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Assessing the Historical Role of Credit: Business Cycles, Financial Crises and the Legacy of Charles S. Peirce

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Assessing the Historical Role of Credit: Business Cycles, Financial Crises and the Legacy of Charles S. Peirce*

Abstract

This paper provides a historical overview on financial crises and their origins. The objective is to discuss a few of the modern statistical methods that can be used to evaluate predictors of these rare events. The problem involves prediction of binary events and therefore fits modern statistical learning, signal processing theory, and classification methods. The discussion also emphasizes the need to supplement statistics and computational techniques with economics. A forecast's success in this environment hinges on the economic consequences of the actions taken as a result of the forecast, rather than on typical statistical metrics of prediction accuracy.

Keywords: correct classification frontier, area under the curve, financial crisis, Kolmogorov-Smirnov statistic

JEL Codes: C14, C18, C25, C44, C46, E32, E51, N10, N20

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1 Introduction

Financial crises are rare, but often have devastating economic consequences. With nearly 11 million jobs lost in OECD economies following the recent global financial crisis –about as many as all currently employed workers in Australia– it is difficult to exaggerate how important it is to understand how these rare events happen. Investigating these infrequent events demands blending the new with the old. In order to provide sufficiently long samples on which to train the modern arsenal of statistical techniques, one must supplement electronic databases by dusting off a few almanacs. The microprocessor today paints a different tableau of finance than one hundred years ago. Yet today's day-trader and the nineteenth century's railroad bond speculator would largely agree on the leading causes of most financial events.

This paper provides a historical overview on financial crises and their origins. The objective is to discuss a few of the modern statistical methods that can be used to evaluate predictors of these rare events. These methods have applicability not only in this context, but in many others not discussed here. Importantly, some of the methods emphasize the need to broaden the discussion away from mean-square metrics typical of conventional forecasting environments. When the problem involves the prediction of binary events, the tools of modern statistical learning, signal processing theory, and classification are particularly useful. The discussion will often emphasize the need to supplement statistics and computational techniques with economics. A forecast's success in this environment hinges on the economic consequences of the actions taken as a result of the forecast, rather than on typical statistical metrics of prediction accuracy.[1]

This journey begins with a review of the last 140 years of economic history for 14 advanced economies. Schularick and Taylor (2012) and Jordà, Schularick and Taylor (2011, 2012) provide important background for the discussion that follows. Some of the long historical trends in the data relate to credit and its composition, and whether one thinks in terms private or public

[1] Clive Granger made this point often. For a recent reference, see e.g. Granger and Machina (2006).

indebtment. Along the way, the Bretton Woods era will stand out as an oasis of calm –a 30-year period with no recorded crises anywhere in our 14 economies– a fact that applies to many economies beyond the scope of our analysis. Other historical developments include the explosion of credit that started at the end of Bretton Woods, the increasing weight of real estate in lending, and the general increase in public debt to GDP ratios experienced as the welfare net was woven increasingly tighter.

Three broad explanations of the causes of financial crises are found in the literature: current account imbalances, profligate governments, and private credit build-ups. In order to assess the ability of these candidate explanations to foretell the next financial crisis, we will turn the page back to 1884 and Charles S. Peirce's discussion on the success of binary predictions. That discussion will be followed by a brief overview of Peterson and Birdsall's (1953) contributions to the theory of signal detection and the receiver operating characteristic (ROC) curve. Even though today the ROC curve is a common tool of analysis of credit risk, economists will probably find that a related measure, the correct classification frontier (CCF) presented in Jordà and Taylor (2011), can be interpreted more easily. The CCF is to crisis prediction what the production possibilities frontier is to factor allocation across the product space, given consumer preferences. This interpretation of probabilities suggests interesting economic possibilities.

At a basic level, a financial crisis originates when borrowers are unable to meet their obligations. Sometimes lenders are able to absorb the loss and carry on lending to others. Sometimes losses precipitate into a cascade of liquidations and reserve provisioning that freezes the normal flow of credit across the board. Thus, while the expansion of credit is a pre-condition for financial distress, recessions do not often turn into financial calamity.

Schularick and Taylor (2012) argue that the growth of bank lending (as a ratio of GDP) is the best predictor of financial crises using historical data. Borio, Drehmann and Tsatsaronis (2011) find a similar result using a more recent sample available at a higher frequency. Within this volume, Drehmann and Juselius argue that debt service ratios (basically the product of debt times the interest rate) are similarly useful in predicting financial events as much as six months in advance. On the other hand, the macroeconomics literature has traditionally found little empirical support for the type of financial accelerator mechanism (e.g. Bernanke and Gertler, 1989 and 1995; Bernanke, Gertler and Gilchrist, 1999) that would give credit a prominent role in explaining economic fluctuations. In a recent paper, Gadea-Rivas and Pérez-Quirós (2012) argue that one of the reasons that credit is found to be a useful predictor of financial crises in historical data is that often one conditions on there being a recession first. However, without that conditioning, credit does not appear to be a very good predictor of financial events.

The analysis that follows connects all of these stories to explain the apparent disparity of views. First, it is important to stipulate that predicting financial crises is difficult, even when we restrict attention to sorting recessions into two bins, which I shall label "normal" and "financial." The predictors that I use here focus on the three broad explanations of financial events presented earlier: current account imbalances, excess bank lending and excessive build up of public debt. Initially, all these variables are measured in cumulative terms during the expansion preceding the peak of economic activity. The first pass on these data confirms extant results in the literature. The expansion of private credit appears to be helpful in sorting recessions into financial or normal. However, the classification ability of private credit in the full sample is relatively limited. It improves considerably after World War II (WWII).

This finding sets the stage for the criticism in Gadea-Rivas and Pérez-Quirós (2012). These authors argue that conditioning on when the recession takes place is unrealistic in real-time policy situations. This is a fair point. In fact, using the same indicators described earlier, this time measured as a moving average over five years to account for the different time-scale of the analysis, there is little evidence that we can predict with much accuracy when the next recession will come. This confirms the main finding in Gadea-Rivas and Pérez-Quirós (2012).

But before we give up on credit as the main propellant of financial events, there is one last cut of the data worth considering. If all we care is to predict the next financial event relative to anything else, be it a typical normal recession or a period of expansion, credit comes back as a very helpful predictor. This is especially the case since WWII. The natural conclusion from this three-step analysis is that policymakers would likely find monitoring the build up of credit useful as a measure imbalances that could trigger a financial crisis.

This finding is not tautological. Although one cannot have a financial event without a considerable expansion of credit, not all credit buildups end in a financial turmoil. Another observation worth making is that the results reported here are not an attempt to discover causal mechanisms. They are however, an attempt to provide policymakers with adequate tools to process information. These tools permit judging alternative indicators on the basis of their ability to anticipate events the policymaker may wish to avoid.

2 Historical Trends: Credit, Public Debt and the Current Account

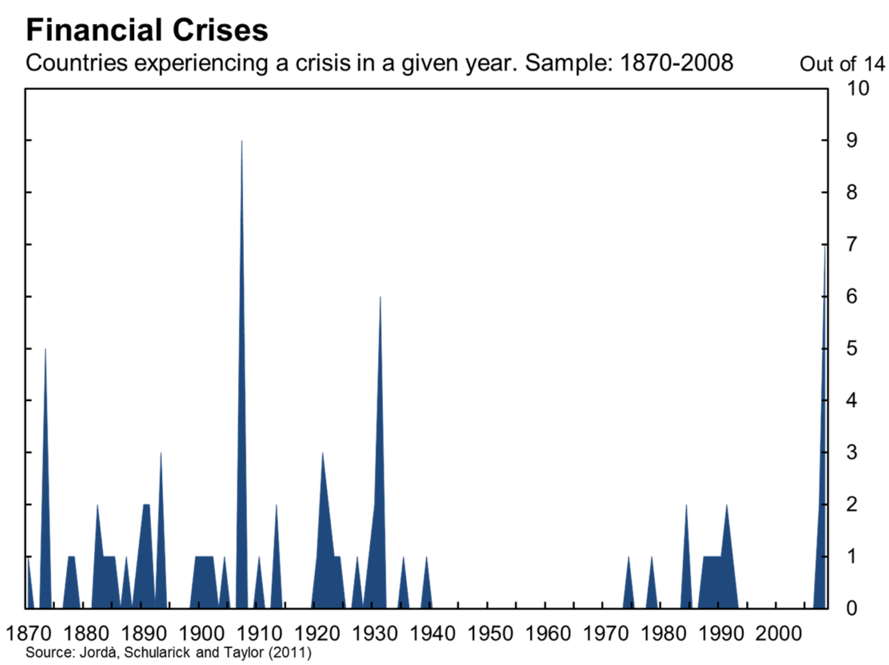
The late 19th century and the first half of the 20th were frequently visited by financial crises. Their origin was attributed to "war or the fiscal embarrassments of governments"[2] by early commentators. Yet even in the early days, a number of global financial events defied these traditional explanations. The financial panic of 1907 is a case in point. The collapse of the Knickerbocker Trust Company in October, much like the fall of Lehmann Brothers in the fall of 2008, threatened to spread across the entire financial system and the economy. The stock market lost 50% from its peak a year earlier. The charter of the Second Bank of the United States, the Fed's ancestor, having been allowed to expire by president Andrew Jackson in 1836, left the economy without an evident backstop to the panic. It was the intervention of J. P. Morgan and the considerable resources that he was able to muster (many from his fellow financiers along with significant help from the U.S. Treasury), that are often credited for saving the day. After the dust cleared,

[2] Wesley C. Mitchell (1927, p. 583).

