

The Real Effects of Disrupted Credit

Evidence from the Global Financial Crisis

Ben S. Bernanke

Distinguished Fellow

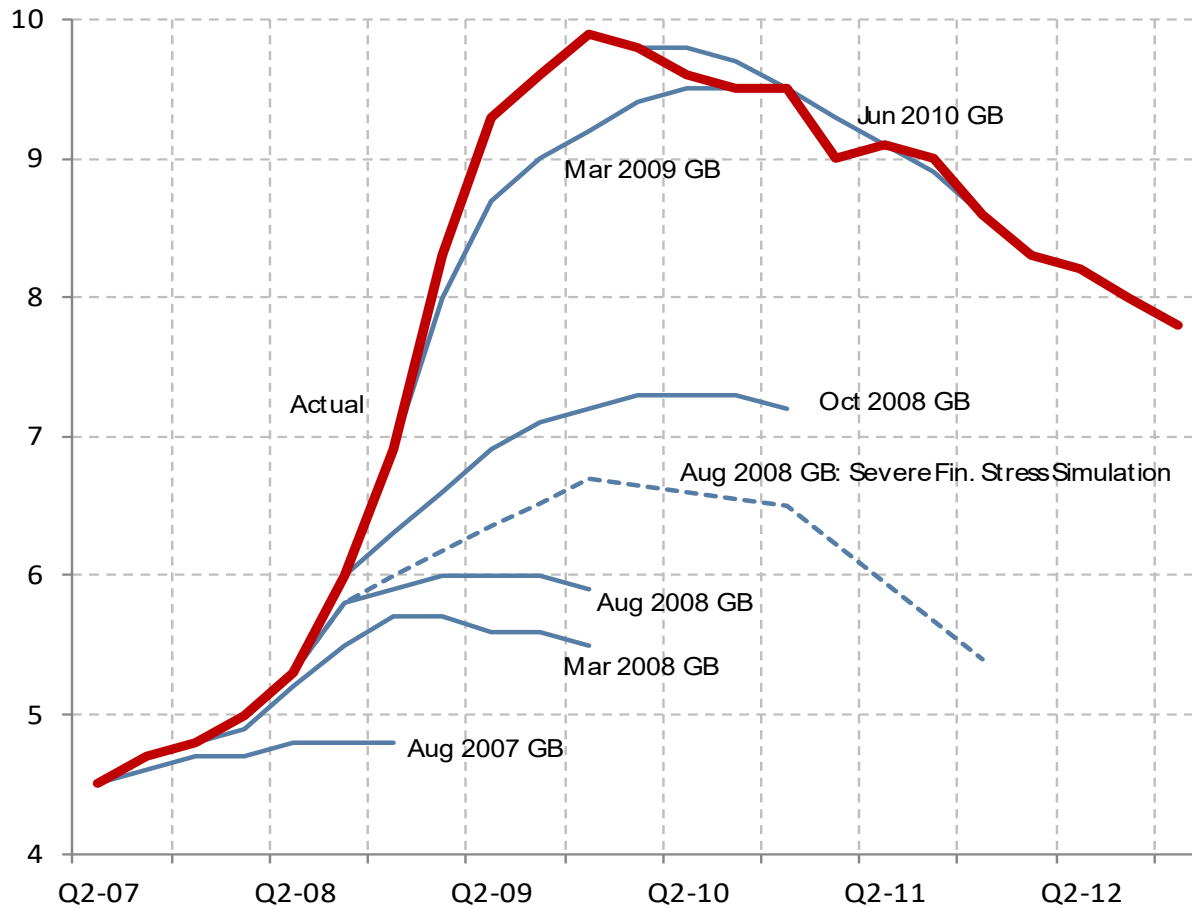
Brookings Institution

Washington, DC

Arthur M. Okun Memorial Lecture, New Haven, CT

April 10th, 2019

Unemployment Rate: Actual Outcome vs. Greenbook Forecasts (%)



Source: Kohn and Sack (2018)

How can credit-market disruptions be incorporated into macro models?

- The process of credit extension is rife with problems that stem from **asymmetric information** between borrowers and lenders (principal-agent problems; adverse selection; costs of screening and monitoring). These costs help to explain the existence of a positive **external finance premium (EFP)** — the all-in cost of borrowing less the opportunity cost of internal funds.
- Potentially, time variation in the EFP can help to explain business cycle dynamics and the powerful effects of financial crises on employment and output.
- The EFP in turn depends, *inter alia*, on the financial health (broadly defined) of both potential borrowers and financial intermediaries.

On the borrowers' side...

- Problems of asymmetric information are ameliorated when borrowers have “skin in the game,” that is, when they have sufficient net worth or collateral at risk to align their incentives with lenders and to reduce lenders’ financial risk.
- Consequently, descriptors of the financial health of borrowers (net worth, collateral, leverage) are state variables that, at least in principle, can affect the level of the EFP and, consequently, macroeconomic dynamics (the *financial accelerator*) --- **Bernanke and Gertler (1989); Kiyotaki and Moore (1997); Geanakoplos (2010).**

On the lenders' side...

- Intermediaries (“banks”) specialize in overcoming the costs of credit intermediation. But banks are borrowers, too, raising funds from ultimate savers, and so their balance sheets matter as well. Cyclicalities in the financial condition of banks (capital, liquidity) affects the EFP and reinforces the financial accelerator.

Panics, disintermediation, and the external finance premium

- Intermediaries often fund themselves cheaply by producing liquid, *information-insensitive liabilities*, such as bank deposits or senior tranches of securitizations --- **Gorton and Pennachi (1990)**. News that leads investors to fear that such liabilities are in fact less than perfectly safe can produce runs --- **Diamond and Dybvig (1983)**, **Gorton (2008)**.
- A panic – widespread runs on banks and other intermediaries --- may result in violent disintermediation and thus a sharp increase in the effective cost of credit --- **Gertler and Kiyotaki (2015)**. Increases in EFP help to explain the adverse real effects of major financial crises --- **Reinhart and Rogoff (2009)**. **Bernanke (1983)** argued that bank failures and debtor insolvency, by raising the EFP, contributed to the severity and duration of the Great Depression.

Credit market frictions were not part of the pre-crisis mainstream...

- Prior to the crisis, mainstream macro models (including policy models used by central banks) included little independent role for credit-market frictions or endogenous variations in the external finance premium. For example, the FRB/US model as formulated in 2008 provided Fed staff little help in forecasting the real effects of the financial crisis (and those effects were seriously underestimated).

But attitudes are changing...

- The experience since the global financial crisis has radically shifted the ground: The Great Recession was the worst downturn since the Depression, and its severity cannot be explained except as the result of credit-market dysfunction --- **Stock and Watson (2012)**.
- Indeed, if credit-market stress played such a large role in the Great Recession, it seems more plausible that it is relevant to garden-variety business cycles as well.

Credit-market frictions in macro models

In earlier quantitative models, including **Bernanke-Gertler-Gilchrist (1999)**, the inclusion of credit-market frictions improved the fit of the model to the data but were not the primary source of variation in output and employment. Early models also did not capture large and discontinuous crises and other nonlinear effects.

Credit-market frictions in macro models (continued)

In contrast, work since the crisis has shown:

(1) Credit-market factors can be important or even dominant drivers of real fluctuations in macro models

- **Christiano, Eichenbaum, and Trabandt (2014)** use a calibrated new Keynesian model to conclude that “the vast bulk of movements in aggregate real economic activity during the Great Recession were due to financial frictions.” See also **Christiano, Motto, Rostagno (2010, 2014)**. **Mian and Sufi (2018)** argued that periodic excessive expansions in household credit supply are a key force in the global business cycle.

