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Explaining the slow U.S. recovery: 2010–2017

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Abstract This paper argues that the slow U.S. recovery after the 2008–2009 recession was due to sluggish government spending. The analysis uses a structural macroeconometric model. Conditional on government policy, the errors in predicting output for the 2009.4–2017.4 period are within what one would expect historically. Productivity and labor force participation are endogenous variables in the model, and so their behaviors in this period are a consequence of the slow growth rather than a cause.

Keywords slow recovery · productivity · labor force participation

1 Introduction

Between 2010 and 2017, the U.S. output expanded more slowly following the 2008–2009 recession than might have been expected historically. Why was the recovery not stronger? This paper argues that the slow recovery was due to sluggish government spending. Conditional on government policy, there is no puzzle. A structural macroeconometric model of the United States, denoted the "US model," is used in the analysis. The results show that conditional on the exogenous government policy variables, the errors in predicting output for the 2009.4–2017.4 period are within what one would expect historically.

To get a quick picture of the argument, Figs. 1, 2, and 3 plot three government spending variables for the 2009.4–2017.4 period. Figure 1 plots federal government purchases of goods in real terms, variable *COG* in the model. This variable fell from the end of 2010 to the end of 2013 and then remained flat. Figure 2 plots federal transfer payments to households in real terms, variable *TRGHQ* in the model. Due to the stimulus measures, transfer payments remained high until the fourth quarter of 2010, then fell rapidly to 2012, and then only slowly recovered after that. State and local government spending decisions also contributed to the problem. Figure 3 plots state and local government purchases of goods in real terms, variable *COS* in the model. This variable fell substantially to 2013 and then only slowly recovered.

Much of the discussion of the sluggish output growth after 2009 has focused on productivity. An important recent paper is by Fernald et al. (2017) (FHSW), who focus on the slow growth of total factor productivity and the decline in labor force participation. However, because of labor and capital hoarding, total factor productivity is endogenous—it depends on output. Also, labor force participation depends on the state of the economy and so is endogenous. Productivity and labor force participation are not exogenous driving forces that explain the disappointing recovery, but rather consequences of whatever the driving forces are. In the US model, productivity and labor force participation are endogenous variables. It will be seen that their sluggish behavior is a consequence of the slow recovery caused by exogenous government spending decisions. The US model is briefly discussed in Sect. 2, and the solutions are discussed in Sect. 3.

This paper is not the first to point out that sluggish fiscal policy may have contributed to the slow growth after 2009. Eichengreen (2015) cites contractionary U.S. fiscal policy

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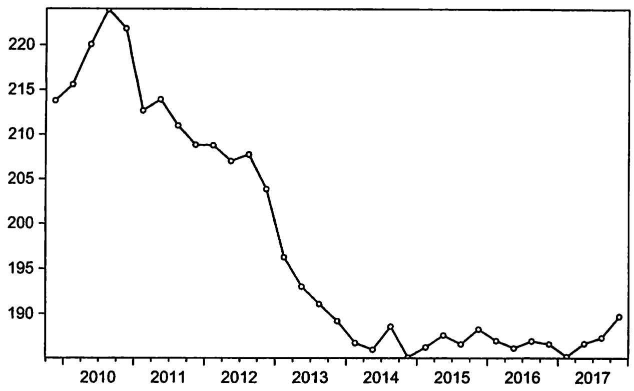

Fig. 1 COG: Federal Government purchases of goods billions of 2009 dollars at quarterly rates 2009.4–2017.4

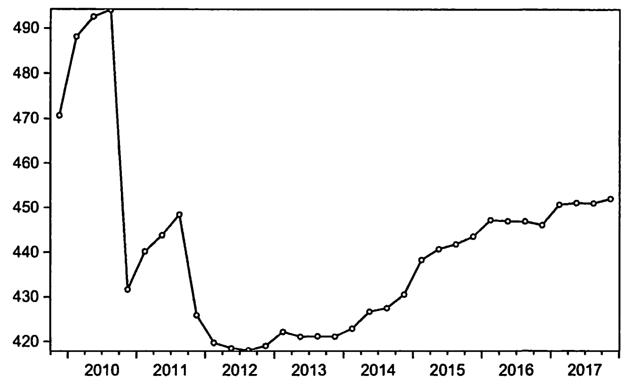

Fig. 2 TRGHQ: Federal government transfer payments to households billions of 2009 dollars at quarterly rates 2009.4–2017.4

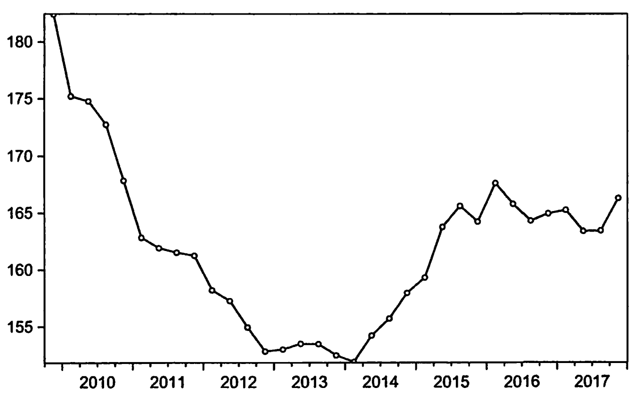

Fig. 3 COS: State and Local Government spending on goods, billions of 2009 dollars at quarterly rates 2009.4–2017.4

during 2011–2013, although he provides no estimates of the effects on the economy. Cashin et al. (2017) using a fiscal effect measure show that fiscal policy was sluggish in this period, especially in 2013. FHSW (2017, pp. 52–53) point out the sluggish federal and state and local government expenditures following the 2008–2009 recession, but, as noted above, their emphasis is on low productivity growth and declining labor force participation.[1]

