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Cyclical Behavior of Inventories and Growth Projections: Recent Evidence from Europe and the United States

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Cyclical Behavior of Inventories and Growth Projections: Recent Evidence from Europe and the United States [1]

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Abstract

In the United States and a few European countries, inventory behavior is mainly the outcome of demand shocks: a standard buffer-stock model best characterizes these economies. But most European countries are described by a modified buffer-stock model where supply shocks dominate. In contrast to the United States, inventories boost growth with a one-year lag in Europe. Moreover, inventories provide limited information to improve growth forecasts particularly when a modified buffer-stock model characterizes inventory behavior.

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I. INTRODUCTION

For decades, economists and policy makers alike have mused on inventory behavior and the business cycle. Views on the relevance of inventories have ranged from "details of such little importance that economists could safely ignore" to "essential to achieving a better understanding not only of the macroeconomics of the business cycle but also of the microeconomics of the firm" (Blinder, 1990, p. 74). More recently, some economists have attributed the "Great Moderation" in the United States (Kim and Nelson, 1999, and Blanchard and Simon, 2001) not just to improvements in management of monetary policy, as argued by Taylor, 1999 and Clarida, Gali, and Gertler, 2000, but mainly to inventory management as discussed in McConnell and Perez-Quirós, 2000, and Kahn, McConnell, and Perez-Quirós, 2002.

In the United States, inventory investment has played a key role in the recovery so far (Figure 1). Specifically, "the biggest source of expansion in the second half of this year [2009 and the first quarter of 2010] is to come from a diminished pace of inventory liquidation by manufacturers, whole sellers, and retailers. Such a pattern is typical of business cycles. Inventory investment is often the catalyst for economic recoveries" (Yellen, 2009). In the third and fourth quarters of 2009, the slowdown in inventory destocking contributed one-third and two-thirds of the overall quarter-on-quarter growth rate, respectively. Indeed, in the postwar period inventory behavior has been found to underlie high-growth recoveries in three-phase business cycles, which have characterized the U.S. economy (Sichel, 1994). Still, some economists have argued that improvements in inventory management may result in a weak recovery in the United States (Camacho, Perez-Quirós, and Rodriguez, 2009).

In Europe, inventory behavior has had less prominence in discussions about economic recoveries. This may reflect the fact that, although European business cycles have been broadly aligned with the United States (with a lag of a quarter or two), upturns have been less pronounced (Cesaroni, Maccini, and Malgarini, 2009, and Agresti and Mojon, 2001).[3] To the best of our knowledge, the existence of a high-growth recovery and their link to inventories have not been systematically analyzed in Europe, notwithstanding Cesaroni, Maccini, and Malgarini (2009) that focused on moderating business cycles in Europe.

This paper analyses inventory behavior in three large European economies—France, Germany, and Italy—focusing on the last 20 years. Section II presents the stylized facts contrasting these with the U.S. experience as well as examining inventories' contribution to growth during expansions. In addition, a scorecard is computed to assess whether standard models of inventory behavior fit the European experience. Section III considers inventories'

[3] A notable exception to this high degree of synchronization was the U.S. recession in the early 1990's. In Europe the effect of the Gulf War appears to have been largely offset by a fiscal expansion associated with the German reunification.

ability to foreshadow output growth, including the consequences of ignoring inventories in growth forecasts. Sections II and III also briefly discuss empirical evidence for a larger group of European countries. Section IV concludes with general remarks.

II. Inventory Behavior

A. Stylized Facts[4]

Over the last twenty years, changes in inventories have not exhibited a trend in the largest European economies, with the exception of Germany (Figure 2). In France and Italy, changes in inventories have averaged about 0.1 percent of GDP and 0.2 percent of GDP and, while inventories have been volatile, their averages have been stable for the most part. Specifically, for the five periods comprising 1991–95, 1996–2000, 2001–05, and 2006–09 the average changes (as a percent of GDP) have been -0.2, 0.3, 0.3, and 0.0 in France and 0.0, 0.4, 0.2, 0.3 in Italy. Similarly, inventory changes in the United States have not experienced a trend but have been higher (0.3 percent of GDP) and less stable. As a percent of GDP, average changes in inventories have been 0.3, 0.6, 0.2, and -0.1 in 1991–95, 1996–2000, 2001–05, and 2006–09. In contrast, a pronounced trend has been observed in the average changes in German inventories, which have experienced a dramatic swing from 0.8 percent of GDP from 1991–2000 to -1.0 percent of GDP more recently.[5]

Inventory's cyclical behavior has been notoriously noisy. In Germany and Italy, the average contribution to growth from inventories has been counter-cyclical (Table 1): in downswings (measured from peak to trough) the average contribution from inventories was positive while in upturns (measured as the change between the trough and the following two quarters) it was negative.[6] This pattern fits the counter-cyclical behavior found previously (Cesaroni, Maccini, and Malgarini, 2009). In France, inventories on average behaved consistently pro-cyclically in downswings, but mostly counter-cyclically in upswings. In the United States, inventories consistently behaved pro-cyclically in recent business cycles.[7] In all three recessions in this sample, the contribution to growth from inventories was negative and explained on average more than a third of the GDP decline. The average contribution was positive in all recent upswings and accounted for nearly half of the GDP increase in

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[4] This study uses Eurostat data (via Haver Analytics). Inventories are computed as the difference between gross capital investment and gross fixed capital investment, except for the United States that reports inventories separately (see Appendix 1 for more details on the data).

[5] While the implied decline in the level of inventories could be consistent with improvements in inventory management, the persistence of the accumulation and de-stocking of inventories indicates that the calculation of inventory investment in Germany serves as a balancing item in the national accounts.

[6] For Italy, the average in downturns is driven by the contribution from inventories in the 2003 recession. In Germany, the negative contribution from inventories in the downturn at end-1995 and the slightly positive contribution in the upturn following the 2003 recession appear to be the only exceptions to the general pattern observed.

[7] Note that the earlier evidence for the United States stems from business cycles dated by the NBER and, while broadly consistent are not strictly comparable to the dates used in this study.

these periods. This pattern has also been reported for earlier U.S. recessions but not necessarily for upturns (Hornstein, 1998).

With a one-year delay, however, inventories have contributed to recent recoveries in the largest European countries (Figure 3). On average, inventories have placed a small drag on economic growth in the first two quarters of recoveries in France and Italy (Figure 3, column 2). In Germany, this initial drag has been more notable and lasted twice as long. Still, inventories have boosted growth roughly a year into a recovery in all three European countries. In contrast, inventories have consistently supported U.S. upswings throughout the first 6 quarters of recovery—even though the boost experienced in upturns since 1991 has been less pronounced than in earlier business cycles (Sichel, 1994).

B. How Well Do Simple Inventory Models Fit the Data?

In the large European countries, output volatility exceeds that of sales—defined as the difference between output and inventories—a pattern that has become more pronounced since 2008 (Table 2). While over the entire sample period Germany was an outlier in this regard, in the more recent period its output variance has also exceeded that of sales. Following the available literature, and to isolate specific business cyclical regularities, "filtered" data have been constructed.[8] Indeed, a similar pattern emerges for these countries when examining movements associated with business cycle frequencies (between six and 24 quarters). However, with the exception of the United States, at a high frequency (between three and six quarters) the data suggest that the variance of output is less than that of inventories.

In addition, sales co-move with changes in inventories. In France and Italy, the correlation of sales and changes in inventories is positive, and has become stronger since 2008. In Germany and the United States, the correlation has been negative for the whole sample but has changed sign in the more recent period. For the most part, these correlations have behaved similarly in the filtered data.

These basic stylized facts of inventory behavior provide support for a standard buffer-stock model of inventories for Germany and the United States (Box 1). To the extent that firms hold inventories as a buffer, part of the volatility in sales would not feed into production: higher than anticipated demand would be satisfied by running down inventories. As a result, the volatility of output would be lower than that of sales and changes in

[8] This paper employs the Christiano-Fitzgerald (2003) band-pass filter that, in contrast with the Baxter-King filter, allows the weights on the leads and lags to differ. This asymmetric filter enables the analyst to use the full sample, which is important given the paper's interest in the most recent observations. Given the fact that the most recent recession was different from previous slowdowns, the question arises to what extent the Christiano-Fitzgerald filter can adequately capture this development. However, this problem would also afflict other filtering techniques. This study defines business cycle as those frequencies between six and 24 quarters; high frequencies are those between three and six quarters (see Figures A2–A5).

inventories would be negatively correlated with sales. In this regard, Germany stands out: it is fully consistent with the standard buffer-stock model (Table 3). In the United States, this is also true for unfiltered data but not for the business cycle or high frequency data movements. In Italy and France, the standard model is consistent only with high frequency data movements. The fact that support for a standard buffer stock model emerges when examining filtered data may reflect the fact that higher frequencies data movements are driven by demand as opposed to supply shocks.

A modified buffer-stock model or an (*S, s*) rule provides a better characterization of the data for France and Italy. If supply (or cost) shocks prevail and firms observe the realization of these shocks before setting production, a buffer-stock model predicts that output would become more volatile than sales and changes in inventories would be positively correlated with sales. While reflecting a different underlying mechanism, similar predictions about volatility and correlation stem from an (*S, s*) rule of inventory. These predictions are consistent with the data in France and Italy (except for high frequency movements), but obviously not with Germany. In the United States, only the inventory behavior at cyclical frequency is consistent with a modified buffer-stock or (*S, s*) rule.

For the United Kingdom and smaller European countries a modified buffer-stock model or an (*S, s*) rule provides a better description of the data. Specifically, the relative volatility of output to sales exceeds one while a positive correlation of sales and changes in inventories has been found in most of these countries (Tables A1 and A2). However, Ireland and the Netherlands stand out in sharp contrast exhibiting high sales volatility and an inverse correlation of sales and changes in inventories. Both countries are thus fully consistent with a standard buffer-stock model.

Even though the predictions of an (*S, s*) rule and a modified buffer-stock model are similar, the empirical evidence favors the later in most countries. The cost structure assumed by simple models of inventory behavior suggests that economies with large manufacturing sectors would be best characterized by production-smoothing and/or standard buffer-stock models; an (*S, s*) rule would likely explain inventory behavior in other economies. That is, the larger (smaller) the manufacturing sector the more (less) likely that the volatility of sales would exceed that of output and the negative correlation between sales and inventories would be higher (lower). A simple bivariate regression confirms this prediction (column 1, Table 4), but these estimates are not statistically significant nor does the regression explain much of the cross-country variation. A tantalizing result emerges, however, when splitting the sample between those countries well characterized by standard buffer-stock model—namely Ireland, Germany, the Netherlands, and the United States—and those that are not. The explanatory power of the regression increases substantially and

Box 1. Two Simple Models of Inventories

Two simple microeconomic frameworks, reflecting the motive to hold and the cost structure to acquire inventories, underlie models of inventory behavior. A production-smoothing/buffer-stock model focuses on the desire to hold a stock of inputs and/or finished goods either to avoid disruptions in production or stock-outs. In this setup, the marginal cost (of inventories) is upward sloping. Inspired by retail sales, the so-called (*S, s*) rule stems from the assumption that the cost of inventory comprises a fixed cost of placing an order and a constant marginal cost for each item ordered. In this model, the firm chooses an optimum *s* that whenever inventories fall below that level an order is placed to restore inventories to their optimal upper limit, *S*. The optimum order size is thus *S*-*s*.

Production-smoothing and/or buffer-stock models of inventories predict that sales are more volatile than output in the presence of demand shocks. Profit maximizing firms, facing increasing marginal costs and uncertain demand, will meet unusually high demand by drawing down inventories rather than by boosting production. Besides reducing the volatility of output, this results in a negative correlation between changes in inventories and sales.

But output could be more volatile than sales if supply shocks prevail. To the extent that firms make production decisions after observing their marginal costs, they will choose to boost production (and thereby build inventories) whenever costs are unusually low. Thus, predictions about the volatility of output and the correlation of changes in inventories with sales are the opposite: output is more volatile than sales and the correlation between changes in inventories and sales is positive.

