Incorporating Macroeconomic and Firm-Level Uncertainties in Stochastic Pro-Forma Financial Modeling

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This paper demonstrates how to incorporate macroeconomic and firm-level uncertainties into stochastic pro-forma financial modeling using EViews. A recent paper by Cuddington and Khindanova (CK) showed how to link a simple univariate sales forecasting equation with a pro forma financial statement model to perform stochastic simulations of financial statements. This study extends the CK analysis to include a multivariate sales forecasting equation with macroeconomic factors. In addition, key ratio equations are estimated and treated as stochastic. The integration of macroeconomic forecasting and financial projections should be especially useful for an analysis of companies in highly cyclical industries.

INTRODUCTION

Spreadsheet program like Excel are a common tool for pro forma statement modeling. Using scenario or 'what-if' analysis, such models can be used to informally study various risks facing a business entity. Add-In programs such as @Risk or Crystal Ball can be used to formally introduce stochastic considerations for a detailed statistical analysis of multiple sources of uncertainty.[1] Cuddington and Khindanova (CK, 2011) recently proposed an alternative tool for carrying out stochastic simulation analysis in financial models, namely the MODEL object in the EViews econometrics program. EViews is not widely used in financial analysis circles, but is a highly regarded platform for estimating small to very large-scale macroeconomic models. It allows for the individual or system estimation of dynamic equations. These estimated stochastic difference equations are then put into EViews' powerful solver called the MODEL object so that they may be solved forward using Monte Carlo simulation to calculate expected future values with confidence bands.

EViews offers several advantages over Excel for financial modeling, as CK (2011) highlight. First, the model equations are written out explicitly rather than being embedded in spreadsheet cell formulas. This makes financial models more transparent and hence easier to audit and debug. Second, EViews' tools can be then used to carry out forecasting with confidence bands for a wide variety of interdependent variables, where the variance-covariance matrix for the error terms in the model is estimated from historical data. Third, there are a number of macroeconomic and industry-level models that use the EViews software (e.g. the IHS Global Insight U.S. macro model and the Fair model). Thus, it is, in principle, possible to integrate EViews-based financial models with such macro models so that macroeconomic sources of uncertainty for a given business are projected from the macro block of the model to the financial planning block. It would be very difficult to carry out this level of macro-industry-firm level integration using Excel, in part because Excel is not a state-of-the-art tool for macroeconomic estimation and forecasting.

This paper extends the CK illustration of the sales-driven pro forma modeling in several directions. CK (2011) assumed that the sales growth equation was the sole source of uncertainty. Other key variables in the income and balance sheets were linked to sales with constant ratio assumptions, which are treated as identities. Here, we illustrate that EViews models allow the uncertainties in such ratio assumptions to be estimated and taken into account in the stochastic simulations used to get confidence bands. It is straightforward to estimate the ratio equations, so that standard econometric diagnostics on them may be performed. Second, we develop a very simple three-equation 'macro' model - a simple vector autoregression (VAR) involving residential building permits, consumer sentiment, and the unemployment rate. This macro module is then used to 'drive' the sales (and potentially other) equations in the financial simulations block of the model. Our macro model is purely illustrative. For financial analysis teams who maintain or subscribe to proprietary macroeconomic models for forecasting purposes, these models can be linked to a financial pro forma statement block of the sort that we develop here in order to carry out an integrated macro/firm-level simulation and forecast.

Our EViews model of financial statements follows Benninga's sales-driven model (Benninga, 2008, Ch. 3). In Benninga's model, the sales growth rate is assumed to be constant (at 20%) over time. The model is 'sales driven' in the sense that several key variables are proportional to sales: Cost of Goods Sold, Other Current Assets, Net Fixed Assets, and Current Liabilities. Cash and Marketable Securities (CASH) is the plug, as long as cash balances remain positive. In situations where there is a 'run down' in CASH, however, it is assumed that the firm will issue new debt as needed in order to prevent CASH from going negative. Thus, DEBT, in effect, becomes the plug when CASH drops to zero. Paid-in capital and outstanding long-term debt remain constant (by rolling over any maturing debt). The equations for Benninga's model are summarized in Table 1.

To develop a stochastic generalization of Benninga's model, CK (2011) estimated a simple univariate forecasting equation for Home Depot sales. The uncertainty regarding future sales was used to 'drive' stochastic simulation of the entire pro forma statement model where all of the items depend directly or indirectly on future sales. This study extends the CK analysis by considering the following macroeconomic factors in the sales forecasts model: the University of Michigan Consumer Sentiment Index, unemployment rate, and new private housing units authorized by building permits. The forecasts of these macroeconomic variables are derived using simple vector autoregression (VAR) equations. The sales equation includes a time trend and the consumer sentiment index. The CK paper assumes that critical ratios are constant. Examples include the cost of goods sold to sales ratio, accounts receivable to sales, etc. In practice, these ratios vary over time and hence represent additional sources of uncertainty that should be accounted for in stochastic simulations. This study models the COGS/SALES, NFA/SALES, and CL/SALES ratios as time-varying variables and integrates them into a stochastic simulation of financial statements. The confidence bands associated with the resulting forecasts then reflect the variances and covariances of the residuals in all regressions in the financial model.