Kydland and Zarazaga (2016) provide an alternative explanation of the slow recovery. Using a calibrated model, they argue that fears of a switch to a higher-tax regime after the 2008–2009 account for much of the slow recovery. Baker et al. (2015) show that their measures of uncertainty are high during much of the slow-growth period, arguing that uncertainty may be a cause of slow growth. Gary and Ohanian (2016) stress productivity shocks and other supply side shocks as causing much of the slow growth, as does Ohanian (2017) in his review of Eichengreen's book.

2 The US model

The US model uses the methodology of structural macroeconometric modeling, sometimes called the "Cowles Commission" approach, which goes back at least to Tinbergen (1939). I have gathered my research in macroeconomics in one document, *Macroeconometric Modeling: 2018* (*MM*), Fair (2018), on my website, and this document contains a complete description and listing of the US model. *MM* is written using the current version of the US model (January 30, 2018), where published results using earlier versions of the model have been updated.[2] The US model is not explained in this paper, and one should think of *MM* as an appendix to it. When appropriate, I have indicated in this paper in brackets the sections in *MM* that contain relevant discussion. This paper is thus not self-contained. It is too much to try to put all the relevant information in one paper—hence the use of *MM* as an appendix. The methodology of the Cowles Commission approach is also discussed and defended in *MM* [Sect. 1.1].

To review briefly, in the Cowles Commission approach, theory is used to guide the choice of left-hand-side and right-hand-side variables for the stochastic equations in a model, and the resulting equations are estimated using a consistent estimation technique—for example, two-stage least squares (2SLS). Sometimes, restrictions are imposed on the coefficients in an equation, and the equation is then estimated with these restrictions imposed. It is generally

[1] Some of the comments in the discussion of the FHSW paper argue that more emphasis should have been given to aggregate demand effects in explaining the slow recovery.

[2] Users can work with the US model on line or can download the model and related software to work with it on their own computer. If the model is downloaded, it can be modified and reestimated. Many of the results in *MM* can be duplicated on line. The US model is a subset of a larger multicountry model, the MC model, but for purposes of this paper the US model has been used alone.

not the case that all the coefficients in a stochastic equation are chosen ahead of time and thus no estimation done. In this sense, the methodology is empirically driven and the data rule.

This approach has been criticized for being ad hoc, but this is not the case in the sense that theory is used to guide the specification of the stochastic equations. The theory behind the specification of the US model is that households maximize expected utility and firms maximize expected profits. Theory is used in a less restrictive way than in, say, DSGE models, and expectations are generally not assumed to be rational. Given that macroeconomics deals with highly aggregated data, it is not clear that the tight theoretical restrictions imposed by the DSGE approach and the assumption of rational expectations are warranted. The US model is much more empirically based than are DSGE models.

In the US model, there are three estimated consumption equations, three investment equations, an import equation, four labor supply equations, two labor demand equations, a price equation, a nominal wage equation, two term structure of interest rate equations, and an estimated interest rate rule of the Federal Reserve, among others. In the interest rate rule, the Fed is estimated to respond to inflation and unemployment. There are a total of 25 estimated equations and about 100 identities. The unemployment rate is determined by an identity; it equals unemployment divided by the labor force. In the identities, all flows of funds among the sectors (household, firm, financial, state and local government, federal government, and foreign) are accounted for. The federal government deficit is determined by an identity, as is federal government debt. There is an estimated equation determining the interest payments of the federal government as a function of interest rates and the government debt.

The estimation period is 1954:1–2017:4, and the estimation technique is 2SLS. The estimation accounts for possible serial correlation of the error terms. When there is serial correlation, the serial correlation coefficients are estimated along with the structural coefficients. Although macroeconometric models have been criticized by Sims (1980) as not being identified, identification is rarely a problem in this analysis. Many exogenous and lagged endogenous variables in the model are excluded from each stochastic equation. Consistent 2SLS estimation of an equation requires that the first-stage regressors be uncorrelated with the error term. In the US model, government policy variables and exports are used as the first-stage regressors in most equations, but always with a lag of one quarter to avoid any possible correlation of the current values of the variables and the error term. (Remember that any serial correlation of the error term has been eliminated in the estimation.)

Table 1 presents the variable notations used in this paper. *MM* [Sect. 6] provides a complete description of the variables. It also includes a list of the first-stage regressors in each equation. The variables are quarterly time series variables. For ease of notation, time subscripts have not been used here.

2.1 Policy effects

Government spending effects are straightforward in the US model through standard multiplier effects. If government spending increases, output and income increase, investment and consumption increase, output and income increase further, etc. There are many secondary effects in the model, both positive and negative, but this is the big picture. Government tax rate changes affect after tax household income, which affects consumption, etc. One key secondary effect in the model is the response of the Fed through the estimated interest rate rule.

