NBER WORKING PAPER SERIES

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Working Paper 18094
http://www.nber.org/papers/w18094

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2012

Prepared for the Brookings Panel on Economic Activity, March 22-23, 2012. We thank John Driscoll, Lutz Kilian, Valery Ramey, Eric Swanson, Egon Zakrajšek, and Tao Zha for providing and/or helping us construct their shock series and for comments. We also thank Alan Blinder, Nick Bloom, Markus Brunnermeier, Marty Eichenbaum, Jon Faust, Florencio Lopez de Silanes, Karel Mertens, Salil Mehta, Neil Shephard, Chris Sims, Mike Woodford, Tom Zimmerman, and the editors for helpful comments and/or discussions. Replication files and the Supplement are available on Watson's Web site. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 18094
May 2012, Revised July 2012
JEL No. E24,E32,E37,E44

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 2007-2009 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 an historically predictable way. Second, the shocks that produced the recession primarily were 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, while 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.

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1. Introduction

The recession that began in the fourth quarter of 2007 was unprecedented in the postwar United States for its severity and duration. Following the NBER-dated peak of 2007Q4, GDP dropped by 5.5 percent and nearly 8.8 million jobs were lost. Based on the most recent revisions, the previous peak in GDP was not achieved for 15 quarters, in 2011Q3, and as of this writing only 3.5 million jobs have been regained. All this suggests that the 2007Q4 recession and recovery were qualitatively, as well as quantitatively, different from previous postwar recessions. The recession also seems unprecedented in its precipitating sources: the first nation-wide persistent 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 dampened the recovery.[1]

The aim of this paper is to take an empirical look at this recession and recovery, with an eye towards 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 from this recession. More specifically, we consider three questions. First, beyond its severity, how did this recession differ from previous postwar recessions? Second, what specifically 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 dynamic factor model and a VAR is that the number of macro shocks does

[1] The view that financial recessions and recoveries are different than "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 why this recovery is exceptional, including deleveraging after a financial crisis (e.g. Mian and Sufi (2011)), regional or industry job mismatch (e.g. Şahin, Song, Topa, and Violante (2011)), changes in labor management practices (e.g. Berger (2011)), and monetary policy rendered ineffective because of the zero lower bound.

not increase with the number of series. Also like 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 macro 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 this recession had new shocks by examining whether the 2007-09 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 using a DFM estimated through 2007Q3 suggests that the same six factors which explained previous postwar recessions also explain the 2007Q4 recession: no new "financial crisis" factor is needed. Moreover, the response of 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 (e.g. Lehman) and novel, aggressive policy responses (e.g. TARP, the Fed's various facilities); our results suggest, however, that the net effect of these failures and responses on the macro economy was not qualitatively different than past disturbances – just larger. 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, were these large economic shocks requires an exercise similar to structural VAR identification. We consider six shocks: oil, monetary policy, productivity, uncertainty, liquidity/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 Kilian's (2008a) series on war-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, uncertainty shocks and liquidity/risk shocks 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 slow recovery in employment growth since 2009Q2, compared to 1960-1982 recoveries, is attributable to cyclical factors (the shocks, or factors, during the recession). Most of the slow recovery, however, is attributable to a long-term slowdown in trend employment growth. Indeed, the slowdown in trend employment growth is dramatic: according to our estimates, trend annual employment growth slowed from 2.4% in 1965 to 0.9% in 2005. The explanation for this declining trend growth rate which we find the most compelling rests on changes in underlying demographic factors, primarily the plateau in the female labor force participation rate (after rising sharply during the 1970s through 1990s) and the aging of the U.S. 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 will have slower recoveries, than historically has been the case.

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

The DFM and the data set are described in Section 2. Section 3 presents a counterfactual exercise of how well the historical shocks and model do at predicting the 2007Q4-2011 experience, along with stability tests. Section 4 discusses identification of the structural shocks and provides empirical analysis of the identified structural shocks. Section 5 focuses on the slow recovery, and Section 6 concludes. Detailed data description and additional empirical results are contained in the Supplement.

2. Empirical Methods and Data

2.1 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 (e.g. Sargent and Sims (1977), Giannone, Reichlin, and Sala (2004)). Sargent (1989) and Boivin and 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 Bernanke, Boivin, and Eliasz (2005).

Because the comovements of the observed series stem from the factors, it is not necessary to model directly the dynamics among observed variables, thus avoiding the proliferation of coefficients found in VARs. Because a DFM has relatively few factors compared to 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, where X_{it} is a single time series, where all series have been transformed to be stationary and to have mean 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}:

$$X_t = \Lambda F_t + e_t, \tag{1}$$

where $e_t = (e_{1t},\ldots, e_{nt})'$ and Λ is a $n\times r$ 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 vector autoregression (VAR):

$$\Phi(\mathrm{L})F_t = \eta_t, \tag{2}$$

where $\Phi(\mathrm{L})$ is a $r\times r$ matrix of lag polynomials with the vector of r innovations η_t.[3] Because the factor VAR (2) is assumed to be stationary, F_t has the moving average representation, $F_t = \Phi(\mathrm{L})^{-1}\eta_t$. 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 (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} onto $\hat{F}_t$. 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)).

[3] Equations (1) and (2) are the static form of the dynamic factor model, so-called because the factors F_t enter with no leads or lags in (1). For a discussion of the relation between the dynamic and static forms of the DFM see Stock and Watson (2011).

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 2.4.

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 of Sections 3 and 5 works with the reduced-form DFM in equations (1) and (2), so this normalization is inconsequential. The analysis of Section 4 requires identification of specific economic shocks, and our identification procedure is discussed there.

2.2 The Data and Preliminary Transformations

The data set consists of quarterly observations from 1959Q1-2011Q2 on 200 U.S. macroeconomic time series (vintage November 2011). The series are grouped into 13 categories (number of series in parentheses): NIPA variables (21); 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 subject to a preliminary screen for outliers then transformed as needed to induce stationarity. The transformation used depends on the category of 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 Supplement.

2.3 Local Means and Detrending

All series were detrended to eliminate very low frequency variation. Specifically, after transforming to stationarity, each series was deviated from a local mean estimated using a biweight kernel with a bandwidth of 100 quarters. The local means estimated using the biweight kernel 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 biweight filter means are less noisy because they avoid the sharp cutoff of a moving window.[4] We refer to these local means as the trend in the series, although it is important to note 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, these trends exhibit considerable variation. 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% per year in 1965 to 2.5% per year in 2005[5], and for the trend annual employment growth rate to have fallen by 1.5 percentage points, from 2.4% in 1965 to 0.9% 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 6.

2.4 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

[4] Endpoints are handled by truncating the kernel and renormalizing the truncated weights to add to one. This approach desirably makes no assumption about reversion of 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 Supplement.

[5] 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 points 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.

consumption were used to estimate the factors, but total consumption was not. Of the 200 series, 132 were used to estimate the factors; the series used to estimate the factors are listed in the Supplement. No top-level macro aggregates (including GDP, consumption, investment, total employment, the total unemployment rate) were used to estimate the factors.

Using these 132 series, the factor loadings Λ were estimated 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 1959Q-2011Q2 sample which correspond to the estimated factors. For the 1959-2007Q3 sample, these are the principal components of the factors; for the post-2007Q4 period, these are the pre-2007Q3 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 post-2007Q4.[6] These "old" factors are used throughout the paper, and, with the single exception of a sensitivity check in Section 3.2, the "old" DFM coefficients, estimated over 1959-2007Q3, are also used throughout.[7]

[6] 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 Supplement). Denote the resulting estimates of $\tilde{\Lambda}$ by $\hat{\tilde{\Lambda}}^{59-07}$, normalized so that $\hat{\tilde{\Lambda}}^{59-07\prime}\hat{\tilde{\Lambda}}^{59-07} = I$. The estimated "old" factors are computed using $\hat{\tilde{\Lambda}}^{59-07}$ as $\hat{F}_t^{59-07} = \hat{\tilde{\Lambda}}^{59-07\prime}\tilde{X}_t$, t = 1959Q1,…, 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 against $\hat{F}_t^{59-07}$ 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 $\hat{\Lambda}^{59-07}\hat{F}_t^{59-07}$.

[7] The assumption that the factors and DFMs can be estimated with no breaks over the 1959-2007Q3 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, Stock, and Watson (2012)). These findings suggest that, in the current study, 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

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 5.[8] As discussed below and shown in the Supplement, there is little sensitivity to our main results as the number of factors is varied over a reasonable range.

3. A Structural Break in 2007Q4?

This section investigates the extent to which the 2007Q4 recession exhibited new macrodynamics, relative to the 1959-2007Q3 experience. This analysis has three parts. First, we examine whether the factors in the 2007Q4 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 pre-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.

3.1. Post-2007 Simulation Using the pre-2007 DFM

We begin by considering the following experiment: suppose you had in hand our 6-factor, 200-variable DFM estimated using data through 2007Q3, and you were told the time path of the six factors from 2007Q4 – 2011Q2. Using the pre-2007Q4 model and the post-2007Q4 values of the old factors, you compute 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 R^2 of the old factors would go down post-2007Q4, relative to pre-2007Q4. Similarly, if the "old" factors had new effects, that is, if

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 Supplement.

