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Aggregate Price Shocks and Financial Instability: A Historical Analysis

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Abstract

This paper presents historical evidence on the relationship between aggregate price and financial stability. We construct an annual index of financial conditions for the United States covering 1790-1997, and estimate the effect of aggregate price shocks on the index using a dynamic ordered probit model. We find that price level shocks contributed to financial instability during 1790-1933, and that inflation rate shocks contributed to financial instability during 1980-97. Our research indicates that the size of the aggregate price shock needed to alter financial conditions substantially depends on the institutional environment, but that a monetary policy focused on price stability would be conducive to financial stability.

JEL classifications: E31, E52, N10, C25

Keywords: price stability; financial insolvency; dynamic probit; U.S. monetary history

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I. INTRODUCTION

The notion that central banks should act as lenders of last resort is not controversial. How best to carry out that responsibility is, however, not widely agreed upon. One view holds that the financial system is inherently fragile, and a central bank should forego other objectives, such as preventing inflation, when financial instability threatens. An alternative view argues that by controlling inflation a central bank will in fact promote financial stability. Anna Schwartz (1988; 1995), for example, contends that financial instability has often been caused by monetary policies that cause fluctuations in the rate of inflation. She argues that monetary policy should focus exclusively on maintaining price stability.

A few countries, e.g., Canada and New Zealand, have recently made inflation control the paramount objective of their central bank's monetary policy, and the Maastricht Treaty, which established monetary union among eleven European Community countries, specifies control of inflation as the principal objective for the European Central Bank. Most countries, however, including the United States, assign their central banks multiple objectives, such as full employment and financial stability, as well as inflation control. Implicitly, the specification of multiple objectives for monetary policy assumes tradeoffs between those goals – that a country might have to accept higher inflation, at least temporarily, to maintain financial stability, for example.

This paper investigates the historical association between aggregate price and financial stability to shed light on the question of whether a commitment to price stability is likely to enhance or lessen financial stability. Specifically, we use data for the United States from 1790 to 1997 to test the hypothesis that aggregate price disturbances cause or worsen financial instability. *Unanticipated* aggregate price declines might increase financial distress by leaving some borrowers with insufficient income to repay contracted nominal debt. Thus unanticipated aggregate price declines would increase insolvency and default rates. Positive aggregate price shocks, on the other hand, might cause default rates to fall below expectations, and could encourage financial expansion if borrowers and lenders are unable to distinguish changes in relative prices from changes in the aggregate price level. Financial expansion based on aggregate price misperceptions can lead to resource misallocation, however, and thereby worsen financial distress associated with subsequent unanticipated aggregate price declines.

During 1790-1933, unanticipated movements in the *price level* best represent price shocks, whereas the persistence of inflation since 1933 led us to examine the impact of unanticipated *inflation* on financial conditions during 1934-97. We use the term "aggregate price shock" to refer to unanticipated movements in either the price level or the inflation rate.

In the absence of consistent time series measures of aggregate financial conditions over a long period, we construct an annual index of financial conditions from both quantitative and narrative sources. We use a dynamic time series probit model to estimate the impact of aggregate price shocks on financial conditions, as reflected in the index. We also regress four series used to construct the index on aggregate price shocks to confirm that the relationship between aggregate price shocks and the index is present in its constituent series. We control for liquidity, real output growth and supply shocks, and test whether relationships changed with changes in monetary or financial regime. Our objective is to shed light on the extent that aggregate price disturbances exacerbate financial instability, and whether the relationship between such disturbances and financial conditions is affected by the institutional environment.

We begin by outlining why aggregate price shocks might cause or worsen financial instability. We then discuss how one might identify the impact of price or inflation disturbances on financial conditions empirically, and describe the construction of an annual index of financial conditions. Next, we describe the dynamic time series probit model used in the estimation and present empirical estimates of the impact of price level and inflation shocks on financial variability, as reflected in the index. We conclude by summarizing and discussing implications of our findings.

II. AGGREGATE PRICE SHOCKS AND FINANCIAL INSTABILITY

Financial instability can have either monetary or non-monetary causes and may be solely domestic or spread among countries. In the United States, the 19th and early 20th centuries were punctuated by banking panics – episodes of widespread panic among depositors leading to bank runs. Banking panics were a principal cause of monetary contraction, deflation, and declines in real economic activity (Friedman and Schwartz, 1963).

Whereas the impact of banking panics on the price level and economic activity is well understood, a falling price level (or inflation rate) also can be a source of financial distress. Because debt contracts typically are written in nominal, fixed rate terms, a decline in the price level increases the real cost of servicing outstanding debt. In the presence of positive recontracting costs, loan defaults and bankruptcies increase which, in turn, puts pressure on lenders. Even a decline in the rate of inflation can cause distress if the decline is unexpected and not hedged, because some borrowers will have insufficient revenue to service debt that could have been repaid in the absence of disinflation.

Fisher (1932, 1933) was among the first to describe the impact of a falling price level on financial conditions in a business cycle framework. According to Fisher, business cycle upturns are triggered by exogenous factors that provide new profit opportunities. Rising prices and profits encourage more investment and also speculation for capital gains. Debt finance through bank loans increases deposits and the money supply, and raises the price level. A general optimism or euphoria takes hold, which increases monetary velocity and further fuels the expansion, while rising prices encourage further borrowing by reducing the real value of outstanding debt.

The process continues until a general state of "overindebtedness" is reached, that is, the point at which individuals, firms, and banks generate insufficient cash flow to service their liabilities. Any shortfall in the price level from its expected value, regardless of cause, will then leave borrowers unable to service their debts and lead to distress selling. As loans are extinguished, bank deposits and the money supply decline, further lowering the price level. Deflation increases the real burden of remaining debt, leading to further bankruptcies and declining economic activity – a process referred to as "debt-deflation." The process continues until either widespread bankruptcy has eliminated the overindebtedness or a reflationary monetary policy has been adopted. Once recovery begins, however, the whole process will repeat itself.

Schwartz (1988, 1995, 1997) offers an alternative explanation, focused explicitly on monetary policy, of how aggregate price instability can lead to financial instability. Schwartz contends that when monetary policy produces fluctuations in the inflation rate, information problems associated with evaluating alternative investments are made worse which, in turn, increases financial instability:

> Both [borrowers and lenders] evaluate the prospects of projects by extrapolating the prevailing price level or inflation rate. Borrowers default on loans not because they have misled uninformed lenders but because, subsequent to the initiation of the project, authorities have altered monetary policy in a contractionary direction. The original price level and inflation rate assumptions are no longer valid. The change in monetary policy makes rate-of-return calculations on the yield of projects, based on the initial price assumptions of both lenders and borrowers, unrealizable. (Schwartz 1995, p. 24)

Schwartz does not model formally how changes in the inflation rate can lead to financial instability, but her description fits well with the "monetary misperceptions" model of Lucas (1972, 1973). In that model, individuals are unable to distinguish with certainty shifts in relative prices from changes in the aggregate price level. This uncertainty can lead to resource misallocation, which is corrected only once the true nature of a price change becomes known.

This model is easily extended to incorporate financial decisions. Uncertainty about the nature of price changes can lead to bad forecasts of real returns to investment projects and, hence, to unprofitable borrowing and lending decisions. Because of misperceptions regarding the nature of individual price changes, inflation tends to encourage overly optimistic forecasts of real returns and, thus, can lead to "lending booms." By the same token, disinflation and, especially, deflation may lead to overly pessimistic forecasts and hence discourage the financing of projects that might otherwise be funded.[1]

When not fully anticipated or hedged, a change in the inflation rate can cause the net realized real return to investment to deviate from what had been expected. Default rates in debt markets can thus be affected. An unanticipated disinflation, for example, can increase default rates by causing realized borrower incomes to fall below expectations. Although disinflation causes the real income to lenders on loans that do not default to exceed expectations, an increase in default rates could more than offset this gain and result in significant distress for lenders. In the aggregate, financial distress is likely to be associated with disinflation because some projects will generate sufficient nominal income to repay loans only if the rate of inflation equals or exceeds the rate that had been expected when the loans were made. Similarly, higher than anticipated inflation can result in lower than expected default rates.[2]

A country's institutional environment can affect the form and possibly the severity of financial instability associated with either a real or an aggregate price shock. Banking panics, for example, are much less likely to occur in the presence of an effective lender of last resort. Similarly, high bank failure rates are less likely in systems dominated by large, branching banks, than in unit banking systems. Nevertheless, regardless of the institutional environment, aggregate price instability can still increase borrower defaults, and thereby reduce banking system profits.

Similarly, the contribution of aggregate price stability to stability of the financial system depends neither on the cause of specific price level movements nor on the nature of the monetary regime, except insofar as they affect the extent that changes in aggregate prices are anticipated.

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1 In addition to causing mistakes that increase default rates, uncertainty about future inflation can add to the cost of finance because lenders may require an inflation risk premium on interest rates that would not exist in the absence of inflation uncertainty.

2 Although Schwartz emphasizes how inflation increases the difficulty of projecting real returns for both borrowers and lenders, variability in the price level, according to Schwartz (1988, p. 49), can also worsen problems associated with asymmetric information between borrowers and lenders because "fraud and mismanagement are more likely to gain ground in conditions of price variability, and institutions of unimpeachable standards of risk management may make judgments that later turn out to be mistaken, if not disastrous."