When government spending increases without any corresponding tax rate increases, the government deficit increases, as does the government debt-to-GDP ratio. The debt-to-GDP ratio would thus have been higher had there been more policy stimulus according to the model. The debt-to GDP ratio has no direct effects in the model. It may be that a rising debt-to GDP ratio leads eventually to government spending decreases or tax rate increases, but this is not modeled.

The following discussion covers the treatment of productivity and labor force participation in the model. Since these have been cited as being a cause of the slow recovery, it is important to see how they are treated in the model.

2.2 Production technology

The production function of the firm sector is postulated to be one of fixed proportions in the short run:

$$Y = \min[LAM \cdot (JF \cdot HF^{a}), MU \cdot (KK \cdot HK^{a})], \tag{1}$$

where Y is production, JF is the number of workers employed, HF^{a} is the number of hours worked per worker, KK is the capital stock, HK^{a} is the number of hours each unit of KK is utilized, and LAM and MU are coefficients that may change over time due to technical progress. The variables Y, JF, and KK are observed; the others are not. For example, data on the number of hours paid for per worker exist, HF in the model, but not on the number of hours actually worked per worker, HF^{a}, unless the two are the same.

If $JF \cdot HF$ is greater than $JF \cdot HF^{a}$, there is excess labor on hand, i.e., more labor than is needed to produce the level of output of the quarter. Because of adjustment costs, when output falls, firms may not decrease labor hours as much as

Table 1 Variables in the US model referred to in this paper

Variable	Type	Description
AA	endo	Total net financial and housing wealth, h, B2009$
cnst	exog	Constant term
cnst2	exog	0.0 before 1969:1, 0.0125 in 1969:1, 0.0250 in 1969:2, ..., 0.9875 in 1988:3, and 1.0 thereafter
COG	exog	Purchases of consumption and investment goods, g, B2009$
COS	exog	Purchases of consumption and investment goods, s, B2009$
D593	exog	1 in 1959:3; 0 otherwise
E	endo	Total employment, civilian and military, millions
GDPD	endo	GDP price deflator
HF	endo	Average number of hours paid per job, f, hours per quarter
HFS	exog	Long-run desired value of *HF*, computed from peak-to-peak interpolations of *HF*
JF	endo	Number of jobs, f, millions
JG	exog	Number of civilian jobs, g, millions
JHMIN	endo	Number of worker hours required to produce Y, millions, *Y/LAM*
JM	exog	Number of military jobs, g, millions
JS	exog	Number of jobs, s, millions
KK	endo	Stock of capital, f, B2009$
L1	endo	Labor force of men 25–54, millions
L2	endo	Labor force of women 25–54, millions
L3	endo	Labor force of all others, 16+, millions
LAM	exog	Amount of output capable of being produced per worker hour, computed from peak-to-peak interpolations of $Y/(JF \cdot HF)$
LM	endo	Number of "moonlighters": difference between the total number of jobs (establishment data) and the total number of people employed (household survey data), millions
PH	endo	Price deflator for consumption plus housing investment inclusive of indirect business taxes
POP	exog	Noninstitutional population 16+, millions
POP1	exog	Noninstitutional population of men 25–54, millions
POP2	exog	Noninstitutional population of women 25–54, millions
POP3	exog	Noninstitutional population of all others, 16+, millions
PROD	endo	Output per paid for worker hour ("productivity"), $Y/JF \cdot HF)$
T	exog	1 in 1952:1, 2 in 1952:2, etc.
TRGHQ	exog	Transfer payments (net), g to h, B2009$
UR	endo	Civilian unemployment rate
WA	endo	After tax wage rate. (Includes supplements to wages and salaries except employer contributions for social insurance.)
Y	endo	Total production, f, B2009$

h household sector, *f* firm sector, *g* federal government sector, *s* state and local government sector, *B2009* billions of 2009 dollars

they could to produce the level of output, which leads to excess labor. Excess labor is measured here from peak-to-peak interpolations of the log of $Y/(JF \cdot HF)$, depicted in Fig. 4. The values of the log of *LAM* lie on the straight lines, where *LAM* can be thought of as potential productivity. At the peaks, it is assumed that $JF \cdot HF$ equals $JF \cdot HF^a$. Given an estimate of *LAM* for each quarter and given data on *Y*, *Y/LAM*, which will be denoted *JHMIN*, is the estimate of the number of worker hours required to produce the output of the quarter.

Hours paid per worker, *HF*, fluctuates much less over the business cycle than does *JF*. Over time, *HF* has a downward trend. A variable, denoted *HFS*, was constructed from peak-to-peak interpolations of *HF*. This variable will be called the "desired" number of hours. It is an estimate of the average number of hours firms would want to pay per worker absent business cycle considerations.

The excess labor variable is then defined to be (in log form): $\log[JF/(JHMIN/HFS)]$. This variable is used in the equations explaining *JF* and *HF* below.