[8] The Bai-Ng (2002) ICP_1 and ICP_2 criteria selects either 3 or 4 factors, depending on the sample period, while their ICP_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 4 or 5 factors then declines slowly.

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 old model/old factors predicted common components (computed as described in footnote 6), along with actual values of the series, for 24 selected time series. For activity variables and inflation, the figure plots the 4-quarter growth rate (that is, the 4-quarter average of quarterly GDP growth) to smooth over quarterly measurement error, while for financial variables the figure plots quarterly changes 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 subsample R^2 of the common component of the 24 selected series, computed over two split-sample periods and over the 15-quarter stretches following all postwar NBER peaks. These R^2's are computed imposing a zero intercept and unit slope on the predicted values over the indicated subsample and thus cannot exceed one but can be negative.[9] The R^2's in Table 1 all pertain to quarterly values whereas 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 declines during 2008Q4-2009, the prolonged trough, and the muted recovery since 2010 in GDP, total consumption, nonresidential fixed investment, industrial production, employment, and the unemployment rate. The pre-2007Q3 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 (2011) excess bond premium spread), the bear market in stocks, and the sharp rise in uncertainty as measured by the VIX, and even the sharp decline and recovery of lending standards reported in the loan officers survey. The DFM correctly predicts the decline in commercial and industrial

[9] Using the notation of footnote 6, let $\hat{e}_t = X_t - \hat{\Lambda}^{59-07}\hat{F}_t^{59-07}$ be the prediction error using the old model/old factors. The subsample R^2 for series i I s computed as $R^2 = 1-\left(\sum_t \hat{e}_{it}^2\right)/\left(\sum_t X_{it}^2\right)$, where the sums are computed over the column subsample.

loans during the early part of the recession, although it underpredicts the depth of their contraction or their long delay in recovering[10]. These qualitative impressions from Figure 2 are confirmed quantitatively by the R^2's in Table 1. For these series, the post-2007Q4 R^2's are well within the range of R^2's for previous recessions. The post-2007Q4 R^2 for GDP growth is somewhat lower than in previous episodes because the DFM misses some high-frequency variation, but as seen from Figure 1a the year-over-year match is very strong. On the other hand, for some series (of those in Table 1, consumption of services, PCE 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, was so large during this recession that the fraction of the variation it explains increased.

There are a few series that are less well explained by the historical factors. Most notably, the model predicts the Fed Funds rate to decline by more than it did, but this is unsurprising because the model is linear and does not have a zero lower bound; we return to this point below. The model also confirms that the Fed's expansion of reserves was unprecedented. Although the historical factors predict house prices in 2007Q4-2011 as well as in previous recessions, they do not fully explain the boom in house prices in 2004-2006 and slightly underpredict the speed of their crash.

Table 2 summarizes the subsample R^2's for all 200 series, by series category (the Figure 2/Table 1 results for all series are provided in the Supplement). For most categories the median R^2 over the 2007Q4 period is comparable to or greater than previous recessions. The only categories for which the actual paths diverge systematically from the predicted paths are earnings & productivity, interest rates, and money & credit. The divergence in interest rates is due mainly to zero lower bound problems, not to failures to match liquidity spikes in the spreads, and the divergence in money and credit is associated with the unprecedented expansion of monetary aggregates. Closer inspection of the divergence in earnings & productivity suggests that these

[10] Giannone, Lenza, and Reichlin (2012) examine the stability of the relation between various loans and macroeconomic indicators in the Eurozone during and after the crisis, relative to a pre-crisis 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.

divergences do not seem to reflect breaks associated with this recession, compared with the two other post-1984 recessions.[11]

3.2. 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 2007Q4 recession. We now provide 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 Andrews' (2003) test for end-of-sample instability.[12] 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 1960-2007Q3 values of the loadings, and the other testing for a break in 2007Q4 relative to the values of the factor loadings over 1984Q1-2007Q3.

Rejection rates of this test for a break in 2007Q4 at the 5% level are summarized by category of series in Table 3. When the post-2007 values are compared with the full sample factor loadings, 15% of series reject at the 5% level, while 12% reject at the 5% level when the comparison is to 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 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 panels j and p). The small number of rejections provides little evidence of a systematic or widespread break in the factor loadings in 2007Q4, relative to their Great Moderation values.

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[11] 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 2007Q4 recession.

[12] 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.

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 eight quarters following 07Q4 (in the notation of footnote 6, 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 eight quarters. A new common factor would produce an unusually large value of this ratio. It turns out that this eigenvalue ratio following 2009Q2 is less than it was during the 1960Q2 and 1973Q4 recessions. 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 following 07Q4 yields a *p*-value of 0.90. This test therefore provides no evidence of a missing factor.

3.3 Increased variance of factors

The findings of Sections 3.1 and 3.2 suggest that the severity of the 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-1983 period, the Great Moderation period, and post-2005, along with the standard deviations of their factor components computed using pre-2007Q3 coefficients and the "old" factors. For these (and other) macro aggregates, volatility post-2005 has returned to or exceeds pre-Great Moderation levels. As the second block 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 were 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 macro variables, so that the entries are the innovation in the common component, by series, by quarter, from 2007Q4-2001Q2, reported in standard deviation units.[13] For the series in Table 5, the factor component of oil prices experienced moderate then large standardized innovations in 2007Q1 and 2008Q2 (1.7 and 3.4, respectively), and the TED spread, the VIX, and housing starts experienced large, then extremely large (approximately 8 standard deviations) innovations in 2008Q3 and 2008Q4. Oil prices experienced a very large negative factor innovation in 2008Q4, then large positive innovations in the next three quarters. Throughout 2007Q1-2009Q1, the factor component innovations for the real variables were moderate by comparison and were generally within the range of pre-2007Q3 experience. By 2009Q4, all the innovations had returned to their normal range, which is consistent both with the large economic shocks having passed and with the pre-2007Q3 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.

3.4 Discussion

The results of this section suggest three main findings. First, there is little evidence of a new factor associated with the 2007Q4 recession and its aftermath; rather, the factors associated with the 2007Q4 recession are those associated with previous recessions and with economic fluctuations more generally from 1959-2007Q3. 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 post-2007Q4 as pre-2007Q4. 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 2007Q4 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 macro variables to these

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[13] Rewrite the factor VAR (1) as $F_t = \tilde{\Phi}(L)F_{t-1} + \eta_t$, so from (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 4-lag VAR estimated using the "old" factors over 1959-2011Q2.

shocks was almost entirely in line with historical experience. The few series for which behavior departed from historical patterns have natural 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 Fed's quantitative easing.

The foregoing interpretation comes with caveats. First, the stability tests in Section 3.2 are based on 15 observations post-2007Q4, 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 macro dynamics 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 TARP, quantitative easing, the auto bailout, and the other extraordinary events of this recession. Our point is that while all these particulars were new, their dynamic effect on the economy was not.

4. Structural Shocks: Identification and Contribution to the 2007Q4 Recession

The analysis of Section 3 suggests that the shocks precipitating the 2007Q4 recession were simply larger versions of shocks experienced by the U.S. 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.

4.1 DFM shock identification using instrumental variables

The identification problem in structural VAR analysis is 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 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. The coefficients of those linear combinations in turn identify the shocks and the impulse response function of the observed variables 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 variable interpretation. When the economic restrictions take the form of exclusion restrictions on the impulse response function (shock A does/does not affect variable B within a quarter; shock C does/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 Romer and 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, rather they 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; in Romer and Romer (2004) this series was treated directly as a monetary policy shock, whereas here it is taken instead 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 which is not itself included in the VAR; in a structural DFM, an external instrument is a variable used for identification which is not itself a factor. With one exception (a productivity shock instrument identified by a Gali (1999)-type long run exclusion restriction discussed below), all the instruments used in this paper are external instruments.

Identification and inference using external instruments[14]. The basic idea of SVAR identification with external instruments is that the structural shock is identified as the predicted

[14] 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 by Mertens and Ravn (2012), which we became aware of after

value in the population regression of the instrument, say Z_t, on the VAR innovations η_t. 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).

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

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

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 (3) is invertible so that the structural shocks can be expressed as linear combinations of the innovations:

$$\varepsilon_t = H^{-1}\eta_t\ . \tag{4}$$

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

presenting the conference draft of this paper. The idea of using constructed exogenous shocks (what we call external instruments) as instruments in SVARs dates at least to Hamilton (2003), also see Kilian (2008a, b).

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

The impulse response function of X_t with respect to the i^{th} structural shock thus is $\Lambda\Phi(\mathrm{L})^{-1}H_i$. As discussed in Section 2, Λ and $\Phi(\mathrm{L})$ 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 shocks are assumed to satisfy three conditions:

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

where D in (iii) is a $r\times r$ 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) is the exogeneity condition stating that Z_t is uncorrelated with the other structural shocks. By (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

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

where the first equality follows from (3) and the final equality follows from (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 (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 (i) – (iii),

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

where the second equality follows from (7) and the final equality follows from (4) and $H^{-1}H_1 = e_1$, where $e_1 = (1\ 0\ \ldots\ 0)'$ so that $\alpha(H_1'H'^{-1})D^{-1} = (\alpha/\sigma_{\varepsilon_1}^2)e_1'$. Equation (8) displays the result 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 you observed ε_t, so you could regress Z_t on ε_t; then by (i), the population coefficient on ε_{1t} would be nonzero, while by (ii) and (iii) the coefficients on the other ε_t's would be zero, so the predicted value would be ε_{1t} up to scale. But by (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}.

