CONFERENCE DRAFT

Disentangling the Channels of the 2007-2009 Recession

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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 that led to unrecognized systemic vulnerability, and collapses 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

[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, 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.

difference between a dynamic factor model and a VAR is that the number of macro shocks does 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 benchmark model has 198 macro variables driven by six macro factors. These six factors drive the 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. In 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 suggest 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, for most series, 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. While there were new events and exceptional policy responses in the 2007Q4 recession, the net effect of these new events and responses was not qualitatively different than past disturbances – just larger. We interpret these results as pointing towards a confluence of large shocks that have been seen before, not towards new shocks that produced unprecedented macroeconomic dynamics.

Second, identifying what, precisely, were these large economic shocks entails an exercise similar to structural VAR identification. We do so not by introducing any new identification schemes, but rather by drawing on the large structural VAR and dynamic stochastic general equilibrium literature to identify six shocks: oil, monetary policy, productivity, uncertainty, liquidity/financial risk, and fiscal policy. We do so through a novel method in which we treat shocks estimated elsewhere in the literature as instrumental variables. Because multiple authors have addressed similar questions, our shock estimates are overidentified, and in fact we have 16 instruments to estimate our six shocks. The results of this exercise are mixed, in large part because the instruments drawn from different recent papers and approaches produce estimates of 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 large oil price shocks followed by multiple financial and uncertainty shocks.

Third, focusing on the recovery subsequent to the 2009Q2 trough, we estimate that slightly less than half of the slow recovery in employment growth since 2009Q2, compared to pre-1984 recoveries, is attributable to cyclical factors (the shocks, or factors, during the recession), but that most of the slow recovery 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 has fallen 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 over the past decade 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 mean productivity growth over this period is small, this slower trend growth in employment corresponds directly to slowdown in trend GDP growth. These demographic changes imply continued low or even declining trend growth rates in employment, which in turn imply that future recessions will be deeper, and will have slower recoveries, than historically has been the case. In other words, jobless recoveries will be the norm.

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, reaching 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 $X_t = (X_{1t},\ldots, X_{nt})'$ denote a vector of n macroeconomic time series, where X_{it} is each individual 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, $F_t = \Phi(\mathrm{L})^{-1}\eta_t$.

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 the multiplicative factor $\bar{\Lambda}$.

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 principle components analysis (Stock and Watson (2002)). We use principle components here to estimate the factors, with a modification for our unbalanced panel (some series are not available

[3] Equations (1) and (2) are the static form of the dynamic factor model, so-called because only 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).

for the full time span). The DFM parameters are then estimated by regression, treating the estimated factors as observed. For details, see Stock and Watson (2011) and the Supplement.

The principle components estimator of the factors consistently estimates F_t up to premultiplication by an arbitrary nonsingular $r\times r$ matrix (the analog 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 principle 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 198 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 (9); 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 spreads appear in levels. The 198 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 Benchmark Model and Estimation Details

The data set contains both high-level aggregates and disaggregated components. To avoid double-counting, in these cases only the disaggregated components were used to estimate the factors; for example, durables consumption, nondurables consumption, and services consumption were used to estimate the factors, but total consumption was not. Of the 198 series, 132 were used to estimate the factors; the series used to estimate the factors are listed in the supplement. In particular, none of the top-level macro aggregates (including GDP, consumption, investment, total employment, the total unemployment rate) were used to estimate the factors.

[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 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.

The benchmark model used in Sections 3 is estimated over the 1959-2007Q3 sample period with no breaks in the factor loadings. This assumption of no breaks adopts a strong version of the "smaller shocks" view of the Great Moderation, in the sense that the only way for the Great Moderation to emerge from this model is as changes in variance of the factors and/or in the (unmodeled) dynamics of the idiosyncratic terms. This assumption is only partially consistent with the empirical evidence. In particular, in Stock and Watson (2009) we use a similar data set and find that there are breaks in the factor loadings in 1984Q1, but that the space spanned by the full-sample (no-break) factors spans the space of the subsample estimates of the factors. These apparently contradictory findings can be explained by the property of DFMs that the space spanned by the factors can be estimated consistently even if there some instability in Λ (Stock and Watson (2002)), and in Stock and Watson (2009). For those series for which the factor loadings break in 1984Q1, the projection of the series onto the factors breaks in 1984Q1. 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 data. We therefore consider a DFM with a break in 1984Q1 as a sensitivity check.

The benchmark model is estimated using 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.[6] As is discussed below and is 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

[6] 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.

some of the shocks have historical precedents, we examine whether these old factors have different dynamic impacts pre-2007 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 benchmark 6-factor, 198-variable DFM estimated using data through 2007Q3, and you were told the time path of the six estimated factors from 2007Q4 – 2011Q2. Using this pre-2007Q4 DFM and the post-2007Q4 values of the old factors, you compute predicted values for the 198 series in our data set. How well would these predicted values track the actuals over the recession and recovery? If there were important new factors not seen in the 1959-2007Q3 data or if the structure of the economy changed in 2007 so that "old" factors had new effects, then the old model/old factors predicted values would be expected to provide worse fits post-2007Q4 than pre-2007Q4.[7]

The results of this exercise are summarized in Figure 2 and in Tables 1 and 2. Figure 2 plots old model/old factors predicted values, along with actual values, for 21 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 noise, 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 21 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

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[7] This exercise was implemented as follows. Let $\hat{\Lambda}^{59-07}$ denote the benchmark model factor loadings, which are estimated by principle components using data from 1959-2007Q3. The estimated factors associated with these factor loadings are $\hat{F}_t^{59-07} = \hat{\Lambda}^{59-07\prime} X_t$, and the vector of common component of X_t associated with these factors and factor loadings is $\hat{\Lambda}^{59-07}\hat{F}_t^{59-07}$. 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 X_t. If there were a new factor the space spanned by the factors would change so the new factor would not be spanned by $\hat{F}_t^{59-07}$.

imposing a zero intercept and unit slope on the predicted values over the indicated subsample and thus cannot exceed one but can be negative.[8] 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 198 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), as well as the bear market in stocks and the sharp rise in uncertainty as measured by the VIX. The DFM correctly predicts the decline in commercial and industrial loans during the early part of the recession, although it underpredicts the depth of their contraction or their long delay in recovering. These qualitative impressions from Figure 2 are confirmed quantitatively by the R^2's in Table 2. 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 average. 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 fraction of the variation it explains increased.

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[8] Using the notation of the previous footnote, let X_{it} denote the i^{th} series and 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 is computed as $R^2 = 1 - \left(\sum_t \hat{e}_{it}^2\right)\Big/\left(\sum_t X_{it}^2\right)$, where the sums are computed over the column subsample.

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 benchmark 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 198 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 predicted paths diverge systematically from the actual 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 divergences do not seem to reflect breaks associated with this recession, compared with the two other post-1984 recessions.[9]

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.[10] 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

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[9] 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.

[10] 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.

(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, 16% of series reject at the 5% level, while 13% 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.

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. 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. In fact, this eigenvalue ratio is less than it was during the 1960Q2 and 1973Q4 recessions. Modifying the subsampling test to examine the 15 quarters following 07Q4 yields a *p*-value of 0.94. This test 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 exhibited considerable volatility 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 their 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 associated with principle 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. Each linear combination is the unexpected movement in the common component for the row series, given past values of the factors. The first block of columns in Table 5 reports standardized factor component innovations by quarter over 2007Q4-2011Q2, and the second block reports the empirical quantile of those innovations relative to the 1959-2007Q3 sample for the column series. For the series in Table 5, the factor component of oil prices experienced moderate then large standardized innovations in 2007Q1 and 2008Q2 (1.8 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 two quarters. Throughout 2007Q1-2009Q1, the factor component innovations for the real variables were moderate and were well within the range of pre-2007Q3 experience. By 2009Q4, all the innovations had returned to their normal range. 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 construction crash, heightened uncertainty, and a sharp unexpected drop in wealth. Notably, there no large surprise movements 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 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 simply 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 Lehmann collapse was unprecedented and the “Lehmann shock” was new; so too for TARP, the auto bailout, and the other extraordinary events of this recession. What the results here suggest is that the shocks associated with these extraordinary events had ordinary impacts, that is, from a macro perspective these shocks had the same effect as previously observed shocks, and thus surface in our model as large innovations to the “old” factors. This caveat returns in the context of identifying the structural shocks and their contribution to the recession, the topic of the next section.

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 move from the effects of the innovations (one step ahead forecast errors) in the observed variables to the effects of 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 this linear combination. The coefficients of this linear combination in turn identify the impulse response function of the observed variables to the shock. Typically, the economic restrictions take the form of exclusion restrictions (shock A does/does not affect variable B within a quarter; shock C does/does not have a long-run effect on variable D), although it is increasingly common to construct exogenous components of shocks directly, an approach pioneered by Romer and Romer (1989). These exogenous components are typically treated as exogenous shocks, however technically they are instrumental variables for the shocks. Our approach to identification in structural DFMs builds off this last observation, and identifies structural DFM shocks using as instrumental variables time series constructed elsewhere in the literature to be exogenous shocks or components thereof.

The identification problem in structural DFMs is analogous to that in the structural VARs: the challenge is to move from the effects of η_t, the innovations to the factor VAR in (2), to the effects of the structural shocks ε_t. Expressed mathematically, we assume that the factor innovations η are linear combinations of q common macroeconomic structural shocks ε_t:

$$\eta_t = H\varepsilon_t = \begin{bmatrix} H^1 & \cdots & H^q \end{bmatrix} \begin{pmatrix} \varepsilon_t^1 \\ \vdots \\ \varepsilon_t^q \end{pmatrix}, \tag{3}$$

where H is a matrix with columns with columns $\{H^i\}$ and ε_t^i is the i^{th} structural shock[11]. In terms of (3), identification of the dynamic effect of ε_t^i on X_t (that is, the impulse response function with respect to ε_t^i) requires identifying the i^{th} column of H, H^i. Specifically, from (2) and (3) we have that $F_t = \Phi(\mathrm{L})^{-1}H\varepsilon_t$ which, when substituted into (1), yields

$$X_t = \Lambda\Phi(\mathrm{L})^{-1}H\varepsilon_t + e_t. \tag{4}$$

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.