A similar procedure is followed in the construction of the model for estimating excess capital—from peak-to-peak interpolations of *Y/KK*, but in the interests of space

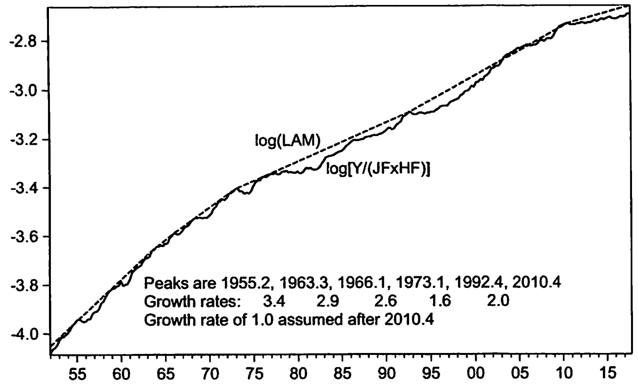

Fig. 4 Peak-to-peak interpolation of the log of productivity 1952.1–2017.4

this will not be discussed here. (See *MM* [Sect. 6.3.9].) The focus here is on labor productivity.

2.3 Potential labor productivity

The view behind the above specification is that technical progress is primarily embodied in new machines with lower worker/machine ratios. This is approximated by the peak-to-peak interpolations of output per worker hour. In this formulation, potential labor productivity is always increasing. It is not cyclical, as is actual productivity. Actual productivity falls when output falls and excess labor is being built up, and it may rise rapidly when output rises and excess labor is being drawn down. The fluctuations in actual productivity are sometimes referred to as "'shocks" in the literature, but this is misleading because they are endogenous. Changes in potential labor productivity can be considered as shocks in this sense, but they are small.

Figure 4 shows that potential productivity growth was higher in the 1950s and 1960s than since, something that is well known. The growth rate in the two decades ending in 2010 is estimated at 2.0% in the figure. Between 1973.1 and 1992.4, it was 1.6%, a well-known slowing of growth. What about since 2010? A peak has probably not been reached by 2017.4, but it clearly looks like there has been a smaller growth rate since 2010. The figure uses 1.0%. This is a considerable decline from 2.0%, but it may be even lower.

No attempt is made in this paper to try to explain the possible decline in potential productivity growth since 2010. Explaining changes in long-run trends is important, but this is beyond the essentially business cycle considerations of this paper. An interesting recent paper examining long-run changes in the U.S. employment/population ratio is by Abraham and Kearney (2018). Some of the factors that they cite could also affect potential productivity. Schmalensee (2018) shows that there was a large decline in productivity growth between 1990–2000 and 2010–2016 for computers and electronic products, due mostly to sharp slowdowns in the decline of the deflators for these products. These changes are large enough to affect the aggregate productivity numbers. These changes could be due to measurement problems or structural changes in the industries, and they may have an effect on aggregate potential productivity.

For the solutions in Sect. 3, three assumptions about potential productivity growth since 2010 have been used: 0.5, 1.0, and 1.5%. The main point of this paper, namely that the output prediction errors are within what one would expect historically, is not sensitive to these values. It will be seen that predictions of employment and the unemployment rates are sensitive to the use of 1.5%—they are not as good.

2.4 Labor demand and labor supply equations

The two labor demand equations explain *JF* and *HF*. The four labor supply equations explain the labor force participation of men 25–54, women 25–54, and all others, *L*1, *L*2, and *L*3, and the number of people holding two jobs (moonlighters), *JM*. The labor demand equations are in Table 2, and the labor supply equations are in Table 3.

The estimated equation for *JF* is based on the following two equations:

$$\log(JF^*/JF_{-1}) = \alpha_0 \log[JF/(JHMIN/HFS)]_{-1} + \alpha_1 \Delta \log Y, \tag{2}$$

$$\log(JF/JF_{-1}) - \log(JF_{-1}/JF_{-2}) = \lambda[\log(JF^*/JF_{-1}) - \log(JF_{-1}/JF_{-2})] + \epsilon, \tag{3}$$

where α_0 is negative, and the other coefficients are positive. The construction of *JHMIN* and *HFS* and the excess labor variable are explained above.

JF^* in Eq. (2) is interpreted as the number of workers the firm would desire to have on hand in the current quarter if there were no costs of changing employment. The desired change, $\log(JF^*/JF_{-1})$, depends on the amount of excess labor on hand and the change in output. This equation says that the desired number of workers approaches *JHMIN*/*HFS* in the long run if output is not changing. Equation (3) is a partial adjustment equation of the actual number of workers to the desired number.

Combining Eqs. (2) and (3) yields

$$\Delta \log JF = \lambda\alpha_0 \log[JF/(JHMIN/HFS)]_{-1} + (1 - \lambda)\Delta \log JF_{-1} + \lambda\alpha_1 \Delta \log Y + \epsilon. \tag{4}$$

The equation in Table 2 is the estimated version of Eq. (4). It has a dummy variable, *D*593, added to pick up the effects of a 1959 steel strike.

