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Disentangling the Channels of the 2007–09 Recession

ABSTRACT This paper examines the macroeconomic dynamics of the 2007–09 recession in the United States and the subsequent slow recovery. Using a dynamic factor model with 200 variables, we reach three main conclusions. First, although many of the events of the 2007–09 collapse were unprecedented, their net effect was to produce macro shocks that were larger versions of shocks previously experienced, to which the economy responded in a historically predictable way. Second, the shocks that produced the recession were primarily associated with financial disruptions and heightened uncertainty, although oil shocks played a role in the initial slowdown, and subsequent drag was added by effectively tight conventional monetary policy arising from the zero lower bound. Third, although the slow nature of the recovery is partly due to the shocks of this recession, most of the slow recovery in employment, and nearly all of the slow recovery in output, is due to a secular slowdown in trend labor force growth.

The recession that began in the fourth quarter of 2007 was unprecedented in the postwar United States for its severity and duration. Following the cyclical peak of 2007Q4, real GDP dropped by 5.1 percent and nearly 8.8 million jobs were lost. According to the most recent data revisions, that peak in GDP was not reattained until 15 quarters later, in 2011Q3, and as of this writing in April 2012 only 3.7 million jobs have been regained. All this suggests that the 2007–09 recession and subsequent recovery were qualitatively, as well as quantitatively, different from previous postwar recessions. The recession also seems unprecedented in its precipitating sources: the first persistent nationwide decline in real estate values since World War II, a financial sector that was unusually vulnerable because of recent deregulation

and little-understood derivatives, and a collapse in lending that also dampened the recovery.¹

This paper takes an empirical look at this recession and recovery, with an eye toward quantifying the extent to which this recession differs from previous postwar recessions, the contributions of various shocks to the recession, and the reasons for the slow recovery. More specifically, we consider three questions. First, beyond its severity, how did this recession differ from previous postwar recessions? Second, what were the economic shocks that triggered this recession, and what were their quantitative contributions to the collapse of economic activity? Third, to what extent does the current “jobless” recovery constitute a puzzle, something out of line with historical patterns and thus requiring a new explanation?²

The organizing framework for our analysis of these three questions is a high-dimensional dynamic factor model (DFM). Like a vector autoregression (VAR), a DFM is a linear time-series model in which economic shocks drive the comovements of the variables; the main difference between a DFM and a VAR is that the number of shocks does not increase with the number of series. Also as in a VAR, some properties, such as stability and forecasts, can be studied using a “reduced form” DFM that does not require identifying factors or structural shocks; however, attributing movements in economic variables to specific economic shocks requires identifying those shocks as in structural VAR analysis.

Our empirical model has 200 macroeconomic variables driven by six macro factors. These six factors drive the macro comovements of all the variables. Shocks that affect only a handful of series, such as a sectoral demand shock that affects a small number of employment and production series, would not surface as a macro factor but would instead imply idiosyncratic variation in those series. Using this model, we can address the question of whether the 2007–09 recession was characterized by a new type of shock by examining whether that recession is associated with new factors.

Our three main findings follow the three questions posed above. First, a combination of visual inspection and formal tests of a DFM estimated

1. The view that financial recessions and recoveries are different from “normal” recessions has been articulated most notably by Reinhart and Rogoff (2009); see also Reinhart and Reinhart (2010), Hall (2010), Mishkin (2010), Bank of Canada (2011), and Jordà, Schularick, and Taylor (2011).

2. Various reasons have been proposed for why this recovery is exceptional, including the deleveraging that followed the financial crisis (for example, Mian and Sufi 2011), regional or industry job mismatch (for example, Şahin and others 2011), changes in labor management practices (for example, Berger 2011), and monetary policy rendered ineffective because of the zero lower bound.

through 2007Q3 suggests that the same six factors that explained previous postwar recessions also explain the 2007–09 recession: no new “financial crisis” factor is needed. Moreover, the response of the macro variables to these “old” factors is, in most cases, the same as it was in earlier recessions. Within the context of our model, the recession was associated with exceptionally large movements in these “old” factors, to which the economy responded predictably given historical experience. Of course, this recession *did* have new and unprecedented failures of the financial plumbing (for example, the fall of the global investment bank Lehman Brothers) as well as novel, aggressive policy responses (such as the Troubled Asset Relief Program, or TARP, and the Federal Reserve’s various facilities); our results suggest, however, that these failures and responses did not have qualitatively different net effects on the macroeconomy than did past disturbances—just larger ones. What the results here suggest is that the shocks arising from these extraordinary events had ordinary impacts: from a macro perspective these shocks had the same effect as previously observed shocks, so the shocks surface in our model as large movements in the “old” factors.

Second, identifying what, precisely, these large economic shocks were requires an exercise similar to structural VAR identification. We consider six shocks: to oil markets, monetary policy, productivity, uncertainty, liquidity and financial risk, and fiscal policy. We identify these shocks using a novel method in which we treat shocks constructed elsewhere in the literature as instrumental variables; for example, one of the three instruments we use to identify the oil shock is Lutz Kilian’s (2008a) series on strife-driven OPEC oil production shortfalls. In all, we have 17 such external instruments with which to estimate our six shocks. The results of this exercise are mixed, in large part because the instruments produce estimates of purportedly different shocks that are correlated. In particular, the uncertainty shocks and the shocks to liquidity and financial risk are highly correlated, which makes their separate interpretation problematic. Despite these drawbacks, the structural analysis is consistent with the recession being caused by initial oil price shocks followed by large financial and uncertainty shocks.

Third, focusing on the recovery following the 2009Q2 trough, we estimate that slightly less than half of the difference between the recovery in employment since 2009Q2 and the average for recoveries between 1960 and 1982 is attributable to cyclical factors (the shocks, or factors, during the recession). Instead, most of the slowness of the recovery is attributable to a long-term slowdown in trend employment growth. Indeed, that slowdown has been dramatic: according to our estimates, trend annual employment growth slowed from 2.4 percent in 1965 to 0.9 percent in 2005. The

explanation for this declining trend growth rate that we find most compelling rests on changes in underlying demographic factors, primarily the plateau in the female labor force participation rate (after a sharp rise during the 1970s through the 1990s) and the aging of the workforce. Because the net change in trend productivity growth over this period is small, this slower trend growth in employment translates into slower trend GDP growth. These demographic changes imply continued low or even declining trend growth rates in employment, which in turn suggest that future recessions will be deeper and longer, and will have slower recoveries, than has been the case historically.

A vast number of papers examine the financial crisis, but relatively few tackle the empirical macro issues discussed here. Some related papers that look at aspects of the problem of shocks and their propagation include Martin Lettau and Sydney Ludvigson (2011) on permanent wealth shocks; the related paper by John Campbell, Stefano Giglio, and Christopher Polk (2010) on reasons for the stock market collapse; Simon Gilchrist, V. Yankov, and Egon Zakrajšek (2011) on credit spreads and their role as measures of financial distress in this and previous recessions; and Robert Hall (2011, 2012) on the postcrisis dynamics. Òscar Jordà, Moritz Schularick, and Alan Taylor (2011) and Michael Bordo and Joseph Haubrich (2011) look at the relationship between the depth and the duration of recessions with a focus on whether financial crises are exceptional and reach opposite conclusions. We are not aware of a comprehensive treatment along the lines discussed here, however.

Section I of the paper describes the DFM and the data set. Section II presents a counterfactual exercise, examining how well the historical shocks and model do at predicting the 2007Q4–2011 experience, along with stability tests. Section III discusses identification of the structural shocks and provides empirical analysis of the identified shocks. Section IV focuses on the slow recovery, and section V concludes. Detailed data description and additional empirical results are contained in the online appendix.³

I. Empirical Methods and Data

We begin by describing our empirical methods and the data used in the analysis.

3. Online appendixes and replication files for the papers in this volume may be accessed on the Brookings Papers website, www.brookings.edu/about/projects/bpea, under “Past Editions.” They are also accessible at Mark Watson’s personal website at Princeton University, www.princeton.edu/~mwatson/.

1.A. Empirical Methods

Dynamic factor models capture the notion that the macroeconomy is driven by a handful of unobserved macro shocks. There is considerable empirical evidence that a DFM with a small number of factors describes the comovements of macroeconomic time series (see, for example, Sargent and Sims 1977, Giannone, Reichlin, and Sala 2004). Thomas Sargent (1989) and Jean Boivin and Marc Giannoni (2010) develop this idea formally, starting from a dynamic stochastic general equilibrium model in which the driving variables are observed with measurement error. There is now a rich set of econometric methods for inference in DFMs (see Stock and Watson 2011 for a survey). Applications of these methods include forecasting (see Eickmeier and Ziegler 2008) and the factor-augmented vector autoregression (FAVAR) method of Ben Bernanke, Boivin, and Piotr Elias (2005).

Because the comovements of the observed series stem from the factors, it is not necessary to model directly the dynamics among observed variables; this avoids the proliferation of coefficients found in VARs. Because a DFM has relatively few factors compared with the number of observed variables, it allows a tractable simultaneous empirical analysis of very many variables in a single, internally consistent framework.

THE DYNAMIC FACTOR MODEL Let $X_t = (X_{1t}, \dots, X_{nt})'$ denote a vector of n macroeconomic time series observed over periods $t = 1, \dots, T$, where X_{it} is a single time series, where all series have been transformed to be stationary and to have a mean of zero (details below), and let F_t denote the vector of r unobserved factors. The DFM expresses each of the n time series as a component driven by the factors, plus an idiosyncratic disturbance term e_{it} :

$$(1) \quad X_t = \Lambda F_t + e_t,$$

where $e_t = (e_{1t}, \dots, e_{nt})'$ and Λ is an $n \times r$ matrix of coefficients called the factor loadings. The term ΛF_t is called the “common component” of X_t .

The factors are modeled as evolving according to a VAR:

$$(2) \quad \Phi(L)F_t = \eta_t,$$

where $\Phi(L)$ is an $r \times r$ matrix of lag polynomials and η_t is an $r \times 1$ vector of innovations.⁴ Because the factor VAR in equation 2 is assumed to be stationary, F_t has the moving-average representation $F_t = \Phi(L)^{-1}\eta_t$. The idiosyncratic errors e_t can be serially correlated, but the methods used here do not require a parametric model of the e_t dynamics.

ESTIMATION OF FACTORS AND DFM PARAMETERS The key insight that makes high-dimensional DFM modeling practical is that if the number of series n is large, the factors can be estimated by suitable cross-sectional averaging. This is most easily seen in the special case of a single factor with a nonzero cross-sectional average value of the factor loadings. Let \bar{X}_t denote the cross-sectional average of the variables at date t , $\bar{X}_t = n^{-1} \sum_{i=1}^n X_{it}$, and similarly let $\bar{\Lambda}$ and \bar{e}_t respectively denote the cross-sectional average factor loading and the cross-sectional average of the idiosyncratic term. By equation 1, the cross-sectional average of the data satisfies $\bar{X}_t = \bar{\Lambda} F_t + \bar{e}_t$. But by assumption the idiosyncratic terms are only weakly correlated, so by the weak law of large numbers, \bar{e}_t tends to zero as the number of series increases. Thus, when n is large, \bar{X}_t consistently estimates $\bar{\Lambda} F_t$; that is, \bar{X}_t estimates the factor up to scale and sign. In this special case, picking the arbitrary normalization $\bar{\Lambda} = 1$ yields the estimated factor time series, \hat{F}_t , and the individual factor loadings can be estimated by regressing each X_{it} on \hat{F}_t . If in fact there is a single-factor structure and n is sufficiently large, \hat{F}_t estimates F_t precisely enough that \hat{F}_t can be treated as data without a “generated regressor” problem (Bai and Ng 2006).

With multiple factors and general factor loadings, this simple cross-sectional averaging does not produce a consistent estimate of the factors, but the idea can be generalized using principal components analysis (Stock and Watson 2002). We use principal components here to estimate the factors; details are discussed in section I.D.

The principal components estimator of the factors consistently estimates F_t up to premultiplication by an arbitrary nonsingular $r \times r$ matrix (the analogue of $\bar{\Lambda}$ in the single-factor example); that is, the principal components estimator consistently estimates not the factors, but rather the space spanned by the factors when n and T are large. This means that the principal components estimator of F_t has a normalization problem, which is “solved” by the arbitrary restriction that $\Lambda' \Lambda = I_r$, the $r \times r$ identity matrix. This arbitrary normalization means that the individual factors do not have a direct economic interpretation (such as an “oil factor”). The analysis in

4. Equations 1 and 2 are the static form of the DFM, so called because the factors F_t enter with no leads or lags in equation 1. For a discussion of the relationship between the dynamic and the static forms of the DFM, see Stock and Watson (2011).

sections II and IV works with the reduced-form DFM in equations 1 and 2, so for that analysis this normalization is inconsequential. The analysis in section III requires identification of specific economic shocks, and our identification procedure is discussed there.

1.B. The Data and Preliminary Transformations

The data set consists of quarterly observations from 1959Q1 through 2011Q2 on 200 U.S. macroeconomic time series (vintage November 2011). The series are grouped into 13 categories: variables from the national income and product accounts (NIPA; 21 series); industrial production (13); employment and unemployment (46); housing starts (8); inventories, orders, and sales (8); prices (39); earnings and productivity (13); interest rates and spreads (18); money and credit (12); stock prices and wealth (11); housing prices (3); exchange rates (6); and other (2).

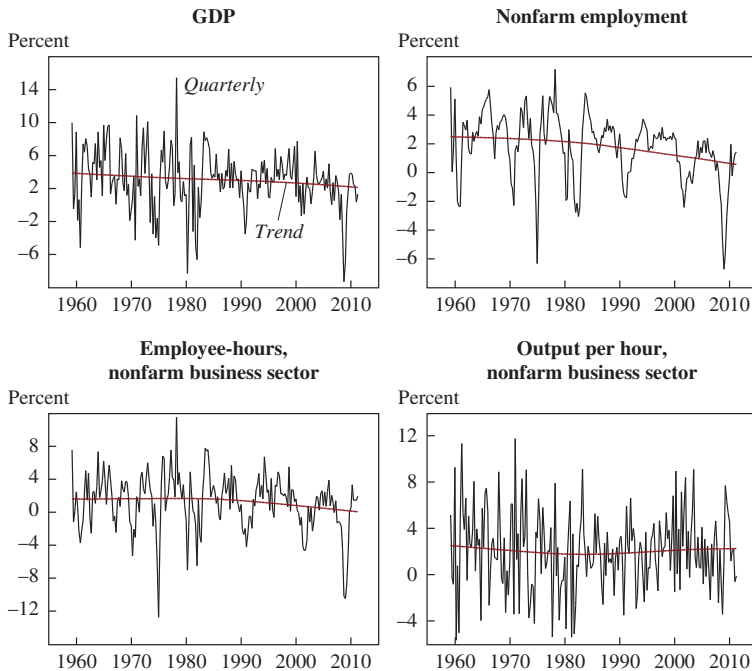
The series were subjected to a preliminary screen for outliers and then transformed as needed to induce stationarity. The transformation used depends on the category of the series. Real activity variables were transformed to quarterly growth rates (first differences of logs), prices and wages were transformed to quarterly changes of quarterly inflation (second differences of logs), interest rates were transformed to first differences, and interest rate spreads appear in levels. The 200 series and their transformations are listed in the online appendix.

