澳門大學

UNIVERSIDADE DE MACAU

UNIVERSITY OF MACAU

Department of Economics

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Instructor: WONG Ka Kei, Gary

Forecasting Total Factor Productivity Growth Rate: Evidence from the United States

LIAO JIAYING, SB923330

YANG WANSONG, SB823316

HE SIYI, SB823412

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1 Introduction

This article aims at forecasting the growth rate of Total Factor Productivity (TFP) to capture the technological progress trend from 2020 to 2029 in the United States(US). Collecting data from 1977 to 2019, we first estimate the National Production Function under the assumption of a typical Cobb-Douglas Model. Then we conduct the Augmented Dickey-Fuller Test(ADF Test) to ensure a stationary series. In addition, we derive the long-run (LR) and short-run (SR) relationship between economic output, capital input and labor input to detect whether these variables are co-integrated. We further estimate their SR relationship using the Error Correction Model (ECM), which could consider both short-run and long-run dynamics. Finally, we use Auto-regressive Integrated Moving Average Model(ARIMA Model) to forecast future capital and labor and calculate the estimated LR Growth Rate of TFP from 2020 to 2029. The result shows that other than 2020, the estimated LR growth rate of technological progress is almost close to zero, implying a relatively stable state for US technical progress.

2 The Growth Accounting Framework

There are lots of production functions with various properties. For simplicity, we employ the Cobb-Douglas functional form (Cobb & Douglas, 1928) of production to decompose output growth into input growths and TFP growth, which is also widely used in other research works. The Cobb-Douglas production function model has many excellent properties for us to investigate growth rate and conduct some transformations. Standard original Cobb-Douglas form can be expressed as:

$$Y_t = A_t K_t^{\alpha} L_t^{\beta}$$

where Y_t represents real GDP, K_t represents the capital stock and L_t represents labor input for a country in year t. Parameters α and β are the shares of contribution for capital and labor, respectively, also known as the capital and labor intensity. The A term represents Total Factor Productivity (TFP for short), which value reflects the state of technology, skill and education level in the workforce. Different α, β will lead to different returns to scale of the Cobb-Douglas production function:

$$\alpha + \beta = 1 \Rightarrow constant\ return\ to\ scale$$

$$\alpha + \beta > 1 \Rightarrow increasing\ return\ to\ scale$$

$$\alpha + \beta < 1 \Rightarrow decreasing\ return\ to\ scale$$

Take natural logarithm on both side, then we can get our linear regression function where α and β can be estimated in the form as below:

$$lnY = ln(AK^{\alpha}L^{\beta}) = lnA + \alpha lnK + \beta lnL$$

$$\Rightarrow y = \delta + \alpha k + \beta l + \epsilon$$

where y=lnY, k=lnK, l=lnL. We can do linear regression using macro-data and estimate the capital intensity and labor intensity represented as alpha and beta with this linear form.

To derive the TFP growth rate from the Cobb-Douglas production function, we need a total differentiation for the logged form from both sides. The growth rate of technology is derived through some simple mathematical manipulation(Barro, 1999).

$$g_Y = g_A + \alpha * g_K + \beta * g_L$$

$$g_A = TFP\ growth\ rate = g_Y - \alpha * g_K - \beta * g_L$$

Improving the total factor productivity is one crucial driving force behind economic growth. Thereby, the late-developing countries need to identify the determinants.

3 Data

3.1 Data Description

To explore our research questions, we collected data from US Federal Reserve Economic Data (FRED), which includes GDP, capital stock and employment level from 1977 to 2019 at the annual level. For better estimation, we further calculated the capital use by applying the measurement of capital from the Bank of England.[1] Also, we introduce some notations below for convenience:

Symbol	Meaning in the Model	Source
Y_t	Real GDP (million)	Federal Reserve Economic Data
K_t	Capital Use at 2017 Prices for US(Million)	Federal Reserve Economic Data
L_t	Employment Level for US(Thousand)	Federal Reserve Economic Data
α	Shares of Contribution for Capital	
β	Shares of Contribution for Labor	
A_t	Total Factor Productivity(TFP)	
g_Y	GDP Growth Rate	Self-Calculated
g_L	Labor Growth Rate	Self-Calculated
g_K	Capital Growth Rate	Self-Calculated
g_A	Total Factor Productivity(TFP) Growth Rate	Self-Calculated
y_t	Logarithmic form of Real GDP	Self-Calculated
k_t	Logarithmic form of Capital Stock	Self-Calculated
l_t	Logarithmic form of Labor	Self-Calculated
a	Logarithmic form of TFP	Self-Calculated
w_t	Gaussian White Noise Series	

3.2 Summary Statistics

Table1 is a summary table of our data, which contains the information of variables' names, the number of observations, average, maximum value, minimum value and standard deviation.

Table 1: Descriptive Statistics

VARIABLES	Obs	Mean	Std.Dev.	Min	Max
GDP	42	1.320e+07	4.197e+06	7.075e+06	2.056e+07
Capital Use	42	4.733e+07	1.318e+07	2.674e+07	6.853e+07
Employment	42	128,953	17,934	97,581	158,772
$\log(GDP)$	42	16.34	0.336	15.77	16.84
$\log(Capital\ Use)$	42	17.63	0.291	17.10	18.04
$\log(Employment)$	42	11.76	0.144	11.49	11.98

[1]capital use in year $t = (K_t * K_{t-1})^{\frac{1}{2}}$, where capital stock denotes as K

4 Methodology and Empirical Results

4.1 Estimation of the National Production Function

4.1.1 The Model

We start our estimation with an assumption that the relationship between the production input and output in US follows a typical Cobb-Douglas model.

$$Y_t = e^{\beta_0} K_t^{\beta_1} L_t^{\beta_2} e^{\varepsilon_t} \tag{1}$$

where Y_t is the total output of US at time t, K_t is the capital input, and L_t is the labor input. ε_t is an error term. β_0, β_1, and β_2 are parameters to be estimated. If we take natural logarithm on both sides of Eq.(1), this equation can be rewritten as:

$$y_t = \beta_0 + \beta_1 k_t + \beta_2 l_t + \varepsilon_t \tag{2}$$

where $k_t \equiv \log(K_t)$ and $l_t \equiv \log(L_t)$.