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

Estimation and tests of overidentifying restrictions. The structural shock is estimated using the sample analogue of (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 only available 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, etc.) are made using $\hat{\varepsilon}_{1t}$.

Correlations among identified shocks. Suppose we have two instruments which purportedly identify different shocks. If the instruments are both valid, then in population these identified shocks will be uncorrelated. But the population projection (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 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.

4.2 Instruments

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

Oil shock. We use three external instruments for the oil shock. The Hamilton (2003) oil shock is a quarterly version of Hamilton's (1996) monthly net oil price increase, constructed over a three-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 three years (constructed from the PPI for oil, available 1960Q1-2011Q4). The Kilian (2008a) oil shock is his 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 macro variables as described in Ramey and Vine (2010), which we recomputed using the most recent data vintage. See Kilian (2008a, b) and Hamilton (2009, 2010) for discussions of various oil shock measures.

Monetary policy shock. We use four external instruments for the monetary policy shock. The first is the Romer and Romer (2004) monetary policy shock, which they computed as the residual of a constructed Fed monetary intentions measure on internal Fed forecasts (quarterly sums of their monthly variable, demeaned, 1969Q1-1996Q4). The second is the shock to the monetary policy reaction function in the Smets-Wouters (2007) dynamic stochastic general equilibrium (DSGE) model, as recomputed by King and Watson (2012) (1959Q1-2004Q4). The third is the monetary policy shock from the Sims and Zha (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 Gürkaynak, Sack, and Swanson (2005), which measures surprise changes in the target Fed Funds rate (quarterly sums of daily data, 1990Q1-2004Q4).[15]

Productivity shock. We use one internal and two external instruments for the productivity shock. The first external instrument is the Basu, Fernald and Kimball (2006)/Fernald (2009) series on quarterly total factor productivity adjusted for variations in factor utilization, as updated by John Fernald (1959Q1-2011Q2). The second external instrument is the productivity shock in the Smets-Wouters (2007) DSGE, as recomputed by King and Watson (2012) (1959Q1-2004Q4). The internal instrument is constructed using Galí's (1999) identification scheme. Specifically this internal instrument is the permanent shock to the factor component of output per hour in nonfarm businesses. In the notation of the DFM, 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 Mertens and Ravn (2010) for a recent discussion and references.

Uncertainty shock. We use two external instruments for the uncertainty shock. The first, motivated by 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).[16] The second is the innovation in the common component of the Baker, Bloom and Davis (2012) policy uncertainty index, which is based on news 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 Bekaert, Hoerova, and Lo Duca (2010) and Bachman, Elstner, and Sims (2010).

Liquidity/risk shock. We use three external instruments for a liquidity/risk shock. The first two are unadjusted and adjusted term spreads: the TED spread (1971Q1-2011Q2) and Gilchrist and Zakrajšek's (2011) excess bond premium (GZ; 1973Q3-2010Q3). Both instruments aim to measure risk in financial markets not associated with predictable default probabilities. The GZ spread is a bond premium which has been adjusted to eliminate predictable default risk. For an early discussion of credit spreads as measures of market

[15] Other candidate instruments include the market announcement movements of Cochrane and Piazzesi (2002) and Faust, Swanson, and Wright (2004).
[16] Lee, Rabanal, and Sandri (2010) take the uncertainty shock to be the innovation to the VIX.

liquidity, see Friedman and Kuttner (1993); for more recent discussion see Gilchrist, Yankov and Zakrajšek (2009) and Adrian, Colla and Shin (2012). The third instrument is Bassett, Chosak, Driscoll, and Zakrajšek's (2011) bank loan supply shock, which they computed as the unpredictable component of bank-level responses to the Fed's Senior Loan Officer Survey (1992Q1-2010Q4).

Fiscal policy shock. We use three external instruments for fiscal policy shocks: Ramey's (2011a) federal spending news instrument (demeaned, 1959Q1-2010Q4), Fisher and Peters' (2010) excess returns on stocks of military contractors (1959Q1-2008Q4), and Romer and Romer's (2010) tax changes relative to GDP ("all exogenous", demeaned, 1959Q1-2007Q4). The first two of these are instruments for federal government spending changes while the Romer-Romer (2010) instrument is an instrument for federal tax changes. For additional discussion see Parker (2011) and Ramey (2011b).

4.3 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 2007Q4 recession. This analysis additionally requires a VAR for the factors, which we estimate using the "old" factors (see footnote 6). 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 Table 1. Whereas the R^2's in Table 1 measure the fraction of the variation in GDP 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.[17] 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 1 reports the non-HAC F statistic testing the hypothesis that the coefficients on the η_t's are all zero in the

[17] In the notation of (3) and (5), the factor component due to the j^{th} structural shock is $\Lambda\Phi(L)^{-1}H_j\varepsilon_{jt}$. The R^2 of the i^{th} variable with respect to the j^{th} shock is thus computed as $R^2 = 1-\left(\sum_t(\hat{e}_{it}^j)^2\right)\big/\left(\sum_t X_{it}^2\right)$, where $\hat{e}_{it}^j = X_{it} - \hat{\Lambda}_i'\hat{\Phi}(L)^{-1}\hat{H}_j\hat{\varepsilon}_{jt}$, where $\hat{\Lambda}_i'$ is the i^{th} row of $\hat{\Lambda}$.

regression of Z_t on η_t, which is a measure of the strength of identification that enters the null distribution of the correlations in Table 7 (Montiel Olea, Stock, and Watson (2012)).

As discussed in Section 4.1, 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 0 across categories. As discussed in Section 4.1, each shock is the predicted value from the regression of its instrument onto the DFM innovations, so in general the correlation between two estimated shocks is different than 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 column 1 of Table 6, which is akin to a first-stage F-statistic in two stage least squares, is small, being less than 5 in ten cases and less than 10 in all but three cases. 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, although 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, while 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 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^2s 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 negative sign 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.

The observation that the different instruments within a category identify different shocks with different effects echoes 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 indented 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. While 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 *un*correlated. 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 bolded in Table 7). One notable set of correlations is between the blocks of monetary and fiscal shocks, for which the mean average absolute correlation between individually-identified shocks across the two categories is 0.51. The monetary and fiscal shock literatures are aware 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 and liquidity/risk shocks, for which 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 0.76 between the shocks identified using the Baker, Bloom, and Davis (2012) policy uncertainty index and the Gilchrist- Zakrajšek (2011) 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 component 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 listed in the final rows of Table 6.

The 2007Q4 recession. Table 8 summarizes the contribution of the shocks in Table 6 to the cumulative growth of GDP and 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 deviated 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 Supplement.

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 (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 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 Fed funds rate was contractionarily high). 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.

4.4 Discussion

Inference about the causes of the 2007Q4 recession based on Table 8 is complicated because on the one hand 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 oversimplifying, 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 be 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 term spread 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 2007Q4-2009Q2 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 in Figure 3 shows that they explain a great deal of the 2007Q4 recession and 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: initially oil shocks, followed by the financial crisis, financial market disruptions, and a prolonged period of uncertainty.

5. 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 the NBER-dated trough of 2009Q2, GDP grew by only 5.0%, compared with an average of 9.2% for the recessions from 1960-2001, and employment increased only 0.6% compared with the 1960-2001 average of 4.0%[18]. The contrast between the current slow recovery and the robust recoveries of 1960-1982 is even more striking: those recessions averaged 8-quarter GDP growth of 11.0% and 8-quarter employment growth of 5.9% 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 2009Q2 recovery in employment been so much slower than the 1960-1982 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 weak 2009Q2 recovery, relative to (say) 1982Q4, could arise from differences in underlying trends (e.g. demographics), differences in recovery paths after different types of recessions (e.g. monetary policy vs. 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 terms 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 – in the 2009Q2 recovery to their values in previous recoveries.

As in Section 4, 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 reflects differences in recovery paths implied by the shocks that produced the recessions. This permits a

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[18] These averages exclude the 1980Q3 recovery because the next recession started within the 8-quarter window of these calculations.

decomposition of the slow recovery of 2009Q2, relative to previous recoveries, into changes in the trend plus changes in the predicted cyclical component.

5.1 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 Reinhart and Rogoff (2009) describe slow recoveries from financial crises. 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 factors) vary across recessions both in composition and magnitude, the recovery paths predicted by the DFM vary across recessions.

Figure 4 plots actual quarterly employment growth, its common component, and its predicted common component following the eight post-1960 troughs. All series are deviated from trend so a value of zero denotes trend employment growth. 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 the common component and actual employment growth 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 (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 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 three quarters after the trough – while 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, in which the next recession occurred shortly into the expansion.

