based on the excess credit variable (ξ):

$$\Delta_h y^k_{it(r)+h} = \alpha^k_i + \theta^k_N N + \theta^k_F F + \beta^k_{h,N} N(\xi_{t(r)} - \overline{\xi_N}) + \beta^k_{h,F} F(\xi_{t(r)} - \overline{\xi_F}) \tag{5}$$
$$+ \sum_{j=0}^{p} \Gamma^k_j Y_{it(r)-j} + u^k_{it(r)}; \quad k = 1, .., K; \quad h = 1, ..., H$$

where α^k_i are country fixed effects, θ^k_N is the common constant associated with *normal* recession treatment $(N = 1)$; θ^k_F is the constant associated with *financial* recession treatment $(F = 1)$; a history of p lags of the control variables Y at time $t(r)$ are included, with coefficients Γ; and u is the error term. There are also two additional treatments admitted via the interaction terms. Notice that the continuous treatment variable ξ enters in deviation from its mean in *normal/financial* recessions respectively. The reason is that these means can (and do) differ depending on the type of recession (see Table 3); hence, the above $\beta^k_{h,N}$ and $\beta^k_{h,F}$ will be homogeneous direct measures of the cumulated marginal effect of a unit treatment applied to ξ in each bin.

The treatment effects (θ, β) will be the chief coefficients of interest, and represent the *conditional path* for the cumulated response of each variable controlling for the history Y; this is in contrast to the *unconditional path* of the kind presented in the previous section. Clearly, for the case where the discrete (0-1) treatment is applied to the indicator variables, it will again be simple to test for the significance of the effects given the θ coefficients. And in the case where the treatment is applied to the excess credit variable ξ, the above panel estimator implies that the marginal effects are given by $\widehat{CR}_N(\Delta_h y^k_{it(r)+h}, \delta) = \widehat{\beta}^k_{h,N}\delta$ and $\widehat{CR}_F(\Delta_h y^k_{it(r)+h}, \delta) = \widehat{\beta}^k_{h,F}\delta$, and it is simple to test for the significance of these effects. In the special case where the two effects are of equal magnitude with $\beta^k_{h,N} = \beta^k_{h,F} = \beta^k_h$ then we would find a common marginal treatment effect with $CR(\Delta_h y^k_{it(r)+h}, \delta) = \beta^k_h$. This hypothesis is also testable.

Fixed effects are a convenient way to allow cross-country variation in the typical path as well as in the average response to excess credit (as one might expect, say, when there is variation in the institutional framework in which financial markets and policies operate in each country), while at the same time allowing us to identify the common component of the response.

3.1 Conditional Paths from Local Projections: GDP

What remains is for us to specify the control variables Y in our system. Using the conditional local projection methods just described, we use a 7-variable system that contains the following variables: (1) the growth rate of real GDP per capita; (2) the growth rate of real loans per capita; (3) the CPI inflation rate; (4) short-term interest rates on government securities (usually 3 months or less in maturity); (5) long-term interest rates on government securities (usually 5 years or more in maturity); (6) the investment to GDP ratio; and (7) the current account to GDP ratio. Notice that including the growth rate of real loans per capita and its lags as controls will considerably stack the odds against finding that the credit build up during the boom matters in explaining the path of the recession and subsequent recovery.

3.2 Conditional Paths: Normal v. Financial

Table 6, panel (a), presents the conditional paths estimated with the LP method using controls to compare findings with the earlier unconditional approach. The sample is now reduced to 132 recessions (101 normal, 31 financial) as we need data for all the controls. The controls are contemporaneous and 1-year lagged values of Y at horizon $h = 0$, and their coefficients are not shown; we focus on the coefficients of the four treatment responses.

The results are consistent with the patterns seen earlier in the unconditional estimation. The path of real GDP per capita in normal recessions sits well above the path seen in financial recessions. In year 1 the levels are -1.5% versus -3.0%. By year 2 they are 0% versus -4.6%. The differences persist, and by year 5, the levels are $+4\%$ versus -2%. Individually, the normal and financial paths are different at each horizon, and an LM test confirms that the same is true in a joint test at all horizons. These conditional results with a full set of controls thus reveal even starker differences between normal and financial recessions as compared to the corresponding unconditional results that we saw in Table 4.