4.1.2 Cointegration Test and LR Relationship

After the stationarity test, facing the potential issue of spurious relationship, the most critical work before doing regression between economic output, capital input, and labor input to obtain their LR and SR relationship is to conduct the cointegration test to detect whether these variables are cointegrated or not. Here, we follow the procedure put forward by Engle & Granger (1987) as follows:

First, we directly regress y_t with k_t and l_t based on the simple OLS and consider the static regression:

$$y_t = \beta_0 + \beta_1 k_t + \beta_2 l_t + u_t \tag{5}$$

Then we test the stationarity of $\widehat{u_t}$ by ADF test and consider the regression:

$$\Delta \hat{u}_t = \delta_0 + \delta_1 \hat{u_{t-1}} + \cdots + \delta_p \hat{u_{t-p}} + v_t \tag{6}$$

If the residuals u_t is stationary, there does exist LR equilibrium between GDP, capital use, and labor force level, and the simple OLS will give us unbiased estimation for this LR relationship.We denote this LR relationship as:

$$y^E = \beta_0 + \beta_1 k^E + \beta_2 l^E \tag{LR}$$

We also consider the meaning of the slope coefficients, and we do mathematical derivation as follows:

$$\beta_1 = \frac{\partial \log(GDP)}{\partial \log(Capital)} = (\frac{\Delta GDP}{GDP})/(\frac{\Delta Capital}{Capital}) = e_{Y,K}$$

$$\beta_2 = \frac{\partial \log(GDP)}{\partial \log(Labor)} = (\frac{\Delta GDP}{GDP})/(\frac{\Delta Labor}{Labor}) = e_{Y,L}$$

Therefore, these coefficients in the LR regression equation can be explained by the LR capital and labor elasticity of output respectively.

4.1.3 Error Correction Model and SR Relationship

If GDP, capital use, and labor force series are co-integrated and all $I(1)$, we can estimate their SR relationship by Error Correction Model (ECM) which could take both SR dynamics and LR dynamic into the consideration.

$$\Delta y_t = \underbrace{\alpha_0 + \alpha_1 \Delta k_t + \alpha_2 \Delta l_t}_{SR\ Dynamic} - \underbrace{\lambda(y_{t-1} - \beta_0 - \beta_1 k_{t-1} - \beta_2 l_{t-1})}_{LR\ Dynamic} + \gamma_t$$

$$\implies \Delta y_t = \alpha_0 + \alpha_1 \Delta k_t + \alpha_2 \Delta l_t - \lambda \widehat{u_{t-1}} + \gamma_t \qquad (SR.1)$$

Here, from Eq.(SR.1), we can see α_1 and α_2 will act as SR capital and labor elasticities respectively, and this equation can be further reparameterized as:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \theta_2 k_t + \theta_3 k_{t-1} + \theta_4 l_t + \theta_5 l_{t-1} + \gamma_t \qquad (SR.2)$$

4.1.4 Empirical Results

The unit root test results, shown in Table 2, imply time-series y_t, k_t, and l_t are all stationary after taking the first-order difference. To test whether these series are cointegrated or not, we conduct an ADF test of residuals from the static regression and compare the ADF test statistic with the critical values from Engle & Granger (1987). As a result, the null hypothesis can be rejected at the 5% significance level, and we can conclude that y_t, k_t, and l_t are all cointegrated.

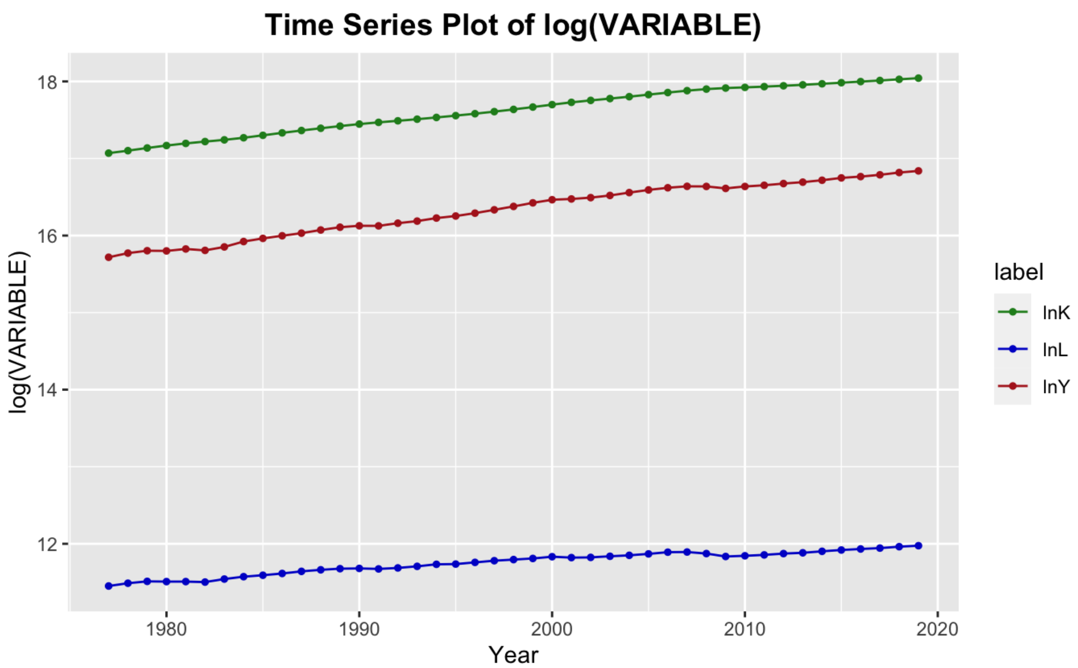


Figure 4.1: Time Series Plot of log(VARIABLES)

The cointegration relationship indicates the existence of LR equilibrium which OLS could unbiasedly estimate. Plus, ECM can be employed to investigate the SR relationship. The regression results of the US are shown in Table 3.

Table 2: ADF Test Statistics

Variables	τ^*	p-value	T	lag	Time Trend	Drift Term
$\log(GDP)_t$	-1.070	0.7268	40	2	NO	YES
$\Delta\log(GDP)_t$	-3.451	0.0093	39	2	NO	YES
$\log(Capital)_t$	-1.468	0.8398	40	1	YES	YES
$\Delta\log(Capital)_t$	-4.227	0.0041	39	1	YES	YES
$\log(Labor)_t$	-1.120	0.7070	40	2	NO	YES
$\Delta\log(Labor)_t$	-3.907	0.0020	39	2	NO	YES
$Static\ Residuals$	-3.796	0.0029	41	1	NO	YES

Table 3: Production Function Estimation

	(1)	(2)
	LR	SR
VARIABLES	y_t	Δy_t
k_t	0.792***	
	(0.0479)	
l_t	0.727***	
	(0.0962)	
Δk_t		0.590**
		(0.196)
Δl_t		0.979***
		(0.093)
$\widehat{u_{t-1}}$		-0.231***
		(0.085)
Constant	-6.171***	0.00075
	(0.333)	(0.00459)
Observations	43	42
R-squared	0.998	0.800

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From the result of SR regression, the significant coefficient of $\widehat{u_{t-1}}$ is -0.231 implying that GDP adjusts to capital and labor with a lag; about 23.1% of the discrepancy between the LR and SR economic performance is corrected within a year.