For example, an abrupt decline in inflation following a sustained price level increase will likely contribute to financial distress regardless of whether a country has a gold standard or a fiat monetary system.

Throughout much of the 19th and 20th centuries, the United States was on either a bimetallic or gold standard.[3] Under a commodity standard, real shocks to the demand or supply of the commodity cause changes in the money stock and, over the long-term, the price level. The underlying shock might be an adverse movement in the trade balance, for example, leading to a gold outflow, monetary contraction and if sustained, a decline in the price level. There may well be theoretical reasons to not offset real shocks of this sort – the classical “rules of the game,” for example, held that gold flows should not be offset, and that the price level should be permitted to adjust to restore equilibrium in the international gold market. Nevertheless, an unstable price level may well increase financial instability.

Even if there are reasons to permit some movement in aggregate prices, a finding that financial distress is worsened by aggregate price instability would suggest that financial instability could be lessened by limiting aggregate price disturbances, and that price and financial stability should be considered complementary, rather than competing policy objectives. We now turn to the historical record to gauge whether there may be support for the proposition that aggregate price instability exacerbates financial instability in general.

III. EMPIRICAL ANALYSIS

Our conjecture is that *unanticipated* movements in the aggregate price level or inflation rate destabilize financial conditions. Negative aggregate price shocks will cause financial distress

[3] The regime changed considerably over time. The Mint Act of 1792 put the United States on a bimetallic (gold and silver) standard, which prevailed until the Civil War, when convertibility was suspended. When convertibility was restored in 1879, the dollar was made officially convertible only into gold. Convertibility was suspended in 1933, and under the Gold Reserve Act of 1934 convertibility was restored only for international payments. The dollar remained convertible into gold for official international transactions under the post-war Bretton Woods System until 1971, when the last ties to gold were broken.

by increasing insolvency and default rates above "normal" levels. Positive aggregate price shocks, on the other hand, will temporarily reduce insolvency and default rates.

The nature of aggregate price disturbances depends on whether the monetary regime is based on a commodity (such as gold) or a fiat regime. Under the gold and bimetallic standards, the U.S. price level had a persistent stochastic trend because real shocks to the demand or supply of gold and silver caused changes in the money stock and, over the long-term, the price level (Bordo and Schwartz, 1999). Before 1933, therefore, we identify aggregate price shocks in terms of the price level.

Inflation has become increasingly persistent since the establishment of the Federal Reserve System in 1914 (Barsky, 1987). This period has witnessed the decline and eventual abandonment of the gold standard in favor of a government managed fiat standard. A substantial shift in regime occurred in 1933 with suspension of the gold standard (Calomiris and Wheelock, 1998). Since then, the price level has risen almost continuously and aggregate price shocks are best measured in terms of unanticipated inflation.

Measuring Financial Conditions

We use a discrete-valued index to measure financial conditions, following the literature on currency crises (e.g., Eichengreen, et. al., 1996; Kaminsky and Reinhart, 1999). Much of the sample variance of continuous measures of financial conditions is generated by variation within the range where financial conditions might be considered normal. Because our goal is to identify variables that cause financial conditions to move from normal conditions to distress or to euphoria, we are unconcerned with explaining financial conditions within the normal range.

Table 1 presents our index of financial conditions, in which each year is placed into one of five categories, from "severe distress" to "financial euphoria." The number of years in each category is noted in parentheses. For 1790-1869, the index is derived from narrative sources, as described below. For 1870-1933, the index is based on annual observations on business and bank failure rates, an ex post real interest rate and an interest rate quality spread.[4] Because of the minimal number of bank failures after the Great Depression, for 1934-97 we dropped the bank failure rate in favor of a series on bank loan charge-offs. Charge-off data are not available prior to 1934 (see Appendix A for data sources and definitions). The index provides a means of capturing in a single variable the different aspects of financial conditions reflected in the four variables that make up the index. For example, it treats a year with severe banking distress and a high business failure rate as having more severe financial distress than a year with severe banking distress but few business failures.

In general, business failure rates, measures of banking conditions, and various financial market indicators are likely to reflect financial conditions well. High rates of firm or bank failures reflect unrealized income expectations and borrower defaults. Bank failure rates, in particular, however, can be affected by regulation and market structure. For example, the Canadian banking system's oligopolistic structure and close ties to the government probably explain why Canada had no bank failures during the Great Depression, despite suffering severe financial distress in the form of firm and household bankruptcies. Similarly, in the United States, the introduction of federal deposit insurance and imposition of barriers to entry and other regulations in the 1930s probably lowered the number of bank failures that would result from a given-sized macroeconomic shock. By including multiple measures of financial conditions in our index, we reduce the influence of such structural breaks on the observed relationship between aggregate price shocks and financial conditions.

In addition to business and bank failure rates, we include an ex post real interest rate and an interest rate quality spread in our index. The disinflationary period of the early 1980s witnessed unusually high real interest rates and interest rate quality spreads. High real interest rates increase the burden of debt on borrowers and may increase the likelihood of loan defaults.

[4] Because of the bank holiday, data on bank failures for 1933 are not comparable with those for other years. For 1933, therefore, our quantitative index is based only on the business failure rate, the real interest rate and the

Increases in observed real interest rates during disinflationary periods may reflect expectations that disinflation is only temporary. After some 15 years of rising inflation before 1980, it might have been reasonable to expect that inflation would also be high during the 1980s – that is, to doubt the credibility of the Federal Reserve's pledge to reduce inflation. Hence, lenders demanded high nominal interest rates to compensate for expected inflation, and (some) borrowers were willing to pay those rates, such that equilibrium nominal rates were high relative to current inflation. Because inflation did come down, and stayed down, ex post real interest rates were high, and consequently default rates were unusually high. If observed high real rates reflected similar expectational errors in other periods, we would expect the real rate to be a reasonable proxy of financial conditions.[5]

The difference in yields on low and high-quality bonds is another possible measure of financial conditions. Friedman and Schwartz (1963) and Mishkin (1991) found that quality spreads historically have reflected financial turbulence. More recently, in the unsettled period following the Russian government's debt default and devaluation in August 1998, spreads between yields on corporate bonds, especially those issued by low-rated firms, and U.S. Treasury securities increased sharply. This was widely interpreted as reflecting a flight to quality in the wake of increased uncertainty about foreign economies generally, and ultimately about the continued strength of the U.S. economic expansion. Quality spreads tend to increase during recessions, reflecting the higher default rates of firms during business cycle downturns. Similarly, by redistributing wealth from debtors to creditors, unexpected deflation (or

quality spread.

5 The observed real rate is simply the nominal interest rate minus the current inflation rate, so a negative correlation between the measured real rate and inflation is not surprising. The nominal interest rate does not adjust fully to changes in the inflation rate simply because some changes are unanticipated or, especially before 1933, because of mean reversion in the inflation rate. Hence, we would be quite surprised not to find a highly negative coefficient on price or inflation shocks in a regression of the real interest rate.

disinflation) reduces the net worth of borrowers and thereby causes markets to demand higher yields on risky debt than on low-risk securities.[6]

We aggregate the four series on business failures, banking conditions, the real interest rate and the quality spread to produce our index for 1870-1997 as follows: For each series, we computed the differences between annual observations and the series median for the subperiod, divided by the subperiod standard deviation. These standardized differences were summed across the four series for each year. We classify years in which the summed differences exceed +/−1.5 standard deviations from the overall mean as years of "euphoria" ("severe distress"); we classify years in which the summed differences are between +/−0.75 and +/−1.5 standard deviations from the mean as years of "moderate" expansion (distress); and we classify years in which the summed differences fall between −0.75 and +0.75 standard deviations from the mean as "normal."

In constructing the index, we treated the two periods, 1870-1933 and 1934-97 entirely separately. Observations in one period have no influence on the classification of years in the other period and, thus, one cannot directly compare index classifications in one period with those in the other. In estimating the probit model, we estimate separate coefficients for each independent variable in each subperiod. Hence, consistency in the index between the subperiods is not important. Appendix A presents additional detail on the construction of the index.

Index for 1790-1869

Except for short periods, continuous, consistent time series data on bank and business conditions for the period of U.S. history before 1870 are unavailable. Thus, to extend the analysis before 1870, we have constructed an index of financial conditions from narrative sources, principally Thorp (1926), who prepared annual summaries of economic and financial conditions for several countries. By comparing Thorp's descriptions of financial conditions across years,

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[6] Asymmetric information between borrowers and lenders implies that a decline in borrower net worth will increase adverse selection and agency problems inherent in credit markets (Mishkin, 1991).

supplemented by other historical accounts, such as Smith and Cole (1935), we place each year into one of five categories of financial conditions.

For example, 1797 is the first year we assign to the "severe distress" category. Thorp describes the year as one of "depression; panic; … falling prices; many failures, foreign trade restricted. Money tight; little speculation; financial panic, autumn" (p. 114). For 1798, which we classify as a year of "moderate distress," Thorp writes: "Continued depression in the North with failures; … prosperity in the South; collapse of land speculation … money very tight" (p. 114). For 1799, which we classify as "normal," Thorp writes: "Revival. Marked improvement in Northern activity; continued prosperity, South … money eases somewhat" (p. 114).