Predictions from an (*S, s*) rule of inventories resemble those of supply shocks but reflect a different underlying mechanism. When faced with unusually high demand, firms sell from inventories but the correlation between the change in inventories and sales will depend on the distribution of initial inventories in the economy. In other words, the correlation will depend on how far inventories are from *s*, which in turn depends on the history of shocks. If initially inventories are low, then the correlation between the change in inventories and sales will be positive; otherwise the correlation will be small (or zero if no firm hits *s*). This implies that the volatility of output will be higher than sales since the variance of output (*Y*) equals the sum of the variance of sales (*S*) and of the change in inventories (ΔInv), plus twice the covariance: $Var(Y) = Var(S) + Var(\Delta Inv) + 2Cov(S, \Delta Inv)$.

estimates become statistically significant (column 2). Moreover, the estimates suggest that the basic stylized facts of inventory behavior become more accentuated with the size of manufacturing: the volatility of output versus sales declines (increases) and the correlation between sales and inventories becomes more negative (positive) in standard buffer-stock (nonstandard buffer-stock) countries. For nonstandard buffer-stock countries, this is the opposite of what would be expected if inventories were best explained by an (*S, s*) rule. A smaller retail (larger manufacturing) should decrease the volatility of output and increase the negative correlation between sales and inventories.

Labor market rigidities also play a role in determining the basic stylized facts of inventory behavior. All else equal, a less flexible labor market would be expected to dampen output volatility by reducing the volatility of labor input (Blanchard, 1983 and Eichenbaum, 1984). A simple bivariate regression does not uncover much evidence in this regard (column 3), but splitting the sample as above dramatically increases the explanatory power of the regression and results in statistically significant estimates (column 4). In this case, greater labor market rigidities—measured using the OECD's employment protection legislation index—accentuate the basic stylized facts for standard buffer-stock countries with little or no effect on nonstandard buffer-stock countries.[9]

III. The Role of Inventories in Forecasting Output Growth

Assessing the extent that changes in inventories can provide information to forecast economic developments can offer further insight into output and inventory cycles. A simple empirical framework has been employed in this regard.

A. Time-Series Models for Output Growth

An autoregressive (AR) model has been estimated to provide baseline forecast performance for output growth. Specifically,

$$\hat{y}_t = A(\mathrm{L}) \cdot \hat{y}_{t-1} + \mu^{(base)}{}_t ,$$

where $\hat{y}_t$ and $\mu^{(base)}{}_t$ denote output growth and a well-behaved error term; $\mathrm{A}(L)$ represents a lag polynomial of order p. Rather than relying on standard information statistics to determine p, this study selects lags to minimize Theil's U-statistic at a forecast horizon of four quarters.[10] The AR models thus extract all the information from the lags of output growth to forecast growth with disregard for parsimony.

An augmented model has also been estimated to examine the information content of inventories in forecasting output growth. Namely,

$$\hat{y}_t = \tilde{A}(\mathrm{L}) \cdot \hat{y}_{t-1} + B(\mathrm{L}) \cdot \Delta\widehat{inv}_{t-1} + \mu^{(aug)}{}_t ,$$

[9] Although the statistical significance for individual regressors fall, the results are qualitatively unchanged when both explanatory variables are included in the regression (columns 5 and 6) or if the dummy variable is added (un-interacted) to the regressions (not shown).

[10] Theil's U-statistic is the ratio of the root mean square error of the forecast model to that of a naïve (no change) forecast. Thus, a U-statistic less than one (at a specific forecast horizon) means that the model outperforms the naïve model (at that horizon). See Diebold (2007) for details.

where $\Delta \hat{inv}_{t-1}$ and $\mu^{(aug)}{}_t$ denote the growth rate in the change in inventories and well-behaved error term; $B(\mathrm{L})$ represents a lag polynomial of order p as above. In this setup, output growth forecasts are conditional on the future path of inventories and the analyst has perfect foresight regarding this path.[11] A more realistic second version of the augmented model has also been analyzed where a second equation simultaneously forecasts $\Delta \hat{inv}_{t-1}$:

$$\Delta \hat{inv}_t = C(\mathrm{L}) \cdot \hat{y}_{t-1} + D(\mathrm{L}) \cdot \Delta \hat{inv}_{t-1} + \tilde{\mu}_t^{(aug)}.$$

In this version both variables are dynamically forecasted by what amounts to a VAR model.

To advance the analysis, the following thought experiment has been examined. Assume that the data generating process (DGP) for the economy can be characterized by the VAR model above. In this setting, what would be the consequence of cavalierly assuming that the change in inventories is zero in the forecast horizon? This question can be examined by a horse race between the forecasts of the augmented (VAR) model and those obtained by using only the first equation of the augmented (VAR) model:

$$\hat{y}_t = \tilde{A}(\mathrm{L}) \cdot \hat{y}_{t-1} + B(\mathrm{L}) \cdot \Delta \hat{inv}_{t-1} + \mu^{(aug)}{}_t,$$

where $\Delta \hat{inv}_{t-1}$ have been set to zero in the forecast period.[12] If the economy's true DGP was best characterized by the augmented (VAR) model, disregarding the inventory cycle should worsen the forecast performance.

B. Forecast Performance

To assess the information content of inventories, the following forecasting horse race has been performed. Setting the highest forecast horizon to eight quarters, the race begins with the output growth forecast for the first quarter of 2005 using data through end-2004. In subsequent quarters, the race continues by updating forecasts obtained by re-estimated models using additional data points. The race extends through the fourth quarter of 2009 and thus provides a total of 20 forecasts at horizon one, 19 forecasts at horizon two, and so on; at horizon eight 13 forecasts are generated. These forecasts are used to compute forecast error statistics for unfiltered data: statistics for cyclical and high frequencies data provided for completeness.

[11] For the discussion below, note that coefficients $\tilde{A}(\mathrm{L})$ of the augmented model differ from $A(\mathrm{L})$ of the base model because the former are jointly estimated with $B(\mathrm{L})$.

[12] This is not equivalent to comparing the base model forecasts to those of the bivariate VAR model since the coefficients of $A(\mathrm{L})$ differs from those of $\tilde{A}(\mathrm{L})$. Moreover, the model's lag have been re-optimized based on the *U*-statistic from the bivariate VAR model.

Before turning to the horse races, a brief summary of the baseline forecast errors of unfiltered growth data can help fix orders of magnitude (Table 5). On average, base models over-shot growth during 2005–09. In Europe, this ranged from about 10–15 basis points at a forecast horizon of one quarter to about 40–70 basis points at a forecast horizon of eight quarters. In the United States, over-shooting was larger at short forecast horizons—about 30 basis points at horizon one quarter—but comparable for forecast horizons greater than three quarters. Still, the difference between the mean absolute error and the mean error suggests that these base models did not systematically over-shoot growth. In addition, Theil *U*-statistics less than one suggest that base models outperformed a naïve forecast (no change) in Germany and France, and, to a lesser extent, in Italy and the United States.

Adding inventories tends to improve output growth forecasts beginning at forecast horizons of four quarters (Table 6). Keeping in mind that differences emerging from most horse races are not statistically significant at conventional significance levels, the *U*-statistics decrease for both the perfect foresight and dynamically forecasted changes in inventories (columns labeled actual and dynamic) compared to the base model, which does not include inventories in its information set. In Italy, adding inventories also improves growth forecasts for forecast horizons of four quarters or less. The beneficial effect on forecasting performance does not hold for unfiltered growth or for high frequencies of growth. At cyclical frequencies in France, however, adding inventories improves forecasts for horizons of four quarters or less. Of note, growth forecasts from perfect foresight inventory models are typically better than those of dynamically forecasted changes in inventories.

Disregarding the change in inventories when forecasting unfiltered output growth improves forecasts in Europe, but worsens forecasts of cyclical or higher frequencies (Table 7). With the proviso that differences are mostly statistically insignificant, and compared to a DGP characterized by the bi-variate VAR discussed above, the results can be summarized as follows:

- For unfiltered data, output growth forecasts broadly improve in Europe with the exception of forecast horizons between four and six quarters in Germany. In the United States, growth forecasts worsen for horizons greater than three quarters.

- For cyclical frequencies, growth forecasts improve for Italy, remain roughly unaffected in France, and worsen in Germany. In the United States, growth forecasts worsen.

- For high frequencies, forecasts broadly worsen, with the exception of horizons greater than six quarters in Italy. In the United States, the impact alternates over various horizons.

Thus, inventories appear to help in forecasting growth primarily at higher frequencies where demand shocks are more likely to dominate.

In addition, forecasting models for the United Kingdom and smaller European countries point to the following:

- On average, base models have also over-shot growth during 2005–09. This ranged from about 10–20 basis points at a forecast horizon of one quarter to about 50–100 basis points at a forecast horizon of eight quarters with the exception of Ireland and Luxembourg where the forecasting errors were much higher (Table A3). As above, the difference between the mean absolute error and the mean error suggests that the base models did not systematically over-shoot growth. In addition, Theil *U*-statistics less than one suggest that the base model outperformed a naïve forecast (no change) in all countries except Spain.

- The evidence in favor of adding inventories to improve output growth forecasts appears mixed. In most countries, the *U*-statistics increases (worsen) for both the perfect foresight and dynamically forecasted changes in inventories (Table A4, columns labeled actual and dynamic) compared to the base model. But the *U*-statistics decrease (improve) for Ireland and the Netherlands, the two countries best characterized by demand shocks.

- Setting changes in inventories equal to zero improves growth forecasts in most countries, except in Ireland and at longer forecast horizons in the United Kingdom (Table A5).

IV. Final Remarks

The "Great Recession" has rekindled the long-standing interest in inventories and the business cycle. In particular, attention has focused on whether the slower pace of destocking or an outright restocking of inventories would be the bellwether of a vigorous inventory-investment led economic recovery as in the past. Could recent improvements in information technology changed the typical recovery profile?

While inventories have been notoriously noisy, in Europe inventories have contributed to economic recoveries with a lag in the past 20 years. In the three largest economies in Europe, the boost provided by inventories has materialized a year into an economic recovery. At the outset of a recovery, however, inventories have posed a small drag on activity, particularly in Germany. This pattern broadly suggests that recoveries in these economies would be best described as U-shaped: recoveries take about a year to take hold. In contrast, inventories in the United States have consistently contributed to growth in a recovery but less sharply than in previous business cycles. Thus, the typical V-shaped recovery appears to continue to depict recent U.S. business cycles, albeit the recovery leg appears to be less pronounced.

Inventory behavior in Ireland, Germany, the Netherlands, and the United States can be characterized by a standard buffer-stock model. The standard buffer-stock model predicates that firms will meet unusually high demand periods by running down inventories thereby mitigating output volatility and resulting in a negative correlation between sales and inventories. In this regard, Ireland, Germany, and the Netherlands stand out: these economies are fully consistent with the standard buffer-stock model. The picture for inventory behavior in the United States is more nuanced: a standard buffer model fits the unfiltered data, but not at business cycle or high frequency movements in the data. This result stands in contrast to the presumption that demand shocks dominate at higher frequencies. Indeed, in Italy and France, the standard model is consistent only with high frequency movements in the data.

A modified buffer-stock provides a better characterization of inventory behavior in France, Italy, and a number of other European economies. This model predicts that output volatility will be greater than that of sales and the correlation between changes in inventories and sales will be positive when supply shocks predominate. These predictions fit well with the stylized facts of inventory behavior in many European economies. In addition, the relation between the size of the manufacturing sector and inventory's stylized facts does not sit well with an (*S, s*) rule. This thus suggests that differences in inventory behavior across Europe appear to be rooted in the nature of the shocks—with supply shocks prevailing in most countries—not in differences in the underlying behavioral model. Further research will be needed, however, to provide direct evidence on the dominance of specific shocks and examine the distribution of shocks, which is a critical element for (*S, s*) rules.

The empirical evidence suggests that inventories provide limited information to forecast output growth. Specifically, when compared to forecasts made using only past values of growth, adding inventories did reduce forecasting errors, particularly at forecast horizons of four quarters or higher. In Italy, beneficial effects were found at shorter horizons. However, the improvement in forecasting performance was neither large nor statistically significant.