3.3 Robustness Check: Excluding the Great Depression

The Great Depression is, without a doubt, the major financial event of the twentieth century. Could the Great Depression be driving our results? Table 6, panel (b), addresses this concern by repeating the analysis but excluding the Great Depression era (years 1928–38 are dropped). The

Table 6: LP Conditional Paths — 7 Variable System, Normal v. Financial Bins

(a) Full sample					
Log real GDP per capita (relative to Year 0, ×100)	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Normal recession (N)	-1.5*	0.0	2.6*	3.1*	4.0*
	(0.3)	(0.6)	(0.9)	(1.1)	(1.2)
Financial recession (F)	-3.0*	-4.6*	-3.9*	-3.4+	-2.0
	(0.5)	(1.0)	(1.4)	(1.8)	(1.9)
F-test Equality of coefficients, Normal=Financial (p)	0.00	0.00	0.00	0.00	0.00
Observations, Normal	101	101	101	101	101
Observations, Financial	31	31	31	31	31
Observations	132	132	132	132	132

(b) Excluding the Great Depression (omit 1928–38)					
Log real GDP per capita (relative to Year 0, ×100)	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Normal recession (N)	-1.5*	0.2	2.6*	3.8*	5.1*
	(0.3)	(0.6)	(0.7)	(0.9)	(1.0)
Financial recession (F)	-2.6*	-4.2*	-2.4*	-0.69	0.9
	(0.5)	(1.0)	(1.2)	(1.6)	(1.6)
F-test Equality of coefficients, Normal=Financial (p)	0.03	0.00	0.00	0.00	0.01
Observations, Normal	94	94	94	94	94
Observations, Financial	24	24	24	24	24
Observations	118	118	118	118	118

Dependent variable: $\Delta_h y_{it(r)+h}$ = (Change in log real GDP per capita from Year 0 to Year h)×100.
Standard errors in parentheses.$^+$ $p < 0.10$, * $p < 0.05$. Country fixed effects not shown.
See text for a list of controls not shown here.
Panel (a): LM test: normal and financial coefficients equal at each horizon: $F(10{,}640) = 9.208$; $p = 0.000$.
Panel (b): LM test: normal and financial coefficients equal at each horizon: $F(10{,}570) = 5.651$; $p = 0.000$.

sample size falls to 118. The results show that the basic story holds even outside this watershed event. Not surprisingly, the paths in both types of recessions are somewhat higher in levels. Looking at panel (b), the year 1 declines are similar to panel (a), but at year 5, the normal path is higher by about +0.9% (5.1% versus 4.0%) and the financial path by +2.9% (+0.9% versus -2.0%). This result merely confirms what we already knew, that downturns in the 1930s, especially those associated with financial crises, were among the worst negative shocks ever seen and recovery from them took unusually long. When these are excluded from our sample, we are bound to find faster recovery paths taking averages over the remaining set of milder recession events left in the historical record.

Table 7: LP Conditional Paths — 7 Variable System, Normal v. Financial Bins and Excess Credit

Log real GDP per capita (relative to Year 0, $\times 100$)	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5
Normal recession (N)	-1.3*	0.7	3.2*	3.8*	4.8*
	(0.4)	(0.6)	(0.9)	(1.1)	(1.2)
Financial recession (F)	-2.8*	-4.1*	-3.6*	-2.8	-1.4
	(0.6)	(1.0)	(1.4)	(1.8)	(1.9)
Excess credit $\times$ Normal recession ($N \times (\xi - \overline{\xi_N})$)	-0.3	-0.7*	-0.8^{+}	-0.9^{+}	-0.7
	(0.2)	(0.3)	(0.4)	(0.5)	(0.6)
Excess credit $\times$ Financial recession ($F \times (\xi - \overline{\xi_F})$)	-0.4^{+}	-1.0*	-0.4	-1.3^{+}	-0.9
	(0.2)	(0.4)	(0.5)	(0.7)	(0.7)
F-test Equality of coefficients, Normal=Financial (p)	0.01	0.00	0.00	0.00	0.00
F-test Equality of coefficients, interaction terms (p)	0.57	0.47	0.49	0.62	0.82
Observations, Normal	92	92	92	92	92
Observations, Financial	29	29	29	29	29
Observations	121	121	121	121	121

Dependent variable: $\Delta_h y_{it(r)+h}$ = (Change in log real GDP per capita from Year 0 to Year h)$\times$100.
Standard errors in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$. Country fixed effects not shown.
See text for a list of controls not shown here.
LM test: All excess credit coefficients equal zero: $F(10{,}585) = 3.026$; $p = 0.001$.
Notes: In each bin, recession indicators (N, F) are interacted with demeaned excess credit, ($\xi - \overline{\xi_N}, \xi - \overline{\xi_F}$).