As in the CK study, the suggested integrated stochastic financial simulations are illustrated using the Home Depot data for 1985-2010.[2] The forecast period is 2011-2016. The illustration considers uncertainties in three macroeconomic factors (housing permits, consumer sentiment, and the unemployment rate), SALES, and in three key ratios (COGS/SALES, NFA/SALES, CL/SALES). Our analysis of the stochastic simulation results concentrates on projected macroeconomic variables, SALES, COGS, PROFIT, CASH, and NFA. The paper demonstrates how multiple sources of uncertainty, including macroeconomic uncertainty, can be taken into account when forecasting future values in *pro forma* income statements and balance sheets. The integration of macroeconomic forecasting and financial projections will be especially useful for an analysis of companies in highly cyclical industries.

TABLE 1
BENNINGA'S MODEL OF PRO-FORMA FINANCIAL STATEMENTS

Formula for Subsequent Periods
SALES = SALES(-1)*1.20 COGS = 0.50*SALES INT_DEBT = .10*(DEBT+DEBT(-1))/2 INT_CASH = .08*(CASH+CASH(-1))/2 DEPN = .10*(FA_COST+FA_COST(-1))/2 PBT = SALES-COGS - INT_DEBT + INT_CASH - DEPN TAXES = .40*PBT PROFIT = PBT – TAXES DIVIDENDS = .50*PROFIT RET_EARNINGS = PROFIT – DIVIDENDS
CASH = CL+DEBT(-1)+EQUITY- OCA + NFA if positive = 0, otherwise OCA = .20*SALES FA_COST = NFA + ACC_DEPN ACC_DEPN = ACC_DEPN(-1) + DEPN NFA = .80*SALES
ASSETS = CASH + OCA + NFA
CL = .08*SALES DEBT = DEBT(-1) if CASH ≥ 0 = OCA + NFA - CL – EQUITY otherwise
LIAB = CL + DEBT
CAPITAL = CAPITAL(-1) ACC_EARNINGS = ACC_EARNINGS(-1) + RET_EARNINGS EQUITY = CAPITAL + ACC_EARNINGS

The remainder of the paper is structured as follows. The second section describes estimation and forecasting of macroeconomic variables. The third section develops a sales forecasting equation. The fourth section explains the modeling of financial ratios. The fifth section integrates the foregoing sources of uncertainty into an empirically-based stochastic model of financial statements. The sixth section summarizes our findings.

FORECASTING OF MACROECONOMIC VARIABLES

This section summarizes forecasting of three macroeconomic variables, some of which are useful in explaining Home Depot sales. In projecting future retail sales, one needs to take into account macroeconomic factors, the retail sales outlook, the company's products, and marketing investments. We focus on the following three macroeconomic factors: the University of Michigan Consumer Sentiment Index, unemployment rate, and new private housing units authorized by building permits. These three factors are often used as leading indicators for the economy and the retail industry. The University of Michigan Consumer Sentiment Index is compiled by Thomson Reuters and University of Michigan. The base value of the index is 100 (in the first quarter of 1966). The unemployment rate among full-time workers is published by the Bureau of Labor Statistics. The building permits series (new private housing units authorized by building permits) is reported by the Census Bureau of the U.S. Department of Commerce. Data on these macroeconomic variables were downloaded from the Federal Reserve

Economic Data (FRED) database (FRED, 2012), which facilitates quick updating of the analysis as more recent data become available. The FRED's ID for the series are: UMCSENT (University of Michigan Consumer Sentiment Index), LNS14100000 (unemployment rate - full-time workers), PERMIT (new private housing units authorized by building permits). In our paper we renamed the unemployment rate series as UNEMPL. The macroeconomic factors' values and the Home Depot sales for 1985-2010 are shown in Figure 1.

FIGURE 1
MACROECONOMIC FACTORS AND HOME DEPOT SALES

We forecast the three interrelated macroeconomic variables using a simple vector autoregression (VAR):

$$\begin{aligned}
\boldsymbol{UMCSENT_t} &= \boldsymbol{a_{11}UMCSENT_{t-1} + a_{12}UNEMPL_{t-1} + a_{13}PERMIT_{t-1}} \\
&\quad \boldsymbol{+ b_{11}UMCSENT_{t-2} + b_{12}UNEMPL_{t-2} + b_{13}PERMIT_{t-2} + c_1 + \varepsilon_{1t}} \\
\boldsymbol{UNEMPL_t} &= \boldsymbol{a_{21}UMCSENT_{t-1} + a_{22}UNEMPL_{t-1} + a_{23}PERMIT_{t-1}} \\
&\quad \boldsymbol{+ b_{21}UMCSENT_{t-2} + b_{22}UNEMPL_{t-2} + b_{23}PERMIT_{t-2} + c_2 + \varepsilon_{2t}} \qquad (1) \\
\boldsymbol{PERMIT_t} &= \boldsymbol{a_{31}UMCSENT_{t-1} + a_{32}UNEMPL_{t-1} + a_{33}PERMIT_{t-1}} \\
&\quad \boldsymbol{+ b_{31}UMCSENT_{t-2} + b_{32}UNEMPL_{t-2} + b_{33}PERMIT_{t-2} + c_3 + \varepsilon_{3t}},
\end{aligned}$$