Improvements in forecasting growth were found to be more prevalent when a standard buffer-stock model best characterized inventory behavior. The improvement was found for Ireland, Germany, and the Netherlands where inventory behavior is fully consistent with a standard demand-shock driven buffer-stock model. Why do inventories help forecast growth when demand shocks prevail? Conceivably, demand shocks may have greater persistence (autocorrelation) and thus inventories would serve to anticipate future demand. In addition, the information content of inventories may increase when output fluctuations are dampened by labor market rigidities, which are correlated with the main predictions of a standard demand-shock drive buffer-stock model. Still, further research would be needed to understand why inventories also help forecast growth in countries best characterized by a nonstandard buffer-stock model.

Still, not much harm is done when inventories are not forecasted separately but seen as an integral part of output growth. Indeed, if anything, forecast performance improves when inventories are not forecasted. In part, this reflects the fact that growth forecasts worsen when inventories are forecasted dynamically. Removing this source of error—ignoring the future evolution of inventories—thus improves the accuracy of output growth forecasts. This does not contradict the fact that inventories provide useful information. What this suggests is that the beneficial effect of inventories stems from estimating the dynamics of output growth—an essential part of accurate forecasting—but the volatility of inventories detracts from output growth forecasts.

Table 1. Inventory Investment and the Business Cycle 1/ 2/

	Change in real GDP	Change in inventory investment	Change in inventory investment as a percentage of the change in real GDP 3/	Average contribution to growth from inventories (quarter-on-quarter, annualized)
Germany				
Peak-to-trough:				
91:2 - 91:3	-5311	19	…	0.0
95:4 - 96:1	-3983	-957	24.0	-0.4
02:4 - 03:2	-4641	2177	…	0.6
08:2 - 09:1	-38530	1216	…	0.2
Average	-13116	614	24.0	0.1
Upturn:				
91:3 - 92:1	14476	-1782	…	-0.8
96:1 - 96:3	9590	-4057	…	-1.7
03:2 - 03:4	4434	147	3.3	0.1
09:1 - 09:3	6291	-3284	…	-1.0
Average	8698	-2244	3.3	-0.9
France 4/				
Peak-to-trough:				
92:4 - 93:1	-3749	-2656	70.8	-1.7
01:2 - 01:4	-688	-1399	203.3	-0.5
08:2 - 09:1	-14299	-4726	33.1	-1.1
Average	-6245	-2927	102.4	-1.1
Upturn:				
93:1 - 93:3	834	408	48.9	0.3
01:4 - 02:2	4431	-212	…	-0.1
09:1 - 09:3	2052	-2626	…	-1.3
Average	2439	-810	48.9	-0.4
Italy				
Peak-to-trough:				
92:2 - 93:3	-4866	-1538	31.6	-0.4
01:2 - 01:4	-1904	105	…	0.1
03:1 - 03:2	-1906	2793	…	1.9
04:4 - 05:1	-688	-188	27.4	-0.1
08:2 - 09:2	-21619	-2356	10.9	-0.6
Average	-6197	-237	23.3	0.2
Upturn:				
93:3 - 94:1	3412	1265	37.1	1.0
01:4 - 02:2	2075	2137	103.0	1.4
03:2 - 03:4	2225	-1082	…	-0.7
05:1 - 05:3	3103	-3589	…	-2.3
Average	2704	-317	70.0	-0.1
United States 5/				
Peak-to-trough:				
90:3 - 91:1	-109	-42	38.5	-0.3
00:4 - 01:4	46	-149	…	-1.3
07:4 - 09:2	-490	-171	34.8	-0.9
Average	-184	-120	36.7	-0.8
Upturn:				
91:1 - 91:3	87	17	19.1	0.4
01:4 - 02:2	159	104	65.6	0.3
09:2 - 09:4	260	143	55.2	2.2
Average	169	88	46.6	1.0

1/ Inventory investment is defined as the change in inventories.

2/ 'Peak-to-trough' episodes are identified by two consecutive quarter-on-quarter negative growth rates, with exceptions, see other footnotes. The 'upturn' is measured as the change between the trough and the following two quarters.

3/ '…' is shown when the sign for the change in real GDP differs from the sign of the change in inventory investment.

4/ For France, we also define 2001 as a recession, although only two in three quartes registered negative q-o-q growth.

5/ For the United States, we use the NBER dates to identify downturns. Note that for the recession in 2001, real GDP actually increased in the time period specified by the NBER.

Table 2. Basic Statistics 1/ 2/

	Var (GDP) / var (sales)		Correlation (sales, ?inv.)	
	91:1 - 09:4	08:1 - 09:4	91:1 - 09:4	08:1 - 09:4
Germany				
Unfiltered series	0.79	1.20	-0.86	0.14
Cyclical component 3/	0.86	1.04	-0.38	0.02
High-frequency component 4/	0.51	0.99	-0.70	-0.30
France				
Unfiltered series	1.02	3.39	0.18	0.61
Cyclical component 3/	2.27	2.67	0.42	0.82
High-frequency component 4/	0.48	0.95	-0.72	-0.41
Italy				
Unfiltered series	1.03	1.08	0.22	0.23
Cyclical component 3/	1.32	1.19	0.46	0.91
High-frequency component 4/	0.35	0.60	-0.81	-0.66
United States				
Unfiltered series	0.99	1.75	-0.24	0.75
Cyclical component 3/	1.55	1.64	0.45	0.98
High-frequency component 4/	1.34	1.53	-0.25	-0.11

1/ All variables are in levels and constant prices.

2/ Sales = GDP - change in inventories.

3/ Derived from a Christiano-Fitzgerald (2003) form of the band-pass filter, choosing periodicities between 6-24 quarters (see Appendix 2).

4/ Derived from a Christiano-Fitzgerald (2003) form of the band-pass filter, choosing periodicities between 3-6 quarters (see Appendix 2).

Table 3. Inventory Model Scorecard 1/

	Germany			France			Italy			United States		
	Unfiltered	Cyclical	High freq.	Unfiltered	Cyclical	High freq.	Unfiltered	Cyclical	High freq.	Unfiltered	Cyclical	High freq.
Smoothing motive												
Demand shocks												
Var (GDP) / var (sales) < 1	5	5	5	0	0	5	0	0	5	5	0	0
Corr (sales, ? inventories) < 0	5	5	5	0	0	5	0	0	5	5	0	5
	10	10	10	0	0	10	0	0	10	10	0	5
Supply shocks												
Var (GDP) / var (sales) > 1	0	0	0	5	5	0	5	5	0	0	5	5
Corr (sales, ? inventories) > 0	0	0	0	5	5	0	5	5	0	0	5	0
	0	0	0	10	10	0	10	10	0	0	10	5
(*S, s*) model												
Var (GDP) / var (sales) > 1	0	0	0	5	5	0	5	5	0	0	5	5
Corr (sales, ? inventories) > 0	0	0	0	5	5	0	5	5	0	0	5	0
	0	0	0	10	10	0	10	10	0	0	10	5

Source: Authors' calculations based on Table 1.
1/ Five points are awarded when the prediction of the model is found in the data.

Table 4. Explaining the Basic Stylized Facts of Inventory Behavior

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:						
Ratio of the variances of ouptut to sales						
Constant	1.04	0.97	0.99	1.02	1.04	1.01
	(14.21)	(14.33)	(20.83)	(32.81)	(10.61)	(14.72)
Share of manufacturing	-0.21	0.27			-0.22	0.11
	-(0.63)	(0.79)			-(0.60)	(0.34)
Share of manufacturing * dummy		-0.40				-0.05
		-(2.36)				-(0.17)
Employment protection legislation			0.001	-0.002	-0.001	-0.002
			(0.07)	-(0.13)	-(0.06)	-(0.15)
Employment protection legislation * dummy				-0.06		-0.05
				-(4.01)		-(1.84)
standard error of the regression	0.067	0.056	0.069	0.043	0.071	0.049
r^2	0.038	0.406	0.000	0.641	0.039	0.647
$rbar^2$	-0.058	0.274	-0.100	0.562	-0.175	0.446
Correlation of sales and the change in inventories						
Constant	0.11	-0.43	-0.13	0.07	-0.07	-0.31
	(0.27)	-(1.53)	-(0.50)	(0.44)	-(0.13)	-(1.08)
Share of manufacturing	-0.47	3.25			-0.25	2.49
	-(0.24)	(2.26)			-(0.12)	(1.86)
Share of manufacturing * dummy		-3.04				-1.38
		-(4.36)				-(1.19)
Employment protection legislation			0.06	0.05	0.06	0.01
			(0.60)	(0.77)	(0.54)	(0.20)
Employment protection legislation * dummy				-0.32		-0.23
				-4.58		-1.96
standard error of the regression	0.388	0.232	0.382	0.220	0.402	0.204
r^2	0.006	0.680	0.035	0.711	0.037	0.807
$rbar^2$	-0.093	0.609	-0.061	0.646	-0.177	0.696

Note: Based on cross sectional averages for 11 European countries and the United States. Dummy is a binary variable that is one for countries best characterized by the demand shock model (Ireland, Germany, Netherlands, and the U.S.). T-statistics are provided in parenthesis.

Table 5. Baseline Forecasting Performance, 2005:Q1 through 2009:Q4

(The mean error (ME), the absolute mean error (MAE), and root mean square error (RMSE) are measured in percentage points; the U-stat is unitless)

	Forecast horizon	Germany						France				
		ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-0.09	0.89	1.28	1.02	20		-0.12	0.43	0.58	0.92	20
(lags=4)	2	-0.08	0.90	1.30	0.81	19	(lags=1)	-0.18	0.46	0.67	0.89	19
	3	-0.15	0.83	1.28	0.73	18		-0.21	0.46	0.72	0.82	18
	4	-0.21	0.82	1.31	0.77	17		-0.28	0.50	0.75	0.79	17
	5	-0.22	0.88	1.34	0.94	16		-0.31	0.51	0.77	0.92	16
	6	-0.27	0.90	1.38	0.89	15		-0.34	0.54	0.80	0.89	15
	7	-0.37	0.89	1.39	0.92	14		-0.41	0.52	0.80	0.92	14
	8	-0.44	0.91	1.44	0.89	13		-0.41	0.54	0.83	0.86	13
Cyclical frequency	1	-2,099.64	2,169.25	6,791.56	0.72	20		-298.30	408.09	840.19	0.73	20
(lags=1)	2	-2,189.40	2,249.70	6,962.04	0.72	19	(lags=4)	-285.76	415.00	855.19	0.72	19
	3	-2,306.41	2,394.89	7,156.00	0.74	18		-195.04	341.65	814.06	0.69	18
	4	-2,455.16	2,516.69	7,371.40	0.73	17		-183.24	322.85	829.91	0.87	17
	5	-2,601.48	2,632.26	7,436.46	0.72	16		-178.23	336.96	859.74	0.93	16
	6	-875.12	914.30	2,308.78	0.30	15		-188.89	366.14	889.03	0.95	15
	7	-932.34	970.16	2,394.26	0.30	14		-227.49	361.72	915.77	0.96	14
	8	-995.53	1,030.45	2,456.00	0.30	13		-234.62	385.93	950.07	1.00	13
High frequency	1	-1,170.16	1,170.16	1,226.68	2.67	20		-113.93	237.21	314.92	0.79	20
(lags=1)	2	-1,168.12	1,168.12	1,227.03	2.58	19	(lags=2)	-98.73	230.71	314.30	0.74	19
	3	-1,181.88	1,181.88	1,243.37	2.49	18		-116.83	236.01	321.94	0.73	18
	4	-1,194.35	1,194.35	1,258.65	2.41	17		-117.32	242.85	329.70	0.72	17
	5	-1,205.99	1,205.99	1,273.23	2.36	16		-115.63	248.00	336.98	0.73	16
	6	-1,216.05	1,216.05	1,286.15	2.31	15		-110.83	251.16	343.46	0.71	15
	7	-1,222.77	1,222.77	1,269.39	2.18	14		-103.35	252.98	349.26	0.70	14
	8	-1,126.49	1,126.49	1,134.27	2.82	13		-92.92	254.05	354.27	0.76	13
		Italy						US				
		ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-0.14	0.60	0.81	1.04	20		-0.33	0.56	0.77	1.13	20
(lags=2)	2	-0.18	0.72	1.08	0.98	19	(lags=1)	-0.46	0.67	0.93	0.98	19
	3	-0.28	0.77	1.10	0.90	18		-0.50	0.69	0.97	0.84	18
	4	-0.45	0.70	1.07	0.92	17		-0.56	0.72	0.99	0.89	17
	5	-0.53	0.76	1.12	1.08	16		-0.58	0.76	1.03	0.94	16
	6	-0.60	0.80	1.17	1.02	15		-0.66	0.76	1.05	1.00	15
	7	-0.67	0.84	1.21	0.94	14		-0.68	0.79	1.07	0.99	14
	8	-0.73	0.89	1.26	0.92	13		-0.67	0.79	1.10	1.08	13
Cyclical	1	257.03	483.67	1,064.21	0.79	20		675.05	747.50	829.80	1.16	20
(lags=18)	2	176.67	441.20	1,066.91	0.77	19	(lags=1)	589.24	665.87	700.76	1.00	19
	3	284.81	361.90	994.16	0.70	18		587.86	666.71	711.43	1.06	18
	4	282.87	360.06	1,019.98	0.98	17		616.98	699.37	728.94	1.00	17
	5	291.21	374.15	1,041.98	1.01	16		615.90	701.69	738.96	1.09	16
	6	267.66	412.04	1,082.37	0.96	15		639.63	730.23	757.84	1.13	15
	7	344.04	428.37	1,116.88	0.97	14		640.07	735.50	768.52	1.35	14
	8	361.27	446.12	1,156.27	1.10	13		657.68	758.63	787.70	1.25	13
High frequency	1	-41.49491	91.01952	145.3893	0.7568	20		28.48	275.58	522.02	0.69	20
(lags=8)	2	-53.41549	83.47726	141.0095	0.7082	19	(lags=4)	18.93	279.48	534.66	0.69	19
	3	-52.15241	86.07578	143.3787	0.693	18		12.47	289.64	549.61	0.69	18
	4	-52.59818	88.96125	147.2336	0.7018	17		13.99	307.19	564.26	0.69	17
	5	-55.54005	93.11832	151.889	0.7091	16		-13.85	283.79	569.70	0.74	16
	6	-48.28793	95.41287	155.7197	0.6975	15		-29.18	296.43	586.94	0.66	15
	7	-40.81658	94.31716	160.3179	0.6944	14		-45.01	302.44	601.99	0.63	14
	8	7.91854	49.76499	82.93222	0.5266	13		-63.85	309.06	620.33	0.70	13