Congress passed the Federal Reserve Act in 1913 creating the Federal Reserve System. Not coincidentally Benjamin Strong,[3] a senior partner at J. P. Morgan & Co., became the first president of the influential Federal Reserve Bank of New York.

Figure 1 provides an overview of the incidence of financial crises in our data. The figure is based on a sample of 14 advanced economies,[4] which both in 1900 and 2000 comprised about 50% of world GDP according to Maddison (2005). Three features stand out in the figure. First, it is clear that crises were relatively common up to the start of World War II. Second, from the creation (in 1944) to the fall (in 1971) of the Bretton Woods system, there were no crises recorded for our sample of countries. Thereafter, a number of isolated economies experienced financial events of varying consequence. The end of the sample includes the recent financial storm, which engulfed virtually every country in our sample.

Figure 1: The Incidence of Crises over Time



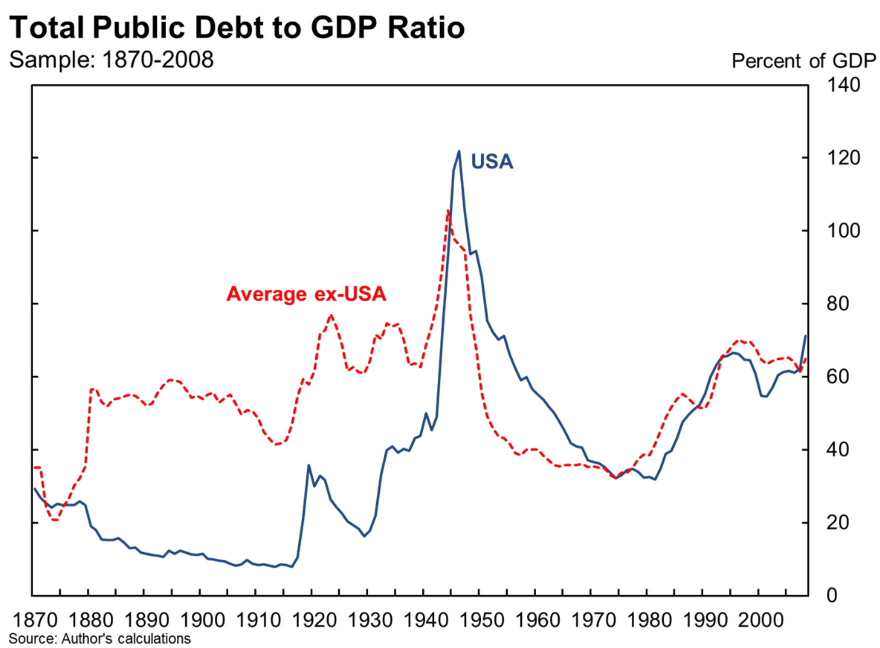
Notes: For any given year, the figure displays how many countries (out of a possible 14) are experiencing a financial crisis. See text.

[3] For a nice overview of Strong's influence in shaping the international monetary system leading up to the Great Depression see Ahamed (2009).

[4] These are: Australia, Canada, Switzerland, Germany, Denmark, Spain, France, the U.K., Italy, Japan, the Netherlands, Norway, Sweden and the U.S.

Since then, the prospects of sovereign default in Europe's periphery have been added to the fears of a banking collapse. The "fiscal embarrassments of governments" we alluded to earlier are another of the leading explanations for financial crises. Figure 2 displays the debt-to-GDP ratios for our 14 economies broken down into a sample that excludes the U.S., and the U.S. series on its own. U.S. government debt levels were very low (below 20 percent of GDP) leading up to World War I, after which they temporarily doubled. They gradually declined thereafter and by the dawn of the Great Depression they had nearly made up for the World War I effort. The debt-to-GDP ratio climbed after the Great Depression, the result of large losses in economic activity rather than to activist fiscal policy or the implementation of the social safety net mechanisms that were to come.

Figure 2: Total Public Debt to GDP Ratio

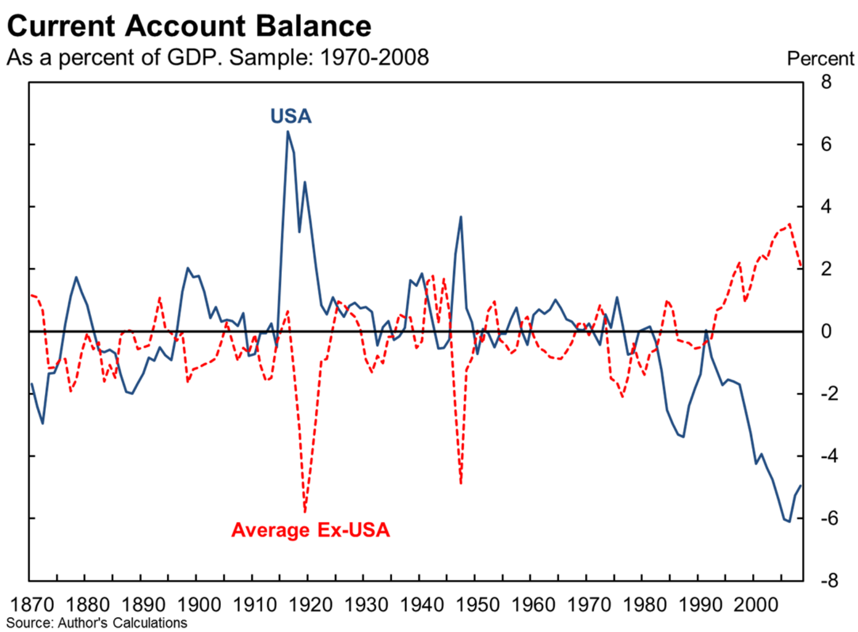


Notes: The figure displays the U.S. and the average for the remaining 13 countries in the sample. See text.

The most defining feature of debt in our data is World War II. Debt levels climbed to 120 percent of GDP in the U.S. Once the war ended, debt levels were continuously reduced until the mid-1970s, bottoming out at about 40 percent of GDP. That inflection point corresponds rather curiously with the resumption of financial crises in our sample. But remember that debt had also continually declined from the end of World War I up to the Great Depression. It is unclear from a cursory look at the data where the debt needle is pointing to on the financial crisis causal-meter.

Although debt levels as a percent of GDP had been substantially higher in the average of countries that excluded the U.S. in the pre-World War II era, thereafter the international experience seems more similar to the U.S. Debt levels began a steady climb in the 1970s with the expansion of the welfare state, from about 40 percent to about 60 percent of GDP when the Great Recession struck.

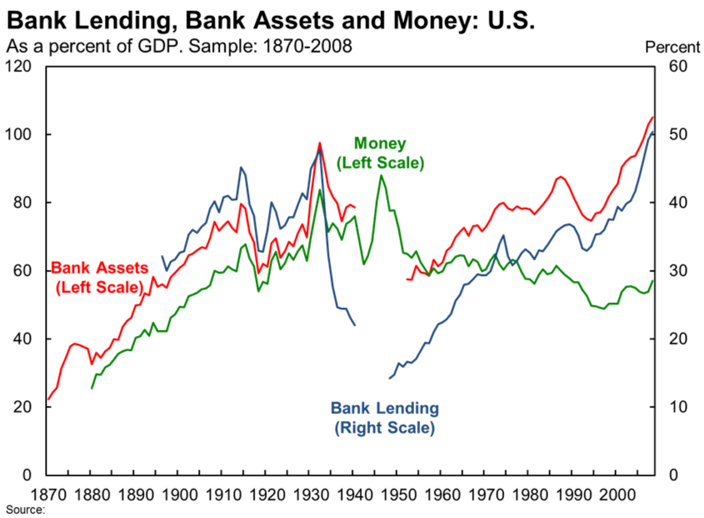
Figure 3: Current Account to GDP Ratio



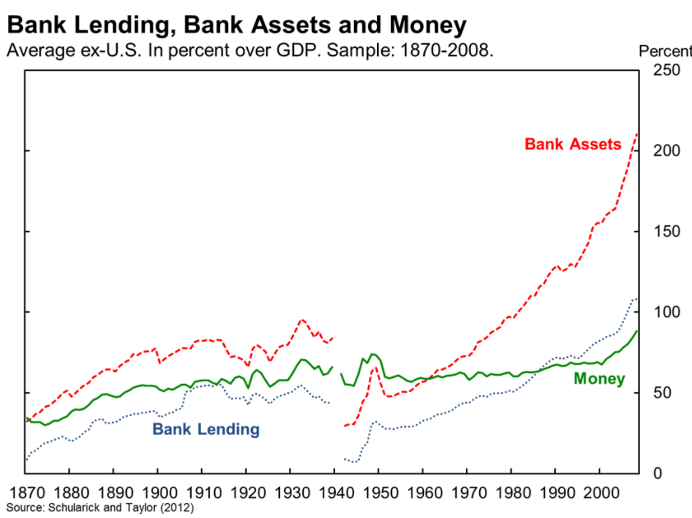
Notes: The figure displays the average for the U.S. and the average for the remaining 13 countries in the sample. See text.