Third, given the values of the factors in 2009Q2, the DFM predicts six quarters of sub-trend employment growth following the 2009Q2 trough. In 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.[19]

5.2 Decomposition of the 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 predicted cyclical components 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 provide the trend/cycle decomposition 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 and most, 3.3 percentage points, is attributed to differences in trend employment growth. The predicted cyclical component of productivity growth in the 2009Q2 recovery is unusually large, 6.3 percentage points, although this predicted value is perhaps comparable to its values in the

[19] Allowing for a break in $\Phi(L)$ in 1984Q1 produces somewhat faster predicted recoveries pre-84 and somewhat slower post-84, for details see the Supplement.

1975Q1 and 1982Q4 recoveries. The difference between the trend components of productivity growth in the 2009Q2 recoveries and the pre-1984 recoveries is 0.5 percentage points, that is, trend productivity growth in 2009Q2 is slightly higher than its average 1960-1982. Most of the difference in productivity growth between the 2009Q4 recovery and the 1960-1982 recoveries is attributed to differences in the cyclical component.[20]

5.3 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 block in 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 to declines in population growth. In this accounting sense, the third block 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, is largely due to declines in the growth rate of the female labor force participation rate. The estimated trends for the terms in the first block in Table 10 are presented for the full 1959-2011 period in Figure 5.

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.[21]

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[20] The Supplement reports results for 5- and 7-factor models. The only notable departure from the results reported in this paper for the 6-factor model is that the 5- and 7-factor models predict stronger post-2009Q2 recoveries, so they attribute even more of the gap between the 2009Q2 recovery and the 1960-1982 recoveries to the slowdown in trend growth.

[21] 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 the establishment survey, with a decline of from 2.1% annually in 1970 to 1.0% annually in 2000; this 1.1 percentage point decline is close to the 1.4 percentage point decline in the establishment survey (see the Supplement). Second, the small

There is a significant literature that examines long-term labor force trends and links them to two major demographic shifts.[22]

Two historic demographic shifts are evident in Figure 6. The first is the increase in the female labor force participation rate from the 1960s through the 1990s and its subsequent plateau, see Goldin (2006) for an extensive discussion. The second is the (smaller) decline in the male labor force participation rate. Aaronson et. al. (2006) and Fallick and 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; also see Fallick, Fleischman, and Pingle (2010). The main conclusion from this demographic work is that, barring a new increase in female labor force participation or a significant increase in the growth rate of the population, these demographic factors point towards a further decline in trend growth of employment and hours in the coming decades. Applying this demographic view to recessions and recoveries suggests that the future recessions with historically typical cyclical behavior will have steeper declines and slower recoveries in output and employment.

6. Conclusions and Discussion

Three main substantive conclusions emerge from this work. First, the recession of 2007-2009 was the result of shocks that were larger versions of shocks previously experienced, to which the economy responded in an historically predictable way. Second, these shocks emanated primarily, but not exclusively, from financial shocks and heightened uncertainty. Third, while the slow nature of the subsequent recovery is partly due to the shocks of this

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net trend in GDP per worker (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.

[22] 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, while there is a debate about the magnitude of the labor supply elasticity, micro studies generally suggest that it is small (see Saez, Slemrod, and Giertz (2011), Chetty (2011), and Chetty, Guren, Manoli, and Weber (2011) 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.

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. This slowdown in trend labor force growth provides a simple explanation for the jobless recoveries of the 2001 and 2007 recessions. To the extent that this secular slowdown in trend labor force growth derives (as the literature suggests) from persistent demographic changes, we can expect recoveries from future recessions 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 to structural VAR analysis.

The three substantive conclusions are subject to a number of caveats. First, while the evidence for the stability of the factor loadings is relatively strong, it is difficult to draw inference on stability of the factor VAR parameters with only 15 quarters of data post-2007Q4, 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, standing 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, and addressing those questions goes 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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Table 1
Subsample R^2's of common component of selected quarterly macro variables, based on six static factors from the DFM estimated over 1959Q1 – 2007Q3.

	1959-2007Q3	1984-2007Q3	Computed over 15 quarters starting at NBER peak							
			60Q1	69Q4	73Q4	80Q1	81Q3	90Q3	01Q1	07Q4
GDP	0.73	0.62	0.81	0.79	0.83	0.79	0.85	0.73	0.64	0.64
Consumption	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
Nonres. 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
IP – automotive	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
Real house prices (OFHEO)	0.49	0.44	.	.	.	0.59	-0.01	0.60	0.42	0.57
Inflation (PCE)	0.51	0.54	0.25	0.70	0.66	0.44	0.40	0.57	0.56	0.82
Gas & energy inflation (PCE)	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 & 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	.	.	0.78	0.74	0.70	-0.05	-0.04	0.76
Gilchrist-Zakrajšek (2011) spread (EBP)	0.48	0.48	.	.	0.89	0.11	0.49	0.12	0.65	.
S&P 500	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	.	0.38	0.74	-0.78	-0.69	0.40	0.75	0.89
SLOOS	0.60	0.18	.	.	0.65	0.79	0.67	0.55	-1.49	0.47
HH Wealth/Disp. Income	0.16	0.14	-0.18	0.67	0.48	0.78	0.06	0.28	-0.46	0.51
HH Liabilities	0.57	0.48	-0.19	0.73	0.90	0.76	0.70	0.79	0.18	0.77

Notes: The predicted values are the "old model/old factors" predicted values computed as described in footnote 6. Table entries are one minus the ratio of the sum of squared prediction errors to the sum of squares of the observed variable (see footnote 9), computed for the row variable over the column subsample.

Table 2

Subsample R^2 of common component of quarterly macro variables by category, based on the six-factor DFM estimated over 1959Q1 – 2007Q3.

Category	**N**	**1959-2007Q3**	**1984-2007Q3**	**Computed over 15 quarters starting at NBER peak**							
				60Q1	**69Q4**	**73Q4**	**80Q1**	**81Q3**	**90Q3**	**01Q1**	**07Q4**
NIPA	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 & Unemp	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, & 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 & 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 & credit	12	0.44	0.26	0.22	0.47	0.55	0.65	0.63	0.40	0.06	-0.37
Stock prices & 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	.	.	.	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

Notes: entries are median subsample R^2's, where the median is computed for the row category of variable over the indicated subsample. See the notes to Table 1.

Table 3

Rejection rates at the 5% significance level, by category, of the test of no break in the factor loadings, 2007Q4 – 2011Q2 using the Andrews (2003) end-of-sample stability test

		Rejection rates testing for a break in 2007Q4 relative to:	
Category	**N**	**1959-2007Q3**	**1984Q1-2007Q3**
NIPA	21	0.00	0.00
Industrial production	13	0.00	0.00
Employment & Unemployment	46	0.15	0.15
Housing starts	8	0.25	0.13
Inventories, orders, & sales	8	0.13	0.13
Prices	39	0.26	0.23
Earnings and Productivity	13	0.15	0.08
Interest rates	18	0.00	0.11
Money & credit	12	0.42	0.17
Stock prices & wealth	11	0.18	0.00
Housing prices	3	0.33	0.33
Exchange rates	6	0.00	0.00
Other	2	0.00	0.00

Notes: Entries are the fraction of series in the row category that reject, at the 5% significance level, the hypothesis of stability of the factor loadings, using the Andrews (2003) end-of-sample stability test. 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 either 1959-2007Q3 (column 3) or 1984Q1-2007Q3 (column 4).

Table 4
Standard deviations of four-quarter growth rates of major activity variables

	Series			**Factor Component**		
	1959-1983	**1984-2004**	**2005-2011**	**1959-1983**	**1984-2004**	**2005-2011**
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
Unemployment rate (4-quarter change)	1.1	0.8	1.5	1.1	0.7	1.4

Notes: Entries in the first three numeric columns are standard deviations of four-quarter detrended growth rates of the row series; entries in the final three columns are standard deviations of the four-quarter growth rate of the factor component (common component) of the row series. For the unemployment rate, the statistics pertain to the four-quarter detrended change, not the four-quarter growth rate. Calculations go through the final quarter in the data set, 2011Q2.

Table 5
Innovations to factor components of selected series, 2007Q1 – 2011Q2 (standard deviation units)

Date	**GDP**	**Consump-tion**	**Invest-ment**	**Employ-ment**	**Prod-uctivity**	**Housing Starts**	**Oil Price**	**Fed Funds**	**Ted spread**	**VIX**	**Wealth (FoF)**
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

Notes: Entries are the standardized innovations in the factor component of the column series at the row date, where the innovations are computed relative to the six factors; standardization is done by dividing by the standard deviation of the 1959-2007Q3 factor component innovations for that series. Standardized innovations exceeding 3 in absolute value appear in bold.