Table 2 Coefficient estimates for jobs (*JF*) and hours (*HF*)

	$\Delta \log JF$	$\Delta \log HF$
cnst	− 0.00008 (− 0.11)	− 0.00485 (− 6.07)
$\log[JF/(JHMIN/HFS)]_{-1}$	− 0.0406 (− 3.39)	− 0.0170 (− 1.69)
$\Delta \log Y$	0.345 (4,63)	0.279 (5.25)
$\Delta \log JF_{-1}$	0.567 (12.61)	
$\log(HF/HFS)_{-1}$		− 0.153 (− 5.42)
T		0.00001 (4.91)
D593	− 0.0168 (− 4.74)	
SE	0.00332	0.00268
R^2	0.705	0.318
DW	2.21	2.11

t statistics are in parentheses. Estimation period is 1954.1–2017.4. Estimation method is 2SLS. Variables are listed in Table 1: *JF* jobs, *HF* hours per job, *JHMIN* required worker hours, *HFS* desired hours per job, *Y* output, *T* time trend, *D593* dummy variable

Table 3 Coefficient estimates for the L1, L2, L3, and LM equations

	$\log(L1/POP1)$	$\log(L2/POP2)$	$\log(L3/POP3)$	$\log(LM/POP)$
cnst	0.0258 (3.08)	− 0.0377 (− 0.97)	0.0414 (2.10)	− 0.239 (− 4.14)
ldv	0.925 (38.49)	0.892 (44.38)	0.973 (70.73)	0.908 (44.92)
$\log(AA/POP)_{-1}$	− 0.00586 (− 3.10)	− 0.01281 (− 1.82)	− 0.01253 (− 2.35)	
UR	− 0.0393 (− 2.73)	− 0.1341 (− 3.79)	− .1282 (− 3.97)	− 1.168 (− 4.31)
$\log(WA/PH)$			0.0161 (2.26)	
T		0.00038 (6.37)		
*cnst*2		0.0692 (5.38)		
$cnst2 \cdot T$		− 0.00032 (− 6.00)		
SE	0.00240	0.00498	0.00521	0.0481
R^2	0.994	0.999	0.987	0.945
DW	2.23	2.22	2.10	2.10

ldv lagged dependent variable. *t* statistics are in parentheses. Estimation period is 1954.1–2017.4. Estimation method is 2SLS. Variables are listed in Table 1

All the variables are significant in the *JF* equation except the constant term. For example, excess labor is a significant factor in explaining the demand for jobs. The estimate of $1 - \lambda$ is .567, and so the implied value of λ is .433. The estimate of $\lambda\alpha_0$ is − .041, and so the implied value of α_0 is − .095. This is the estimate of the size of the effect of excess labor on the desired number of workers.

The ideas behind this employment demand equation and the hours demand equation discussed next go back 50 years to my Ph.D. dissertation, Fair (1969). See also Fair (1985), which shows that the aggregate equations are consistent with the survey results of Fay and Medoff (1985). These two equations have held up remarkably well over the years.

The estimated equation for *HF* is

$$\Delta \log HF = \lambda \log(HF_{-1}/HFS_{-1}) + \alpha_0 \log[JF/(JHMIN/HFS)]_{-1} + \alpha_1 \Delta \log Y + \epsilon. \tag{5}$$

The first term on the right-hand side of Eq. (5) is the (logarithmic) difference between the actual number of hours paid for in the previous quarter and the desired number. The reason for the inclusion of this term in the hours equation but not in the employment equation is that, unlike *JF*, *HF* fluctuates around a slowly trending level of hours. This restriction is captured by the first term in (5). The other two terms are the amount of excess labor on hand and the current change in output. Both of these terms affect the employment decision, and they should also affect the hours decision since the two are closely related. The *HF* equation in Table 2 is the estimated version of Eq. (5). The estimate of λ is $-.153$, and the estimate of α_0 is $-.017$.

The labor supply equations are consistent with the standard household utility maximization model. Labor supply depends on the real wage and wealth, where the effect of wealth is unambiguously negative because it is a pure income effect, but the effect of the real wage can go either way depending on the size of the income and substitution effects. Wealth appears in all three labor force participation equations, but the real wage was only important in the *L*3 equation. The unemployment rate was added to each equation to pick up potential discouraged worker effects. The wealth variable, *AA*, is the real value of net household financial and housing wealth. Its main fluctuations are from fluctuations in stock price and housing prices. It is discussed in Sect. 3. The theory is that this variable should have a negative effect on labor supply.

The first equation in Table 3 explains the labor force participation rate of men 25–54. It is in log form and includes as explanatory variables, the wealth variable and the unemployment rate. As just noted, the unemployment rate is meant to pick up a discouraged worker effect. The wealth variable has a negative coefficient estimate, as expected, as does the unemployment rate. All the coefficient estimates are significant.

The second equation explains the labor force participation rate of women 25–54. It is in log form and includes as explanatory variables the wealth variable, the unemployment rate, and a time trend. In addition, the constant term and the coefficient of the time trend are assumed to be time varying. (See *MM* [Sect. 2.3.2] for the treatment of time varying coefficients.) This is handled by adding $cnst2$ and $cnst2 \cdot T$ as explanatory variables. There is an economically unexplained trend in *L*2, especially in the 1970s, due to social movements, which is the reason the time trend is added. As in the first equation, the wealth variable has a negative coefficient estimate, as does the unemployment rate, although the *t* statistic for the wealth variable is only -1.82. The time trend is highly significant.

The third equation explains the labor force participation rate of all others 16+. It is also in log form and includes as explanatory variables the real wage, the wealth variable, and the unemployment rate. All the coefficient estimates are significant. The coefficient estimate of the real wage is positive, which suggests that the substitution effect dominates, and the coefficient estimates of the wealth variable and the unemployment rate are negative.