We classify 1824 as a year of "financial euphoria." Thorp describes this year as one of "prosperity; widespread activity; excited speculation … bank mania; many new banks chartered … money easy" (p. 119). For 1850, a year we classify as one of "moderate" financial expansion, Thorp writes: "money easy; revival of stock market … influx of gold from California" (p. 125). By contrast, for 1855 Thorp writes: "money eases, but tightens, autumn; railroad securities reach low point and recover somewhat." We classify the year as "normal."

We also classify 1853 as "normal." For that year, Thorp writes: "continued activity and expansion, slackening last quarter … very active railroad construction; extensive speculation … money tightens severely; panics and distress in interior cities; decline in railroad stock prices" (p. 125). 1853 illustrates the difficulty of assigning some years to a single category because financial conditions can change markedly within a year.

For the antebellum era, we also relied on narrative and quantitative information provided by Smith and Cole (1935). Smith and Cole refer to the financial distress of 1818-19 as America's "first major banking crisis," and describe how a decline in commodity prices "meant serious losses to merchants who had speculated in commodities. … Banks with extended loans to speculators were now confronted with a demand for specie … and the curtailment of bank loans made the position of the American merchant even more difficult" (p. 20). This description seems consistent with later financial crises in which sudden declines in commodity prices resulted in financial losses, especially for speculators who had bet on continued price increases, and the bankers who supported them. More severe price declines were associated with widespread bank and business failures and recessions.

Figures 1-3 plot our index against price level (inflation) shocks. Index categories are ordered from 1 ("severe distress") to 5 (financial "euphoria"), with 3 assigned to "normal" years. We use a trend-cycle decomposition to identify aggregate price shocks in terms of the price level for 1795-1933 and inflation rate for 1934-97, as described in Appendix A.

During 1795-1869, price level shocks were large in comparison with those of later years, and the index varies considerably from year to year. Moderate or severe financial distress occurred in several years that had deflationary shocks, though deflationary shocks also occurred in a few years, e.g., 1823-24, in which our narrative sources indicate that financial conditions were strong. Moreover, a few years of moderate or severe financial distress, e.g., 1819, 1837 and 1857, were not characterized by large deflationary shocks. Our narrative sources place a great deal of emphasis on financial panics, which often occurred at the beginning of major declines in prices. Our concern here, however, is with financial distress characterized by bank and other commercial failures and losses, which tended to occur during the deflationary periods that followed panics.

Figure 2 plots our index against price level shocks for 1870-1933. Price level shocks are plotted on the same scale as in Figure 1, and it is readily apparent that price shocks were considerably smaller on average in the later period. Only the deflationary shock of 1921 rivals the worst shocks of 1795-1869. Nevertheless, considerable financial distress was associated with deflation during the 1870s and during 1930-33. Financial euphoria, characterized by unusually low business and bank failure rates, and low real interest rates and quality spreads, occurred during the highly inflationary years of World War I (1916-18).

Figure 3 plots the index against inflation rate shocks for 1934-97. The later years of World War II and the immediate postwar years were the most financially expansive or euphoric. Most of the 1950s-70s fall into the "normal" category, whereas much of the early 1980s are classified as years of "moderate" or "severe" financial distress. The 1980s had the highest rates of bank loan charge-offs and business failures since the Great Depression, alongside unusually high real interest rates and quality spreads.

IV. MODEL AND ESTIMATION RESULTS

We gauge the impact of aggregate price shocks on U.S. financial conditions historically by estimating both a dynamic probit model in which our categorical index of financial conditions is the dependent variable, and OLS regressions for the individual series used to construct the index for 1870-1997. In estimating the impact of aggregate price shocks, we control for real output, supply side, and liquidity shocks.

Dynamic Probit Model

The dynamic ordered probit model is designed explicitly for discretely-valued time series data in which pressure for a discrete change can build over time. The model also can account for features of time series data, such as serial correlation and heteroscedasticity. The general set-up is that an observed variable, y, takes on one of J different discrete values. A continuous latent level, $y*$, follows a standard time series process and determines the discrete level of y. The mapping between the continuous latent variable and the discrete variable is

$y_t \in \text{category } j \text{ if } y_t^* \in \left(c_{j-1}, c_j\right)$, where c is a vector of cut-off parameters that determine the boundaries of the categories.

A basic time-series probit model of y^* includes at least one autoregressive term on the right-hand side of the equation for the latent variable:

$$y_t^* = \rho y_{t-1}^* + \mathrm{X}_t \beta + \varepsilon_t \qquad (1)$$

The dynamic ordered probit model of Eichengreen, et. al. (1985) serves as a time-series probit because it allows the continuous latent variable to move gradually toward the boundary with another category over several periods. The maximum-likelihood estimation procedure of Eichengreen et. al. (1985) requires numerical evaluation of an integral for each observation in order to obtain the density, h, of y_t^*, where ϕ is the standard normal density and I_t is the information available up to time *t*:

$$h\left(y_t^* \left| I_t\right.\right) \; = \; 1/\sigma_\varepsilon \int_{l_{t-1}}^{U_{t-1}} \; \phi\left(y_t^* \left|\sigma_\varepsilon\right.\right) h\left(y_{t-1}^* \left| I_t\right.\right) dy_{t-1}^*, \qquad (2)$$

where $\left\{l_t, U_t\right\} \; = \; \left\{c_{j-1}, \, c_j\right\}$ if $y_t \in cat.j$. Because numerical evaluation of these integrals is time-consuming and approximate, it is not tractable under direct maximum-likelihood estimation to extend the model to include additional features, such as regime-switching parameters.

Gibbs sampling offers a tractable method of estimating the dynamic probit model, as well as other models where the joint density of y_t^* and y_{t-1}^* is difficult to evaluate. Gibbs sampling involves generating a sample of draws from a joint distribution through a sequence of draws from the respective conditional distributions. In the present context, such data augmentation allows one to treat augmented values of y_s^*, $s \neq t$, as observed data when evaluating the conditional density of y_t^*. Thus, one conditions the density of y_t^* on a *value*, instead of a *density*, of y_{t-1}^*, making the problem much simpler than recursive evaluation of the integral in equation (2). Furthermore, once the latent variable has been augmented, it becomes straightforward to model any regime switching, such as conditional heteroscedasticity.

Markov regime switching

We include two forms of regime switching in the latent variable for the time-series probit. First, our model allows for heteroscedasticity by way of Markov-switching variances. Both the explanatory variables and the data that went into the construction of the quantitative index contain outliers that should be downweighted when estimating the regression coefficients.

Therefore we introduce switching between a high and low variance level governed by a binary variable, $S1$: $\sigma^2_{S1_t} \in \{\sigma^2_0, \sigma^2_1\}$.

Second, the model includes Markov switching in the intercept, β_0, to allow for shifts in the unconditional level of the financial conditions index. The binary variable that governs drift switching is $S2$:

$$\begin{aligned}
y_t^* &= \rho y_{t-1}^* + \beta_0(S2_t) + X_t'\beta + \sigma_{S1_t} e_t \qquad (3)\\
\beta_0(S2_t) &\in \{\beta_{01}, \beta_{0h}\}\\
e_t &\sim N(0,1)\\
\varepsilon_t &= \sigma_{S1_t} e_t
\end{aligned}$$

The transition probabilities for the state variables, $S1$ and $S2$, are:

$$\begin{aligned}
&\text{Prob}(S1_t = 0 \mid S1_{t-1} = 0) = p_1\\
&\text{Prob}(S1_t = 1 \mid S1_{t-1} = 1) = q_1\\
&\text{Prob}(S2_t = 0 \mid S2_{t-1} = 0) = p_2\\
&\text{Prob}(S2_t = 1 \mid S2_{t-1} = 1) = q_2. \qquad (4)
\end{aligned}$$

Appendix B contains additional details of the regime switching and the Gibbs sampling framework as applied to the dynamic ordered probit.

Explanatory Variables

We use the unanticipated components of the price level and inflation described above to estimate the effects of aggregate price shocks on financial conditions. We control for the possible impacts of both real and liquidity shocks on financial conditions. All data are annual and, except for a lagged dependent variable, contemporaneously timed.

We control for real output fluctuations using available data on GDP. We expect that negative shocks to GDP growth increase financial distress.[7] We also include the growth rates of potential GDP and labor productivity to control for the effects of possible supply side and natural rate disturbances on the estimated relationship between aggregate price shocks and financial conditions. Gray and Spencer (1990) find that the estimated impact of price surprises on real activity is sensitive to the inclusion of such disturbances in their empirical model. The same might be true for financial conditions. For example, a negative productivity shock might generate both a positive price shock and an increase in financial distress which, unless controlled for, would make it appear as though a *positive* price surprise worsened financial distress. We test whether supply side effects are important by reporting one specification that includes potential GDP growth and productivity growth and one that does not.

Finally, we also include the growth rate of the monetary base as an independent variable. Over time, nominal money supply shocks will affect inflation. In the short run, however, liquidity shocks might contribute to financial distress independent of their impact on the price level or inflation. We expect that declines in base growth, for example, will increase financial distress.

Dynamic Probit Model Results

As in Figures 1-3, we assign values to the index categories listed in Table 1, from 1 for "severe distress" to 5 for financial "euphoria." Hence, in the ordered probit model, a positive coefficient on an independent variable would indicate that an increase in the value of that variable would *lower* financial distress or, equivalently, encourage financial expansion or euphoria. We expect to find positive coefficients on the price level and inflation shock variables, indicating, for example, that an unanticipated decline in the price level worsens financial distress.