In this paper, we use one or more instrument variables Z_t^i to identify H^i. The key requirement is that Z_t^i is correlated with the shock of interest, ε_t^i, but is uncorrelated with all other shocks; that is, the instrument Z_t^i is assumed to satisfy the two conditions,

$$\text{(i) } E\left(\varepsilon_t^i Z_t^i\right) \neq 0 \text{ and (ii) } E\left(\varepsilon_t^j Z_t^i\right) \neq 0, j \neq i. \tag{5}$$

Condition (i) says that Z_t^i is correlated with the shock of interest, ε_t^i, that is, that Z_t^i is relevant instrument. Condition (ii) is the exogeneity condition stating Z_t^i is uncorrelated with the other structural shocks. By (i) and (ii), Z_t^i is correlated with η_t only because it is correlated with ε_t^i.

Condition (5) implies that,

$$E\left(\eta_t Z_t^{i\prime}\right) = E\left(H\varepsilon_t Z_t^{i\prime}\right) = H^i\sigma_{\varepsilon^i Z^i}{}', \tag{6}$$

[11] Equation (3) requires that the factor innovations span the space of the structural shocks. Failure of this condition is referred to as the nonfundamentalness problem and results in the structural impulse response functions being unidentified. The most common way to address this problem is to increase the number of series, which is readily done using a DFM. For a detailed discussion see Forni, Giannone, Lippi, and Reichlin (2009).

where $\sigma_{\varepsilon^i Z^i} = E\left(\varepsilon_t^i Z_t^i\right)$. The instrument Z_t^i thus identifies H^i up to scale and sign. The scale and sign are set by an arbitrary normalization, for example, we normalize a positive unit oil price shock to increase oil prices by 1% on impact.

Unlike standard VAR identification schemes, the external instrument approach in (5) does not impose the additional restriction that the structural shocks be mutually uncorrelated.

Internal and external instruments. We use two types of instruments. By external instruments, we mean series taken from some other source which are not included in our data set for estimation of the factor model. For example, one of our external instruments for the oil shock is the Hamilton (1996) oil shock series; in Hamilton (1996) this series was taken to be the oil shock, here it is taken to be correlated with the oil shock and no other shock.

By internal instruments, we mean instruments constructed from series in the data set. An example is our instrument for the productivity shock, which we construct analogously to Galí (1999) using output per hour for nonfarm business, a series in our data set (details are discussed below).

When there are multiple external instruments, the exogeneity condition (ii) in equation (5) imposes overidentifying restrictions, which we test. In the event that an instrument is available for only a subset of the data, H^i is estimated using that subset and the estimates can be used to construct the associated identified shock over the full period. Details of estimation and testing of overidentifying restrictions are discussed in the Supplement.[12, 13]

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[12] If there is a single Z_t^i then (6) exactly identifies H^i up to scale and sign, so H^i can be estimated by a regression of η_t onto Z_t^i. If there are multiple Z_t^i's then H^i is overidentified. In the empirical work in this paper, we impose the overidentifying conditions by estimating H^i by the reduced rank regression of η_t onto $\left(T^{-1}\sum_t Z_t^i Z_t^{i\prime}\right)^{-1} Z_t^i$. If $\varepsilon_t^i Z_t^i$ is heteroskedastic and/or serially correlated then this convenient reduced rank regression estimator will be consistent, but GMM using a HAC weight matrix will be more efficient. In the reduced rank regression framework that we use, we test the overidentifying restrictions by testing the reduced rank regression restriction; were GMM to be used, the overidentification test would be the usual *J*-statistic.

[13] This discussion conforms with standard econometric practice by considering identification of parameters. In contrast, the structural VAR literature often discusses identification of shocks. Under (5), the population projection of Z_t^i onto η_t is linear in ε_t^i, so (5) can equivalently be

4.2 Specific shocks: instruments

We focus on six possible shocks, all of which have been discussed in the context of the crisis: oil, monetary policy, productivity, uncertainty, financial market liquidity and risk (implemented through credit spreads), and fiscal policy.

Oil shock. We use two external instruments for the oil shock: the Hamilton (1996) oil shock (constructed from oil prices, available 1960Q1-2011Q4) and the Kilian (2009) oil shock (current and first lag), available 1971Q1-2004Q3. We also use oil prices as an internal instrument; specifically we use the innovation in the common component of oil prices. In the DFM context, this is equivalent to treating oil price innovations as exogenous as is done for example by Blanchard and Galí (2010). See Kilian (2008) and Hamilton (2009, 2010) for discussions of various oil shock measures.

Monetary policy shock. We use three external and one internal monetary policy shock instruments. The external instruments are the Romer and Romer (2004) monetary policy shock (here, quarterly sums of their monthly variable), the shock to the monetary policy reaction function in the Smets-Wouters (2004) dynamic stochastic general equilibrium (DSGE) model, and the monetary policy shock from the Sims and Zha (2006) structural VAR.[14] The final instrument is an internal instrument constructed using a conventional recursive approach in which the instrument is the innovations to the factor component of the federal funds rate, after controlling for the factor components of the innovations in GDP and the GDP deflator.[15]

Productivity shock. We use one internal and one external instrument for the productivity shock. The external instrument is the productivity shock in the Smets-Wouters (2004) DSGE. The internal instrument is constructed using Galí's (1999) identification scheme. Specifically the instrument is the permanent shock to the factor component of output per hour in nonfarm

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thought of as identifying the shock ε_t^i. In sample ε_t^i can be estimated by regression of Z_t^i onto η_t (reduced rank regression if there are multiple instruments).

[14] The Romer and Romer (2004) instruments are available from 1969-1996. The Smets-Wouters (2007) instrument is computed using the replication files available from their paper, with the model parameters set to the posterior mode. The instrument is available from 1959-2004. The Sim-Zha (2006) instrument is constructed the version of their model that allows for shifts in shock variances, but constant coefficients. We use the quarterly average of their monthly money shock instruments, with data available from 1960-2003.

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

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 $\lambda_{OPH}'\Phi(1)^{-1}\eta_t$. We note that Galí's (1999) identification scheme is controversial and has generated a large literature, see Mertens and Ravn (2010) for references.

Credit spread shock. We use two internal instruments for a credit spread shock, each instrument being the innovation to the common component of a different spread. The two spreads are the TED spread and Gilchrist and Zakrajšek's (2011) excess bond premium (EBP), which has been adjusted to eliminate predictable default risk and this aims at being a measure of liquidity and/or additional market risk. For an early discussion of credit spreads as measures of market liquidity, see Friedman and Kuttner (1993); for a more recent discussion see Gilchrist, Yankov and Zakrajšek (2009).

Uncertainty shock. We use two internal instruments for the uncertainty shock. The first, motivated by Bloom (2009), is the innovation in the common component associated with the VIX, where we use Bloom's (2009) series that links the VIX to other market uncertainty measures before the VIX was traded.[16] (Lee, Rabanal, and Sandri (2010) take the uncertainty shock to be the innovation to the VIX.) 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.

Fiscal policy shock. We use three external fiscal policy shock instruments: Ramey's (2011) federal spending news instrument (available from 1959-2010), Fisher and Peters' (2010) excess returns series (available from 1959-2008, and Romer and Romer's (2010) tax change instrument ("all exogenous", available from 1959-2007). Note that the first two of these are

[16] The VIX is an imperfect measure of uncertainty for at least two reasons. First, as pointed out by Bekaert, Hoerova, and Lo Duca (2010), even as a measure of stock market uncertainty the VIX can be decomposed into an expected stock market volatility term plus a risk premium; they argue that this time-varying risk premium is correlated with monetary policy shocks. Second, at best the VIX measures uncertainty about stock prices, but other uncertainty measures might matter more for consumer and business decisions and thus for the determination of real activity. To this end, Bachman, Elstner, and Sims (2010) use confidential data from the Third FED District Business Outlook Survey to construct an alternative index of uncertainty (based on respondent disagreement about the future) and identify the uncertainty shock by assuming it to have a zero long-run effect on real activity measures; these authors reach quite different conclusions than Bloom (2009) and find a modest role for uncertainty.

instruments for federal government spending changes while the Romer-Romer (2010) instrument is an instrument for federal tax changes.

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. The 16 instruments listed in Section 4.2 permit estimation of 16 separate shocks which fall into six categories. Within the categories, multiple external instruments provide overidentifying restrictions that can be tested and can be used to estimate the effect of the shock. For this section (and only this section), the 6-factor DFM is estimated over the full 1959-2011Q2 sample, with constant coefficients.

Historical contributions and correlations. Table 6 summarizes the contributions to quarterly GDP growth of the 16 individually identified shocks 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. Table 6 also reports R^2's for shocks estimated using multiple external instruments within the same category.

As discussed in Section 4.1, our instrumental variable 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. Finite-sample inference on the correlations in Table 7 is complicated because the shocks are computed using estimated parameters, because of multiple comparisons, and because the 16 individual shocks are computed from only 6 innovations. Still, the correlations in Table 7 provide some general insights.

Tables 6 and 7 suggest three main findings.

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[17] In the notation of (3) and (4), the factor component due to the j^{th} structural shock is $\Lambda\Phi(L)^{-1}H^j\varepsilon_t^j$. 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 $\hat{e}_{it}^j = X_{it} - \hat{\Lambda}\hat{\Phi}(L)^{-1}\hat{H}^j\hat{\varepsilon}_t^j$.

First, within the categories of oil, monetary policy, productivity, and fiscal policy shocks, the estimated shocks and their effects differ considerably. For example, the oil shocks identified using Hamilton's (1996) shock series or simply by taking oil prices to be exogenous are highly correlated (.95), but the correlation between the shocks identified using the Hamilton (1996) and Kilian (2009) instruments is only 0.38. Although the overidentifying restrictions imposed by using both instruments are not rejected, inferences from that test are suspect because both instruments, especially the Kilian (2009) instrument, appear to be weak. Similarly, within the monetary policy shocks, the shocks identified individually using the Romer-Romer (2004) instrument and the Sims-Zha (2006) instrument are highly correlated, as are those using the Smets-Wouters (2007) instrument and recursive identification. However the correlations across these two these sets of monetary shocks are 0.11 and 0.17. The R^2's in Table 6 of these individually identified monetary policy shocks differs considerably, and the overidentifying restrictions implied by the three external instruments are rejected at the 1% level. Among fiscal policy shocks, the correlation between the shocks identified using the Ramey (2011) and Romer and Romer (2010) instruments is 0.52, and the correlation between the Ramey (2011) and Fisher-Peters (2010) identified shocks is only .44. In contrast, the correlation between the Fisher-Peters (2010) and Romer-Romer (2010) identified shock is 0.93, surprisingly large given that Fisher and Peters (2010) focus on exogenous changes in government spending whereas Romer and Romer (2010) focus on exogenous tax changes. The low R^2 between the instruments and the shocks suggests that the fiscal instruments are weak, so that these estimates presumably contain considerable sampling uncertainty.