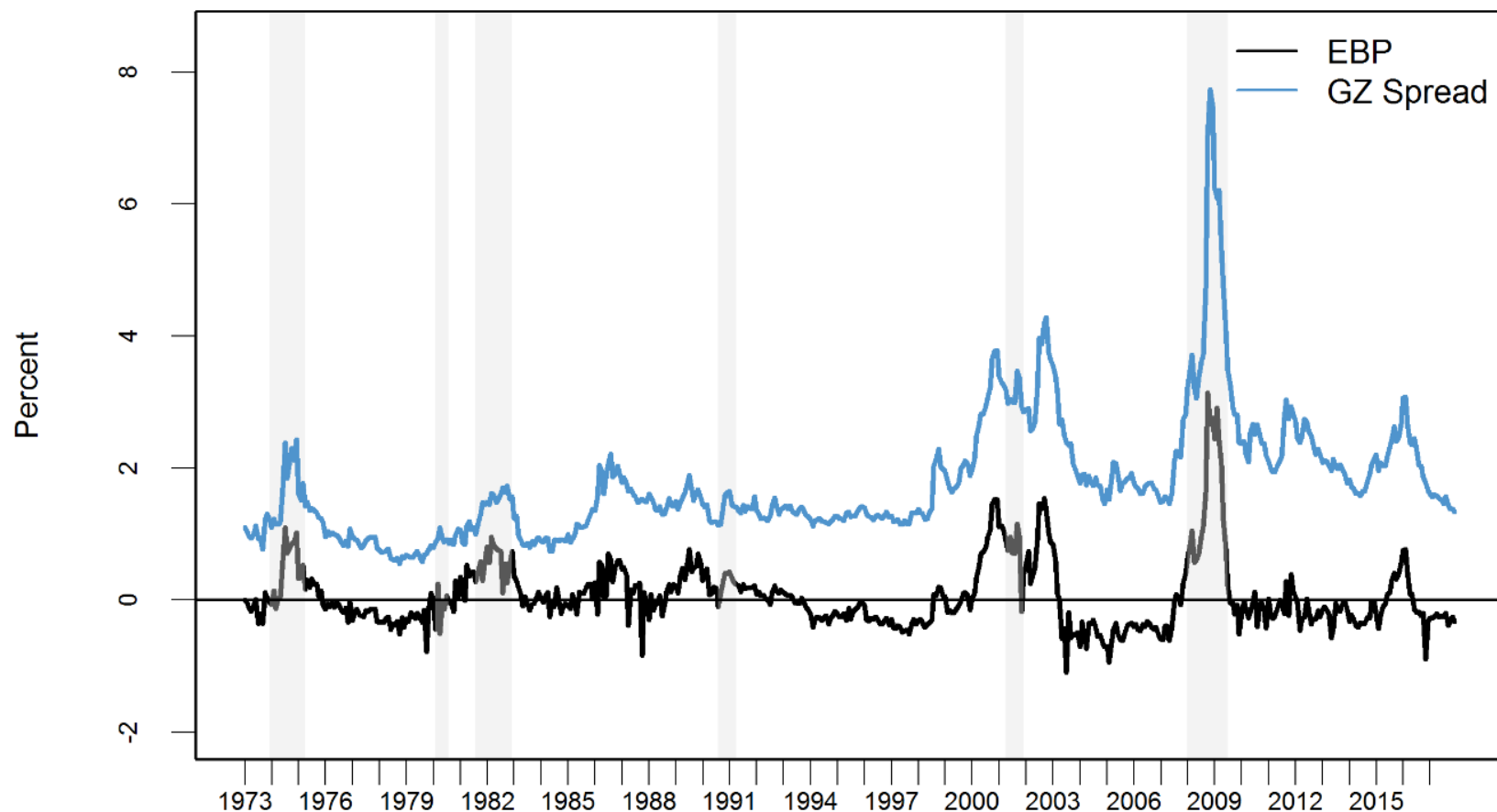
(2) Financial shocks can have large, nonlinear effects on activity

- **Gertler and Kiyotaki (2015)** and **Gertler-Kiyotaki-Prestipino (2017)** incorporated banking panics in a macro model and show that they can produce severe, highly nonlinear contractions in economic activity. **Brunnermeier and Sannikov (2014)** studied a model in which financial frictions create highly nonlinear amplification of shocks and lead to occasional crisis episodes.

(3) Reduced-form models based on financial factors can help predict real developments.

- **Gilchrist and Zakrajsek (2012)** demonstrated empirically that a corporate credit spread they construct, related to the external finance premium, is a strong predictor of economic activity.

Figure 1. Two Measures of the External Finance Premium for Nonfinancial Corporations



Source: Gilchrist and Zakrajšek (2012); updated data from Favara et al. (2016)

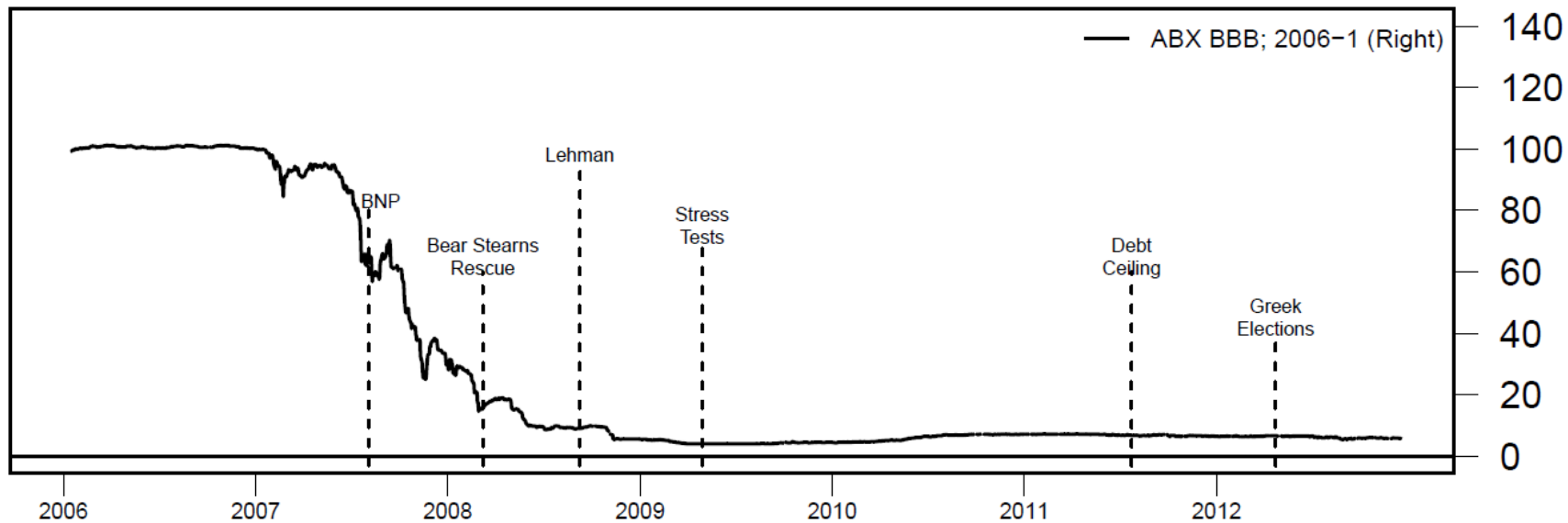
How did the financial crisis most affect the real economy?

Hypotheses

- 1) Household balance sheets → Effective demand for credit
- 2) Panic in wholesale funding, fire sales → Effective supply of credit

The two hypotheses have very different policy implications

Figure 2. Stages of the Financial Crisis

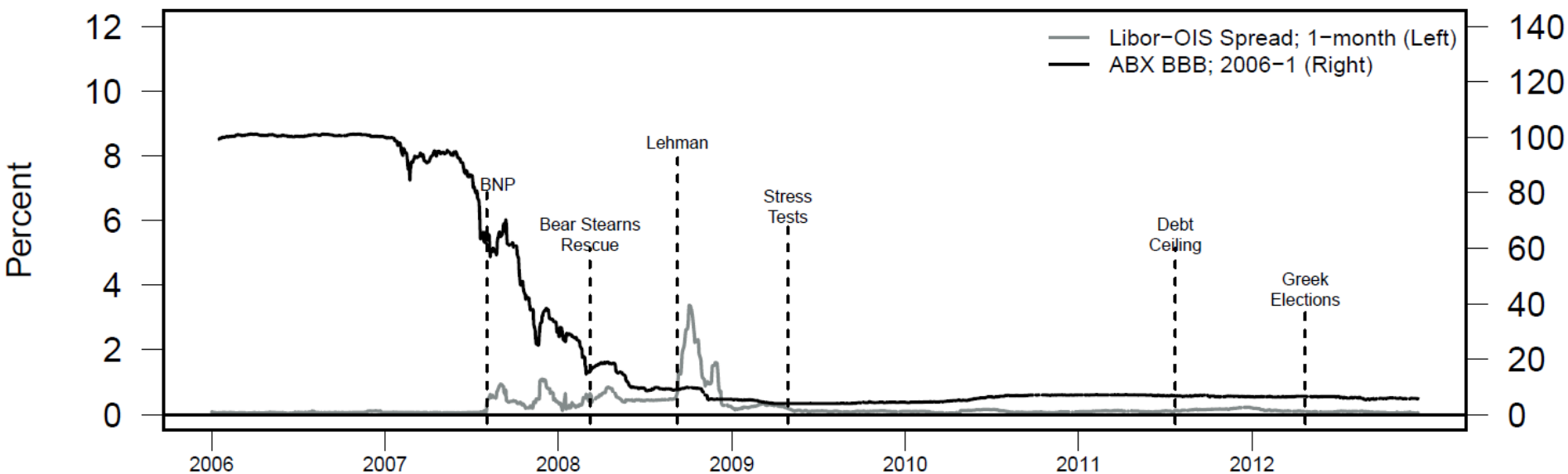


Source: Bloomberg, Haver.