We can also notice the LR R-Squared is more than 99%, which is much greater than the SR R-Squared, only 80%. This can be explained by the fact that the variation of LR output could be explained by the variation of LR capital accumulation and level of labor force very well, while in SR, the situation is very different and much more complicated. Therefore, the SR economic fluctuation is very difficult to explain, which will be determined by many factors other than capital and labor variation.

We are most concerned about the estimated capital and labor elasticities of total output. The LR capital and labor elasticities of total output are 0.792 and 0.727 respectively, while the

SR capital and labor elasticities of output are 0.590 and 0.979. Therefore, after 1977, in LR, labor and capital contribute almost at the same level, while in SR, labor contributes more than capital to determine economic performance.

4.2 Forecasting Future Capital and Labor

Next, we use ARIMA to forecast capital and labor. ARIMA is an extension of the ARMA model that includes a differencing process and is commonly used for time series modeling of non-stationary data.

After adequately processing the data, the next step is to determine the autoregressive order p, the difference order d and the moving-average order q. In the previous stationarity and cointegration tests, we obtained that Y, K and L are all I(1). That is, Y, K and L are all first-order smooth, so we determine d = 1.

With the initial value of d confirmed, the next step is to look at the differenced ACF and PACF values and determine the order of the ARMA model based on the shape of the ACF and PACF plots. Note that the two models that look very different may be very similar. Therefore we may keep multiple ARIMA models at this stage and exclude poorly fitted models in the model diagnosis and comparison stage.

The next step in model fitting is the model diagnosis, which includes residual analysis and model comparison. Looking at the residuals' Q-Q plot helps identify whether the residuals follow a normal distribution with constant variance. The Q-test, also known as the Ljung-Box Test (Ljung & Box, 1978), is used to test whether the series has the properties of white noise and is a crucial test necessary to test the validity of the ARIMA model we have estimated. If more than one available model passes the Q-test, we will compare the AIC values of each model and prefer the model with a smaller AIC (Burnham & Anderson, 2004). After fully identifying the model used, we use the model to forecast the future values of this series.

4.2.1 Model Identification

We determine the unknown orders p and q for the ARIMA model (p, 1, q) by plotting the autocorrelation and partial autocorrelation functions for capital and labor. If the ACF plot has a cut-off shape after order q, i.e., all subsequent ACFs are within the blue dashed line, we can determine the unknown order of the moving average process as q. Similarly, if the Partial-ACF plot has a cut-off shape after order p, i.e., all subsequent PACFs are within the threshold that can be considered as white noise, we can determine the unknown order of the moving average process as q. On the other hand, the partial-ACF plot takes a cut-off shape after order p, i.e., all subsequent PACFs are within the threshold that can be considered as white noise, we can determine the unknown order in the autoregressive process as p. Combining the characteristics in both processes, we can determine the order of ARMA(p, q) in the above way.

As shown from the figure, both ACF and PACF of capital and labor are not one-side dampening but oscillate on both sides of 0. In the ACF plot of capital, r_k is within the critical value from r_3; in the PACF plot, only the first two orders are beyond the critical value dashed line, so we identify the model of capital as ARIMA(2, 1, 1). Similarly, in both the ACF and PACF plots of labor, only the first order exceeds the blue dashed line representing the critical value. Hence, we determine the model of labor as ARIMA(1, 1, 0). The following is the mathematical expression of the ARIMA model, where $x_t \in \{K_t, L_t\}$.

Capital: ARIMA(2,1,1)

$$x_t = (1-\phi_1)x_{t-1} + (\phi_1 - \phi_2)x_{t-2} + \phi_2 x_{t-3} + w_t + \theta_1 w_{t-1}$$
$$x_t = -0.45x_{t-1} + 1.91x_{t-2} - 0.46x_{t-3} + w_t + w_{t-1}$$

Labor: ARIMA(1,1,0)

$$x_t = (1-\phi)x_{t-1} + \phi x_{t-2} + w_t = 0.33x_{t-1} + 0.67x_{t-2} + w_t$$

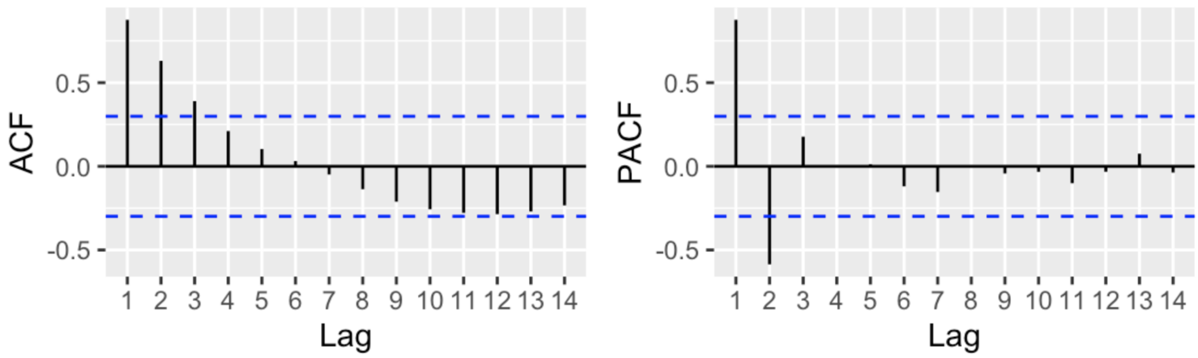


Figure 4.2: ACF & Partial-ACF Plot for ΔK_t

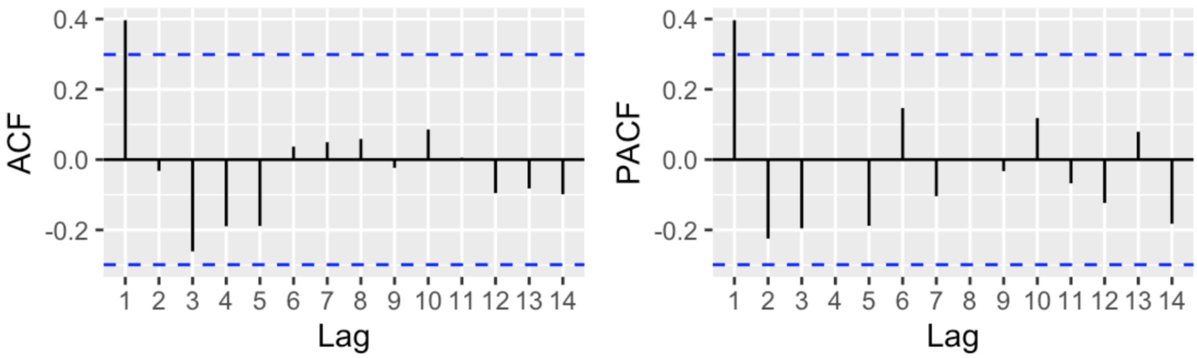


Figure 4.3: ACF & Partial-ACF Plot for ΔL_t

Note that we did not select the most appropriate order for the ARIMA model at once; we tried several models of different orders and chose the model with both a larger R-squared and a smaller AIC. All the coefficients of our selected ARIMA model are significant under the 0.1% significance level, with the complete ARIMA results attached in the appendices. The model selection and comparison process are very tedious, so we do not go into details here.