Note: Based on individual country univariate AR models for output growth with lags selected to minimize the Theil U-stat at four quarters in the forecast period.

Table 6. Assessing the Information Content of Inventories in Forecasting Output Growth

		Germany Theil U-stat					France Theil U-stat				
	Forecast horizon	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value
Unfiltered	1	1.018	1.026	0.22	1.026	0.22	0.921	0.926	0.29	0.926	0.29
	2	0.811	0.817	0.49	0.823	0.27	0.887	0.890	0.37	0.888	0.39
	3	0.731	0.741	0.44	0.737	0.37	0.820	0.820	0.48	0.821	0.33
	4	0.769	0.765	0.47	0.772	0.50	0.791	0.790	0.46	0.791	0.23
	5	0.939	0.920	0.34	0.942	0.24	0.915	0.913	0.26	0.915	0.34
	6	0.894	0.876	0.30	0.895	0.41	0.892	0.890	0.20	0.892	0.50
	7	0.921	0.898	0.19	0.923	0.50	0.921	0.918	0.50	0.921	0.30
	8	0.887	0.865	0.12	0.887	0.44	0.864	0.861	0.08	0.864	0.15
Cyclical frequency	1	0.723	0.723	0.11	0.723	0.11	0.727	0.958	0.18	0.958	0.18
	2	0.720	0.721	0.11	0.720	0.15	0.719	0.962	0.28	0.957	0.28
	3	0.740	0.741	0.10 *	0.740	0.21	0.694	0.974	0.28	0.698	0.20
	4	0.733	0.734	0.10 *	0.733	0.31	0.872	0.749	0.22	0.868	0.24
	5	0.720	0.720	0.14	0.720	0.27	0.926	0.784	0.10 *	0.922	0.13
	6	0.304	0.304	0.06 *	0.304	0.48	0.948	0.794	0.10 *	0.946	0.17
	7	0.300	0.301	0.00 ***	0.300	0.50	0.956	0.809	0.02 **	0.953	0.13
	8	0.296	0.296	0.50	0.296	0.48	0.996	0.842	0.50	0.997	0.27
High frequency	1	2.671	2.667	0.17	2.667	0.17	0.789	0.790	0.07 *	0.790	0.07 *
	2	2.580	2.580	0.47	2.580	0.16	0.739	0.740	0.06 *	0.741	0.01 ***
	3	2.487	2.497	0.42	2.487	0.32	0.731	0.732	0.03 **	0.731	0.14
	4	2.410	2.394	0.26	2.410	0.40	0.723	0.724	0.03 **	0.723	0.36
	5	2.359	2.397	0.29	2.359	0.50	0.732	0.734	0.00 ***	0.732	0.50
	6	2.313	2.345	0.01 ***	2.313	0.44	0.711	0.712	0.50	0.711	0.50
	7	2.182	2.222	0.50	2.182	0.49	0.705	0.706	0.50	0.705	0.50
	8	2.819	2.754	0.30	2.819	0.17	0.758	0.759	0.50	0.758	0.50

		Italy Theil U-stat					US Theil U-stat				
		Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value
Unfiltered	1	1.041	0.983	0.04 **	0.983	0.04 **	1.135	1.200	0.22	1.200	0.22
	2	0.975	0.924	0.08 *	0.957	0.07 *	0.975	1.017	0.12	0.976	0.21
	3	0.899	0.870	0.16	0.887	0.41	0.842	0.873	0.15	0.842	0.22
	4	0.921	0.907	0.13	0.919	0.10 *	0.888	0.920	0.15	0.889	0.18
	5	1.076	1.060	0.15	1.075	0.23	0.942	0.974	0.12	0.943	0.19
	6	1.019	1.005	0.15	1.019	0.16	1.004	1.041	0.05 **	1.004	0.26
	7	0.941	0.926	0.14	0.941	0.16	0.990	1.027	0.50	0.990	0.27
	8	0.918	0.894	0.00 ***	0.918	0.12	1.080	1.121	0.50	1.080	0.18
Cyclical	1	0.785	1.313	0.15	1.313	0.15	1.158	1.205	0.00 ***	1.205	0.00 ***
	2	0.770	2.046	0.07 *	1.908	0.07 *	1.002	1.051	0.01 ***	1.000	0.28
	3	0.700	3.528	0.14	3.352	0.13	1.064	1.118	0.01 ***	1.065	0.11
	4	0.983	1.524	0.18	1.893	0.17	1.000	1.051	0.50	1.000	0.00 ***
	5	1.014	2.219	0.22	3.149	0.22	1.093	1.150	0.50	1.094	0.05 **
	6	0.964	3.387	0.24	5.338	0.24	1.129	1.190	0.02 **	1.130	0.00 ***
	7	0.970	6.030	0.25	10.228	0.25	1.354	1.429	0.01 ***	1.356	0.00 ***
	8	1.099	11.845	0.27	21.837	0.26	1.250	1.319	0.03 **	1.251	0.00 ***
High frequency	1	0.757	0.788	0.17	0.788	0.17	0.688	2.842	0.19	2.842	0.19
	2	0.708	0.733	0.07 *	0.733	0.06 *	0.687	2.799	0.16	1.092	0.14
	3	0.693	0.719	0.03 **	0.703	0.03 **	0.688	2.778	0.17	1.102	0.17
	4	0.702	0.727	0.08 *	0.712	0.14	0.694	2.806	0.16	1.029	0.00 ***
	5	0.709	0.736	0.10 *	0.719	0.20	0.743	3.114	0.17	0.757	0.24
	6	0.698	0.726	0.06 *	0.708	0.00 ***	0.661	2.994	0.18	0.663	0.14
	7	0.694	0.720	0.03 **	0.701	0.50	0.634	1.992	0.15	0.639	0.10 *
	8	0.527	0.576	0.11	0.527	0.32	0.701	2.072	0.13	0.703	0.22

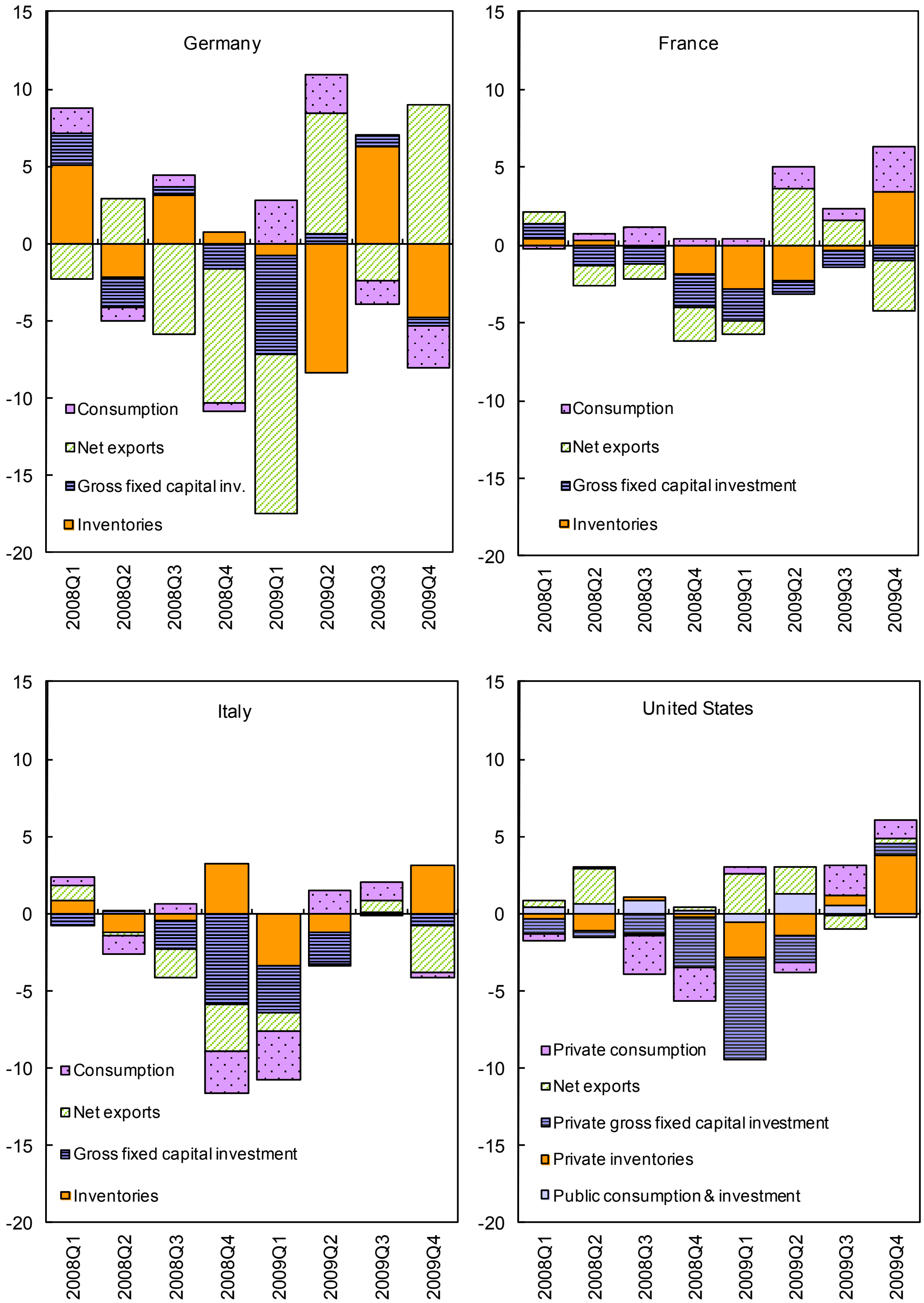
Note: Based on individual country AR models for output growth (see Table 4). Calculations for augmented models are obtained by including correspoinding lags in the "growth" of the change in inventories. The columns labeled "actual" assume perfect inventory foresight in the forecast horizon; those labeled "dynamic" forecast inventories dynamically using a bivariate VAR model. The p-value corresponds to a one-sided t-test--with degrees of freedom equal to the number of forecasts at the specific horizon minus one--comparing the mean square errors of the base model to that of the augmented models. The test is based on a modified Diebold-Mariano test Harvey, Leybourne, and Newbold, 1997). Significance at 10 percent, 5 percent, and 1 percent is denoted by *, **, and ***.