External imbalances are another oft cited suspect in the financial crisis mystery. Data on current account balances as a percent of GDP are displayed in Figure 3. Again, the U.S. and the average across the sample excluding the U.S. are displayed in tandem. Trends in the current account are harder to discern than trends in debt with a few exceptions. The U.S. ran large surpluses in World War I and at the end of World War II. The Bretton Woods era stands out as a period in which imbalances were very moderate, perhaps not surprisingly. In addition to fixed exchange rates, the Bretton Woods system imposed severe restrictions to capital mobility. Starting in the mid-1970s as these restrictions became gradually undone, imbalances grew as a percent of GDP. In the case of the U.S., they reached nearly 6 percent of GDP as the real estate bubble hit its zenith, before the start of the Great Recession.

Figure 4: Money, Bank Lending and Bank Assets



(a) U.S.

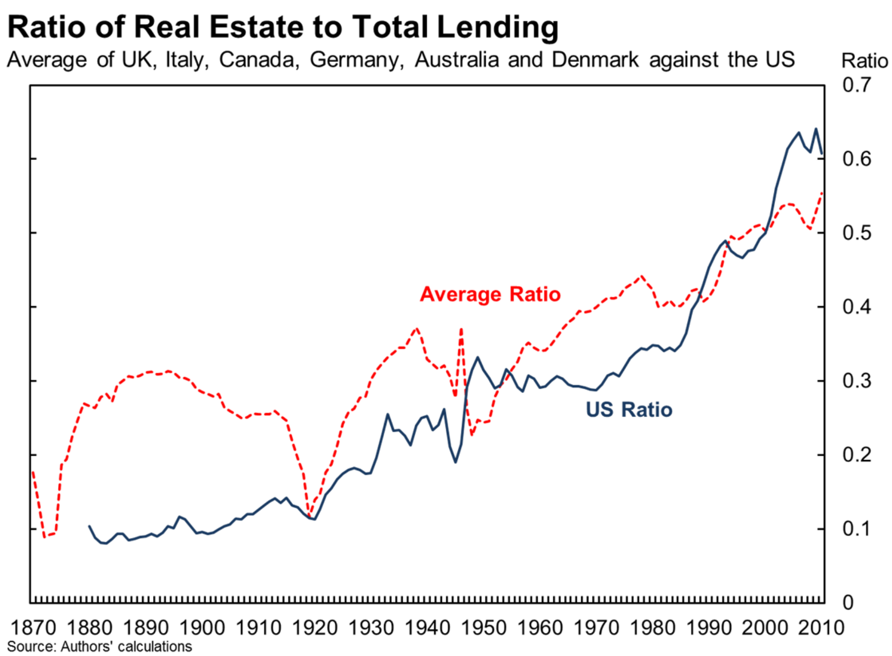


(b) Non-U.S.

Notes: See text.

Schularick and Taylor (2012) document the fast rise of private credit after World War II, which only accelerated further after the fall of Bretton Woods. Figure 4 displays how the tight link between broad measures of money and bank lending broke down after World War II. The era of money ushered in the era of credit. The figure displays a ”Money” variable (typically M2 or M3), ”Bank Lending” which refers to outstanding domestic loans, and ”Bank Assets” which supplement bank lending with other assets held by banks such as Treasury securities, and so on.

Figure 5: Share of Real Estate Lending relative to Total Lending



Notes: See text.

Figure 5 provides a more detailed view of what may be behind this steep increase in lending. It displays the ratio of real estate lending (commercial and by households) to total lending. For the U.S., real estate lending was a relatively small share of total lending (under 15 percent) up until the end of World War I. Thereafter the ratio climbed to 30 percent by the 1970s. In the short span of the next 40 years, the ratio would double again to about 60 percent.

External imbalances, credit expansions and large capital financial flows are not independent from one another. Often they reflect opposite sides of the same coin. And if our objective were to assign a causal interpretation, it could be a daunting task to separate their independent effects. Our objective is different, more pragmatic. Can these variables help us anticipate the next financial crisis? How can we can conceptualize the trade-offs involved in a policy designed to head-off a crisis even if we mistakenly expect one to happen? The next section introduces a toolkit to think more clearly about how this can be done.

3 Evaluating Predictions of Economic Episodes

3.1 Statistical Framework

There is a vast literature in econometrics dedicated to models of binary dependent models. This section is not about finding which of these models provides a more accurate prediction. It is about evaluating predictors and predictions themselves, and it is about presenting the trade-offs associated with decisions based on these predictions. Denote $y_\tau \in \{0,1\}$ the binary indicator we want to predict. If we are interested in predicting financial crises themselves, y may indicate if at time τ a country is experiencing a crisis or not, for example. It could also refer to a classification of recessions into *financial* and *normal* bins instead. The subindex k indicating the country in $y_{k\tau}$ is omitted to make the presentation more fluid.

Let the scalar $x_\tau \in (-\infty, \infty)$ denote the *scoring classifier* or *classifier* for short. This could be a single predictor, an index based on several predictors, a probability forecast, and so on. The definition of what is a classifier is quite general. What is important is that predictions $\widehat{y}_\tau \in \{0,1\}$ for y_τ will be the result of the rule $\widehat{y}_\tau = sign(x_\tau - c)$ where $c \in (-\infty, \infty)$. Note that the implicit assumption here is that the larger x_τ is, the more likely $y_\tau = 1$. Trivially, one can take the negative of a given candidate classifier if the opposite is true. It should be clear that any monotone transformation of x_τ will not make the predictions any more accurate. Given the sign-rule used to generate $\widehat{y}_\tau$, a monotone transformation simply scales c up or down accordingly.

The probabilities of success and failure associated with the prediction-outcome pair $\{\widehat{y}_\tau, y_\tau\}$ can be summarized by the following contingency table:

		Prediction	
		Negative	Positive
Outcome	Negative	$TN(c) = P(\widehat{y}_\tau = 0 \mid y_\tau = 0)$	$FP(c) = P(\widehat{y}_\tau = 1 \mid y_\tau = 0)$
	Positive	$FN(c) = P(\widehat{y}_\tau = 0 \mid y_\tau = 1)$	$TP(c) = P(\widehat{y}_\tau = 1 \mid y_\tau = 1)$

$TN(c)$ denotes the *true negative* rate for a given threshold c. Recall that $\widehat{y}_\tau = 0$ if $x_\tau < c$ so that $\widehat{y}_\tau$ is implicitly a function of c although it is not indicated explicitly to save on notation. Similarly $TP(c)$ denotes the *true positive* rate for a given threshold c. These are the rates of successful predictions whose counterparts are $FN(c)$ for *false negatives* and $FP(c)$ for *false positives* when the predictions are incorrect instead. Notice that by construction, $TN(c) + FP(c) = 1$ and $FN(c) + TP(c) = 1$. In the statistics literature, $TP(c)$ is sometimes called *sensitivity,* and $TN(c)$ *specificity.*

Notice that as $c \to \infty$, $TN(c) \to 0$ and $TP(c) \to 1$ whereas if $c \to -\infty$ then $TN(c) \to 1$ and $TP(c) \to 0$. Thus, choosing the threshold c is like, say, choosing how much steel to allocate between the production of forks (here $TN(c)$ say) and knives ($TP(c)$ in following the example). Allocate more steel to producing knives ($TP(c)$) –that is, choose a larger value of c– and you will produce less forks ($TN(c)$). But the better the technology (the better the classification ability), the more of both can be produced with the same amount of steel, whichever the combination. In economics, this is the familiar environment characterized by the production possibilities frontier. Jordà and Taylor (2011) use this similarity to label the set of $\{TN(c), TP(c)\}$ for all values of c as the *correct classification frontier* (CCF). In statistics it is common to display the set of $\{TP(c), FP(c)\}$ for all values of c. That curve is the well-known *receiver operating characteristics* (ROC) curve. The ROC curve is common in the biological and medical sciences for the purposes of assessing medical diagnostic procedures, although its origin is in signal detection theory (Peterson and Birdsall, 1953). Nowadays, ROC methods are well-established in statistics. Two worthwhile monographs on the subject are Pepe (2003) and Zhou, Obuchowski and McClish (2011).