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 (2011) and Fisher-Peters (2010) instruments are indented to identify spending shocks. Similarly, Kilian (2008) argues that the Kilian (2009) 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.

Second, 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. 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 0.52. The correlations are particularly large between the Romer-Romer (2004) identified monetary shock and the Ramey (2011) identified spending shock (correlation = -0.87), and between the Smets-Wouters (2007) identified monetary shock and the Romer-Romer (2011) identified tax shock. The monetary and fiscal shock literatures are aware of the difficulty of identifying one shock while holding the other constant and this difficulty is evident in the large correlations between the shocks from these two literatures.

Another notable block of large correlations is between the two uncertainty and two spread shocks, for which the average absolute correlation between shocks in the different groups is 0.85. 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 fundamental which enhanced uncertainty and financial sector risk would appear as shocks to both series. We find it more surprising that the correlation is 0.79 between the shocks identified using the Baker, Bloom, and Davis (2012) policy uncertainty index and the Gilchrist- Zakrajšek (2011) EBP spread. In any event, these two sets of instruments do not seem to be identifying distinct shocks. As a result, we also consider two composite of these four shocks constructed as the first two principle component of the four identified shocks. The subsample R^2's for the first principle component, and for the first and second principle components combined, are listed in the final rows of Table 6.

The 2007Q4 recession and recovery. Table 8 summarizes the contribution of the shocks in Table 6 to the growth of GDP and employment over three periods starting in 2007Q4. Because the shocks are correlated these contributions do not constitute 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 6.2 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.

Except for the Galí productivity shock, every shock makes a negative contribution to GDP over the 2007Q4-2009Q2 period. The largest negative shock contributions are seen in the financial shock measures (credit spread and uncertainty shocks). Oil shocks and monetary policy shocks both make moderate negative contributions, with the exception of the Smets-Wouters (2007) identified shock; note however that the Smets-Wouters (2007) identified shock is highly correlated with the TED spread shock (correlation of .73 from Table 7) which makes it difficult to interpret this shock as strictly a monetary shock. The Romer-Romer (2004), Sims-Zha (2006), and recursive monetary policy identification schemes indicate that monetary policy was neutral to 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); recall from Section 4 that the factors do not capture the unconventional monetary policy of the crisis and recovery.

4.4 Discussion

Inference about the shocks leading to 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. With the risk of simplification, 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. This 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. Even so, 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 what we would consider a compelling decomposition.

Despite this substantial caveat, some substantive results emerge from Tables 6 and 8. First, the contributions of productivity, monetary policy, and fiscal policy shocks to the 2007Q4-2009Q2 decline are small (putting aside the Smets-Wouters (2007) monetary policy shock for reasons discussed above). Oil shocks made a contribution to the decline before the financial crisis, although the contribution of the combined Hamilton/Kilian overidentified shock to the full 2007Q4-2009Q2 decline is nearly zero.

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 principle component of these four 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. The two shocks that make the most lasting net negative contribution over the full 2007Q4-2011Q2 period are the two highly correlated Baker, Bloom, and Davis (2012) policy uncertainty and TED spread shocks (again putting aside the Smets-Wouters (2007) monetary policy shock). Taken at face value, this suggests an economy being hit in close succession by a sequence of unusually large shocks, all of which have been experienced before, but not in such magnitude or close succession: an initial oil shock, followed by the financial crisis, financial market disruptions, and prolonged uncertainty due in part to policy uncertainty.

5. The Slow Recovery

On its face, the unusually slow recovery following the 2009Q2 trough seems inconsistent with the conclusion of the previous section 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.

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

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.

For the calculations in this section, we return to the benchmark model of Section 3, which was estimated over 1959-2007Q3, with the "old" factors computed over 2007Q4-2011Q2 as described in footnote 6.

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. Stated 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 at 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 the paths of the common component, the predicted common component, and actual employment growth 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 benchmark model and the values of the factors at the trough; that is, the predicted common component represents 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 given the parameters of the benchmark model. 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 common shocks (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. Notably, strong positive employment growth is predicted following the 1982Q4 trough, while slow employment growth 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 nearly two years 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 faster than predicted; from the perspective of the DFM forecasts, the puzzle, if there is one, is why the recovery was as strong as it has been.[19]

5.2 Decomposition of the 2009Q2 recovery into trend and cyclical components

Employment growth during a recovery is the sum of 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. In this section, we compare the values of the first two of these terms – the trend and the predicted cyclical common component – in the 2009Q2 recovery to their values in previous recoveries. This permits a decomposition of the slow recovery of 2009Q2, relative to previous recoveries, into changes in the trend plus changes in the predicted cyclical component. As in the previous subsection, we hold the DFM coefficients constant, so the cyclical part of the decomposition only reflects differences in the state of the economy (the factors) at the trough.

Table 9 summarizes the predicted 8-quarter cumulative post-trough growth of GDP, employment, and productivity, shown as the sum of the trend in the series at the trough plus the predicted common component of the detrended series, where the predicted cyclical component is computed using the factors as of the trough. For the employment column, the predicted cyclical component is the sum of the predicted quarterly growth rates for the first 8 quarters shown in Figure 4.

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 5, there is considerable variation in the predicted cyclical components, which arises from variation in the composition and magnitude of the factors at 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.

trough. The predicted cyclical contributions to 8-quarter employment growth range from +1.1 percent following the 1982Q4 trough to -3.1 percent following the 2009Q2 trough.

The final block of Table 9 provides the trend/cycle decomposition of the difference of predicted 8-quarter growth from the 2009Q2 trough from the averages for pre-1984 recoveries. Predicted GDP growth emerging from 2009Q2 is 2.7 percentage points less than the pre-1984 average; nearly all of this gap (2.3 percentage points) is due to differences in trend. Predicted employment growth is 5.8 percentage points less than the pre-1984 average; of this gap, 2.5 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, 6.0%, although this predicted value is comparable to its values in the 1975Q1 and 1982Q4 recoveries. Note that difference between the trend components of productivity growth in the 2009Q2 recoveries and the pre-1984 recoveries is small (0.6 percentage points); most of the difference in predicted productivity arises from the cyclical component.

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 an accounting sense, almost entirely due to declines in trend employment, which in turn is approximately equally due to declines in the employment-population ratio and to declines in the population. 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 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.[20] There is a significant literature that examines long-term labor force trends and links them to two major demographic shifts.[21]

These two demographic shifts are evident in Figure 6. The first is the historic 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 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

[20] 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 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.

[21] 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) and Chetty (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, although they focus on the implications of this plateau for income inequality rather than the growth of the labor force. It goes beyond the scope of this paper to examine these factors in any detail.

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 recession, most of the slow nature of the 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.

These 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 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 estimates shocks that are correlated with each other. We view the ability to estimate this correlation, rather than needing to impose it as an identifying restriction, to be a strength of this methodology. However, finding positive correlations across different types of shocks suggests that the 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. In particular, 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 benchmark 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	0.63	0.81	0.79	0.82	0.79	0.85	0.74	0.65	0.64
Consumption	0.63	0.44	0.58	0.77	0.66	0.82	0.71	0.73	0.04	0.56
Consumption – services	0.35	0.22	0.27	0.46	-0.07	0.62	0.47	0.47	-0.17	0.83
Nonres. fixed investment	0.63	0.56	0.64	0.77	0.90	0.58	0.57	0.50	0.69	0.86
Industrial production - total	0.87	0.80	0.90	0.86	0.94	0.93	0.94	0.89	0.76	0.95
IP - automotive	0.59	0.30	0.59	0.62	0.71	0.64	0.38	0.67	0.16	0.62
Nonfarm employment	0.92	0.91	0.93	0.94	0.93	0.95	0.98	0.93	0.92	0.96
Unemployment rate	0.84	0.75	0.77	0.89	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	0.89	0.84	0.81	0.75	0.77
Long-term unemployment rate	0.61	0.58	0.57	0.61	0.68	0.74	0.71	0.45	0.49	0.64
Housing starts	0.59	0.39	0.25	0.58	0.83	0.79	0.76	0.62	0.32	0.53
Real house prices (OFHEO)	0.46	0.40	.	.	.	0.57	-0.03	0.64	0.35	0.55
Inflation (PCE)	0.51	0.54	0.25	0.69	0.66	0.45	0.40	0.56	0.56	0.82
Gas & energy inflation (PCE)	0.37	0.48	-0.45	-1.71	-0.63	0.25	0.25	0.55	0.48	0.71
Federal funds rate	0.45	0.35	-0.07	0.46	0.58	0.49	0.42	0.72	0.15	-1.54
Real monetary base	0.17	0.09	0.20	0.40	0.24	0.65	0.59	-0.19	-0.36	-0.03
Real commercial & industrial loans	0.44	0.54	0.49	0.47	0.54	-1.41	-1.05	0.71	0.63	0.47
TED spread	0.55	0.05	.	.	0.79	0.75	0.71	0.00	-0.09	0.78
Gilchrist-Zakrajšek (2011) spread (EBP)	0.47	0.46	.	.	0.90	0.07	0.46	0.16	0.63	.
S&P 500	0.72	0.69	0.74	0.68	0.89	0.61	0.64	0.35	0.80	0.87
VIX	0.46	0.50	.	0.34	0.74	-0.78	-0.71	0.39	0.75	0.89