The fourth equation determines the number of moonlighters. It is in log form and includes the unemployment rate as an explanatory variable. The coefficient estimate of the unemployment rate is negative and significant, which is the discouraged worker effect applied to moonlighters.

The total number of people employed in the economy, denoted *E*, is equal to the total number of jobs minus the number of moonlighters:

$$E = JF + JG + JM + JS - JM, \tag{6}$$

where *JG* is the number of federal civilian jobs, *JM* is the number people in the military, and *JS* is the number of state and local jobs. The unemployment rate, *UR*, is then

$$UR = \frac{L1 + L2 + L3 - E}{L1 + L2 + L3}. \tag{7}$$

3 Solutions of the model

The model was solved using stochastic simulation as explained in the appendix. This allows standard errors of the predictions to be computed. The solution period is 2009.4–2017.4. The quarter 2009.4 is the first quarter that the recovery began.[3]

This solution uses actual values of the exogenous variables, and so it is not a prediction that could be made in real time. (Also, the solution is not outside the estimation period.) The solution asks the question that, conditional on the exogenous variables, what does the model predict about the recovery?

The main exogenous variables are government policy variables, population and age distribution variables, exports, and the price of imports. Three of the main government spending variables have been plotted in Figs. 1, 2 and 3.

A key variable in the US model is *AA*, the total real net financial and housing wealth of the household sector. It appears in the three labor force participation equations in Table 3. It is also an important explanatory variable in the three consumption equations and the housing investment equation in the model (lagged one quarter). There are large estimated wealth effects in the equations. Changes in *AA* are primarily affected by changes in stock prices and changes in housing prices. *AA* is also affected by the saving of the household sector, but most of the fluctuations in *AA* are due to capital gains or loses on stocks and housing.

$\log(AA/POP)$ is plotted in Fig. 5 for the 1990.1–2017.4 period. Fig. 5 shows that since 1995 there have been huge fluctuations in financial and housing wealth, which is well known. What is important for present purposes is that *AA* has risen substantially since 2010—primarily because of

[3] As noted in Sect. 2, the January 30, 2018, version of the US model is used here. This version uses actual (sometimes preliminary) data through the fourth quarter of 2017. The data thus do not incorporate the NIPA revisions released in July 2018. The revisions were fairly minor, and it is unlikely that the present results would change much if the revised data had been used.

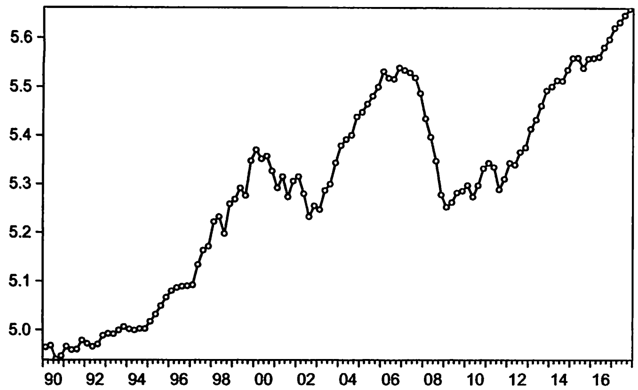

Fig. 5 log(AA/POP): Log of real net household wealth per capita 1990.1–2017.4

rising stock prices. In the solution of the model, the change in stock prices and the change in housing prices have been taken to be exogenous. This means that most of the fluctuations in *AA* in Fig. 5 are exogenous. The solution thus takes into account the increase in wealth in the period. Had smaller values of *AA* been used, the recovery would have been predicted to be slower. In practice, changes in *AA* are, of course, largely unpredictable, since changes in stock prices and housing prices are largely unpredictable.[4]

Fed behavior has also been taken to be exogenous. The estimated interest rate rule has been dropped. The solution is thus conditional on actual Fed behavior, which kept interest rates low during this period.

Finally, the potential productivity variables, *LAM* and *MUH*, have been taken to be exogenous. As discussed in Sect. 2, an important question is what has been the growth rate of *LAM* since 2010? Figure 4 uses 1.0%, and this has been used as the base case. However, solutions have also been run using 0.5% and 1.5% to examine the sensitivity of the results to these changes.

For each variable of interest, the growth rate over the 33 quarter intervals has been computed and put at an annual rate. For the unemployment rate, the predicted value in the last quarter has been used. Results are presented in Table 4 for 11 variables. The first column lists the actual values and the second column lists the predicted values. The prediction error is in the third column and the estimated standard error of the prediction in the fourth column.

With one exception, the predicted values are within one standard error of the actual values. The exception is productivity, where the error is 0.29 and the standard error is 0.231. Output growth is overpredicted—2.76% versus 2.55% actual—but not by much. Job growth is underpredicted—1.39% versus 1.54%, although hours growth is overpredicted—0.32% versus 0.25%. The net effect of these is that productivity growth was overpredicted—1.03% versus 0.74%—because output was overpredicted and employment was underpredicted. The labor force participation variables were predicted well. One reason for the predictions of sluggish labor force growth is the increase in the wealth variable, *AA*. The unemployment rate at the end of the period was predicted to be 4.82%, which compares to the actual value of 4.09%. This error is primarily due to the fact that job growth was underpredicted. But again these are all within a standard error.