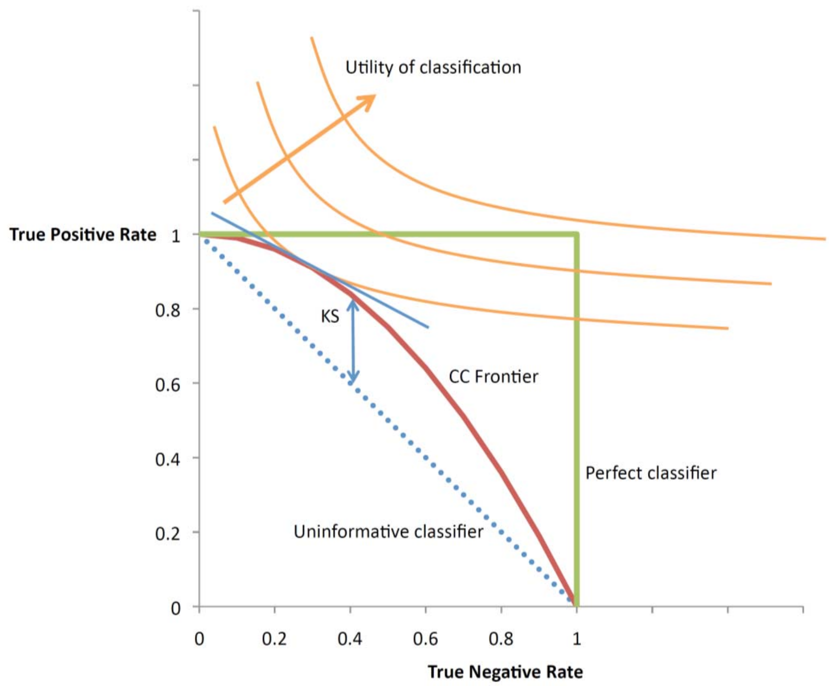
Consider our production possibilities frontier analogy one more time. The amount of input optimally allocated to producing each good will depend on the relative demand for each good. The optimal production mix is one in which technology is used to its potential and the share produced of each good (the marginal rate of transformation) is determined by the marginal rate of substitution between the goods. Peirce (1884) had a similar insight when considering the accuracy of binary predictions. His 'utility of the method' is what we might call today *expected utility* and when it refers to choosing the threshold c, it can be expressed as maximizing:

$$\max_c E(U(c)) = U_{pP}TP(c)\pi + U_{nP}\left(1 - TP(c)\right)\pi + \tag{1}$$
$$U_{pN}(1 - TN(c))(1-\pi) + U_{nN}TN(c)(1-\pi)$$

where $\pi = P(y_\tau = 1)$, that is, the unconditional probability of an event or a positive. The notation U_{xX} uses the lower case to denote the prediction and the uppercase to denote the actual, where $x \in \{p, n\}$ and $X \in \{P, N\}$. *P, p* stand for "positive" and *N, n* stand for "negative."

Before discussing what the optimal choice of threshold c is, it may be useful to display graphically the CCF against $U(c)$ to discuss the features of the problem. This is done in Figure 6. We say that a predictive technology $\widehat{y}_\tau$ is uninformative for y_τ if $TP(c) = 1 - TN(c)$, that is, one cannot improve the correct classification rate for positives without diminishing the classification rate for negatives by the exactly same amount. This is displayed in the figure as the diagonal dotted line from the point $[0, 1]$ to $[1, 0]$. Consider the other extreme, a situation in which the predictive technology $\widehat{y}_\tau$ perfectly classifies y_τ. In that case we obtain the CCF corresponding to the north-east corner of the unit-square. Typically we will be in the intermediate case between these two extremes, displayed in the figure with the concave curve. The closer to the diagonal, the worse the predictive technology.

Figure 6: The Correct Classification Frontier



Notes: The dotted diagonal line refers to an uninformative classifier. The vertical distance between the CC frontier in red and the dotted line is the Kolmogorov-Smirnov (KS) distance. The green morth-east corner of the unit square corresponds to the perfect classifier. Example indifference curves are presented in orange. The tangent of the indifference curve to the correct classification frontier denotes "optimal operating point." See text.

Overlaid on the figure is a set of indifference curves. The closer the indifference curve to the origin, the lower the utility. Since the CCF displays the highest correct classification rates for each threshold c, optimality is achieved when the CCF is tangent to the indifference curve. We have displayed an extreme case in which the policymaker has preferences weighed towards getting accurate predictions of events ($y_\tau = 1$). Clearly, when the predictive technology $\widehat{y}_\tau$ perfectly classifies y_τ, the relative preferences of one correct classification rate over the other do not matter since we have a corner solution.

A few examples help understand the set up better. Suppose the policymaker values correct classification of positives (say recessions) and negatives (expansions) equally and that he dislikes errors equally. Moreover, suppose he dislikes errors by the same amount he values correct predictions. Further, suppose that the unconditional incidence of events (recessions in the example) is $\pi = 1/2$. Indeed, lots of assumptions. Then the optimal threshold c is that point in the CCF that has slope -1 since the relative marginal rate of substitution is also -1 in that case. This point happens to maximize the distance between the CCF and the benchmark diagonal and is displayed in Figure 6 with a "KS." The reason it is labeled KS is that it corresponds to the well known Kolmogorov-Smirnov statistic

$$KS = \max_c \left| 2\left(\frac{TN(c) + TP(c)}{2} - \frac{1}{2} \right) \right|. \tag{2}$$

The KS statistic maximizes the difference between the average correct classification rates of the candidate predictive technology and the average correct classification rates of the benchmark uninformative classifier. Since in the latter case $TN(c) = 1 - TP(c)$, then that average is simply 1/2 for any value of c. The difference is scaled by 2 so that $KS \in [0, 1]$. By construction, the KS statistic also maximizes the Youden (1950) J index

$$J(c) = TP(c) - FP(c).$$

The Youden index is referred to as the "science of the method" in Peirce (1884).

Other commonly reported statistics can be seen as special cases of the set-up in (1). For example, by setting utility weights of 1 for correct calls and 0 for incorrect calls, one obtains and *accuracy rate*

$$A(c) = TP(c)\pi + TN(c)(1 - \pi)$$

whereas setting utility weights to 0 for correct calls and 1 for incorrect calls, one obtains the *error rate* instead

$$E(c) = 1 - A(c) = FN(c)\pi + FP(c)(1 - \pi).$$

Moreover, it is easy to see that

$$A(c) = \frac{1 + J(c)}{2}; \qquad E(c) = \frac{1 - J(c)}{2}.$$

In general, π will not be 1/2 and the utility weights need not be constrained the way we have described in the computation of *KS*, *A(c)* and *E(c)*. Rather, the utility weights will depend on the policymaker's trade-offs in correctly diagnosing the appropriate policy stance, versus mistakes of commission (implementing policy when it is not needed) or omission (failing to act when it is needed). Using the set-up in expression (1), the *optimal operating point* (as is known in the literature) and denoted c^* is the point where

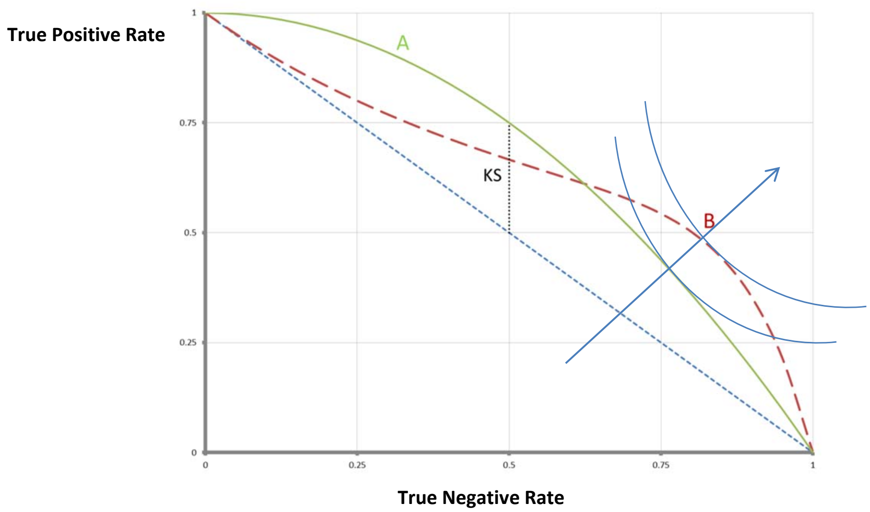
$$\left. \frac{dTP(c)}{dTN(c)} \right|_{c=c^*} = -\frac{(1-\pi)}{\pi} \frac{(U_{nN} - U_{pN})}{(U_{pP} - U_{nP})}. \tag{3}$$

That is, the point were the *marginal rate of transformation* (in keeping with our analogy to the production possibilities frontier) between $TP(c)$ and $TN(c)$ and the expected marginal rate of substitution (given by the right hand side of (3)), equal each other.