where the University of Michigan Consumer Sentiment Index (*UMCSENT*), unemployment rate (*UNEMPL*), and new private housing permits (*PERMIT*) are endogenous variables, c_i are constants, ε_{it} are innovations, i =1, 2, 3, t = 1985,…, 2010. Each endogenous variable is a function of lagged values of all three endogenous variables. The estimation results are displayed in Table 2. Each column in the table represents an equation in the VAR system (1). The reported numbers are estimated coefficients and the t-statistics (in square brackets). In the Consumer Sentiment Index equation, the coefficients of the first lag

TABLE 2
VAR COEFFICIENT ESTIMATES FOR MACROECONOMIC FACTORS

Explanatory Variables (Lagged Dependent Variables)	Dependent Variables		
	UMCSENT	UNEMPL	PERMIT
UMCSENT(-1)	0.568 [2.290]	-0.077 [-4.248]	3.819 [0.737]
UMCSENT(-2)	0.297 [0.960]	0.036 [1.584]	1.729 [0.268]
UNEMPL(-1)	0.574 [0.240]	0.716 [4.092]	63.000 [1.265]
UNEMPL(-2)	1.955 [0.962]	-0.372 [-2.498]	-54.261 [-1.279]
PERMIT(-1)	0.018 [1.926]	-0.002 [-2.365]	1.585 [7.983]
PERMIT(-2)	-0.023 [-2.342]	0.001 [1.121]	-0.844 [-4.055]
C	5.178 [0.124]	8.652 [2.824]	-181.789 [-0.208]
Adjusted R-squared	0.68	0.91	0.89

of the index and the second lag of private housing permits are statistically significant. In the unemployment rate equation, the coefficients of first lag of the Consumer Sentiment Index, the first and second lags of the unemployment rate, the first lag of the housing permits, and the constant are statistically significant. In the private housing permits equation, the coefficients of its first and second lag are statistically significant. The adjusted R^2 values for each equation are provided in the bottom row. Granger causality test results are provided in Table 3. The test results show that housing permits and unemployment rate Granger cause the Consumer Sentiment Index, the Consumer Sentiment Index and housing permits Granger cause the unemployment rate, the unemployment rate and the Consumer Sentiment Index do not Granger cause the housing permits.

The next section takes into account impacts of the macroeconomic variables (Consumer Confidence Index, unemployment factor, and housing permits) on the Home Depot sales forecasts.

TABLE 3
GRANGER CAUSALITY TEST RESULTS

Dependent variable: UMCSENT			
Excluded	Chi-sq	Df	Prob.
UNEMPL	1.300	2	0.522
PERMIT	5.492	2	0.064
All	11.225	4	0.024
Dependent variable: UNEMPL			
Excluded	Chi-sq	Df	Prob.
UMCSENT	18.056	2	0.000
PERMIT	8.236	2	0.016
All	48.853	4	0.000
Dependent variable: PERMIT			
Excluded	Chi-sq	Df	Prob.
UMCSENT	0.859	2	0.651
UNEMPL	2.404	2	0.301
All	2.629	4	0.622

THE SALES FORECASTING EQUATION

As in the CK paper, our models of financial statements are based on Benninga's deterministic sales-driven model. Benninga projects future sales assuming the constant growth rate. The CK study estimated the sales growth rates using a univariate time trend model. This study extends the Benninga and CK models by considering impacts of macroeconomic factors on the Home Depot sales. Our sales model assumes that the continuously compounded annual SALES growth rate (equal to the first difference of the natural logarithm of SALES) depends on a time trend and the consumer sentiment index:[3]

$$\boldsymbol{LOG(SALES_t) - LOG(SALES_{t-1}) = c + b_1 t + b_2 LOG(MCSENT_t) + \varepsilon_t} \quad (2)$$

where *LOG* denotes the natural logarithm function, *t* is time, t = 1985, …, 2010, *SALES* is the Home Depot sales, $\boldsymbol{LOG(SALES_t) - LOG(SALES_{t-1}) = DLOG(SALES_t)}$ in the EViews notations, *MCSENT* is the University of Michigan Consumer Confidence Index, ε_t is the residual term. As we showed in the previous section, the Consumer Confidence Index is associated with two other macroeconomic factors: the unemployment rate and housing permits. Thus, the sales model in (2) directly or indirectly takes into account the three interrelated macroeconomic factors on the Home Depot sales forecasts. The estimation output results are given in Table 4. The time trend and consumer sentiment *t*-statistics are above two, indicating that these regressors are statistically significant. The adjusted R^2 value (.92) indicates that model (2) provides a good fit. Graphs of actual and fitted values of the dependent variable LOG(SALES) and graphs of the residuals are shown in Figure 2. The correlogram of the residuals is flat, suggesting an absence of serial correlation. The Breusch-Godfrey LM test of the null hypothesis that there is no first or second-order correlation is not rejected (χ^2=1.41).