1.C. Local Means and Detrending

All series were detrended to eliminate very low frequency variation. Specifically, after transforming the series to stationarity, we calculated the deviations of each series from a local mean estimated using a biweight kernel with a bandwidth of 100 quarters. These local means are approximately the same as those computed as the average of the transformed data over a centered moving window of ± 30 quarters, except that the former are less noisy because they avoid the sharp cutoff of a moving window.⁵ We refer to the local mean as the trend in the series, although it is important to note

5. Endpoints are handled by truncating the kernel and renormalizing the truncated weights to add to 1. This approach has the desirable feature that it makes no assumption about reversion to the local mean, in contrast to the mean reversion imposed by the standard approach of using a stationary time-series model to pad the series with forecasts and backcasts. We alternatively computed the local means using a Baxter-King (1999) high-pass filter with a pass band of periods with ≤ 200 quarters, and using the trend implied by a "local level" model (the sum of independent random walk and white noise with a ratio of disturbance standard deviations of 0.025), and obtained similar results. The weights for these different filters are given in the online appendix.

Figure 1. Growth Rates of GDP, Nonfarm Employment, Employee-Hours, and Labor Productivity, Quarterly and Trend, 1959Q1–2011Q2



Sources: Data sources listed in the online appendix and authors' calculations.

that these are trends in transformed series; for example, for GDP the estimated trend is the local mean value of GDP growth.

For some series, the values of these trends (that is, local means) change substantially over the 1959–2011 period. Figure 1 plots the quarterly growth rates of GDP, employment, employee-hours, and labor productivity, along with their trends. We estimate the trend GDP growth rate to have fallen 1.2 percentage points, from 3.7 percent per year in 1965 to 2.5 percent per year in 2005,⁶ and the trend annual employment growth

6. Our procedure produces a smooth but not necessarily monotonic trend. Kim and Eo (2012) model the trend decline in the growth rate of GDP as a single Markov switching break and estimate a decline of 0.7 percentage point over this period, less than our estimate of 1.2 percentage points. If the trend is in fact smoothly declining, one would expect their step-function approximation to estimate a smaller average decline than our local mean.

rate to have fallen by 1.5 percentage points, from 2.4 percent in 1965 to 0.9 percent in 2005. On the other hand, trend productivity (output per hour) has recovered from the productivity slowdown of the 1970s and 1980s and shows essentially no net change over this period. These trends are discussed further in section V.

1.D. Estimation Details

The data set contains both high-level aggregates and disaggregated components. To avoid double counting, in these cases only the disaggregated components were used to estimate the factors; for example, durables consumption, nondurables consumption, and services consumption were used to estimate the factors, but total consumption was not. Of the 200 series, 132 were used to estimate the factors; these are listed in the online appendix. No top-level macroeconomic aggregates (including GDP, consumption, investment, total employment, and the total unemployment rate) were used to estimate the factors.

Using these 132 series, we estimated the factor loadings Λ by principal components over 1959–2007Q3. These pre-2007Q4 factor loadings were then used to estimate the six linear combinations of X_t over the full 1959Q1–2011Q2 sample, which correspond to the estimated factors. For the 1959Q1–2007Q3 sample, these are the principal components of the factors; for the post-2007Q3 period, these are the pre-2007Q4 principal components factors, extended through the 2007Q4–2011Q2 sample. We refer to these six factors as the “old” factors because they are the factors for the “old” (pre-2007Q4) DFM, extended beyond 2007Q3.⁷ These “old” factors are used throughout the paper; with the single exception of a sensitivity

7. Specifically, let \tilde{X}_t denote the vector of 132 disaggregated time series used to estimate the factors, and let $\tilde{\Lambda}$ denote their corresponding factor loadings. These factor loadings $\tilde{\Lambda}$ are estimated by principal components using data on \tilde{X}_t over 1959Q1–2007Q3 (modified for some series having missing observations; see the online appendix). Denote the resulting estimates of $\tilde{\Lambda}$ by $\hat{\tilde{\Lambda}}^{59-07}$, normalized so that $\hat{\tilde{\Lambda}}^{59-07'} \hat{\tilde{\Lambda}}^{59-07} = I$. The estimated “old” factors are computed using $\hat{\tilde{\Lambda}}^{59-07}$ as $\hat{F}_t^{59-07} = \hat{\tilde{\Lambda}}^{59-07'} \tilde{X}_t$, $t = 1959Q1, \dots, 2011Q2$. The values of \hat{F}_t^{59-07} post-2007Q4 are those of the “old” factors in the sense that they are based on the pre-2007Q4 linear combinations of \tilde{X}_t . The factor loadings for the remaining 68 series (the high-level aggregates) are obtained by regressing each series on \hat{F}_t^{59-07} using data through 2007Q3; these estimates, combined with $\hat{\tilde{\Lambda}}^{59-07}$, yield the estimated “old” factor loadings, $\hat{\Lambda}^{59-07}$. The vector of common components of the full vector of time series associated with these “old” factors and “old” factor loadings is $\hat{\Lambda}^{59-07} \hat{F}_t^{59-07}$.

check in section II.B, the “old” DFM coefficients, estimated over 1959–2007Q3, are also used throughout.⁸

The DFM is estimated with six factors, a choice consistent with Bai-Ng (2002) tests for the number of factors, visual inspection of the scree plot, and the number of distinct structural shocks we examine in section IV.⁹ As discussed below and shown in the online appendix, our main results are not very sensitive to varying the number of factors over a reasonable range.

II. A Structural Break in 2007Q4?

This section investigates the extent to which the 2007–09 recession exhibited new macrodynamics relative to the 1959Q1–2007Q3 experience. This analysis has three parts. First, we examine whether the factors in the 2007–09 recession were new or, alternatively, were combinations of “old” factors seen in previous recessions. Second, to the extent that at least some of the shocks have historical precedents, we examine whether these “old” factors have different dynamic impacts before 2007Q4 than in 2007Q4–2011. Third, we examine the volatility of these “old” factors over the recession. The analysis in this section uses the reduced-form factors and does not require identifying individual structural shocks.

II.A. Post-2007 Simulation Using the Pre-2007 DFM

We begin by considering the following experiment: suppose a forecaster in 2007Q3 had in hand our six-factor, 200-variable DFM estimated using data through 2007Q3 and was magically given a sneak preview of the six

8. The assumption that the factors and DFMs can be estimated with no breaks over the 1959Q1–2007Q3 period is only partially consistent with the empirical evidence. On the side of stability, in Stock and Watson (2009) we use a similar data set and find that the space spanned by the full-sample (no-break) factors spans the space of the factors estimated using pre- and post-1984 subsamples; against this, there we also find breaks in some factor loadings in 1984Q1. These apparently contradictory findings can be reconciled by the property of DFMs that the space spanned by the factors can be estimated consistently even if there is instability in Λ (Stock and Watson 2002, 2009, Bates and others 2012). These findings suggest that, in the present analysis, we can ignore the 1984Q1 break when estimating the factors; however, tests of coefficient stability might be sensitive to whether the comparison sample includes pre-1984Q1 data. We therefore consider a DFM with a break in 1984Q1 as a sensitivity check. Additional sensitivity checks, with breaks in 1984Q1, are reported in the online appendix.

9. The Bai-Ng (2002) IC_{p_1} and IC_{p_2} criteria select either three or four factors, depending on the sample period, whereas their IC_{p_3} criterion selected 12 factors. The scree plot (the plot of the ordered eigenvalues of the sample covariance matrix of X_t) drops sharply to four or five factors and then declines slowly.

“old” factors (but only those six factors) from 2007Q4 through 2011Q2. Using the pre-2007Q4 model and the post-2007Q3 values of the old factors, this hypothetical forecaster computes predicted values for all 200 series in our data set. How well would these predicted values track the actuals over the recession and recovery? If there were an important new factor not seen in the 1959–2007Q3 data—say, a seventh, “financial crisis” factor—that factor would end up in the error term, and the fraction of the variation in the 200 macro variables explained by the “old” factors would be lower after 2007Q4 than before. Similarly, if the “old” factors had new effects—that is, if their factor loadings changed—then again the R^2 s computed using the pre-2007Q4 factor loadings would drop.

The results of this exercise are summarized in figure 2 and in tables 1 and 2. Figure 2 plots the common components as predicted using the “old” model and factors (computed as described in footnote 7), along with actual values, for 24 selected time series from 2000Q1 through 2011Q2. For activity variables and inflation, the figure plots the 4-quarter growth rate (that is, the annualized 4-quarter average of quarterly growth) to smooth over quarterly measurement error, whereas for financial variables the figure plots quarterly changes or levels to provide a better picture of the financial market volatility of 2008–09.

Table 1 summarizes the patterns observed in figure 2 by reporting the R^2 s of the common components of the 24 selected series, computed over various subsamples: two split-sample periods and the 15-quarter stretches following all postwar cyclical peaks. These R^2 s are computed imposing a zero intercept and unit slope on the old model/old factors predicted values over the indicated subsample and thus cannot exceed 1 but can be negative.¹⁰ The R^2 s in table 1 all pertain to quarterly values, transformed as described in section I.B, whereas, as already noted, some plots in figure 2 are 4-quarter values.

The results in figure 2 and table 1 suggest that knowledge of the historical DFM and future values of the “old” factors explains most—for some series, nearly all—of the movements in most of the 200 macroeconomic time series. The predicted values in figure 2 capture the initially slow decline in early 2008, the sharp decline during 2008Q4–2009, the prolonged trough, and the muted recovery since 2010 in GDP, total consumption, nonresidential fixed investment, industrial production, employment,

10. Using the notation of footnote 7, let $\hat{\varepsilon}_i = X_i - \hat{\Lambda}^{59-07} \hat{F}_i^{59-07}$ be the prediction error using the “old” model and factors. The subsample R^2 for series i is computed as $R^2 = 1 - \left(\sum_t \hat{\varepsilon}_i^2 \right) / \left(\sum_t X_i^2 \right)$ where the sums are computed over the column subsample.

Figure 2. Selected Macroeconomic Variables, Actual and Common Components, 2000Q1–2011Q2^a

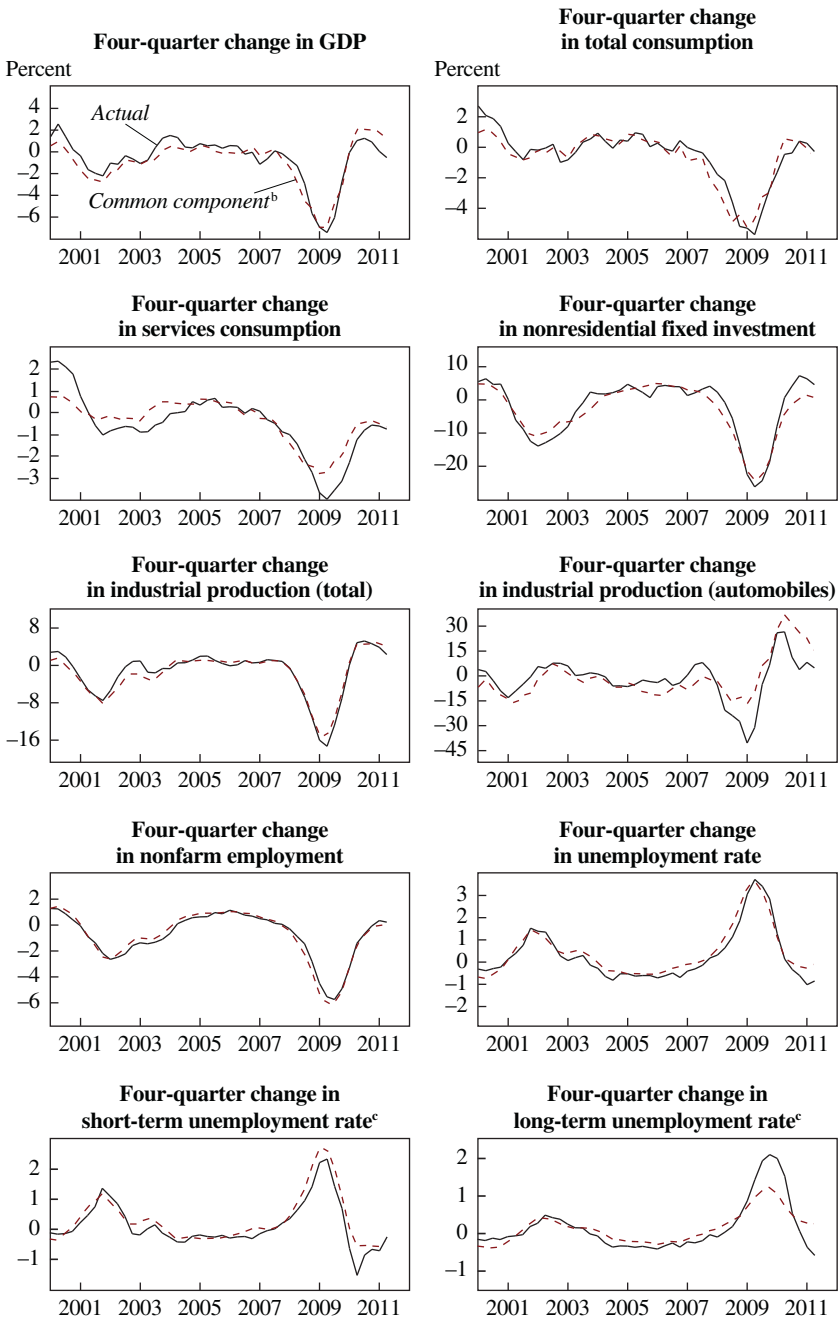


Figure 2. Selected Macroeconomic Variables, Actual and Common Components, 2000Q1–2011Q2^a (Continued)