4.2.2 Q-Test for Residuals

The results of the Q-test, or Ljung-Box test, show that almost all p-values are greater than the critical value, so the null hypothesis that the residual series is white noise cannot be rejected, which implies that our model is satisfactory.

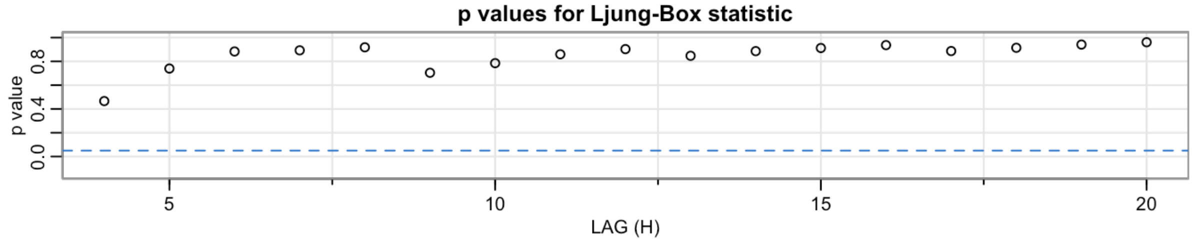


Figure 4.4: Q-Test Results for Capital

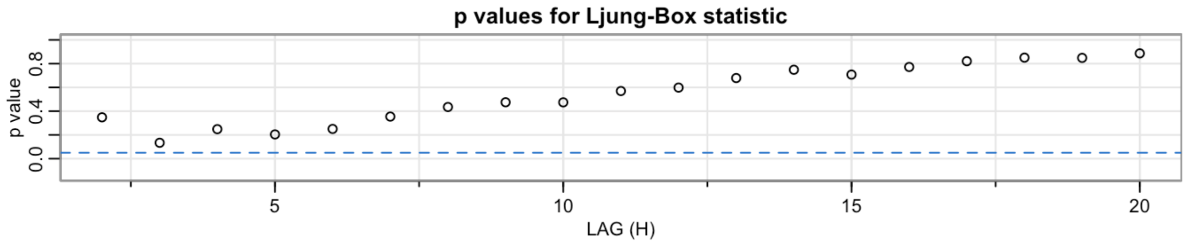
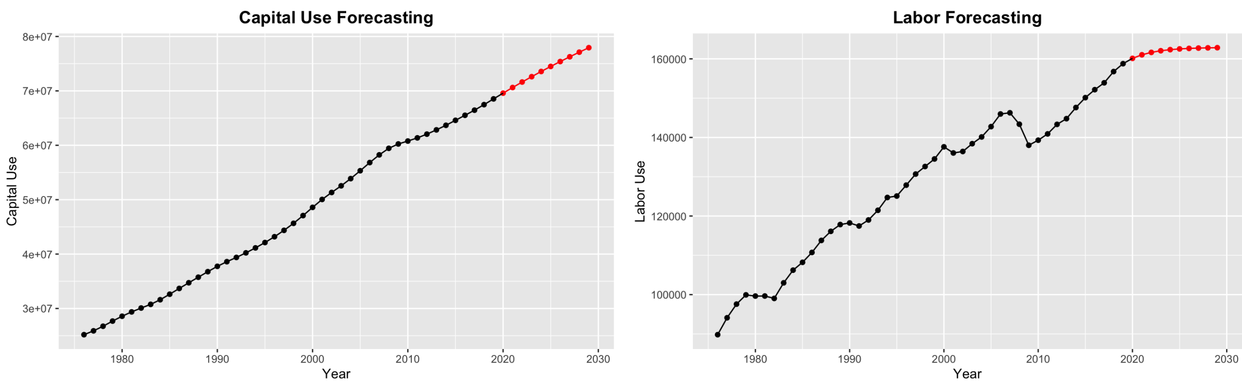


Figure 4.5: Q-Test Results for Labor

4.2.3 Forecast

We forecast separately for capital and labor based on the identified ARIMA model. Considering that the ARIMA model only uses historical data as a reference and does not consider many other environmental or political factors, we use this model only for shorter periods. Here we project forward to 2029. Due to the lack of data for 2020-2022, this part of the data will also be presented in our model as forecast values.



(a) Forecast of Capital (b) Forecast of Labor

4.3 Forecasting Future TFP

4.3.1 Growth Rate Calculation

Based on the ARIMA models of capital and labor and the forecasts that we have identified in the previous question, we will calculate the year-by-year growth rates of capital and labor from 1977-to 2029 in this part. The following is the mathematical expression of the growth rate calculation, where $x_t \in \{K_t, L_t\}$.

$$g_x = \frac{x_t - x_{t-1}}{x_{t-1}}$$

The simulation of the short-term ECM reflects the growth rate relationship of output, capital, and labor to perform the growth rate calculation of output in 2020-2029 based on the ECM relationship obtained from the regression.

4.3.2 Forecast TFP for the long run

The simulation of the short-term ECM reflects the growth rate relationship of output, capital, and labor to perform the growth rate calculation of output in 2020-2029 based on the ECM relationship obtained from the regression. After calculating the growth rate of output, the TFP growth rate for the next ten years can be obtained by substituting the LR elasticity of capital and labor according to the formula of TFP growth rate calculation as shown in Figure 4.7 below.