Table 7. To What Extent Does Setting to Zero the Forecast for Inventories Worsen Output Growth Forecasts?

Unfiltered	Forecast horizon	Germany Theil U-stat Augmented	Germany Theil U-stat Δinv=0	Germany p-value		France Theil U-stat Augmented	France Theil U-stat Δinv=0	France p-value		Italy Theil U-stat Augmented	Italy Theil U-stat Δinv=0	Italy p-value		US Theil U-stat Augmented	US Theil U-stat Δinv=0	US p-value
(lags=15)	1	1.086	1.035	0.01 ***	(lags=1)	0.927	0.892	0.16	(lags=2)	0.984	0.977	0.08 **	(lags=4)	1.392	1.132	0.03 **
	2	0.951	0.820	0.50		0.889	0.858	0.15		0.952	0.854	0.48		0.999	0.908	0.28
	3	0.767	0.771	0.36		0.821	0.797	0.16		0.885	0.828	0.19		0.940	0.855	0.33
	4	0.709	0.814	0.27		0.791	0.778	0.07 *		0.919	0.916	0.16		0.885	0.908	0.40
	5	0.869	0.962	0.07 *		0.914	0.903	0.14		1.072	1.066	0.47		0.921	0.974	0.10 *
	6	0.875	0.867	0.31		0.889	0.877	0.18		1.016	1.004	0.16		0.988	1.045	0.05 **
	7	1.028	0.830	0.00 ***		0.923	0.911	0.09 *		0.939	0.925	0.06 **		0.984	1.036	0.00 ***
	8	0.951	0.765	0.50		0.863	0.850	0.50		0.914	0.900	0.50		1.064	1.121	0.50
Cyclical																
(lags=1)	1	0.723	0.732	0.05 **	(lags=4)	0.958	0.718	0.15	(lags=16)	0.950	0.708	0.13	(lags=5)	1.172	1.316	0.01 ***
	2	0.721	0.728	0.03 **		0.960	0.711	0.27		1.044	0.703	0.15		0.988	1.154	0.03 **
	3	0.740	0.747	0.03 **		0.697	0.708	0.20		1.309	0.689	0.16		1.026	1.214	0.03 **
	4	0.734	0.739	0.04 **		0.869	0.877	0.22		0.973	0.970	0.20		0.955	1.118	0.01 ***
	5	0.736	0.742	0.10 *		0.922	0.930	0.18		1.008	1.009	0.31		1.012	1.199	0.50
	6	0.304	0.330	0.11		0.943	0.952	0.16		0.932	0.928	0.50		1.127	1.238	0.02 **
	7	0.301	0.325	0.14		0.954	0.963	0.17		0.955	0.936	0.50		1.346	1.470	0.04 **
	8	0.300	0.323	0.09		0.996	1.003	0.50		1.082	1.063	0.50		1.268	1.354	0.16
High frequency																
(lags=1)	1	2.703	3.086	0.00 ***	(lags=3)	0.801	0.810	0.01 ***	(lags=7)	0.763	0.769	0.04 **	(lags=15)	2.341	0.875	0.05 **
	2	2.613	2.950	0.00 ***		0.744	0.748	0.30		0.712	0.721	0.05 **		0.770	0.863	0.19
	3	2.521	2.823	0.00 ***		0.737	0.744	0.25		0.698	0.702	0.50		1.428	0.859	0.11
	4	2.445	2.717	0.00 ***		0.724	0.735	0.20		0.706	0.708	0.50		0.710	0.868	0.32
	5	2.396	2.640	0.02 **		0.735	0.744	0.21		0.713	0.717	0.15		0.756	0.928	0.00 ***
	6	2.352	2.572	0.04 **		0.714	0.724	0.17		0.711	0.710	0.41		0.723	0.710	0.13
	7	2.266	2.463	0.08 *		0.708	0.720	0.02 **		0.712	0.709	0.36		0.688	0.693	0.46
	8	2.882	3.179	0.12		0.763	0.778	0.50		0.532	0.522	0.28		0.791	0.783	0.36

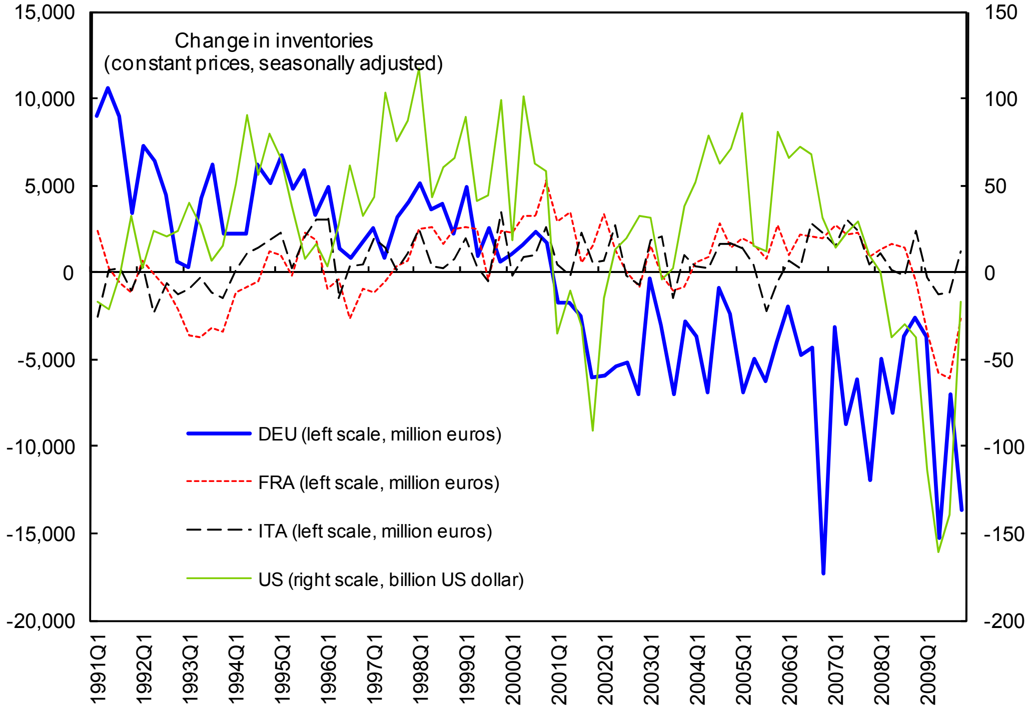
Note: Based a bi-variate VAR models for output growth and "growth" in the change in inventories with lags selected with the same criteria as in Table 4 applied to the VAR model (see Table 5). The U-stat for Δinv=0 columns corresponds to forecasts when the "growth" in the change in inventories is set to zero in the forecast period. The p-value corresponds to a one-sided t-test--with degrees of freedom equal to the number of forecasts at each horizon minus one--comparing the MSE of these two models forecasts. The test is based a modified Diebold-Mariano test (see Harvey, Leybourne, and Newbold, 1997).

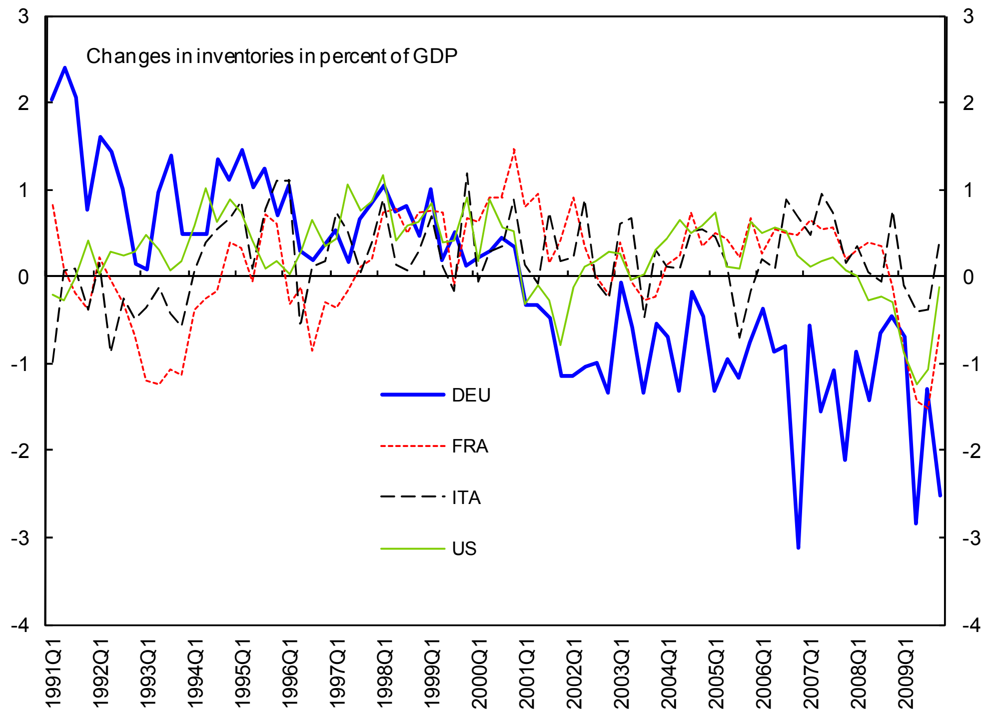
Figure 1. Contributions to Growth, 2008Q1 - 2009Q4
(q-o-q annualized, percentage points)



Sources: Eurostat; BEA; IMF staff calculations.

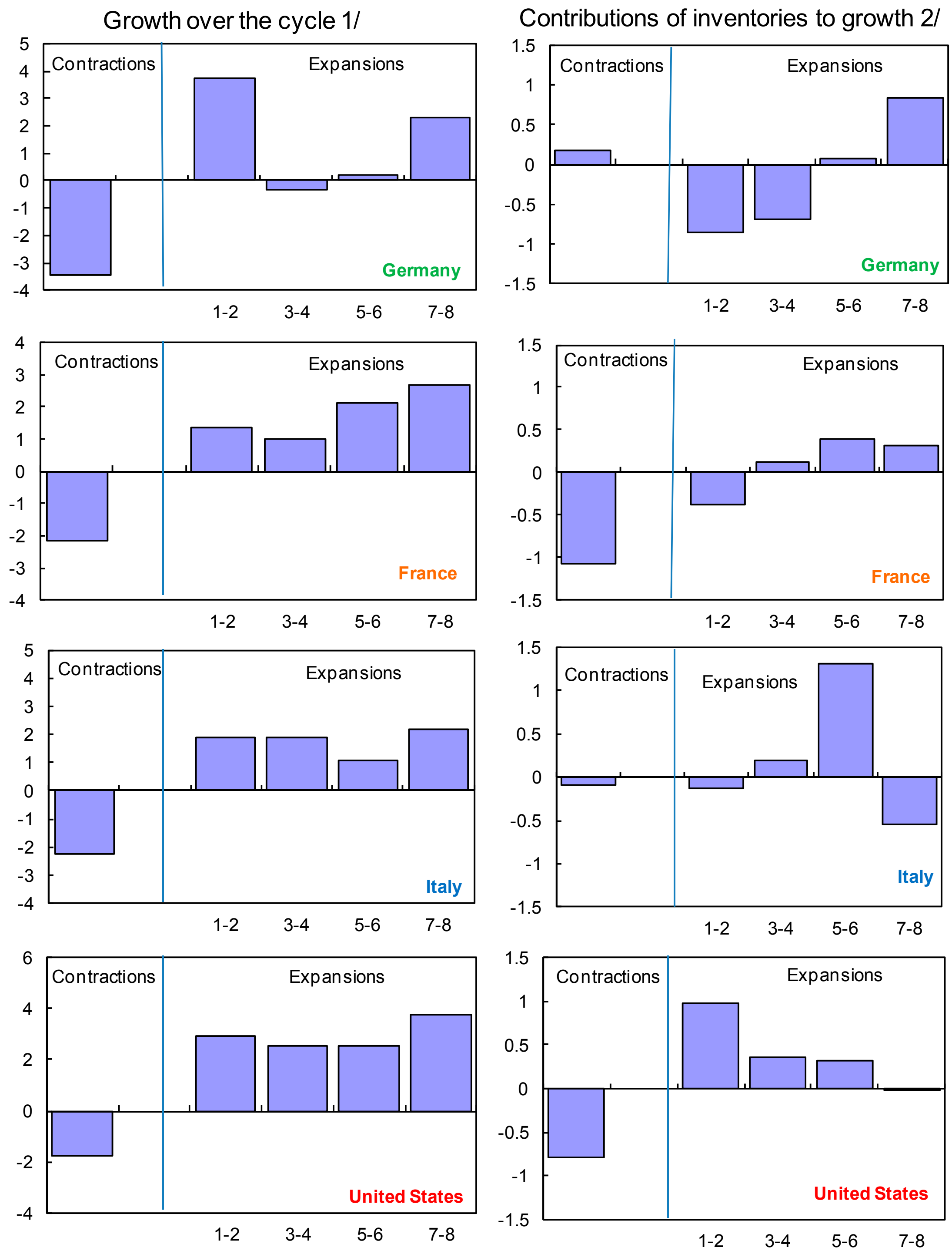
Figure 2. Inventories in Germany, France, Italy, and the US (1991Q1 - 2009Q4)





Sources: Eurostat; BEA; and IMF staff calculations.