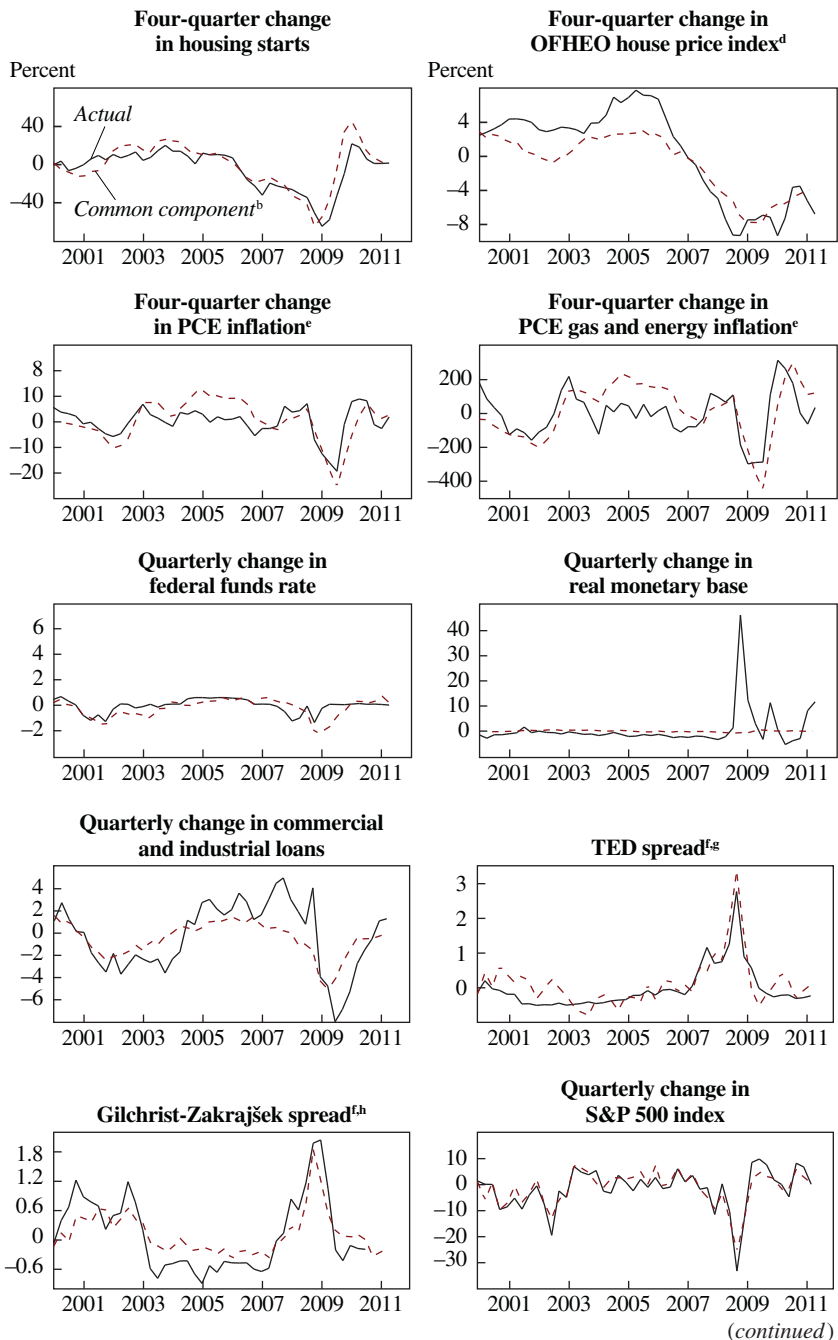
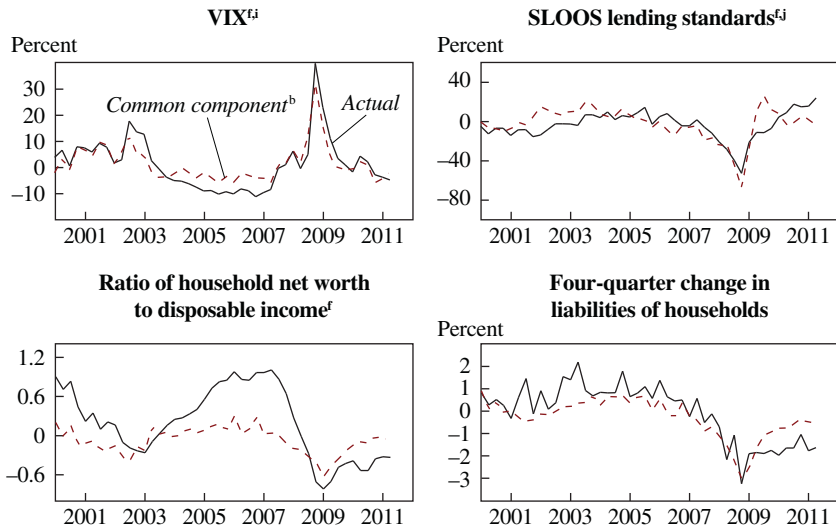


Figure 2. Selected Macroeconomic Variables, Actual and Common Components, 2000Q1–2011Q2^a (Continued)



Sources: Authors' calculations; see the online appendix for details of the data sources.

a. For real activity variables and prices, which are in logarithms, the 4-quarter or quarterly changes are scaled to be percentage changes at an annual rate.

b. Computed using pre-2007Q4 coefficients and 2007Q4–2011 values of the “old” factors, derived from the 1959–2007Q3 DFM model as described in footnote 7 in the text.

c. Short-term and long-term unemployment refer to spells of <27 weeks and ≥ 27 weeks, respectively.

d. Reported values are adjusted for inflation. OFHEO = Office of Federal Housing Enterprise Oversight. Since 2008 the index has been published by the Federal Housing Finance Agency (FHFA) and is known as the FHFA house price index.

e. Four-quarter change in 400 times the change in log prices. PCE = personal consumption expenditures.

f. The series is the level of the indicator, not a change.

g. Difference between the 3-month London interbank offer rate and the 3-month Treasury interest rate.

h. Excess bond premium spread from Gilchrist and Zakrajšek (forthcoming).

i. Chicago Board of Options Exchange Market Volatility Index.

j. Federal Reserve Senior Loan Officer Opinion Survey measure of lending standards (net percentage of domestic respondents tightening standards for commercial and industrial loans).

and the unemployment rate. The pre-2007Q4 model and historical factors predict the prolonged, accelerating decline of housing starts, although the anemic recovery of housing is slightly overpredicted. Given these factors, there are no major surprises in overall inflation or even energy price inflation. The historical factors even explain the general pattern of interest rate spreads (the TED spread and the Gilchrist-Zakrajšek excess bond premium spread, from Gilchrist and Zakrajšek forthcoming), the bear market in stocks, and the sharp rise in uncertainty as measured by the VIX, and even

Table 1. Subsample R²s of Regressions of Common Components on Actual Data for Selected Macroeconomic Variables^a

Series	Computed over 15 quarters starting at indicated cyclical peak														
	1959– 2007Q3	1984– 2007Q3	1960Q2	1969Q4	1973Q4	1980Q1	1981Q3	1990Q3	2001Q1	2007Q4					
GDP	0.73	0.62	0.81	0.79	0.83	0.79	0.85	0.73	0.64	0.64					
Consumption (total)	0.63	0.45	0.59	0.77	0.66	0.82	0.72	0.74	0.02	0.57					
Consumption (services)	0.35	0.22	0.28	0.46	-0.06	0.62	0.47	0.47	-0.25	0.84					
Nonresidential fixed investment	0.63	0.57	0.64	0.77	0.90	0.58	0.57	0.50	0.69	0.86					
Industrial production (total)	0.87	0.79	0.90	0.86	0.94	0.93	0.94	0.89	0.76	0.95					
Industrial production (automobiles)	0.58	0.29	0.59	0.61	0.70	0.64	0.39	0.66	0.13	0.57					
Nonfarm employment	0.92	0.91	0.93	0.94	0.93	0.95	0.98	0.93	0.91	0.96					
Unemployment rate	0.84	0.75	0.77	0.88	0.95	0.91	0.88	0.76	0.79	0.89					
Short-term unemployment rate	0.82	0.70	0.81	0.87	0.90	0.88	0.84	0.81	0.75	0.78					
Long-term unemployment rate	0.61	0.58	0.55	0.62	0.68	0.74	0.71	0.44	0.51	0.64					
Housing starts	0.59	0.39	0.27	0.59	0.83	0.79	0.76	0.62	0.29	0.53					
OFHEO house price index	0.49	0.44	n.a.	n.a.	n.a.	0.59	-0.01	0.60	0.42	0.57					
PCE inflation	0.51	0.54	0.25	0.70	0.66	0.44	0.40	0.57	0.56	0.82					
PCE gas and energy inflation	0.37	0.48	-0.42	-1.69	-0.63	0.25	0.23	0.55	0.48	0.71					
Federal funds rate	0.44	0.34	-0.01	0.47	0.57	0.48	0.41	0.72	0.14	-1.51					
Real monetary base	0.16	0.09	0.18	0.39	0.22	0.65	0.59	-0.18	-0.35	-0.03					
Real commercial and industrial loans	0.44	0.54	0.48	0.47	0.55	-1.42	-1.07	0.70	0.62	0.46					
TED spread	0.54	0.02	n.a.	n.a.	0.78	0.74	0.70	-0.05	-0.04	0.76					
Gilchrist-Zakrajšek spread	0.48	0.48	n.a.	n.a.	0.89	0.11	0.49	0.12	0.65	n.a.					
S&P 500 index	0.72	0.69	0.75	0.68	0.89	0.62	0.65	0.37	0.81	0.89					
VIX	0.47	0.50	n.a.	0.38	0.74	-0.78	-0.69	0.40	0.75	0.89					
SLOOS lending standards	0.60	0.18	n.a.	n.a.	0.65	0.79	0.67	0.55	-1.49	0.47					
Household net worth–disposable income ratio	0.16	0.14	-0.18	0.67	0.48	0.78	0.06	0.28	-0.46	0.51					
Household liabilities	0.57	0.48	-0.19	0.73	0.90	0.76	0.70	0.79	0.18	0.77					

Source: Authors' calculations; see the notes to figure 1 and the online appendix for further details.

a. Common components are calculated using the six static factors from the DFM estimated using quarterly data over 1959Q1–2007Q3; predicted values are the “old model/old factors” values computed as described in footnote 7 in the text. All entries are 1 minus the ratio of the sum of squared prediction errors to the sum of squares of the observed variable (see footnote 10). “n.a.” indicates that the regression was not performed because data for that series were not available for the indicated period. All series are transformed and detrended as described in sections I.B and I.C and in the online appendix.

Table 2. Subsample R^2 's of the Common Component Regressions by Category^a

Series category	N	R^2														
		1959–		1984–		Computed over 15 quarters starting at indicated cyclical peak										
		2007Q3	1984–	2007Q3	1960Q2	1969Q4	1973Q4	1980Q1	1981Q3	1990Q3	2001Q1	2007Q4				
National income and product accounts	21	0.56	0.43	0.56	0.46	0.62	0.66	0.59	0.64	0.49	0.65					
Industrial production	13	0.72	0.60	0.78	0.77	0.86	0.86	0.80	0.66	0.61	0.80					
Employment and unemployment	46	0.62	0.50	0.64	0.68	0.76	0.76	0.81	0.61	0.63	0.78					
Housing starts	8	0.37	0.21	0.09	0.26	0.54	0.46	0.54	0.44	-0.16	0.27					
Inventories, orders, and sales	8	0.54	0.35	0.39	0.69	0.72	0.73	0.68	0.66	0.43	0.64					
Prices	39	0.15	0.05	0.00	0.15	0.37	0.18	0.08	0.03	0.14	0.13					
Earnings and productivity	13	0.37	0.29	0.52	0.38	0.35	0.30	-0.03	0.32	0.36	-0.11					
Interest rates	18	0.40	0.30	-0.07	0.39	0.30	0.50	0.44	0.29	0.07	-0.50					
Money and credit	12	0.44	0.26	0.22	0.47	0.55	0.65	0.63	0.40	0.06	-0.37					
Stock prices and wealth	11	0.47	0.52	0.00	0.67	0.74	0.62	0.50	0.37	0.31	0.77					
Housing prices	3	0.67	0.67	n.a.	n.a.	n.a.	0.59	-0.01	0.60	0.72	0.57					
Exchange rates	6	0.56	0.66	-2.64	0.47	0.64	0.48	0.66	0.75	0.72	0.60					
Other	2	0.42	0.42	-0.40	0.15	0.87	0.89	0.89	0.48	-0.60	0.31					

Source: Authors' calculations.

a. Based on the six-factor DFM estimated over 1959Q1–2007Q3. Entries are the median of the R^2 's of the common component, computed for the series in the row category over the indicated period, where the R^2 is computed as described in the notes to table 1. "n.a." indicates that the regression was not performed because data for that series were not available for the indicated period.

the sharp decline and recovery of lending standards reported in the Federal Reserve's Senior Loan Officer Opinion Survey. The DFM correctly predicts the decline in commercial and industrial loans during the early part of the recession, although it underpredicts the depth of their contraction and their long delay in recovering.¹¹ These qualitative impressions from figure 2 are confirmed quantitatively by the R^2 s in table 1. For these series, the post-2007Q3 R^2 s are well within the range of R^2 s for previous recessions. The post-2007Q3 R^2 for GDP growth is somewhat lower than in previous episodes because the DFM misses some high-frequency variation, but as seen from the first panel of figure 2, the year-over-year match is very strong. On the other hand, for some series (among those in table 1, consumption of services, personal consumption expenditures inflation, and the VIX), the post-2007Q4 R^2 s are substantially greater than their historical averages. One interpretation of this improved fit during 2007Q4–2011 is that the movements in the common component of these series, computed using the pre-2007Q4 factors, were so large during this recession that the fraction of the variation it explains increased.

A few series are less well explained by the historical factors. Most notably, the model predicts a larger decline in the federal funds rate than occurred, but this is unsurprising because the model is linear and lacks a zero lower bound; we return to this point below. The model also confirms that the Federal Reserve's expansion of reserves was unprecedented. Although the historical factors predict home prices in 2007Q4–2011 as well as in previous recessions, they do not fully explain the boom in home prices in 2004–06, and they slightly underpredict the speed of their crash.

Table 2 summarizes the subsample R^2 s for all 200 series, by series category (the online appendix reports results corresponding to those in figure 2 and table 1 for all series). For most categories the median R^2 over the period since 2007Q4 is comparable to or greater than that in previous recessions and recoveries. The only categories for which the predicted and actual paths diverge systematically are earnings and productivity, interest rates, and money and credit. The divergence in interest rates is due mainly to problems relating to the zero lower bound, not to failures to match liquidity spikes in the spreads, and the divergence in money and credit is associated

11. Giannone, Lenza, and Reichlin (2012) examine the stability of the relationship between various types of loans and macroeconomic indicators in the euro zone during and after the crisis, relative to a precrisis benchmark; they find no surprising behavior of loans to nonfinancial corporations, conditional on aggregate activity, although there are departures from historical patterns for household loans.

with the unprecedented expansion of monetary aggregates. Closer inspection of the divergence in earnings and productivity suggests that it does not reflect breaks associated with this recession compared with the two other post-1984 recessions.¹²

II.B. Tests for a Break in the Factor Loadings, 2007Q4–2011

The results in the previous subsection suggest that the DFM did not suffer a structural break or regime shift in the 2007–09 recession. We now turn to two tests of this hypothesis.

The first test is of the hypothesis that the factor loadings are constant, against the alternative that they suffered a break in 2007Q4–2011. We do this using Donald Andrews' (2003) test for end-of-sample instability.¹³ As discussed above, there is evidence of a break in 1984Q1 in a substantial fraction of the factor loadings. We therefore consider two versions of the Andrews (2003) test, one testing the hypothesis of stability of a break in 2007Q4 relative to the 1959Q1–2007Q3 values of the loadings, and the other testing for a break in 2007Q4 relative to the values of the loadings over 1984Q1–2007Q3.