In column (5), where the growth rate of *LAM* is lowered to 0.5%, the predicted value of output is little affected, but the growth rate of jobs is now larger. In this run, there is less excess labor since potential productivity is less, which leads firms to hire more—remember that excess labor has a negative effect on employment demand. For this run, the predicted value of the unemployment rate at the end of the period is essentially perfect—4.10% versus 4.09%.

When the growth rate of *LAM* is increased to 1.5% in column (7), output growth is again little affected, but the growth rate of jobs is now lower because excess labor is larger. The predicted unemployment rate at the end is 5.62% versus 4.09% actual. The larger unemployment rates in this run lead the predicted values of the labor supply variables to be smaller because of the discouraged worker effect. This run is the least accurate of the three for the employment variables.

An important point about the results in Table 4 is that output growth is not sensitive to assumptions about potential productivity. Output growth is accurately predicted in all three cases. Job growth and the unemployment rate are fairly well predicted in the first two cases, but if potential productivity really grew at 1.5%, the model noticeably underpredicts job growth and overpredicts the unemployment rate.

Finally, to give a little more detailed picture of the results, Figs. 6, 7 and 8 plot for the 2009.4–2017.4 period the actual and predicted values of output, productivity, and the unemployment rate along with one standard error bands. The predicted values are for the growth rate of *LAM* of 1.0%. For the most part, the actual values are within the error bands. Output was underpredicted in the first half and overpredicted in the second. Productivity was overpredicted beginning about 2013 by about a standard error. The unemployment rate was generally overpredicted, but quite accurate from 2015 on.

[4] There is actually a lot of macro information in Fig. 5, at least from the perspective of the US model. The results in Fair (2004) show that most of the boom in the U.S. economy in the last half of the 1990s was due to the increase in *AA*—the wealth effect at work. The results in Fair (2005) show that much of the sluggish economy in the 2000.4–2004.3 period was due to the fall in *AA*. Finally, the results in Fair (2017) show that much of the 2008–2009 recession was due to the huge fall in *AA*. In this latter case, much of the fall in *AA* was from the huge decline in housing prices.

Table 4 Predictions from the model

	g(LAM) = 1.0				g(LAM) = 0.5		g(LAM) = 1.5	
	Actual (1)	Pred. (2)	Error (3)	SE (4)	Pred. (5)	Error (6)	Pred. (7)	Error (8)
Y	2.55	2.76	0.21	0.234	2.73	0.18	2.78	0.23
JF	1.54	1.39	− 0.15	0.316	1.62	0.08	1.24	− 0.30
HF	0.25	0.32	0.07	0.074	0.32	0.07	0.31	0.06
PROD	0.74	1.03	0.29	0.231	0.87	0.13	1.31	0.57
L1	− 0.13	− 0.15	− 0.02	0.089	− 0.13	0.00	− 0.19	− 0.06
L2	− 0.11	− 0.10	0.01	0.166	− 0.01	0.10	− 0.19	− 0.08
L3	1.43	1.26	− 0.17	0.297	1.36	− 0.07	1.15	− 0.28
LM	4.22	4.54	0.32	1.857	5.31	1.09	3.69	− 0.53
E	1.13	0.97	− 0.16	0.232	1.13	0.00	0.79	− 0.34
UR	4.09	4.82	0.73	1.078	4.10	0.01	5.62	1.53
GDPD	1.65	1.71	0.06	0.256	1.82	0.17	1.58	− 0.07

Dynamic stochastic simulation for 2009.4–2017.4. Values are growth rates over the 33 quarters at an annual rate except for *UR*. The *UR* value is the prediction for 2017.4. Values are mean values from the stochastic simulation, 2000 trials. SE roughly the same for $g(LAM) = 0.5$ and 1.5. Variables are listed in Table 1