Figure 3. Output Growth and Inventories, 1991 - 2009



Sources: Eurostat via Haver; IMF staff calculations.
1/ The first bar on the left shows the average rate of decline (percent, q-o-q annualized) during contractions. The bars to the right show the average growth rate during different parts of the expansion (quarters 1-2, quarters 3-4 etc.).
2/ The first bar on the left shows the average contribution to GDP growth (percentage points, q-o-q annualized) during contractions. The bars to the right show the average contribution rate during different parts of the expansion (quarters 1-2, quarters 3-4 etc.).

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Appendix 1: Data

The data used here consists of quarterly data from 1991:Q1 to 2009:Q4. The data for the United States originates from the Bureau of Economic Analysis and the data for the three European countries is from Eurostat. For the United States, real changes in inventories are reported separately. For Germany, France, and Italy, the change in inventories is calculated as the difference between real gross capital formation and real gross fixed capital formation, as is common.

To check how large the difference is between inventory series when calculated as a residual and when reported separately by the authorities, we look at inventories data of two European countries that report real changes in inventories separately, Spain and Belgium, as well as inventories data from the United States. The differences between the two differently calculated inventory series in these three countries appear very small and the correlations are 1.00 (Figure A1, see page 33).

Table A1. Basic Statistics 1/ 2/

	Var (GDP) / var (sales)		Correlation (sales, ∆inv.)	
	91:1 - 09:4	08:1 - 09:4	91:1 - 09:4	08:1 - 09:4
Austria	1.04	1.07	0.53	0.50
Belgium	1.03	2.52	0.25	0.87
Ireland 3/	0.99	1.66	-0.08	0.90
Luxembourg 4/	1.01	0.83	-0.02	-0.51
Netherlands	0.97	1.39	-0.35	0.65
Portugal 4/	1.01	1.26	0.06	0.33
Spain 4/	1.01	0.98	0.40	-0.46
UK	1.01	1.84	0.07	0.71

Sources: Eurostat; IMF staff calculations.
1/ All variables are in levels and constant prices.
2/ Sales = GDP - change in inventories.
3/ Sample begins in 1991Q1
4/ Sample starts in 1995Q1

Table A2. Inventory Model Scorecard 1/

	Austria	Belgium	Ireland	Luxembourg	Netherlands	Portugal	Spain	UK
Smoothing motive								
Demand shocks								
Var (GDP) / var (sales) < 1	0	0	5	0	5	0	0	0
Corr (sales, ? inventories) < 0	0	0	5	5	5	0	0	0
	0	0	10	5	10	0	0	0
Supply shocks								
Var (GDP) / var (sales) > 1	5	5	0	5	0	5	5	5
Corr (sales, ? inventories) > 0	5	5	0	0	0	5	5	5
	10	10	0	5	0	10	10	10
(*S, s*) model								
Var (GDP) / var (sales) > 1	5	5	0	5	0	5	5	5
Corr (sales, ? inventories) > 0	5	5	0	0	0	5	5	5
	10	10	0	5	0	10	10	10

Source: Authors' calculations based on Table A1.
1/ Five points are awarded when the prediction of the model is found in the data.

Table A3a. Baseline Forecasting Performance, 2005:Q1 through 2009:Q2

(The mean error (ME), the absolute mean error (MAE), and root mean square error (RMSE) are measured in percentage points; the U-stat is unitless)

	Forecast	Austria						Belgium				
	horizon	ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-0.02	0.51	0.80	1.23	20		-0.24	0.49	0.83	1.24	20
(lags=15)	2	-0.17	0.72	1.04	0.99	19	(lags=16)	-0.25	0.54	0.89	0.83	19
	3	-0.16	0.69	1.07	0.86	18		-0.30	0.55	0.92	0.75	18
	4	-0.28	0.60	0.93	0.78	17		-0.35	0.56	0.94	0.85	17
	5	-0.30	0.62	0.95	0.86	16		-0.39	0.55	0.95	1.02	16
	6	-0.34	0.65	0.97	0.90	15		-0.42	0.57	0.98	0.98	15
	7	-0.36	0.68	0.99	0.83	14		-0.43	0.62	1.02	0.90	14
	8	-0.40	0.68	1.02	0.77	13		-0.47	0.65	1.05	0.87	13
		Ireland						Luxembourg				
		ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-1.39	2.20	2.86	0.81	19		-0.79	1.70	2.33	0.98	19
(lags=2)	2	-1.06	2.14	2.73	0.89	18	(lags=1)	-0.53	1.43	1.88	0.96	18
	3	-1.68	2.51	3.11	1.01	17		-0.72	1.60	2.12	0.84	17
	4	-1.50	2.31	2.97	0.92	16		-0.64	1.56	2.11	0.93	16
	5	-1.68	2.57	3.15	0.90	15		-0.72	1.63	2.19	0.79	15
	6	-1.82	2.59	3.20	0.93	14		-0.80	1.73	2.27	0.85	14
	7	-1.93	2.82	3.36	0.84	13		-0.85	1.83	2.35	0.92	13
	8	-2.08	2.96	3.46	0.89	12		-0.88	1.97	2.46	0.80	12

Note: Based on individual country univariate AR models for output growth with lags selected to minimize the Theil U-stat at four quarters in the forecast period.

Table A3b. Baseline Forecasting Performance, 2005:Q1 through 2009:Q2

(The mean error (ME), the absolute mean error (MAE), and root mean square error (RMSE) are measured in percentage points; the U-stat is unitless)

	Forecast horizon	Netherlands						Spain				
		ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-0.15	0.60	0.81	1.04	20		-0.10	0.30	0.44	1.30	20
(lags=1)	2	-0.21	0.73	1.01	0.89	19	(lags=1)	-0.19	0.51	0.80	1.34	19
	3	-0.31	0.71	1.04	0.86	18		-0.31	0.68	1.02	1.34	18
	4	-0.37	0.75	1.08	0.84	17		-0.54	0.69	1.02	1.21	17
	5	-0.39	0.80	1.11	0.78	16		-0.69	0.77	1.09	1.17	16
	6	-0.43	0.84	1.15	0.86	15		-0.78	0.85	1.16	1.12	15
	7	-0.52	0.82	1.15	0.89	14		-0.85	0.91	1.21	1.06	14
	8	-0.53	0.87	1.19	0.84	13		-0.92	0.97	1.26	1.02	13
		Portugal						UK				
		ME	MAE	RMSE	U-stat	obs		ME	MAE	RMSE	U-stat	obs
Unfiltered	1	-0.12	0.62	0.87	0.93	20		-0.17	0.49	0.75	1.14	20
(lags=5)	2	-0.11	0.66	0.90	0.78	19	(lags=1)	-0.28	0.63	1.06	1.09	19
	3	-0.22	0.61	0.86	0.79	18		-0.39	0.74	1.24	1.01	18
	4	-0.26	0.55	0.83	0.88	17		-0.60	0.73	1.18	0.96	17
	5	-0.35	0.59	0.88	0.93	16		-0.70	0.78	1.22	1.04	16
	6	-0.40	0.58	0.92	0.94	15		-0.78	0.80	1.26	1.03	15
	7	-0.45	0.59	0.95	0.90	14		-0.81	0.84	1.30	1.00	14
	8	-0.46	0.65	0.98	0.86	13		-0.86	0.90	1.35	1.02	13

Note: Based on individual country univariate AR models for output growth with lags selected to minimize the Theil U-stat at four quarters in the forecast period.

Table A4a. Assessing the Information Content of Inventories in Forecasting Output Growth

		Austria Theil U-stat					Belgium Theil U-stat				
	Forecast horizon	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value
Unfiltered	1	1.230	1.938	0.01 ***	1.938	0.01 ***	1.244	3.617	0.06 *	3.617	0.06 *
	2	0.995	1.622	0.10 *	1.670	0.12	0.833	2.255	0.09 *	1.431	0.09 *
	3	0.864	1.570	0.11	2.856	0.12	0.754	2.088	0.09 *	1.345	0.03 **
	4	0.782	1.530	0.22	8.522	0.20	0.845	2.323	0.04 **	1.504	0.12
	5	0.855	1.179	0.24	25.799	0.20	1.023	2.354	0.04 **	1.598	0.19
	6	0.902	1.208	0.29	80.211	0.21	0.975	2.327	0.15	1.332	0.27
	7	0.831	1.279	0.33	218.110	0.22	0.896	2.872	0.26	1.778	0.18
	8	0.770	1.384	0.29	585.995	0.22	0.867	2.332	0.03 **	2.306	0.50

		Ireland Theil U-stat					Luxembourg Theil U-stat				
		Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value	Base model	Augmented model with change in inventories (growth) actual	p-value	dynamic	p-value
Unfiltered	1	0.815	0.715	0.02 **	0.715	0.02 **	0.978	0.984	0.220	0.984	0.22
	2	0.886	0.796	0.04 **	0.830	0.00 ***	0.965	0.969	0.254	0.961	0.16
	3	1.007	0.889	0.00 ***	0.902	0.06 *	0.843	0.850	0.275	0.844	0.33
	4	0.917	0.864	0.06 *	0.905	0.15	0.929	0.938	0.221	0.929	0.10 *
	5	0.901	0.825	0.50	0.867	0.50	0.790	0.798	0.241	0.790	0.39
	6	0.930	0.857	0.50	0.904	0.04 **	0.848	0.857	0.259	0.848	0.06 *
	7	0.839	0.773	0.50	0.811	0.50	0.921	0.930	0.286	0.920	0.15
	8	0.888	0.816	0.19	0.855	0.05 **	0.797	0.807	0.296	0.797	0.36

Note: Based on individual country AR models for output growth (see Table 4). Calculations for augmented models are obtained by including correspoinding lags in the "growth" of the change in inventories. The columns labeled "actual" assume perfect inventory foresight in the forecast horizon; those labeled "dynamic" forecast inventories dynamically using a bivariate VAR model. The p-value corresponds to a one-sided t-test--with degrees of freedom equal to the number of forecasts at the specific horizon minus one--comparing the mean square errors of the base model to that of the augmented models. The test is based on a modified Diebold-Mariano test Harvey, Leybourne, and Newbold, 1997). Significance at 10 percent, 5 percent, and 1 percent is denoted by *, **, and ***.