We now have a good understanding of the building blocks of the problem at hand. Importantly, the statistical and economic layers of the problem critically interact with each other. Preferences appear to play an important role. An the unconditional incidence of events, which we denoted as π, also seems to matter. How then should one choose one classifier over another? Are traditional metrics appropriate? As a way to set the stage for the next section, consider Figure 7.

Figure 7 displays two CCFs. One CCF is labeled "A" and the other "B." CCF_A clearly achieves a higher value of the KS statistic than CCF_B. On the other hand, the preferences of the policymaker, indicated by the indifference curves tangent to the CCFs, suggest that CCF_B would allow the policymaker to achieve a higher degree of utility. In this example, the policymaker cares more about correctly calling expansions or negatives ($y_\tau = 0$) than recessions. The traditional

Figure 7: Which of Two CCFs is Preferable?



Notes: The CCF labeled "A" and displayed in green has a higher KS value than the CCF labeled "B" and displayed in a dashed red line. However, preferences displayed by indifference curves in blue would suggest that classifier "B" is preferable to "A." See text.

statistical metric (here based on the KS statistic) may an insufficient measure of what option is preferable.

The basic point is self-evident by now. Consider one last example. Suppose that the unconditional incidence $\pi = 0.05$, a situation that will arise when evaluating rare events almost definitionally. A prediction technology consisting in assigning $\widehat{y}_\tau = 0 \ \forall \tau$ will have a success rate in predicting non-events of 100%. Typical measures of fit for binary models will therefore have difficulty separating the performance of one model against another. In fact, the accuracy rate defined earlier will be above 90% and the error rate below 10%. Clearly a better measure of performance is needed. The next section provides one such measure.

3.2 The Area Under the Curve: AUC

Although the KS statistic relies on a number of empirically inconvenient assumptions, it has a long tradition in statistics. At an intuitive level, the KS is a sensible measure of distance. It can be thought of as the uniform distance between the empirical distribution of $\widehat{y}_\tau$ when $y_\tau = 0$, versus the empirical distribution of $\hat{y}_\tau$ when $y_\tau = 1$. The distribution of the KS statistic, although non-standard, is well-understood. Nowadays, derivation of this distribution often relies on empirical process theory (see e.g. Shorack and Wellner, 1986). Whenever a parametric model is used to compute $\hat{y}_\tau$, say by estimating a probit or a logit using a vector of covariates, its distribution will change –an inconvenient feature.

In practice, the CCF summarizes the range of $\{TP, TN\}$ choices for a given predictive technology. The better the prediction technology, the higher the TP rate for a given TN rate or vice versa. And we know that the further from the uninformative classifier diagonal, the better. One popular summary statistic of the CCF is to calculate the area under that curve or AUC.

Consider the uninformative classifier first, a diagonal bisecting the unit square. That classifier obviously has an AUC = 1/2. The CCF for the perfect classifier hugs the north-east corner of the unit square, as we saw in Figure 6, and hence has an AUC = 1. Typical empirical CCFs will have an AUC in-between. The closer to 1, the better the classifier, the closer to 0.5, the worse.

The AUC is easy to calculate empirically using non-parametric methods. Given a sample of M observations, let M_0 indicate the number of observations for which $y_\tau = 0$, and let M_1 denote the number of observations for which $y_\tau = 1$ instead, with $M = M_0 + M_1$. Moreover, let $\{v_j\}_{j=1}^{M_0}$ denote the classifier x_τ when $y_\tau = 0$ and let $\{u_i\}_{i=1}^{M_1}$ denote the classifier x_τ when $y_\tau = 1$. Then

$$\widehat{AUC} = \frac{1}{M_0 M_1} \sum_{\forall v} \sum_{\forall u} \Upsilon\left(v, u\right) \tag{4}$$

where $\Upsilon(v, u) = 1$ if $v < u$, $\Upsilon(v, u) = 0$ if $v > u$ and $\Upsilon(v, u) = 1/2$ if $v = u$.

Under standard regularity assumptions, Hsieh and Turnbull (1996) use empirical process theory and show that

$$\sqrt{M}\left(\widehat{AUC} - P(v < u)\right) \to N(0, \sigma^2). \tag{5}$$

The formula for the variance term σ^2 is provided in that paper. Hanley and McNeil (1982) and Obuchowski (1994) provide a convenient approximation for σ^2 using the interpretation of the

AUC as a Mann-Whitney U-statistic. DeLong, DeLong and Clarke-Pearson (1988) provide a more general formula that is available in the statistical packages SAS and STATA. Jackknife and bootstrap procedures are also available (see Pepe, 2003 and references therein).

Asymptotic normality of the AUC is very convenient for inference, specially when compared to the KS statistic. Several features must be kept in mind, however. First a predictive technology A stochastically dominates a technology B if $CCF_A > CCF_B$ uniformly over some region, and $CCF_A = CCF_B$ otherwise. However, $AUC_A > AUC_B$ does not necessarily imply this condition. As Figure 7 showed, $AUC_A > AUC_B$ but $CCF_A < CCF_B$ over some region, which happened to be the relevant region to the policymaker in that example. Our applications do not display this feature so we will be content with comparing $AUCs$. For a more expansive discussion of how to deal with crossing $CCFs$ and appropriate inferential procedures for that case, the reader is referred to Jordà and Taylor (2011).

4 Recessions, Financial Crises and the Role of Credit

Credit buildups have been identified as a predictor of financial crises by Claessens, Kose and Terrones (2011); Borio, Drehmann and Tsatsaronis (2012) and Schularick and Taylor (2012) among others. However, Gadea-Rivas and Pérez-Quirós (2012), henceforth denoted GRPQ, dispute these findings. They argue that there is considerable uncertainty in determining when the recession will come. Therefore, sorting whether a recession is financial in nature or not given knowledge of when the recession strikes, provides the analyst with undue advantage and is unrealistic in a real-time policy setting. GRPQ show that credit has little predictive ability if one removes that advantage.

This section investigates these issues in more detail. The first step is to examine the basic findings in the literature regarding the role of credit in sorting recessions into "financial" or "normal." Thus, the dependent variable is defined over the sample of recession periods only, and takes the value of 1 whenever the recession is financial, 0 if it is not. That is, the frequency of the data is *event-time*. Next, the objective is to investigate the claims in GRPQ. Here the objective is to sort the data into expansions and recessions at a yearly frequency rather than in event-time. The third and final experiment, also at a yearly frequency rather than in event-time, directly examines whether financial crises can be predicted in a policy-relevant time-scale. That is, the dependent variable takes the value of 1 whenever there is a recession tied to a financial crisis, and 0 otherwise. Thus, the 0 category includes “normal” recessions *and* expansions.

The data for the analysis consists of a subset of the data in Jordà, Schularick and Taylor (2011) and Schularick and Taylor (2012), extended with data for debt-to-GDP ratios through a larger and ongoing research effort.[5] A detailed description is available in the references. Here I provide a broad description of the salient features.

The sample reaches back to 1870 and ends in 2008. Observations are available at a yearly frequency for 14 advanced economies. These countries are: Australia, Canada, Japan, Austria, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, the U.K. and the U.S. For each country data on expansions, recessions and financial crises are borrowed from Jordà, Schularick and Taylor (2011).[6] Then I consider three potential classifiers: the current account balance, expressed as a ratio to GDP, the public debt to GDP ratio, and the ratio of bank loans to GDP as a measure of private credit. In addition, data on long-term government debt interest rates (usually with a maturity of about 5 years) is used as a proxy for the debt service ratio when interacted with debt measures, whether public or private. Absent data on private debt, government debt interest rates are the best we can do. Although it is possible that the spread between private and government yields varies over the business cycle, the hope is that this variation is small relative to the level effects.

[5] This research effort is funded with a grant from the Institute of New Economic Thinking and consists of a considerable data collection and processing effort by coauthors, Moritz Schularick and Alan Taylor, and a small army of research assistants.

[6] Briefly, the classification of recessions as financial blends financial episodes identified by Reinhart and Rogoff (2009) with episodes identified by Laeven and Valencia (2008). It then identifies a recession as “financial” if a financial crisis takes place within a two year window

Sometimes data are not available from the beginning of the sample. As a result and depending on the candidate classifier, the sample varies from over 1,550 to over 1,350 country-year observations when determining whether a particular year is classified as an expansion or a recession. When the objective is to sort recessions into financial or normal recessions, the sample ranges from 204 to 160 country-recession observations. World War I and II are excluded from the sample.

