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Tracking Financial Fragility

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Tracking Financial Fragility*

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Abstract

In constructing an indicator of financial fragility, the choice of which filter (or transformation) to apply to the data series that appear to trend in sample is often considered a technicality, but in fact turns out to matter a great deal. The fundamental assumption about the likely nature of observed trends in the data, for example, the ratio of credit to GDP, has direct effects on the measured gap or vulnerability. We discuss shortcomings of the most common filters used in the literature and policy circle, and propose a fairly simple and intuitive alternative - the local level filter. To the extent that validation will always be a challenge when the number of observed financial crises (in the US) is small, we conduct a simulation exercise to make the case. We also conduct a cross country analysis to show how qualitatively different the estimated credit gaps were as of 2017, and hence their policy implications in 29 countries. Finally, we construct an indicator of financial fragility for the US economy based on the view that systemic fragility stems mainly from high level of debts (among households and corporations) associated with high valuations for collateral assets (real estate, stocks). An indicator based on the local level filter signals elevated financial fragility in the US financial system currently, whereas the HP filter and the ten-year moving average provide much more benign readings.

*The views expressed in this paper are those of the authors only, and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System. The authors are responsible for any errors or omissions. Paolo Giordani is grateful to the Cleveland Fed for hospitality while working at this project.

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1 Introduction

Since the 2008 global financial crisis, efforts to strengthen financial stability have advanced to a new level as lawmakers and policy makers realized the sizable welfare lost due to a deep and widespread financial crisis. Debate about whether using monetary policy to lean against the build-up of financial excesses has received prominent attention by central bankers and researchers. The availability and the effectiveness of macroprudential tools to address financial imbalances have been studied carefully by policymakers and regulators. At the heart of safeguarding financial stability is to obtain accurate and relevant information about the fragility of the financial system in real time, before any discussion about whether and what policy action(s) is warranted. Central banks, financial stability bodies (for example, Office of Financial Research in the U.S., European Systemic Risk Board in the euro area, Financial Stability Board in G20), and banking supervisors have devoted a significant amount of resources to financial stability monitoring. While there are differences across surveillance models and financial stability indicators, there is broad consensus about a core group of variables for monitoring financial stability: the financial system is more fragile when high levels of debt (high leverage) are associate with high valuations in the assets that serve as collateral.

In fact, there is a well established literature in finance and economics that views the expansion and contraction of credit and collateral values to be of first-order importance in understanding macroeconomic developments in general, and financial crises in particular. For example, John Stuart Mill, writing after the financial crisis of 1826, clearly connected it to the preceeding credit expansion. Ludwig von Mises anticipated the economic crash of 1929 and attributed it squarely to the great credit expansion of the previous decades. Irving Fisher (1933) concluded that all the worst economic crises in US history had followed periods of rapid credit expansion. Hyman Minsky and Charles Kindlebergher, both writing in the 70s, placed credit expansion at the heart of financial crises. By that time, however, the US economy was on a thirty (soon to be forty) year streak of smooth and seemingly uneventful increase in the ratio of total private credit to GDP, starting from a very low level after World War II. Observers noted that economy-wide credit busts seemed to belong to the realm of economic history and developing countries. At the same time, modern economic theory was developed largely without any significant role for credit aggregates and financial prices (Schularick and Taylor (2012)).

However, the 2008 global financial crisis reignited a large body of research on the role of credit and collateral value in financial crises and in macroeconomic fluctuations more generally (see for example, Reinhart and Rogoff (2009), Schularick and Taylor (2012), Drehmann and Juselius (2013), Mian and Sufi (2016), and Brunnermeier and Schnabel (2016)). These studies, mostly empirical, have confirmed that protracted credit expansion and collateral appreciation (housing, commercial property, stocks, corporate bonds) are reliable precursors to major financial crises. While incorporating these features into macroeconomic models for policy analysis is largely work-in-progress, a key challenge has to do with measuring financial fragility accurately in real time.

In the financial crisis literature, while different models use different variables to predict financial crises, the input variables can be grouped into two strands: credit aggregates and asset prices. In the policy circle, heat maps to monitor financial vulnerability have been developed by many central banks and public institutions that have financial stability mandates, and the number of indicators under surveillance can be quite large. Nevertheless, as informed by historical experiences and research, most of the variables being monitored are measures of leverage across various sectors, and measures of prices or valuations across various asset classes. Although identifying the relevant variables for financial stability monitoring may seem rather straightforward, interpreting the data to make financial stability assessment is not. This is because in order to judge whether the observed level of leverage or valuation is high, a reference point of "equilibrium" or "sustainable" level is needed. The primary focus of this paper is to understand the assumptions and implications behind common methods of extracting these unobservable "equilibrium" of long-term values from the data.

In the US, the key data series used in financial stability monitoring show at least some mean reversion but with very high persistence when taking a century-long historical perspective, and generally display a pronounced upward trend after the Second World War. We argue that given the observable statistical features of the data, both the sample size and the algorithms used to filter a time series into a sustainable trend and a mean-reverting deviation (gap) have a first-order impact on the measurement of financial fragility. Under plausible data generating process, we further show that two financial fragility indicators using the same input variables but different filtering techniques provide qualitatively very different results about the fragility of the US financial system, and hence have very different policy implications.

The rest of the paper is organized as the followings. Section 2 lays the foundation for understanding how seemingly standard and non-conspicuous choices in filtering or transforming the data have strong effects on measuring financial fragility. It is particularly important for the users of financial stability indicators to understand the assumptions and parameters underlying the models when the results are highly dependent on those assumptions and choices of parameters. In Section 2.3 we propose a rather simple method to filter the data that is well known in econometric and statistics, but has not been used in the financial crisis literature. Although validating the filtering method is infeasible due to data limitation (to be discussed more fully in the section), our preferred filter is shown to have better statistical properties under plausible data generating processes for the financial series that are widely used in the financial stability literature. In Section 3 we construct two financial fragility indicators using standard variables to measure leverage and asset valuations to show qualitatively different results when the data is filtered differently. Using the proposed filter, our indicator signals elevated financial fragility in the US financial system currently, whereas indicators using the HP filter or a ten year moving average provide more benign readings. Section 4 concludes.

2 Choice of sample and filter are crucial for highly persistent series

In financial stability monitoring, the discussion of which variables are useful measures of increased financial fragility has received a lot of attention (see for example, Schularick and Taylor (2012) and Kiley (2018)). What has been less studied is that the sample period and the method used to filter the data (HP filter, moving average, differences ...) can have a first-order impact on measuring financial fragility in real time.

2.1 Trending ratios and filters: the HP filter and moving average filters

High quality quarterly data for many US macroeconomic series becomes available between 1947 and 1975. Using post-war data, most credit ratios show a clear upward trend, a feature shared by many other countries. While Alan Taylor has described this worldwide phenomenon as "the great leveraging," other economists refer to it as "financial deepening." Although either "leveraging" or "deepening" can be used to describe the same data, the interpretations are qualitatively different. Similarly, the implications based on different choices of filtering the data are also different.

It is quite clear that the financial sector and the total level of private debt are at their highest level (Taylor 2014). The widespread availability of mortgage credit to households is the most distinguishing feature of the great leveraging period. Faced with trending series and used to working with stationary series, supervisory authorities and academics, starting with several influential papers by the Bank for International Settlements (BIS), have opted to pass trending series through the HP filter, with a large penalization parameter ($\lambda = 400000$) to reflect the notion that financial cycles have much longer duration than business cycles (Drehmann and Juselius, 2013). Other alternative methods include detrending the data using a moving average, and computing the growth rates over say, the preceeding five year period. Given the prevalence of using the HP filter for financial stability monitoring and financial regulation, including the determination of the counter cyclical capital buffer for banking organizations under the Basel Capital Requirements, we first take a close look at using the HP filter for financial stability analysis. We identify three significant concerns about using the HP filter for financial stability purposes.

First limitation of the HP filter: (partial) mean reversion needs a long sample. The notion that financial cycles have very long durations has been fairly well established. Drehmann and Juselius (2013) estimated that the average duration of a financial cycle is about four time longer than that of the business cycle, using data since 1980. Their choice of setting $\lambda = 400000$ in the HP filter is intended to isolate frequencies shorter than fourty years. Hence, a sample of a few decades is expected to contain at most two to three *complete* financial cycles, and possibly not even one. It is therefore more constructive to think of a sample of 50 years of data containing anywhere between zero to three observations of the phenomenon being studied, rather than (misleadingly) thinking in terms of 200 quarterly data points. As a result, any attempt to infer a trend from such limited data is problematic (and perhaps even more so when the results are conditioning on a point estimate of the trend). For example, it is quite possible that we are currently close to the peak of a financial cycle, and that adding 10 to 20 years of data might reveal a significant amount of mean reversion in credit aggregates.

History provides several cases of credit series that showed very long trends but eventually mean reverted (at least to a considerable degree). In the U.S., the non-financial business sector was more leveraged (as a share of GDP) at the pre-Great Depression peak than ever before or after, notwithstanding decades of trending growth after 1945. In Australia, non-financial business debt-to-GDP peaked in the early 1890s after three decades of growth, followed by a protracted decline lasting another three decades; and it has not been until recently that the debt-to-GDP in Australia surpassed its 1890 peak, driven by the rapid growth in household credit. In Japan, after the bursting of the real estate bubble almost thirty years ago, property prices there currently are at about 40% of their 1990 peak. Of course, sizable mean reversion is anything but certain. More importantly, history does tell us that any trend that may be apparent in a few decades of data is estimated with a large degree of uncertainty. We should always be mindful of the gap, that is, the common practice of examining the deviations from a fitted trend is acceptable if and only if the trend can be estimated with an acceptable level of uncertainty.

Figure 1 shows total bank loans as a share of GDP in the US from 1880 to 2012. Although this series may not be an accurate representation of total private credit in the US without counting the shadow banking system and corporate debt instruments, it does show decades long patterns of credit fluctuations that cannot be captured by a short sample. The very long duration of these financial cycles makes applying off-the-shelf statistical procedures to credit aggregates inappropriate.

Second limitation of the HP filter: it implies all "financial deepening", and no "leveraging". Our modern economy is more financialized than before. Assuming the change in finance is structural and permanent, the ratio of credit-to-gdp would assume a higher mean in the current environment than in the 1980s and 1990s. From a purely time-series perspective, if the goal is to forecast the credit-to-gdp ratio, it would call for the class of models of mean-adjustment or trend fitting (see Giordani et al., 2011 for a review of applicable statistical models). However, if the goal is to measure financial fragility in real time, the HP filter assumes "financial deepening" with certainty; that is, the higher (trend) level of credit can be sustained without any increases in financial fragility.