Table A4b. Assessing the Information Content of Inventories in Forecasting Output Growth

	Forecast horizon	Netherlands Theil U-stat: Base model	Augmented model with change in inventories (growth): actual	p-value	dynamic	p-value	Spain Theil U-stat: Base model	Augmented model with change in inventories (growth): actual	p-value	dynamic	p-value
Unfiltered	1	1.040	1.027	0.14	1.027	0.14	1.299	1.320	0.11	1.320	0.11
	2	0.893	0.872	0.15	0.890	0.02 **	1.339	1.352	0.04 **	1.360	0.16
	3	0.858	0.838	0.16	0.857	0.09 *	1.336	1.356	0.11	1.372	0.15
	4	0.838	0.819	0.15	0.838	0.31	1.206	1.228	0.14	1.294	0.17
	5	0.782	0.761	0.16	0.782	0.39	1.166	1.201	0.15	1.374	0.15
	6	0.858	0.831	0.06 *	0.857	0.14	1.116	1.128	0.23	1.566	0.12
	7	0.892	0.862	0.50	0.892	0.50	1.059	1.062	0.22	1.969	0.05 **
	8	0.840	0.824	0.00 ***	0.841	0.50	1.016	1.017	0.34	2.763	0.50

	Forecast horizon	Portugal Theil U-stat: Base model	Augmented model with change in inventories (growth): actual	p-value	dynamic	p-value	UK Theil U-stat: Base model	Augmented model with change in inventories (growth): actual	p-value	dynamic	p-value
Unfiltered	1	0.934	3.159	0.38	3.159	0.38	1.138	1.146	0.23	1.146	0.23
	2	0.782	2.640	0.13	4.251	0.13	1.094	1.100	0.12	1.094	0.09 *
	3	0.787	3.493	0.15	7.386	0.15	1.010	1.016	0.12	1.012	0.29
	4	0.878	4.198	0.14	14.531	0.15	0.962	0.971	0.11	0.964	0.09
	5	0.931	5.017	0.11	47.782	0.12	1.035	1.050	0.09 *	1.037	0.11
	6	0.939	5.298	0.14	33.547	0.04 **	1.026	1.044	0.03 **	1.028	0.11
	7	0.903	5.959	0.11	142.134	0.50	1.005	1.027	0.50	1.005	0.15
	8	0.862	4.994	0.23	286.298	0.50	1.016	1.039	0.50	1.016	0.21

Note: Based on individual country AR models for output growth (see Table 4). Calculations for augmented models are obtained by including correspoinding lags in the "growth" of the change in inventories. The columns labeled "actual" assume perfect inventory foresight in the forecast horizon; those labeled "dynamic" forecast inventories dynamically using a bivariate VAR model. The p-value corresponds to a one-sided t-test--with degrees of freedom equal to the number of forecasts at the specific horizon minus one--comparing the mean square errors of the base model to that of the augmented models. The test is based on a modified Diebold-Mariano test Harvey, Leybourne, and Newbold, 1997). Significance at 10 percent, 5 percent, and 1 percent is denoted by *, **, and ***.

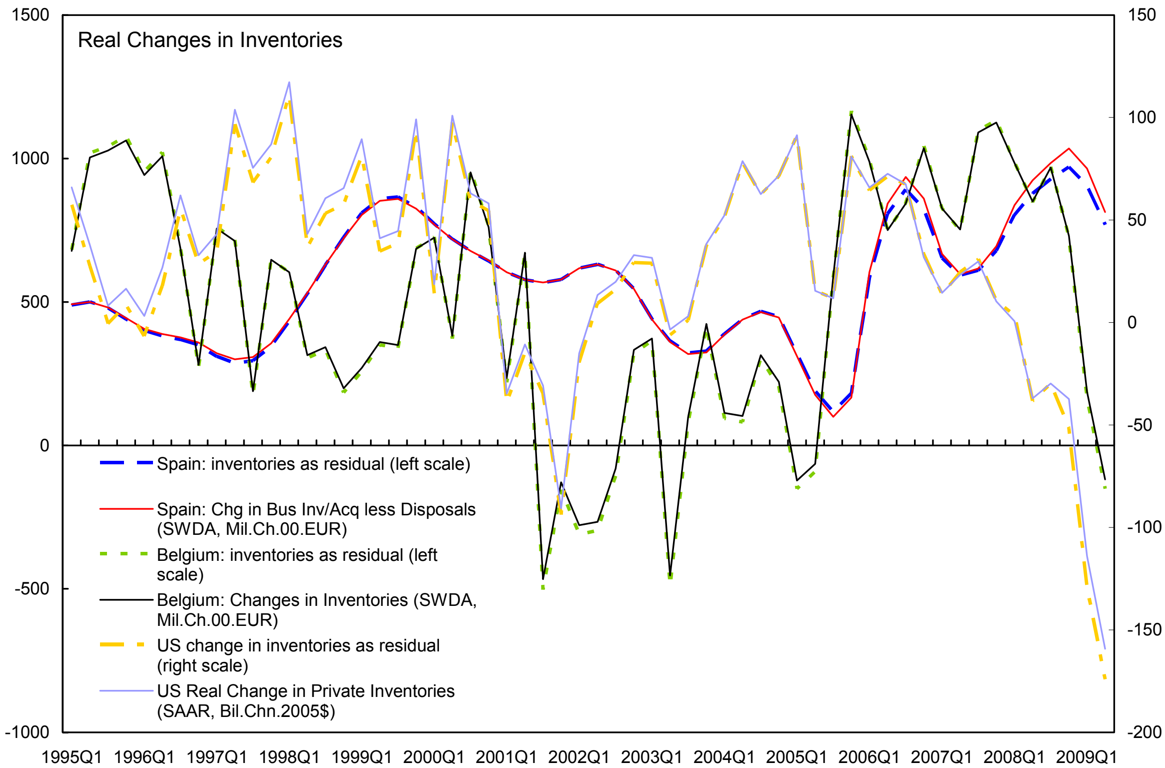
Table A5. To What Extent Does Setting to Zero the Forecast for Inventories Worsen Output Growth Forecasts?

	Forecast	Austria Theil U-stat				Belgium Theil U-stat				Ireland Theil U-stat				Luxembourg Theil U-stat		
Unfiltered	horizon	Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value
(lags=12)	1	1.255	1.019	0.02 **	(lags=2)	7.434	1.175	0.22	(lags=3)	0.721	0.827	0.02 **	(lags=1)	0.979	1.016	0.05 **
	2	1.000	0.792	0.13		4.553	0.779	0.17		0.850	0.877	0.31		0.961	0.955	0.12
	3	0.878	0.722	0.14		0.775	0.713	0.12		0.945	0.951	0.29		0.848	0.842	0.43
	4	0.788	0.762	0.12		0.869	0.799	0.15		0.896	0.899	0.37		0.928	0.922	0.03 **
	5	1.029	0.831	0.50		1.082	0.980	0.16		0.853	0.864	0.16		0.789	0.783	0.07 *
	6	0.899	0.876	0.20		1.033	0.935	0.16		0.910	0.904	0.24		0.848	0.844	0.12
	7	1.080	0.812	0.32		0.947	0.856	0.21		0.792	0.808	0.47		0.921	0.919	0.23
	8	1.130	0.754	0.50		0.921	0.829	0.04		0.873	0.864	0.50		0.790	0.789	0.50

	Forecast	Netherlands Theil U-stat				Spain Theil U-stat				Portugal Theil U-stat				UK Theil U-stat		
Unfiltered	horizon	Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value		Augmented	Δinv=0	p-value
(lags=1)	1	1.031	1.080	0.06 *	(lags=2)	1.437	1.850	0.05 **	(lags=1)	0.956	0.937	0.10 *	(lags=3)	1.205	1.262	0.11
	2	0.886	0.879	0.20		1.430	1.382	0.22		0.873	0.826	0.11		1.168	1.025	0.23
	3	0.856	0.847	0.48		1.471	1.275	0.41		0.879	0.878	0.08 *		1.096	0.897	0.39
	4	0.838	0.825	0.28		1.285	1.262	0.19		0.966	0.996	0.07 *		0.959	0.970	0.27
	5	0.781	0.767	0.20		1.182	1.197	0.44		1.058	1.024	0.04 **		1.032	1.051	0.16
	6	0.854	0.841	0.18		1.416	1.125	0.34		1.029	1.023	0.16		1.036	1.048	0.18
	7	0.893	0.880	0.22		1.632	1.063	0.08 *		0.998	0.986	0.09 *		1.019	1.026	0.21
	8	0.840	0.828	0.16		1.612	1.019	0.50		0.891	0.936	0.00 ***		1.030	1.036	0.22

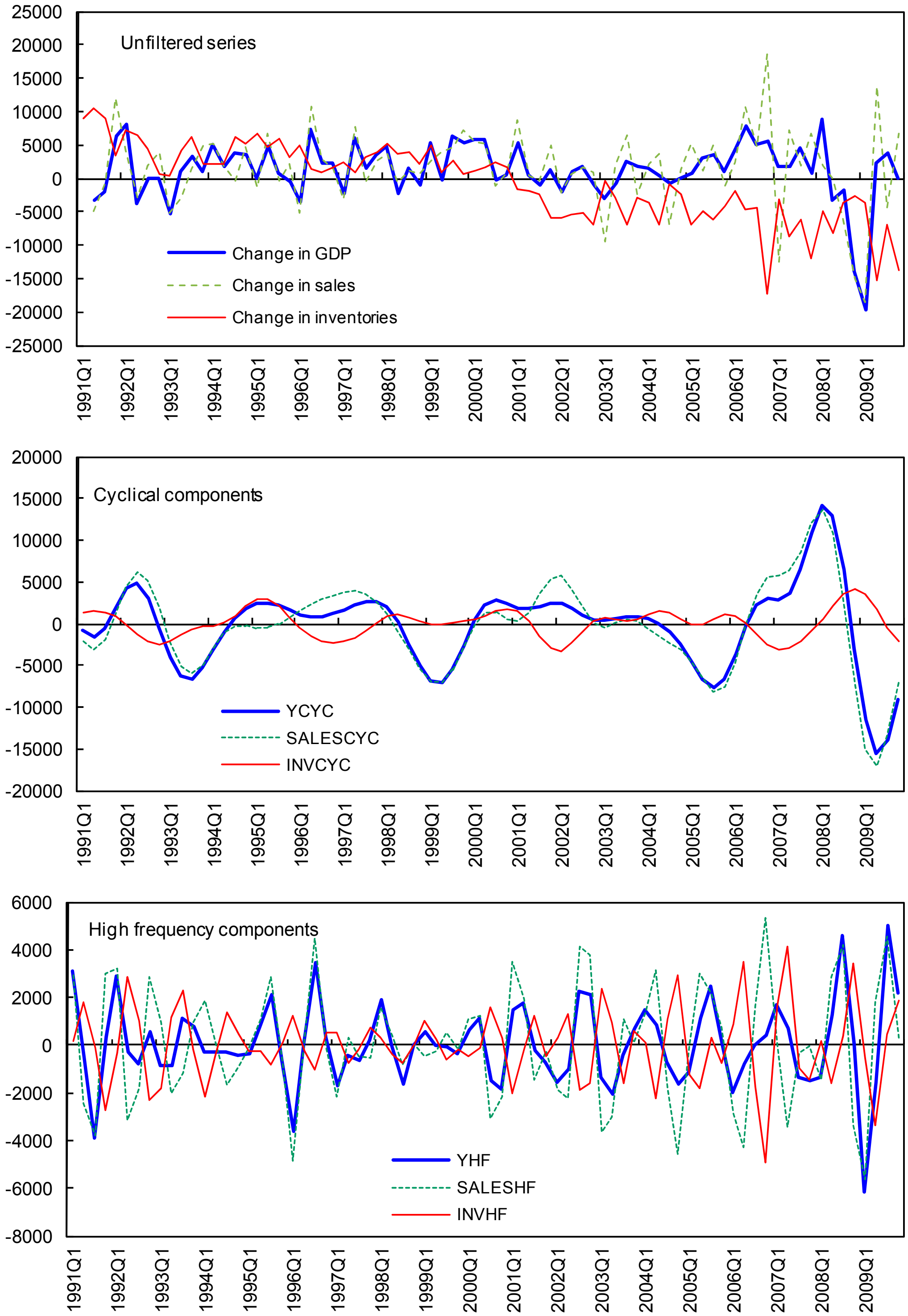
Note: Based a bi-variate VAR models for output growth and "growth" in the change in inventories with lags selected with the same criteria as in Table 4 applied to the VAR model (see Table 5). The U-stat for Δinv=0 columns corresponds to forecasts when the "growth" in the change in inventories is set to zero in the forecast period. The p-value corresponds to a one-sided t-test--with degrees of freedom equal to the number of forecasts at each horizon minus one--comparing the MSE of these two models forecasts. The test is based a modified Diebold-Mariano test (see Harvey, Leybourne, and Newbold, 1997).