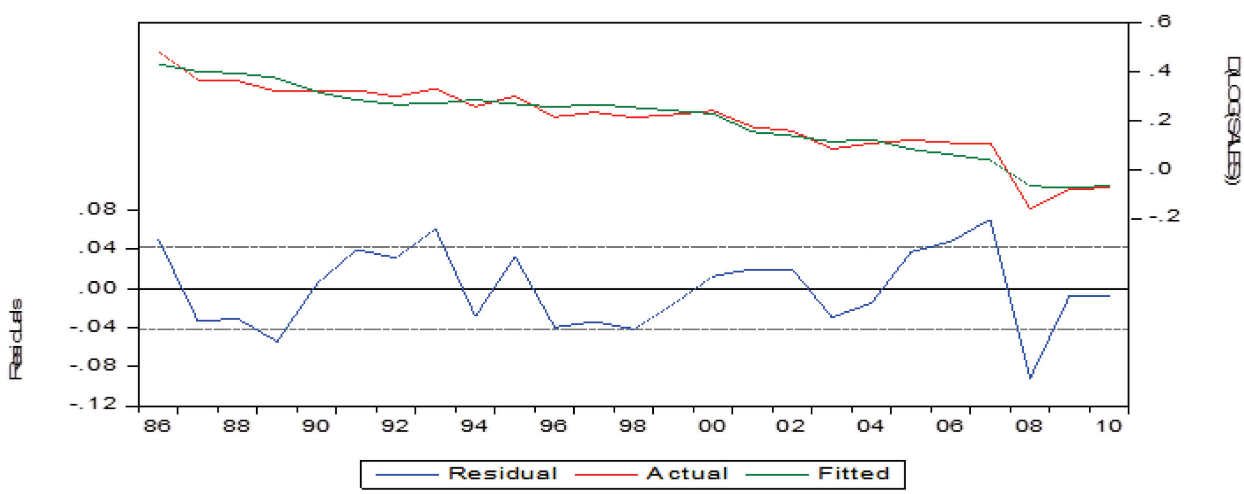
TABLE 4
ESTIMATED SALES EQUATION

Dependent Variable: DLOG(SALES)
Method: Least Squares
Date: 02/28/12 Time: 00:15
Sample (adjusted): 1986 2010
Included observations: 25 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.930	0.363	-2.560	0.018
@TREND	-0.017	0.001	-13.725	0.000
LOG(UMCSENT)	0.303	0.080	3.781	0.001

R-squared	0.928	Mean dependent var	0.201
Adjusted R-squared	0.922	S.D. dependent var	0.152
S.E. of regression	0.043	Akaike info criterion	-3.364
Sum squared resid	0.040	Schwarz criterion	-3.217
Log likelihood	45.044	Hannan-Quinn criter.	-3.323
F-statistic	141.926	Durbin-Watson stat	1.800
Prob(F-statistic)	0.000		

FIGURE 2
SALES EQUATION RESIDUALS



MODELING OF FINANCIAL RATIOS

The CK paper assumes that critical ratios are constant. Examples include the Cost of Goods Sold to Sales (COGS/SALES) ratio, Net Fixed Assets to Sales (NFA/SALES), Current Liabilities to Sales (CL/SALES), etc. In practice, these ratios vary over time and hence represent additional sources of uncertainty that should be accounted for in stochastic simulations. This study models the listed three ratios as time-varying variables:

$$\left(\frac{COGS}{SALES}\right)_t = c_{COGS} + a_{COGS,1}\left(\frac{COGS}{SALES}\right)_{t-1} + a_{COGS,2}\left(\frac{NFA}{SALES}\right)_t + \varepsilon_{COGS,t}$$

$$\left(\frac{NFA}{SALES}\right)_t = c_{NFA} + a_{NFA,1}\left(\frac{NFA}{SALES}\right)_{t-1} + \varepsilon_{NFA,t} \tag{3}$$

$$\left(\frac{CL}{SALES}\right)_t = c_{CL} + a_{CL,1}\left(\frac{CL}{SALES}\right)_{t-1} + \varepsilon_{NFA,t}$$

The estimation results are displayed in Table 5, with *t*-statistics are in square brackets. In the COGS/SALES model, NFA/SALES and one lag of COGS/SALES have *t*-statistics above two, indicating that their coefficients are statistically significant. In the NFA/SALES and CL/SALES models, the first lags of dependent variables are statistically significant, too.