We argue that a more reasonable, and also more conservative interpretation

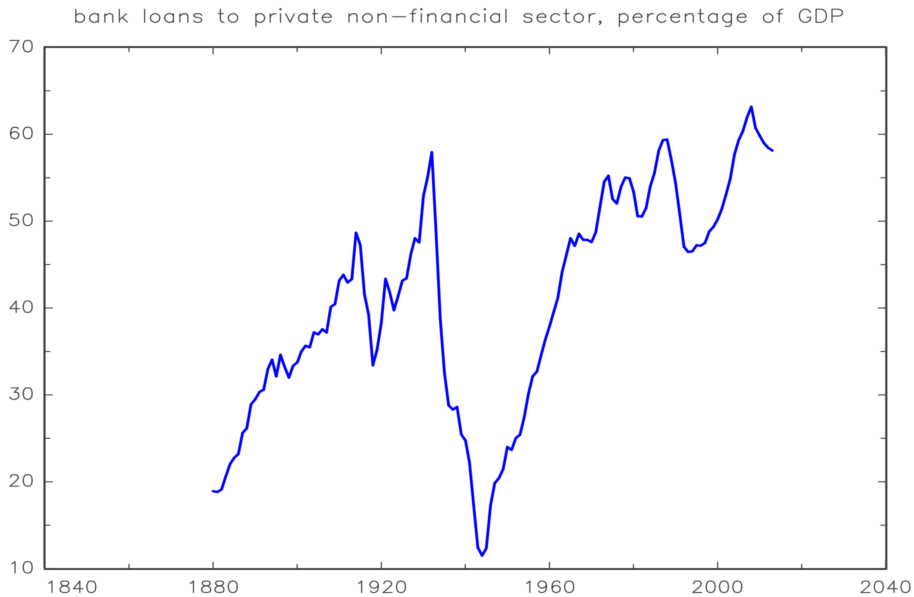

Figure 1: Total bank loans to private non-financial sector as a percentage of GDP, 1880-2013. Source: Jorda-Schularick-Taylor Macrohistory Database.

of the data in real time is to let the increase in the (trend) credit-to-gdp ratio consist of at least some increase in financial leverage, implying that the fragility of the financial system has risen. Note that in the financial stability literature, it is common practice to filter the data prior to their inclusion in, say, a logit regression of financial crisis; this would automatically default to the 100% "financial deepening" interpretation of the data. Ideally, one should endogenize the filtering method and calibration, and extend the sample to include both periods of very low and very high credit-to-gdp ratio. It is arguably not a coincidence that in the thirty years of low leverage between 1944 and 1973, there was not a single financial crisis in any of the 17 countries surveyed by Schularick and Taylor (2012). This suggests that financial deepening is intertwined with fragility.

Third limitation of the HP filter: it is an implausible time series model for credit-to-gdp and the other variables in our indicator. The filter proposed by Hodrick and Prescott (1981) is written as the solution to

$$\min_{\mu_{1:T}} \sum_{t=1}^{T} \left(y_t - \mu_t\right)^2 + \lambda \left(\Delta\mu_t - \Delta\mu_{t-1}\right)^2,$$

where λ is a parameter which penalizes changes in the growth rates of μ_t but, importantly, not the growth rate $\Delta\mu_t$ itself. This is asymptotically equivalent to the state space model first proposed by Akaike (1980)

$$\begin{aligned} y_t &= \mu_t + \epsilon_t,\ \epsilon_t \sim NID(0, \sigma_\epsilon^2) \\ \mu_t &= \mu_{t-1} + \beta_{t-1} \\ \beta_t &= \beta_{t-1} + \xi_t,\ \xi_t \sim NID(0, \sigma_\xi^2), \end{aligned}$$

with $\lambda = \sigma_\epsilon^2/\sigma_\xi^2$. The model is designed to capture a smoothly changing trend, and in continuous time becomes itself equivalent to a cubic spline (Wecker and Ansley, 1983).

The most common use of such filters in statistics and engineering is to eliminate the independent and identically distriburted (iid) noise term ϵ_t and keep μ_t for subsequent analysis. In contrast, for typical economic application, economists are usually less interested in the trend μ_t and focus on keeping the ϵ_t for subsequent analysis. Notice that in doing so, economists usually do not estimate λ using any standard method (which is also a departure from common statistical practices), because any estimation naturally would attempt to make ϵ_t an uncorrelated process. Instead, in typical economic application, a high value of λ is (artificially) imposed on the data to produce a highly autocorrelated ϵ_t. Proponents motivated this procedure as an alternative to a frequency domain filter, where $\lambda = 1600(400000)$ tends to cut out frequencies corresponding to periods above 10 (40) years.

There is an important shortcoming: attempt to cut out frequencies corresponding to periods above 40 years when the sample size is also only around 40 years would result in large estimation errors. This sizable estimation error is, however, completely ignored by conditioning on a single path of the (highly uncertain) trend. In other words, the results are interpreted as if the trend is certain when in fact it is estimated very imprecisely, even by assuming the underlying statistical model is correct. As a result, the HP filter will be very unstable in real time, as commonly observed, and very sensitive to extensions of the sample (see for example, Edge and Meisenzahi (2011)).

Another major shortcoming of using the HP filter in financial stability monitoring is that the key variables of interest, including the ratio of credit-to-gdp and the ratio of stock price-to-earnings, cannot be expected to trend indefinitely, at least not strongly. The HP filter does not penalize the steepness of the trend, and projects the trend observed at the end of the sample to continue in the future. (Using $\lambda = 400000$ often delivers a fairly straight line.) This does not look like a reasonable assumption for the ratio of credit-to-gdp or almost any variables used in the financial stability literature. Even if the trend in the credit-to-gdp ratio observed in the data was due to a structural change that will not mean revert, it seems highly unlikely that the credit-to-gdp ratio will double again in the next thirty years. Regardless, such strong underlying assumptions would need to be made as explicit and transparent as possible, since they can have a very large impact on the results and cannot be left entirely to the data to decide. In practice, there is simply not enough data to ascertain the underlying trend.

Moving averages and growth rates. Taylor (2014) and Schularick and Taylor (2012) use the five year growth rate of credit (or 5 lags of the growth rate) in their research on what lead to financial crises. This works reasonably well in their context because they condition their analysis on having observed a financial crisis. Their conclusion is that financial crises were preceded by strong growth in credit. However, in order to to build an index of financial fragility or early warning indicator, using credit growth works less well here: strong growth in credit aggregates could also start from low levels of leverage, but this kind of credit growth from low leverage is arguably benign or perhaps even healthy, such as the case after the Second World War between 1945 and 1975 in the US and around the world. Hence, the indicator using credit growth will provide too many false positives. Even in the case of true positives, eliminating any information on the levels (by differencing or HP filtering) would lead to an indicator that does not distinguish between mild and severe fragility, or the intensity of the vulnerability, which would be particularly valuable to policy makers for risk management purposes. Moreover, measuring credit growth over a horizon of three, five or even ten years is essentially at the business cycle frequency, which does not seem to fit well with the notion that financial cycles can have very long duration.

Figure 2 shows the effect of the (two-sided) HP filter and of a ten year moving average filter (used by Aikman et al. 2015, and highly correlated with a five year difference) on the ratio of corporate credit to GDP (the local level filter shown in the third row will be introduced in the next section). Even though this ratio is currently as high as in early 2008, the HP filter credit gap is close to zero. Using the 10 year moving average provides a similar conclusion. Notice also how values of the gap comparable to 2008 were reached in the mid 70s and late 80s, both periods of high credit growth from lower levels.

2.2 The local level filter for fragility and early warning indicators

2.3 The local level filter

The HP filter was originally designed for series, like GDP, which can be naturally thought of as a trending variable, possibly with a time-varying trend. On the other hand, financial ratios such as the ratio of credit-to-gdp, or the ratio of price-to-earnings, cannot be trending variables indefinitely. We therefore choose to model financial ratios as slowly reverting around a possibly time-varying centrality value. Hence, a filter that allows for increased financialization or higher asset prices to have taken place in-sample, but would not extrapolate in-sample growth out-of-sample would be of desirable properties. Note that the HP filter smoothes growth rates: if we used it to make a prediction on μ_t it would extrapolate the in-sample growth in credit ratios to continue in the years ahead and, given a $\lambda = 400000$, it would do so with confidence.

The class of models that explicitly models the time series process of the shifting trend can be found in Giordani et al. (2011). Within this class of

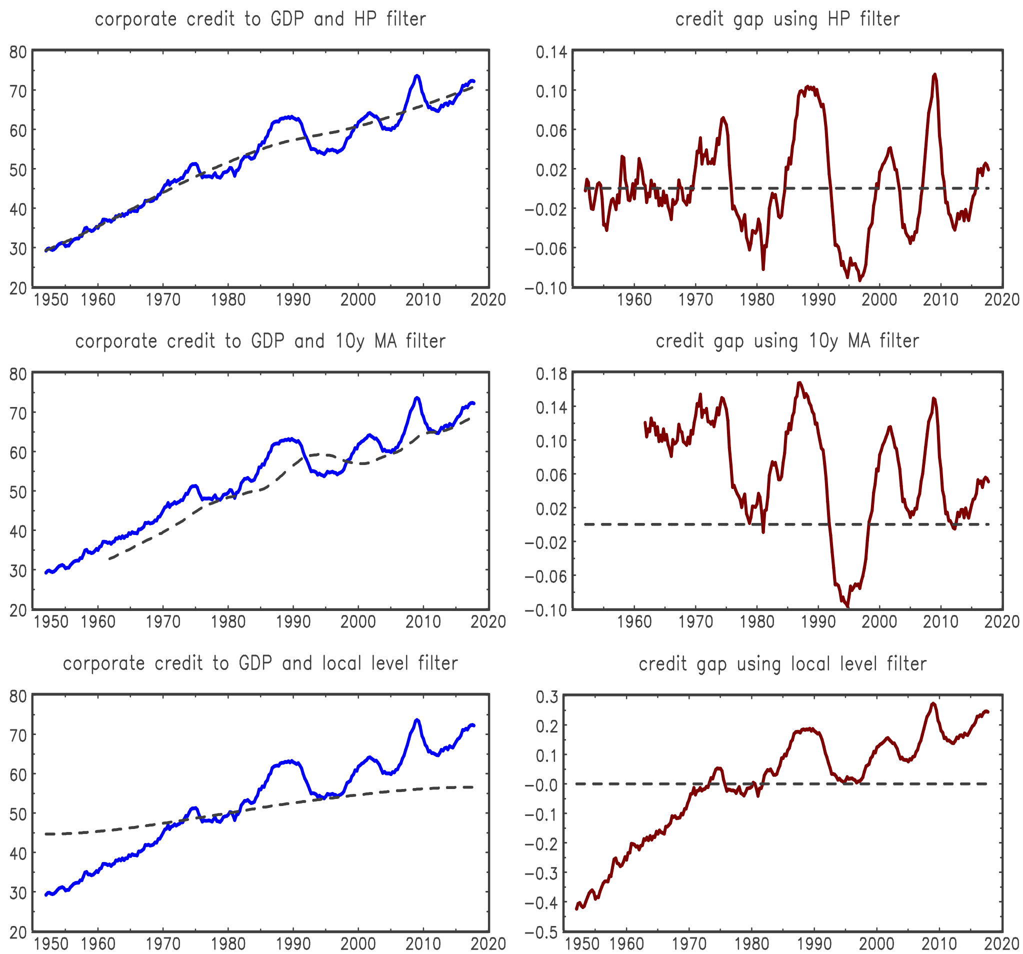

Figure 2: Corporate credit to corporate gross value added, 1951q1 2018q1. HP filter with $\lambda = 400000$, ten year moving average filter, and local level filter with equivalent sample size of thirty years.