ABX BBB (black, right scale) is an index of the value of BBB-rated, 2006-vintage **subprime mortgages**. It shows the market's sharply declining assessment of housing/mortgages beginning in mid-2006. The decline in mortgage values reflected the deterioration of household balance sheets; damaged the balance sheets of banks and investment banks; and ultimately triggered the panic.

Source: IHS Markit.

Figure 2. Stages of the Financial Crisis

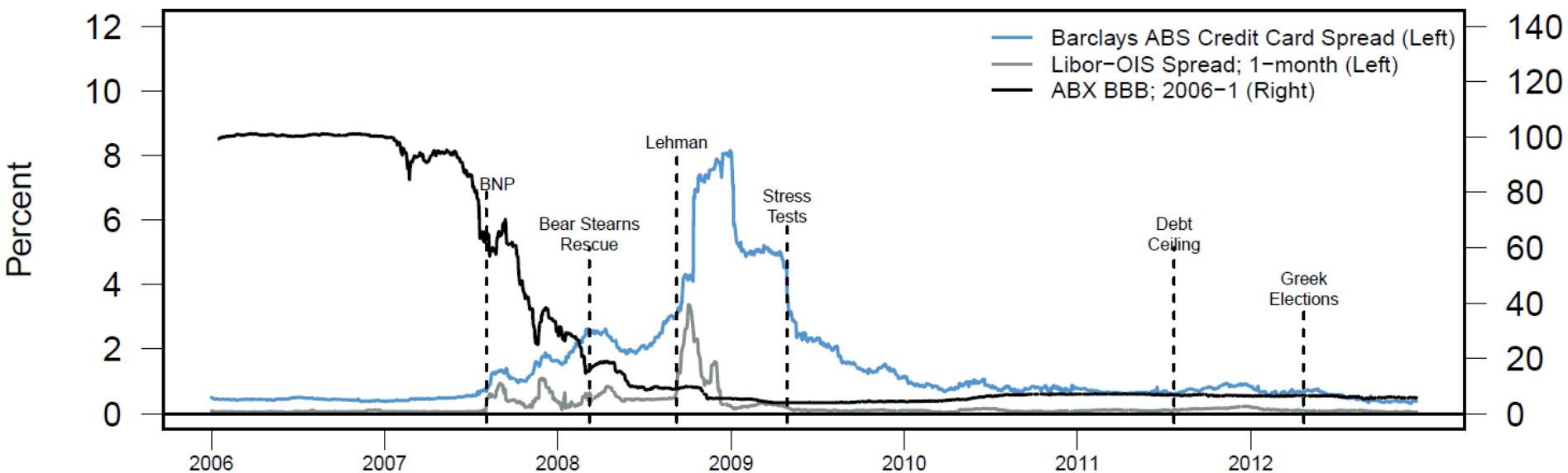


Source: Bloomberg, Haver.

LIBOR – OIS (grey, left scale) is the one-month inter-bank lending rate less an indicator of expected safe rates; it measures the risk of short-term lending. Sharp increases in LIBOR – OIS indicate **panic in wholesale funding**. As Gorton-Metrick (2012) point out, this variable remained stable even as ABX declined, rising only after BNP Paribas announced it couldn't value subprime mortgages in August 2007. It rose around the Bear Stearns episode, spiked during the Lehman crisis, then declined with the passage of TARP and Fed interventions in fall 2008.

Source: IHS Markit, Bloomberg Finance L.P.

Figure 2. Stages of the Financial Crisis

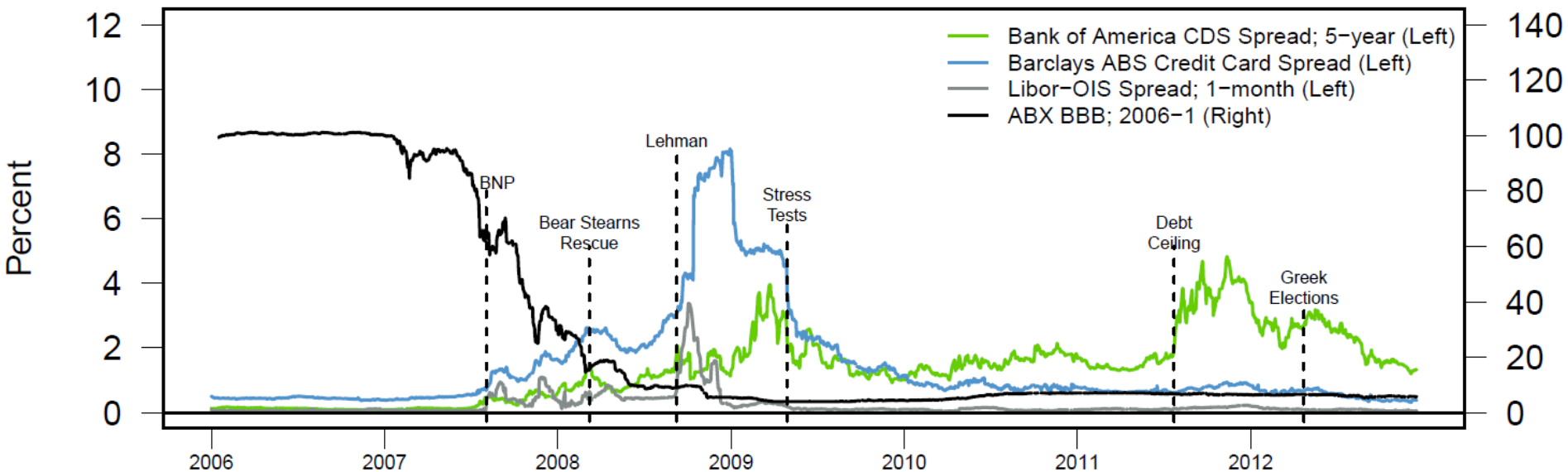


Source: Bloomberg, Haver.

ABS spreads for credit card debt (blue, left scale) shows the yield spread on a **non-mortgage securitization**. The ABS spread began to rise in late summer 2007 but jumped sharply after Lehman. Gorton-Metrick interpret the spike as the “run on repo,” in which investors would not lend against securitizations except with very high haircuts. Relatedly, the spike probably also reflects **fire sales**, as assets that could not be financed were dumped and disintermediated.

Source: IHS Markit, Bloomberg Finance L.P.

Figure 2. Stages of the Financial Crisis



Source: Bloomberg, Haver.

The CDS spread of a large bank (green, left scale) shows the effect of mortgage deterioration, funding shocks, and declines in the value of credit products on the **solvency of banks**. Bank health worsens through early 2009, improves following the spring 2009 stress tests, then worsens again about the time of the U.S. government's downgrade and continuing pressures in Europe.

Source: IHS Markit, Bloomberg Finance L.P.

Questions for further analysis

- Are the patterns in Figure 1 representative?
- Do the discontinuities in the data in fact allow for identification of the effects of each stage of the crisis on the broader economy? E.g., what were the direct macroeconomic effects of mortgage losses? Of the panic, including the run on securitizations? Of weakening bank balance sheets?
- If the broader effects can be identified, what does this tell us about the desirable response to this crisis and to future ones?

Methodology and data

We use **factor analysis** to analyze daily financial data (75 series, 2006-2012) in four broad categories:

- **Housing/mortgages** (17 series): Securitized mortgage indices (ABX); ABS spreads for home equity loans; homebuilder stock prices; REIT stock prices; subprime lender stock prices (all stock prices are relative to SP500)
- **Short-term funding** (15 series): LIBOR – OIS spreads; TED spreads; ABCP spreads; repo spreads (GCF MBS and agency over Treasury repo)
- **Non-mortgage credit** (22 series): ABS spreads (credit cards, auto loans, student loans); ABS indices (consumer loans); corporate bond spread indexes (CDX IG, CDX HY, Merrill Lynch indices); A2P2 commercial paper spread over OIS
- **Bank solvency** (21 series): For the largest US commercial and investment banks, CDS spreads and stock prices (relative to SP500)