3.4 More Treatments: Accounting for Excess Credit

Table 7 now presents, for our full sample excluding the great wars, the conditional paths estimated with the continuous excess credit treatment added. The sample is now reduced to 121 recessions as we need data on not only the excess credit variable, but also for all the controls. The controls are contemporaneous and 1-year lagged values of Y at horizon $h = 0$, and their coefficients are not shown; we focus on the coefficients of the four treatment effects as before.

For the average treatments, results are very similar to Table 6, and compared to the unconditional results in Table 5, normal recessions display a slightly faster recovery path in these LP results; the average normal recession (row 1) suffers only -1.5% loss in output per capita in year 1 and recovers to $+4.4\%$ in year 5. The average financial recession (row 2) looks a little more severe with output per capita levels at -3.0%,-4%, and -3.4% in years 1, 2 and 3, recovering to only -2.7% in year 4, and still stuck below the reference level at -1.4% in year 5.

Moving on to the marginal treatments in Table 7 based on excess credit (ξ), we see here that both normal and financial recessions display negative and significant correlations between excess credit and the trajectory of output per capita. All 10 coefficients (rows 3 and 4) are negative and they pass a joint significance test ($F(10{,}585) = 2.186$; $p = 0.017$). Equality of these marginal effects across each recession type cannot be rejected at any horizon. To get a grasp of the quantitative significance of these marginal treatment effects, the average coefficient for normal recessions across the five horizon years is -0.51%; in the case of financial recessions the average coefficient is half again as large, -0.76%.

Given that the s.d. of the excess credit variable is 2 ppy for normal recessions and 2.5 ppy in financial recessions (Table 3), these coefficients imply that a +1 s.d. change in excess credit in each bin would depress output in each bin by nontrivial amounts: the 5-year post-peak recovery path would be lower on average by about 1% in normal recessions and by 2% in financial recessions.

3.5 Summary: Financial v. Normal plus Variable Credit Scenarios

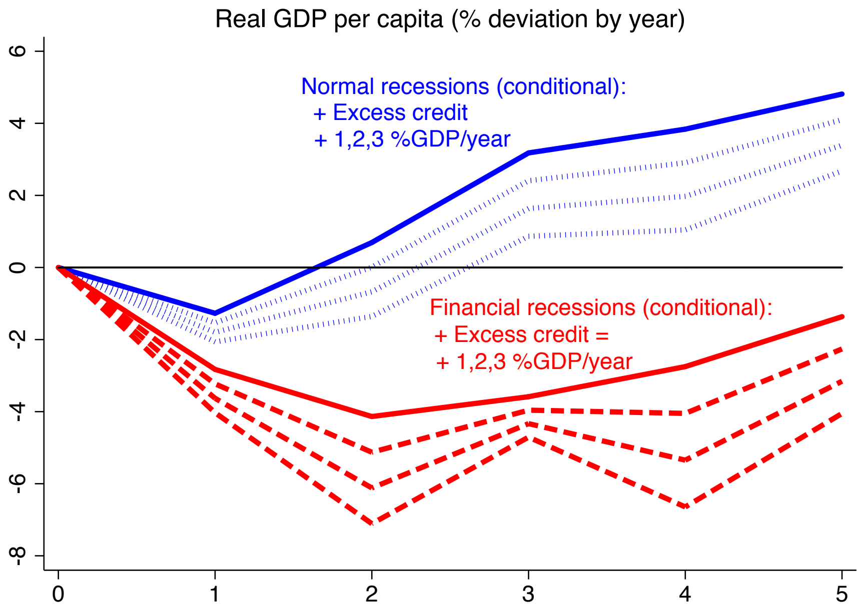
Our preliminary findings based on unconditional paths remain robust, and are now even strengthened once we implement a fully conditional LP path estimation. Average treatments show that financial recessions are unambiguously more painful than normal recessions, to an even greater degree than before. And the marginal treatment based on excess credit comes through as a statistically and quantitatively significant source of additional drag on the pace of economic recovery in both types of recession. To sum up our preferred result concerning the influence of recession type and excess credit on the path of real GDP per capita, Figure 3 shows the corresponding recession paths derived from Table 7.