Rejection rates of this test for a break in 2007Q4 at the 5 percent level are summarized by series category in table 3. When the post-2007 values are compared with the full-sample factor loadings, the hypothesis is rejected at the 5 percent level for 15 percent of all series, and for 12 percent when the comparison is with the 1984Q1–2007Q3 factor loadings (final column of table 3). This slightly higher rejection rate for the tests against the full pre-2007Q4 sample is consistent with a break in the factor loadings in 1984Q1 as found in Stock and Watson (2009).

When evaluated against the 1984Q1–2007Q3 loadings, all but a handful of rejections are concentrated in three areas: commodity and materials producer price inflation indexes, the durational composition of unemployment, and monetary aggregates. Some examples are shown in figure 2 (see the panels for long-term unemployment and the monetary base). The small number of rejections provides little evidence of a systematic or widespread

12. The negative quarterly R^2 s for output per hour reflect a timing mismatch, and 4-quarter growth in productivity is well predicted. The predicted values for average hourly earnings growth change from procyclical to countercyclical in the mid-1980s, and the negative R^2 reflects this apparent instability in the factor loadings in 1984, not something special to the 2007–09 recession.

13. The Andrews (2003) test is based on an analogue of the usual (homoskedasticity-only) Chow break-test statistic, with a p value that is computed by subsampling.

Table 3. Tests of Absence of a Break in Factor Loadings

<i>Series category</i>	<i>N</i>	<i>Percent of series in the category for which the hypothesis of a break at 2007Q4 is rejected at the 5 percent level^a</i>	
		<i>1959–2007Q3</i>	<i>1984Q1–2007Q3</i>
National income and product accounts	21	0	0
Industrial production	13	0	0
Employment and unemployment	46	15	15
Housing starts	8	25	13
Inventories, orders, and sales	8	13	13
Prices	39	26	23
Earnings and productivity	13	15	8
Interest rates	18	0	11
Money and credit	12	42	17
Stock prices and wealth	11	18	0
Housing prices	3	33	33
Exchange rates	6	0	0
Other	2	0	0

Source: Authors' calculations.

a. The Andrews (2003) end-of-sample stability test is used to test the hypothesis of stability of the factor loadings. The statistic tests the null hypothesis of constant factor loadings against the alternative of a break in the final 15 quarters (2007Q4–2011Q2) relative to the value of the factor loading estimated over the indicated period.

break in the factor loadings in 2007Q4, relative to their Great Moderation values.

As a second test, we examine evidence for a new factor by testing whether the idiosyncratic disturbances, computed relative to the pre-2007Q4 factors, show unusual evidence of common structure in the current recession. Specifically, we used the pre-2007Q4 factors to compute the vector of idiosyncratic disturbances for the 8 quarters starting with 2007Q4 (in the notation of footnote 7, this vector is $X_t - \hat{\Lambda}^{59-07} \hat{F}_t^{59-07}$). The sample second-moment matrix of these disturbances has rank 8, and the ratio of the first eigenvalue of this matrix to the sum of all eight nonzero eigenvalues is a measure of the correlation among the idiosyncratic disturbances during these 8 quarters. A new common factor would produce an unusually large value of this ratio. It turns out that this eigenvalue ratio following 2007Q3 is less than it was during the recessions that began in 1960Q2 and 1973Q4. The p value testing the hypothesis that this ratio is the same as its pre-2007Q4 mean, computed by subsampling consecutive 8-quarter periods, is 0.59. Modifying the subsampling test to examine the 15 quarters starting

with 2007Q4 yields a p value of 0.90. This test therefore provides no evidence of a missing factor.

II.C. Increased Variance of Factors

The findings of sections II.A and II.B suggest that the severity of the 2007–09 recession was associated with large unexpected movements in the factors, not with some new factor or with changes in macroeconomic dynamics (changes in coefficients). Indeed, the factors were highly volatile over this period. Table 4 summarizes the standard deviations of selected variables over the pre–1984 period, the Great Moderation period, and the post-2004 period, along with the standard deviations of their factor components computed using pre-2007Q3 coefficients and the “old” factors. For these (and other) macroeconomic aggregates, volatility since 2004 has returned to or exceeds pre–Great Moderation levels. As the right-hand panel of table 4 shows, this increased volatility is associated with increased volatility of the factor components, which (because the coefficients are constant) derives from increased volatility of the factors themselves.

Table 5 takes a closer look at the factor innovations over this period. Because the factors are identified by the arbitrary normalization of principal components analysis, the innovations to individual factors are hard to interpret. Table 5 therefore examines linear combinations of the factor innovations determined by the factor loadings for various macroeconomic variables, so that the table entries are the innovations in the common component, by series, by quarter, from 2007Q1 through 2011Q2, reported in standard deviation units.¹⁴ Among the series in table 5, the factor component of oil prices experienced a moderate positive standardized innovation in 2007Q1, then a large positive standardized innovation in 2008Q2 (1.7 and 3.4 standard deviations, respectively), and the TED spread, the VIX, and housing starts experienced large innovations in 2008Q3, then extremely large (approximately 8 standard deviations) innovations in 2008Q4. Oil prices experienced a very large negative factor innovation in 2008Q4, then large positive innovations in the next three quarters. Throughout 2007Q4–2009Q1, the factor component innovations for the real variables were moderate by comparison and were generally within the range of pre-2007Q4 experience. By 2009Q4, all the innovations had

14. Rewrite the factor VAR (equation 1) as $F_t = \tilde{\Phi}(L)F_{t-1} + \eta_t$, so, from equation 2, $X_t = \Lambda F_t + e_t = \Lambda \tilde{\Phi}(L)F_{t-1} + \Lambda \eta_t + e_t$. Then $\Lambda \tilde{\Phi}(L)F_{t-1}$ is the contribution of the past factors and $\Lambda \eta_t$ is the innovation in the common component. The innovations in table 5 are the residuals from a four-lag VAR estimated using the “old” factors over 1959–2011Q2.

Table 4. Standard Deviations of Four-Quarter Growth Rates of Major Activity Variables^a

<i>Series</i>	<i>Standard deviation of series</i>			<i>Standard deviation of factor component</i>		
	1959–83	1984–2004	2005–11 ^b	1959–83	1984–2004	2005–11 ^b
GDP	2.6	1.6	2.8	2.6	1.4	2.8
Consumption	2.1	1.3	2.3	2.1	1.2	2.4
Investment	11.4	8.5	15.3	10.5	6.8	11.4
Industrial production (total)	5.2	3.1	6.4	4.9	3.2	5.9
Nonfarm employment	2.0	1.4	2.3	1.9	1.3	2.5
Change in unemployment rate ^c	1.1	0.8	1.5	1.1	0.7	1.4

a. Entries are standard deviations of 4-quarter detrended growth rates, except where noted otherwise, over the indicated period. The first three columns report standard deviations of the row series, and the second three columns report standard deviations of the factor component of the row series.

b. Calculations go through the final quarter in the data set, 2011Q2.

c. Entries refer to the 4-quarter detrended change in the unemployment rate.

Table 5. Innovations to Factor Components of Selected Series, 2007Q1–2011Q2

Standard deviation units

<i>Quarter</i>	<i>GDP</i>	<i>Total consumption</i>	<i>Investment</i>	<i>Employment</i>	<i>Productivity</i>	<i>Housing starts</i>	<i>Oil price</i>	<i>Federal funds rate</i>	<i>TED spread</i>	<i>VIX</i>	<i>Household wealth</i>
2007Q1	-0.9	-1.3	-0.4	-0.7	-1.2	0.2	1.7	0.3	0.0	-0.6	0.0
2007Q2	0.3	-0.2	0.5	-0.1	0.2	0.8	1.1	0.5	-0.9	-1.4	0.8
2007Q3	-0.3	-0.8	0.0	-0.7	0.0	-0.7	0.3	-0.6	0.7	1.2	-1.0
2007Q4	-0.3	-1.3	0.1	0.3	-0.7	-1.3	1.3	0.4	0.4	0.5	-0.9
2008Q1	-0.3	-0.7	0.1	0.2	-0.4	-1.3	0.2	-0.1	1.4	2.2	-2.0
2008Q2	-1.4	-2.1	-0.4	-1.1	-2.1	1.0	3.4	0.5	0.1	-0.4	-0.8
2008Q3	-1.7	-1.7	-1.0	-0.7	-1.4	-3.5	-0.6	0.2	3.9	2.9	-2.6
2008Q4	1.0	2.1	-0.1	-0.4	4.6	-8.3	-10.3	-2.5	7.7	8.3	-4.1
2009Q1	0.3	-2.7	2.3	0.9	-0.3	-4.7	2.5	3.5	4.0	1.4	-3.3
2009Q2	2.9	1.8	3.3	3.8	0.7	2.9	2.8	3.8	-3.0	-3.4	1.2
2009Q3	1.6	0.4	1.9	2.3	-0.6	4.8	5.0	1.5	-5.2	-3.5	1.5
2009Q4	-1.2	-0.9	-2.0	-2.1	-0.2	0.1	-0.4	-2.1	-1.7	-2.1	2.7
2010Q1	0.3	-0.1	0.6	0.5	0.0	-0.5	0.3	1.2	0.9	0.0	-0.6
2010Q2	0.7	0.3	0.7	0.3	1.3	-2.4	-1.8	0.3	2.1	1.6	-1.2
2010Q3	0.8	-0.3	1.1	0.4	0.9	-1.7	0.0	0.9	1.0	0.3	-0.7
2010Q4	0.3	-0.6	0.6	0.0	0.0	0.6	1.7	0.8	-1.0	-1.8	0.8
2011Q1	0.4	-0.6	1.1	0.5	-0.6	1.5	2.8	1.2	-0.9	-0.8	-0.5
2011Q2	-0.9	-0.8	-1.1	-1.3	-0.6	0.5	0.4	-1.5	-0.7	0.1	0.3

Sources: Authors' calculations.

a. Entries are the standardized innovations in the factor component of each series, computed relative to the six factors; series are standardized by dividing by the standard deviation of the 1959–2007Q3 factor component innovations for that series. Standardized innovations equal to or exceeding 3 in absolute value are italicized.

returned to their normal range, which is consistent both with the large economic shocks having passed and with the pre-2007Q4 model coefficients continuing to describe the macrodynamics.

The picture of the recession that emerges from table 5 is one of increases in oil prices through the first part of the recession, followed in the fall of 2008 by financial sector volatility, a housing construction crash, heightened uncertainty, and a sharp unexpected drop in wealth. Notably, there are few large surprise movements in the common components of the real variables, given the factors through the previous quarter.

II.D. Discussion

The results of this section suggest three main findings. First, there is little evidence of a new factor associated with the 2007–09 recession and its aftermath; rather, the factors associated with that recession are those associated with previous recessions and with economic fluctuations more generally from 1959 through 2007Q3. Second, for most of the series in our data set and in particular for the main activity measures, the response to these “old” factors seems to have been the same after 2007Q4 as before. Third, there were large innovations in these “old” factors during the recession, especially in the fall of 2008.

We believe that the most natural interpretation of these three findings is that the 2007–09 recession was the result of one or more large shocks, that these shocks were simply larger versions of ones that had been seen before, and that the response of macroeconomic variables to these shocks was almost entirely in line with historical experience. The few series for which behavior departed from historical patterns have straightforward explanations; in particular, the DFM predicts negative interest rates because it does not impose a zero lower bound, and the DFM does not predict the Federal Reserve’s quantitative easing.

This interpretation comes with caveats. First, the stability tests in section II.B are based on 15 post-2007Q3 observations, so their power could be low; however, the plots in figure 2 and the R^2 s in tables 1 and 2 provide little reason to suspect systematic instability that is missed by the formal tests.

Second, although the results concern the factors and their innovations, our interpretation shifts from factor innovations to shocks. A new shock that induced a new pattern of macrodynamics would surface in our DFM as a new factor, but we find no evidence of a missing or new factor. However, the possibility remains that there was a new shock in 2007Q4 that has the same effect on the factors as previously observed shocks. Indeed,

at some level this must be so: the Lehman collapse was unprecedented and the “Lehman shock” was new, and so were the TARP, quantitative easing, the auto bailout, and the other extraordinary events of this recession. Our point is that although all these particulars were new, their dynamic effect on the economy was not.

III. Structural Shocks: Identification and Contribution to the 2007–09 Recession

The analysis of section II suggests that the shocks precipitating the 2007–09 recession were simply larger versions of shocks experienced by the economy over the previous five decades. We now turn to the task of identifying those shocks and quantifying their impact, starting with our general approach to identification.

III.A. DFM Shock Identification Using Instrumental Variables

The identification problem in structural VAR analysis is how to go from the moving-average representation in terms of the innovations (the one-step-ahead forecast errors of the variables in the VAR) to the moving-average representation in terms of the structural shocks, which is the impulse response function with respect to a unit increase in the structural shocks. This is typically done by first assuming that the innovations can be expressed as linear combinations of the structural shocks, then by imposing economic restrictions that permit identification of the coefficients of those linear combinations. Those coefficients in turn identify the shocks and the impulse response function of the observed variables with respect to the shocks. This approach can be used to identify all the shocks, a subset of the shocks, or a single shock.

Most identification schemes for structural VAR analysis have an instrumental variables interpretation. When the economic restrictions take the form of exclusion restrictions on the impulse response function (shock A does or does not affect variable B within a quarter; shock C does or does not have a long-run effect on variable D), the restrictions turn certain linear combinations of the innovations into instrumental variables that in turn identify the structural impulse response functions. We refer to such instruments as “internal” instruments because they are linear combinations of the innovations in variables included in the VAR. An alternative method, pioneered by Christina Romer and David Romer (1989), is to use information from outside the VAR to construct exogenous components of specific shocks directly. These exogenous components are typically treated

as exogenous shocks; however, technically they are instrumental variables for the shocks: they are not the full shock series, but rather measure (typically with error) an exogenous component of the shock, so that the constructed series is correlated with the shock of interest but not with other shocks. We refer to these constructed series as “external” instruments, because they use information external to the VAR for identification. For example, one of our external instruments for the monetary policy shock is the Romer and Romer (2004) monetary shock series; there this series was treated directly as a monetary policy shock, whereas here it is taken to be correlated with the monetary policy shock and uncorrelated with all other structural shocks. More generally, in a structural VAR, an external instrument is a variable used for identification that is not itself included in the VAR; in a structural DFM, an external instrument is a variable used for identification that is not itself a factor. With one exception—a productivity shock instrument identified by a long-run exclusion restriction as in work by Jordi Galí (1999), discussed below—all the instruments used in this paper are external instruments.

IDENTIFICATION AND INFERENCE USING EXTERNAL INSTRUMENTS The basic idea of structural VAR identification with external instruments is that the structural shock is identified as the predicted value in the population regression of the instrument, say, Z_t , on the VAR innovations η_t .¹⁵ For this result to hold, the instrument needs to be valid; that is, it must be relevant (correlated with the structural shock of interest) and exogenous (uncorrelated with all other structural shocks), and the structural shocks must be uncorrelated. We now summarize the math of this identification argument for the case of a single instrument, which is the relevant case for this paper because we estimate shocks using one instrument at a time. This discussion is written in terms of structural DFMs, but the argument applies directly to structural VARs with the interpretation that η_t are the reduced-form VAR innovations. For technical details, the extension to multiple instruments, system and subsystem estimation, and inference with weak and strong instruments, see Montiel Olea, Stock, and Watson (2012).