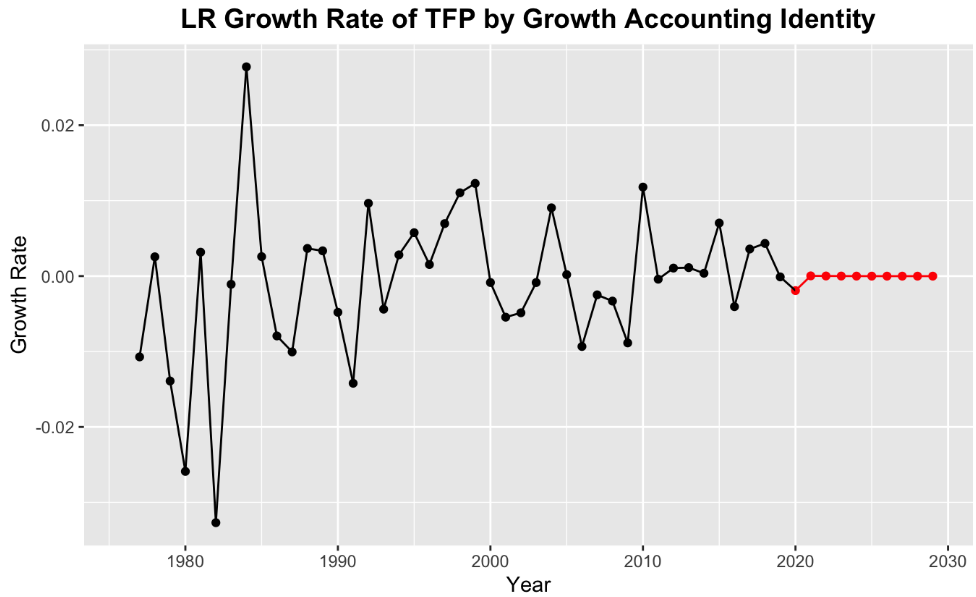


Figure 4.7: LR Growth Rate of TFP

By observing the trend of the growth rate of TFP over time, we can see that, except for 2020, the LR forecasts of the growth rate of technological progress after that are almost close to zero, and the Q-test also indicates that the growth rate of TFP can be approximated as stationary. And our estimated TFP for 2020 to 2029 is close to 0.00208, which, according to the ADF test, is also stationary.

With all the historical data on the TFP growth rate, we were curious to see if we could use ARIMA to forecast TFP based on its historical performance and see if there was a big difference between the short-term forecasts given by the ARIMA model and the calculated long-term forecasts.

As mentioned above, we have already examined the stationarity of the TFP growth rate, so we directly build an ARMA model for it, ARIMA (1, 0, 1), and the mathematical representation of the model is as follows.

TFP: ARMA(1,1) $\quad x_t = \phi x_{t-1} + w_t + \theta_1 w_{t-1} = -0.72x_{t-1} + w_t + 0.93w_{t-1}$

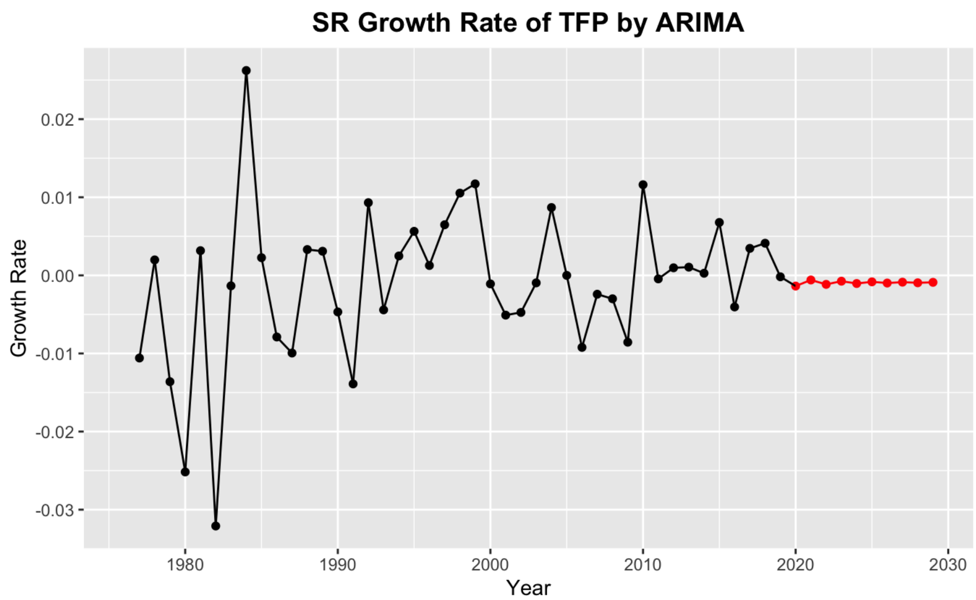


Figure 4.8: SR Growth Rate of TFP

Similarly, ARMA(1,1) is the best performing model among many different models in both AIC statistics and R-squared. We plot the short-term TFP growth rate trends predicted by this model in Figure 4.8 and compare the results calculated from the long-term relationship with the short-term results estimated using ARIMA, see Figure 4.9.

The calculated value of the TFP growth rate for 2020 is our forecast for the coming year based on 2019 data from the ECM, which is about -0.192%, which is within a reasonable range of (-2%, 2%). The long-run calculated value after 2020 suggests that for the US, a developed country, TFP growth will converge to 0 in the long run. The ARIMA predictions obtained in the short run hint at the possible future fluctuations of TFP growth.

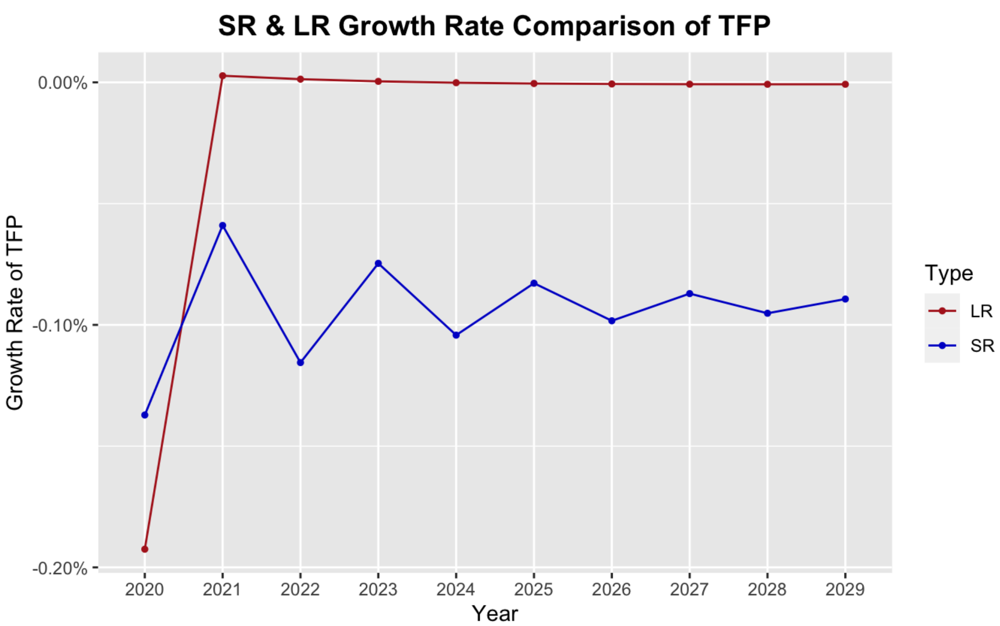


Figure 4.9: SR LR Growth Rate Comparison of TFP

5 Conclusion

Our forecast result for the TFP and TFP growth rate can be explained by the fact that the US economic model is reaching a relatively stable state and remains flat in technological progress.