models, we choose a rather straight forward approach that is both transparent and easy to implement: the local level model for the trend. The local level model has a long tradition in statistics and econometrics, and it has a good track record of forecasting performance for economic time series. The local level model specifies the local mean μ_t as a driftless random walk. Specifically, we propose to set μ_t to solve the minimization problem

$$\min_{\mu_{1:T}} \sum_{t=1}^{T} (y_t - \mu_t)^2 + \lambda_{LL}(\Delta\mu_t)^2,$$

where λ_{LL} would penalize changes in the local mean (local level) μ_t. This is asymptotically equivalent to the local level model (see Harrison and West, 1989):

$$\begin{aligned} y_t &= \mu_t + \epsilon_t,\ \epsilon_t \sim NID(0, \sigma_\epsilon^2) \\ \mu_t &= \mu_{t-1} + u_t \sim NID(0, \sigma_u^2), \end{aligned}$$

where $\lambda_{LL} = \sigma_\epsilon^2/\sigma_u^2$. The local level model is therefore nothing but a driftless Gaussian random walk with an additional measurement error. The one-sided version of the filter is a simple exponential moving average, so that

$$\begin{aligned} \widetilde{\mu}_1 &= y_1 \\ \widetilde{\mu}_t &= \delta\widetilde{\mu}_{t-1} + (1-\delta)y_t, \end{aligned}$$

where aymptotically $\lambda_{LL} = \delta/(1-\delta)^2$. For $\lambda_{LL} \to \infty$, μ_t becomes a constant (the sample mean). At the last available observation y_T, the local level filter is therefore asymptotically equivalent to a simple exponential moving average.

To set λ_{LL}, we propose thinking in terms of either the half-life of the process or the equivalent sample size. Having set H, a desired half-life for the process, expressed in number of periods (e.g. 40 for 10 years of quarterly data), we solve for λ_{LL} (or, equivalently, δ), to satisfy $0.5 = \delta^H$. The equivalent sample size can be thought of as the solution to $\sum_{i=0}^{\infty} \delta_{t-i}$, which is $\delta/(1-\delta)$. The equivalent sample size is roughly 1.5 times the half-life. For example, setting the equivalent sample size at thirty years can be thought of as approximately using thirty years of data to estimate μ_t.

Users of the indicator, including policy makers, are free to set a half life or equivalent sample size of their choosing, and then compute the corresponding indicators under their chosen parameters. In suggesting a reasonable range of parameters, we should be mindful of the (very) long financial cycles. An equivalent sample size of thirty years seems like a good starting point, based on the historical experience of financial cycles usually lasting a few decades. A shorter horizon, say ten years, would capture mostly fluctuations at business cycle frequencies. We propose computing the indicator at several different values of equivalent sample size in order to have a good understanding of the role of this key assumption, as well as how sensitive to this parameter the results might be. While the trends computed with an equivalent sample size of twenty or thirty years are much flatter than their HP filter counterparts, this merely reflects the fact that relatively little evidence of any actual drifts can be obtained from the data. On the other hand, in the case of the HP filter, a drift is assumed and there is no prior constraint on its size.

2.4 Performance of filters using simulated data

To the extent that validating the choice of filter using historical data with only a few observable crises is statistically infeasible, in this section, we simulate time series for a synthetic credit (or valuation) ratio under a variety of assumptions about the degree of "financial deepening" to inform our choice. As such, we can make judgment about how to filter the data based on our own criteria or our own prior about the data generating process. The takeaway is that the HP filter underperforms the local level filter under nearly all plausible (data generating) scenarios.

We simulate data for a variable y_t (for example, a credit ratio or a valuation ratio) constructed as the sum of two components: a credit gap x_t, modeled as an AR(1) process, and a possibly time-varying local mean μ_t, which is intepreted as the local equilibrium level:

$$
\begin{aligned}
y_t &= \mu_t + x_t \\
x_t &= \rho x_{t-1} + \epsilon_t,\ \epsilon_t \sim N(0, \sigma_\epsilon^2(1-\rho^2)).
\end{aligned}
$$

Here ρ is set to match a desired half-life, reflecting a view on the duration of financial cycles; the variance of ϵ_t is set so that the unconditional variance of x_t is one. For our purpuses, we interpret every move in μ_t as a shift in the long-term forecast of the variable y_t which does not have any effect on financial fragility (for example, no effect on the probability and severity of financial crises). This is, implicitly, the interpretation made in the literature whenever series are filtered or transformed prior to their inclusion in an indicator such as ours. If a priori we thought that increased leverage, even if permanent, did increase fragility with some positive probability, we would want to make the filter less aggressive.

The simulation is structured as follows. The persistence (of the financial cycle) parameter ρ can take three values, corresponding to a half-life of three, ten, and twenty years. The process for the mean μ_t can take one of seven forms: a) constant, b) a "medium" break of size one (the unconditional standard deviation of x_t is also one) in the middle of the sample, so that μ is zero for the first twenty years and one for the second twenty years, c) a "large" break of size two, d) a "medium" linear trend in μ_t to half sample, which increases linearly from zero to one during the first twenty years, and then stays at one, e) a "large" linear trend to half sample, so μ_t rises linearly from one to two and then stays at two, f) a "medium" trend rising linearly throughout the sample from 0 to 1, and g) a "large" trend rising linearly throughout the sample from 0 to 2.

The sample size is fourty years (160 quarterly observations). The local level filter is compared to the HP filter and to a ten year moving average filter. The

HP filter has $\lambda = 400000$ and the local level filter has an equivalent sample size of twenty years (roughly a half-life of thirteen years). We compute the root-mean-square error (RMSE) in estimating x_T, where T is the last observation in sample. Table 1 and Table 2 provide the ratio of the RMSE of the HP filter and the 10 year moving average, over the RMSE of the local level filter, respectively. Numbers smaller than one (in bold) are cases where the local level filter underperforms.

Table 1 shows that the HP filter performs relatively poorly in all cases except when there is a *large* linear trend in the data throughout the sample. Note that if the trend took place only during the first half of the sample, the HP filter performs poorly. Table 2 shows that the ten year moving average does a slightly better job than the HP filter, and beats the local level filter in two cases: a large break and a large continuous trend. Results from this excercise suggest that to model a variable like the credit ratio (e.g. credit-to-GDP) or the valuation ratio (e.g. price-earnings ratio), unless shifts in mean dominate the volatility around the mean, the local level filter has lower RMSE.

	H.L. 3y	H.L. 10y	H.L. 20y
constant μ	1.89	1.44	1.25
medium break	1.57	1.32	1.17
large break	1.17	1.11	1.02
medium trend to half sample	1.82	1.43	1.24
large trend to half sample	1.62	1.35	1.19
medium trend	1.47	1.27	1.13
large trend	**0.99**	**0.99**	**0.92**

Table 1. Ratio of RMSE of HP filter over local level filter.

	H.L. 3y	H.L. 10y	H.L. 20y
constant μ	1.55	1.27	1.14
medium break	1.28	1.16	1.07
large break	**0.92**	**0.95**	**0.91**
medium trend to half sample	1.48	1.24	1.13
large trend to half sample	1.32	1.17	1.08
medium trend	1.23	1.13	1.05
large trend	**0.87**	**0.91**	**0.88**

Table 2. Ratio of RMSE of 10 year MA over local level filter.

2.5 Cross countries comparison

So far, we have been using either US data or simulated data to illustrate the qualitatively different conclusions when the credit series is detrended using the HP filter versus the Local Level filter. To further make the case that the choice of filter matters in understanding the level of credit boom and policy implications, this section conducts a comparison of the two filters using international data.

We obtain private debt and GDP data for all countries available in the International Monetary Fund Global Debt Database. However, for many countries in this database, the annual data does not go back very far. As of 2017, only 29 countries have at least 20 years of data; 37 countries have at least 10 years of data. We conduct the analysis in this section using 29 countries that have at least 20 years of data, which are listed in Table 3.

United States	Sweden	Czech Republic
United Kingdom	Canada	Slovak Republic
Austria	Japan	Estonia
Belgium	Finland	Latvia
Denmark	Greece	Hungary
France	Malta	Lithuania
Germany	Portugal	Slovenia
Italy	Spain	Poland
Netherlands	Cyprus	Romania
Norway	Bulgaria	

Table 3: countries included in cross country comparison

For each country, private debt includes all debt instruments to households and nonfinancial corporations. The log of credit-to-GDP for each country is filtered by both the HP filter with lambda equals 1600 (which corresponds to 400,000 for quarterly data) and the local level filter with equivalent sample size of 10 years. (The local level filter with equivalent sample size of 30 years provides similar results, which are available upon request.) Hence, for each country, two credit-to-GDP trends (HP and LL) are estimated, which can be used to compute two corresponding credit-to-GDP gaps.

As of 2017, the HP-filter credit-to-GDP gap was negative for 25 out of the 29 countries, implying that the level of private debt in these countries was relatively benign (below trend) compared to the size of the economy; only 4 countries had a positive HP-filter credit-to-GDP gap which indicates above-trend private debt levels. On the other hand, the LL-filter credit-to-GDP gap was positive in 23 out of 29 countries in 2017, pointing to above-trend level of private debt in these countries; only 6 countries had private debt below the trend estimated using the local level filter. Figure 3 charts the two credit gap estimates for the 29 countries, ordered from the lowest credit gap on the left to the highest credit gap on the right.