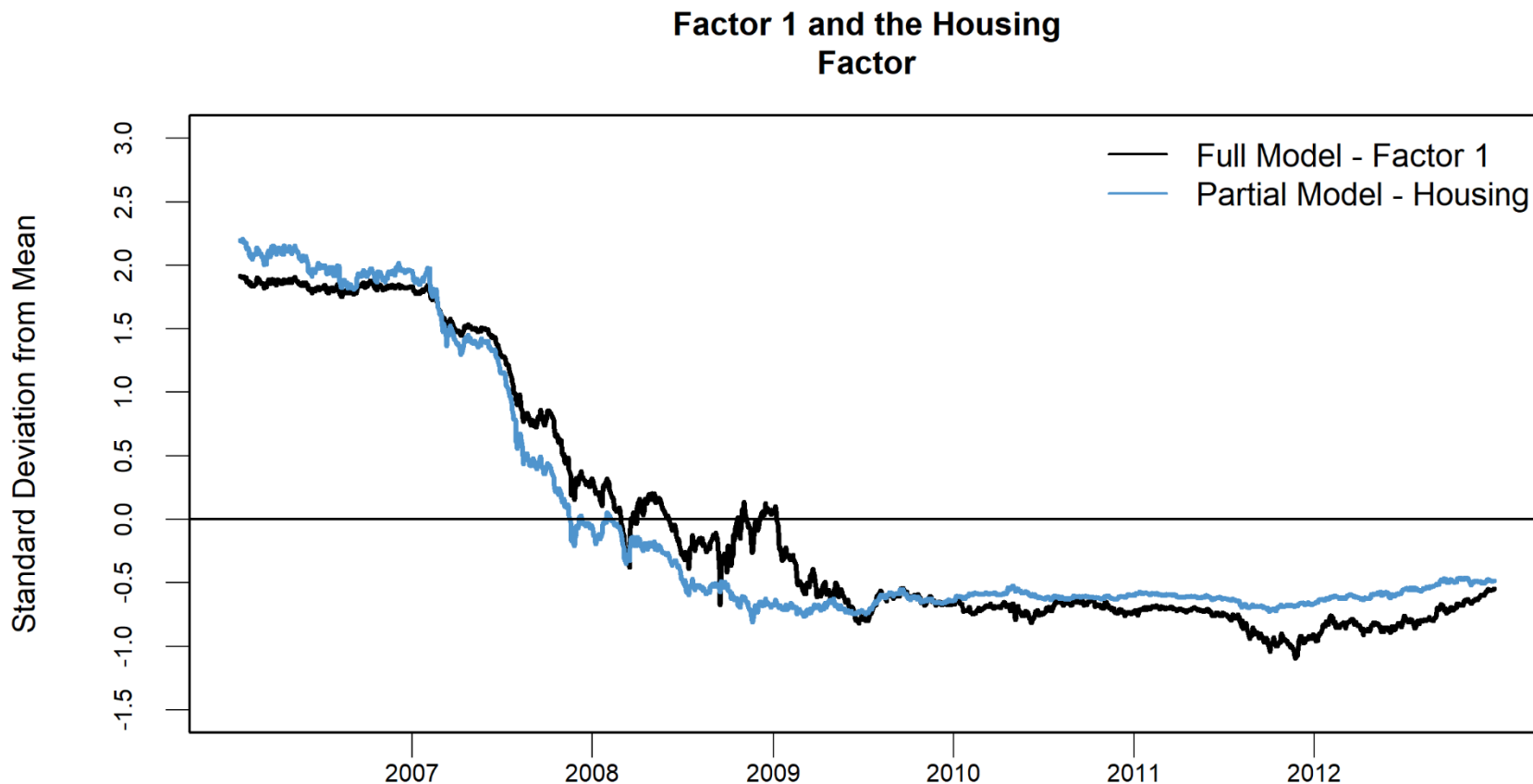
Factor analysis

Factor analysis is a data reduction process that represents n time series variables as linear combinations of k underlying, orthogonal factors plus idiosyncratic noise.

We do two exercises:

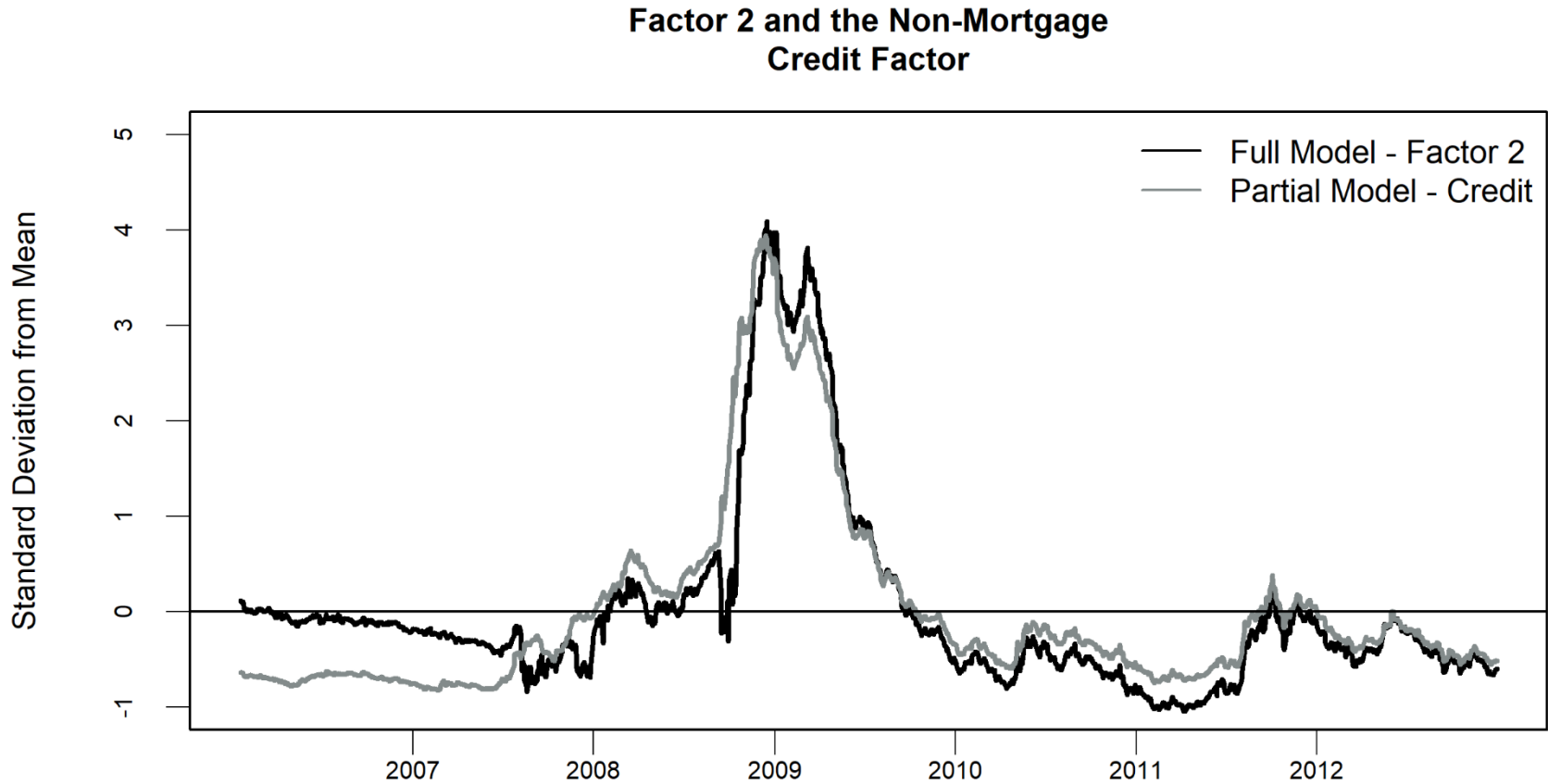
- We apply factor analysis to the **full sample** of 75 variables, extracting four independent factors. Three of the factors appear essential, while the fourth is borderline.
- We apply factor analysis to each of the four **subgroups** of data described above, extracting one factor from each. A single factor typically explains about 70 percent of the sum of squared residuals in each subgroup.

Figure 3. Full Sample Factor 1 and Subgroup Housing/Mortgage Factor



However, as it turns out, the factors estimated by the two methods are very similar. Here is the first estimated factor from the full sample (“Factor 1”) compared to the single factor estimated for the housing/mortgages subgroup.