Again, this phenomenon could be interpreted as a shortcoming of the ARIMA model, where the forecasts may converge to a large extent to 0 when the historical data behave as an approximate white noise series. The oversimplified functional form of the Cobb-Douglas function (Meeusen & van Den Broeck, 1977) is also a possible cause of the unrealistic-looking results. There could be improvements if a more relevant functional form were chosen.

The actual future TFP and its growth rate may be subject to many stochastic exogenous shocks, such as the turbulence of the international economic situation or, very realistically, the COVID-19 epidemic. Therefore it is almost impossible to converge exactly to 0 but rather oscillate around 0. For instance, the high unemployment rate caused by the epidemic may lead to redistribution of capital, labor and their growth rate, causing the future TFP to fluctuate beyond expected. Our model could be further modified once the data for 2020 and later are released, as they can be discussed separately with different approaches.

6 Appendices

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Figures&Results

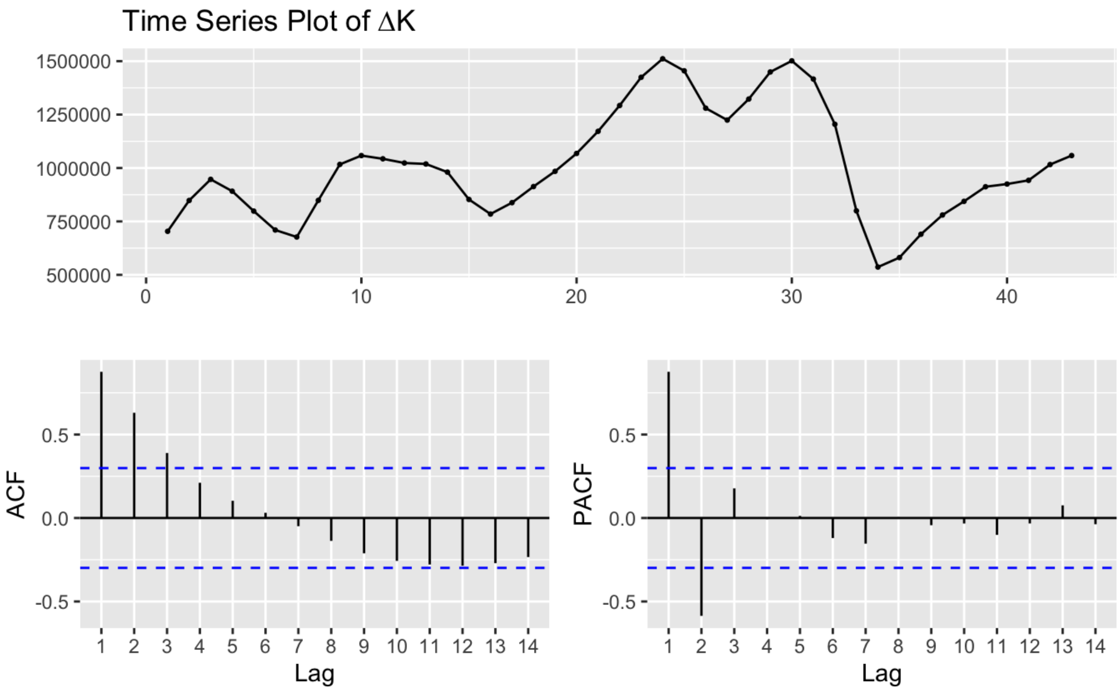

Figure 6.1: ACF & PACF Plots for ΔK

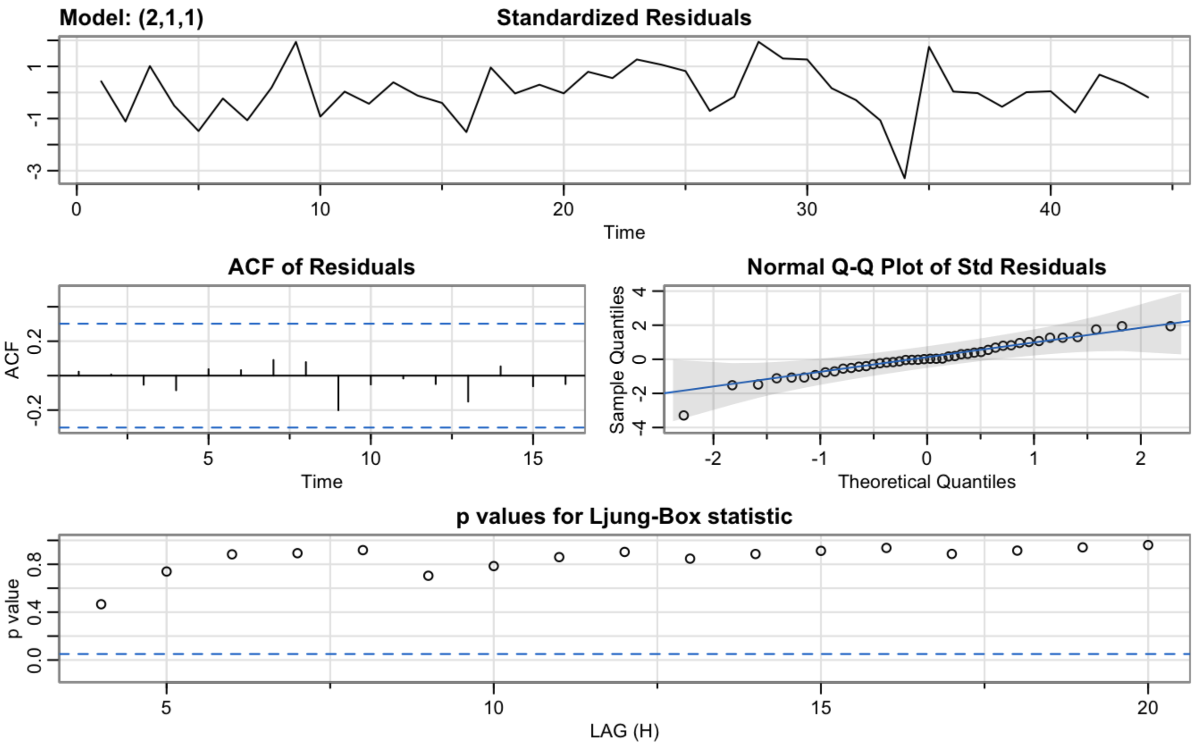

Figure 6.2: Model Diagnostic Results for ΔK

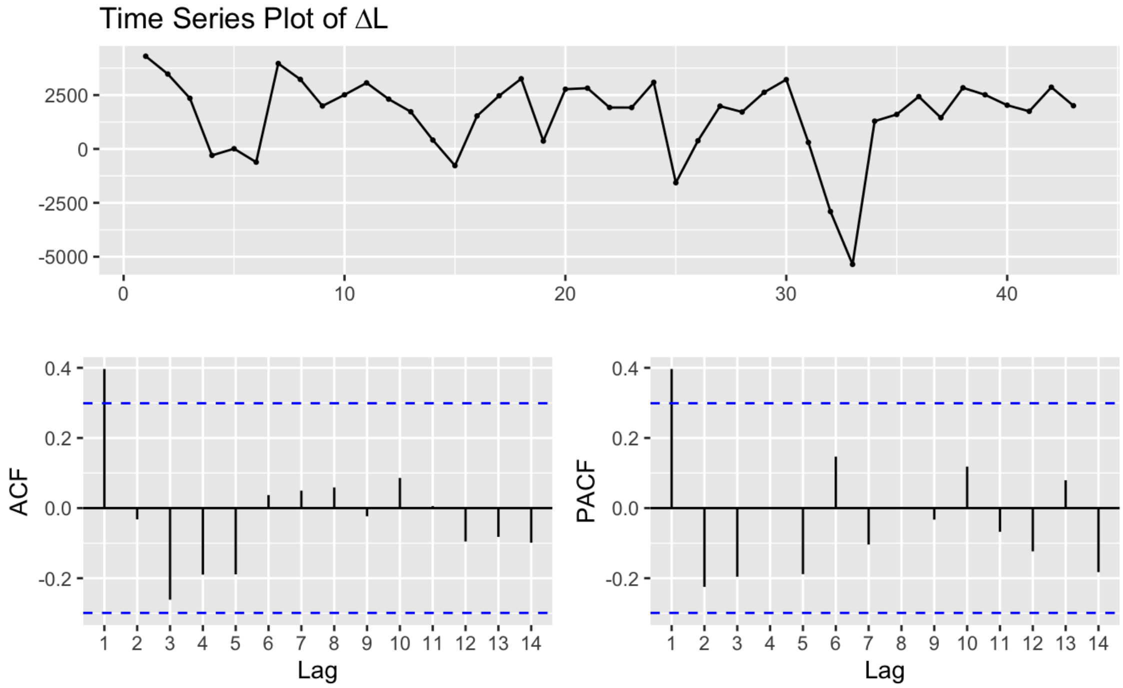

Figure 6.3: ACF & PACF Plots for ΔL

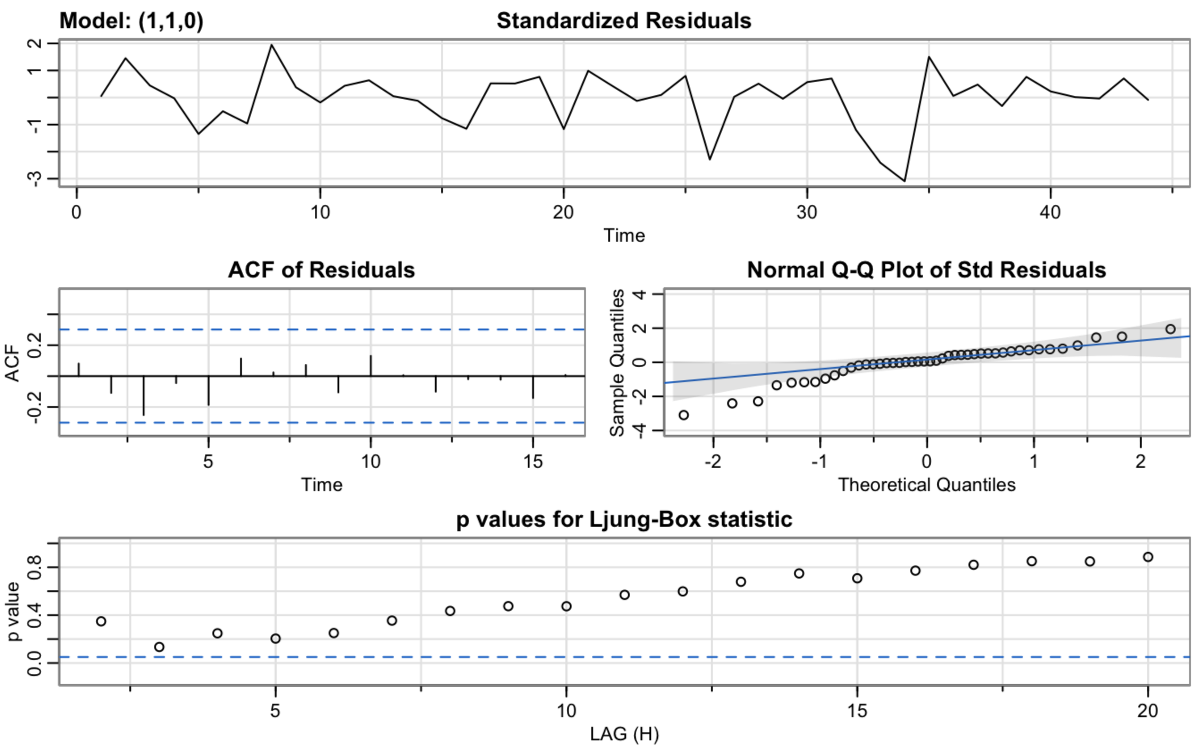

Figure 6.4: Model Diagnostic Results for ΔL

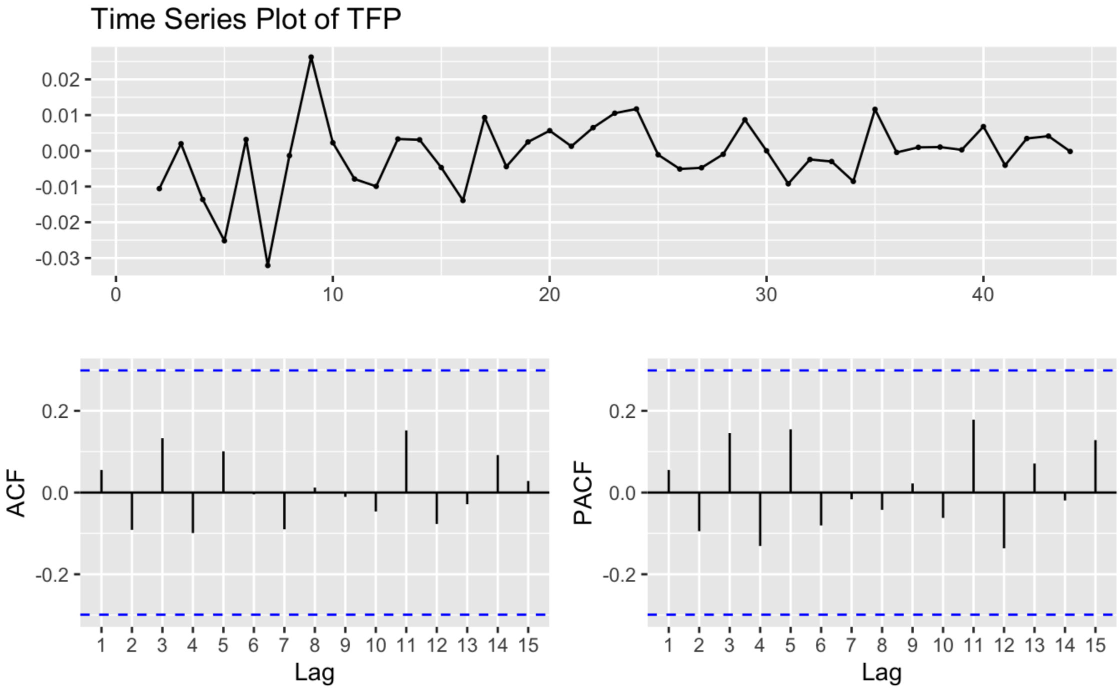

Figure 6.5: ACF & PACF Plots for TFP

Table 4: ARIMA Model Results for K, L and gA

	K	L	gA
ar1	1.45^{***}	0.67^{***}	-0.72^{***}
	(0.13)	(0.12)	(0.17)
ar2	-0.46^{***}	1.45^{***}	
	(0.13)		
ma1	1.00^{***}		0.93^{***}
	(0.25)		(0.10)
AIC	1087.92	772.30	-272.61
BIC	1094.97	775.82	-265.57
Log Likelihood	-539.96	-384.15	140.31