Notes: The predicted values are the "old model/old factors" predicted values computed as described in footnote 7. 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 8), 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 benchmark 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	0.55	0.42	0.56	0.46	0.62	0.66	0.59	0.63	0.48	0.65
Industrial production	13	0.72	0.60	0.79	0.77	0.86	0.86	0.80	0.67	0.60	0.82
Employment & Unemp	46	0.62	0.50	0.64	0.68	0.76	0.77	0.81	0.61	0.64	0.77
Housing starts	8	0.35	0.22	0.09	0.28	0.53	0.46	0.55	0.43	-0.09	0.28
Inventories, orders, & sales	8	0.55	0.35	0.39	0.69	0.72	0.73	0.68	0.66	0.43	0.64
Prices	39	0.15	0.05	-0.01	0.15	0.38	0.18	0.08	0.03	0.13	0.14
Earnings & productivity	13	0.37	0.29	0.51	0.37	0.34	0.30	-0.03	0.33	0.36	-0.12
Interest rates	18	0.40	0.30	-0.11	0.39	0.27	0.51	0.45	0.28	0.08	-0.48
Money & credit	12	0.44	0.25	0.28	0.47	0.54	0.65	0.63	0.38	0.05	-0.40
Stock prices & wealth	9	0.54	0.51	0.52	0.68	0.74	0.37	0.61	0.39	0.71	0.79
Housing prices	3	0.65	0.65	.	.	.	0.57	-0.03	0.64	0.68	0.58
Exchange rates	6	0.56	0.66	-2.74	0.46	0.64	0.48	0.67	0.74	0.73	0.60
Other	2	0.42	0.42	-0.33	0.14	0.87	0.89	0.89	0.48	-0.64	0.33

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	0.31	0.26
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	9	0.22	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	2.9
Consumption	2.1	1.3	2.3		2.1	1.2	2.3
Investment	11.4	8.5	15.3		10.5	6.8	11.8
Industrial production – total	5.2	3.1	6.4		4.9	3.2	6.0
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 four-quarter growth rate. Calculations go through the final quarter in the data set, 2011Q2.

Table 5
Innovations to factor components of selected series, by quarter, 2007Q1 – 2011Q2
A. Standardized innovations

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	0.3	1.8	0.3	0.0	-0.6	0.0
2007Q2	0.3	-0.1	0.5	-0.1	0.2	0.8	1.1	0.6	-0.9	-1.4	0.8
2007Q3	-0.3	-0.8	-0.1	-0.6	0.0	-0.7	0.3	-0.6	0.6	1.1	-0.9
2007Q4	-0.3	-1.3	0.1	0.3	-0.7	-1.2	1.3	0.4	0.3	0.5	-0.8
2008Q1	-0.4	-0.7	0.0	0.2	-0.5	-1.2	0.1	-0.2	1.4	2.1	-1.9
2008Q2	-1.6	-2.1	-0.6	-1.2	-2.2	1.0	**3.4**	0.3	-0.1	-0.6	-0.6
2008Q3	-1.8	-1.7	-1.3	-0.9	-1.5	**-3.4**	-0.7	-0.1	**3.7**	2.7	-2.4
2008Q4	0.7	2.1	-0.6	-0.5	**4.3**	**-8.2**	**-10.4**	-2.8	**7.5**	**8.1**	**-3.9**
2009Q1	0.0	-2.9	1.9	0.5	-0.5	**-4.7**	2.5	**3.3**	**4.0**	1.4	**-3.2**
2009Q2	2.9	1.7	**3.3**	**3.7**	0.8	2.7	2.7	**3.6**	-2.8	**-3.1**	1.0
2009Q3	1.7	0.4	2.1	2.4	-0.5	**4.8**	**5.0**	1.6	**-5.0**	**-3.2**	1.3
2009Q4	-1.0	-0.8	-1.8	-2.0	0.0	0.1	-0.4	-1.9	-1.8	-2.1	2.8
2010Q1	0.2	-0.1	0.6	0.5	-0.1	-0.5	0.3	1.2	0.9	0.0	-0.6
2010Q2	0.6	0.3	0.6	0.2	1.3	-2.3	-1.9	0.3	2.0	1.6	-1.1
2010Q3	0.7	-0.3	1.1	0.3	1.0	-1.7	-0.1	0.9	1.0	0.3	-0.6
2010Q4	0.4	-0.6	0.7	-0.1	0.1	0.5	1.7	0.9	-0.9	-1.6	0.7
2011Q1	0.5	-0.5	1.3	0.6	-0.4	1.6	2.8	1.3	-0.9	-0.8	-0.5
2011Q2	-0.8	-0.7	-1.0	-1.2	-0.5	0.6	0.4	-1.4	-0.8	0.0	0.4

B. Quantile of historical innovation distribution

Date	GDP	Consump-tion	Invest-ment	Employ-ment	Prod-uctivity	Housing Starts	Oil Price	Fed Funds	Ted spread	VIX	Wealth (FoF)
2007Q1	0.16	0.09	0.31	0.21	0.11	0.62	0.96	0.60	0.52	0.28	0.47
2007Q2	0.63	0.44	0.72	0.46	0.58	0.78	0.87	0.71	0.19	0.06	0.81
2007Q3	0.38	0.20	0.48	0.25	0.48	0.25	0.61	0.26	0.74	0.88	0.15
2007Q4	0.37	0.08	0.54	0.61	0.22	0.11	0.93	0.65	0.67	0.75	0.17
2008Q1	0.35	0.23	0.48	0.58	0.32	0.10	0.54	0.36	0.92	0.97	0.05
2008Q2	0.04	0.03	0.25	0.11	0.02	0.86	1.00	0.65	0.49	0.32	0.23
2008Q3	0.02	0.06	0.07	0.16	0.06	0.00	0.22	0.42	1.00	0.99	0.02
2008Q4	0.80	0.98	0.25	0.28	1.00	0.00	0.00	0.01	1.00	1.00	0.01
2009Q1	0.49	0.00	0.95	0.75	0.30	0.00	0.99	0.99	1.00	0.92	0.01
2009Q2	1.00	0.95	1.00	1.00	0.78	0.99	0.99	1.00	0.01	0.00	0.88
2009Q3	0.96	0.71	0.97	0.98	0.32	1.00	1.00	0.95	0.00	0.00	0.93
2009Q4	0.12	0.19	0.03	0.02	0.47	0.57	0.35	0.03	0.02	0.01	1.00
2010Q1	0.58	0.48	0.74	0.72	0.45	0.29	0.65	0.90	0.80	0.53	0.23
2010Q2	0.75	0.66	0.74	0.61	0.90	0.01	0.04	0.58	0.98	0.95	0.12
2010Q3	0.80	0.32	0.86	0.65	0.85	0.04	0.46	0.80	0.86	0.70	0.22
2010Q4	0.66	0.26	0.77	0.48	0.52	0.70	0.95	0.80	0.17	0.03	0.79
2011Q1	0.71	0.30	0.88	0.75	0.33	0.97	0.99	0.93	0.17	0.19	0.27
2011Q2	0.16	0.22	0.13	0.11	0.32	0.72	0.68	0.07	0.21	0.51	0.66

Notes: Panel A reports the standardized innovations to 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. Panel B reports the empirical quantile of the innovation in the corresponding cell of panel A, relative to its 1959-2007Q3 distribution.

Table 6

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

Structural Shock	$R^2_{Z,\eta}$	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	0.11	0.18	0.00	0.31	0.46	0.11	0.11	0.17	-0.52	-0.27
Killian	0.05	0.08	-0.02	0.14	0.08	0.20	0.23	-0.02	-0.27	0.34
Hamilton + Kilian	0.13	0.16	0.00	0.26	0.42	0.10	0.11	0.17	-0.57	-0.32
Exogenous	1.00	0.10	-0.09	0.16	0.39	0.07	0.02	-0.03	-0.48	-0.09
2. Monetary policy										
Romer and Romer	0.21	0.22	-0.15	0.34	0.29	0.56	0.57	0.16	0.08	0.27
Smets-Wouters	0.24	0.18	-0.02	0.24	0.26	0.32	0.23	0.37	0.15	0.46
Sims-Zha	0.19	0.18	-0.30	0.29	0.43	0.54	0.51	-0.02	0.05	0.06
RR + SW + SZ	0.43	0.18	0.01	0.22	0.02	0.33	0.28	0.51	0.06	0.73
Recursive	1.00	0.12	-0.06	0.21	0.27	0.25	0.24	0.16	-0.02	0.00
3. Productivity										
Long-run OPH	1.00	0.07	0.00	0.12	0.09	0.12	0.07	-0.02	-0.18	-0.03
Smets-Wouters	0.20	0.20	-0.03	0.36	0.37	0.17	0.15	-0.05	-0.34	-0.14
4. Uncertainty										
Fin Unc (VIX)	1.00	0.10	0.00	0.15	0.21	0.23	0.38	0.31	0.33	0.57
Pol Unc (BBD)	1.00	0.13	-0.02	0.19	0.42	0.21	0.21	0.43	0.13	0.61
5. Credit spread										
GZ EBP Spread	1.00	0.13	-0.02	0.20	0.15	0.31	0.50	0.27	0.45	0.62
TED Spread	1.00	0.20	-0.09	0.25	0.28	0.38	0.38	0.28	0.30	0.67
6. Fiscal policy										
Ramey Spending	0.02	0.21	-0.06	0.37	0.33	0.51	0.55	0.08	0.01	0.19
Fisher-Peters Spending	0.04	0.22	0.05	0.26	0.01	0.34	0.40	0.42	0.13	0.16
Ramey+FP Spending	0.04	0.25	0.02	0.32	0.06	0.42	0.49	0.40	0.24	0.15
Romer-Romer Taxes	0.02	0.17	-0.19	0.21	0.22	0.39	0.35	0.12	-0.25	0.07
PCs of uncertainty and credit spread shocks										
1 PC	1.00	0.15	-0.03	0.20	0.28	0.28	0.39	0.36	0.29	0.65
2 PCs	1.00	0.26	-0.18	0.44	0.55	0.62	0.63	0.55	0.26	0.87

Notes: The value of $R^2_{Z,\eta}$ in the first column is the full-sample R^2 in the regression of the instrument on the six factor innovations; in the case of multiple instruments this is the squared canonical correlation between the instruments and the innovations. The remaining R^2's are for the contribution of the row shock, computed over the column subsample, as described in footnote 17. The structural shocks are computed using the instrument listed in the first column, as described in Sections 4.1 and 4.2.