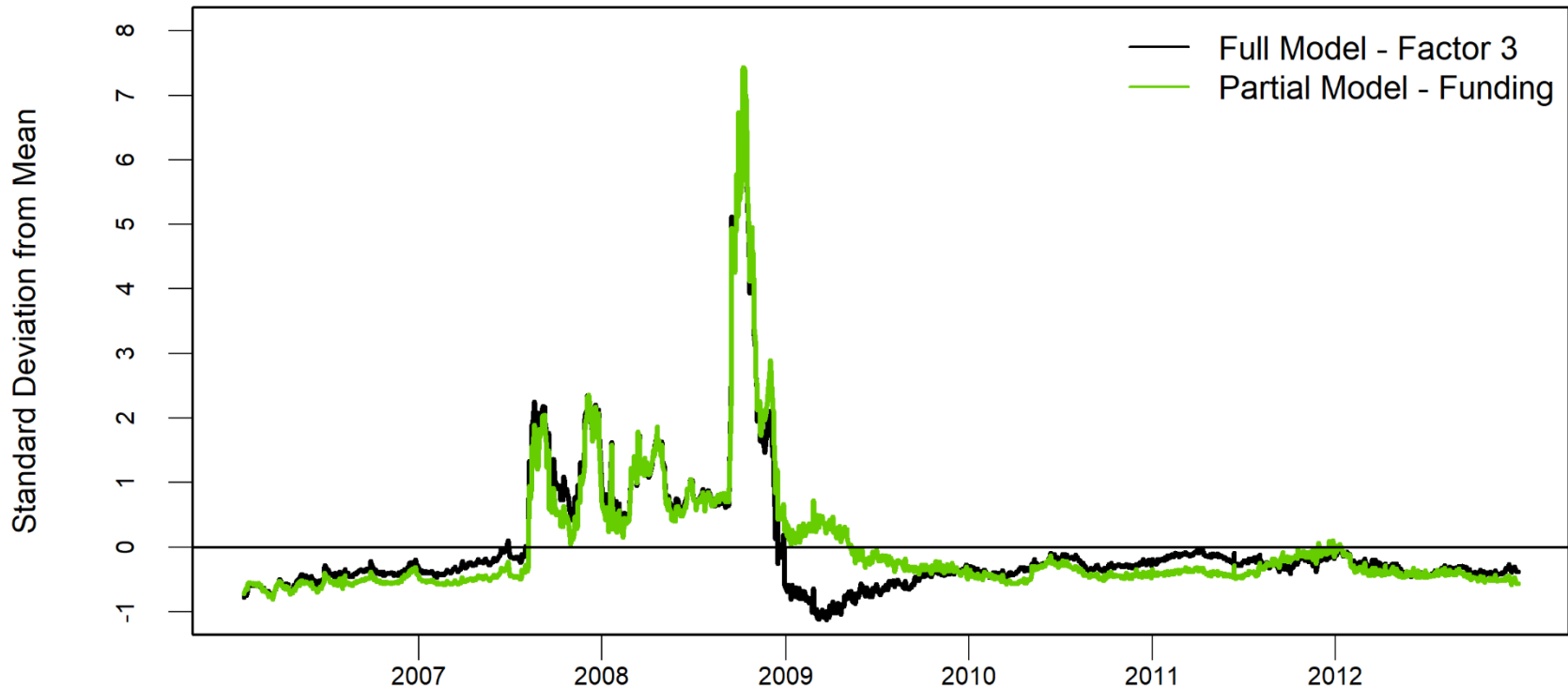
Figure 3. Full Sample Factor 2 and Subgroup Non-Mortgage Credit Factor



Here is Factor 2 and the factor from the non-mortgage credit subgroup.

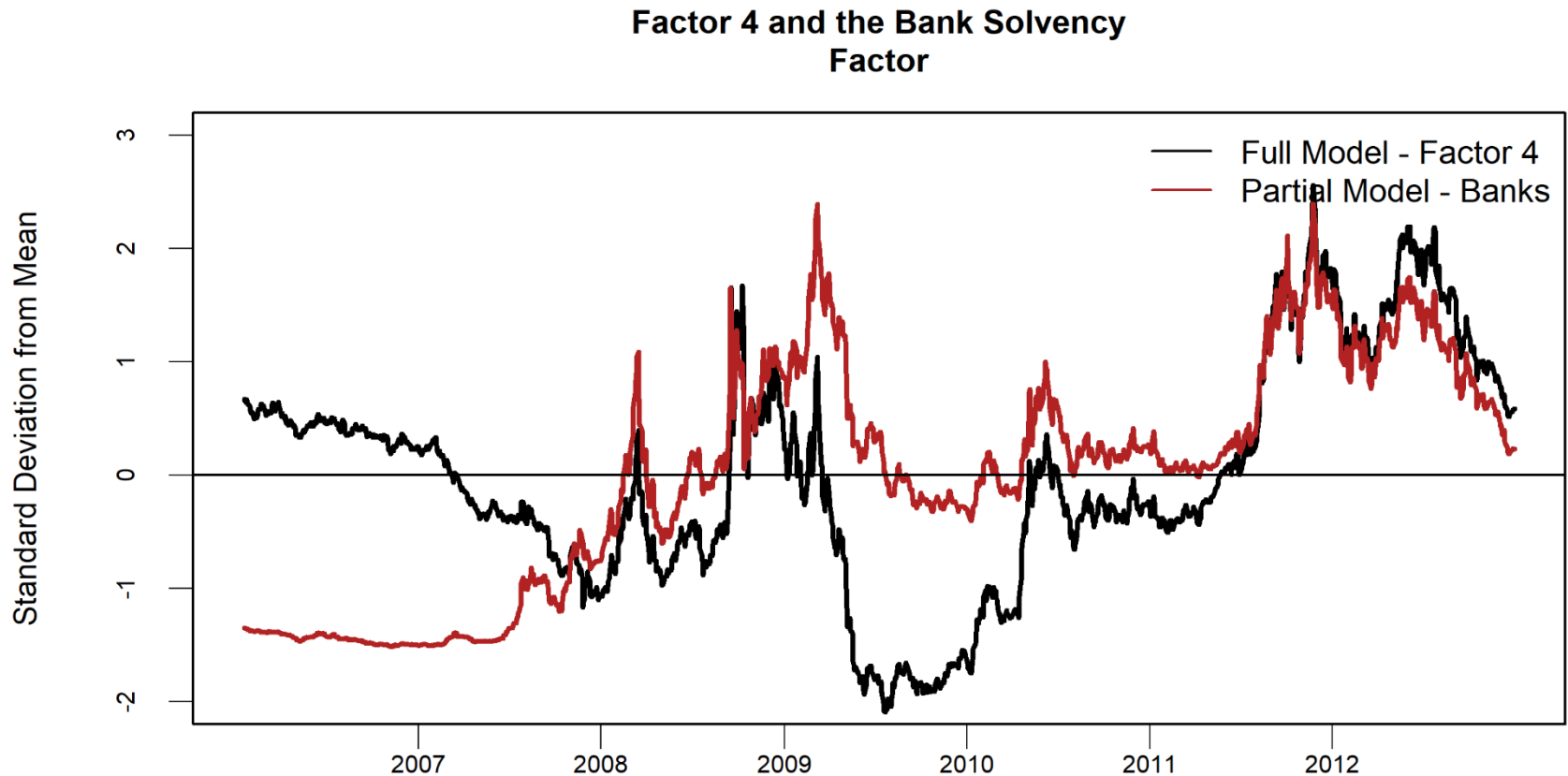
Figure 3. Full Sample Factor 3 and Subgroup Short-Term Funding Factor

**Factor 3 and the Short-Term
Funding Factor**



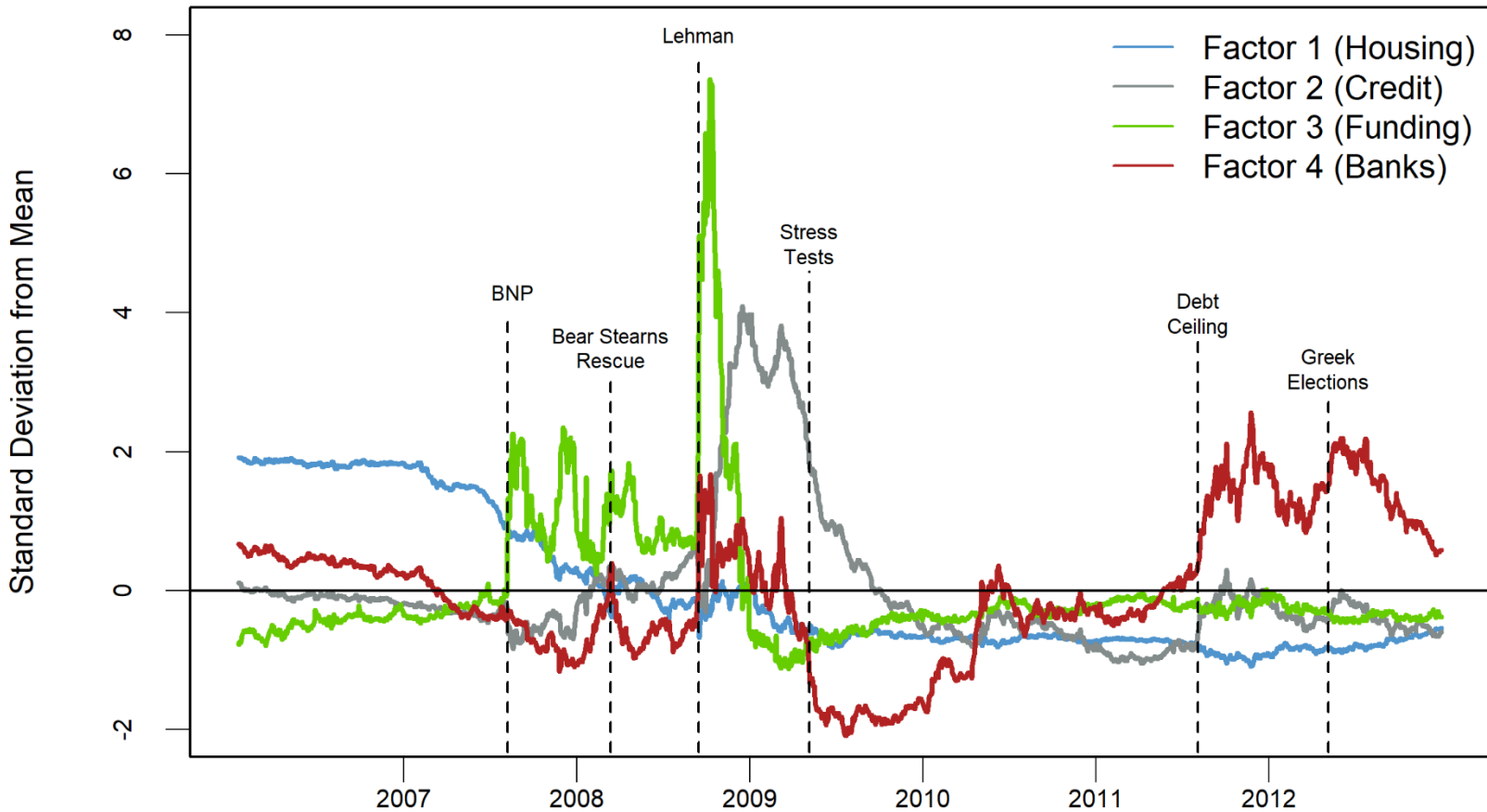
And Factor 3 from the full sample, together with the factor estimated from the short-term funding subgroup