3.6 Conditional Paths: Full System

Of course, an advantage of system estimation (5) is that it can furnish conditional forecast paths not only for output per capita, but for all macroeconomic variables of interest in Y. It would be cumbersome to present seven tables of results like Table 6, but a clear and concise picture can be delivered by plotting the corresponding cumulative-response curves for each variable given by the predicted values from the fixed-effects panel estimator; that is, we can construct the analogs to Figure 2 for all controls Y.

The conditional paths for the 7-variable system are shown in Figure 4. The path for normal recessions is again shown with a 95% confidence interval (dark solid line, shaded area), and the path for financial recession is also depicted (light solid line, with no shaded area). We also show

Figure 3: Conditional Paths, Continuous excess credit treatment



Notes: See text. Solid lines show coefficient values from Table 7, that is, when the excess credit variable ξ is assume to be at its mean in each bin. The dotted and dashed lines show predicted paths when the excess credit variable ξ is perturbed in 3 increments of +1 percentage points per year in each bin. For each case all the controls are set to their historical mean values and the average country fixed effect is imposed.

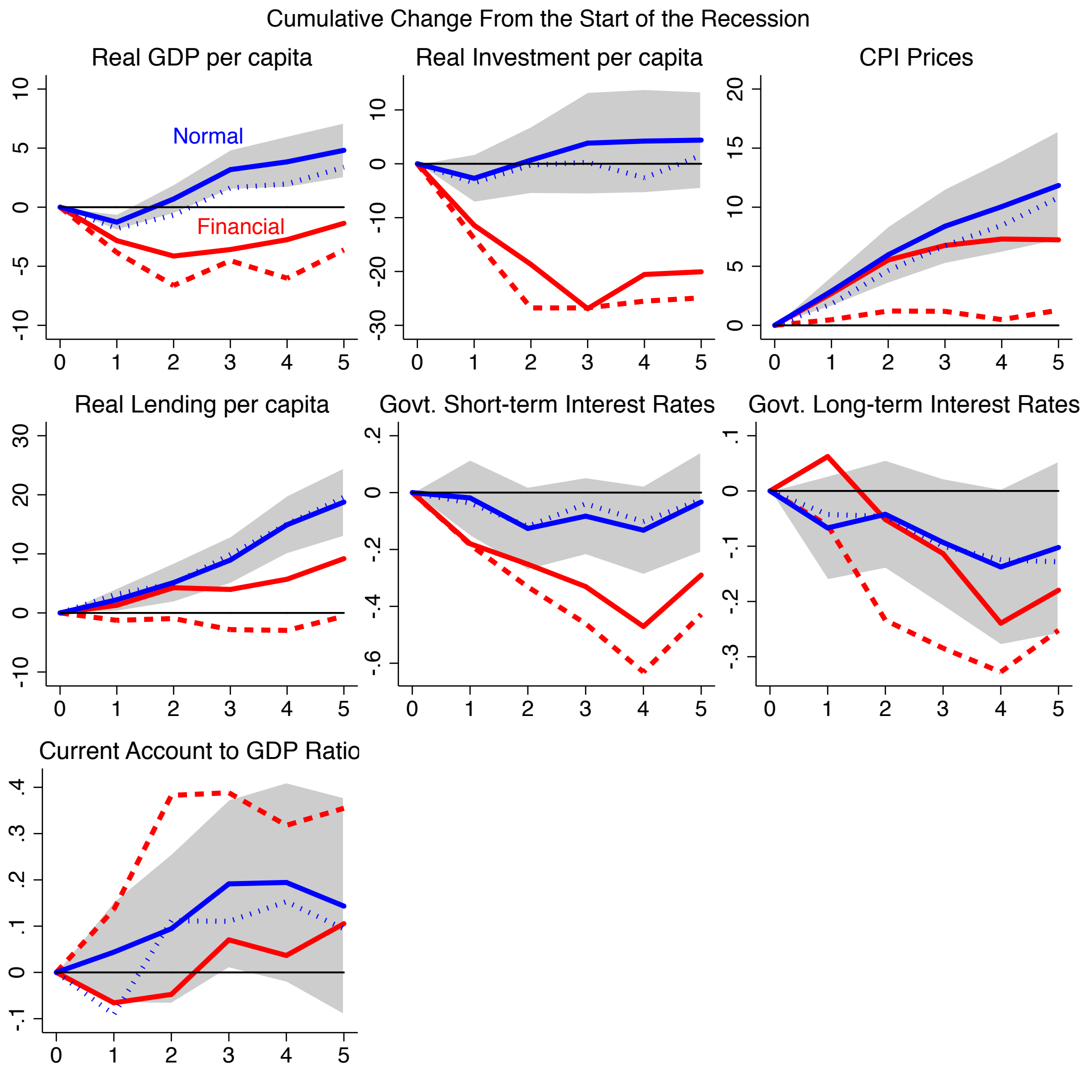
perturbations to these paths when the excess credit variable ξ is set one standard deviation above its mean level in each bin, which we shall think of as characterizing a "highly-levered" scenario after a credit boom. As noted, this corresponds to about an extra +2 ppy change in the loans to GDP ratio per year in the normal case, and about +2.5 ppy in the financial crisis case.