TABLE 5
RATIOS MODELING RESULTS

Dependent Variables					
COGS/SALES		NFA/SALES		CL/SALES	
Explanatory Variables	Coefficient Estimates	Explanatory Variables	Coefficient Estimates	Explanatory Variables	Coefficient Estimates
C	0.793 [10.995]	C	0.399 [2.227]	C	0.160 [1.423]
NFA/SALES	0.260 [2.850]	AR(1)	0.938 [10.739]	AR(1)	0.954 [9.952]
AR(1)	0.923 [12.206]				
Adjusted R^2	.79		0.81		0.81

For comparison, we estimated the ratios' equations assuming that ratios are constant:

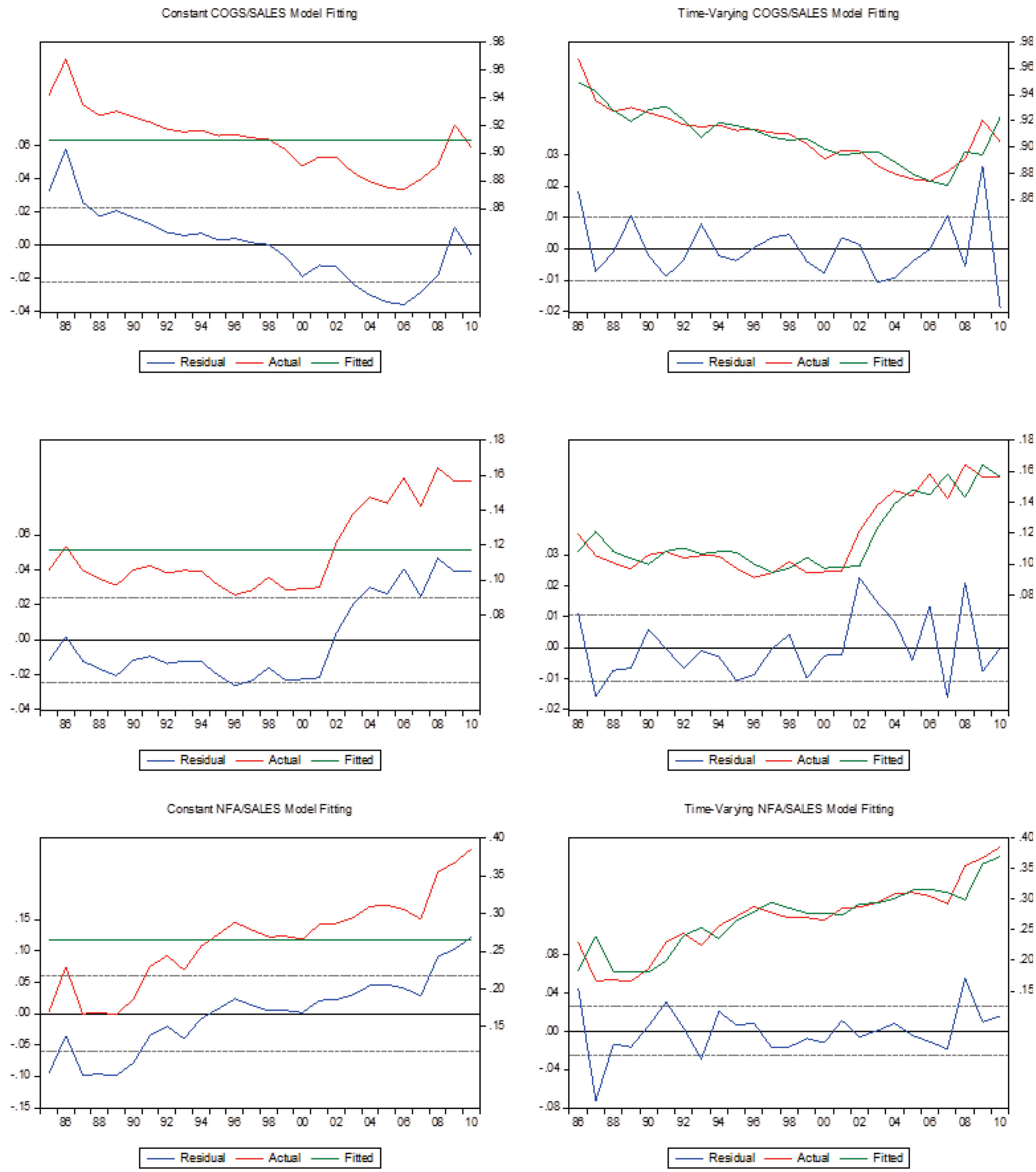
$$\left(\frac{COGS}{SALES}\right)_t = c_{COGS} + u_{COGS,t}$$

$$\left(\frac{NFA}{SALES}\right)_t = c_{NFA} + u_{NFA,t} \tag{4}$$

$$\left(\frac{CL}{SALES}\right)_t = c_{CL} + u_{NFA,t}.$$

Figure 3 displays the actual, fitted, and residual values for models (3) and (4). The figure demonstrates how badly the constant ratio models fit the data while the time-varying models adequately describe the data. Thus, the ratio specifications in (3) are integrated in our stochastic simulation of financial statements.