Table 2 reports coefficient estimates and corresponding probability values for statistical significance for two specifications of the dynamic probit model.[8] To produce reliable estimates of the cut-off parameters – which provide an indication of how much the values of the independent variables must change to move from one category of financial distress to another – we need reasonably large numbers of observations in each category. Hence, we estimated the

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[7] We experimented with using NBER business cycle dates instead of GDP and found no substantive differences in our results for the effects of aggregate price shocks on financial conditions.

[8] The p-values are posterior means of the 5000 values calculated at each iteration of the Gibbs sampler: one p-value per iteration.

models over the entire 1795-1997 period, allowing for the coefficients on the independent variables to differ between subperiods. In addition to the parameters reported in Table 2, each specification included individual dummy variables for major war periods.[9]

We investigate whether the impact of price level shocks differed between 1792-1869 and 1870-1933 because the price level was more stable after the Civil War, and because 1870 marks the point at which our index of financial conditions is based purely on quantitative information.[10] We estimate the impact of inflation rate shocks for 1934-97, with a break at 1979/80 to test whether inflation shocks had a different impact during the recent era of financial deregulation. Further, we include various coefficient breaks for the growth rates of GDP, potential GDP, labor productivity, and the monetary base at points where there are changes in data sources or definitions (see Appendix A).[11]

For 1795-1933, the results reported in Table 2 support the hypothesis that shocks to the price level affected financial conditions. The positive coefficients on the price level shock variables for 1795-1869 and 1870-1933 indicate that deflationary price level shocks worsened financial distress (or, equivalently, that positive price level shocks lessened financial distress). For 1795-1869, the coefficients on aggregate price shocks for the two specifications are statistically significant at 90 percent or better (p-value of 0.10 or less). For 1870-1933, the coefficient on price shocks is significant at better than 95 percent in both specifications. We also estimate a high degree of persistence in financial conditions, as reflected in a large positive and statistically significant coefficient on the lagged index. Finally, for 1795-1933, we estimate positive coefficients for the growth rates of GDP, potential GDP, labor productivity and the monetary base, though for the most part they are not statistically significant at conventional

[9] The following years were treated as war (and post-war) years, and thus were assigned dummy variables: 1813-15, 1861-67, 1917-21, and 1942-49. The inclusion of dummy variables for war years is not crucial for our results with respect to the impact of aggregate price shocks on financial conditions. See Bordo, et. al. (2000) for probit model estimates that exclude war year dummies.

[10] Bordo, et. al. (2000) extend the narrative-based index forward to 1997 and find that the estimated impact of aggregate price shocks on financial conditions is not qualitatively different using narrative-based index to measure financial conditions from the results presented here.

levels. Comparison of the two specifications reported reveals that controlling for the growth of potential output and productivity has little impact on the estimated relationship between aggregate price shocks and financial conditions, raising the price shock coefficient estimate for 1870-1933 only slightly.

The impact of aggregate price shocks on financial conditions can be measured by the average size shock required to move financial conditions from one state to another. In standard probit estimation, the mean of the latent variable is not recovered. Because the Gibbs sampler used here provides inferred values (draws) of the latent variable, y^*, however, we can calculate $\beta\sigma_x / \sigma_{y*}$ and $\bar{y}^* / \sigma_{y*}$. The former indicates the immediate change in y^* caused by a one standard deviation size price shock ("impact effect"), and the latter indicates the average distance that y^* lies from the boundary between the moderate distress and normal states ("average distance"). Here we have normalized distances between categories of financial conditions by defining $y^* = 0$ at the boundary between the normal and moderate distress states.

For 1795-1869, the impact effect is 0.188 and the average distance is 0.369. Thus, on average, a two standard deviation size negative price shock was necessary to cause financial conditions to deteriorate immediately from the average level (which was in the normal state) to moderate distress, all else equal. The dynamic probit also captures the long-run effects of changes in the explanatory variables. With a coefficient of approximately 0.50 on the lagged dependent variable, the long-run impact of an aggregate price shock is roughly double the initial impact. Hence, a one standard deviation size aggregate price shock is sufficient to move financial conditions to the moderate distress state in the long-run.

We estimate that aggregate price shocks had a larger impact on financial conditions during 1870-1933. For that period, the impact effect is 0.449 and the average distance 0.625. Thus, on average, a negative price shock of approximately 1.4 standard deviations was required

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[11] Consistent annual data on potential GDP and labor productivity are not available before 1875.

to produce immediate deterioration in financial conditions from average to moderate distress. A 0.7 standard deviation size shock would produce a similar effect in the long run.

One also can calculate the contribution of aggregate price shocks (or any independent variable) to the probability that financial conditions are in a particular state. The marginal impact of an independent variable on the probability of being in a particular state is often evaluated at the mean of the data. Here it is meaningful to calculate the marginal effect of aggregate price shocks at the boundary between the moderate distress and normal states, however, i.e., where $y^* = 0$. At this point the probability that a random disturbance will tip financial conditions into a distress state is 0.50. Moreover, evaluating the marginal effect at $y^* = 0$ in each subperiod, rather than at subperiod specific mean values of y^*, facilitates comparison of the marginal effects across subperiods.

In our model, the probability of *not* being in one of the two states of financial distress is $1 - \Phi\left(-X_t' \beta / \sigma_t\right)$, where Φ is the normal cumulative density function and ϕ is its derivative. Hence, the marginal effect of a change in X at $y^* = 0$ is:

$$\frac{\partial Pr(\text{no distress})}{\partial x_i}\sigma_{x_i} = \phi\left(y^* = 0\right) \beta_i \sigma_{x_i} \tag{5}$$

The partial derivative is multiplied by the standard deviation of x_i to reflect the size of the shocks. Assuming the normal density for ϕ, the marginal impact effect is 0.04 for 1795-1869 and 0.10 for 1870-1933, indicating that a one standard deviation size negative price shock increases the probability of distress from 50 to 54 percent during 1795-1869 and to 60 percent during 1870-1933.[12]

[12] One caveat regarding these results is that with Markov switching the actual density is not normal but a mixture of normals. The distortion from using the normal density is not large, however. For example, we can bound the marginal effect of 0.10 during 1870-1933 to the interval (0.096, 0.1175). Details are available from the authors.

Whereas we find a statistically close relationship between aggregate price shocks and financial conditions before 1933, our coefficient estimates for the impact of inflation rate shocks during 1934-79 are small and not statistically significant. We test, however, whether aggregate price shocks had a stronger impact during the 1980s and 1990s when Depression-era financial regulations were being dismantled. Indeed, we estimate a strong, statistically significant impact of inflation rate shocks for 1980-97. For this period, we estimate that the marginal effect of inflation shocks on the probability of being in a particular state is 0.17. Hence, a one standard deviation size negative shock to inflation would increase the probability of financial conditions being in a state of distress from 50 to 67 percent. At the mean level of financial conditions for the period, located in the region of moderate distress, we calculate that a positive inflation shock of size 0.84 standard deviations would lift financial conditions into the normal state immediately. A shock of size 0.42 standard deviations would have a similar impact in the long run. In sum, we find that aggregate price shocks were an important contributor to financial instability historically, except during 1934-79, but that their impact on financial conditions varied somewhat over time in magnitude.

Boundary and Markov Switching Parameter Estimates

The cut-off coefficients reported in the second panel of Table 2 provide information on the extent to which the category boundaries around the "normal" financial conditions category are symmetrical. We look for symmetry by comparing the distance between the upper bound of the "normal" category and the lower bound of the "financial euphoria" category with the distance between the lower bound of the "normal" category and the upper bound of the "severe distress" category. That is, we ask whether shocks of a given magnitude will move financial conditions from normal to either extreme, or whether a larger shock is needed in one direction. The comparison is between $0 - c_1$ and $c_3 - c_2$.

For the full specification, we estimate that the moderate distress category is wider than the moderate expansion category: c_1 is greater in absolute value (0.7) than $c_3 - c_2$ (0.45). Hence, the magnitude of the shock required to move financial conditions from the bottom boundary of the normal range to the upper boundary of the severe distress range is greater than the magnitude of the shock needed to move financial conditions from the upper boundary of normal to the lower boundary of financial euphoria. This asymmetry could occur simply because the moderate distress region contains more observations than the moderate expansion region.

The bottom panel of Table 2 reports the transition probabilities for Markov switching. These probabilities sum to little more than one (p+q) in both specifications, indicating that the states are not strongly serially correlated. Episodes of high volatility are not clustered in a way that make it valuable to estimate two transition probabilities instead of setting $q = (1\text{-}p)$. In this way the latent variable for financial conditions does not act like most other financial data, where volatility clustering is prevalent.

Estimation for Individual Time Series

For additional insight into the impact of aggregate price shocks on financial conditions historically, we estimated separate regressions for each of the series used to construct the index for 1870-1997. Doing so provides an indication of whether the individual series underlying the quantitative index are themselves associated with aggregate price shocks.