Table 6
Subsample R^2's of the factor component of GDP growth associated with individual identified shocks, computed using the full-sample six-factor DFM

Structural Shock	*F*	R^2 for Structural Shock								
		1959-2007Q3	1984-2007Q3	Computed over 15 quarters starting at NBER peak						
				69Q4	73Q4	80Q1	81Q3	90Q3	01Q1	07Q4
1. Oil										
Hamilton	2.9	0.18	0.01	0.26	0.49	0.10	0.11	0.23	-0.55	-0.14
Killian	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
2. Monetary policy										
Romer and 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
GSS	0.6	0.12	-0.07	0.07	0.39	0.26	0.26	0.00	-0.05	0.34
3. Productivity										
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 OPH)	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
4. Uncertainty										
Fin Unc (VIX)	43.2	0.08	0.03	0.12	0.16	0.18	0.31	0.22	0.23	0.34
Pol Unc (BBD)	12.5	0.11	0.02	0.15	0.40	0.15	0.14	0.48	0.15	0.62
5. Liquidity/risk										
GZ EBP 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
BCDZ Bank Loan	4.4	0.11	0.04	0.20	0.25	0.13	0.31	0.27	0.45	0.41
6. Fiscal policy										
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 Taxes	0.5	0.16	-0.20	0.21	0.25	0.36	0.31	0.08	-0.38	-0.02
PCs of uncertainty and credit spread shocks										
1 PC	na	0.14	-0.03	0.21	0.36	0.25	0.26	0.30	0.23	0.48
2 PCs	na	0.19	0.07	0.17	0.49	0.31	0.40	0.38	0.32	0.54

Notes: The value of *F* in the first column is the (non-HAC) *F*-statistic from the regression of the row instrument on the six factor innovations. The R^2's in the remaining columns are for the contribution of the row shock to GDP growth, computed over the column subsample, as described in footnote 18. The structural shocks are computed using the instrument listed in the first column, as described in Sections 4.1 and 4.2.

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}	S_{GZ}	S_{TED}	B_{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

Notes: Entries are correlations between individually identified shocks. Correlations are computed over the full 1959-2011Q2 sample. Shaded background denotes correlations within categories of shocks, bold denotes cross-category absolute correlations exceeding 0.60. Row and column labels correspond to the identified shocks:

Oil: O_H – Hamilton (1996, 2003); O_K – Kilian (2008a); O_{RV} – Ramey-Vine (2010)

Monetary Policy: M_{RR} – Romer and Romer (2004); M_{SW} – Smets-Wouters (2007); M_{SZ} – Sims-Zha (2006); MGSS – Gürkaynak, Sack, and Swanson (2005)

Productivity P_F – Fernald (2009); P_G – Gali (1999); P_{SW} – Smets-Wouters (2007)

Uncertainty: U_{VIX} – VIX/Bloom (2009); U_{BBD} – policy/Baker, Bloom, and Davis (2012)

Liquidity/risk: L_{GZ} – Gilchrist-Zakrajšek (2011) excess bond premium; L_{TED}: TED spread; L_{BCDZ} – Bassett, Choak, Driscoll, Zakrajšek (2011) bank loan

Fiscal Policy: F_R – Ramey (2011); F_{FP} – Fisher-Peters (2010); F_{RR} – Romer-Romer (2010)

Table 8

Contributions of identified shocks to cumulative post-2007Q4 growth of GDP and employment

	Cumulative Percentage Change in Detrended GDP			**Cumulative Percentage Change in Detrended Payroll Employment**			**2009Q2 Forecast Growth in Factor Component 2009Q2-2011Q2**	
	2007Q4-2008Q3	**2007Q4-2009Q2**	**2007Q4-2011Q2**	**2007Q4-2008Q3**	**2007Q4-2009Q2**	**2007Q4-2011Q2**	**GDP**	**Emp**
Actual	-2.8	−8.7	−8.2	-1.4	−6.2	−7.4		
Factor Component	-4.0	−9.2	−6.0	-2.1	−7.3	−8.9		
1. Oil								
Hamilton	-1.0	-0.8	-0.8	-0.4	-1.1	-1.0	1.8	1.0
Killian	-1.0	-2.1	-0.6	-0.5	-1.7	-1.2	1.3	0.3
Ramey-Vine	-1.4	-1.6	0.7	-1.1	-2.1	0.2	1.5	1.2
2. Monetary policy								
Romer and Romer	-1.1	-1.6	0.1	-0.7	-2.1	0.4	1.4	1.2
Smets-Wouters	-0.4	-3.7	-5.0	-0.5	-2.5	-6.2	-0.6	-3.3
Sims-Zha	-0.3	-0.1	-0.1	-0.5	-1.0	0.3	0.4	0.8
GSS	-0.8	-3.2	-4.3	0.0	-1.0	-3.8	-1.3	-2.7
3. Productivity								
Fernald	-0.7	0.0	1.4	-0.1	0.1	0.9	0.2	0.2
Gali	0.4	0.3	1.1	0.0	-0.6	-0.9	1.0	0.5
Smets-Wouters	-0.5	-0.1	0.6	0.2	-0.1	0.4	0.9	0.7
4. Uncertainty								
Fin Unc (VIX)	-1.0	-4.1	0.2	-0.9	-3.7	-2.2	3.5	0.6
Pol Unc (BBD)	-2.3	-5.8	-4.8	-1.6	-4.6	-6.8	1.4	-2.0
5. Liquidity/risk								
GZ EBP 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
BCDZ Bank Loan	-2.0	-3.2	0.1	-1.5	-3.5	-1.1	2.7	1.3
6. Fiscal policy								
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 Taxes	0.2	0.3	-0.2	0.2	0.0	0.3	-0.1	0.3
PCs of uncertainty and credit spread shocks								
1 PC	-1.5	-6.2	-3.4	-1.0	-4.5	-5.8	2.4	-1.8
2 PCs	-2.3	-7.6	-5.4	-1.5	-5.8	-8.4	2.7	-2.5

Notes: Entries are the contribution of the row shock to cumulative growth in GDP (first three columns) and employment (second three columns) over the indicated period, where the shock contribution is computed as described in footnote 18. The final two columns are the implied forecasts of growth constructed in 2009Q2 associated with the particular shock.

Table 9
Predicted and actual cumulative percent growth of output, employment, and productivity in the 8 quarters following a NBER trough

Trough date	Source	GDP	Nonfarm Employment	Output per Hour (nonfarm business)
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
Averages				
1960-1982	Cyclical	3.0	-0.4	3.6
	Trend	6.8	4.5	4.0
	Total	9.8	4.1	7.6
	Actual[a]	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[a]	9.2	4.0	7.2
Differences				
2009Q2 – average, 1960-1982	Cyclical	-0.6	-2.7	2.7
	Trend	-2.4	-3.3	0.5
	Total	-3.0	-6.0	3.2

Notes: Entries are the cumulative predicted percent growth (total, not per annum) of the common component of the series in the column heading, where predictions are made using the factors at the trough and the DFM estimated through 2007Q3. The predicted paths are decomposed into the detrende cyclical component (the contribution of the factors at the trough) and the trend growth rate.
[a]Averages of actuals exclude the 1980Q3 recovery because the next recession commenced within the 8-quarter window of this table.

Table 10
Contributions of trend productivity, labor force, and population to the trend GDP growth rate.

Series	Component	Trend Growth Rates			Difference, 2005-1965
		1965	1985	2005	
GDP		3.7	3.1	2.5	-1.2
	GDP/Employment	1.6	1.3	1.5	-0.1
	Employment/Population	0.3	0.4	-0.2	-0.5
	Population	1.7	1.4	1.1	-0.6
GDP/Employment		1.6	1.3	1.5	-0.1
	GDP/Output(NFB)	-0.2	-0.3	-0.2	0.0
	Output(NFB)/Hours(NFB)	2.3	1.8	2.2	-0.1
	Hours(NFB)/Employment(NFB)	-0.4	-0.3	-0.2	0.2
	Employment(NFB)/Employment(NonFarm)	0.0	0.1	-0.3	-0.3
Employment/Population		0.3	0.4	-0.2	-0.5
	Employment/LaborForce	0.0	0.1	0.0	0.0
	LaborForce/Population	0.3	0.4	-0.1	-0.5
LaborForce/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
LaborForce		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

Notes: Entries in the first three numeric columns are the trend components of the row series, computed as described in Section 2.3, in percent growth per year. The final column is the difference between the 2005 and 1965 trend values. Line items within a block add to the first row in a block, up to 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 Supplement.