FIGURE 3
RATIOS MODELS FITTING



INTEGRATED STOCHASTIC MODEL OF FINANCIAL STATEMENTS

This section describes integration of the macroeconomic forecasts, sales forecasts, the ratios' models, and the financial statement model. We wrote a program that automates the EViews implementation of the integrated stochastic financial modeling for Home Depot. The program creates an annual frequency workfile with the time range 1985-2016 (the historical and forecast periods), fetches the macroeconomic series from the Federal Reserve Economic Data (FRED) database, imports the balance sheet and the income statement for 1985-2010 from Excel spreadsheets, runs a vector autoregression (VAR) for the macroeconomic factors, estimates equations for uncertain financial variables (SALES, COGS, NFA, CL), creates and solves the stochastic financial statement model. The model integrates forecasts for the Consumer Sentiment Index, unemployment rate, and housing permits by adding a link to their vector autoregression in the workfile (type in the model text a colon followed by a name of a vector autoregression. For example, *:VAR_MACRO*). The stochastic model has links to sales and ratios' forecasting equations (type in the model text a colon followed by a name of the regression. For example, *:EQ_SALES, :EQ_COGS, :EQ_NFA, :EQ_CL*). We add the @IDENTITY specification to other equations in the MODEL object, which are not estimated. (Otherwise, EViews will attempt to include these equations' uncertainty in the stochastic forecast, even when the equations are not explicitly estimated.) The integrated model equations are provided in Table 6. Our solution of the model uses the stochastic simulation features in the EViews MODEL to forecast macroeconomic factors, sales and all of the other income and balance sheet items into the future. Through Monte Carlo simulation methods (using 10,000 stochastic repetitions), the means and the 67% confidence bands for each variable at each future dates are obtained.

TABLE 6
EVIEWS MODEL EQUATIONS

```
' Macroeconomic Variables
:VAR_MACRO
' Income Statement
:EQ_SALES
:EQ_COGS
@IDENTITY INT_DEBT  = (DEBT(-1)  + DEBT)  / 2  * 0.07
@IDENTITY INT_CASH  = (CASH(-1)  + CASH)  / 2  * 0.01
@IDENTITY PBT  = SALES  - COGS  - INT_DEBT  + INT_CASH  - DEPN
@IDENTITY TAXES  = 0.36  * PBT
@IDENTITY PROFIT  = PBT  - TAXES
@IDENTITY DIVIDENDS  = 0.58  * PROFIT
@IDENTITY RET_EARNINGS  = PROFIT  - DIVIDENDS
' Balance Sheet
' create a dummy variable that is 1 if CASH would be negative in the absence of additional debt,  and zero
otherwise.
' Using EViews syntax, everything after the equal sign is treated as a logical condition.  If it holds, DUM
is 1; zero otherwise.
@IDENTITY DUM  =  - OCA  - NFA  + CL  + DEBT(-1)  + EQUITY < 0
' define CASH as the balance sheet plug, if positive, and ZERO otherwise by creative use of the dummy:
@IDENTITY CASH  = (- OCA  - NFA  + CL  + DEBT(-1)  + EQUITY)  * (1  - DUM)
@IDENTITY OCA  = 0.18  * SALES
:EQ_NFA
@IDENTITY DEPN  = 0.05  * (FA_COST(-1)  + FA_COST)  / 2
@IDENTITY ACC_DEPN  = ACC_DEPN(-1)  + DEPN
@IDENTITY FA_COST  = NFA  + ACC_DEPN
```

```
@IDENTITY ASSETS  = CASH  + OCA  + NFA
:EQ_CL
' when DUM=1, cash is negative, so DEBT is the plug; when DUM=0, cash is positive, so debt is unchanged from the previous period
@IDENTITY DEBT  = (OCA  + NFA  - CL  - EQUITY)  * DUM  + DEBT(-1)  * (1  - DUM)
@IDENTITY LIAB  = DEBT  + CL
@IDENTITY CAPITAL  = CAPITAL(-1)
@IDENTITY MINORITY  = MINORITY(-1)
@IDENTITY TSTOCK  = TSTOCK(-1)
@IDENTITY ACC_EARNINGS  = ACC_EARNINGS (-1)  + RET_EARNINGS
@IDENTITY EQUITY  = CAPITAL  + ACC_EARNINGS  + MINORITY  + TSTOCK
```

Figure 4 displays the forecasts for the Consumer Sentiment Index, unemployment rate, and private housing permit. Our simple macroeconomic model predicts that the consumer sentiment will increase in 2011 and 2012, stabilize in 2013, and begin a slight declining trend in 2014. The unemployment rate is projected to decrease in 2011 – 2014 and increase in 2015 and 2016. The number of housing permits is expected to grow in 2011-2016. Figure 5 shows the generated forecasts for SALES, COGS, and PROFIT for Home Depot. SALES are projected to stay at almost the same level over the 2011-2014 period and decline in 2015 and 2016. The COGS and PROFIT forecasts exhibit similar trends. The forecasts for all income statement variables are illustrated in Appendix A. Figure 6 displays the CASH and NFA forecasts. The CASH balances are projected to increase, while the NFA numbers are not expected to change much in 2011-2014 but will drop in 2015 and 2016. The graphs of forecasts for all balance sheet variables are also provided in Appendix A.