15. The approach to structural VAR identification laid out here, including the estimator in the just-identified case, was originally presented in Stock and Watson (2008). This approach was also developed independently in Mertens and Ravn (2012), of which we became aware after presenting the conference draft of this paper. The idea of using constructed exogenous shocks (what we call external instruments) as instruments in structural VARs dates at least to Hamilton (2003); also see Kilian (2008a, 2008b).

As is standard in the structural VAR literature, we assume that the r innovations η_t are linear combinations of r structural shocks ε_t , so that

$$(3) \quad \eta_t = H\varepsilon_t = \begin{bmatrix} H_1 & \cdots & H_r \end{bmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{rt} \end{pmatrix},$$

where H_1 is the first column of H , ε_{1t} is the first structural shock, and so forth. Thus $\Sigma_{\eta\eta} = H\Sigma_{\varepsilon\varepsilon}H'$, where $\Sigma_{\eta\eta} = E(\eta_t\eta_t')$ and $\Sigma_{\varepsilon\varepsilon} = E(\varepsilon_t\varepsilon_t')$. We also assume, as is standard in the structural VAR literature, that the system described in equation 3 is invertible, so that the structural shocks can be expressed as linear combinations of the innovations:

$$(4) \quad \varepsilon_t = H^{-1}\eta_t.$$

A key object of interest in structural VAR/DFM analysis is the impulse response function with respect to a structural shock. From equations 2 and 3, we have that $F_t = \Phi(L)^{-1}H\varepsilon_t$, which, when substituted into equation 1, yields

$$(5) \quad X_t = \Lambda\Phi(L)^{-1}H\varepsilon_t + e_t.$$

The impulse response function of X_t with respect to the i th structural shock thus is $\Lambda\Phi(L)^{-1}H_i$. As discussed in section I, Λ and $\Phi(L)$ are identified from the reduced form, so it remains only to identify H_i .

We consider the problem of identifying the effect of a single shock, which for convenience we take to be the first shock ε_{1t} , using the single instrumental variable Z_t . The instrument and the shocks are assumed to satisfy three conditions:

$$(6) \quad \begin{aligned} & \text{(i)} E(\varepsilon_{1t}Z_t) = \alpha \neq 0 \text{ (relevance)} \\ & \text{(ii)} E(\varepsilon_{jt}Z_t) = 0, j = 2, \dots, r \text{ (exogeneity)} \\ & \text{(iii)} \Sigma_{\varepsilon\varepsilon} = D = \text{diag}(\sigma_{\varepsilon_1}^2, \dots, \sigma_{\varepsilon_r}^2) \text{ (uncorrelated shocks)}, \end{aligned}$$

where D in condition (iii) is an $r \times r$ diagonal matrix. Condition (i) says that Z_t is correlated with the shock of interest, ε_{1t} ; that is, Z_t is a relevant instrument. Condition (ii) says that Z_t is uncorrelated with the other structural shocks. By conditions (i) and (ii), Z_t is correlated with η_t only because it is

correlated with ε_{1t} . Condition (iii) is the standard structural VAR assumption that the structural shocks are uncorrelated. Condition (iii) does not fix the shock variance, and normalization of the shocks is discussed below.

Conditions (i) and (ii) imply that

$$(7) \quad E(\eta_t Z_t) = E(H\varepsilon_t Z_t) = [H_1 \quad \cdots \quad H_r] \begin{pmatrix} E(\varepsilon_{1t} Z_t) \\ \vdots \\ E(\varepsilon_{rt} Z_t) \end{pmatrix} = H_1 \alpha,$$

where the first equality follows from equation 3 and the final equality from conditions (i) and (ii). The instrument Z_t thus identifies H_1 up to scale and sign.

The shock ε_{1t} is identified (up to scale and sign) by further imposing condition (iii), which implies that $\Sigma_{\eta\eta} = HDH'$. Define Π to be the matrix of coefficients of the population regression of Z_t on η_t . Then, under conditions (i) through (iii),

$$(8) \quad \begin{aligned} \Pi\eta_t &= E(Z_t \eta_t') \Sigma_{\eta\eta}^{-1} \eta_t = \alpha H_1' (HDH')^{-1} \eta_t \\ &= \alpha (H_1' H^{-1}) D^{-1} (H^{-1} \eta_t) = (\alpha / \sigma_{\varepsilon_1}^2) \varepsilon_{1t}, \end{aligned}$$

where the second equality follows from equation 7 and the final equality follows from equation 4 and $H^{-1}H_1 = e_1$, where $e_1 = (1, 0, \dots, 0)'$ so that $\alpha(H_1' H^{-1}) D^{-1} = (\alpha / \sigma_{\varepsilon_1}^2) e_1'$.

Equation 8 displays the result anticipated in the opening sentence of this subsection: the shock identified using the instruments Z_t is the predicted value from the population regression of Z_t on the innovations η_t , that is, $\Pi\eta_t$, up to scale and sign. Additional intuition for this result is as follows. Suppose one observed ε_t , so that one could regress Z_t on ε_t ; then, by condition (i) the population coefficient on ε_{1t} would be nonzero, whereas by conditions (ii) and (iii) the coefficients on the other ε_{it} s would be zero, so the predicted value would be ε_{1t} up to scale and sign. But by equations 3 and 4, the projection of Z_t on η_t has the same predicted value as the regression of Z_t on ε_t , so the predicted value from the population regression of Z_t on η_t is ε_{1t} (up to scale and sign).

The scale and sign of ε_{1t} and H_1 are set by normalizing the shock to have a unit impact on a given variable; for example, an oil price shock is normalized so that a 1-unit positive shock increases the (log) oil price by 1 unit.

ESTIMATION AND TESTS OF OVERIDENTIFYING RESTRICTIONS The structural shock is estimated using the sample analogue of equation 8; that is, $\hat{\varepsilon}_{1t}$ is

computed as the predicted value of the sample regression of Z_t on $\hat{\eta}_t$, where $\hat{\eta}_t$ is the vector of residuals from the reduced-form VAR estimated using \hat{F}_t . If Z_t is available only for a subperiod, the coefficients of this regression are used to compute the predicted values for the span for which $\hat{\eta}_t$ is available but Z_t is not. All subsequent calculations of interest here (decompositions, correlations, and so forth) are made using $\hat{\epsilon}_t$.

CORRELATIONS AMONG IDENTIFIED SHOCKS Suppose one has two instruments that purportedly identify different shocks. If both instruments are valid, then in the population these identified shocks will be uncorrelated. But the population projection (equation 8) does not impose that the two shocks be uncorrelated; in fact, if one or both instruments are not valid, then in general the two shocks will be correlated. Similarly, two valid instruments that identify the same shock will produce identified shocks that are perfectly correlated in the population. The sample correlation between two estimated shocks therefore provides insight into the joint validity of the two instruments. Note that in general the correlation between the two identified shocks differs from the correlation between the two instruments themselves.

III.B. Instruments

We now turn to a discussion of the 18 instruments we use to identify structural shocks. We consider six structural shocks: to oil prices, monetary policy, productivity, uncertainty, liquidity and financial risk, and fiscal policy. Although this list is not exhaustive, these shocks feature prominently in discussions of the crisis and recovery, and each has a substantial literature upon which we can draw for its identification. The instruments are summarized here; specific sources and calculation details are provided in the online appendix.

OIL SHOCK We use three external instruments. The Hamilton (2003) oil shock is a quarterly version of James Hamilton's (1996) monthly net oil price increase, constructed over a 3-year window as in Hamilton (2003) as the percentage amount by which the oil price in a quarter exceeds the previous peak over the past 3 years (constructed from the producer price index for oil, available for 1960Q1–2011Q4). The Kilian (2008a) oil shock is Lutz Kilian's OPEC production shortfall stemming from wars and civil strife (1971Q1–2004Q3). The Ramey-Vine (2010) instrument is the residual from a regression of adjusted gasoline prices on various lagged macroeconomic variables as described in Valerie Ramey and Daniel Vine (2010), which we recomputed using the most recent data vintage. See Kilian (2008a, 2008b) and Hamilton (2009, 2010) for discussions of various oil shock measures.

MONETARY POLICY SHOCK We use four external instruments. The first is the Romer and Romer (2004) monetary policy shock, which they computed as the residual of a constructed Federal Reserve monetary intentions measure regressed on internal Fed forecasts (quarterly sums of their monthly variable, de-meaned, 1969Q1–1996Q4). The second is the shock to the monetary policy reaction function in Frank Smets and Raf Wouters’ (2007) dynamic stochastic general equilibrium (DSGE) model, as recomputed by Robert King and Watson (2012; 1959Q1–2004Q4). The third is the monetary policy shock from Christopher Sims and Tao Zha’s (2006) structural VAR allowing for shifts in shock variances but constant VAR coefficients (quarterly average of their monthly money shock, 1960Q1–2003Q4). The final instrument is the “target” factor of Refet Gürkaynak, Brian Sack, and Eric Swanson (2005), which measures surprise changes in the target federal funds rate (quarterly sums of daily data, 1990Q1–2004Q4).¹⁶

PRODUCTIVITY SHOCK We use one internal and two external instruments. The first external instrument is the series of Susanto Basu, John Fernald, and Miles Kimball (2006; Fernald 2009) on quarterly total factor productivity adjusted for variations in factor utilization, as updated by Fernald (1959Q1–2011Q2). The second external instrument is the productivity shock in the Smets-Wouters (2007) DSGE model, as recomputed by King and Watson (2012; 1959Q1–2004Q4). The internal instrument is constructed using Galí’s (1999) identification scheme and is the permanent shock to the factor component of output per hour in nonfarm businesses. In DFM notation, let λ_{OPH}' denote the row of Λ corresponding to output per hour; then this internal instrument is $\lambda_{OPH}'\Phi(1)^{-1}\eta_t$ (1959Q1–2011Q2). Galí’s (1999) identification scheme is controversial and has generated a large literature; see Karel Mertens and Morten Ravn (2010) for a recent discussion and references.

UNCERTAINTY SHOCK We use two external instruments. The first, motivated by Nicholas Bloom (2009), is the innovation in the VIX, where we use Bloom’s (2009) series that links the VIX to other market uncertainty measures before the VIX was traded; the innovation is computed as the residual from an AR(2) (1962Q3–2011Q2).¹⁷ The second is the innovation in the common component of the policy uncertainty index of Scott Baker, Bloom, and Steven Davis (2012), which is based on news

16. Other candidate instruments include the market announcement movements of Cochrane and Piazzesi (2002) and Faust, Swanson, and Wright (2004).

17. Lee, Rabanal, and Sandri (2010) take the uncertainty shock to be the innovation to the VIX.

media references to uncertainty in economic policy (1985Q1–2011Q2). The construction of measures of uncertainty is relatively new, and finding exogenous variation in uncertainty is challenging; for discussions see Geert Bekaert, Marie Hoerova, and Marco Lo Duca (2010) and Ruediger Bachman, Steffen Elstner, and Eric Sims (2010).

LIQUIDITY AND FINANCIAL RISK SHOCK We use three external instruments. The first two are unadjusted and adjusted term spreads: the TED spread (1971Q1–2011Q2) and Gilchrist and Zakrajšek’s (forthcoming) excess bond premium (1973Q3–2010Q3). Both instruments aim to measure risk in financial markets not associated with predictable default probabilities. The Gilchrist-Zakrajšek measure is a bond premium that has been adjusted to eliminate predictable default risk. For an early discussion of credit spreads as measures of market liquidity, see Benjamin Friedman and Kenneth Kuttner (1993); for more recent discussion see Gilchrist, Yankov, and Zakrajšek (2009) and Tobias Adrian, Paolo Colla, and Hyun Song Shin (forthcoming). The third instrument is William Bassett and coauthors’ (2011) bank loan supply shock, which they compute as the unpredictable component of bank-level changes in lending standards, based on responses to the Federal Reserve’s Senior Loan Officer Opinion Survey (1992Q1–2010Q4).

FISCAL POLICY SHOCK We use three external instruments: Ramey’s (2011a) federal spending news instrument (de-meaned, 1959Q1–2010Q4), Jonas Fisher and Ryan Peters’s (2010) measure of excess returns on stocks of military contractors (1959Q1–2008Q4), and Romer and Romer’s (2010) measure of tax changes relative to GDP (“all exogenous,” de-meaned, 1959Q1–2007Q4). The first two of these are instruments for federal government spending changes, and the third is an instrument for federal tax changes. For additional discussion see Jonathan Parker (2011) and Ramey (2011b).

III.C. Empirical Estimates of the Contribution of Various Shocks

With these instruments in hand, we now undertake an empirical analysis of the contributions of the identified shocks to the 2007–09 recession. This analysis additionally requires a VAR for the factors, which we estimate using the “old” factors (see footnote 7). The VAR has four lags and is estimated over the full 1959Q1–2011Q2 sample.