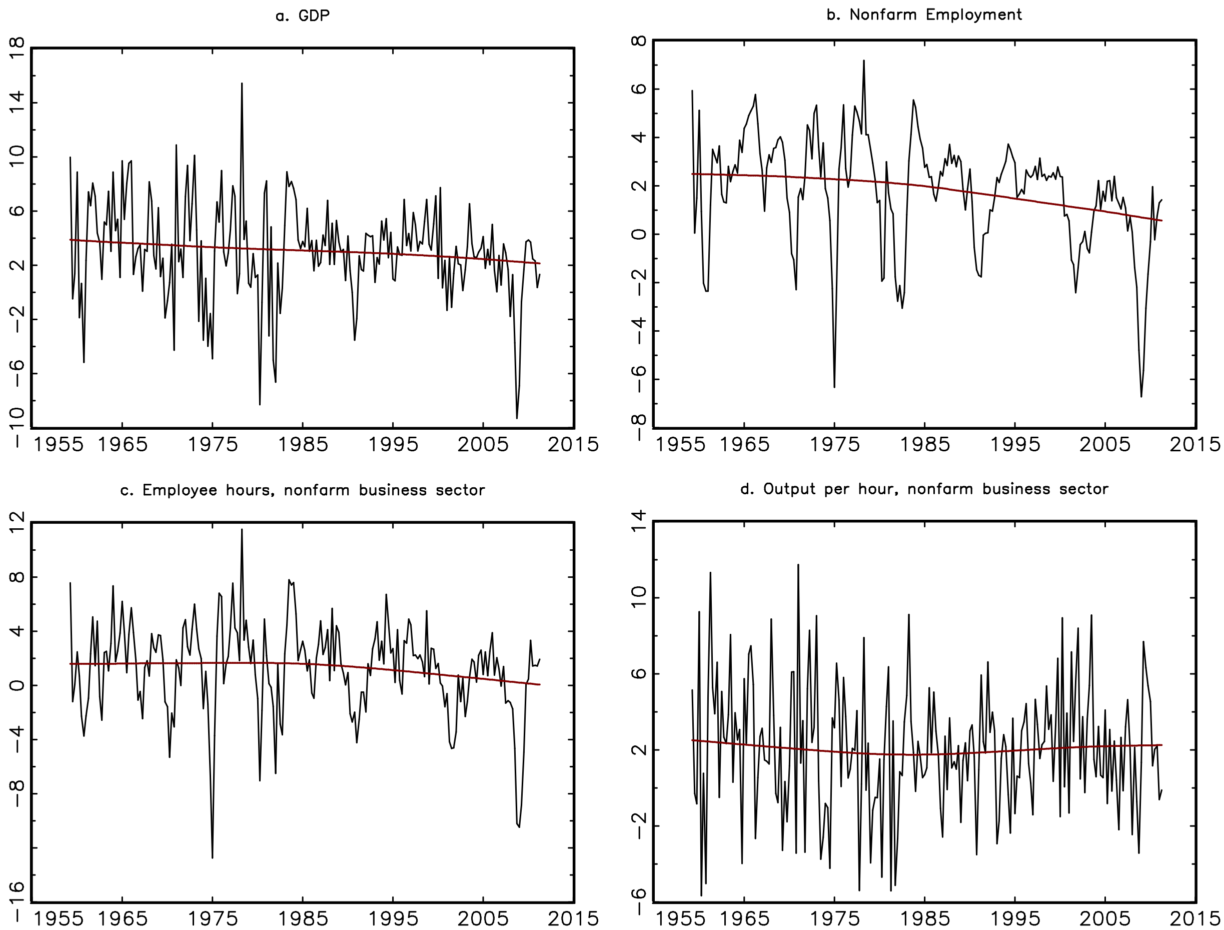
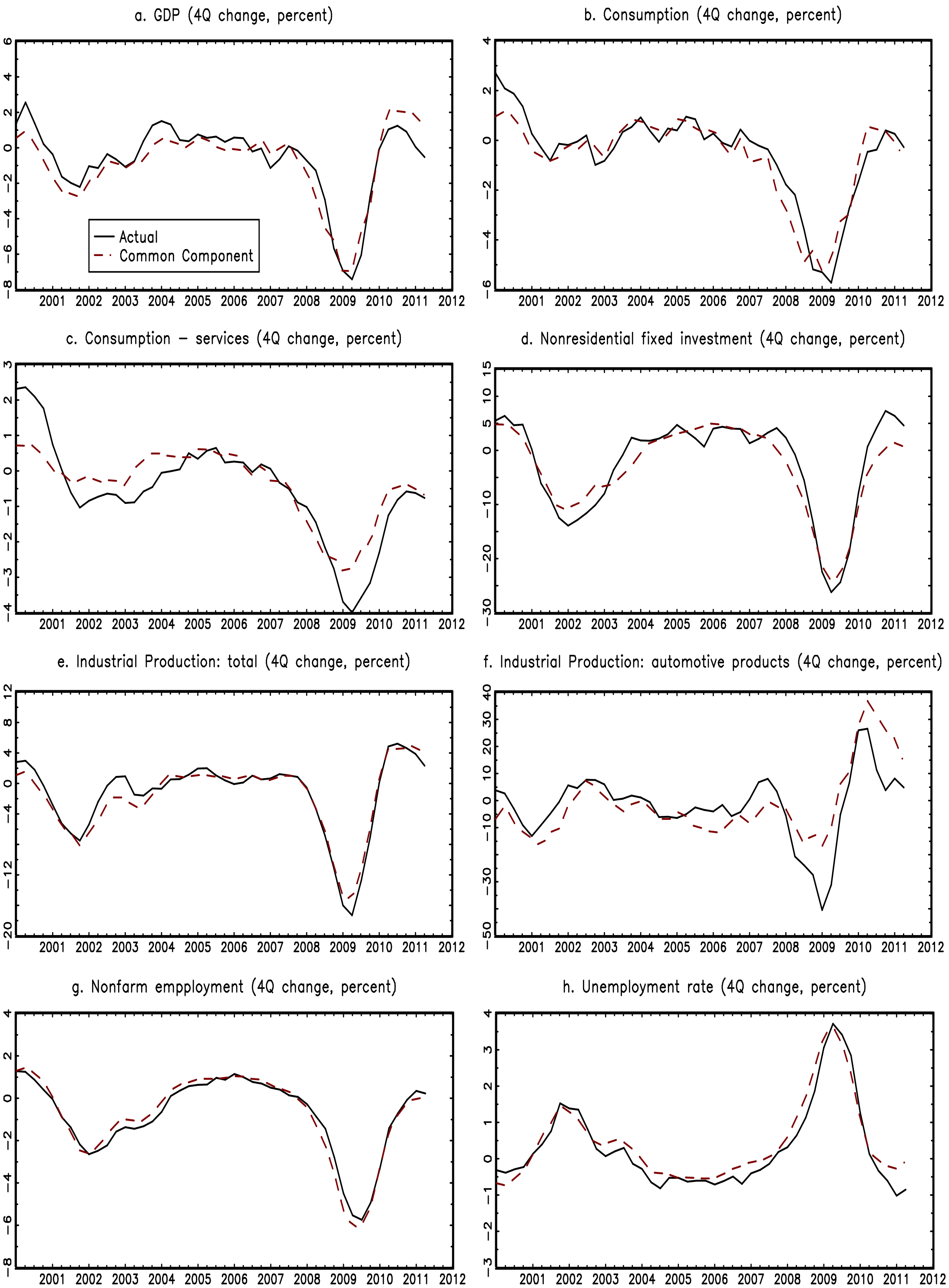
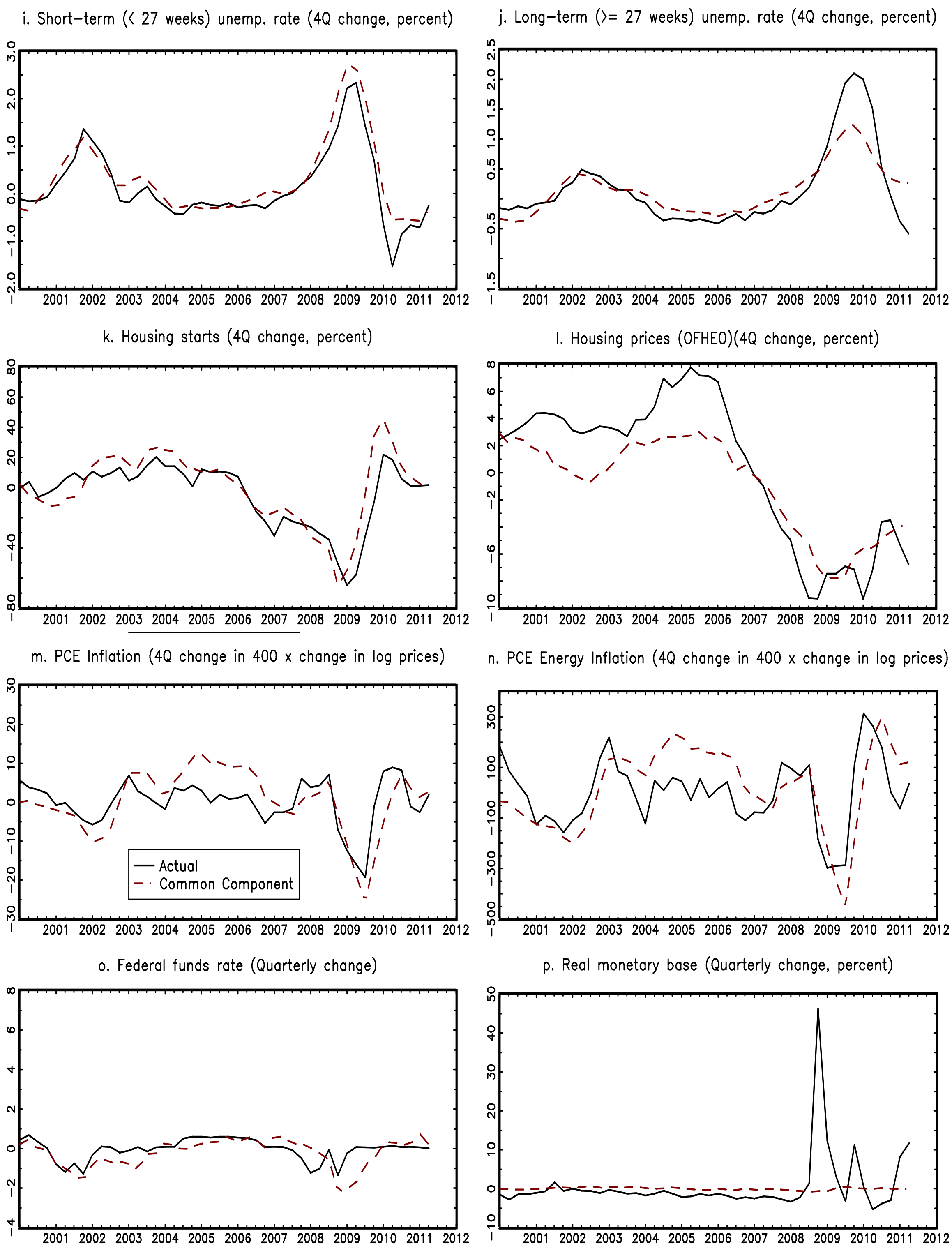