Figure 3 provides a snap shot of the two credit gaps across 29 countries, without putting them into the context of time-series variations in credit gaps within each country. To put the 2017 estimated credit gaps into historical perspective, it is useful to standardize each country's credit gap using its own history. After standardizing each country's 2017 credit gap using a scale of -1 for the lowest credit gap and +1 for the highest credit gap by country by filter, Figure 4 shows the standardized credit gap, by HP and LL filters, for the 29 countries, again ordered from low gap to high gap from left to right. Note that for 12 out of 29 countries, their 2017 HP-filter credit-to-GDP gaps were at each country's record low level. On the other hand, 6 countries had 2017 LL-filter

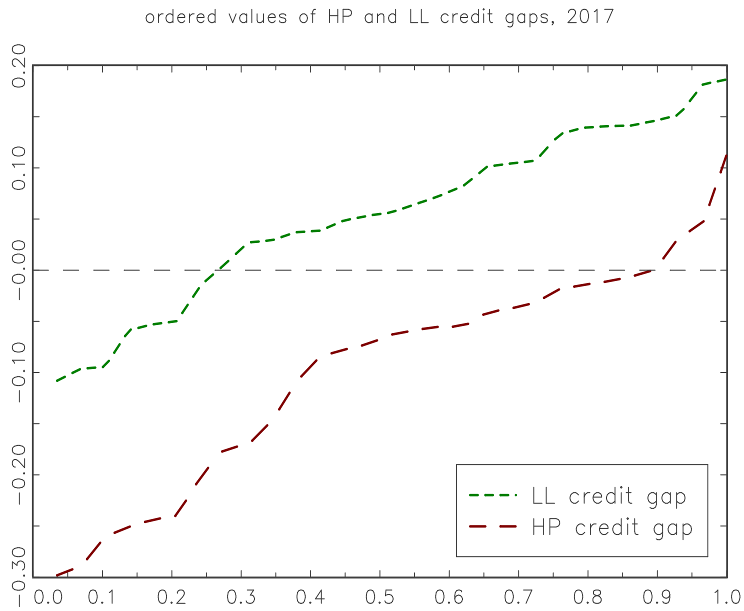

Figure 3: Local level filter with ten years equivalent sample size. Credit gaps based on de-trended logs of credit-to-gdp.

credit-gap at the highest point based on the countries' own experience, and a large number of countries were near their highest LL-filter-credit gap.

Figure 5 shows the intuition underlying the above results by depicting the simple cross country average credit-to-GDP ratio, and the two trends estimated using the HP filter and the LL filter. The estimated LL-trend is much flatter than the estimated HP-trend.

It is clear that detrending the credit-to-GDP series using different methods leads to different conclusions that have different policy implications. While validating the choice of filter may be challenging for a variety of reasons, including the number of financial crises ever observed and the binary classification of crises often found in the literature, we shall conduct validation exercise in future research. For now, users of credit-to-GDP gap should at least be cognizant about how the credit gap is estimated and its robustness.

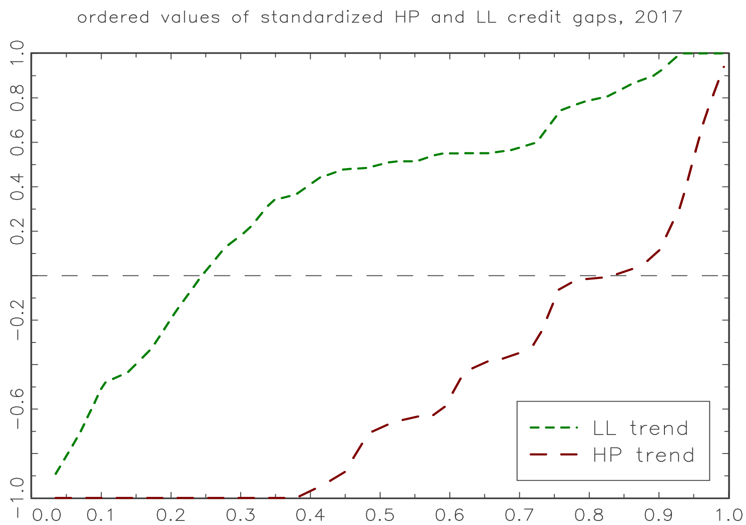

Figure 4: Local level filter with ten years equivalent sample size. Credit gaps based on de-trended logs of credit-to-gdp and then standardized to the [-1 +1] interval for each country and each filter.

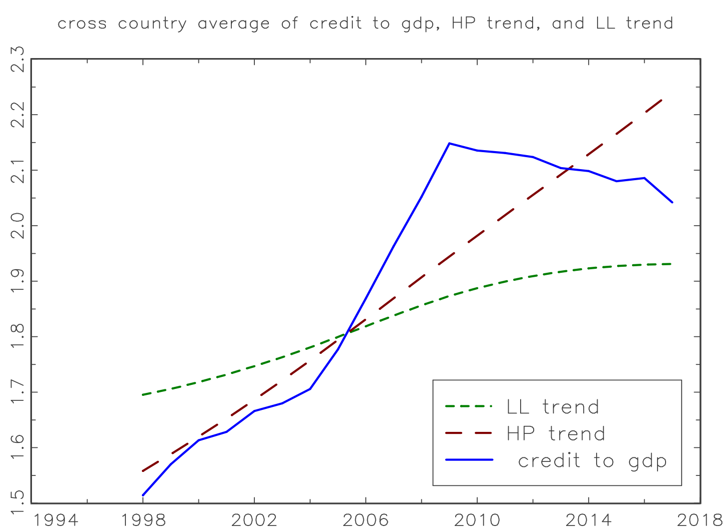

Figure 5: The figure plots credit-to-gdp with its HP and LL (10 years ESS) trends for the sample 1998-2017. All series are unweighted averages across 29 countries.

3 Two financial fragility indicators

3.1 Tracking financial fragility

In the context of financial stability monitoring, we prefer to measure "fragility" to ”instability” or ”vulnerability” in the financial system due to its more precise definition. Following Taleb et al (2012), we view the financial system as becoming more fragile if it suffers greater welfare loss by a given stressor (deviation from the status quo), and if the loss increases more than linearly with the size of the stressor. A fragile financial system is (very) likely to show severe distress at some future point in time, but the timing of such occurrence is (highly) imprecise. A considerable share of the literature on early warning indicators has investigated the timing ability of different indicators using a binary classification of financial crises. Our own view of financial fragility leads us to deemphasize the role of the indicator for timing financial crises, because we view financial crises as nonlinear and non-Gaussian phenomena, making precise timing difficult. While a fragile financial system is (very) likely to experience severe stress at some point, the triggering event(s) may not appear for many years; nor the effects of the same triggering events would necessary tip the system into crisis were it not in a fragile state. Hence, our view of "fragility" does not suggest that accurate forecasts of financial crises years in advance are possible. What we can say with more confidence is that a higher level of fragility is more vulnerable to a given triggering event due to nonlinearity. Moreover, financial crises can vary from mild to severe, a distinction that is lost by a binary classification. It may be useful to draw a sharper distinction between the probability of a crisis and the losses given a crisis; it is the latter that our proposed fragility indicator would like to emphasize.

3.2 Variables included in the indicators

To make the point about the effects of the choice of filter more concrete, we use US data on a set of well-known financial stability variables to build a financial fragility indicator using the local level filter. We compare this indicator to an otherwise similar indicator based on the same raw data but using the HP filter or moving average filter.

Following existing literature, we view financial fragility stemming in large part from high levels of debt and overvalued assets (collateral). Higher debt increases leverage and hence the risk of failure. With higher debt, both household and business have higher debt service burden, and the burden increases with the level of interest rates and credit spreads. The risk of failure also increases when the collateral value is high and above its fundamental value. High valuations of collateral increase the likelihood of a sharp correction; the tendency of asset prices to overshoot and fire sale externalities compound the fragility. Upon falling collateral values, the involuntary deleveraging of leveraged borrowers to meet margin requirement, to meet minimum capital standard, or to strategic default could lead to a negative feedback loop and a vicious cycle. Hence, including both credit aggregates and asset prices to construct our fragility indicator would seem like a good starting point.

An important contribution of this paper is about the methodology, or how the filtering of the data has first-order effect on measuring financial fragility. We therefore focus on a small group of core variables to make our point, as well as to enhance the interpretability of our indicator. As discussed in Section 2, various underlying assumptions in filtering, as related to the intepretation of rising credit ratios as "financial deepening" or "leveraging" have large quantitative and qualitative effects on the signal provided by the indicator. It would be constructuve to make the composition of the index and the procedures used in filtering and aggregating the data as transparent as possible.

3.2.1 A two-variable financial fragility indicator

To begin, we construct a financial fragility indicator using only two financial variables, one measuring credit or leverage and the other measuring asset prices. This results in a simple indicator, useful to highlight the methodological point of the choice of filter. The indicator is built from two financial ratios:

1. Private credit to GDP ratio.

The aggregate volume of total credit to the private nonfinancial sector appears as a key indicator in virtually all the literature on financial cycles and crises. The credit-to-gdp ratio is also the single best performing indicator according to Drehmann and Juselius (2013), and it has a formal role in determining the counter cyclical capital buffer in banking organizations under the Basel III capital framework. This measure includes all private credit by nonfinancial institutions: mortgage debt, consumer debt, and corporate debt (from both financial insitutions and credit instruments). The credit-to-gdp ratio has trended up strongly after WWII, with a modest dip in the early 90s and a more pronounced retracement after 2008. The recent decline is largely due to mortgage defaults when the home ownership rate dropped from a peak of 69% to about 63%.

2. House price to rent ratio.

The housing market is at the core of what Alan Taylor calls the "great leveraging". Compared to corporate debt and non-mortgage consumer debt, the growth in mortgage credit after the Second World War was unprecedented in both the United States and abroad. In the U.S., home owernship rate increased rapidly amid various government policies promoting the American Dream of owning a house. At the same time, house price appreciation has accelerated (see Jorda et al. (2014)). Since house purchases are often made with considerable leverage, households have become more sensitive to increases in interest rates and declines in house valuations. To measure house prices, we use the monthly CoreLogic House Price Index based on repeated sales. To gauge the valuation in housing, we compare the house prices to rental price in residental housing, assuming that similar housing services can be obtained by either buying or renting. The rental series of primary residence that is used by the BLS to compute the monthly CPI index is used to construct the house price to rent ratio.

3.2.2 A five-variable financial fragility indicator

To add some richness, we also construct a five variable fragility indicator by decomposing the total private credit into three components, as well as adding another asset price measure[1,2]:

1. Mortgage credit to GDP ratio.

About three quarters of total household debts are mortgages, which are used to finance the purchase of a house. Mortgage expansion often plays a major role in credit booms in the economy, and hence warrant monitoring separately. It can easily lead to a housing boom and inflated asset prices. Compounding the vulnerabiity is the high degree of leverage in mortgage finance, so house prices do not need to fall a lot to wipe out the housing equity.