The results are striking but intuitive, and we discuss them in turn.

- **GDP per capita** Previous results are robust. Financial recessions are more painful, with recovery to previous peak taking about 5 years, versus 2 in the normal case. The financial trough is 3% below peak on average, the normal trough only 1.5%. The paths are significantly worse when excess credit is raised by 1 s.d.; the normal path is dragged down by about 1%, and the financial path by about 2%. Highly-levered recessions are more painful.

- **Real investment per capita** Investment falls about 5% in normal recessions, and more than GDP, in the usual procyclical pattern. It then recovers starting in year 2. In financial recessions investment collapses by 20% and remains depressed out to year 5. In the highly-

Figure 4: All Conditional Paths: Financial v. Normal Recessions



Notes: See text. These responses correspond to estimates of regression equation (5) for four different treatments using the full sample. The solid dark lines with shaded 95% confidence interval show predicted values for the case of an average normal recession ($N = 1, \xi = \overline{\xi_N}$). The solid light lines show predicted values for the case of an average financial recession ($F = 1, \xi = \overline{\xi_F}$). The dotted and dashed lines show the predicted values for the cases of normal recession and financial recession respectively, where ξ is set at 1 s.d. above the mean in each bin. For each case all the controls are set to their historical mean values and the average country fixed effect is imposed.

levered scenarios, the paths are significantly worse when excess credit is raised by 1 s.d.; the normal path is dragged down by about 3 or 4 percentage points, and the financial path by a similar amount. Highly-levered recessions put a serious brake on investment.

- **CPI prices** These follow an upward track on average in normal recessions, gaining 10% in 5 years, so inflation averages about 2% per year in the window. In financial recessions, a slightly deflationary deviation appears, and prices rise only about 6% or 7% over 5 years, In the highly-levered scenarios, the paths are significantly depressed in the financial recession case where inflation is held at a level close to zero. Highly-levered financial crises appear to carry a lasting deflationary kick for several years, all else equal.

- **Real lending per capita** This follows an upward track on average in normal recessions, gaining 15% to 20% in 5 years. In financial recessions, the trend is muted, perhaps around 10% in 5 years. In the highly-levered scenarios, the paths are significantly worse only in the financial recession case where the lending is flat for the entire 5 year window. Highly-levered financial crises end with prolonged credit crunches.

- **Government short and long term rates** Both follow a downward trend in recessions, but given the scales as shown, the collapse in rates is more pronounced on the short end of the yield curve, as one would expect. Financial recessions are not so different on average, with a slightly steeper dip in short-term rates perhaps reflecting more aggressive policy. However, in the highly-levered scenarios, the paths are significantly down only in the financial recession case where the rates drop further and for a more extended period. Highly-levered financial crises presage unusually low interest-rate environments.

- **Current account to GDP ratio** The external balances shift sharply towards surplus in normal recessions, and less dramatically after financial recessions, when the response appears delayed. However, the change is pronounced in a financial recession after a credit boom. Highly-levered financial crises seem to lead to more acute external forces requiring large and fast current account adjustment.

4 History versus Reality: USA 2007–2012

A practical interpretation of our results can be obtained by considering the U.S. experience in the recent crisis as an example, and using our empirical work to give an out-of-sample prediction. With this we can assess the question as to whether U.S. economic performance in the recession and recovery phase has been above or below what might have been reasonably expected.