[a] The p-values for the test of overidentifying restrictions, implemented when there are multiple external instruments for shocks within the same category, are: Hamilton + Kilian oil shocks, p = 0.34; Romer-Romer + Smets-Wouters + Sims-Zha monetary policy shocks, p = 0.00; Ramey + Fisher-Peters fiscal spending shocks, p = 0.73.

Table 7

Correlations among estimated structural shocks

	O_H	O_K	O_e	M_{RR}	M_{SW}	M_{SZ}	M_{rec}	P_G	P_{SW}	U_B	U_{BBD}	S_{GZ}	S_{TED}	F_R	F_{FP}	F_{RR}
O_H	**1.00**															
O_K	0.38	**1.00**														
O_e	**0.95**	0.55	**1.00**													
M_{RR}	0.34	0.66	0.49	**1.00**												
M_{SW}	0.07	0.11	-0.08	0.11	**1.00**											
M_{SZ}	0.33	0.35	0.41	**0.93**	0.17	**1.00**										
M_{rec}	0.16	0.22	0.05	0.41	**0.85**	0.47	**1.00**									
P_G	-0.47	0.29	-0.44	-0.34	0.33	-0.57	0.08	**1.00**								
P_{SW}	**-0.91**	-0.01	**-0.79**	-0.23	-0.07	-0.36	-0.11	**0.70**	**1.00**							
U_B	-0.29	-0.35	-0.36	-0.49	0.29	-0.42	-0.23	0.37	0.15	**1.00**						
U_{BBD}	-0.08	0.00	-0.14	-0.17	0.50	-0.18	0.00	0.40	0.03	**0.90**	**1.00**					
S_{GZ}	-0.24	-0.50	-0.33	-0.65	0.23	-0.52	-0.27	0.29	0.08	**0.96**	**0.79**	**1.00**				
S_{TED}	-0.08	-0.21	-0.20	-0.28	**0.73**	-0.17	0.32	0.36	0.00	**0.82**	**0.83**	**0.81**	**1.00**			
F_R	-0.10	-0.65	-0.19	**-0.87**	-0.33	**-0.74**	-0.50	0.03	0.00	0.34	-0.03	0.56	0.17	**1.00**		
F_{FP}	0.04	-0.21	-0.18	**-0.73**	0.20	**-0.80**	-0.06	0.46	-0.01	0.26	0.21	0.33	0.21	0.44	**1.00**	
F_{RR}	-0.22	-0.20	-0.37	**-0.80**	0.12	**-0.90**	-0.09	0.65	0.30	0.22	0.10	0.31	0.17	0.52	**0.93**	**1.00**

Notes: Entries are correlations between individually identified shocks. Correlations are computed over the full 1959-2011Q2 sample. Grey background denotes correlations within categories of shocks, bold denotes absolute correlations exceeding 0.70. Row and column labels correspond to the identified shocks:

- O_H: oil – Hamilton (1996)
- O_K: oil – Kilian (2009)
- O_e: oil – exogenous
- $M_{RR:}$ monetary policy – Romer and Romer (2004)
- $M_{SW:}$ monetary policy – Smets-Wouters (2007)
- $M_{SZ:}$ monetary policy – Sims-Zha (2006)
- $M_{rec:}$ monetary policy – recursive
- P_G: productivity – Gali (1999)
- P_{SW}: productivity – Smets-Wouters (2007)
- U_{VIX}: uncertainty – VIX/Bloom (2009)
- U_{BBD} uncertainty – policy/Baker, Bloom, and Davis (2012)
- S_{GZ}: spread – Gilchrist-Zakrajšek (2011) excess bond premium
- S_{TED}: spread – TED spread
- F_R: fiscal policy – Ramey (2011)
- F_{FP}: fiscal policy – Fisher-Peters (2010)
- F_{RR}: fiscal policy – Romer-Romer (2010)

Table 8

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

	Accumulated Percentage Change in Detrended GDP			**Accumulated 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	-4.1	−9.3	−6.2	-2.1	−7.2	−8.8		
Oil								
Hamilton	-0.8	-0.5	0.1	-0.3	-0.8	-0.2	1.8	1.3
Killian	-1.0	-1.9	-0.5	-0.4	-1.5	-0.9	1.2	0.4
Hamilton + Kilian	-0.7	-0.2	0.3	-0.4	-0.9	0.0	2.2	1.7
Exogenous	-0.5	-0.5	0.4	-0.1	-1.0	0.3	2.4	1.8
Money								
Romer- Romer	-1.2	-1.7	0.1	-0.7	-2.2	0.4	1.6	1.3
Smets-Wouters	-0.5	-3.7	-5.1	-0.5	-2.6	-6.3	-0.6	-3.3
Sims-Zha	−0.4	-0.2	0.0	-0.5	-1.1	0.3	0.6	1.0
RR + SW + SZ	-0.8	-4.9	-3.1	-0.7	-4.1	-5.4	2.0	-1.4
Recursive	0.1	-0.1	-1.7	-0.3	-0.5	-1.8	-0.9	-1.2
Productivity								
Long-run OPH	0.5	0.3	1.1	0.1	-0.6	-0.7	1.1	0.7
Smets-Wouters	-0.6	-0.3	0.6	0.1	-0.2	0.2	0.9	0.6
Uncertainty								
Fin Unc (VIX)	-1.6	-5.4	-0.6	-1.2	-4.6	-2.9	3.8	0.5
Pol Unc (BBD)	-2.1	-6.3	-4.6	-1.4	-4.7	-6.6	1.8	-2.0
Credit spread								
GZ EBP Spread	-1.9	-5.9	0.1	-1.2	-4.9	-2.0	4.2	1.1
TED Spread	-1.7	-7.6	-4.2	-0.9	-5.2	-6.4	2.6	-2.2
Fiscal								
Ramey-Spending	-1.6	-1.6	-1.1	-0.8	-1.6	0.5	0.2	0.0
Fisher-Peters-Spending	-0.5	-0.7	0.2	-0.4	-1.2	0.0	0.7	0.7
Ramey+FP Spending	-0.8	-0.9	0.4	-0.5	-1.3	0.4	0.8	0.8
Romer-Romer - Taxes	0.0	-0.1	0.1	0.0	-0.6	0.3	0.5	0.7
PCs of Uncertainty and Credit Spread Shocks								
1 PC	-2.0	-6.9	-2.3	-1.3	-5.3	-4.8	3.5	-0.6
2 PCs	-3.8	-10.2	-7.9	-2.7	-8.9	-10.4	2.8	-2.8

Notes: Entries are the contribution of the row shock to GDP growth (first three columns) and employment (second three columns) over the indicated period, where the shock contribution is computed as described in footnote 17. The final two columns are the implied forecasts of growth constructed in 2009Q2 associated with the particular shock.

Table 9
Predicted and actual cumulative 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	1.3	-0.9	2.1
	Trend	7.5	4.9	4.8
	Total	8.8	4.1	6.9
1970Q4	Cyclical	2.4	-0.1	2.7
	Trend	6.9	4.7	4.0
	Total	9.3	4.6	6.7
1975Q1	Cyclical	3.2	-1.8	5.3
	Trend	6.6	4.5	3.7
	Total	9.8	2.7	9.1
1980Q3	Cyclical	1.2	-1.5	2.9
	Trend	6.3	4.2	3.5
	Total	7.5	2.8	6.4
1982Q4	Cyclical	5.0	1.1	4.2
	Trend	6.2	4.1	3.5
	Total	11.2	5.2	7.7
1991Q1	Cyclical	0.7	-1.6	2.4
	Trend	5.9	3.3	3.8
	Total	6.6	1.6	6.2
2001Q4	Cyclical	2.9	0.5	2.6
	Trend	5.1	2.1	4.3
	Total	8.0	2.6	7.0
2009Q2	Cyclical	2.2	-3.1	6.0
	Trend	4.4	1.2	4.5
	Total	6.6	-1.9	10.5
Averages				
1960-1982	Cyclical	2.6	-0.6	3.4
	Trend	6.7	4.5	3.9
	Total	9.3	3.9	7.4
	Actual[a]	11.0	5.9	7.3
1960-2001	Cyclical	2.4	-0.9	3.5
	Trend	6.1	3.6	4.0
	Total	8.5	2.7	7.6
	Actual[a]	9.2	4.0	7.2
Differences				
2009Q2 – average, 1960-1982	Cyclical	-0.4	-2.5	2.6
	Trend	-2.3	-3.3	0.6
	Total	-2.7	-5.8	3.1

Notes: Entries are the cumulative predicted growth (total, not per annum) of the common component of the series in the column heading, as of the trough. The predicted paths are decomposed into the contribution of the factors at of the trough (the cyclical component) 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.