Figure 3. Factor 4 and the Bank Solvency Factor



The correspondence of Factor 4 and the bank solvency factor is good, but less good than the others. Factor 4 has only limited marginal value in explaining the full data set, and the bank solvency factor is correlated with Factor 1 as well as Factor 4. Since Factor 1 loads heavily on mortgages, I interpret that as showing a strong link between mortgage losses and overall bank health.

Figure 4. Estimated factors from the Full Sample



Note the strong similarity to Figure 1, which was used to motivate the exercise.

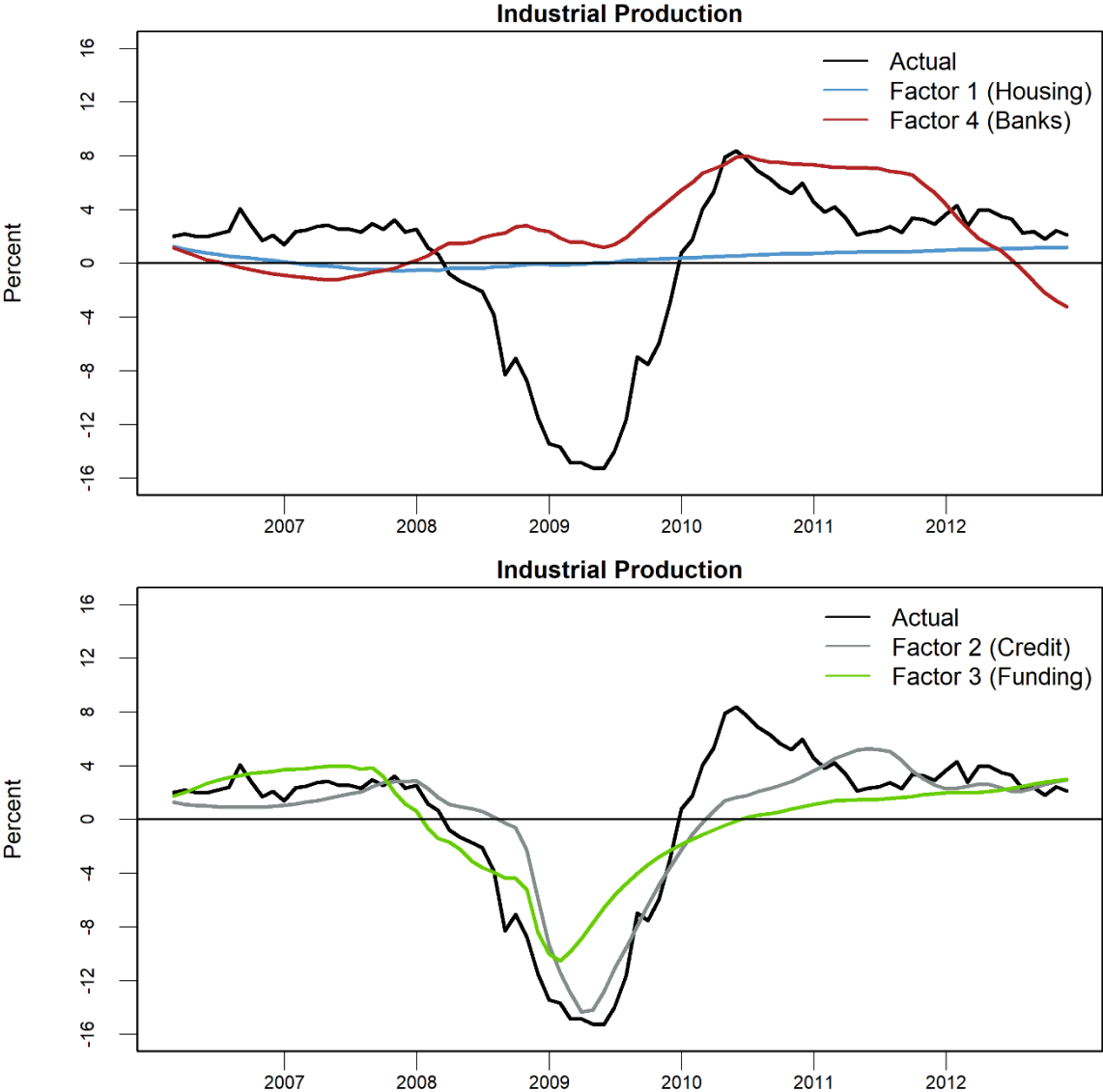
Table 1. F-statistics for Inclusion of Each Factor in Prediction Equations

Forecasted variable	Factor 1 (Housing)	Factor 2 (Non-mortgage Credit)	Factor 3 (Funding)	Factor 4 (Banks)
GDP	0.12	4.95***	3.26**	0.42
Industrial Production	0.04	7.82***	4.76***	1.60
Employment Ex Construction	1.66	8.75***	2.52*	0.29
Unemployment	1.16	11.35***	2.56*	1.09
Real PCE	0.41	4.20***	3.69**	0.77
Real PCE (Durables)	0.18	3.12**	3.67**	0.46
Retail Sales	0.15	11.02***	4.54***	2.79**
Housing Starts	1.34	1.69	0.96	1.74
Capital Goods Orders	0.40	9.45***	2.89**	3.07**
ISM Manufacturing Index	0.62	23.97***	13.09***	1.42*
Core PCE Inflation	0.99	1.90	0.83	0.44
df	(3;76)	(3;76)	(3;76)	(3;76)

To assess economic significance, we used the prediction equations to perform dynamic simulations of each macro variable.

- Simulations are for the whole sample period, beginning in 2006
- Simulations use estimated values for the factor being assessed, zeroing out other factors in the prediction equation
- Simulations are *dynamic*, in that the lagged macro variables are fitted (i.e., as predicted by the estimated factor alone), not actual

Figure 5. Dynamic simulations using estimated full-sample factors



Another way to phrase the issue: How important was the panic – the run on wholesale funding that expanded into a run on securitized credit – versus other financial factors, including bank and borrower balance sheet factors?

The following results combine Factor 2 (credit) and Factor 3 (funding), attributing their joint predictive power to “panic.” Factors 1 and 4 are jointly labeled “non-panic.”