2. Consumer credit to GDP ratio.

Consumer credit currently accounts for roughly one quarter of total household debt, and seems to pose a smaller threat to financial stability than mortgage debt or corporate debt. It is nonetheless worth monitoring due to its shorter duration and higher interest rates. Mian and Sufi (2016) find that an increase in the household debt to GDP ratio in the medium term is contemporaneously associated with a consumption boom and a trade deficit, and predicts lower subsequent GDP growth. Their analysis does not distinguish between mortgage and consumer credit.

3. Corporate credit to GDP ratio.

Corporate credit is currently about equal in size to household credit in the US. However, while household credit is mostly funded by financial institutions, approximately two thirds of corporate credit are from credit instruments, mostly commercial paper and corporate bonds. While the level of total corporate credit is quite cyclical, its composition is rather stable through the business cycle.

4. Stock price to earnings ratio.

[1] Note that the balance sheet of banks and shadow banks (including their large derivative positions) is not included, even though it is quite clear that the financial sector was highly leveraged prior to the great financial crisis. Also, the relentless emphasis by post-crisis regulations to enhace resiliency of the banking sector is akin to severely constraining bank leverage. For our purposes, since our object of interest is financial crisis rather than banking crisis, though they are related, banking sector leverage would be somewhat narrow at the macroeconomic level (D'Hulster, 2009). This is particularly true for the U.S. which has a large and well developed capital market. Furthermore, international research on more bank centric economies has not found banking sector leverage to be a very informative early warning indicator (e.g. Guimaraes et al. 2013), perhaps due to measurement problems of using backward-looking accounting values of assets and liabilities to compute leverage.

[2] Our index (as many others) treats the US as a closed economy, even though the largest contractions in US GDP have all coincided with very sharp reductions in exports and large drops in the ratio of exports to GDP. The largest shares of exports to GDP in US history were reached during World War I. A nearly 50% reduction in exports from 1920 to 1921 coincided with GDP dropping 17% for the year. Exports dropped by 60% in real terms (80% in nominal terms) from 1929 to 1932, and the share of exports to GDP was cut by 40%. Real exports dropped by 18% from 2008 to 2009.

Historically, severe financial crises have often been associated with sharp drops in stock prices. Brunnermeir and Schnabel (2016) find that deep stock market losses have larger negative economic impacts when the previous market expasions were associated with leveraging. While the stock price to earnings ratio is widely used to gauge stock market valuation, there are several variations in computing this ratio. We use Shiller's Cyclically Adjusted Price Earnings ratio (CAPE) to construct our indicator. Using the price-to-book ratio, or the market capitalization-to-GDP ratio provide similar results.

5. House price to rent ratio.

This is the same ratio used in the two-variable indicator.

Whether using two variables or five variables, we attempt no formal comparative test of performance because we simply do not have enough data to validate the indicator with confidence (see earlier discussion). Interpreting our results narrowly, we show the effects of the choice of filter on the signal provided by the fragility indicator. Interpreting them more broadly, the signal from our local level filter fragility indicator warrants policymakers' attention.

3.3 Choice of starting date, standardization, and weighting

3.3.1 Pre-WWII data.

Figures (6, 7, 8) show a version of the indicator with a small set of variables (for which data is available) using annual US data from 1890 to 1928. There are a number of challenges when the data goes back that far, including very large movements in GDP and CPI during World War I (when exports skyrocketed) and the data on private credit includes only bank loans; data on rent was not available then so we use nominal house prices for illustration.

The exercise is nonetheless instructive. Using local level filter, a very simple indicator of financial fragility shows that fragility had been building up before the onset of the great depression. However, if we filter the data using the HP filter or the 10-year moving average, no signs of financial fragility could be detected.

3.3.2 Starting date: 1975.

We chose to include data going back to 1975, which is longer than some early warning indicators. For example, Aikman et al. 2015 use data from 1990 "rather than something longer because of the major structural changes that have occurred in the financial system in recent decades ... ". Shortening the sample due to concerns about structural changes is not uncommon in economic studies. There is also little doubt that the financial landscape in the U.S. today looks different than in the 1970s. For example, the banking system (which features prominently in Aikman et al.) has become more concentrated, more leveraged, and underwent several rounds of deregulation including the Gramm-Leach-Bliley

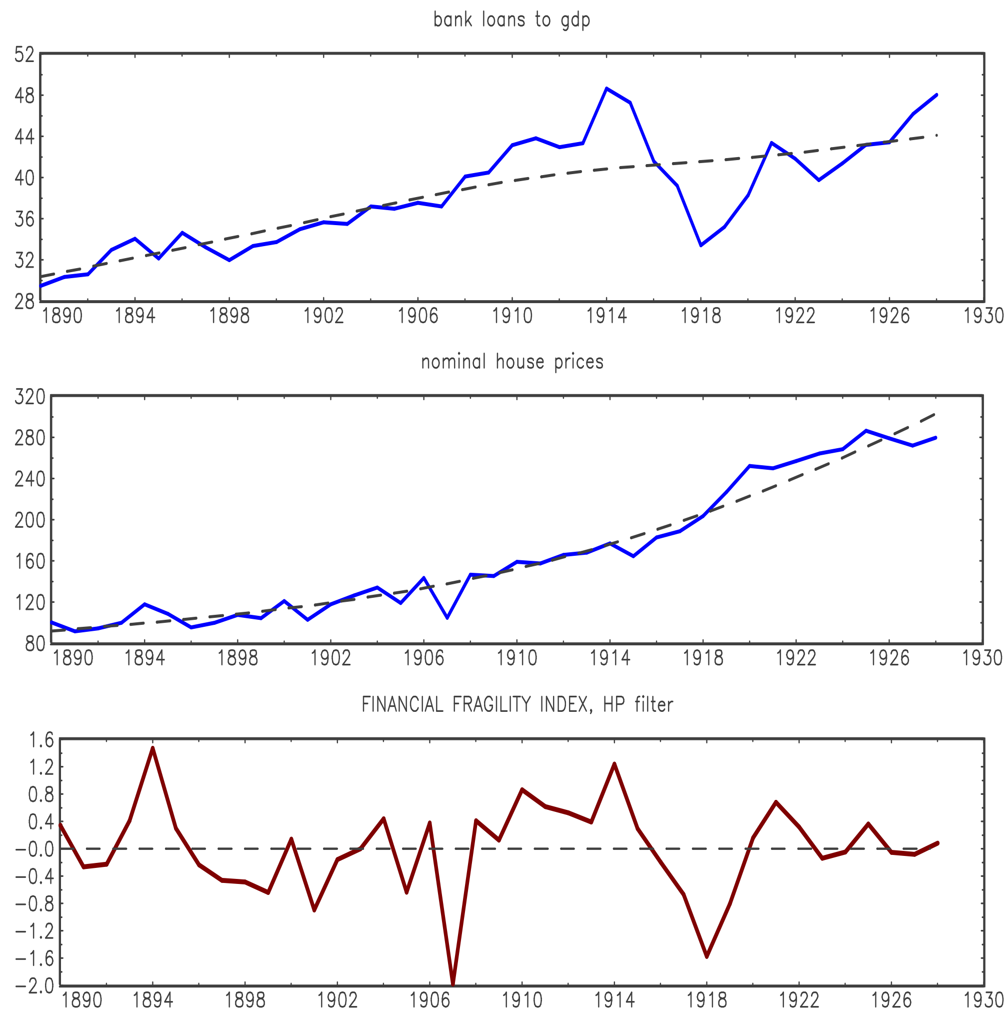

Figure 6: A financial fragility indicator using data from 1890 to 1928. HP filter.

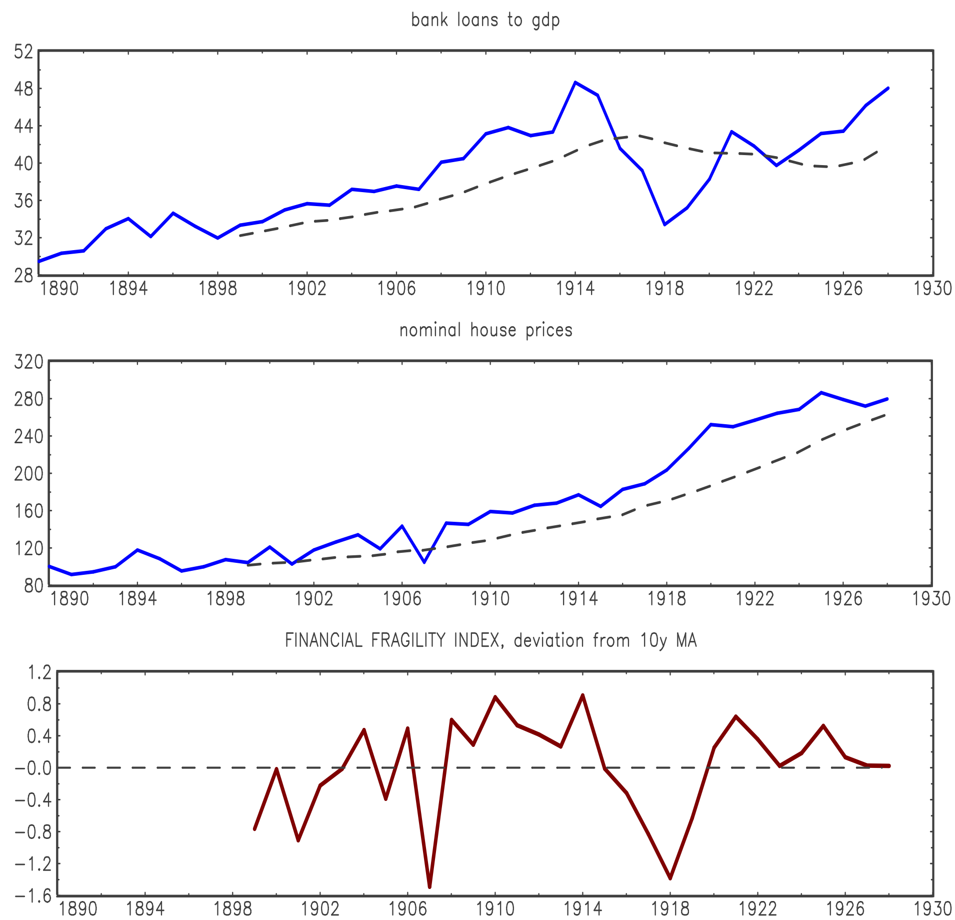

Figure 7: A financial fragility indicator using data from 1890 to 1928. 10 year MA filter.