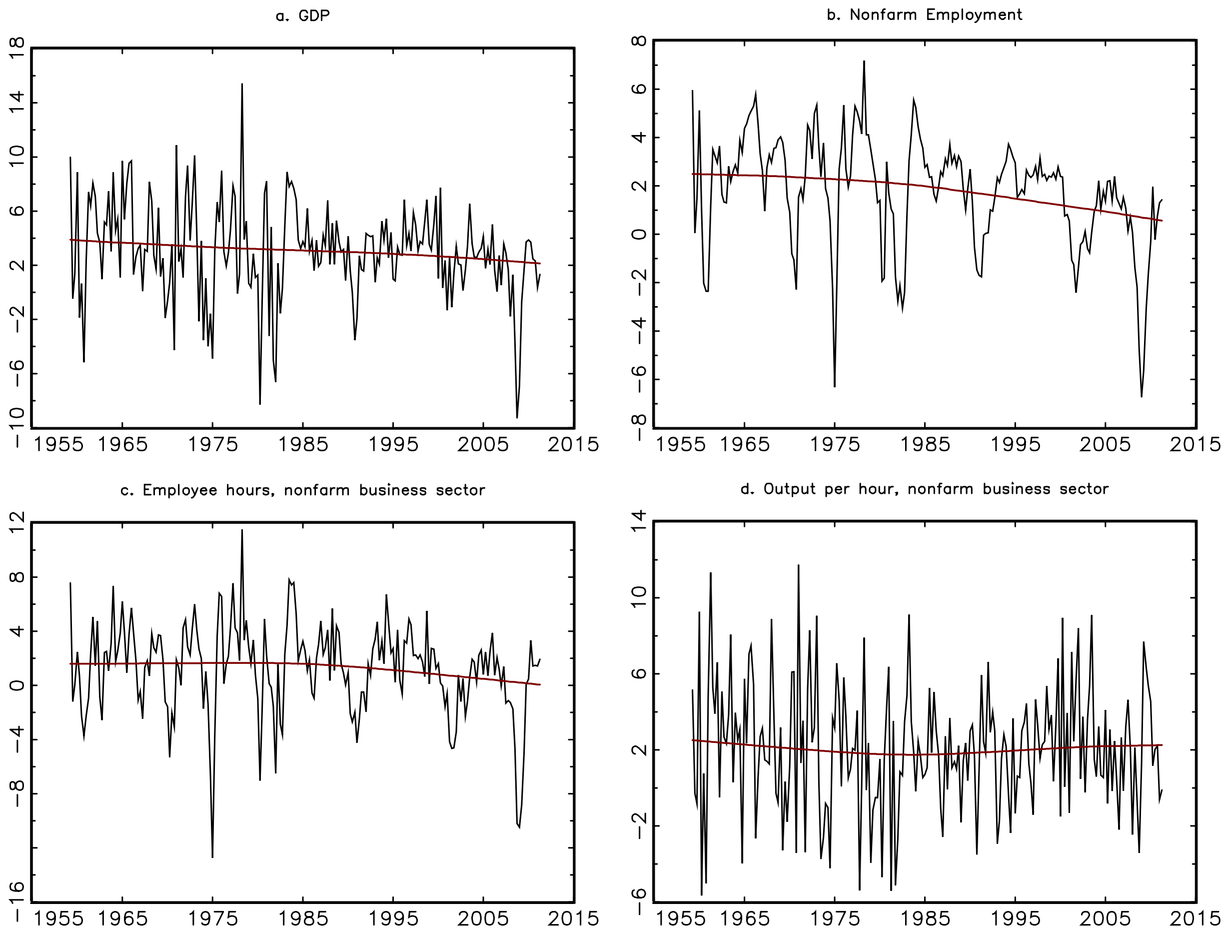
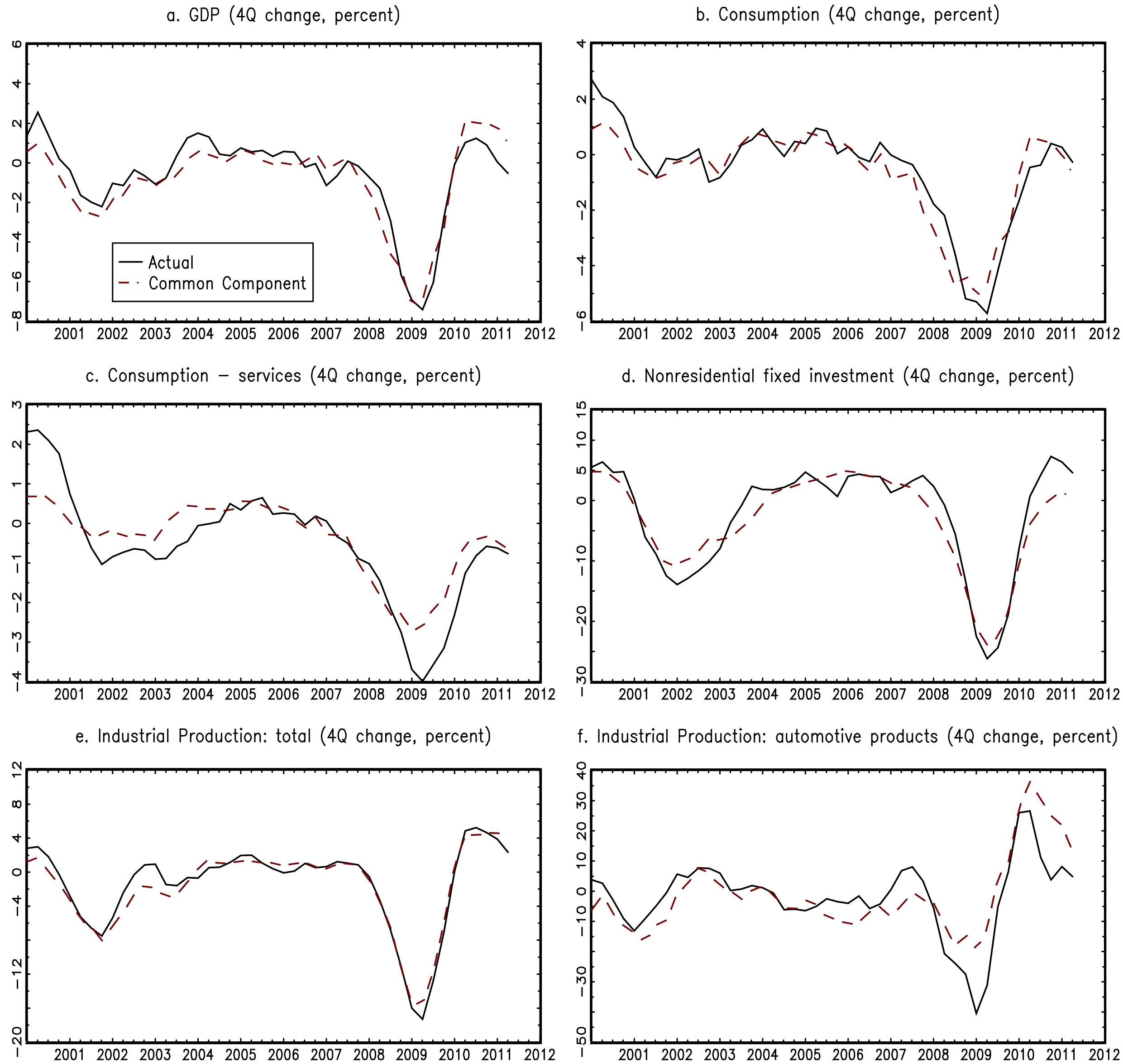
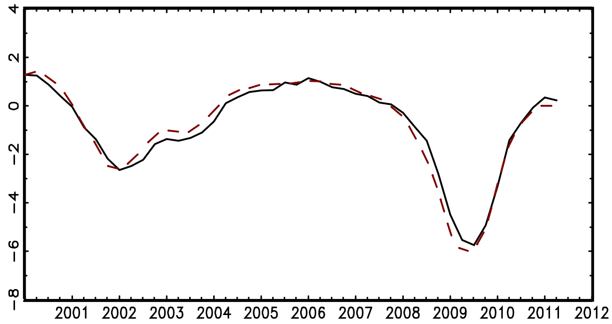


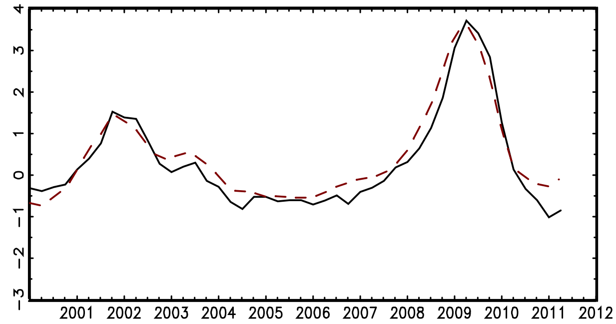
Figure 1. Quarterly growth rates of GDP, nonfarm employment, employee-hours, and labor productivity growth, and their local means ("trends").


a. GDP (4Q change, percent)
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)
Actual
Common Component
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012

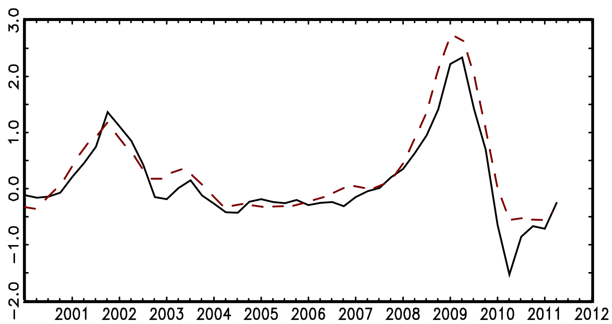
g. Nonfarm empployment (4Q change, percent)



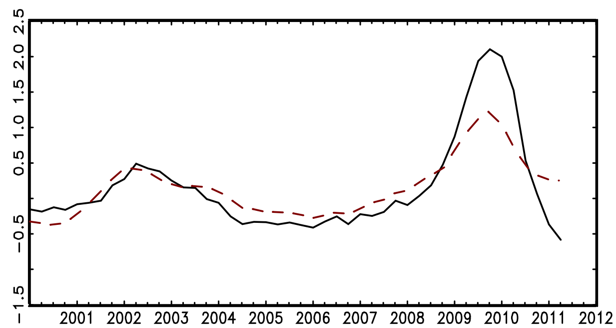
h. Unemployment rate (4Q change, percent)



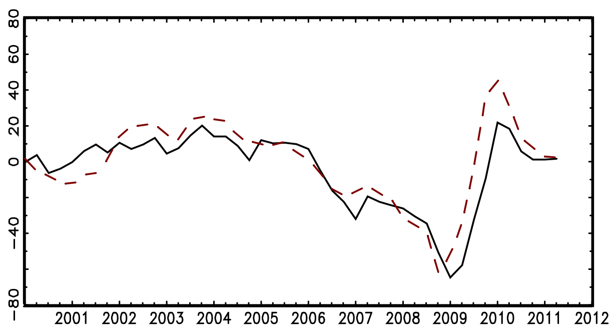
i. Short−term (< 27 weeks) unemp. rate (4Q change, percent)



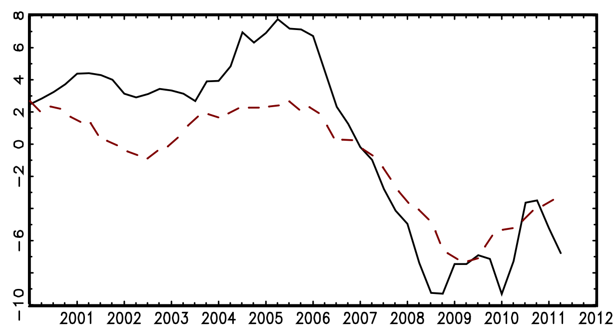
j. Long−term (>= 27 weeks) unemp. rate (4Q change, percent)