SE estimated standard error of the prediction

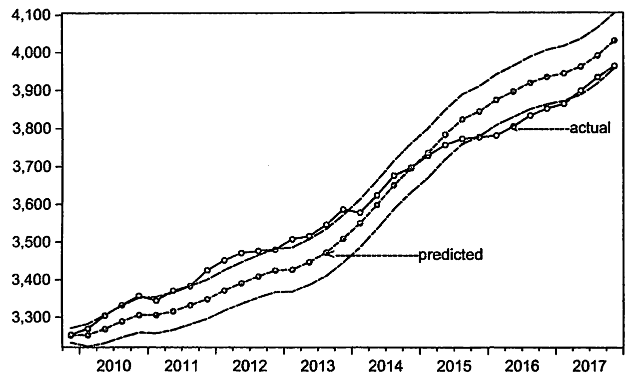

Fig. 6 Actual and predicted Y and standard error bands 2009.4–2017.4

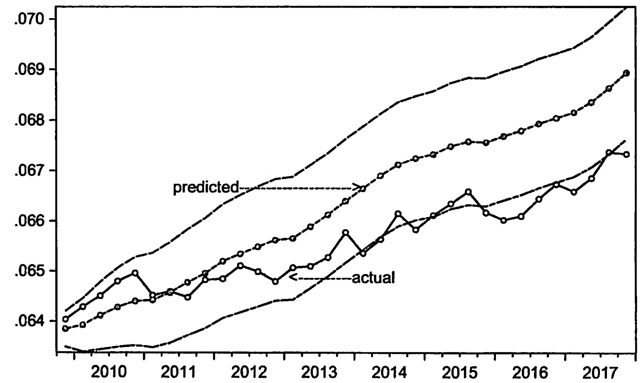

Fig. 7 Actual and predicted PROD and standard error bands 2009.4–2017.4

4 Conclusion

This paper has attempted to provide a casual explanation of the slow output growth after the 2008–2009 recession, namely sluggish government spending. According to the model, conditional on wealth, monetary policy, and fiscal policy, output grew about as expected during this period. On the plus side were the larger than average rise in wealth and easy monetary policy. On the minus side was the sluggish government spending. The net effect was a sluggish recovery.

The puzzle regarding the relationship between output and the unemployment rate is not a puzzle unless the growth rate of potential productivity is about 1.5% or greater. More time is needed before one has a good estimate of this rate since 2010. Although for the present purposes, essentially business cycle analysis, the assumption of exogenous potential labor productivity growth is unlikely to bias the results much, an important area of research is to explain why potential productivity growth may have slowed.

No attempt has been made in this paper to consider possible optimal policies. The paper deals only with the actual policies. Had the policies been more stimulative, output would have been higher, inflation would have been higher, and the government debt-to GDP ratio would have been higher. How one evaluates this depends on one's loss function, which is beyond the scope of this paper.

Having said this, it is possible to use the model to run counterfactual experiments. Consider the following

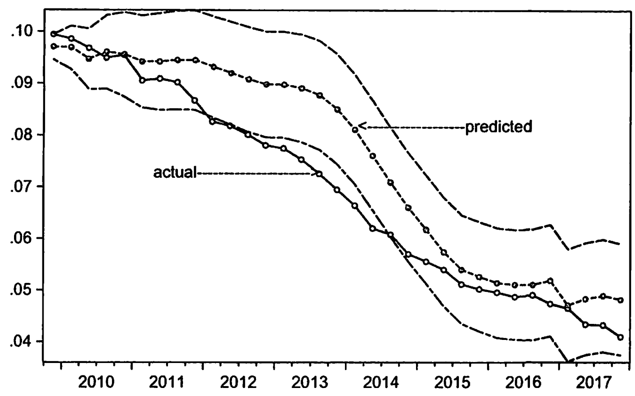

Fig. 8 Actual and predicted UR and standard error bands 2009.4–2017.4

experiment. *COG* in Fig. 1 was taken to be 215.0 from 2011:1 on; *TRGHQ* in Fig. 2 was taken to be 460.0 from 2011:1 on; and *COS* in Fig. 3 was taken to be 170.0 from 2011:1 on. This basically assumes away the sluggish government spending. The model was then solved for the 2011:1–2017:4 period. As was done for the above results, this solution takes stock prices, housing prices, Fed behavior, and potential productivity as exogenous. It is thus artificial in that it is likely that had government spending been higher, the Fed would have raised interest rates some. The experiment is just meant to get a sense of magnitudes.

For the solution, the estimated residuals were added to the stochastic equations and taken to be exogenous. This means that when the model is solved using the actual values of all the exogenous variables, a perfect tracking solution is obtained. The model was then solved using the changed values of the three government spending variables. The difference between the solution value of an endogenous variable for a particular quarter and the actual value is the estimated effect of the government spending changes.

The peak estimated effects were in 2014. Real output (*Y*) was higher by about 2.6%; the number of jobs (*JF*) was higher by about 2.4%; and the unemployment rate (*UR*) was lower by about 1.1 percentage points. The level of the GDP deflator (*GDPD*) was higher by about 1.4%. The federal government debt-to-GDP ratio at the end of 2017 was 3.9 percentage points higher.

Appendix: Computing standard errors

There are 25 estimated equations in the US model, but two of these have been dropped for purposes of this paper—the capital gains equation and the Fed rule. This gives 23 equations. The estimation period is 1954.1–2017.4, 256 quarters. For each estimated equation, there are 256 estimated residuals. Let $\hat{u}_t$ denote the 23-dimension vector of the estimated residuals for quarter t, $t = 1,\ldots,256$.[5]

The solution period is 2009.4–2017.4, 33 quarters. The model was solved 2,000 times for this period. Each trial is as follows. First, 33 error vectors are drawn with replacement from the 256 error vectors $\hat{u}_t$, $t = 1,\ldots,256$. These errors are added to the equations, and the model is solved dynamically for the 2009.4–2017.4 period. The predicted values are recorded. This is one trial. This procedure is then repeated 2000 times, which gives 2000 predicted values of each variable. The mean and standard error are then computed for each variable. See *MM* [Sects. 2.6, 2.7] for more details.

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[5] If the initial estimate of an equation suggests that the error term is serially correlated, the equation is reestimated under the assumption that the error term follows an autoregressive process (usually first order). The structural coefficients in the equation and the autoregressive coefficient or coefficients are jointly estimated (by 2SLS). The $\hat{u}_t$ error terms are after adjustment for any autoregressive properties, and they are taken to be *iid* for purposes of the draws.

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