Table 3 reports regression estimates for 1875-1933 (1932 in the case of the bank failure rate).[13] We find support for the hypothesis that price level disturbances affect financial conditions in the behavior of the business failure rate, real interest rate and interest rate quality spread. Unanticipated deflation, for example, increased the rate of business failures, and drove up the real interest rate and quality spread.[14] The coefficient on price level shocks is, however, not

[13] We begin with 1875, rather than 1870, because of the absence of data on potential GDP and labor productivity before 1875. In addition, the bank failure rate regression ends at 1932 because the Bank Holiday, and subsequent government licensing procedures for re-opening banks, makes the computation of a bank failure rate for 1933 on a basis that is consistent with other years impossible.

[14] The quality spread regressions also include a dummy variable to account for a change in the series' measure in 1919. See Appendix A for details.

significant for the bank failure rate, which seems to have been driven more by fluctuations in the growth of real output.[15]

Table 4 reports similar regressions for 1934-97. Again we estimate a statistically significant impact of aggregate price shocks on the business failure rate and real interest rate. As before 1933, a negative aggregate price shock increased the business failure rate and real interest rate. In contrast with 1875-1933, we estimate a positive impact of aggregate price shocks on the interest rate quality spread during 1934-97. Similar to the earlier period, however, we find that banking conditions were affected more by the growth of real output than by aggregate price disturbances.

V. CONCLUSION

Our investigation finds that *unanticipated* movements in the price level and inflation rate have contributed historically to financial instability in the United States. Negative aggregate price shocks have tended to worsen financial distress, while positive price shocks have tended to encourage financial expansion.

Our evidence for the impact of price level shocks is strongest for the period 1870-1933, during most of which the United States was anchored to the gold standard. Because of this anchor, the price level was expected to change little over the long run, with price level declines expected to follow increases of similar magnitude. Indeed, except during World War I, the price level changed little between 1870 and 1929 in comparison with either the antebellum or post-World War II periods. Serious financial distress accompanied severe deflation during the Great Depression of 1930-33, however, paving the way for fundamental reforms to protect the financial system from macroeconomic shocks while partially insulating the U.S. money stock from gold shocks.

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[15] Our results contrast with those of Weber (1986) who, using Granger-causality analysis, finds a statistically significant impact of price shocks on the bank failure rate in this period.

For 1934-97, we find that inflation shocks had a statistically significant impact on financial conditions, as reflected in business failures. Our results suggest, however, that aggregate price shocks did not have as strong an impact on financial conditions after 1933 as price level shocks had in the years before. The New Deal introduced several institutional changes, including construction of a safety net for the financial sector, especially for the banking system, and reorganization of the Federal Reserve into an effective lender of last resort that appear to have insulated the financial system somewhat from macroeconomic shocks. Under the new regime, financial response to macroeconomic shocks, including inflation shocks, appears to have been slower and perhaps less severe than it had been to similar shocks before 1934.

Environmental changes in the late 1970s and 1980s made the financial system more vulnerable to macroeconomic shocks, even though key features of the safety net, such as deposit insurance and "too big to fail" closure policies, remained in place and partly insulated and certainly delayed the impact of disinflation on financial intermediaries. Considerable financial instability accompanied high inflation during the 1970s and, especially, sharp disinflation during the 1980s. Our dynamic probit model estimates indicate that financial conditions were more affected by inflation shocks during the 1980s and 1990s than they had been during 1934-79. These results suggest the need for further research to investigate the specific channels by which macroeconomic shocks and environmental changes interacted to increase financial stresses. Despite the influence of regulation and other institutional factors at various times, however, our results indicate that a monetary regime that produces aggregate price stability will, as a byproduct, tend to promote stability of the financial system.

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Appendix A: Data Sources and Definitions

Bank Failure Rate: Number of Banks, 1865-96, White (1983, Table 1.1); 1896-1997, Federal Reserve Board, *Banking and Monetary Statistics* and *Annual Statistical Digest* (various years). Number of Failures, 1865-91, FDIC *Annual Report* (1934, p. 92); 1892-1933, Federal Reserve Board, *Banking and Monetary Statistics* (1943, p. 283); 1934-97, FDIC.

Bank Loan Charge-off Rate: Net loan charge-offs at commercial banks divided by total commercial bank assets, 1934-97, FDIC.

Business Cycle Reference Dates: 1790-1854, Economic Cycle Research Institute web site, www.businesscycle.com; 1854-1997, National Bureau of Economic Research web site, www.nber.org.

Business Failure Rate: 1870-1970, *Historical Statistics of the United States* (1976, Series V-23); 1971-97, Economic Report of the President (1999, Table B-96).

Gross Domestic Product: 1789-1874, Berry (1988); 1875-1959, Gordon (2000, Table A-1); 1959-97, U.S. Department of Commerce.

Labor Productivity: 1875-1997, Gordon (2000, Table A-1).

Monetary Base: 1790-1866, Friedman and Schwartz (1970); 1867-1935, Friedman and Schwartz (1963, Table B-3); 1936-97, Federal Reserve Bank of St. Louis, adjusted monetary base.

Potential GDP: 1875-1997, Gordon (2000, Table A-1).

Price Level: 1789-1947, David and Solar (1977); 1948-97, Bureau of Labor Statistics CPI measure.

Real Interest Rate (Commercial Paper Rate minus current year's inflation rate): Commercial Paper Rate: 1831-1900, Homer and Sylla (1996, Table 44); 1901-97, Federal Reserve Board.

Quality Spread: 1857-1918, spread between low and high quality railroad bond yields from Macaulay (1938, pp. aa34-aa90) (3 lowest and 3 highest bonds, 1857-66; 5 lowest and 5 highest bonds, 1867-81; 8 lowest and 8 highest, 1882-1887; 10 lowest and 10 highest, 1888-1918); 1919-97, spread between average yield on Moody's Baa-rated corporate bonds and U.S. long-term Treasury composite bond, Federal Reserve Board.

Appendix A, continued

Construction of Index of Financial Conditions for 1870-1997

The index is derived from four series for each of two subperiods. For 1870-1933, these series are the bank failure rate (except for 1933), the business failure rate, the real interest rate and the quality spread. For 1934-1997, the series are the bank loan charge-off rate, the business failure rate, the real interest rate and the quality spread.

For each variable in each subperiod, we compute the distances between each observation and the subperiod median for that variable. We measure distances from the median, rather than mean, because the distributions of the variables tend to be skewed. Because of skewness, we also evaluate the distances for observations that are below the median separately from those above the median. Distances for those observations that are below the median are divided by the standard deviation of a series consisting of all observations below the median and an equal number of generated observations of equal distances above the median. Similarly, distances for observations that are above the median are divided by the standard deviation of a series consisting of all observations above the median and an equal number of generated observations of equal distance below the median. The generated observations are then discarded, leaving a series of observations for each variable consisting of standardized distances from the median.

For each year, we compute a simple unweighted average (Z_t) of these standardized distances across the four variables. Next, we compute an overall subperiod mean and standard deviation of these average distances. Following the approach of Kaminsky and Reinhart (1999), we assign Z_t larger than 1.5 standard deviations above the subperiod mean to the "severe distress" category; Z_t larger than 0.75 standard deviations above the subperiod mean to the "moderate distress" category; Z_t falling between +/– 0.75 standard deviations of the mean to the "normal" category; Z_t between –0.75 and –1.5 standard deviations of the mean to the "moderate expansion" category; and Zt below –1.5 standard deviations of the mean to the "euphoria" category.

Expected/Unexpected Aggregate Price Decomposition

We use a trend/cycle decomposition of inflation as the basis for our calculation of the inflation/price level explanatory variables. The following unobserved-components model is estimated via the Kalman filter:

$$\begin{aligned} y_t &= y_{1t} + y_{2t} \\ \textit{Trend}: \quad y_{1t} &= \mu + y_{1,t-1} + n_t, \\ \textit{Cycle}: \quad y_{2t} &= \phi_1 y_{2,t-1} + \phi_2 y_{2,t-2} + e_t, \\ \textit{variance parameters}: \quad & \sigma_n^2, \sigma_e^2, \sigma_{n,e} \end{aligned}$$

The expected price level (inflation rate) is then

$$y_{1,t-1} + \mu + \phi_1 y_{2,t-1} + \phi_2 y_{2,t-2}.$$

Appendix B: The Dynamic Ordered Probit Model in Detail

The Gibbs sampler and conditional distributions

The Gibbs sampler is an attractive estimation procedure for the time-series probit because the conditional distribution of the latent variable is easy to derive, given the other parameters and state variables $(\beta, \rho, S1, S2, p_j, q_j)$, $j = 1, 2$, and the conditional distributions of the state variables are simple, given values for the latent variable and parameters. The key idea behind Gibbs sampling is that after a sufficient number of iterations, the draws from the respective conditional distributions jointly represent a draw from the joint posterior distribution, which often cannot be evaluated directly (Gelfand and Smith, 1990).