Num. obs.	43	43	44

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

year	gA_LR	gA_SR	GDP_full	gY_LR	Capital_full	gK	Labor_full	gL
1976	NA	NA	6407651	NA	25185706	NA	89803	NA
1977	-1.071%	-1.058%	6703952	4.624%	25889423	2.794%	94105	4.790%
1978	0.256%	0.198%	7075036	5.535%	26737473	3.276%	97581	3.694%
1979	-1.391%	-1.361%	7299041	3.166%	27684389	3.542%	99933	2.410%
1980	-2.590%	-2.517%	7280301	-0.257%	28575869	3.220%	99634	-0.299%
1981	0.317%	0.316%	7465055	2.538%	29374212	2.794%	99645	0.011%
1982	-3.269%	-3.209%	7330469	-1.803%	30084018	2.416%	99032	-0.615%
1983	-0.109%	-0.134%	7666493	4.584%	30761129	2.251%	102996	4.003%
1984	2.774%	2.623%	8221288	7.237%	31609606	2.758%	106223	3.133%
1985	0.258%	0.226%	8564087	4.170%	32626469	3.217%	108216	1.876%
1986	-0.794%	-0.789%	8860631	3.463%	33684634	3.243%	110728	2.321%
1987	-1.005%	-0.994%	9167170	3.460%	34727733	3.097%	113793	2.768%
1988	0.367%	0.331%	9550089	4.177%	35751182	2.947%	116104	2.031%
1989	0.335%	0.309%	9900830	3.673%	36770057	2.850%	117830	1.487%
1990	-0.480%	-0.468%	10087555	1.886%	37750732	2.667%	118241	0.349%
1991	-1.421%	-1.390%	10076635	-0.108%	38603574	2.259%	117466	-0.655%
1992	0.965%	0.931%	10431579	3.522%	39388210	2.033%	118997	1.303%
1993	-0.439%	-0.442%	10718744	2.753%	40225985	2.127%	121464	2.073%
1994	0.281%	0.248%	11150584	4.029%	41139224	2.270%	124721	2.681%
1995	0.575%	0.564%	11449898	2.684%	42123712	2.393%	125088	0.294%
1996	0.153%	0.126%	11881846	3.773%	43191871	2.536%	127860	2.216%
1997	0.696%	0.648%	12410257	4.447%	44363603	2.713%	130679	2.205%
1998	1.104%	1.053%	12966412	4.481%	45656051	2.913%	132602	1.472%
1999	1.229%	1.171%	13582736	4.753%	47080689	3.120%	134523	1.449%
2000	-0.085%	-0.109%	14143361	4.127%	48591973	3.210%	137614	2.298%
2001	-0.545%	-0.509%	14284560	0.998%	50046874	2.994%	136047	-1.139%