Table 2. F-statistics for Inclusion of Pairs of Factors in Prediction Equations

Forecasted variable	Panic Factors	Balance Sheet Factors
	(Factors 2 and 3)	(Factors 1 and 4)
GDP	3.58***	0.25
Industrial Production	5.82***	0.86
Employment Ex Construction	4.65***	1.16
Unemployment	7.67***	1.69
Real PCE	4.31***	0.88
Real PCE (Durables)	5.34***	0.34
Retail Sales	9.19***	1.77
Housing Starts	1.37	1.50
Capital Goods Orders	5.34***	1.86**
ISM Manufacturing Index	17.53***	0.99
Core PCE Inflation	1.13	0.99
df	(6;73)	(6;73)

Figure 6. Dynamic simulations: Panic and Balance Sheet Factors

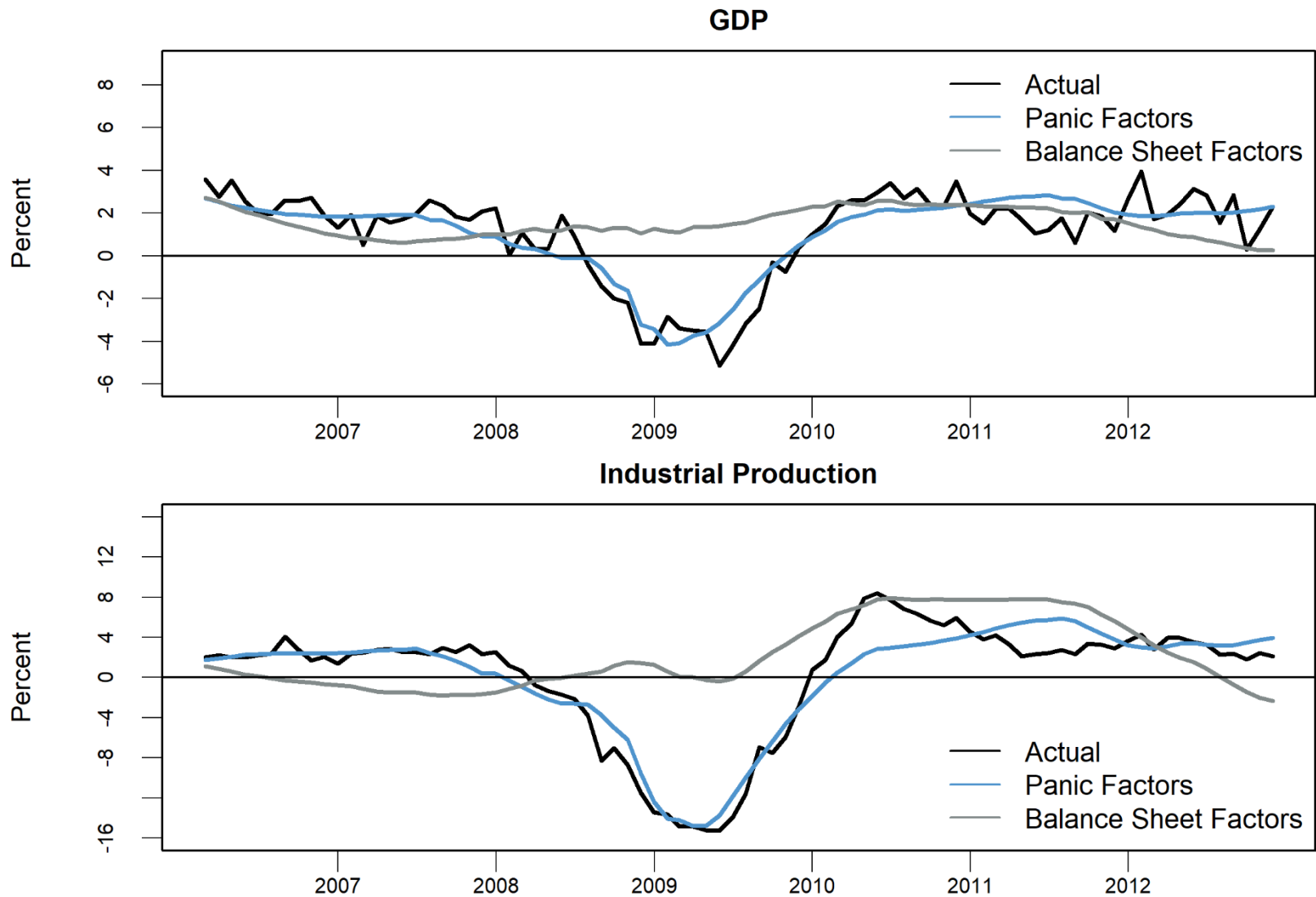
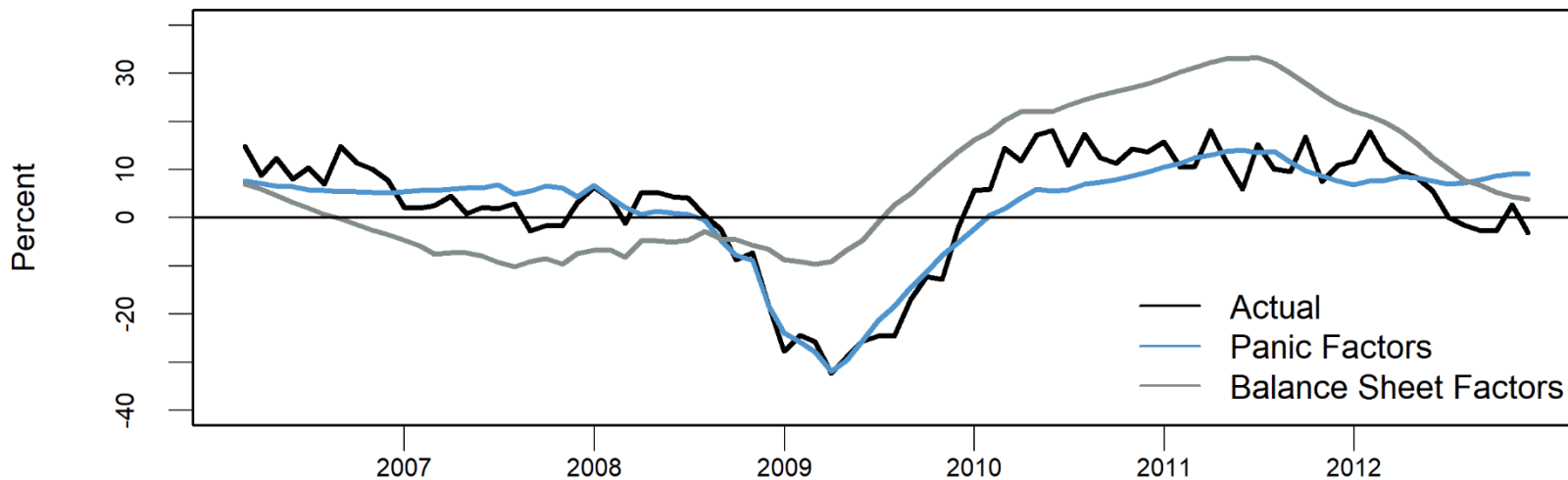