Gibbs sampling consists of iterating through cycles of draws of parameter values from conditional distributions as follows:

$$\begin{aligned}
& f\left(\varsigma_1^{(i+1} \left| \varsigma_2^{(i)}, \varsigma_3^{(i)}, \varsigma_4^{(i)}, \mathrm{Y}_T\right.\right) \qquad \text{(B.1)}\\
& f\left(\varsigma_2^{(i+1} \left| \; \varsigma_1^{(i+1)}, \varsigma_3^{(i)}, \varsigma_4^{(i)}, \mathrm{Y}_T\right.\right)\\
& f\left(\varsigma_3^{(i+1} \left| \varsigma_1^{(i+1)}, \varsigma_2^{(i+1)}, \varsigma_4^{(i)}, \mathrm{Y}_Y\right.\right)\\
& f\left(\varsigma_4^{(i+1} \left| \varsigma_1^{(i+1)}, \varsigma_2^{(i+1)}, \varsigma_3^{(i+1)}, \mathrm{Y}_T\right.\right)
\end{aligned}$$

where Y_T stands for the entire history of the data and superscript *i* indicates run number *i* through the Gibbs sampler. At each step, a value of ς is drawn from its conditional distribution. As discussed in Albert and Chib (1993), all of the necessary conditional distributions can be standard statistical distributions, given appropriate choices for prior distributions.

We ran the Gibbs sampler a total of 8000 iterations for each model specification. We discarded the first 3000 iterations to allow the sampler to converge to the posterior distribution. For this application, parameters and latent data are sampled in the following groups:

$$\begin{aligned}
\varsigma_1 &= \{y_t^*\}, t = 1, \ldots, \mathrm{T} \text{ latent variables}\\
\varsigma_2 &= (\{S1_t\}, \{S2_t\}), \; t = 1, \ldots, \mathrm{T} \text{ states}\\
\varsigma_3 &= (\beta, \rho) \text{ regression coefficients}\\
\varsigma_4 &= (p_j, q_j), \; j = 1,2 \text{ transition probabilities.}
\end{aligned}$$

Gibbs sampling distributions

We drew the Markov switching parameters in accordance with the procedures of Dueker (1999). In all cases the Markov state variables, $S1$ and $S2$, were treated symmetrically, so in the following description we drop references to a particular state variable.

The likelihood function for a discrete binary random variable governed by a first-order Markov process is

$$L(p,q) = p^{n00}(1 - p)^{n01} q^{n11}(1 - q)^{n10} \qquad \text{(B.2)}$$

where n_{ij} is the number of transitions between $S_{t-1} = i$ and $S_t = j$.

The prior is to assign parameters u_{ij}, where the ratio between u_{00} and u_{01}, for example, represents a prior guess for the ratio between the corresponding numbers of actual transitions, n_{00} / n_{01}. The magnitudes of the u_{ij} relative to the sample size indicate the strength of the prior. As a weak prior, we set $u_{00} = 4$, $u_{01} = 1$, $u_{10} = 1$, and $u_{11} = 4$, such that the sum of the u_{ij} is low relative to the sample size.

The beta distribution is conjugate to itself, so the posterior is also beta and is the product of the prior and the likelihood of the observed transitions, so that we may draw transition probabilities from

$$p \mid \tilde{S}_T \sim beta\ (u_{00} + n_{00},\, u_{01} + n_{01}) \qquad \text{(B.3)}$$
$$q \mid \tilde{S}_T \sim beta\ (u_{11} + n_{11},\, u_{10} + n_{10}), \qquad \text{(B.4)}$$

where $\tilde{S}_T = \{S_t\}$, $t = 1,\ldots,\mathrm{T}$. We set the initial values for p and q at the start of the Gibbs sampling at $p = 0.8$ and $q = 0.6$.

Priors and posteriors for Markov state variables

We wish to sample the states in reverse order from the following probability, where T stands for the entire history of the observed and latent data and υ_t is the observed and latent data at a point in time:

$$P(S_t = 0 \mid S_{t+1},\ \ldots,\ S_T, Y_T) \qquad \text{(B.5)}$$

By Bayes theorem, and as outlined in Chib (1996),

$$
\begin{aligned}
P\left(S_t = 0 \mid S_{t+1}, \ldots,\ S_T, {}_T\right) &\propto f\left(\upsilon_{t+1}, \ldots, \upsilon_T,\ S_{t+1},\ \ldots, S_T \mid \upsilon_1,\ \ldots, \upsilon_t, S_t\right) \times \\
&\quad P\left(S_t \mid\ \upsilon_1, \ldots, \upsilon_t\right) \\
&\propto f\left(\upsilon_{t+1}, \ldots, \upsilon_t, S_{t+2}, \ldots, S_T \mid \upsilon_1,\ \ldots, \upsilon_t, S_t, S_{t+1}\right) \times \\
&\quad P\left(S_{t+1} \mid S_t\right) \times P\left(S_t \mid \upsilon_1, \ldots, \upsilon_t\right) \\
&\propto P\left(S_{t+1} \mid S_t\right) \times P\left(S_t \mid \upsilon_1, \ldots, \upsilon_t\right). \qquad \text{(B.6)}
\end{aligned}
$$

The first and second proportions in equation (B.6) are simply applications of Bayes' theorem. Because the density $f\left(\upsilon_{t+1}. \ldots, \upsilon_T, S_{t+2}, \ldots, S_T \mid \upsilon_1, \ldots, \upsilon_t, S_t, S_{t+1}\right)$ is independent of S_t, it can be subsumed into the constant of proportionality, which can easily be recovered in order to draw states. As shown in equation (B.6), the only necessary inputs are the transition probabilities and the filtered probabilities conditional on the contemporaneous data.

Priors and posteriors for β coefficients

Following Albert and Chib (1993), the prior for β is diffuse and the initial value for β in the first cycle of the Gibbs sampler is the ordinary least square estimate from the regression of the initial draw of $y*$ on the right-hand variables. Like Albert and Chib (1993, p. 671), we use a flat uninformative prior for β because our initial draw of $y*$ is uninformative. For this reason, we do not wish to allow a prior distribution around the starting OLS estimate to influence the posterior distribution.

With $\sum_T$ denoting the diagonal matrix with entries from the vector $\left(\sigma^2_{S1_t},\ t = 1,\ldots,\mathrm{T}\right)$, the posterior distribution for β is the multivariate normal distribution for generalized least squares coefficients:

$$\beta \sim \mathrm{N}\left(\left(\mathrm{X}'\textstyle\sum_T^{-1}\mathrm{X}\right)^{-1}\mathrm{X}'\textstyle\sum_T^{-1}y*, \left(\mathrm{X}'\textstyle\sum_T^{-1}\mathrm{X}\right)^{-1}\right),$$

where the matrix X is understood to include the lagged dependent variable and intercept dummies for $S2$ and $(1-S2)$. Hence the β coefficients described here include the autoregressive and drift coefficients.

Generating latent variables, y_t^*

The initial values of y_t^*, $t = 1,\ldots,\mathrm{T}$ are drawn from $f\left(y_t^* \mid y_{t-1}^*, y_t \in \text{cat.}\, j\right)$. In this case,

$$y_t^* \sim \mathrm{N}\left(\rho y_{t-1}^* + X_t'\beta, \sigma_{St}^2\right)$$

with truncation such that $y_t^* \in \left(c_{j-1}, c_j\right)$. These expressions imply that the disturbance, ε_t, is in the interval $[-\rho y_{t-1}^* - \mathrm{X}_t'\beta + c_{j-1},\ \rho y_{t-1}^* - \mathrm{X}_t'\beta + c_j)$. Denote this interval as $[l_t,\ u_t)$. The standardized shock, $\varepsilon_t\ /\ \sigma_{s\,t}^2$ is in the interval $\left[-\rho y_{t-1}^* - \mathrm{X}_t'\,\beta + c_{j-1},\ \ \rho y_{t-1}^* - \mathrm{X}_t'\beta + c_j\right]$. Let Φ denote the cumulative normal density function. To sample from the truncated normal, we first draw a uniform variable, υ_t, from the interval $[\Phi(l_t/\sigma s_{1t}),\ \Phi(u_t/\sigma s_{1t})]$. The truncated normal draw for the standardized shock is then $\Phi^{-1}(v_t)$.

We take subsequent draws from

$$f\left(y_t^{*(i+1)} \middle| \, y_{t-1}^{*\ (i+1)}, y_{t+1}^{*\ (i)}, y_t \in cat.\, j\right), \tag{B.7}$$

where, as in equation (B.1), superscript *i* denotes the i^{th} cycle of the Gibbs sampler. We use the density from equation (B.7), because sampling the entire vector jointly from $f\left(y_1^*,\ldots,y_T^* \,\middle|\, Y_T\right)$ would require evaluation of a density equivalent to the cumbersome likelihood function from equation (2). To draw from (B.7), we note that unconditionally $\left(\varepsilon_t,\ \varepsilon_{t+1}\right)$ are distributed as independent, bivariate normals with mean zero:

$$f\left(\varepsilon_t,\ \varepsilon_{t+1}\right) = \frac{1}{2\pi\sigma_{S_t}\sigma_{S_{t+1}}} \exp\left\{-.5\varepsilon_t^2 \middle/ \sigma_{S_t}^2 \ - .5\varepsilon_{t+1}^2 \middle/ \sigma_{S_{t+1}}^2\right\}. \tag{B.8}$$

Given equation (1), we can write

$$\begin{aligned} y_{t+1}^* &= \rho y_t^* + \mathrm{X}_{t+1}'\beta + \varepsilon_{t+1} \\ &= \rho^2 y_{t-1}^* + \rho \mathrm{X}_t'\beta + \rho\varepsilon_t + \mathrm{X}_{t+1}'\beta + \varepsilon_{t+1}. \end{aligned} \tag{B.9}$$

Conditional on values for y^*_{t-1} and y^*_{t+1}, we know the particular value, denoted r_0, of $\rho\varepsilon_t + \varepsilon_{t+1}$. Substitute $r_0 - \rho\varepsilon_t$ for ε_{t+1} in the joint density of equation (B.8) and after some algebra we find that

$$y^*_t \sim \mathrm{N}\left(\rho y^*_{t-1} + \mathrm{X}'_t\beta + \frac{\rho r_0 \sigma^2_{S_t}}{\rho^2\sigma^2_{S_t} + \sigma^2_{S_{t+1}}}, \frac{\sigma^2_{S_{t+1}}\sigma^2_{S_t}}{\rho^2\sigma^2_{S_t} + \sigma^2_{S_{t+1}}}\right) \tag{B.10}$$

We then draw y^*_t as a truncated normal as described above.