2002	-0.486%	-0.475%	14533353	1.742%	51326870	2.558%	136426	0.279%
2003	-0.086%	-0.096%	14949183	2.861%	52551151	2.385%	138411	1.455%
2004	0.905%	0.869%	15517086	3.799%	53873943	2.517%	140125	1.238%
2005	0.019%	0.000%	16062235	3.513%	55323499	2.691%	142752	1.875%
2006	-0.933%	-0.922%	16520807	2.855%	56825001	2.714%	145970	2.254%
2007	-0.249%	-0.242%	16830766	1.876%	58241436	2.493%	146273	0.208%
2008	-0.331%	-0.300%	16807780	-0.137%	59446158	2.068%	143369	-1.985%
2009	-0.886%	-0.856%	16381405	-2.537%	60245709	1.345%	138013	-3.736%
2010	1.180%	1.161%	16801388	2.564%	60782114	0.890%	139301	0.933%
2011	-0.041%	-0.045%	17061950	1.551%	61362884	0.955%	140902	1.149%
2012	0.106%	0.097%	17445766	2.250%	62052967	1.125%	143330	1.723%
2013	0.112%	0.105%	17767130	1.842%	62833015	1.257%	144778	1.010%
2014	0.038%	0.027%	18215924	2.526%	63677011	1.343%	147615	1.960%
2015	0.703%	0.678%	18776158	3.076%	64589327	1.433%	150128	1.702%
2016	-0.405%	-0.404%	19097498	1.711%	65514336	1.432%	152157	1.352%
2017	0.359%	0.346%	19542980	2.333%	66456617	1.438%	153904	1.148%
2018	0.433%	0.411%	20128580	2.996%	67472928	1.529%	156767	1.860%
2019	-0.011%	-0.018%	20563592	2.161%	68531191	1.568%	158772	1.279%
2020	-0.192%	-0.137%	20648060	0.411%	69584716	1.537%	160124	0.851%
2021	0.003%	-0.059%	20977298	1.595%	70619671	1.487%	161035	0.569%
2022	0.001%	-0.116%	21273453	1.412%	71629958	1.431%	161650	0.382%
2023	0.000%	-0.075%	21544447	1.274%	72613148	1.373%	162064	0.256%
2024	0.000%	-0.104%	21795921	1.167%	73568540	1.316%	162344	0.172%
2025	0.000%	-0.083%	22031881	1.083%	74496242	1.261%	162532	0.116%
2026	-0.001%	-0.098%	22255174	1.013%	75396735	1.209%	162659	0.078%
2027	-0.001%	-0.087%	22467829	0.956%	76270665	1.159%	162745	0.053%
2028	-0.001%	-0.095%	22671309	0.906%	77118742	1.112%	162802	0.035%
2029	-0.001%	-0.089%	22866681	0.862%	77941696	1.067%	162841	0.024%