FIGURE 4
MACROECONOMIC FORECASTS

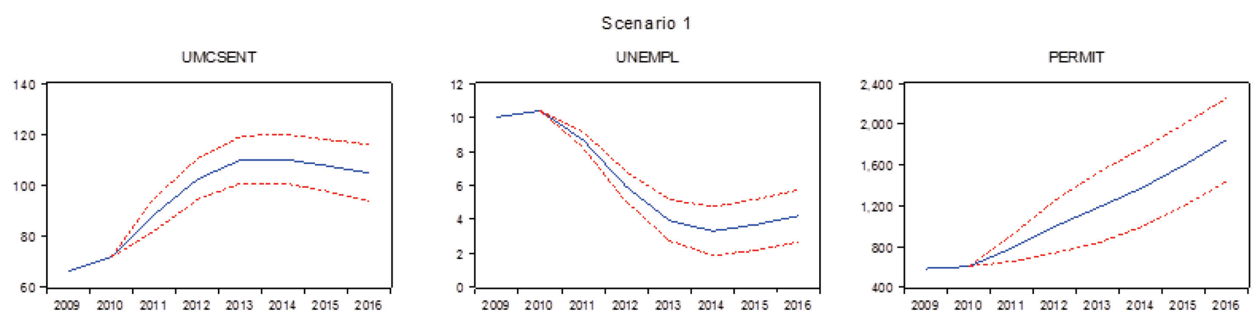


FIGURE 5
THE SALES, COGS, AND PROFIT FORECASTS

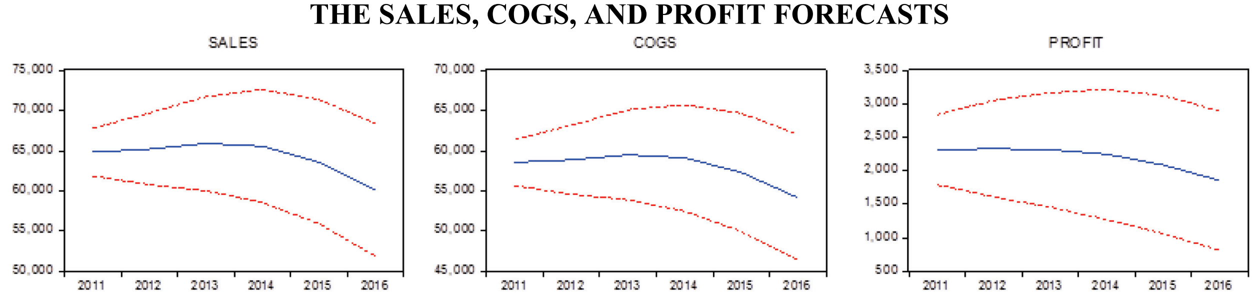
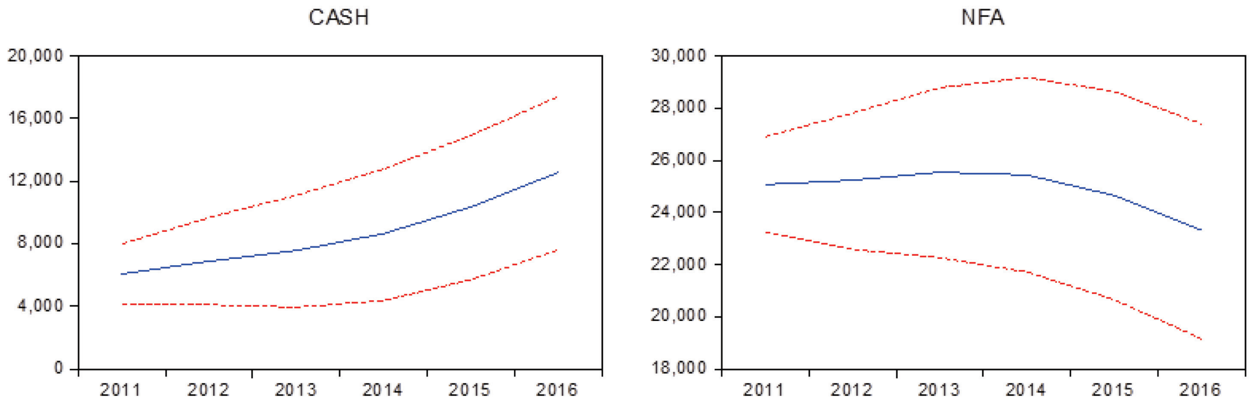