Figure 1. Quarterly growth rates of GDP, nonfarm employment, employee-hours, and labor productivity growth, and their local means ("trends").


a. GDP (4Q change, percent)
Actual
Common Component
b. Consumption (4Q change, percent)
c. Consumption – services (4Q change, percent)
d. Nonresidential fixed investment (4Q change, percent)
e. Industrial Production: total (4Q change, percent)
f. Industrial Production: automotive products (4Q change, percent)
g. Nonfarm empployment (4Q change, percent)
h. Unemployment rate (4Q change, percent)
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012


i. Short-term (< 27 weeks) unemp. rate (4Q change, percent)
j. Long-term (>= 27 weeks) unemp. rate (4Q change, percent)
k. Housing starts (4Q change, percent)
l. Housing prices (OFHEO)(4Q change, percent)
m. PCE Inflation (4Q change in 400 x change in log prices)
n. PCE Energy Inflation (4Q change in 400 x change in log prices)
o. Federal funds rate (Quarterly change)
p. Real monetary base (Quarterly change, percent)
Actual
Common Component

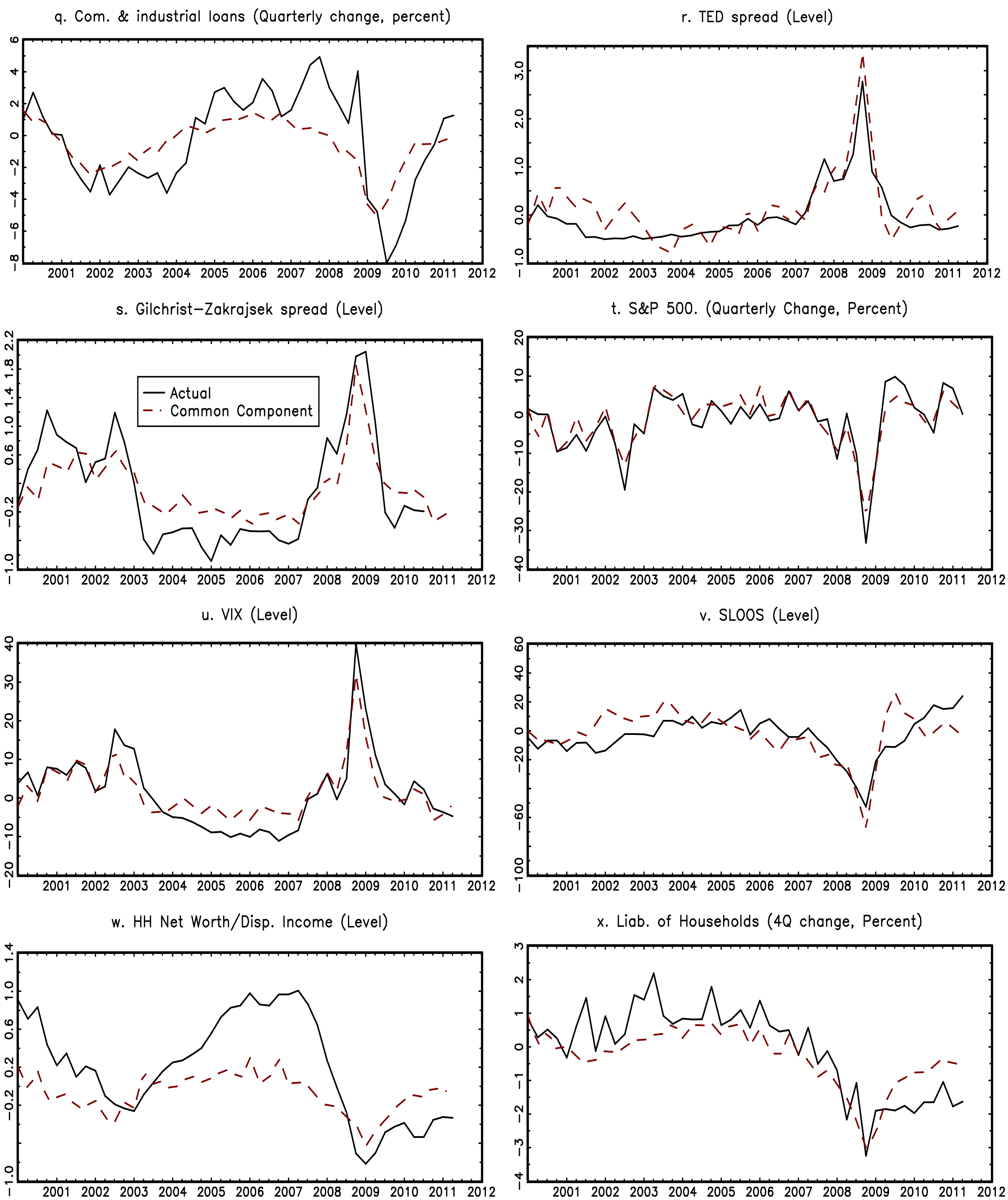


Figure 2. Selected macro variables (solid) and their common components (dashed); plots are of four-quarter changes, quarterly changes, or levels depending on the variable. For real variables and prices, which are in logarithms, quarterly or four-quarter changes are scaled to be percentage changes at an annual rate. The common components are computed using pre-2007Q3 coefficients and 2007Q4-2011 values of the "old" factors, derived from the 1959-2007Q3 model as described footnote 6.

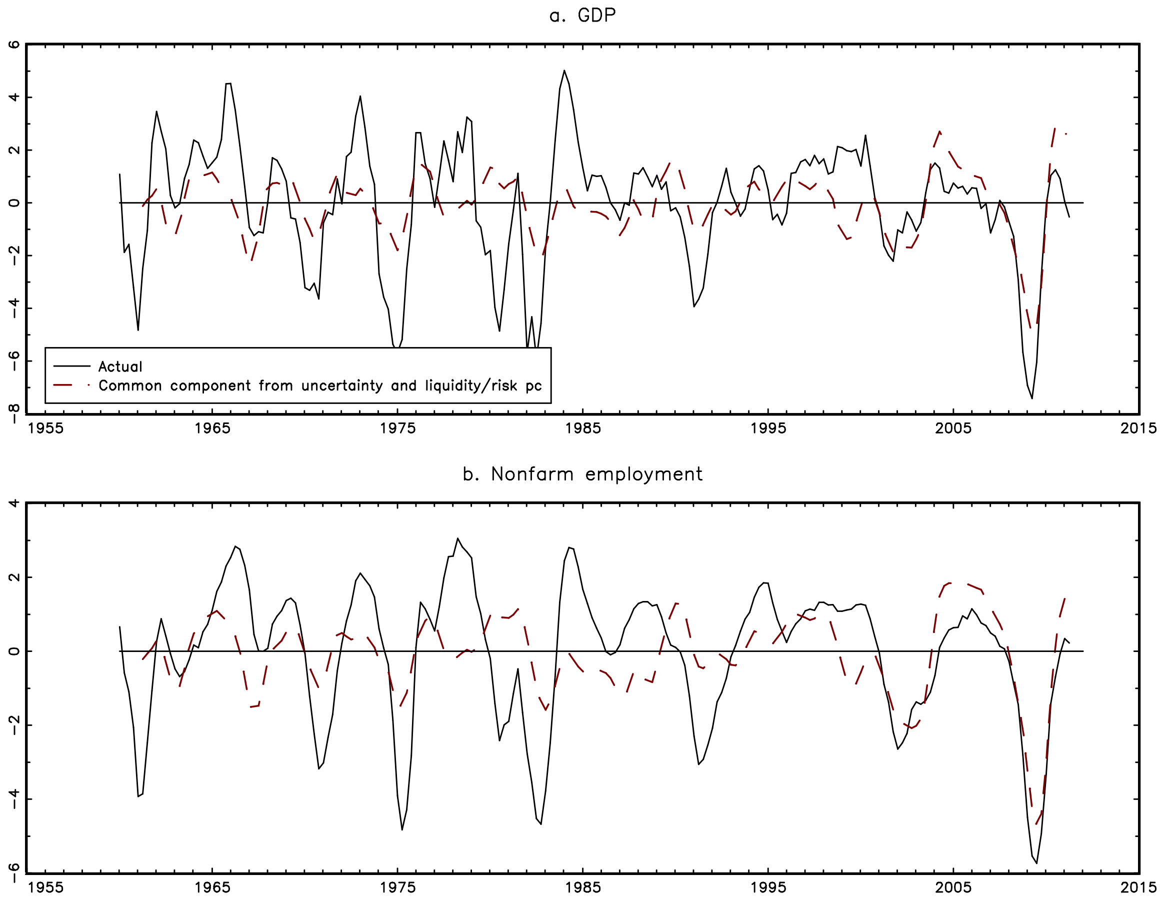


Figure 3. Contribution to 4-quarter growth of (a) GDP and (b) nonfarm employment of the first principal component of the five identified financial shocks (uncertainty and liquidity/risk shocks)