Figure A1: Calculations of Inventories



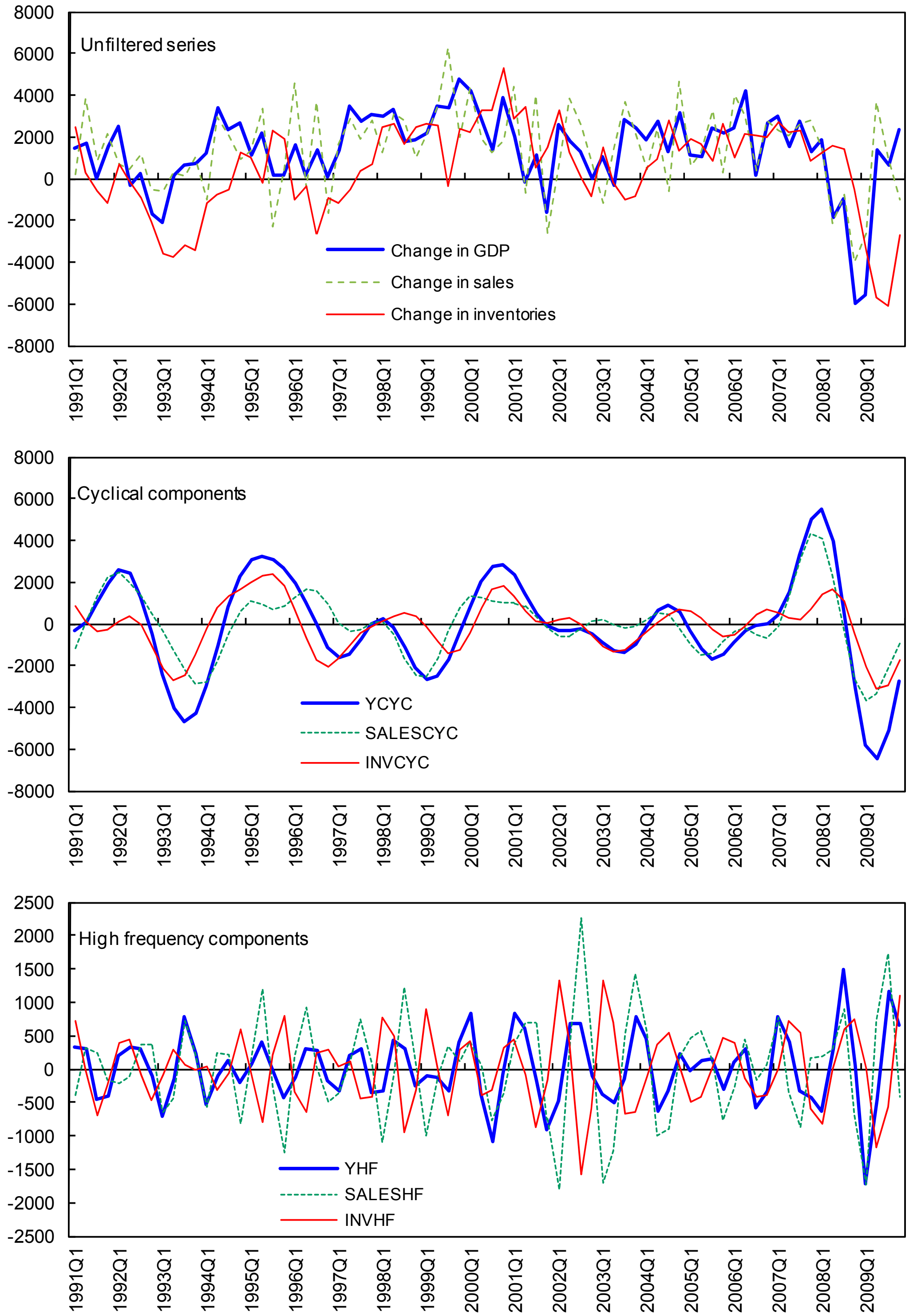
Sources: Eurostat; BEA; and IMF staff calculations.

Figure A2. Germany: GDP, Sales, Changes in Inventories, 1991Q1 - 2009Q4
(constant prices, million euros)



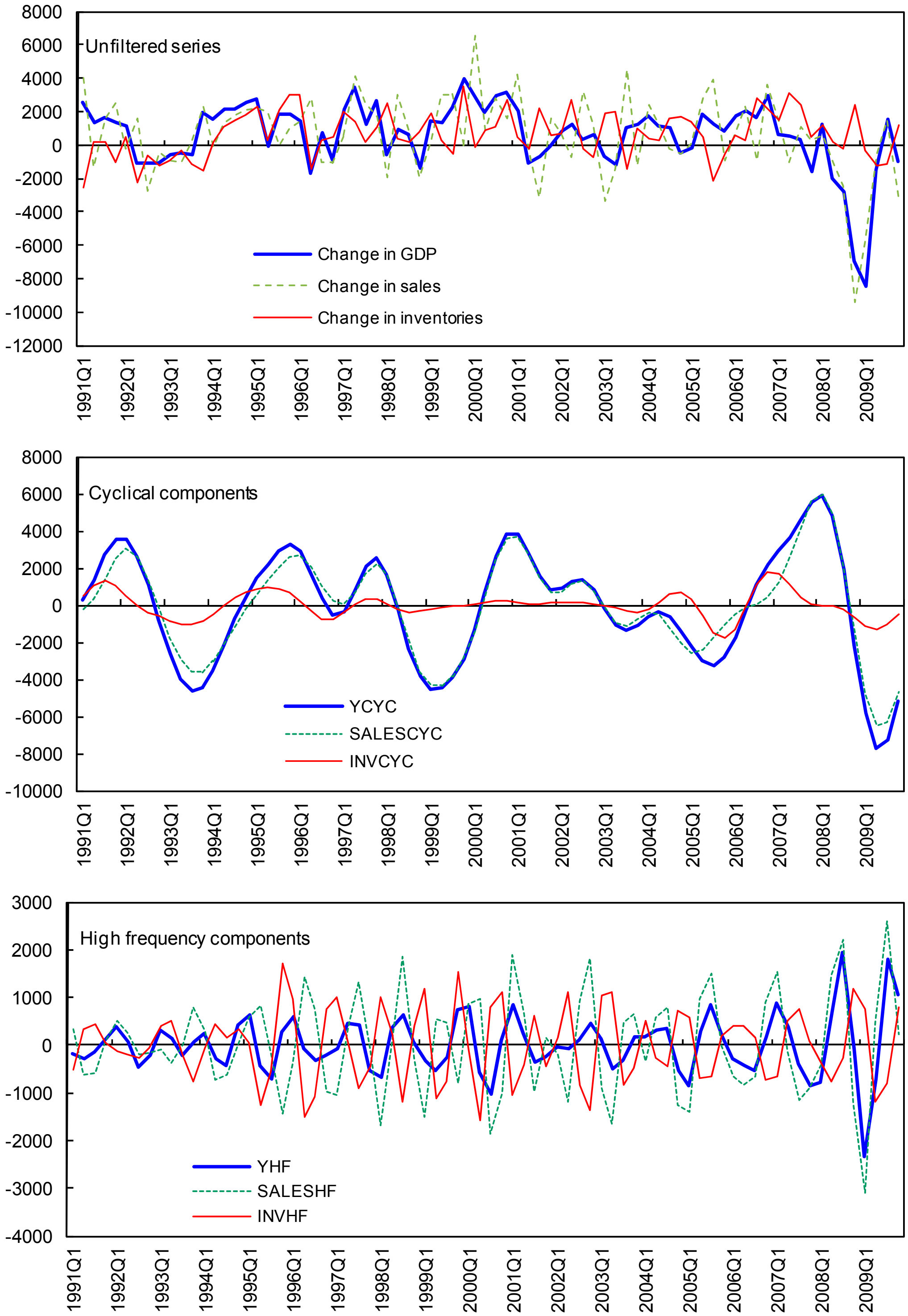
Sources: Eurostat; IMF staff calculations.

Figure A3. France: GDP, Sales, Changes in Inventories, 1991Q1 - 2009Q4
(constant prices, million euros)



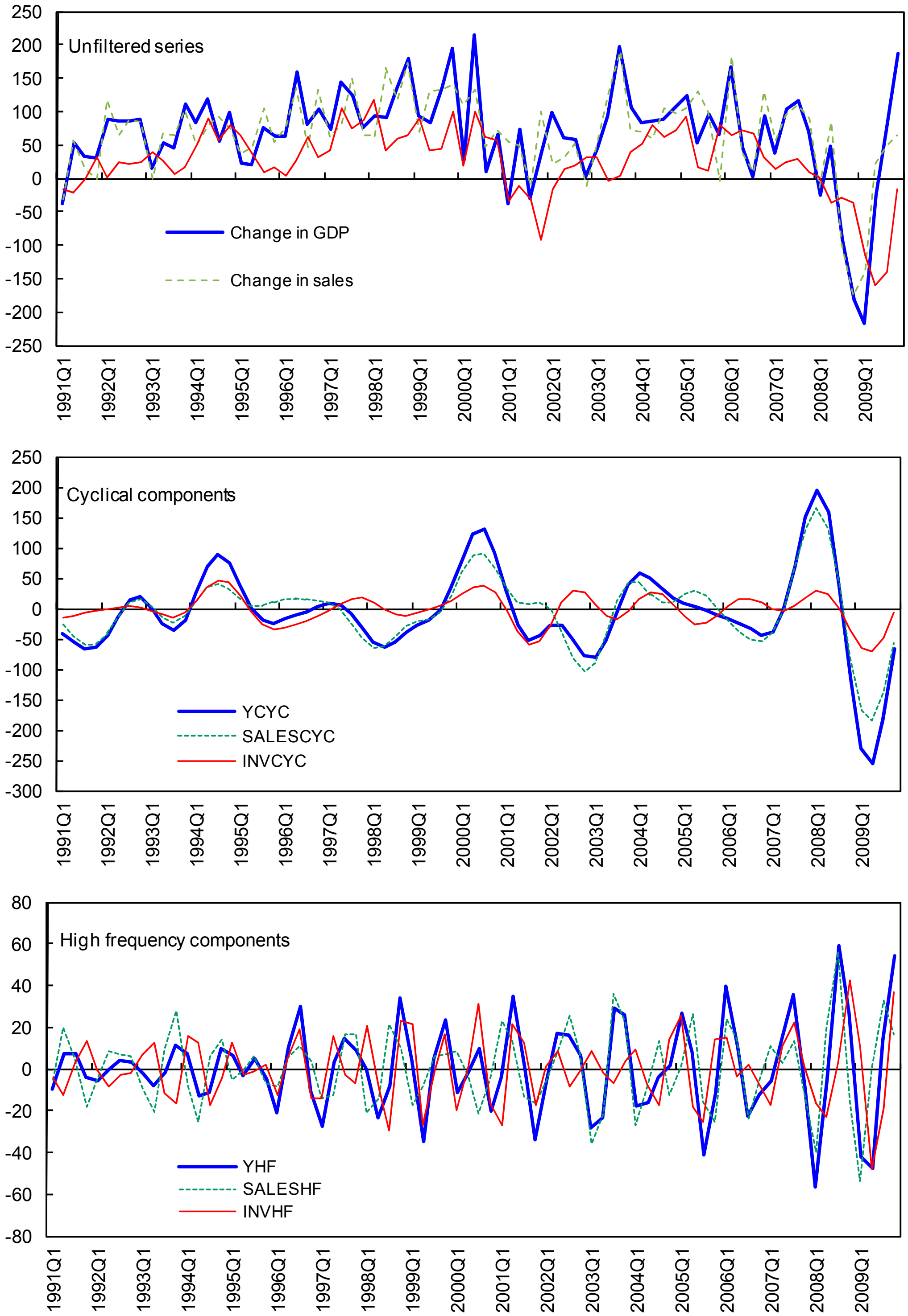
Sources: Eurostat; IMF staff calculations.

Figure A4. Italy: GDP, Sales, Changes in Inventories, 1991Q1 - 2009Q4
(constant prices, million euros)



Sources: Eurostat; IMF staff calculations.

Figure A5. United States: GDP, Sales, Changes in Inventories, 1991Q1-2009Q4
(constant prices, billion US dollars)



Sources: BEA; IMF staff calculations.