4.1 Financial versus Normal Recessions

The goal of this section is to replicate the basic finding in Schularick and Taylor (2012), among others, that credit buildups during expansions predict the likelihood of financial crisis. Consider three indicators often used for this purpose: (1) the accumulated growth in the current account to GDP ratio over the expansion (Current Account); (2) the accumulated growth in bank lending as a ratio of GDP over the expansion (Private Credit); and (3) the accumulated growth of public debt as a ratio of GDP during the expansion (Public Debt). In addition, I also consider interacting (2) and (3) with the 5-year government bond interest rate to calculate an approximate measure of *burden* as in Drehmann and Juselius (this volume). I call these respectively *Private Burden* and *Public Burden*. Finally, I also consider the combination of (1)-(3), which I call *Joint* and the combination when Private Credit and Public Debt are interacted with the 5-year government bond rate. I call this variable *Joint Burden*. Notice that the frequency of the data is event-time: it is conditioned on there being a recession. Notice also that the indicators contain information prior to the beginning of the recession but not after.

When considered singly, there is no need to specify a model relating each of the indicators and the dependent variable, in this case, a dummy variable that takes the value of 1 if the recession is "financial," 0 if it is "normal." One of the features of the CCF and the AUC is that their value remains unchanged by monotone transformations of the classifier. This is a useful feature: the value of the classifier does not depend on the modeling skills of the analyst.

Although a model is not necessary to investigate classifiers one at a time, it is when more than one classifier is considered. There are many modeling options available. Here I assume that the log-odds ratio of the financial/normal recession conditional probabilities are a linear function of the classifiers so that

$$\log \frac{P\left[y_{k\tau}=0|X_{k\tau-1}\right]}{P\left[y_{k\tau}=1|X_{k\tau-1}\right]}=\beta_0+\boldsymbol{\beta}' X_{k\tau-1} \tag{6}$$

where the index k refers to the country and $X_{k\tau-1}$ refers to a vector of classifiers observed before the τ recession starts. This is a popular model for classification in statistics and with a long-standing tradition in economics, the logit model. Hastie, Tibshirani and Friedman (2009) recommend such a specification as a matter of empirical practice. Notice that expression (6) does not allow for fixed effects. The reason is that in the subsample analysis (to be discussed shortly), some of the countries did not experience a financial crisis. Therefore, including a fixed effect would leave no variability in the data to identify the effect of $X_{k\tau-1}$. Another reason to exclude fixed effects is that in a model with no classifiers, fixed effects would generate a null AUC above 0.5. Knowledge of the average recessions that are financial across countries would be informative.

Robustness checks include two modifications. First, results for the full sample and the pre- and post-World War II eras are calculated. The motivation was discussed earlier in light of Figure 4. Second, the appendix replicates the results reported in Table 1 using fixed effects estimators. This robustness check confirms that the relative ranking of the classifiers discussed below remains the same, only the AUC values attained are slightly higher, as would be expected.

Table 1: Classifying recessions into financial or normal

Classifier	AUC	SE	95% Conf. Interval	N. Obs
		(a) Full Sample		
Current Account	0.49	0.05	[0.40, 0.59]	204
Private Credit	0.61**	0.05	[0.50, 0.72]	184
Private Burden	0.61**	0.05	[0.50, 0.71]	184
Public Debt	0.52	0.05	[0.43, 0.62]	196
Public Burden	0.52	0.05	[0.43, 0.61]	194
Joint	0.64**	0.06	[0.53, 0.75]	160
Joint Burden	0.61**	0.06	[0.50, 0.72]	160
		(b) Pre-WWII Sample		
Classifier	AUC	SE	95%Conf. Interval	N. Obs
Current Account	0.49	0.06	[0.38, 0.61]	136
Private Credit	0.54	0.07	[0.42,0.67]	118
Private Burden	0.56	0.07	[0.43, 0.69]	118
Public Debt	0.53	0.06	[0.42, 0.65]	130
Public Burden	0.54	0.06	[0.43, 0.65]	128
Joint	0.62*	0.07	[0.49, 0.76]	100
Joint Burden	0.61*	0.07	[0.47, 0.74]	100
		(c) Post-WWII Sample		
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.48	0.09	[0.31, 0.65]	68
Private Credit	0.82**	0.07	[0.69, 0.95]	66
Private Burden	0.78**	0.08	[0.62, 0.93]	66
Public Debt	0.48	0.08	[0.31, 0.64]	66
Public Burden	0.54	0.08	[0.38, 0.71]	66
Joint	0.84**	0.05	[0.74, 0.95]	60
Joint Burden	0.79**	0.07	[0.64, 0.93]	60

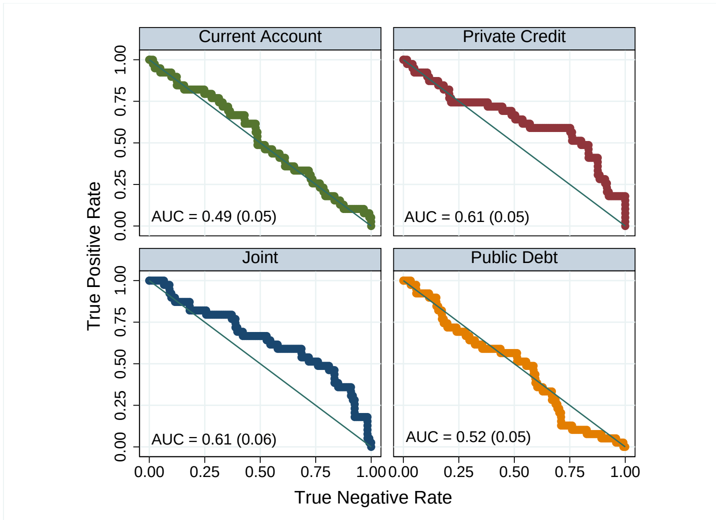
The data are in *event* time and refer to recession episodes identified by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The classification into "financial" and "normal" is explained in Jordà, Schularick and Taylor (2011). It is largely based on Reinhart and Rogoff (2009) and Laeven and Valencia (2008). The analysis precludes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. *Current Account* refers to the accumulated current account balance in the preceding expansion as a ratio to GDP. *Private Credit* refers to the accumulated growth in bank lending during the preceding expansion, as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to the accumulated growth in public debt as a ratio to GDP in the preceding expansion. *Public Burden* interacts Public Debt with the 5-year government debt interest rate. *Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate. $^{*}p < 0.10$, $^{**}p < 0.05$. See text.

Table 1 reports the results of this analysis, which by and large confirm what the literature has reported. Panel (a) in the table refers to the full sample and shows that the variables based on measures of the accumulated growth in private credit have significant (albeit a low AUC of 0.61) classification ability relative to all the others, which are not significant. When the variables are combined together, the AUC increases to 0.64, a very slight improvement.

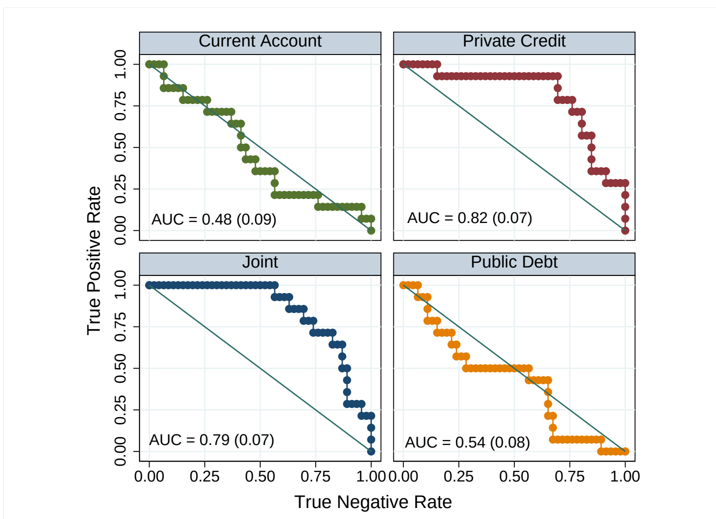
Panels (b) and (c) in Table 1 break down the sample at World War II. In the pre-WWII era, private credit remains the most relevant variable but even its classification ability is no better than a coin toss. There are some gains from combining the private and public data, with an AUC that is about 0.62 and significant. However, the post-WWII era tells a somewhat different story. Here the role of credit buildups is very clear. Private credit achieves an AUC of around 0.8, highly significant and much closer to the ideal value of 1. Meanwhile, the alternative classifiers attain very low AUCs, as we saw earlier. Using private and public data improves the AUC somewhat but the results are clearly driven by what happens with private credit rather than public debt.