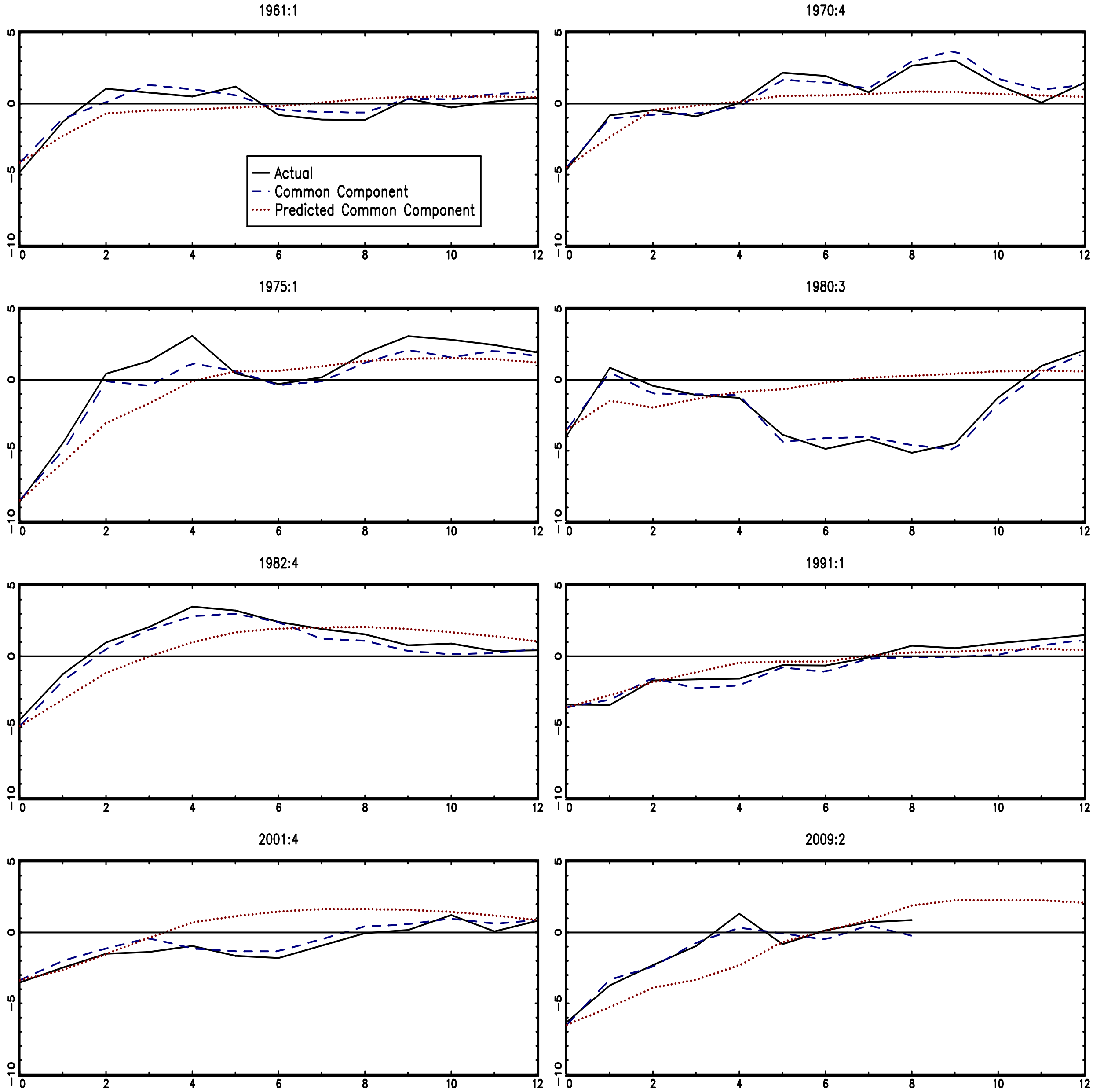


Figure 4. Deviation of quarterly employment growth (at an annual rate) from trend during the twelve quarters following the post-1960 troughs: actual (solid), the actual (estimated) common component, and the predicted common component based on the factors at the trough (dots).

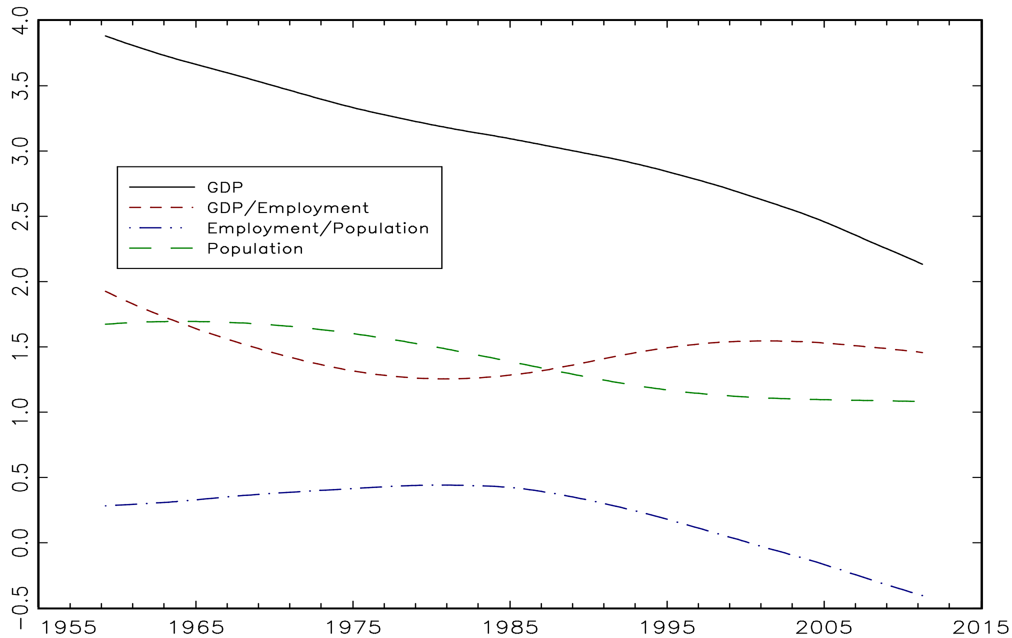


Figure 5. Trend components of the annual growth rates of GDP, the GDP-employment ratio, the employment-population ratio, and population, 1959 – 2011

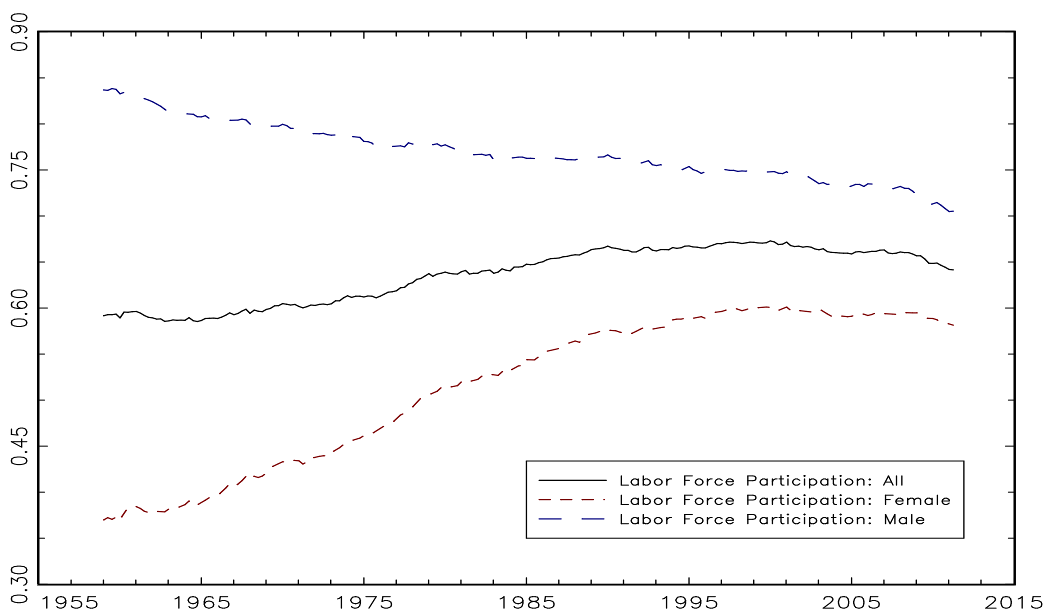


Figure 6. Civilian labor force participation rates: men, women, and total