HISTORICAL CONTRIBUTIONS AND CORRELATIONS Table 6 summarizes the contributions to quarterly GDP growth of the 18 individually identified shocks (one shock per instrument) over the same subsamples as in table 1. Whereas the R^2 s in table 1 measure the fraction of the variation in GDP

Table 6. Subsample R^2 's of Regressions Evaluating the Factor Component of GDP Growth Associated with Individual Identified Shocks^a

Structural shock and instrument	F statistic ^b	R^2											
		1959–2007Q3	1984–2007Q3	1969Q4	1973Q4	1980Q1	1981Q3	1990Q3	2001Q1	2007Q4	Computed over 15 quarters starting at indicated cyclical peak		
<i>Oil shock</i>													
Hamilton	2.9	0.18	0.01	0.26	0.49	0.10	0.11	0.23	-0.55	-0.14			
Kilian	1.1	0.08	-0.03	0.15	0.10	0.20	0.24	-0.03	-0.26	0.37			
Ramey-Vine	1.8	0.14	-0.04	0.27	0.24	0.38	0.49	0.20	0.40	0.23			
<i>Monetary policy shock</i>													
Romer-Romer	4.5	0.23	-0.16	0.35	0.31	0.57	0.57	0.16	0.08	0.26			
Smets-Wouters	9.0	0.18	-0.01	0.24	0.25	0.32	0.23	0.37	0.16	0.46			
Sims-Zha	6.5	0.19	-0.30	0.29	0.44	0.54	0.51	-0.01	0.03	0.03			
Gürkaynak-Sack-Swanson	0.6	0.12	-0.07	0.07	0.39	0.26	0.26	0.00	-0.05	0.34			
<i>Productivity shock</i>													
Fernald TFP	14.5	0.29	0.14	0.39	0.08	0.31	0.28	0.33	-0.42	-0.14			
Gali long-run output per hour	NA	0.07	0.02	0.12	0.06	0.10	0.05	0.00	-0.11	-0.04			
Smets-Wouters	7.0	0.20	-0.04	0.35	0.39	0.18	0.17	-0.05	-0.36	-0.17			

(continued)

Table 6. Subsample R^2 's of Regressions Evaluating the Factor Component of GDP Growth Associated with Individual Identified Shocks^a (Continued)

Structural shock and instrument	F statistic ^b	R^2											
		1959– 2007Q3	1984– 2007Q3	1969Q4	1973Q4	1980Q1	1981Q3	1990Q3	2001Q1	2007Q4	Computed over 15 quarters starting at indicated cyclical peak		
<i>Uncertainty shock</i>													
Bloom financial uncertainty (VIX)	43.2	0.08	0.03	0.12	0.16	0.18	0.31	0.22	0.23	0.34			
Baker-Bloom-Davis policy uncertainty	12.5	0.11	0.02	0.15	0.40	0.15	0.14	0.48	0.15	0.62			
<i>Liquidity-financial risk shock</i>													
Gilchrist-Zakrajšek spread	4.5	0.12	-0.09	0.17	0.21	0.25	0.38	0.07	0.30	0.57			
TED spread	12.3	0.18	-0.08	0.28	0.45	0.31	0.21	0.21	0.30	0.38			
Bassett and others bank loan supply	4.4	0.11	0.04	0.20	0.25	0.13	0.31	0.27	0.45	0.41			
<i>Fiscal policy shock</i>													
Ramey spending	0.5	0.21	-0.06	0.36	0.35	0.50	0.55	0.06	0.01	0.19			
Fisher-Peters spending	1.3	0.23	0.04	0.27	0.02	0.32	0.36	0.41	-0.06	0.09			
Romer-Romer tax	0.5	0.16	-0.20	0.21	0.25	0.36	0.31	0.08	-0.38	-0.02			
<i>Principal components of uncertainty and credit spread shocks</i>													
First principal component	NA	0.14	-0.03	0.21	0.36	0.25	0.26	0.30	0.23	0.48			
Second principal component	NA	0.19	0.07	0.17	0.49	0.31	0.40	0.38	0.32	0.54			

Source: Authors' calculations.

a. Structural shocks are computed using the full-sample six-factor DFM and the indicated instrument, as described in sections III.A and III.B of the text. R^2 's are for the contribution of the indicated shock to the variation in GDP growth, computed over the indicated subsample, as described in footnote 19. NA = not applicable.

b. Non-HAC F statistic from the regression of the indicated instrument on the six factor innovations.

growth attributed to all the factors, the R^2 s in table 6 measure the fraction of the variance attributed to current and past values of the individual row shock.¹⁸ As in table 1, the R^2 is negative over subsamples in which the factor component arising from the identified shock covaries negatively with GDP growth. Additionally, the first column of table 6 reports the non-HAC (non-heteroskedasticity-and-autocorrelation-consistent) F statistic testing the hypothesis that the coefficients on the $\eta_{i,s}$ are all zero in the regression of Z_i on $\eta_{i,s}$, which is a measure of the strength of identification that enters the null distribution of the correlations in table 7 (Montiel Olea and others 2012).

As discussed in section III.A, the external instrument identification approach does not restrict the shocks to be uncorrelated. Table 7 reports the full-sample correlations among the shocks. If all the instruments within a category were identifying the same shock, and if the shocks were orthogonal, then the entries in the population version of table 7 would be 1 within categories and zero across categories. As discussed in section III.A, each shock is the predicted value from the regression of its instrument on the DFM innovations, so in general the correlation between two estimated shocks is different from the correlation between the instruments themselves.

Tables 6 and 7 suggest three main findings. First, for many of the external instruments, the F statistic in table 6, which is a measure of the strength of the instrument relevant to the distribution of the correlations in table 7, is small: it is less than 5 in 10 cases and less than 10 in all but 3. These small F statistics reinforce and extend Kilian's (2008b) observation that oil price shock series appear to be weak instruments. This suggests that there is considerable sampling uncertainty in the remaining statistics based on these instruments, but we do not attempt to quantify that uncertainty here.

Second, with this weak-instrument caveat, there is considerable variation of results across instruments within categories in tables 6 and 7. For example, whereas the correlation between the oil shocks identified using the Kilian (2008a) and Ramey-Vine (2010) instruments is 0.60, the correlation between the oil shocks identified using the Hamilton (2003) and Ramey-Vine (2010) instruments is only 0.15. Not surprisingly in light of these low correlations, the episode R^2 s in table 6 vary considerably across

18. In the notation of equations 3 and 5, the factor component due to the j th structural shock is $\Lambda\Phi(L)^{-1}H_j\hat{\epsilon}_{j,t}$. The R^2 of the i th variable with respect to the j th shock is thus computed as $R^2 = 1 - \left(\sum_t (\hat{\epsilon}_i^j)^2\right) / \left(\sum_t X_i^2\right)$, where $\hat{\epsilon}_i^j = X_i - \hat{\Lambda}_i' \hat{\Phi}(L)^{-1} \hat{H}_j \hat{\epsilon}_{j,t}$, where $\hat{\Lambda}_i'$ is the i th row of $\hat{\Lambda}$.

Table 7. Correlations among Estimated Structural Shocks

	O_H	O_K	O_{RV}	M_{RR}	M_{SW}	M_{SZ}	M_{GSS}	P_F	P_G	P_{SW}	U_B	U_{BBD}	L_{GZ}	L_{TED}	L_{BCDZ}	F_R	F_{FP}	F_{RR}
O_H	1.00																	
O_K	0.42	1.00																
O_{RV}	0.15	0.60	1.00															
M_{RR}	0.37	0.65	0.77	1.00														
M_{SW}	0.09	0.11	0.39	0.09	1.00													
M_{SZ}	0.33	0.35	0.68	0.93	0.16	1.00												
M_{GSS}	0.44	-0.12	-0.08	0.24	0.43	0.39	1.00											
P_F	-0.64	0.30	0.24	0.20	-0.09	0.06	-0.57	1.00										
P_G	-0.40	0.34	0.01	-0.30	0.35	-0.53	-0.37	0.52	1.00									
P_{SW}	-0.91	-0.03	0.00	-0.24	-0.07	-0.36	-0.59	0.82	0.68	1.00								
U_B	-0.37	-0.37	-0.58	-0.39	0.30	-0.29	0.37	0.19	0.34	0.27	1.00							
U_{BBD}	0.10	0.11	-0.37	-0.17	0.45	-0.22	0.57	-0.06	0.45	-0.01	0.78	1.00						
L_{GZ}	-0.20	-0.42	-0.51	-0.41	0.44	-0.24	0.34	0.07	0.24	0.08	0.92	0.66	1.00					
L_{TED}	-0.09	0.01	-0.05	0.03	0.73	0.10	0.48	0.21	0.37	0.09	0.80	0.76	0.84	1.00				
L_{BCDZ}	0.04	0.22	0.79	0.56	0.13	0.55	0.04	-0.09	-0.28	-0.06	-0.69	-0.54	-0.73	-0.40	1.00			
F_R	-0.17	-0.64	-0.77	-0.84	-0.32	-0.72	-0.34	-0.17	-0.01	0.01	0.26	-0.08	0.40	-0.13	-0.13	1.00		
F_{FP}	0.04	-0.21	-0.35	-0.72	0.20	-0.78	-0.03	-0.49	0.40	-0.02	0.03	0.25	0.03	-0.12	-0.12	0.38	1.00	
F_{RR}	0.20	0.15	0.30	0.77	-0.10	0.88	0.37	0.18	-0.59	-0.28	0.01	-0.10	0.02	0.19	0.19	-0.45	-0.93	1.00

Source: Authors' calculations.

a. Entries are correlations between individually identified shocks, computed over the full 1959–2011Q2 sample. Shading denotes correlations within categories of shocks; italicized entries are cross-category correlations exceeding 0.60 in absolute value. Shocks are those listed in table 6, abbreviated as follows:

- O_H : Hamilton (1996, 2003); O_K : Kilian (2008a); O_{RS} : Ramey-Vine (2010)
- Monetary policy: M_{RR} , Romer and Romer (2004); M_{SWS} : Smets and Wouters (2007); M_{SZ} : Sims and Zha (2006); M_{GSS} : Gürkaynak, Sack, and Swanson (2005)
- Productivity: P_F , Fernald (2009) TFP; P_G , Galí (1999); P_{SW} : Smets and Wouters (2007)
- Uncertainty: U_{MIX} : Bloom (2009) financial uncertainty; U_{BBD} , Baker, Bloom, and Davis (2012) policy uncertainty
- Liquidity and financial risk: L_{GZ} : Gilchrist and Zakrajšek (forthcoming) spread; L_{TED} , TED spread; L_{BCDZ} : Bassett and others (2011) bank loan supply
- Fiscal policy: F_R : Ramey (2011a) spending; F_{FP} : Fisher-Peters (2010) spending; F_{RR} : Romer-Romer (2010) tax.

instruments within a shock category; for example, the Hamilton-identified oil shock has a subsample R^2 of -0.14 for 2007Q4–2011Q2, whereas for the Kilian-identified oil shock this R^2 is 0.37 . Wide ranges of correlations are also evident among the four monetary policy shocks, although, interestingly, the variation in the subsample R^2 s is less, with perhaps the exception of the Sims-Zha (2006) identified shock. Among fiscal policy shocks, the correlation between the shocks identified using the Ramey (2011a) and Romer and Romer (2010) instruments is -0.45 (the sign is negative because one is spending, the other tax), and the correlation between the Ramey (2011a) and Fisher-Peters (2010) spending shocks is only 0.38 . In contrast, the correlation between the Fisher-Peters (2010) and Romer-Romer (2010) identified shocks is surprisingly large, -0.93 , given that Fisher and Peters (2010) focus on exogenous changes in government spending whereas Romer and Romer (2010) focus on exogenous tax changes.¹⁹

The observation that the different instruments within a category identify different shocks with different effects echoes Glenn Rudebusch's (1998) critique of monetary policy shocks in structural VARs. One response is that these instruments are intended to estimate different effects; for example, the Romer-Romer fiscal instrument is intended to identify a tax shock, whereas the Ramey (2011a) and Fisher-Peters (2010) instruments are intended to identify spending shocks. Similarly, Kilian (2008b, 2009) argues that the Kilian (2008a) instrument estimates an oil supply shock, whereas the Hamilton instrument does not distinguish among the sources of price movements. Although the response that the different instruments are intended to estimate different shocks has merit, it then confronts the problem that the individually identified shocks within a category are not *uncorrelated*. For example, the correlation of -0.93 between the fiscal shocks identified by the Romer-Romer (2010) tax instrument and the Fisher-Peters (2010) spending instrument makes it problematic to treat these two shocks as distinct.

Third, again with the weak-instrument caveat, there is considerable correlation among individually identified shocks across categories of shocks, which suggests that superficially different instruments are capturing the same movements in the data (cross-category correlations exceeding 0.6 in absolute value are italicized in table 7). One notable set of correlations

19. Again, to be clear, these statements concern correlations among the shock series estimated using the instruments, not correlations among the underlying instruments themselves. For example, whereas the correlation between the shock estimated using the Fisher-Peters (2010) spending instrument and the shock estimated using the Romer-Romer (2010) tax instrument is -0.93 , the correlation between the Fisher-Peters and the Romer-Romer instruments themselves is only -0.06 .

is between the blocks of monetary and fiscal shocks: the mean average absolute correlation between individually identified shocks across the two categories is 0.51. The monetary and fiscal shock literatures speak of the difficulty of identifying one shock while holding the other constant, and this difficulty seems to arise in the large absolute correlations between the shocks from these two literatures.

Another notable block of large correlations is between the uncertainty shock and the liquidity and financial risk shock: the average absolute correlation between shocks across the two categories is 0.73. Indeed, for these categories the cross-category correlations are comparable to the within-category correlations. The subsample R^2 s in table 6 also display similar patterns across these four identified shocks. It is perhaps not surprising that the VIX shock and the TED spread shock are correlated, because neither isolates a specific source for the shock; for example, a financial market disruption that both heightened uncertainty and increased financial sector risk would appear as shocks to both series. We find it more surprising that the correlation is 0.66 between the shocks identified using the Baker, Bloom, and Davis (2012) policy uncertainty index and the Gilchrist-Zakrajšek (forthcoming) excess bond premium spread. In any event, these two sets of instruments do not seem to be identifying distinct shocks. As a result, we also consider two composites of these five shocks constructed as the first two principal components of the five identified shocks. The subsample R^2 s for the first principal component and for the first and second principal components combined are reported in the final rows of table 6.

THE 2007–09 RECESSION Table 8 summarizes the contribution of the shocks in table 6 to the cumulative growth of GDP and of employment over three periods starting in 2007Q4. Because the shocks are correlated, these contributions are not an additive decomposition of the total factor component. Because all contributions and actuals are expressed in terms of deviations from trend, in 2011Q2 GDP remained 8.2 percent below its trend value, extrapolated from the 2007Q4 peak, of which 6.0 percentage points was the contribution of the factors. Plots of the contributions of the individual shocks over the full sample, along with the shock contributions to other variables, are presented in the online appendix.