FIGURE 6
THE CASH AND NFA FORECASTS



CONCLUSIONS

EViews financial modeling has the flexibility of incorporating macroeconomic and firm-level uncertainties into a core financial model. This paper illustrates these features using the Home Depot data. First, we forecast macroeconomic factors affecting the Home Depot sales and estimate the sales and financial ratios' models. Then, we utilize the EViews features to seamlessly link the estimated models for uncertainties with the pro forma financial statement model. Such integration allows us to conduct empirically-based stochastic simulations and generate future values of financial variables with confidence bands reflecting the covariance structure of the error terms in all regressions in the financial model. The paper illustrates how multiple sources of uncertainty, including macroeconomic uncertainty, can be taken into account when forecasting future values in pro forma income statement and balance sheet. The integration of macroeconomic forecasting and financial projections will be especially useful for an analysis of companies in highly cyclical industries.

ENDNOTES

1. See Charnes (2007) and Winston (2008).
2. Aljihrish et al (2011) are considering multiple sources of uncertainty for projecting Newmont Mining Corporation's financial variables.
3. Admittedly, it is quite unorthodox to have a time trend in a DLog model, but this specification dominated a number of more traditional trend and difference stationary specifications that we considered.

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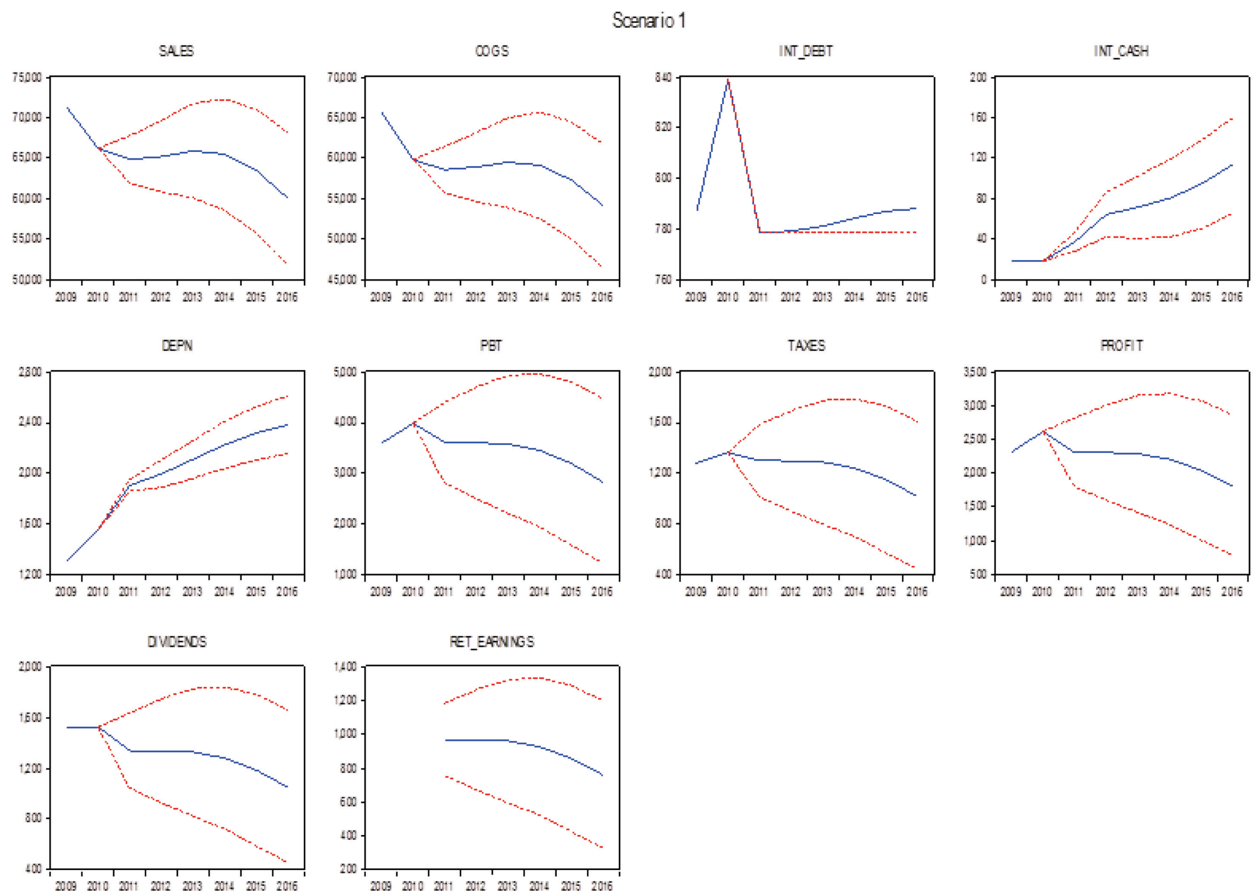
APPENDIX A

INCOME STATEMENT FORECASTS



THE BALANCE SHEET FORECASTS