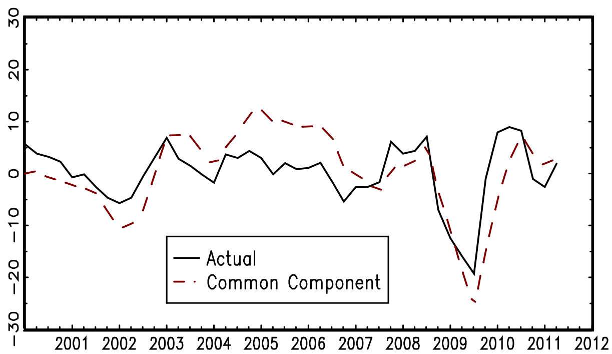
k. Housing starts (4Q change, percent)



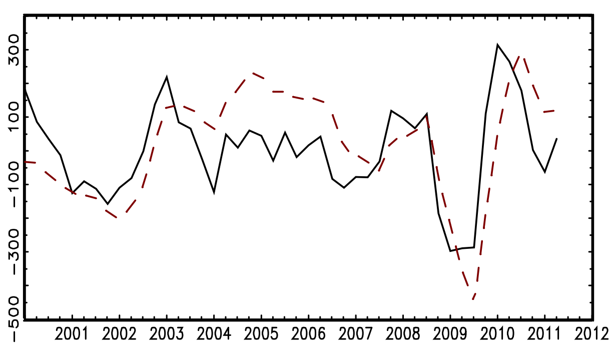
l. Housing prices (OFHEO)(4Q change, percent)



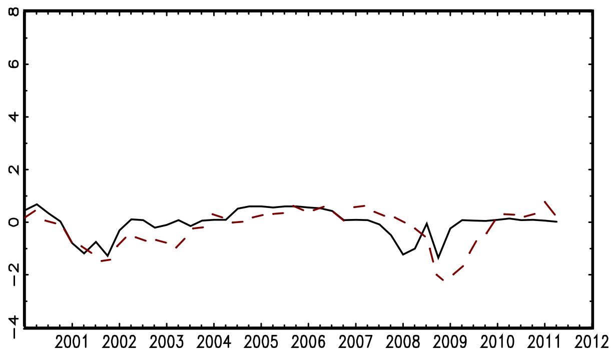
m. PCE Inflation (4Q change in 400 x change in log prices)



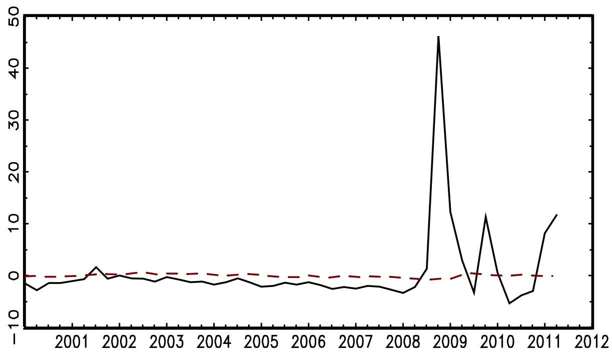
n. PCE Energy Inflation (4Q change in 400 x change in log prices)



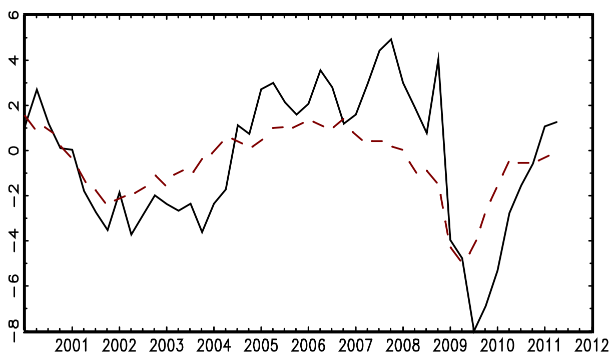
o. Federal funds rate (Quarterly change)



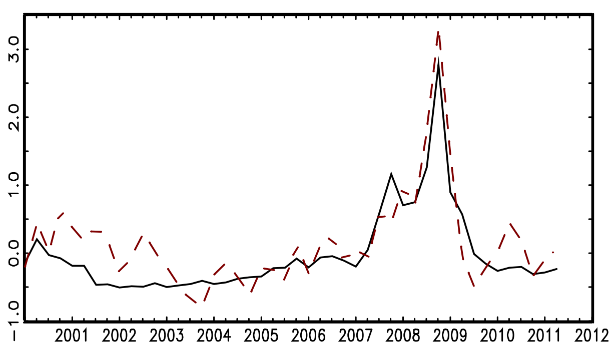
p. Real monetary base (Quarterly change, percent)



q. Com. & industrial loans (Quarterly change, percent)



r. TED spread (Level)



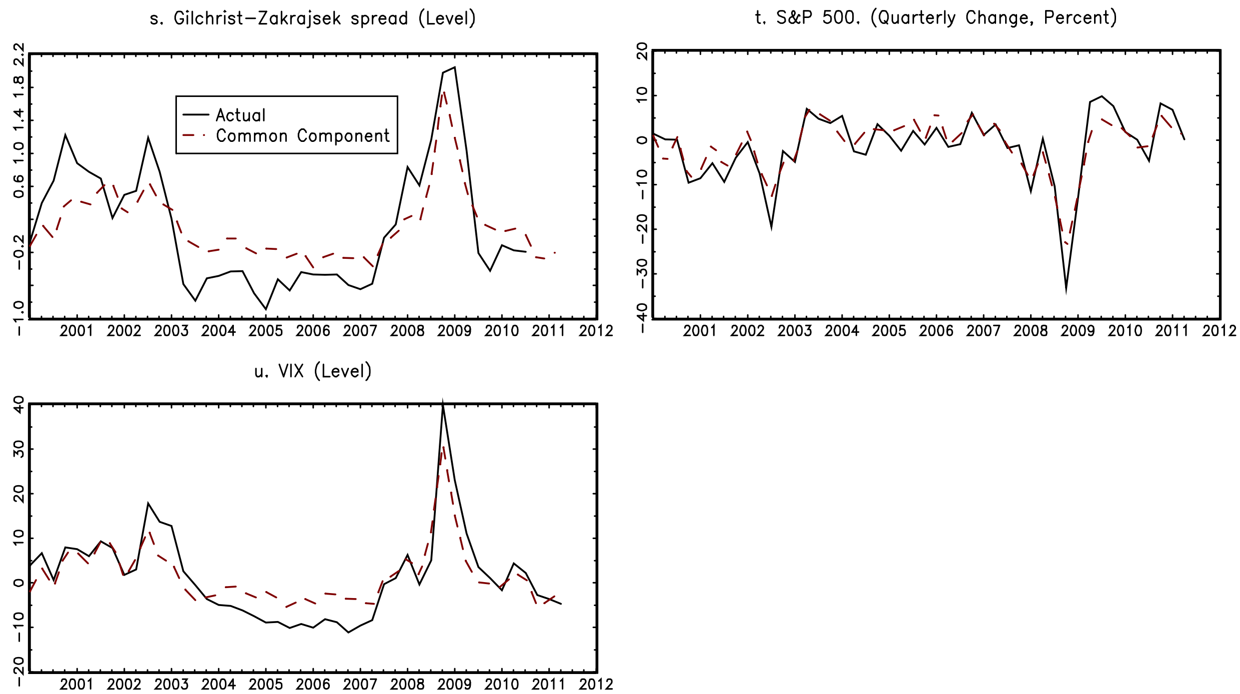


Figure 2. Common component (dashed) and actual (solid) values of selected macro variables (four-quarter changes, quarterly changes, or levels depending on the series). Common components are computed using pre-2007Q3 coefficients and 2007Q4-2011 values of the "old" factors, derived from the benchmark 1959-2007Q3 model as described footnote 7.