Figure 6. Dynamic simulations

Capital Goods Orders



Employment Ex. Construction

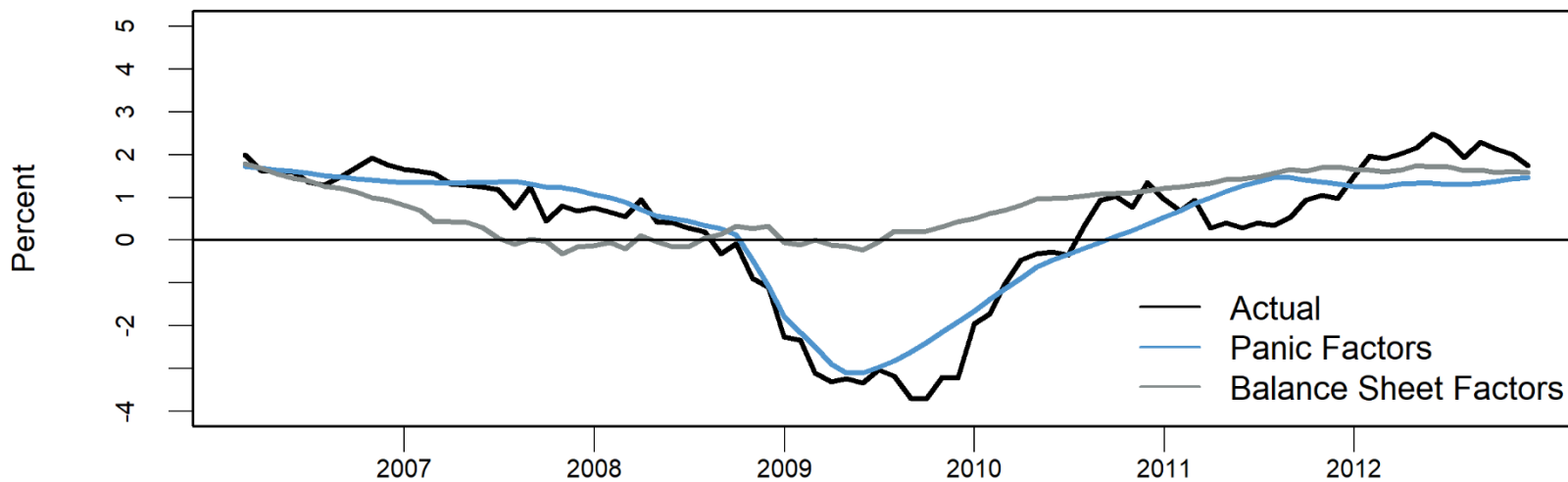


Figure 6. Dynamic simulations

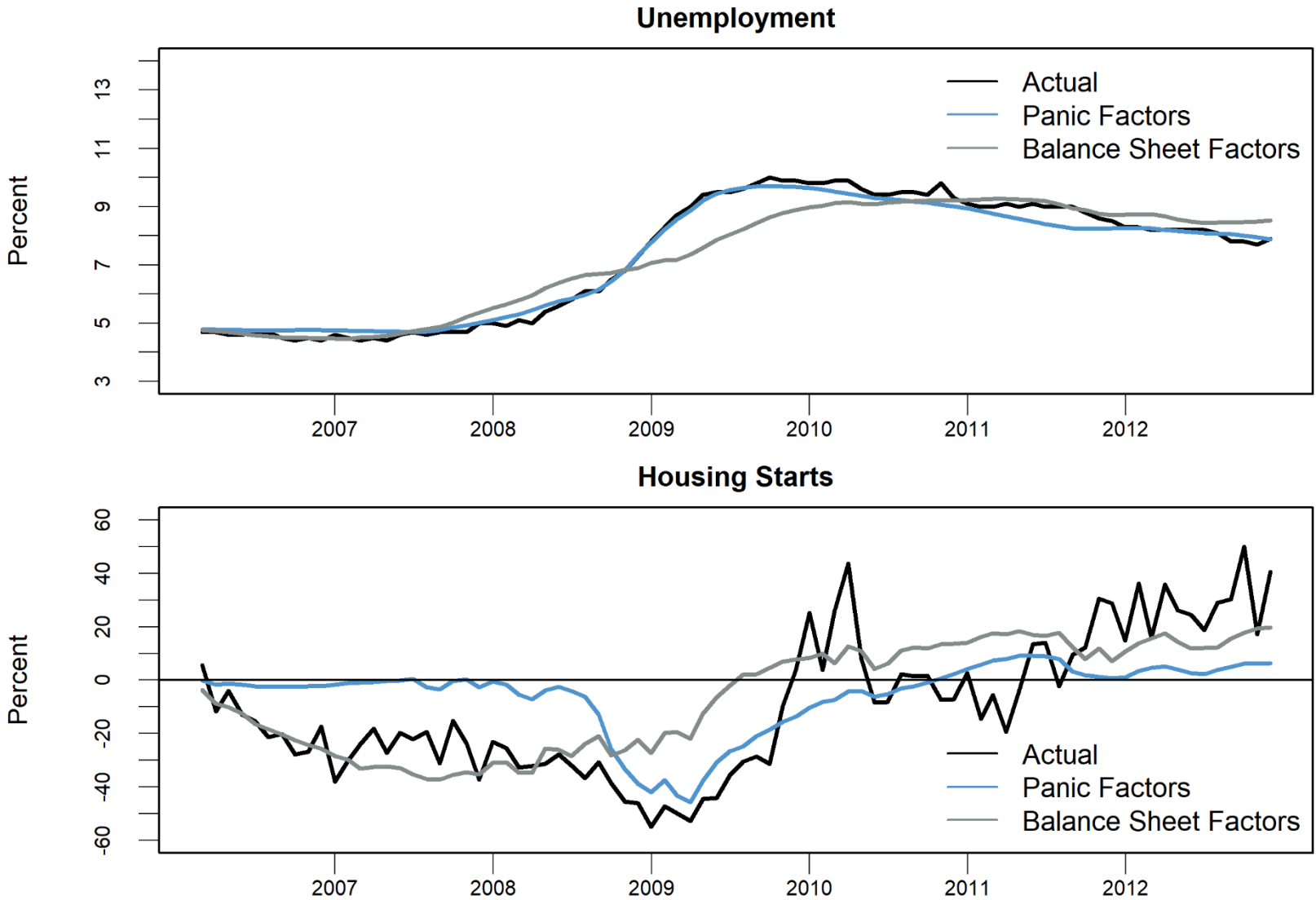
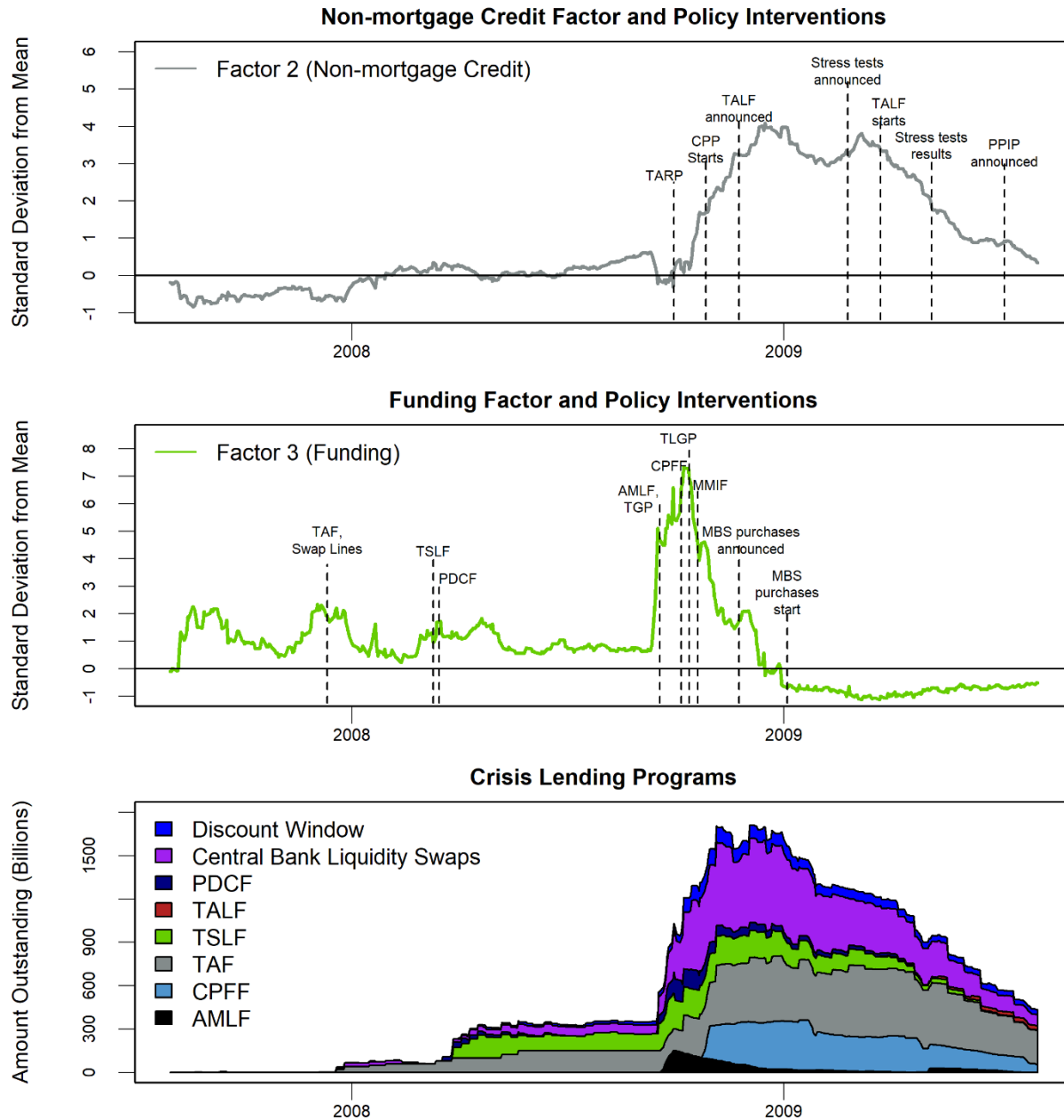


Table 3. F-statistics for Inclusion of Alternative Crisis Measures

Forecasted variable	House Prices	Delinquencies	EBP	EBP (Ortho.)
GDP	2.62*	2.73**	7.85***	8.39***
Industrial Production	1.98	2.84**	11.12***	13.75***
Employment Ex Construction	0.75	5.69***	8.44***	9.09***
Unemployment	1.71	9.32***	15.24***	14.76***
Real PCE	2.51*	2.95**	7.56***	8.12***
Real PCE (Durables)	2.55*	2.05	6.1***	7.13***
Retail Sales	1.30	2.22*	8.93***	10.07***
Housing Starts	3.52**	3.14**	1.71	2.01
Capital Goods Orders	1.08	3.07**	7.91***	8.89***
ISM Manufacturing Index	1.81	4.78***	15.47***	15.58***
Core PCE Inflation	1.01	1.81	1.86	1.63
df	(3;76)	(3;76)	(3;76)	(3;76)

Figure 7. Policy Interventions



On the role of credit factors in macroeconomics

- Empirical work since the crisis has tended to confirm the importance of credit factors in the behavior of households, firms, and banks
- New modeling techniques show how to incorporate these factors into macro analysis
- Macro modeling and forecasting should pay greater attention to changes in credit conditions

On the real effects of the Global Financial Crisis

- Financial distress of households, firms, and banks certainly played a role
- However, the financial panic explains the extraordinary severity of the initial downturn
- This finding justifies strong actions to control panics before they sink the economy