This question has attracted much attention in current debates in the academic and policy communities. Despite the seemingly broad agreement in the previous literature, and notably the widely-cited work of Reinhart and Rogoff (2009ab), as we noted above some uncertainty seems to remain as to whether financial recessions are really more painful, and if so, by how much and for whom. For example, in studies such as Howard et al. (2011) and Bordo and Haubrich (2010), which focus on just the history of U.S. recessions, a clear picture may be hard to discern given the small sample size; and by focusing on the speed of the recovery (normalizing at the trough rather than, as is typical, at the peak), the goalposts are in a different place. Another issue arises because a majority of past studies have pooled advanced and emerging/developing countries in their sample. A recent U.S. budget analysis, seemingly referring to the IMF's studies and others, said: "Some international economic organizations have argued that a financial recession permanently scars an economy... The statistical evidence... comes mostly from the experiences of developing countries and its relevance to the current situation in the United States is debatable" (OMB 2012). We share concerns that emerging market experience may not provide an entirely suitable parallel for most advanced countries, and we also worry that a focus on a single-country sample provides too few recession observations for meaningful, robust inference. We see such doubts as an argument for the type of analysis we have undertaken here, which focuses *only* on the experience of advanced countries.

How does the recovery from the Great Recession in the U.S. compare to historically informed expectations? To apply our model to the current situation, our treatment needs to be calibrated to actual U.S. data for the 2007 business cycle peak. The easy part is to set $F = 1$ for a financial crisis peak. What about excess credit? For that we need data from the prior expansion from 2001 to 2007. In the U.S. actual excess credit based on the change in bank loans was $+1.74$ percentage points of GDP over the six years. This corresponds to the 60th percentile of ξ in the F bin over our full historical sample.

However, one major concern is that the U.S. credit boom from 2001 to 2007 is not fully captured by aggregate loans on banks' loan books. This might lead us understate the "excess credit" treatment in our out-of-sample prediction. In particular, and far more than any other episode in our historical sample, the U.S. boom was also fed by the shadow banking system, via the creation of credit instruments to support mortgage, auto, student, credit card and other types of securitized lending outside the traditional banking channels. Whether nonbank sources of credit should be included in the analysis is an open question. In the previous sections we have only looked at loans extended by the domestic banking sector to non-financial business and households. There are plausible arguments both for and against the inclusion of credit extension by nonbanks.[8]

These remain open questions for future research. But to attempt to measure the importance of shadow system loans—to see if such distinctions might matter—we use Federal Reserve Flow of Funds statistics and compute the change in total credit market liabilities (change in stock of all credit market liabilities of the non financial sector minus corporate bonds) for the 2001–07 expansion. This broad excess credit measure, on the liability side of nonbanks, rose by +5.0 percentage points of GDP per year, well above the +1.75 percentage points of GDP per year for just bank loans, and an excess of +3.75 percentage points per year relative to the historical mean of excess credit in the F bin ($\overline{\xi_F} = +1.26$). This broad measure would clearly put the U.S. boom at the higher end of the historical range, and definitively in the top tercile of the F bin.

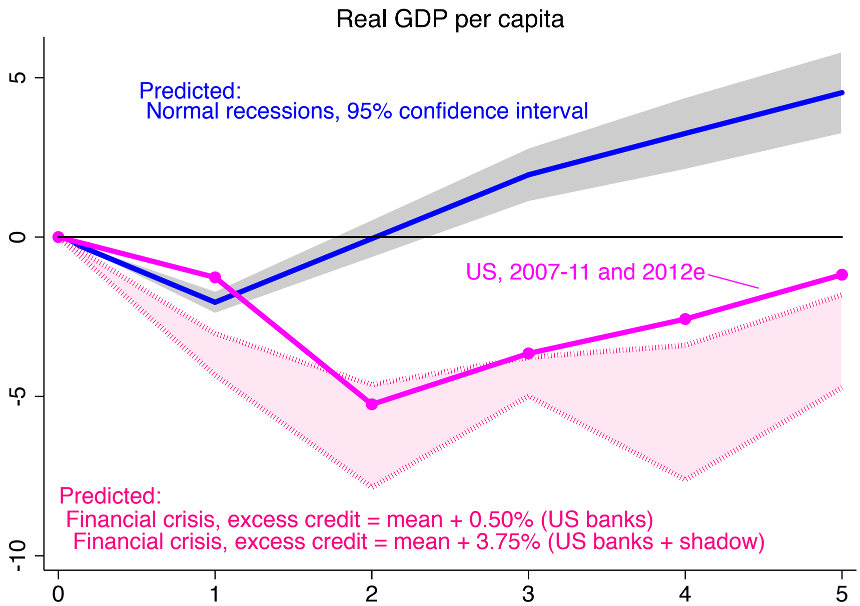
In Figure 5, we use these measures of U.S. excess credit before the crisis to compare outcomes (IMF WEO actual data to 2011, to plus 2012 estimate) with the path that would have been predicted based on historical experience. The conditional forecast in Figure 5 is based on Table 5 and uses the actual measures of excess credit seen in the U.S. expansion from 2001 to 2007, either for strictly bank loans or for the whole system including shadow credit, and it sets all other control variables equal to their historical mean values.[9]