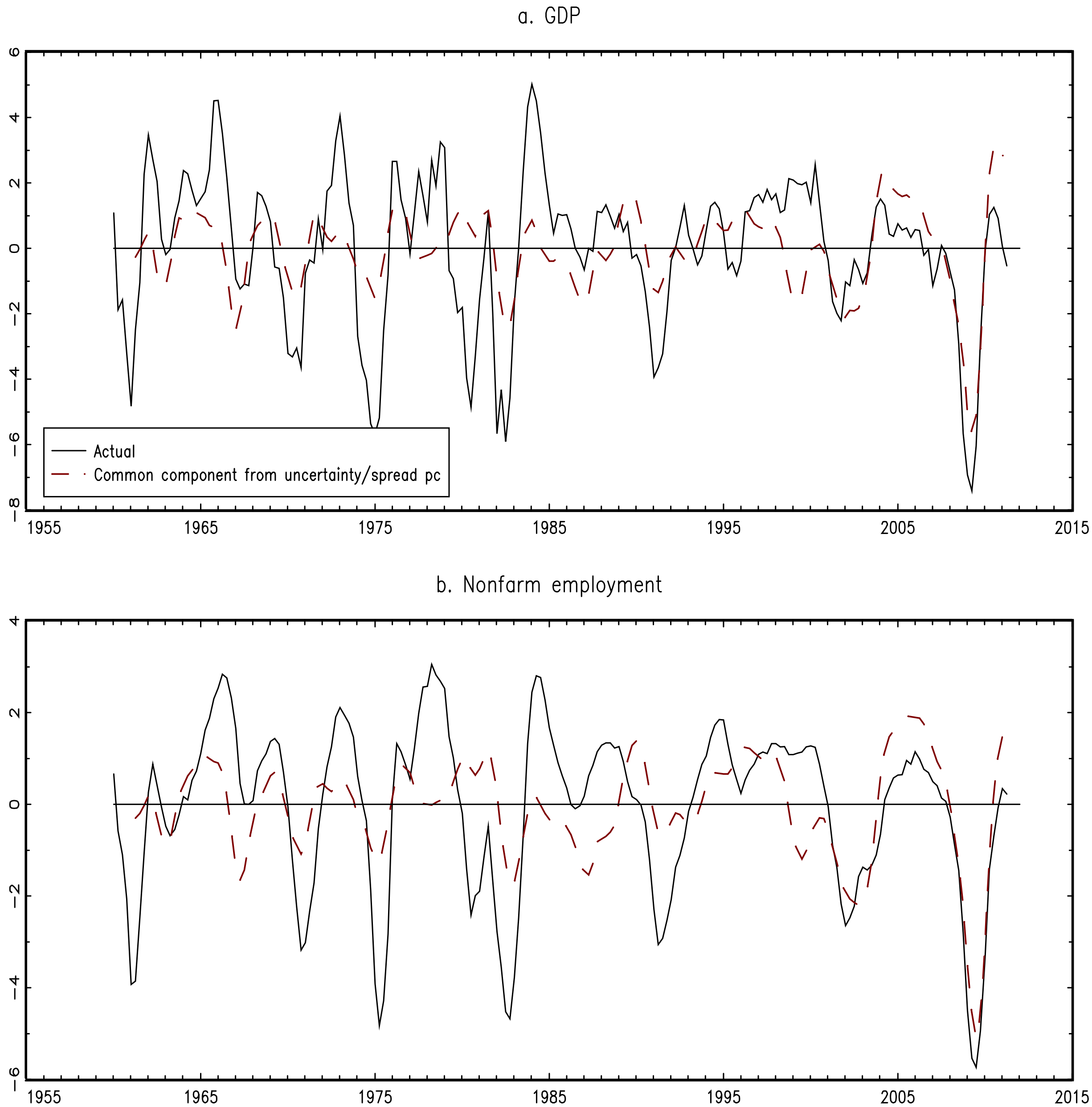


Figure 3. Contribution to 4-quarter growth of (a) GDP and (b) nonfarm employment of the first principle component of the four identified financial shocks (uncertainty and spread shocks)

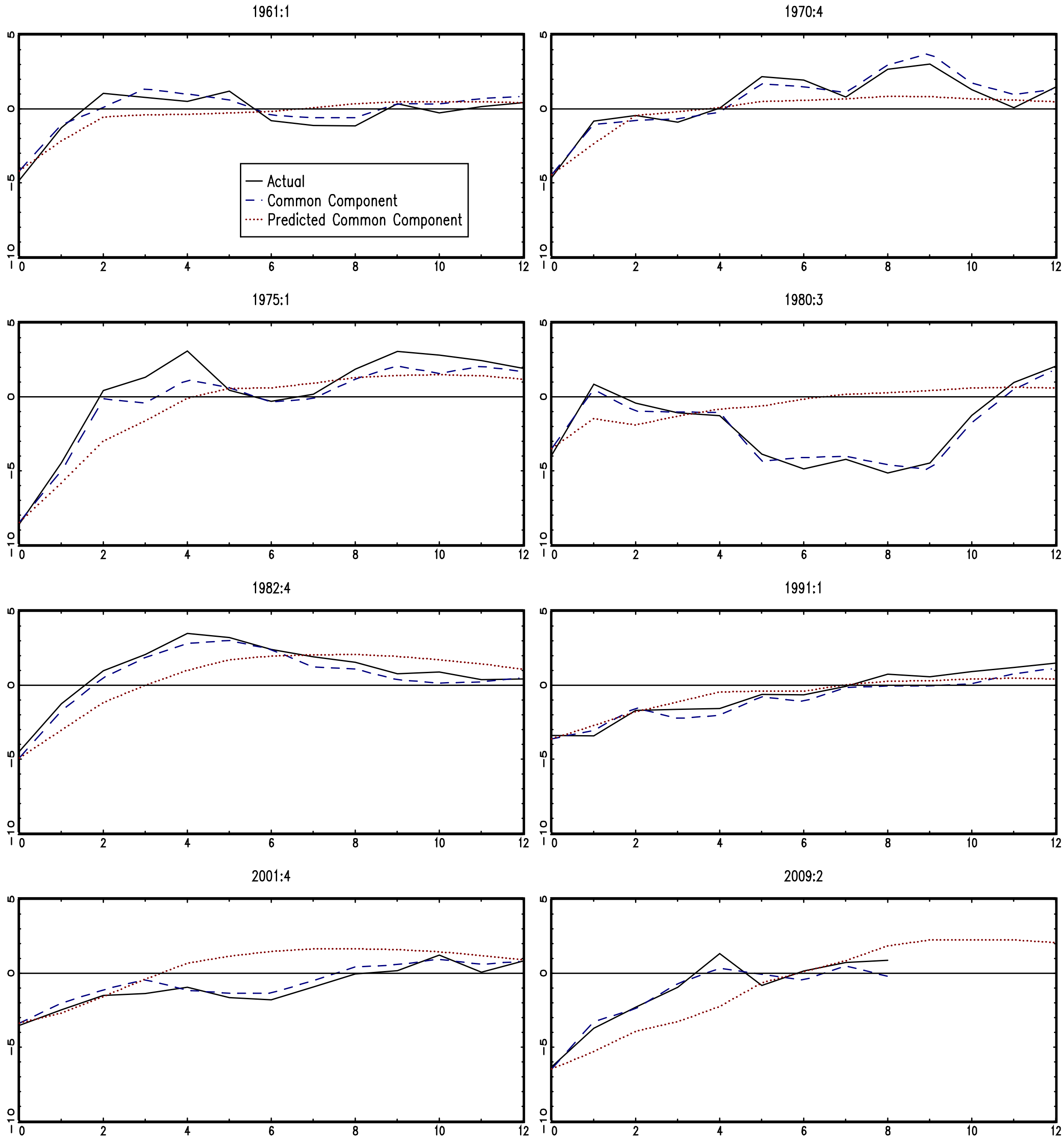


Figure 4. Employment growth during the twelve quarters following the post-1960 troughs: the common component estimated using the benchmark model, the predicted common component based on the factors at the trough, and actual.

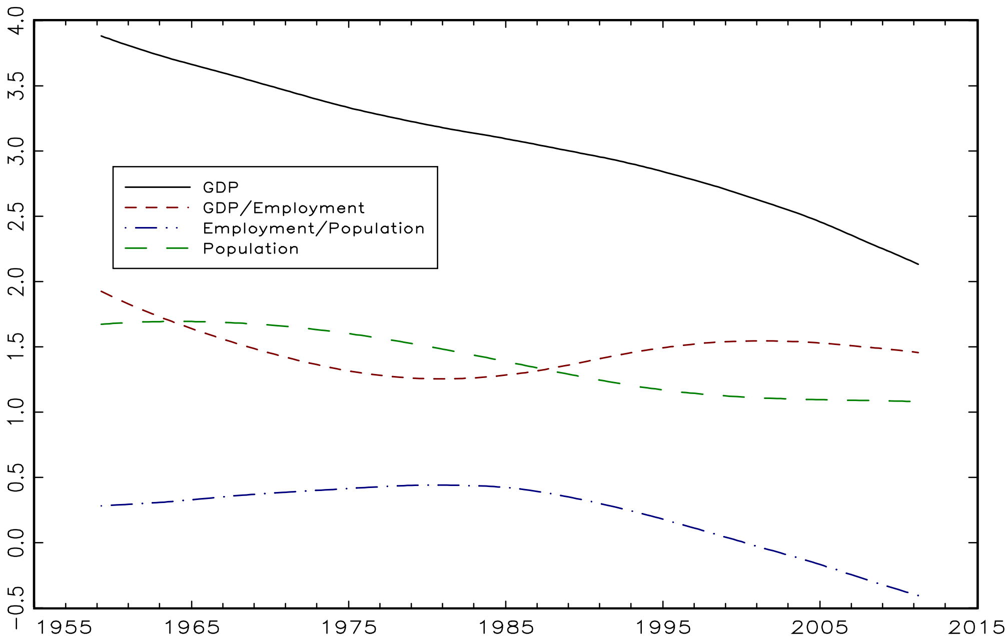


Figure 5. Trend components of the annual growth rates of GDP, the GDP-employment ratio, the employment-population ratio, and population, 1959 – 2011

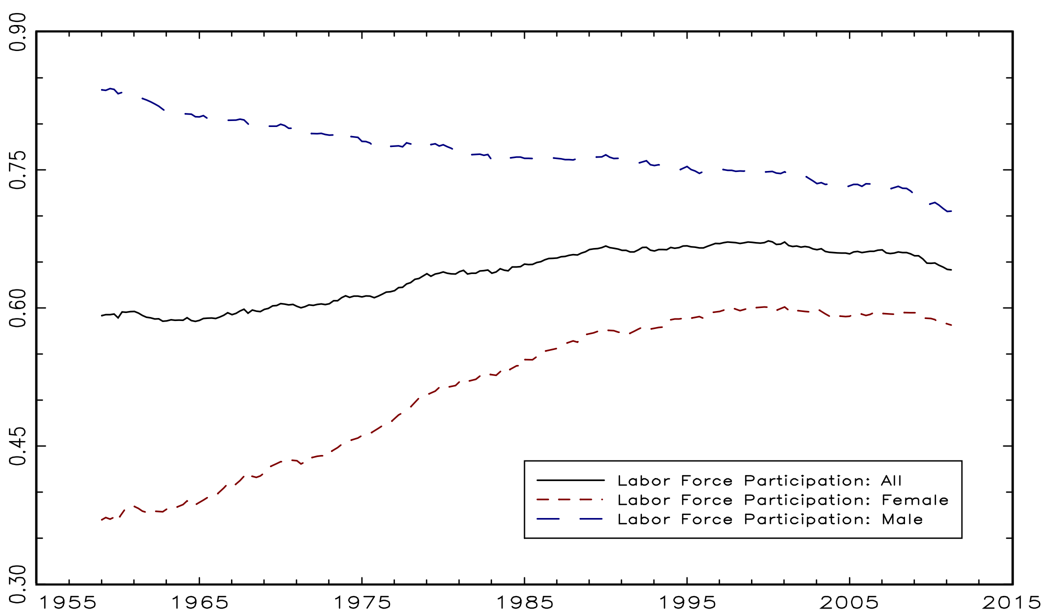


Figure 6
Civilian labor force participation rates: men, women, and total