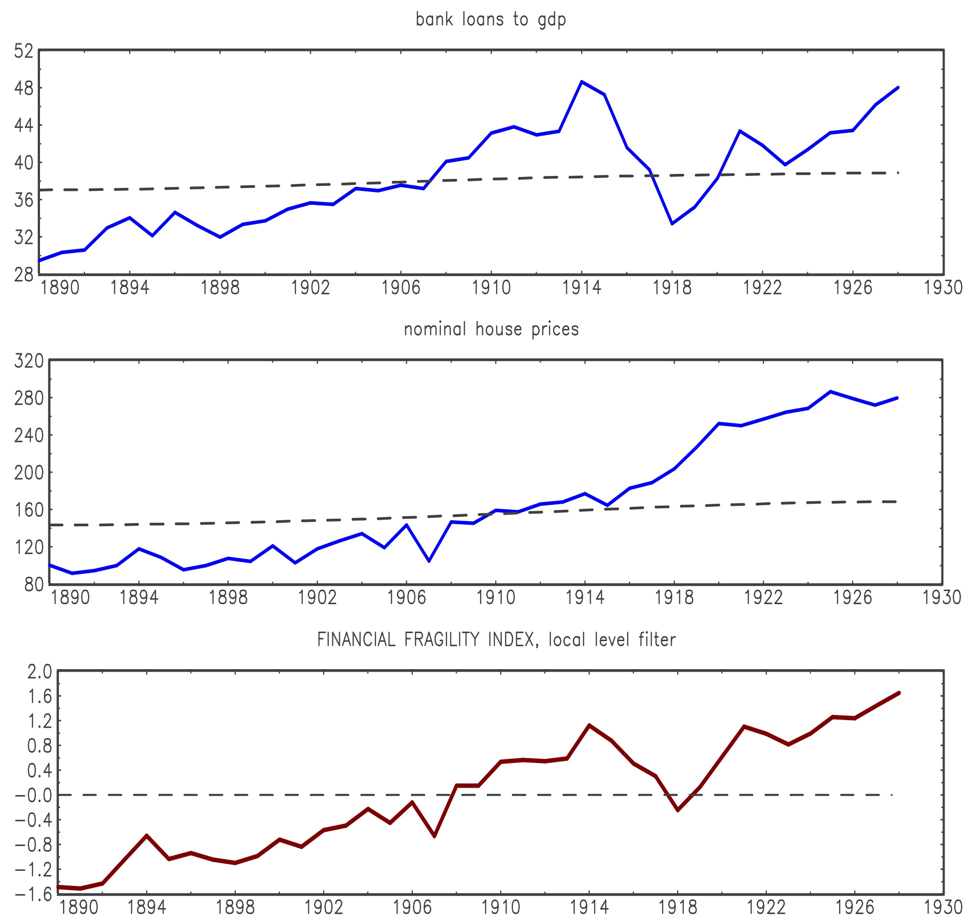

Figure 8: A financial fragility indicator using data from 1890 to 1928. Local level filter with equivalent sample size 30 years.

Financial Modernization Act of 1999 that repealed the Glass-Steagall Act separating commercial banking and investment banking. Nevertheless, this seems less relevant for our fragility indicator when our focus is on credit aggregates and financial prices. Admittedly, by starting the sample in 1975 rather than 1945, we excluded a period when the US economy was quite underleveraged by modern standard. The most obvious "break" in the post-war sample, also noted in Jorda et al. (2014), was the increase in home ownership and the associated mortgage debt. But by 1975, the home ownership rate had already reached 64.5%, higher than in 2016 (63%), and the credit-to-gdp ratio had almost doubled from its low value in 1945. It is noteworthy that the rapid increase in mortgage debt and home ownership between 1945 and 1975 did not lead to very large movements in house prices; whereas during the 2001-2006 housing boom, home ownership rate barely moved (from 68% to 69%). If "financial deepening" refers to more individuals having access to credit, this kind of deepening was mostly completed by 1975; if that is the case, one can view the increase in leverage since then had contributed to financial fragility. However, this does not necessarily imply that the level of leverage was optimal in 1975: the additional leverage may have increased efficiency on average (although it may be hard to make the case empirically (Jorda et al. (2014))), but at the cost of increased frequency and severity of financial crises. In constructing the financial fragility indicator, we normalize its value at 1975q1 to zero.

Variable standardization and aggregation method. Since the weights assigned to each variable are not estimated, indicators such as ours need to decide on a procedure to standardize each variable. The most common approach is to divide each de-meaned variable by its standard deviation. We prefer to use the mean absolute deviation, which is more stable for non-Gaussian variables, but the differences are neglegible in our case.[3] Various aggregation methods are discussed in Aikman et al. (2015). We use a simple and transparent weighted average, where the default is that all variables have equal weight. These weights can be a matter of policy discussion.

One-sided or two-sided filters. The HP filter and the local level filter have a one-sided and a two-sided version (moving averages are one-sided). The one-sided versions use only observations available in real-time to infer μ_t, whereas the two-sided versions use the entire sample. The one-sided and two-sided estimates are often referred to as "filtering" and "smoothing" in statistics. The filtering problem solves $E(\mu_t|y_{1:t})$, the smoothing problem solves $E(\mu_t|y_{1:T})$. In general the two are the same only at the end of the sample ($t = T$). When performing a pseudo out-of-sample evaluation, one-sided filters are appropriate. Moreover, in the early warning literature (and in the credit gap measure which is used to set counter cyclical capital buffer in Basel III) it has become standard to use the one-sided HP filter, even when the intention

[3] Yet another approach is to map each variable to the unit line by inverting the cdf, as in Aikman et al. (2015).

is to show the value of an indicator in relation to its past values. This choice is unusual in a statistical sense, since the most statistically efficient use of the data when comparing two points in the sample is to condition on all available information. For example, imagine that instead of the HP filter we wanted to plot a time series together with its sample mean. If the context suggests that we should choose the full sample mean (as standard), which is a two-sided filter, rather than the running one-sided mean, we should also show two-sided HP and local level filters.

Filtering method and parameter. Our preferred filter is the local level. This leaves one parameter for the user to set, which is the half-life of changes in the time varying mean of each variable (or the equivalent sample size used in estimating the mean). A small number, like 5 or 10 years of equivalent sample size, extracts movements at business cycle frequencies and tends to produce a mean reverting indicator. While it might be useful to illustrate how credit and asset prices move at business cycle frequencies, it is less useful to understand if financial fragility is building at lower frequencies. To the extent that financial fragility builds up slowly over time, financial cycles can span several business cycle, perhaps twenty to fifty years. This was indeed the intention of Drehmann and Juselius (2013) in setting $\lambda = 400000$ rather than the custumary 1600, but unfortunately the HP filter does not "penalize" the trend and therefore in practice does not respect this intention. In this paper, we use an equivalent sample size of thirty years, and fifty years.

Results: Two-variables fragility indicator. Figure 9 shows the financial fragility indicator constructed from two variables, private credit-to-gdp ratio and house price-to-rent ratio, using the HP filter. The private credit-to-gdp ratio is currently below the trend, and the house price-to-rent ratio is currently at the trend, when each trend is obtained using the HP filter. As such, the financial fragility indicator using the HP filter is currently below trend, suggesting somewhat low fragility in the financial system.

Figure 10 shows the two-variables fragility indicator when the trend is computed using the 10-year moving average. Currently, the private credit-to-gdp ratio is slightly below its ten-year moving average, and the house price-to-rent ratio is slightly above its 10-year moving average. As such, the financial fragility indicator currently is also below trend, indicating low fragility in the financial system.

Figure 11 shows the two-variables fragility indicator using the local level filter with 30-years equivalent sample size. Currently, both the private credit-to-gdp ratio and the house price-to-rent ratio are slightly above trend. The two-variables financial fragility indicator using the local level filter is clearly elevated, albeit nowhere near the peak during the 2008 crisis. In contrast to the HP filter or the ten-year moving average, this indicator suggests nontrivial fragility in the financial system.

In Figure 12 we set the equivalent sample size to 50 years in the local level

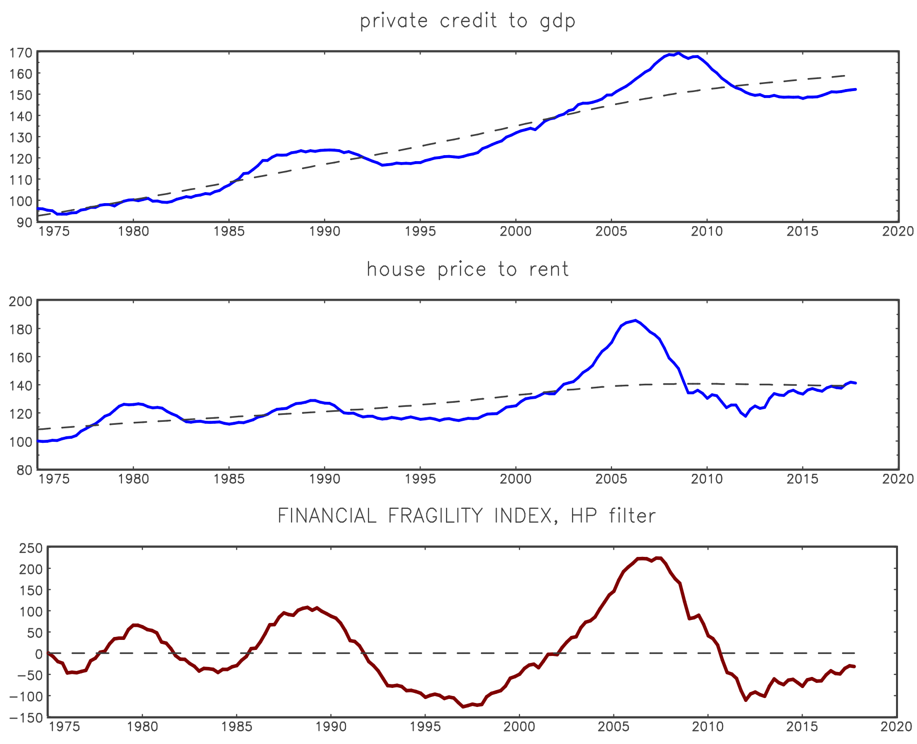

Figure 9: Two-variables financial fragility indicator with HP filter.