Consider the recession period, 2007Q4–2009Q2. The largest negative shock contributions to the drops in GDP and employment are seen in the financial shock measures (the liquidity-risk and uncertainty shocks). The composite uncertainty-liquidity shock based on the first principal component of the five estimated shocks in this category attributes approximately two-thirds of the recession's decline in GDP and employment to financial

Table 8. Contributions of Identified Shocks to Cumulative Post-2007Q4 Growth of GDP and Employment

<i>Shock and instrument</i>	<i>Cumulative percentage change in detrended GDP^a</i>				<i>Cumulative percentage change in detrended payroll employment^a</i>				<i>2009Q2 forecast growth in factor component, 2009Q2–2011Q^b</i>	
	<i>2007Q4–2008Q3</i>	<i>2007Q4–2009Q2</i>	<i>2007Q4–2011Q2</i>	<i>2007Q4–2011Q2</i>	<i>2007Q4–2008Q3</i>	<i>2007Q4–2009Q2</i>	<i>2007Q4–2011Q2</i>	<i>2007Q4–2011Q2</i>	<i>GDP</i>	<i>Employment</i>
	Actual outcome	-2.8	-8.7	-8.2	-7.4	-1.4	-6.2	-7.4		
Factor component	-4.0	-9.2	-6.0	-8.9	-2.1	-7.3	-8.9			
<i>Oil shock</i>										
Hamilton	-1.0	-0.8	-0.8	-1.0	-0.4	-1.1	-1.0	1.8	1.0	
Kilian	-1.0	-2.1	-0.6	-1.2	-0.5	-1.7	-1.2	1.3	0.3	
Ramey-Vine	-1.4	-1.6	0.7	0.2	-1.1	-2.1	0.2	1.5	1.2	
<i>Monetary policy shock</i>										
Romer-Romer	-1.1	-1.6	0.1	0.4	-0.7	-2.1	0.4	1.4	1.2	
Smets-Wouters	-0.4	-3.7	-5.0	-6.2	-0.5	-2.5	-6.2	-0.6	-3.3	
Sims-Zha	-0.3	-0.1	-0.1	0.3	-0.5	-1.0	0.3	0.4	0.8	
GSS	-0.8	-3.2	-4.3	-3.8	0.0	-1.0	-3.8	-1.3	-2.7	
<i>Productivity shock</i>										
Fernald	-0.7	0.0	1.4	0.9	-0.1	0.1	0.9	0.2	0.2	
Galí	0.4	0.3	1.1	-0.9	0.0	-0.6	-0.9	1.0	0.5	
Smets-Wouters	-0.5	-0.1	0.6	0.4	0.2	-0.1	0.4	0.9	0.7	

(continued)

Table 8. Contributions of Identified Shocks to Cumulative Post-2007Q4 Growth of GDP and Employment (Continued)

<i>Shock and instrument</i>	<i>Cumulative percentage change in detrended GDP^a</i>				<i>Cumulative percentage change in detrended payroll employment^a</i>				<i>2009Q2 forecast growth in factor component, 2009Q2–2011Q2^b</i>	
	2007Q4–2008Q3	2007Q4–2009Q2	2007Q4–2011Q2	2007Q4–2011Q2	2007Q4–2008Q3	2007Q4–2009Q2	2007Q4–2011Q2	2007Q4–2011Q2	GDP	Employment
<i>Uncertainty shock</i>										
Financial uncertainty (VIX)	-1.0	-4.1	0.2	-0.9	-3.7	-2.2	3.5	0.6		
Political uncertainty (BBB)	-2.3	-5.8	-4.8	-1.6	-4.6	-6.8	1.4	-2.0		
<i>Liquidity/financial risk shock</i>										
Gilchrist-Zakrajsek spread	-1.5	-6.3	-1.2	-0.8	-4.6	-3.5	3.6	-0.4		
TED spread	-1.2	-5.6	-4.9	-0.8	-3.7	-6.8	0.8	-3.2		
Bassett and others bank loan	-2.0	-3.2	0.1	-1.5	-3.5	-1.1	2.7	1.3		
<i>Fiscal policy shock</i>										
Ramey spending	-1.6	-1.6	-1.0	-0.9	-1.6	-0.5	0.3	0.1		
Fisher-Peters spending	-0.3	-0.3	0.3	-0.2	-0.7	0.3	0.4	0.5		
Romer-Romer tax	0.2	0.3	-0.2	0.2	0.0	0.3	-0.1	0.3		
<i>Principal components of uncertainty and credit spread shocks</i>										
First principal component	-1.5	-6.2	-3.4	-1.0	-4.5	-5.8	2.4	-1.8		
Second principal component	-2.3	-7.6	-5.4	-1.5	-5.8	-8.4	2.7	-2.5		

Source: Authors' calculations.

a. Each entry after the top panel is the contribution of the indicated shock to cumulative growth in GDP or employment over the indicated period, computed as described in footnote 19 in the text.

b. Implied forecasts of GDP or employment growth from 2009Q2 to 2011Q2, constructed in 2009Q2 associated with the indicated shock.

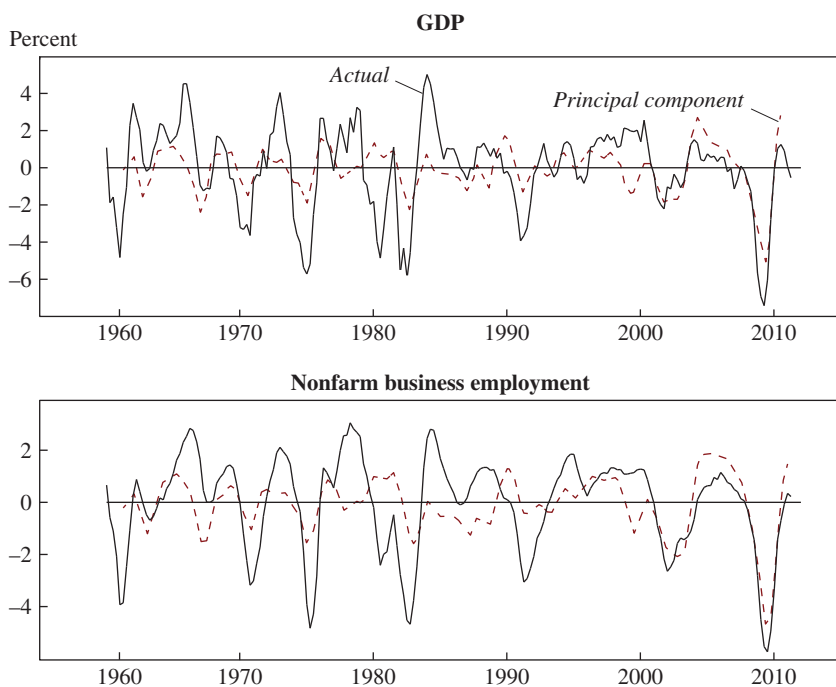
factors (6.2 of 9.2 percentage points and 4.5 of 7.3 percentage points, respectively). Oil shocks and monetary policy shocks both make moderate negative contributions, with the exception of the Sims-Zha (2006) identified shock. The Romer-Romer (2004), Smets-Wouters (2007), and Gürkaynak, Sack, and Swanson (2005) shocks indicate that monetary policy was neutral or contractionary during the recession and recovery, which is consistent with the model being linear and not incorporating a zero lower bound (so the federal funds rate, which cannot drop below zero, exerted a contractionary effect). Unfortunately, our identification scheme does not capture the unconventional monetary policy of the crisis and recovery. During 2007Q4–2009Q2, the effects of productivity and fiscal policy shocks on GDP growth are estimated to be small.

III.D. Discussion

Inference about the causes of the 2007–09 recession based on table 8 is complicated because the different instruments identify shocks that in several cases have a low correlation within category, and in other cases have high correlations across categories. Because our approach is to adopt identification schemes from the literature, this suggests internal inconsistencies in the identified VAR literature concerning individual identified shocks. Perhaps to oversimplify, what some authors call a monetary policy shock looks much like what other authors call a fiscal policy shock, and what some authors call an uncertainty shock looks much like what others call a liquidity or excess financial risk shock. These puzzling results might come about because our analysis is insufficiently nuanced to distinguish between the different estimands of the different instruments, or because we have too few factors to span the space of the potentially many structural shocks, or because of large sampling uncertainty arising from weak instruments. In any event, the low correlations among some of the monetary policy shocks, the high correlations between the monetary and fiscal policy shocks, and the high correlations among the uncertainty and the liquidity/financial risk shocks preclude a compelling decomposition.

Despite this substantial caveat, some substantive results emerge from tables 6 and 8. The contributions of productivity, monetary policy, and fiscal policy shocks to the 2007–09 recession are small. Oil shocks contributed to the decline, especially before the financial crisis. The main contributions to the decline in output and employment during the recession are estimated to come from financial and uncertainty shocks. The plot of the contribution of the first principal component of these five individually identified shocks (figure 3) shows that they explain a great deal of

Figure 3. Contribution to Detrended Four-Quarter Growth of GDP and Nonfarm Employment of the First Principal Component of the Identified Financial and Uncertainty Shocks^a



Source: Authors' calculations.

a. The five identified shocks are the three liquidity and financial risk shocks and the two uncertainty shocks listed in table 6.

the 2007–09 recession and subsequent recovery, and that they also play an important but lesser role in prior fluctuations. Taken at face value, this suggests an economy being hit by a sequence of unusually large shocks, all of which have been experienced before, but not with such magnitude or in such close succession: oil shocks initially, followed by the financial crisis, financial market disruptions, and a prolonged period of uncertainty.

IV. The Slow Recovery

On its face, the unusually slow recovery following the 2009Q2 trough seems inconsistent with the conclusion of the previous sections that the macroeconomic dynamics of this recession are consistent with those of

prior recessions, simply with larger shocks. Indeed, during the 8 quarters following that trough, GDP grew by only 5.0 percent, compared with an average of 9.2 percent after 8 quarters for the recessions from 1960 through 2001, and employment increased by only 0.6 percent, compared with a 1960–2001 average of 4.0 percent.²⁰ The contrast between the current slow recovery and the robust recoveries of 1960–82 is even more striking: those recessions averaged 8-quarter GDP growth of 11.0 percent and 8-quarter employment growth of 5.9 percent following the trough. In this section we therefore take a closer look at the extent to which the current slow recovery is or is not consistent with historical experience.

Why has the recovery in employment since 2009Q2 been so much slower than the 1960–82 recoveries? In the context of the DFM, employment growth after a trough is the sum of four terms: trend employment growth, the predicted cyclical common component (deviations from trend) given the state of the economy at the trough, the prediction errors in the cyclical common component, and the series-specific idiosyncratic errors. Accordingly, the weakness of the recovery since 2009Q2 relative to, say, that after 1982Q4 could arise from differences in underlying trends (such as in demographics), differences in recovery paths after different types of recessions (such as one induced by monetary policy versus one following a financial crisis), differences in macroeconomic luck once the recovery commenced, or peculiarities of employment unrelated to the rest of the economy. Although the latter two terms might be of historical interest, the former two shed more light on structural differences between the two recoveries. In this section we therefore focus on the first two of these terms—the trend and the predicted cyclical common component—comparing their values in the post-2009Q2 recovery with their values in previous recoveries.

As in section III, the calculations here require a VAR for the factors, which we estimate using four lags and the “old” factors over the 1959–2007Q3 period. With this model held constant, differences in the predicted cyclical component across recoveries reflect differences in recovery paths implied by the shocks that produced the recessions. This permits a decomposition of the slow pace of the recovery after 2009Q2, relative to previous recoveries, into changes in the trend plus changes in the predicted cyclical component.

20. These averages exclude the recovery that began in 1980Q3 because the next recession started within the 8-quarter window of these calculations.

IV.A. *Different Shocks Imply Different Recovery Paths*

Different structural shocks induce different macroeconomic responses. For example, Bloom (2009) predicts a fast recovery after an uncertainty shock (investment and consumption pick up as soon as the uncertainty is resolved), whereas Carmen Reinhart and Kenneth Rogoff (2009) describe recoveries from financial crises as typically slow. In terms of the factor model, the state of the economy at the trough is summarized by the current and past values of the factors as of the trough. Because the values of the shocks (and thus of the factors) vary across recessions both in composition and in magnitude, the recovery paths predicted by the DFM also vary across recessions.

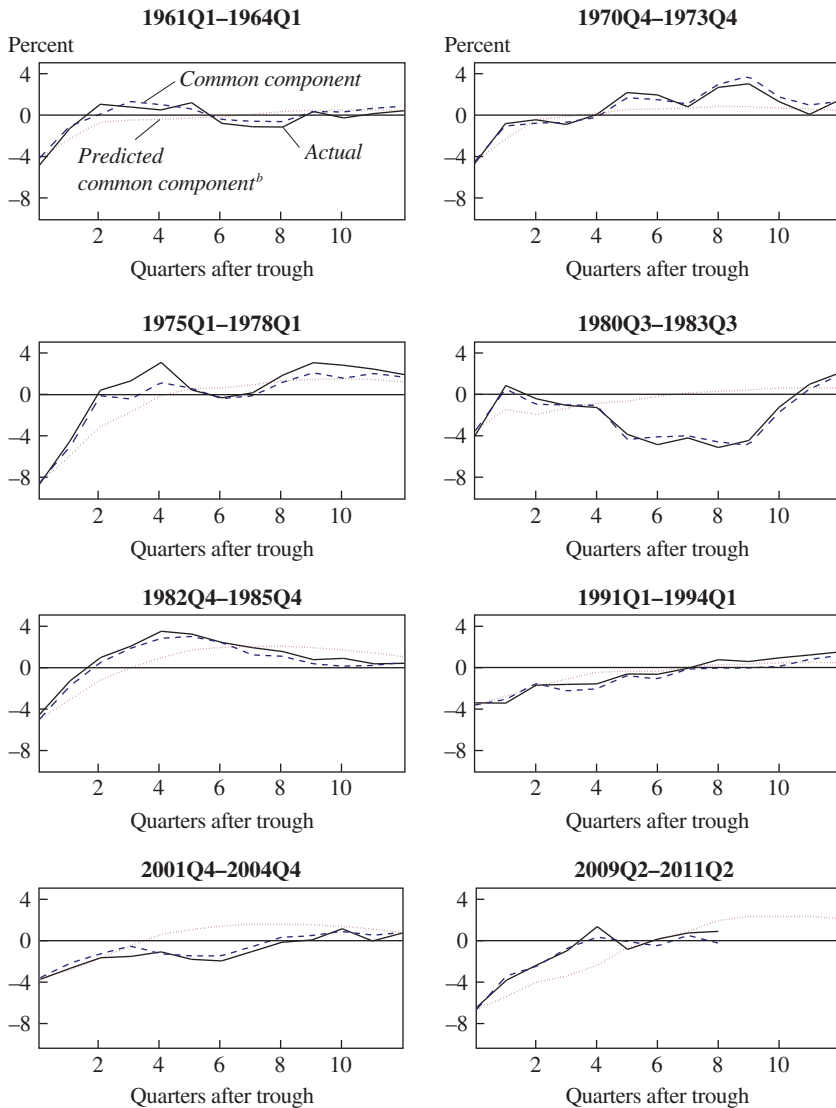
Figure 4 plots actual quarterly employment growth, its common component, and its predicted common component following each of the eight post-1960 troughs. All series are expressed as deviations from trend, so that a value of zero denotes employment growth at trend. The predicted common component is computed using the values of the factors through the trough date; that is, the predicted common component is the forecast of the common component one would make standing at the trough, given the historical values of the factors through the trough date and the model parameters (because the DFM was estimated through 2007Q3, the predicted components in figure 4 are in-sample for the first seven recessions and pseudo-out-of-sample forecasts for 2009Q2). The difference between actual employment growth and its common component is the idiosyncratic disturbance (e_t in equation 1). The difference between the common component and the predicted common component arises from the factor innovations (η_t in equation 2) that occurred after the trough.

Three features of figure 4 are noteworthy. First, there is considerable heterogeneity across recessions in both the shape and the magnitude of predicted recoveries of employment. By construction, the sole source of this heterogeneity is differences in the state of the economy, as measured by the factors, at the trough. Strong positive employment growth is predicted following the 1982Q4 trough—employment growth returns to trend only 3 quarters after the trough—whereas slow employment growth is predicted following 1980Q3, 1991Q1, and 2009Q2.

Second, in most recessions the predicted values track the actual common component. The main exception is the 1980Q3 recovery, which was interrupted early on by the next recession.