Drawing Threshold coefficients

With five discrete categories for financial conditions, we need to draw four cut-off coefficients for the vector $c_j,\ j = 0,\ldots,4$ where $c_0 = -\infty$ and $c_4 = \infty$. For the discrete variable, y_t is in category j when the latent variable $y^*_t \in \left(c_{j-1}, c_j\right)$. The threshold coefficients also delimit *ex ante* probabilities for being in a given category prior to knowing what disturbance will hit the latent variable:

$$\begin{aligned}
&\mathrm{Prob}(\mathit{Euphoria}) = 1 - \Phi\left((-\mathrm{X}'_t\,\beta + c_3)/\sigma_t\right),\\
&\mathrm{Prob}(\mathit{Mod.Expansion}) = \Phi\left((-\mathrm{X}'_t\,\beta + c_3)/\sigma_t\right) - \Phi\left((-\mathrm{X}'_t\,\beta + c_2)/\sigma_t\right),\\
&\mathrm{Prob}(\mathit{Normal}) = \Phi\left((-\mathrm{X}'_t\,\beta + c_2)/\sigma_t\right) - \Phi\left((-\mathrm{X}'_t\,\beta/\sigma_t\right),\\
&\mathrm{Prob}(\mathit{Mod.Distress}) = \Phi\left(-\mathrm{X}'_t\,\beta/\sigma_t\right) - \Phi\left((-\mathrm{X}'_t\,\beta + c_1)/\sigma_t\right),\\
&\mathrm{Prob}(\mathit{Sev.Distress}) = \Phi\left((-\mathrm{X}'_t\,\beta + c_1)/\sigma_t\right).
\end{aligned} \tag{B.11}$$

The relevant conditioning information for the draw of c_j is $\left\{c_{j-1}, \mathrm{y}^*_t,\ t = 1,\ldots,\mathrm{T}\right\}$. Given this information, the posterior distribution for c_j is uniform on the interval

$\left(c_{j-1}, \min\left\{y^*_t : y^*_t \in cat.\ j+1\right\}\right)$.

Table 1

Index of Financial Conditions, 1790-1997

Severe Distress (12)	Moderate Distress (46)	Normal (107)	Moderate Expansion (30)	Euphoria (13)
1797	1796	1790	1791	1795
1819	1798	1792-94	1804	1805
1837	1808-09	1799-1803	1806	1824
1857	1812	1807	1813	1917-19
1878	1814-16	1810-11	1823	1943-48
1931-32	1818	1817	1835-36	1951
1982-86	1820	1821	1847	
	1822	1827-28	1850	
	1825-26	1830-32	1852	
	1829	1834	1862-64	
	1833	1843-45	1903-07	
	1838-42	1849	1909-13	
	1846	1851	1916	
	1848	1853	1920	
	1854	1855-56	1942	
	1858	1859-60	1950	
	1861	1865-68	1952-55	
	1869	1870-72		
	1873-77	1879-83		
	1884	1885-92		
	1893	1894-1902		
	1921-22	1908		
	1930	1914-15		
	1933-34	1923-29		
	1938	1935-37		
	1981	1939-41		
	1987-92	1949		
		1956-80		
		1993-97		

Numbers of observations in each category are indicated in parentheses.

Source: See text and Appendix A.

Table 2

Probit Model Coefficient Estimates

Dependent Variable: Index of Financial Conditions

P^{ue}, 1795-1869 (p-value for significance)	1.73 (0.08)	1.59 (0.10)
P^{ue}, 1870-1933 (p-value)	5.97 (0.00)	6.14 (0.00)
π^{ue}, 1934-1979 (p-value)	0.02 (0.20)	0.00 (0.22)
π^{ue}, 1980-1997 (p-value)	0.22 (0.01)	0.24 (0.01)
Δ *ln*GDP, 1795-1874 (p-value)	0.01 (0.20)	0.01 (0.17)
Δ *ln*GDP, 1875-1933 (p-value)	0.02 (0.10)	0.02 (0.17)
Δ *ln*GDP, 1934-1997 (p-value)	0.01 (0.17)	0.03 (0.12)
Δ *ln*Base, 1795-1833 (p-value)	0.00 (0.19)	0.00 (0.18)
Δ *ln*Base, 1834-1933 (p-value)	0.02 (0.18)	0.01 (0.16)
Δ *ln*Base, 1934-1997 (p-value)	0.01 (0.13)	0.01 (0.17)
Δ *ln* Potential GDP, 1875-1933 (p-value)		0.01 (0.22)
Δ *ln* Potential GDP, 1934-1997 (p-value)		0.04 (0.16)
Δ *ln* Labor Prod., 1875-1933 (p-value)		0.01 (0.21)
Δ *ln* Labor Prod., 1934-1997 (p-value)		−0.04 (0.13)
Lagged Index (p-value)	0.52 0.00	0.50 (0.00)

Variables:
P^{ue} = price level shock.
π^{ue} = inflation rate shock.
Δ *ln* GDP = log change in GDP
Δ *ln* Base = log change in the monetary base
Δ *ln* Potential GDP = log change in potential GDP
Δ *ln* Labor Prod. = log change in labor productivity
Lagged Index = autoregressive coefficient

Table 2, continued

Cut-off Constants for Category Boundaries

Severe/Moderate Distress (c1)	–0.66	–0.70
Moderate Distress/Normal	Fixed at 0	Fixed at 0
Normal/Expansion (c2)	0.76	0.77
Expansion/Euphoria (c3)	1.22	1.22

Transition Probabilities for Markov Switching

Trans. Prob. p1	0.76	0.77
Trans. Prob. q1	0.30	0.30
Trans. Prob. p2	0.66	0.66
Trans. Prob. q2	0.36	0.36
Intercept S2=0	0.06	0.01
Intercept S1=1	0.13	0.10

Note: The variances are fixed at 0.10 when S1=0 and 0.50 when S1=1.

Table 3

Regression Estimates for Alternative Measures of Financial Conditions, 1875-1933

Dependent Variable:	Business Failure Rate	Bank Failure Rate	Real Interest Rate	Interest Rate Quality Spread
Intercept	38.08	0.01	4.58	0.09
(p-value)	(0.01)	(0.43)	(0.00)[a]	(0.74)
P^{ue}	−124.35	0.01	−87.12	−2.62
(p-value)	(0.04)	(0.88)	(0.00)[a]	(0.11)
Δ *ln* GDP	−159.89	−0.13	−1.46	−3.03
(p-value)	(0.00)	(0.02)	(0.71)[a]	(0.04)
Δ *ln* Base	−96.75	0.02	−10.65	2.72
(p-value)	(0.02)	(0.61)	(0.01)[a]	(0.00)
Δ *ln* Potential GDP	397.71	−0.04	−17.67	5.54
(p-value)	(0.18)	(0.88)	(0.45)[a]	(0.45)
Δ *ln* Labor Prod.	77.72	0.14	−0.97	2.72
(p-value)	(0.41)	(0.11)	(0.92)[a]	(0.25)
Lag Dep. Var.	0.66	0.57	0.33	0.82
(p-value)	(0.00)	(0.00)	(0.00)[a]	(0.00)
Lag2 Dep. Var.	−0.09	0.28	−0.02	−0.31
(p-value)	(0.41)	(0.24)	(0.59)[a]	(0.05)
1919 Dummy				1.18
(p-value)				(0.00)
Adjusted R^2	.69	.61	.96	.94
Q-statistic	1.50	0.15	5.72	0.64

Note:
[a] P-value based on robust standard errors (Newey-West correction for autocorrelation).