As an illustration, Figure 8 displays the CCFs for each of the cases considered, that is, when variables (1)-(3) are used singly and the their combination. The top panel displays the CCF using the full sample and the bottom panel displays the CCFs using the post-WWII sample. These CCFs are direct non-parametric estimates of the combinations $\{TP(c), TN(c)\}$ calculated over different values of the threshold c. Smoother CCFs can be obtained by using parametric models, such as the binormal model (see, e.g., Pepe, 2003). Figure 8 is meant to show that CCFs are straightforward to calculate.

Figure 8: Nonparametric Estimates of the CCF



(a) Full Sample



(b) Post-WWII Sample

Notes: Each chart displays the CCF for a particular classifier along with the value of the AUC and its standard error (in parenthesis). Estimates of the AUC correspond to those reported in Table 1. The diagonal line represents the null CCF of no classification ability. The top panel based on the full sample, the bottom panel based on post-WWII data only. See text.

4.2 Expansions versus Recessions

The results of the previous section suggest that the more credit builds up during the expansion, the more probable the subsequent recession will be financial in nature. GRPQ argue that this result is of little practical relevance: Predicting when the next recession will happen is very difficult anyway. Obsessive control of credit may snuff economic growth unnecessarily. Or in the parlance of Peirce, there would be too many false positives if authorities constantly responded to credit buildups. This section examines this proposition. Moving from event-time to calendar-time, the question is whether any of the indicators exploited in the previous section would help predict whether a recession is likely happen in a given year. Instead of using the indicators measured over the expansion, since that information is unavailable a priori, I examine 5-year moving averages to smooth over cyclical fluctuations and get a sense of medium run build-ups of stress.

Table 2 reports the results of this exercise, which by and large confirm GRPQ. Using the full sample, panel (a) shows that neither private lending nor private debt (or the related "burden" measures) appear to have much classification ability, although used jointly, the AUC attains a value of 0.59. This value is relatively low, but statistically different from the coin toss null. Interestingly, the current account balance has similar classification ability, with an AUC of 0.58. Panels (b) and (c) in Table 2 breakdown the analysis by era. Panel (b) focuses on the pre-WWII sample, whereas panel (c) focuses on the post-WWII period. Unlike the previous section, the subsample analysis delivers similar results to the full sample results reported in panel (a).

Table 2: Sorting Expansions and Recessions

(a) Full Sample

Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.58^{**}	0.02	[0.54, 0.61]	1559
Private Credit	0.52	0.02	[0.48, 0.55]	1468
Private Burden	0.53^{*}	0.02	[0.50, 0.57]	1462
Public Debt	0.51	0.02	[0.47, 0.54]	1534
Public Burden	0.50	0.02	[0.47, 0.54]	1521
Joint	0.59^{**}	0.02	[0.55, 0.62]	1351
Joint Burden	0.59^{**}	0.02	[0.55, 0.62]	1351

(b) Pre-WWII Sample

Classifier	AUC	SE	95%Conf. Interval	N. Obs
Current Account	0.57^{**}	0.02	[0.52, 0.61]	744
Private Credit	0.52	0.02	[0.47,0.56]	661
Private Burden	0.52	0.02	[0.47, 0.56]	655
Public Debt	0.50	0.02	[0.45, 0.54]	727
Public Burden	0.50	0.02	[0.45, 0.54]	716
Joint	0.59^{*}	0.02	[0.54, 0.63]	579
Joint Burden	0.59^{*}	0.02	[0.54, 0.64]	579

(c) Post-WWII Sample

Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.62^{**}	0.03	[0.56, 0.68]	815
Private Credit	0.51	0.03	[0.44, 0.57]	807
Private Burden	0.51	0.03	[0.45, 0.58]	807
Public Debt	0.56^{*}	0.03	[0.49, 0.62]	805
Public Burden	0.55^{*}	0.03	[0.49, 0.62]	805
Joint	0.61^{**}	0.03	[0.55, 0.68]	772
Joint Burden	0.61^{**}	0.03	[0.54, 0.67]	772

The data are at yearly frequency. Recessions and expansions determined by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The analysis precludes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. Classifiers calculated as 5-five year moving averages. *Current Account* refers to the current account balance as a ratio to GDP. *Private Credit* refers to bank lending as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to public debt as a ratio to GDP. *Public Burden* interacts Public Debt with the 5-year government debt interest rate.*Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate. $^{*}p < 0.10$, $^{**}p < 0.05$. See text.

4.3 Detecting Financial Recessions Only

The final experiments reported in this section are an attempt to reconcile the results discussed in sections 4.1 and 4.2. Can we discriminate recessions enveloped in financial distress from any other event, be it a typical recession of a period of expansion? The answer is reported in Table 3.

Table 3: Financial Recessions against the Rest

		(a) Full Sample		
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.59^{**}	0.03	[0.54, 0.64]	1559
Private Credit	0.60^{**}	0.03	[0.54, 0.66]	1468
Private Burden	0.59^{*}	0.03	[0.53, 0.65]	1462
Public Debt	0.52	0.03	[0.47, 0.58]	1534
Public Burden	0.52	0.03	[0.47, 0.58]	1521
Joint	0.67^{**}	0.03	[0.61, 0.72]	1351
Joint Burden	0.61^{**}	0.03	[0.55, 0.67]	1351
		(b) Pre-WWII Sample		
Classifier	AUC	SE	95%Conf. Interval	N. Obs
Current Account	0.57^{**}	0.03	[0.51, 0.62]	744
Private Credit	0.61^{**}	0.03	[0.55, 0.67]	661
Private Burden	0.62^{*}	0.03	[0.56, 0.68]	655
Public Debt	0.53	0.03	[0.46, 0.59]	727
Public Burden	0.52	0.03	[0.46, 0.59]	716
Joint	0.67^{**}	0.03	[0.60, 0.73]	579
Joint Burden	0.66^{**}	0.03	[0.60, 0.73]	579
		(c) Post-WWII Sample		
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.70^{**}	0.05	[0.61, 0.80]	815
Private Credit	0.78^{**}	0.06	[0.66, 0.90]	807
Private Burden	0.79^{*}	0.06	[0.67, 0.92]	807
Public Debt	0.57	0.08	[0.42, 0.72]	805
Public Burden	0.60	0.08	[0.45, 0.75]	805
Joint	0.80^{**}	0.06	[0.69, 0.92]	772
Joint Burden	0.79^{**}	0.07	[0.66, 0.92]	772

The data are at yearly frequency. Recessions and expansions determined by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The analysis precludes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. Classifiers calculated as 5-five year moving averages. *Current Account* refers to the current account balance as a ratio to GDP. *Private Credit* refers to bank lending as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to public debt as a ratio to GDP. *Public Burden* interacts Public Debt with the 5-year government debt interest rate. *Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate. $^{*}p < 0.10$, $^{**}p < 0.05$. See text.

Consider panel (a) in the table first. Here the role of private lending and the current account appear to have resurrected somewhat, with AUCs of about 0.60 and statistically significant. Using the classifiers jointly, the AUC improves even more to a respectable 0.67 even though public debt on its own appears to be no better than the toss of a coin. The subsample analysis is especially revealing here. Whereas results using the pre-WWII sample and reported in panel (b) of Table 3, are very similar to the full sample results in panel (a), the story is quite different in the post-WWII sample. Panel (c) of Table 3 clearly suggests that bank lending can be a very useful indicator, with an AUC of about 0.8, closer to the ideal value of 1. Notice that combining information does nothing to improve classification ability since the AUC remains at about 0.80.

5 Conclusion

Evaluating competing statistical models of events rarely observed is difficult. Because events are observed infrequently, one requires long samples to gain enough variability to identify the trigger factors. In addition, because the unconditional probabilities of observing an event are low, traditional metrics fail to select the model that provides the best economic advantage. This paper presents some solutions in the context of predicting financial crises. The novelty of these solutions is that they bring statistical as well as economic principles in unified fashion.

In good times, private credit is viewed as subsidiary to explaining fluctuations in macroeconomic aggregates. Despite an extensive collection of theoretical models in which credit plays a role in amplifying fluctuations of the cycle, the literature has found scant support for this role empirically. No doubt this reflects, at least in part, the difficulties in isolating the independent effect of credit channels from more traditional and well understood monetary channels.

The elementary analysis of the business cycle provided here reinforces typical findings in the literature. Growth in private credit does not appear to foretell the next recession much better than random chance. How much public debt increases relative to GDP turns out to be a just as poor an indicator although somewhat improved since WWII.

These results collide with a more recent literature on the role of credit in financial crises. In fact, when one conditions on a recession taking place, private credit emerges as an important sorting variable of when a recession is likely to turn into a financial crisis. To a large extent, this result is driven by the post-WWII sample and the era of financialization.