The U.S. is seen to have performed as could have been expected given the historical outturn

[8] On the one hand, to the extent that such shadow credit creates macroprudential/crisis shocks via over-leveraged debits on borrowers' balance sheets (leading to deleveraging and subdued borrowing, i.e., damage on the credit demand side), a loan is a loan, whether it ends up as a credit on a bank loan book or in a securitized product held elsewhere. It is a financial obligation for the borrower and the distinction whether the creditor is a bank or someone else may not matter. On the other hand, to the extent that it is the loans appearing on bank balance sheets that create macroprudential/crisis shocks via the banking channel (overlending followed by a crunch and limited bank intermediation, plus payments-system risk/panic, i.e., damage on the credit supply side) then by dispersing risk, the non warehoused securitized loans held outside the banking system may—in theory—mitigate or cushion the impact of crises on banks themselves and help to shield the real economy.

[9] We do not show the case where conditioning variables are set equal to USA 2007 values. This would actually produce an even more adverse real GDP path, around 200–300 bps below that shown here, so the main conclusion (the U.S. has done better than expected) would not be changed, only amplified.

Figure 5: The United States, 2007–12: Actual v. Predicted Paths



Notes: See text. The output per capita forecast paths are based on Table 6. For the forecast paths, the excess credit variable must be chosen. The USA actual excess credit variable based on the change in bank loans was 1.74 percentage points of GDP for the prior expansion from 2001 to 2007. The value of 0.5 (upper boundary of predicted range) corresponds to the difference between the actual level (1.74) and the mean of excess credit in the F bin (1.26). The value of 3.75 (lower boundary of predicted range) corresponds to the difference between the estimated excess credit for both conventional and shadow systems (5.0) and the mean of excess credit in the F bin (1.26). In the predictions, all other control variables (Y) are set at the historical sample mean.

for financial recessions. Allowing for the shadow system it did rather well. Initially the U.S. did considerably better than could have been expected, although the favorable outcome in year 1 might have reflected the delay of the full-blown impact of the crisis until late-2008 after the Lehman collapse and related events, as compared to the milder effects following the 2007 subprime tensions and less catastrophic early-2008 Bear Stearns event. By years 3, 4, and 5 (2010–11), however, we see that the U.S. economic recovery may have faced stronger headwinds in this later phase of the recovery period. It may be tempting for some readers to see these paths, by historical standards, as a partial or relative success story, and even as a reflection of unprecedented policy responses.

5 Conclusion

We tracked the effects of credit booms on outcomes in normal and financial crisis recessions. The latter are typically more painful. All else equal, the aftermath of leveraged booms is associated with slower growth, investment spending and credit growth than usual. If the recession coincides with a financial crisis, these effects are compounded and accompanied by pronounced deflationary pressures. Whilst confirming the plausibility of estimates typically found in the literature, we also show how the economic costs of crises vary considerably depending on the run-up in leverage during the preceding boom. These are potentially important stylized facts about the nature of the business cycle.

Our objective was to demonstrate these effects empirically without imposing a tight theoretical frame *a priori*. Generally speaking, a credit build-up in the boom seems to heighten the vulnerability of economies. For now, we content ourselves with documenting these new important facts about the role of credit in the modern business cycle. Our results do not speak as to the causes of credit accelerations nor can we make strong inferences yet about the net effects of credit booms, these being goals of our ongoing work. Yet our results would generally seem compatible with the idea that financial factors play an important cyclical role. Potential explanations for these effects include the possibility that financial accelerator effects are larger with more leveraged balance sheets; that debt-overhang pressures are more acute after credit-intensive booms; or that expectational shifts have more serious effects when credit intensity has risen in a more extreme fashion. Investigating these different channels is an important task for future research.

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