Third, given the values of the factors in 2009Q2, the DFM predicts 6 quarters of subtrend employment growth following the 2009Q2 trough. In

Figure 4. Deviations of Employment Growth from Trend Following Cyclical Troughs, 1961–2011^a



Source: Authors' calculations.

a. Growth rates are annualized quarterly rates. A value of zero indicates no deviation from trend.

b. Predicted based on the factors at the trough.

fact, the DFM predicts a slower employment recovery from the 2009Q2 trough than actually occurred; that is, the current recovery in employment is actually *stronger* than predicted.²¹

IV.B. Decomposition of the Post-2009Q2 Recovery into Trend and Cyclical Components

We now turn to the decomposition of the post-1959 recoveries into their trend and predicted cyclical components, where the latter are computed as described in the previous subsection using the factors at the trough. Table 9 summarizes the results for 8-quarter cumulative post-trough growth of GDP, employment, and productivity.

Consistent with the trends plotted in figure 1, table 9 shows that the trend component of predicted growth in GDP and employment falls over time. Consistent with the cyclical components plotted in figure 4, there is considerable variation in the predicted cyclical components, which arises from variation in the composition and magnitude of the factors at the trough. The predicted cyclical contributions to 8-quarter employment growth range from +1.1 percentage points following the 1982Q4 trough to -3.1 percentage points following the 2009Q2 trough.

The final rows of table 9 report the decomposition into trend and cycle of the difference between the predicted 8-quarter growth following 2009Q2 and the corresponding averages for pre-1984 recoveries. Predicted GDP growth emerging from 2009Q2 is 3.0 percentage points less than the pre-1984 average; four-fifths of this gap (2.4 percentage points) is due to differences in trend. Predicted employment growth is 6.0 percentage points less than the pre-1984 average; of this gap, 2.7 percentage points is attributed to differences in the cyclical components, whereas most, 3.3 percentage points, is attributed to differences in trend employment growth. The predicted cyclical component of productivity growth in the post-2009Q2 recovery is unusually large, 6.3 percentage points, although this predicted value is perhaps comparable to its values in the recoveries after 1975Q1 and 1982Q4. The difference between the trend components of productivity growth in the recovery after 2009Q2 and in the average for the pre-1984 recoveries is 0.5 percentage point; that is, trend productivity growth in the post-2009Q2 episode is slightly higher than its 1960–82 average. Most of the difference in productivity growth

21. Allowing for a break in $\Phi(L)$ in 1984Q1 produces somewhat faster predicted recoveries before 1984 and somewhat slower ones after 1984; for details see the online appendix.

Table 9. Predicted and Actual Cumulative Growth of Output, Employment, and Productivity Following a Cyclical Trough^a

Percent

<i>Trough</i>	<i>Source</i>	<i>Cumulative growth of common component (or actual) over 8 quarters following trough</i>		
		<i>GDP</i>	<i>Nonfarm employment</i>	<i>Output per hour (nonfarm business)</i>
1961Q1	Cyclical	1.1	-1.0	2.0
	Trend	7.5	4.9	4.8
	Total	8.7	4.0	6.8
1970Q4	Cyclical	2.4	0.0	2.6
	Trend	6.9	4.7	4.0
	Total	9.3	4.6	6.6
1975Q1	Cyclical	3.3	-1.8	5.4
	Trend	6.6	4.5	3.7
	Total	9.9	2.7	9.1
1980Q3	Cyclical	1.1	-1.5	2.9
	Trend	6.3	4.2	3.5
	Total	7.5	2.7	6.4
1982Q4	Cyclical	5.0	1.1	4.3
	Trend	6.2	4.1	3.5
	Total	11.2	5.2	7.8
1991Q1	Cyclical	0.8	-1.6	2.5
	Trend	5.9	3.3	3.8
	Total	6.7	1.6	6.3
2001Q4	Cyclical	2.9	0.5	2.6
	Trend	5.1	2.1	4.3
	Total	8.0	2.6	6.9
2009Q2	Cyclical	2.4	-3.1	6.3
	Trend	4.4	1.2	4.5
	Total	6.8	-1.9	10.8
<i>Averages</i>				
1960-82	Cyclical	3.0	-0.4	3.6
	Trend	6.8	4.5	4.0
	Total	9.8	4.1	7.6
	Actual ^b	11.0	5.9	7.3
1960-2001	Cyclical	2.6	-0.5	3.2
	Trend	6.4	3.9	4.0
	Total	9.0	3.5	7.3
	Actual ^b	9.2	4.0	7.2
<i>Differences</i>				
2009Q2 minus average, 1960-82	Cyclical	-0.6	-2.7	2.7
	Trend	-2.4	-3.3	0.5
	Total	-3.0	-6.0	3.2

Source: Authors' calculations.

a. Entries are cumulative predicted growth rates of the common component (or the actual value) of the indicated series, computed using the factors at the trough and the DFM estimated through 2007Q3. Predicted paths are decomposed into the detrended cyclical component (the contribution of the factors at the trough) and the trend growth rate.

b. Excludes the post-1980Q3 recovery because the next recession commenced within the 8-quarter window used in this table.

between the post-2009Q2 recovery and the 1960–82 recoveries is attributed to differences in the cyclical component.²²

IV.C. The Slowdown in Trend Labor Force Growth and Slow Recoveries

A striking result of the previous section is that the decline in the trend component accounts for nearly all of the slowdown in GDP growth, and for over half the slowdown in employment growth, in the current recovery relative to the pre-1984 averages. Table 10 decomposes the change in trend GDP growth from 1965 to 2005 into GDP per employee, the employment-population ratio, the labor force participation rate, and the growth of the labor force. As seen in the first panel of table 10, the decline in the trend growth rate of GDP of 1.2 percentage points from 1965 to 2005 is, in this accounting sense, almost entirely due to declines in trend employment, which in turn is approximately equally due to declines in growth of the employment-population ratio and in population growth. In this accounting sense, the third panel of the table shows that declines in the growth of the employment-population ratio are in turn due to declines in the growth of the labor force participation rate, which in turn are largely due to declines in the growth rate of the female labor force participation rate. Figure 5 presents the estimated trends for the terms in the first panel in table 10 for the full 1959–2011 period.

Because the trend value of the unemployment rate is approximately the same in the 1960s as in the early 2000s (after peaking in the early 1980s), understanding the decline in mean employment growth amounts to understanding the decline in the growth of the labor force.²³ A significant literature examines long-term labor force trends and links them to two major

22. The online appendix reports results for five- and seven-factor models. The only notable departure from the results reported in this paper for the six-factor model is that the five- and seven-factor models predict a stronger post-2009Q2 recovery, so they attribute even more of the gap between that recovery and the 1960–82 recoveries to the slowdown in trend growth.

23. Two pieces of evidence suggest that the observed decline in employment growth is not an artifact of long-term mismeasurement. First, trend growth in employment measured by the household survey exhibits the same pattern as that in the establishment survey, with a decline from 2.1 percent annually in 1970 to 1.0 percent annually in 2000; this 1.1-percentage-point decline is close to the 1.4-percentage-point decline in the establishment survey (see the online appendix). Second, the small net trend in GDP per worker (from the establishment survey) matches the small net trend in output per hour (nonfarm business), which would not be the case if nonfarm business hours (a narrower measure) are correctly measured but employment is increasingly underestimated.

Table 10. Contributions of Trend Productivity, Labor Force, and Population to Trend GDP Growth Rate^a

<i>Series and component</i>	<i>Trend growth rate^b (percent per year)</i>			<i>Difference, 2005 minus 1965^c (percentage points)</i>
	1965	1985	2005	
GDP	3.7	3.1	2.5	-1.2
GDP-employment ratio	1.6	1.3	1.5	-0.1
Employment-population ratio	0.3	0.4	-0.2	-0.5
Population	1.7	1.4	1.1	-0.6
GDP-employment ratio	1.6	1.3	1.5	-0.1
Ratio of GDP to NFB output	-0.2	-0.3	-0.2	0.0
Ratio of NFB output to NFB hours	2.3	1.8	2.2	-0.1
Ratio of NFB hours to NFB employment	-0.4	-0.3	-0.2	0.2
Ratio of NFB employment to total nonfarm employment	0.0	0.1	-0.3	-0.3
Employment-population ratio	0.3	0.4	-0.2	-0.5
Employment as share of labor force	0.0	0.1	0.0	0.0
Labor force as share of population	0.3	0.4	-0.1	-0.5
Labor force share of population	0.3	0.4	-0.1	-0.5
Female	0.5	0.4	0.0	-0.5
Male	-0.2	-0.1	-0.2	0.1
Labor force	2.0	1.7	0.9	-1.1
Female (prime-age)	0.7	0.8	0.3	-0.4
Male (prime-age)	0.4	0.6	0.2	-0.2
Female (non-prime-age)	0.5	0.2	0.2	-0.3
Male (non-prime-age)	0.4	0.1	0.2	-0.2

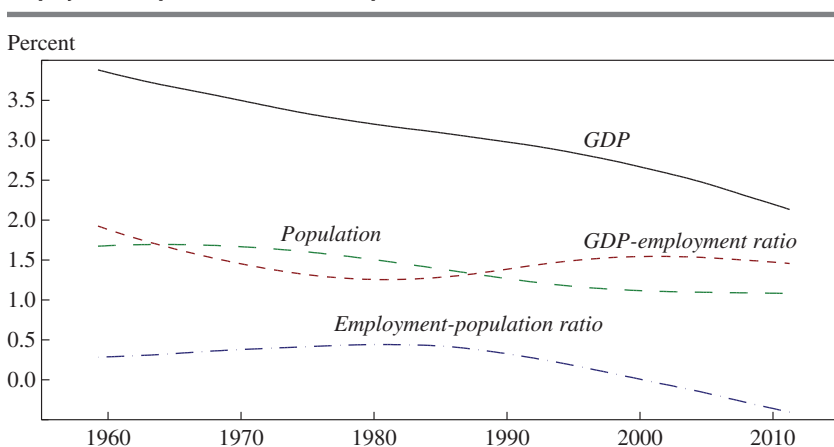
Source: Authors' calculations.

a. Growth rates and differences for components may not sum to those for totals because of rounding. Standard errors for the estimated trends range from 0.1 for the labor force variables to 0.5 for GDP; for details see the online appendix. NFB = nonfarm business.

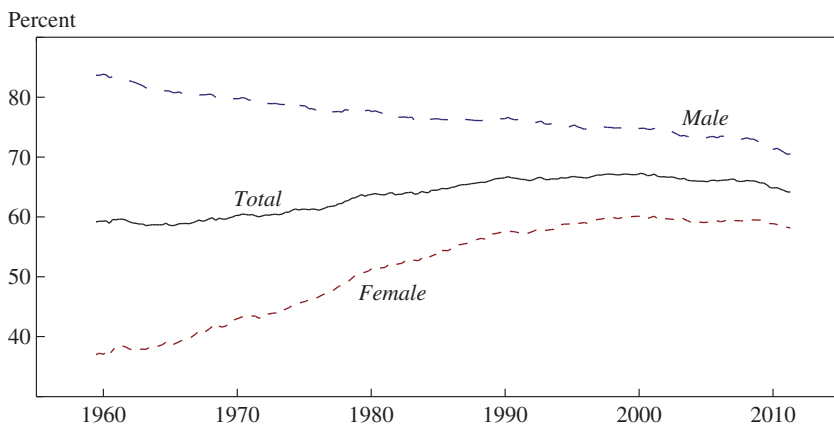
b. Each entry is the growth in the trend component of the indicated series in the indicated year, computed as described in section I.C.

c. Difference between 2005 and 1965 trend values.

Figure 5. Trend Components of Growth of GDP, the GDP-Employment Ratio, the Employment-Population Ratio, and Population, 1959–2011



Source: Authors' calculations.

Figure 6. Civilian Labor Force Participation Rates, Total and by Sex, 1959–2011

Source: Bureau of Labor Statistics.

demographic shifts (figure 6).²⁴ The first is the historic increase in the female labor force participation rate from the 1960s through the 1990s and its subsequent plateau; see Claudia Goldin (2006) for an extensive discussion. The second is the (smaller) decline in the male labor force participation rate. Stephanie Aaronson and others (2006) and Bruce Fallick and Jonathan Pingle (2008) attribute this decline to a combination of changes in the age distribution of workers and changing cohort labor force participation rates associated with the aging of the baby-boom generation (also see Fallick, Fleischman, and Pingle 2010). The main conclusion from this demographic work is that, barring a new surge in female labor force participation or a significant increase in the growth rate of the population, these demographic factors point toward a further decline in trend growth of

24. Focusing solely on demographic shifts ignores other potential factors affecting labor force participation. One such factor is an endogenous response to the stagnation of median real wages; however, although the magnitude of the labor supply elasticity is debated, micro studies generally suggest that it is small (see Saez, Slemrod, and Giertz 2012, Chetty 2011, and Chetty and others forthcoming for discussions). Another such factor is a possible trend increase in the mismatch between worker skills and available jobs. For example, Goldin and Katz (2008) point to a plateau in the supply of educated Americans around 1980. Jaimovich and Siu (2012) present evidence that the trend adjustments in employment occur mainly through permanent losses of mid-skill jobs during and following recessions; this view of step-like adjustments differs from our smooth trend. It goes beyond the scope of this paper to examine these factors in any detail.

employment and hours in the coming decades. Applying this demographic view to recessions and recoveries suggests that future recessions with historically typical cyclical behavior will have steeper declines and slower recoveries in output and employment.

V. Conclusions and Discussion

Three main substantive conclusions emerge from this work. First, the recession of 2007–09 was the result of shocks that were larger versions of shocks previously experienced, to which the economy responded in a historically predictable way. Second, these shocks emanated primarily, but not exclusively, from financial upheaval and heightened uncertainty. Third, although the slow nature of the subsequent recovery is partly due to the nature and magnitude of the shocks that caused the recession, most of the slow recovery in employment, and nearly all of that in output, is due to a secular slowdown in trend labor force growth. This slowdown provides a simple explanation for the jobless recoveries of the 2001 and 2007–09 recessions. To the extent that it derives (as the literature suggests) from persistent demographic changes, recoveries from future recessions can be expected to be “jobless” as well. To these substantive conclusions we would add a fourth, methodological conclusion: that ignoring these changing trends will impart low-frequency movements to the errors, which seems likely to introduce subtle problems into structural VAR analysis.

The above three substantive conclusions are subject to a number of caveats. First, although the evidence for the stability of the factor loadings is relatively strong, it is difficult to draw inferences about the stability of the factor VAR parameters with only 15 quarters of post-2007Q3 data, particularly in the presence of evident heteroskedasticity in the factor innovations. The fact that the current recovery in employment has been stronger than predicted by the DFM given the state of the economy at the trough could reflect the effectiveness of the extraordinary monetary and fiscal policy measures taken during the recession, or it could be an indication of parameter instability; we are unable to distinguish between these two possibilities with the current limited data.

Second, the structural DFM analysis using the method of external instruments estimates shocks that are correlated with each other. The ability to estimate this correlation, rather than needing to impose it as an identifying restriction, is a strength of this methodology. Finding sometimes-large correlations across different types of shocks suggests that different identification strategies are estimating similar features of

the data, but interpreting them differently. This raises broader challenges for the structural DFM and VAR literatures, which lie beyond the scope of this analysis. Sorting out credible instrumental variables methods for separately identifying liquidity shocks, market risk shocks, exogenous wealth shocks, and uncertainty shocks constitutes a large research agenda.

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