Variables:
P^{ue} = price level shock
Δ *ln* GDP = log change in GDP
Δ *ln* Base = log change in the monetary base
Δ *ln* Potential GDP = log change in potential GDP
Δ *ln* Labor Prod. = log change in labor productivity
Lag Dep. Var. = lagged dependent variable
Lag2 Dep. Var. = second lag of dependent variable
1919 Dummy = dummy set equal to 1 in 1919 and subsequent years

Table 4

Regression Estimates for Alternative Measures of Financial Conditions, 1934-97

Dependent Variable:	Business Failure Rate	Bank Loan Charge off Rate	Real Interest Rate	Interest Rate Quality Spread
Intercept	22.65	0.07	1.02	0.47
(p-value)	(0.01)	(0.16)[a]	(0.39)[a]	(0.11)
π^{ue}	−1.24	0.00	−0.69	0.04
(p-value)	(0.06)	(0.75)[a]	(0.00)[a]	(0.10)
Δ *ln* GDP	−88.45	−0.60	4.48	−7.10
(p-value)	(0.07)	(0.12)[a]	(0.68)[a]	(0.00)
Δ *ln* Base	13.41	0.02	2.13	0.66
(p-value)	(0.63)	(0.93)[a]	(0.71)[a]	(0.63)
Δ *ln* Potential GDP	−346.73	−1.25	−26.70	−1.01
(p-value)	(0.09)	(0.29)[a]	(0.49)[a]	(0.89)
Δ *ln* Labor Prod.	62.76	0.60	7.60	5.91
(p-value)	(0.30)	(0.21)[a]	(0.49)[a]	(0.02)
Lag Dep. Var.	1.10	1.31	0.77	0.93
(p-value)	(0.00)	(0.00)[a]	(0.00)[a]	(0.00)
Lag2 Dep. Var.	−0.27	−0.39	−0.22	−0.14
	(0.01)	(0.00)[a]	(0.00)[a]	(0.20)
Adjusted R^2	.89	.92	.76	.78
Q-statistic	0.97	5.33	8.77	0.24

Note:
[a] P-value based on robust standard errors (Newey-West correction for autocorrelation).

Variables:
π^{ue} = inflation rate shock.
Δ *ln* GDP = log change in GDP
Δ *ln* Base = log change in the monetary base
Δ *ln* Potential GDP = log change in potential GDP
Δ *ln* Labor Prod. = log change in labor productivity
Lag Dep. Var. = lagged dependent variable
Lag2 Dep. Var. = second lag of dependent variable

Figure 1: Index of Financial Conditions and Price Level Shocks

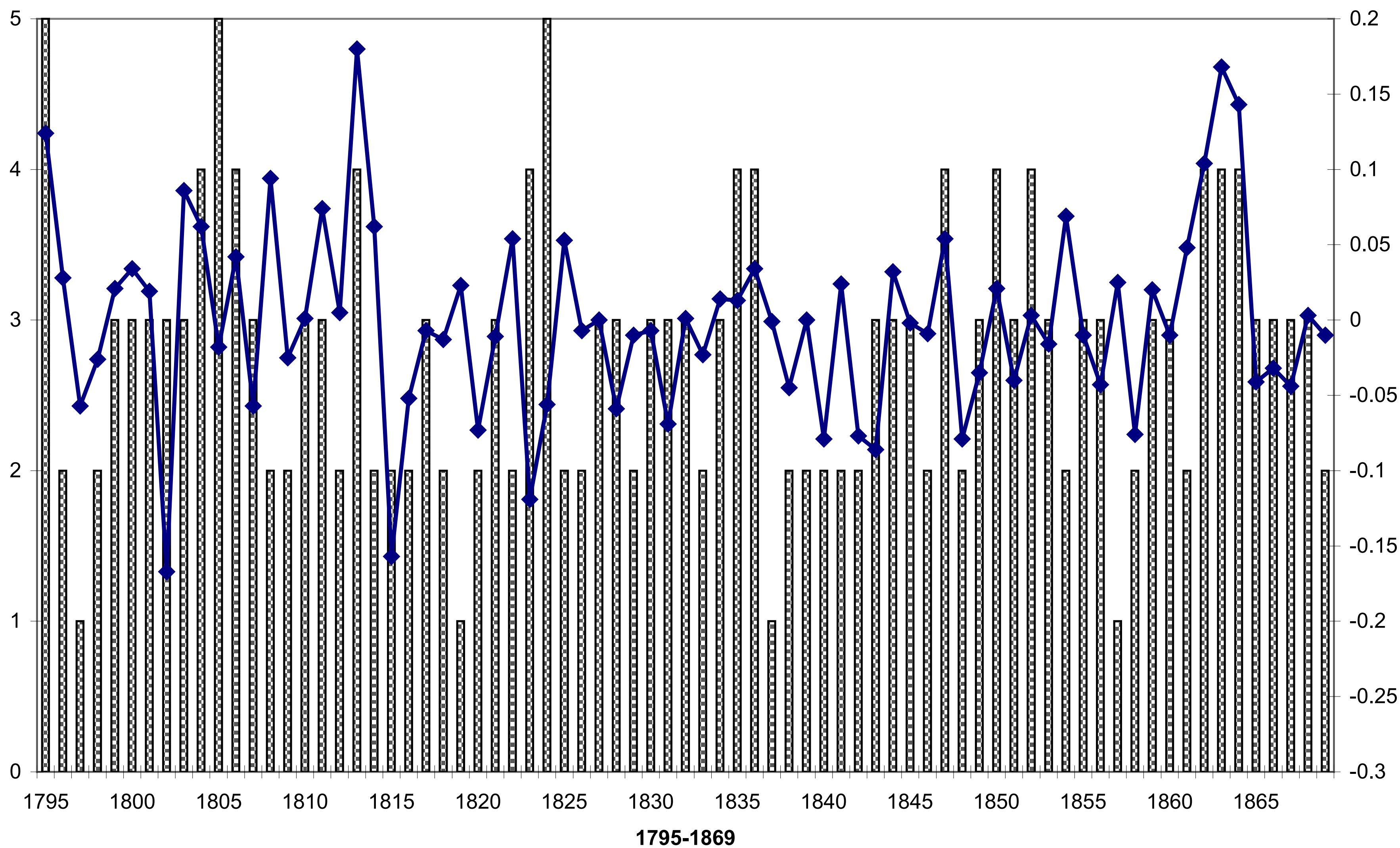

Figure 2: Index of Financial Conditions and Price Level Shocks

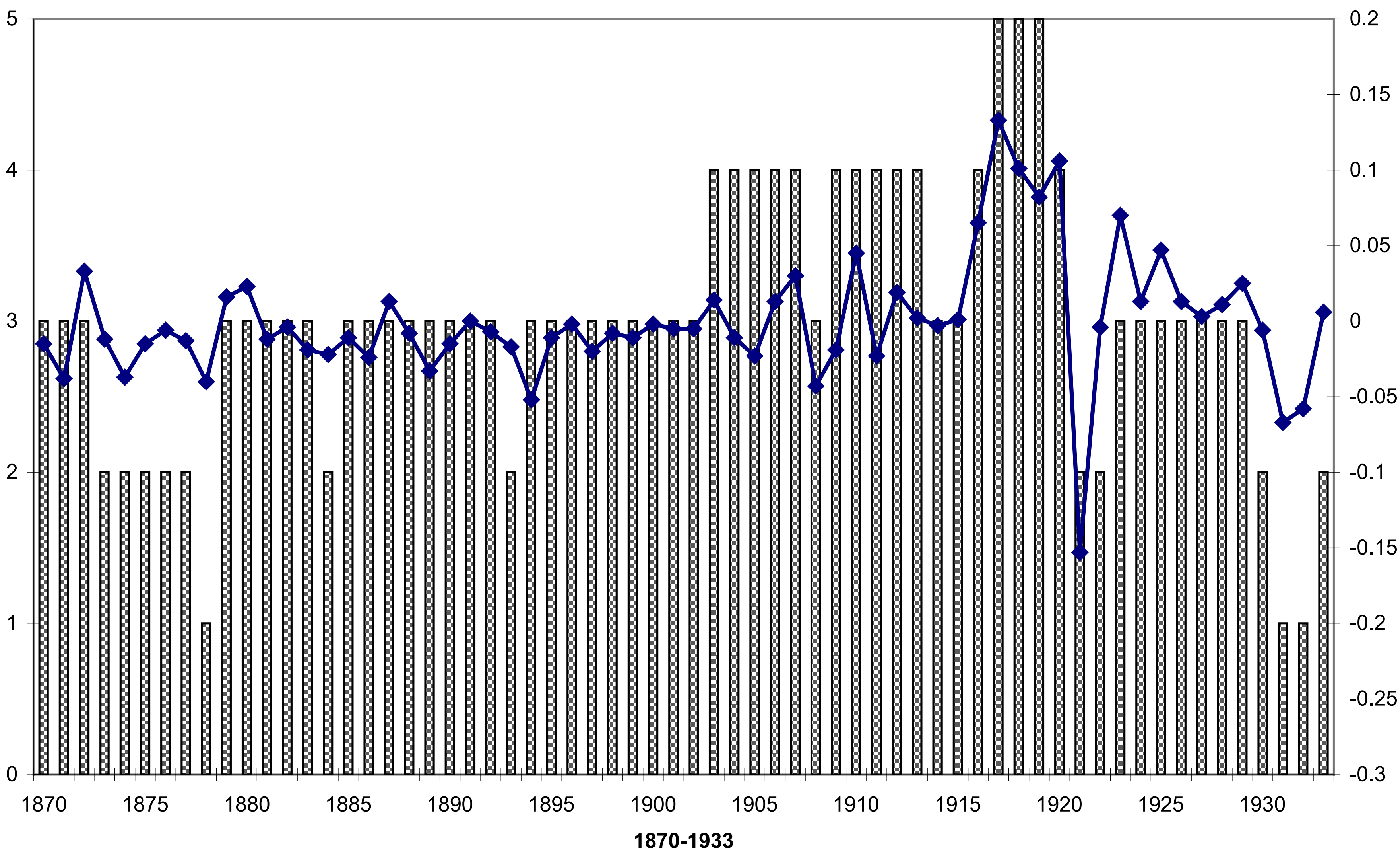

Figure 3: Index of Financial Conditions and Inflation Shocks