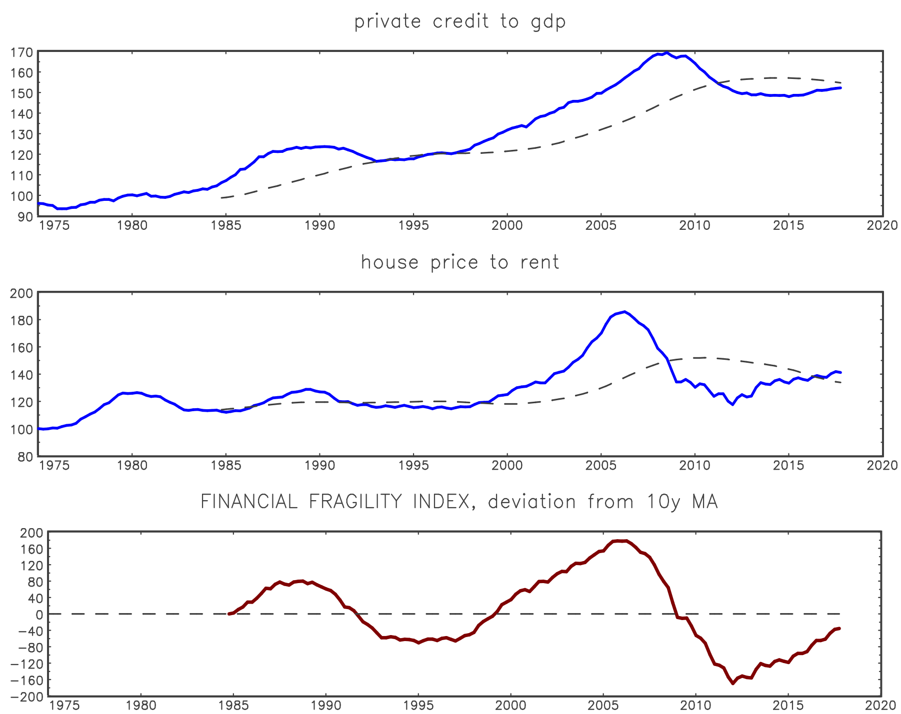

Figure 10: Two-variables financial fragility indicator with 10y MA filter.

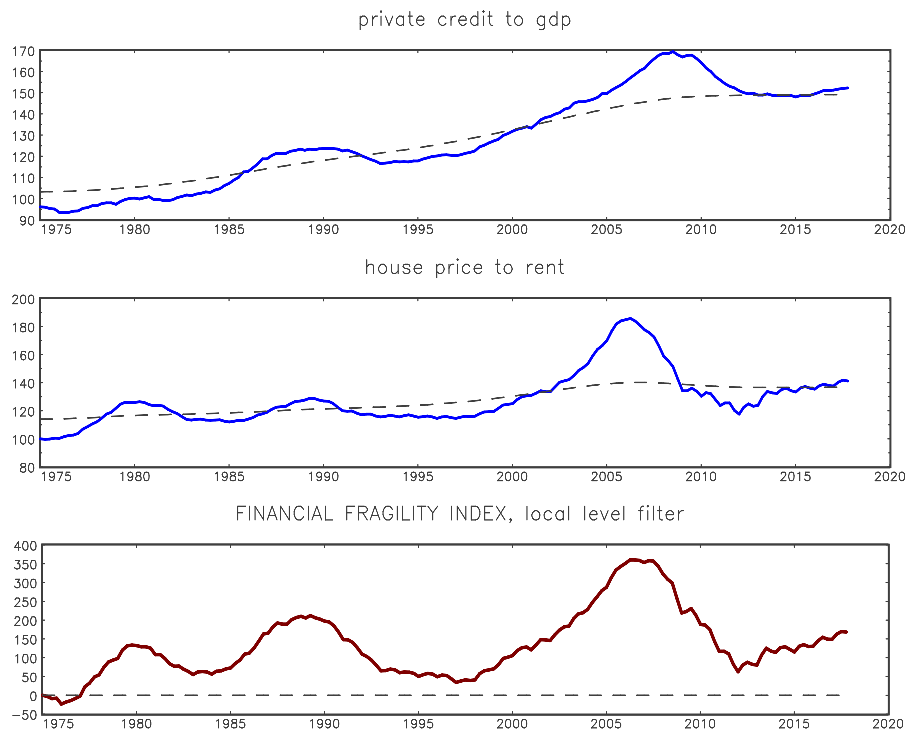

Figure 11: Two-variables financial fragility indicator with local level filter, equivalent sample size of 30 years.

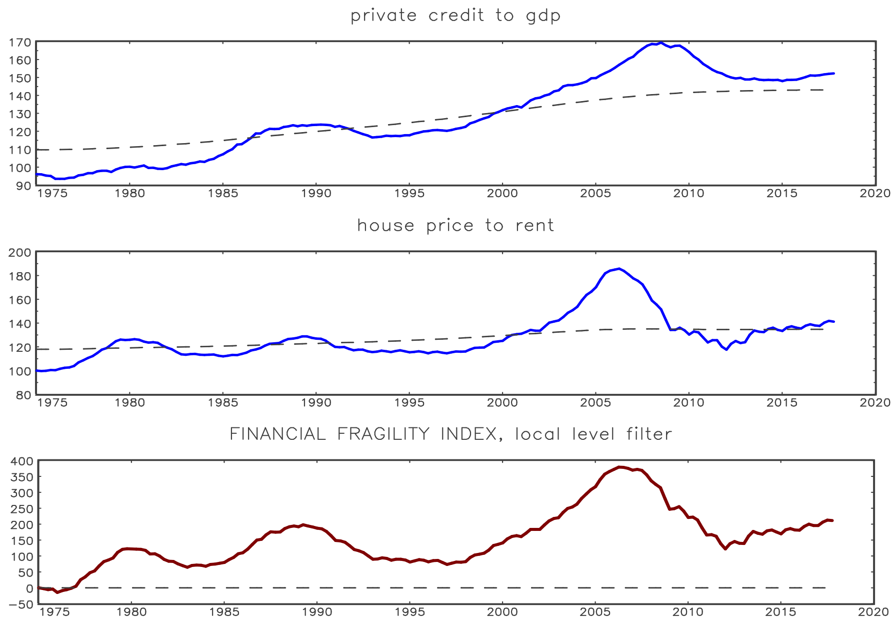

Figure 12: Two-variables financial fragility indicator with local level filter, equivalent sample size of 50 years.

filter. Financial fragility is even more elevated, and it is higher than the peak in the 1990s when the US economy suffered from the Savings and Loan crisis and the commercial real estate crisis.

Results: Five-variables fragility indicator. Figure 13 shows the financial fragility indicator constructed from five variables, the three components in the private credit-to-gdp ratio and two asset valuation ratios, using the HP filter. The mortgage credit-to-gdp ratio is currently well below trend, although the corporate credit is slightly above trend and consumer credit is at the trend. While the house price is at the trend line, the CAPE is above trend. Together, the five-variables financial fragility indicator is well below trend using the HP filter, suggesting low fragility in the financial system currently.

Figure 14 shows the five-variables fragility indicator when the trend is computed using the 10-year moving average. Currently, the mortgage credit-to-gdp ratio is well below its ten-year moving average. Even though the other four ratios are all above their respective 10-year moving average. Interestingly, the five-variables financial fragility indicator is still slightly below trend. This indicator paints a benign fragility picture in the current environment.

Figure 15 shows the five-variables fragility indicator using the local level filter with 30-years equivalent sample size. In contrast to the HP filter or the ten-year moving average, this fragility indicator suggests elevated fragility in

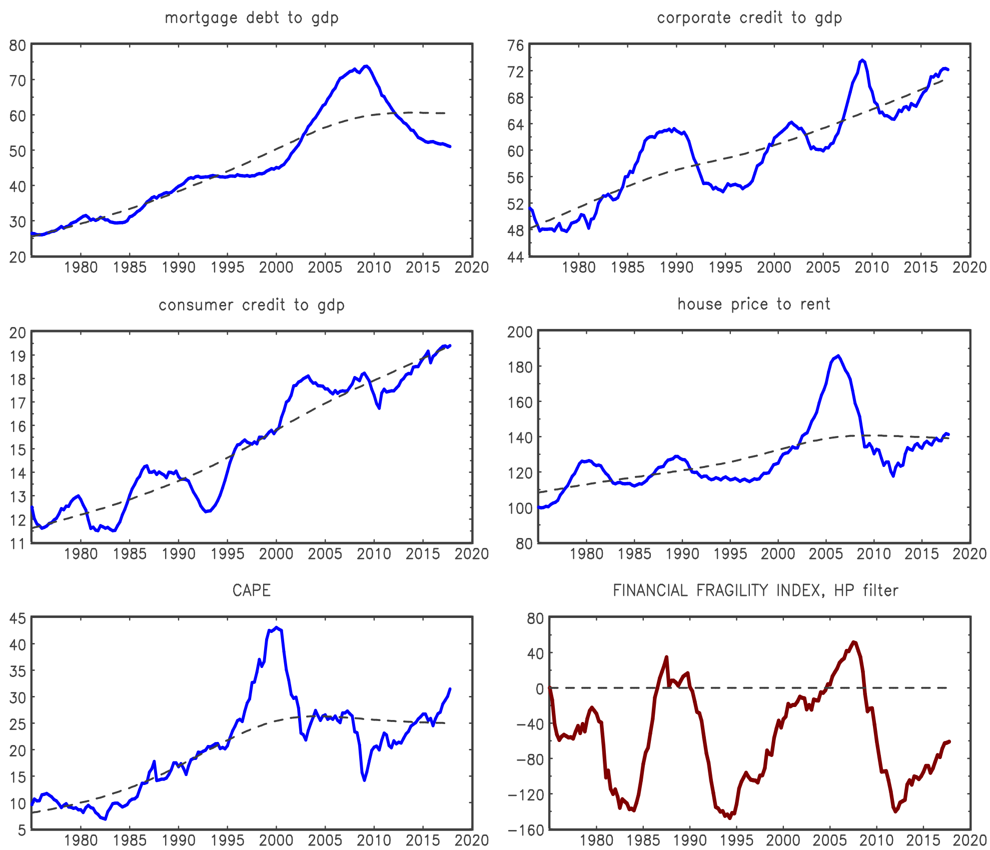

Figure 13: Five-variables financial fragility indicator with HP filter.