The pieces start to fall into place. In the post-World War II experience the Bretton-Woods era of stringent capital controls emerges as an oasis of financial calm. Whether it was due to stronger regulation, fiscal rebalancing following the war effort, or entirely different reasons, we need to understand better why the Bretton Woods period stands alone in the history of the last 140 years.

The end of Bretton-Woods saw a variety of new trends develop, from governments carrying higher debt burdens to a veritable explosion of credit at an international level. And in recent times, real-estate lending has taken over as the primary purpose of bank lending. Credit may not explain the run-of-the mill recessions but it can explain when recessions turn into financial crises. Complementary evidence from Jordà, Schularick and Taylor (2012) indicates that once the recession breaks out, regardless of its cause, higher levels of private credit accumulation during the expansion make the recovery slower.

If the goal is to single out periods of turmoil from all others, the role of credit comes to the fore once again. And once again its relevance seems mostly driven by the experience of the post-WWII era. We do not yet understand the role that credit plays in the economy well, but we understand well enough that monitoring credit closely appears to be a worthwhile enterprise.

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Appendix

Financial Crises versus Normal Recessions: Fixed Effects Estimates

This section replicates the results in Table 1, section 4.1, but allowing for fixed effects.

Table A1: Classifying recessions into financial or normal: Fixed Effects Estimates

(a) Full Sample

Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.62^{**}	0.05	[0.54, 0.71]	204
Private Credit	0.66^{**}	0.05	[0.57, 0.76]	184
Private Burden	0.66^{**}	0.05	[0.57, 0.75]	184
Public Debt	0.66^{**}	0.04	[0.57, 0.74]	196
Public Burden	0.65^{**}	0.04	[0.57, 0.74]	194
Joint	0.71^{**}	0.05	[0.62, 0.75]	160
Joint Burden	0.70^{**}	0.05	[0.60, 0.81]	160

(b) Pre-WWII Sample

Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.63^{**}	0.05	[0.52, 0.73]	136
Private Credit	0.65^{**}	0.06	[0.54,0.76]	118
Private Burden	0.65^{**}	0.06	[0.54, 0.76]	118
Public Debt	0.67^{**}	0.05	[0.56, 0.78]	130
Public Burden	0.66^{**}	0.05	[0.55, 0.77]	128
Joint	0.70^{**}	0.06	[0.58, 0.82]	97
Joint Burden	0.69^{**}	0.06	[0.57, 0.81]	97

(c) Post-WWII Sample

Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.72^{**}	0.09	[0.55, 0.89]	49
Private Credit	0.92^{**}	0.06	[0.81, 1]	47
Private Burden	0.81^{**}	0.08	[0.65, 0.96]	47
Public Debt	0.72^{**}	0.09	[0.55, 0.89]	47
Public Burden	0.74^{**}	0.09	[0.56, 0.91]	47
Joint	0.99^{**}	0.01	[0.97, 1]	43
Joint Burden	0.89^{**}	0.05	[0.79, 1]	43

The data are in *event* time and refer to recession episodes identified by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The classification into "financial" and "normal" is explained in Jordà, Schularick and Taylor (2011). It is largely based on Reinhart and Rogoff (2009) and Laeven and Valencia (2008). The analysis precludes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. *Current Account* refers to the accumulated current account balance in the preceding expansion as a ratio to GDP. *Private Credit* refers to the accumulated growth in bank lending during the preceding expansion, as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to the accumulated growth in public debt as a ratio to GDP in the preceding expansion. *Public Burden* interacts Public Debt with the 5-year government debt interest rate. *Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate. $^{*}p < 0.10$, $^{**}p < 0.05$. See text.

Expansions v. Recessions: Fixed Effects Estimates

This section replicates the results in Table 2, section 4.2, but allowing for fixed effects.

Table A2: Sorting Expansions and Recessions: Fixed Effects Estimates

(a) Full Sample				
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.60^{**}	0.02	[0.57, 0.64]	1559
Private Credit	0.56^{**}	0.02	[0.53, 0.60]	1468
Private Burden	0.56^{**}	0.02	[0.52, 0.60]	1462
Public Debt	0.57^{**}	0.02	[0.54, 0.61]	1534
Public Burden	0.58^{**}	0.02	[0.54, 0.61]	1521
Joint	0.61^{**}	0.02	[0.57, 0.64]	1351
Joint Burden	0.61^{**}	0.02	[0.57, 0.64]	1351
(b) Pre-WWII Sample				
Classifier	AUC	SE	95%Conf. Interval	N. Obs
Current Account	0.64^{**}	0.02	[0.60, 0.68]	744
Private Credit	0.62^{**}	0.02	[0.58, 0.67]	661
Private Burden	0.62^{**}	0.02	[0.58, 0.67]	655
Public Debt	0.60^{**}	0.02	[0.56, 0.64]	727
Public Burden	0.60^{**}	0.02	[0.56, 0.64]	716
Joint	0.68^{**}	0.02	[0.63, 0.72]	579
Joint Burden	0.68^{**}	0.02	[0.63, 0.72]	579
(c) Post-WWII Sample				
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.66^{**}	0.03	[0.61, 0.72]	815
Private Credit	0.60^{**}	0.03	[0.55, 0.66]	807
Private Burden	0.61^{**}	0.03	[0.56, 0.67]	807
Public Debt	0.64^{*}	0.03	[0.59, 0.70]	805
Public Burden	0.64^{*}	0.03	[0.59, 0.70]	805
Joint	0.67^{**}	0.03	[0.61, 0.72]	772
Joint Burden	0.67^{**}	0.03	[0.61, 0.72]	772

The data are at yearly frequency. Recessions and expansions determined by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The analysis includes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. Classifiers calculated as 5-five year moving averages. *Current Account* refers to the current account balance as a ratio to GDP. *Private Credit* refers to bank lending as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to public debt as a ratio to GDP. *Public Burden* interacts Public Debt with the 5-year government debt interest rate. *Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate.
$^{*}p < 0.10$, $^{**}p < 0.05$. See text.

Detecting Financial Recessions Only: Fixed Effects Estimates

This section replicates the results in Table 3, section 4.3, but allowing for fixed effects.

Table A3: Classifying Financial Recessions Only: Fixed Effects Estimates

(a) Full Sample				
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.70^{**}	0.03	[0.65, 0.75]	1559
Private Credit	0.74^{**}	0.02	[0.69, 0.79]	1468
Private Burden	0.71^{**}	0.03	[0.66, 0.76]	1462
Public Debt	0.68^{**}	0.03	[0.62, 0.73]	1534
Public Burden	0.68^{**}	0.03	[0.63, 0.73]	1521
Joint	0.77^{**}	0.02	[0.72, 0.82]	1351
Joint Burden	0.74^{**}	0.03	[0.69, 0.79]	1351
(b) Pre-WWII Sample				
Classifier	AUC	SE	95%Conf. Interval	N. Obs
Current Account	0.73^{**}	0.03	[0.67, 0.79]	744
Private Credit	0.77^{**}	0.03	[0.71, 0.82]	661
Private Burden	0.75^{**}	0.03	[0.69, 0.81]	655
Public Debt	0.71^{**}	0.03	[0.65, 0.77]	727
Public Burden	0.71^{**}	0.03	[0.65, 0.77]	716
Joint	0.79^{**}	0.03	[0.73, 0.85]	561
Joint Burden	0.79^{**}	0.03	[0.73, 0.84]	561
(c) Post-WWII Sample				
Classifier	AUC	SE	95% Conf. Interval	N. Obs
Current Account	0.74^{**}	0.05	[0.64, 0.84]	582
Private Credit	0.85^{**}	0.05	[0.75, 0.96]	574
Private Burden	0.82^{**}	0.06	[0.70, 0.93]	574
Public Debt	0.66^{*}	0.07	[0.52, 0.79]	588
Public Burden	0.68^{*}	0.06	[0.55, 0.80]	588
Joint	0.86^{**}	0.05	[0.76, 0.96]	560
Joint Burden	0.83^{**}	0.06	[0.72, 0.94]	560

The data are at yearly frequency. Recessions and expansions determined by Jordà, Schularick and Taylor (2011) using the Bry and Boschan (1971) algorithm. The analysis includes fixed effects as explained in the text. The appendix replicates the table using fixed effects. The number of observations varies due to differences in data availability across classifiers. Classifiers calculated as 5-five year moving averages. *Current Account* refers to the current account balance as a ratio to GDP. *Private Credit* refers to bank lending as a ratio to GDP. *Private Burden* interacts *Private Credit* with the 5-year government bond rate. *Public Debt* refers to public debt as a ratio to GDP. *Public Burden* interacts Public Debt with the 5-year government debt interest rate. *Joint* combines the previous classifiers in a logit model and *Joint Burden* also combines variables but with Private Credit and Public Debt interacted with the 5-year government bond interest rate. $^{*}p < 0.10$, $^{**}p < 0.05$. See text.