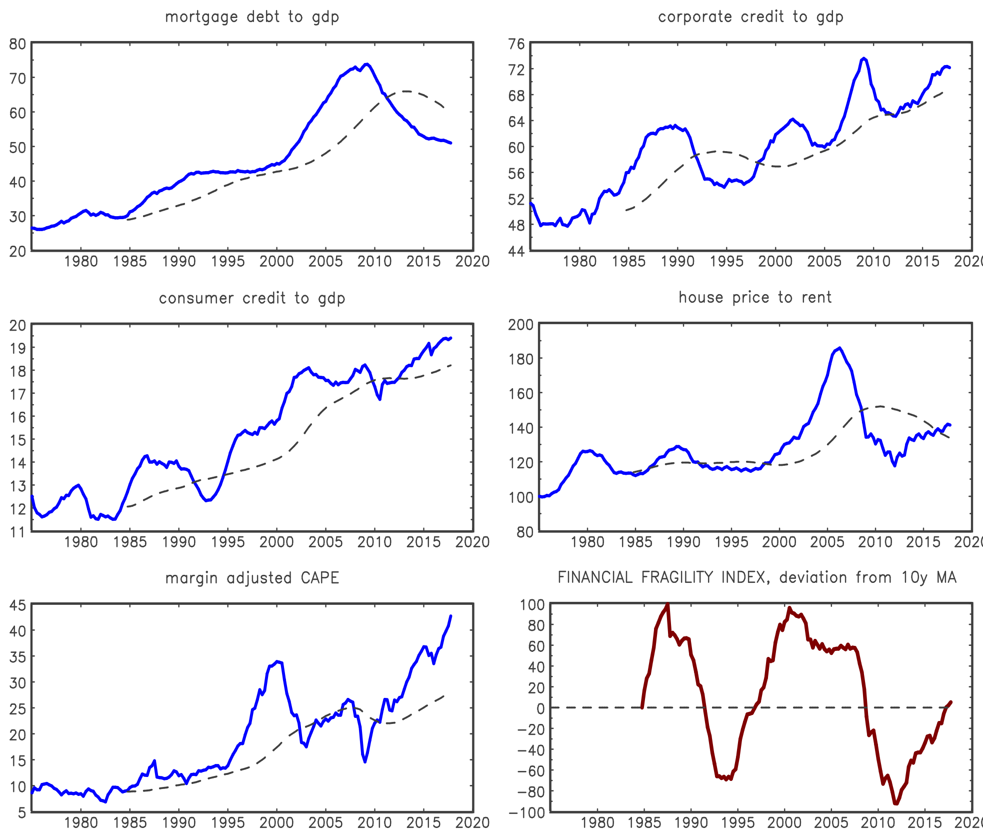

Figure 14: Five-variables financial fragility indicator with 10y MA filter.

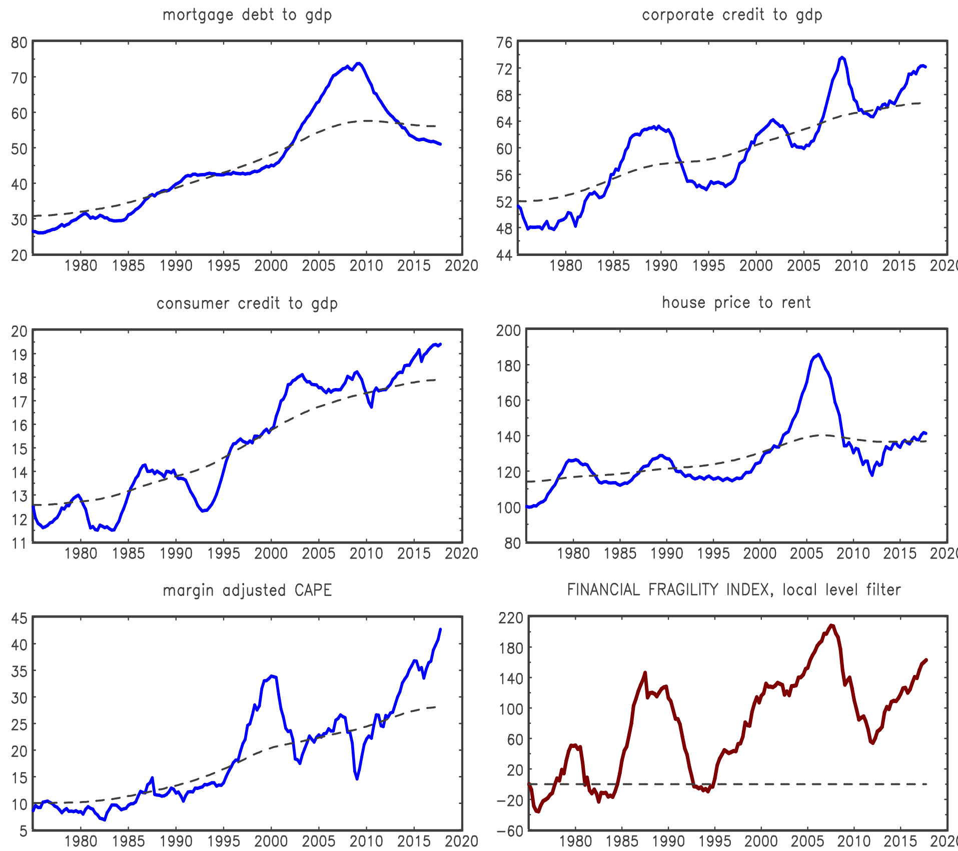

Figure 15: Five-variables financial fragility indicator with local level filter, equivalent sample size of 30 years.

the financial system currently. It is as high as in the 1990s and is approaching the peak in the 2008 financial crisis.

In Figure 16, the equivalent sample size in the local level filter is set to 50 years. The signal from this indicator is alarming. Financial fragility currently is very elevated. It surpassed the 1990s peak and is closing in the 2008 financial crisis peak.

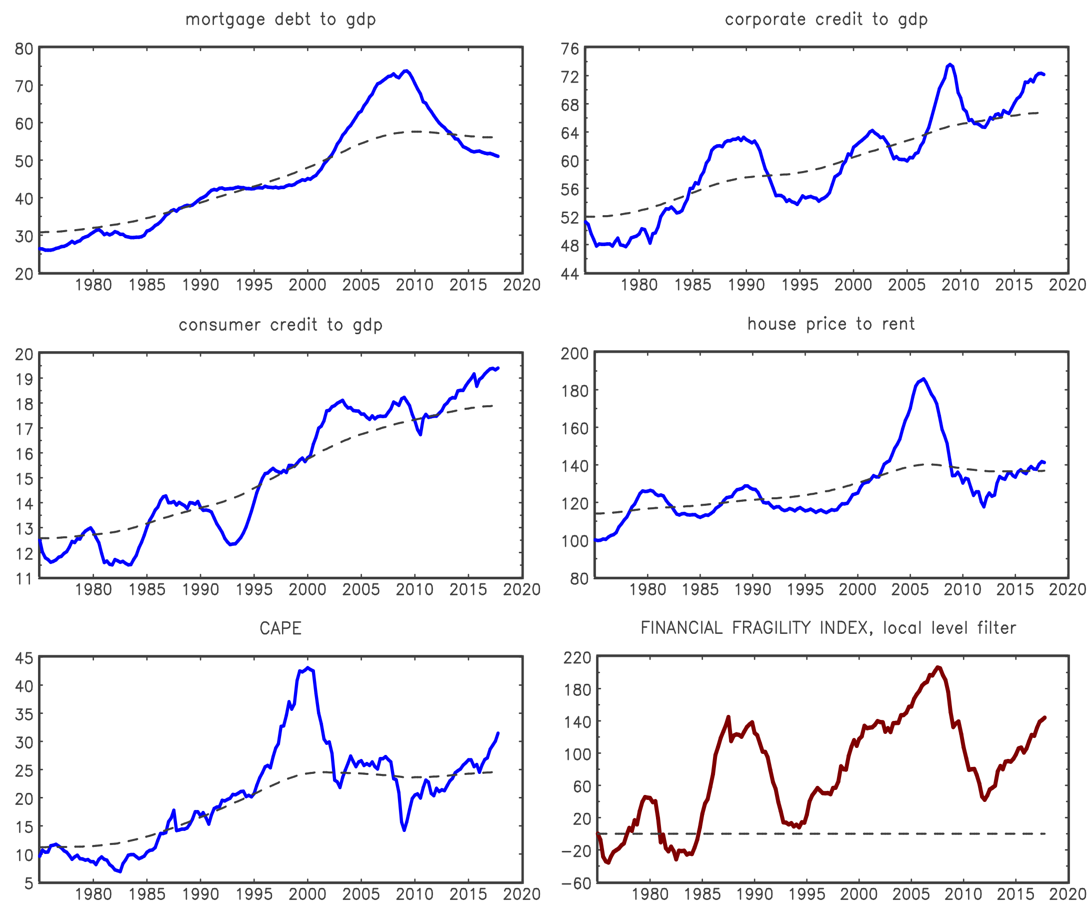

Figure 16: Five-variables financial fragility indicator with local level filter, equivalent sample size of 50 years.

4 Conclusion

Since the 2008 global financial crisis, efforts to strengthen financial stability have advanced to a new level as lawmakers and policy makers realized the sizable welfare lost due to a deep and widespread financial crisis. Debate about whether using monetary policy to lean against the build up of financial excesses has received prominent attention by central bankers and researchers. The availability and the effectiveness of macroprudential tools to address financial imbalances have been studied carefully by policymakers and regulators. At the heart of safeguarding financial stability is to obtain accurate and relevant information about the fragility of the financial system in real time before anything can be done about it. Central banks, financial stability bodies (for example, Office of Financial Research in the U.S., European Systemic Risk Board in the euro area, Financial Stability Board in G20), and banking supervisors have allocated a significant amount of resources to financial stability monitoring. However, due to financial modernization and financial innovation over time, and most importantly, the rarity of financial crisis in modern time among advance economies, assessing financial stability remains elusive.

In this paper, we take a critical look at a couple of the most widely used methods in the financial stability monitoring community to filter the data for providing a signal about financial fragility to policymakers and other decision makers. They are the HP filter and the moving average filter. We argue that these widely used data filtering techniques are not well suited for financial stability monitoring under the premises that financial cycles have a very long duration, and financialization simply cannot be trending forever. Moreover, despite the fact that debt financing could be welfare enhancing under certain circumstances, the presence of default risk will always be destabilizing at the margin, however small it might be.

Given the shortcomings of estimating the trend using the HP filter or the moving average for financial stability monitoring, we propose filtering the data by the local level filter to generate a signal of fragility for financial stability assessment. This is grounded by the assumption that financial cycle has long duration, and we choose an equivalent sample size of 30 years that is in line with the BIS view and the way the Basel Committee implements the counter cyclical capital buffer for banking organizations.

Using our methodology, we construct a two-variable financial fragility indicator for the U.S. using the private credit-to-gdp ratio and the house price-to-rent ratio. Our indicator signals elevated financial fragility in the current environment, while the indicators using the same two variables but filter the data by HP or 10-year moving average signal little to none fragility in the financial system. Expanding the number of variables to include more granular credit aggregates by sectors and adding the cyclically adjusted price earnings ratio for stocks provide similar results: our indicator currently signals elevated financial fragility when the data is filtered by the local level filter, but no such signal when the HP filter or 10-year moving average is used to estimate the trend.

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