Testing for Granger Causality in American Growth and Innovation

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Abstract

Using monthly data from the Federal Reserve Economic Database, and the United States Patent and Trademark Office, I test for Granger Causality between Income, measured as real GDP, and Innovation, measured as patent applications. Including controls for savings, unemployment, population and government spending, I find no evidence to suggest Granger causality between innovation and growth, either unilaterally or bilaterally. These results hold for several different lag structures, and for trend stationary series. Moreover, portmanteau tests on the residuals indicate that the errors under the model, although white noise, are not Gaussian. I hypothesize that this result may be due to omitted variables, which is consistent with the literature on Granger Causality.

Introduction

One of the oldest-studied relationships in economics is the link between technological advancement and income growth. Almost every effective theoretical model includes some reference to technology, whether it be direct through components like capital, or indirect through total factor productivity (for example). The Nobel prize winning model of long-run growth created by

Robert Solow and Trevor Swan uses only 2 factors: capital accumulation (i.e. machines), and total factor productivity ('the mysterious black box'); see Solow 1956. However, although most models generally accept and include a component for technology, very few attempt to explicitly define its relationship to growth.

There are many good reasons for this. Chief among them is that both growth and technological advancement are difficult to define, and even more difficult to measure. This is why many approaches mirror the Solow model in using a *residual approach* - that is, they model all other variables, and whatever is left unexplained must be technological change. Another reason is that, even if we do measure growth and technology appropriately, it is still very difficult to obtain a large enough representative sample (both in terms of time and space) to reveal with any certainty an accurate long-run relationship. This is especially true for countries in later stages of development, where technological gains may have diminishing returns; see Stiroh 2001. One other reason is model-based: we simply do not yet have the tools to identify such complex relationships.

For any of these and other reasons, the problem of defining the growth-technology relationship is currently stuck in what one might call a chicken-egg problem. We know that technological advancement is a necessary condition for long-term economic development; see Mokyr 1992. What is unclear is the causal relationship between the two. Does increasing income bring about increases in technological development? Is it the other way around? Or is there some other confounding variable that causes both to increase in tandem?

In this paper, I explore the question above using data on GDP growth collected from the economic database of the St Louis branch of the United States Federal Reserve. To serve as a proxy for technological development, I use the annual number of patents filed, collected from the Historical Patent Data Files of the United States Patent Office. I also include controls for unemployment, population, personal savings and government spending. To infer the direction of causation (or the possibility that there is no causation either way), I use a model of Granger causality, based on a Vector Auto-regression of the six series listed above. After transforming the above variables using first-differencing to induce stationarity, I find no evidence of causality in either direction. Tests for goodness of fit reveal that, although some of the residuals do meet the serial independence and zero mean criteria, overall, they do not resemble Gaussian white noise. Thus, the model has failed to completely explain the relation of interest.

Background and Related Work

There have been many studies involving the use of Granger Causality tests to infer relationships between macroeconomic variables. Perhaps the most famous example demonstrates that the causality between Money supply and Income is unilateral; see Sims 1972. Most macroeconometrics is driven by models involving basic pillars of the economy (income, investment, savings, technology, etc..), where each of the components is in some way connected to every other, either directly, or indirectly. This endogeneity problem has led to the careful study of inference, and in particular, causal inference, as policymakers and business owners try to grapple with how best to control an economy.

Such models are also effective in an international setting. Recent work has found evidence of predictive causality between international trade and technology; see Gosh and Yamarik 2007. Causality between Growth and Savings has not reached consensus. Studies have shown causality in both directions; see Agrawal 2010. Results have also shown that the magnitude and existence of such causality can vary from country to country. For instance, GC between innovation and growth varies widely among European nations in recent decades; see Maradana et. Al 2019. Lastly, although widely studied in the field, the link between growth and inequality has only recently been shown unilaterally (growth g-causes inequality); see Assane and Grammy 2010.

Studies also show that under misspecification, the causality test can give incorrect results. In some cases, a bivariate system has been known to exhibit Granger causality because of an omitted variable; see Lutkepohl 1982. In other scenarios, omitted variables have been known to incorrectly lead to rejection of the alternative (causality). Thus all statements concerning causality should be carefully intepreted. In the context of this paper, I use the world causality loosely, though I only ever take it to mean power of prediction.

Methodology

Although there is no empirical way to test for causality with absolute certainty, there are ways of evaluating the predictive nature of two variables to give evidence on which causes the other. I use a technique called Granger Causality, which analyzes predictive power in place of formal causality; see Granger 1969. Intuitively, if past variables of X are strong predictors of Y, but the opposite relation does not hold, we can say that X 'Granger-causes' or 'Granger-predicts' Y. Note that Granger causality is not a direct substitute for the philosophical notion of causality. The original author was clear to call this 'predictive causality', since it is based only on predictive power between two series.

More formally, for two times series V_t and W_t, the definition of *Bivariate Granger Causality* is:

$$MSE(\hat{E}(w_{t+i}|w_t, w_{t-1}\dots)) \neq MSE(\hat{E}(w_{t+i}|w_t, w_{t-1}\dots, v_t, v_{t-1}, \dots))$$

Intuitively this makes sense. V is said to Granger-cause W in the above equation because, accounting for all lagged values of w, v still leads to a change in the average forecasting performance on future values of w. It can be shown that testing the MSE condition above is equivalent to jointly testing the coefficients on lagged values of w; see Hamilton (1994). Under this scenario, the null hypothesis is that the relation fails Granger-causality (all lagged coefficients are zero), whereas the alternative is that v g-causes w (at least one equality does not hold).

Under the above definition, there is one other criterion: V must occur before W. This makes it impossible for two covariates to simultaneously cause each other, since one must occur first. Because of this criterion, several covariates can be tested for Granger causality simultaneously by using a system of regression equations, where each regression represents the prediction of a different future covariate using present and lagged values of the other predictors. I use a similar Vector Autoregression to test for causality in technological development and income growth. The system of equations is stated in full in the Analysis section.

Data

I use several different data sources to gather the variables of interest. I collect patent application data from the Historical Patent Data Files from the United States Patent and Trademark Office. This series reports total number of US patent application filings, reported monthly from January 1981 to December of 2014 (after which such information is presented on a year-by-year basis).

The unemployment rate series, the personal savings rate series, and the population series (reported in thousands) are all collected from the Federal Reserve Economic Database (FRED) maintained by the St. Louis branch of the United States Federal Reserve. These series are also reported monthly, from January 1981 to December of 2014[1].

Figure 1 shows preliminary plots of each of the uninterpolated series. A couple of things stand out. For population and patent applications, there is a clear positive trend that will need to be accounted for. Savings and Unemployment rate, however, do not appear to follow a long-term trend. The personal savings rate appears to be falling for most of our study period, and only recently has began to increase. Notice also that the population curve is quite smooth. This is because the series is seasonally adjusted.

For the gross domestic product and government spending variables, I use the quarterly estimates from FRED, since monthly estimates for the given time period are unavailable. These series run from the first quarter of 1980 to the forth quarter of 2014. In order to convert the series from quarterly to monthly, I use a technique called cubic spline interpolation. This involves using piece-wise polynomial functions (splines) to estimate the points in the months between the quarterly intervals already reported. Splines are preferred to high-degree polynomials because they avoid the high error that high-degree polynomials often give around the edges of the estimates (this is called *Runge's phenomenon*; see Fornberg and Zuev 2007.

[1]The corresponding FRED variable codes are UNRATE, PSAVERT, and POPTHM.

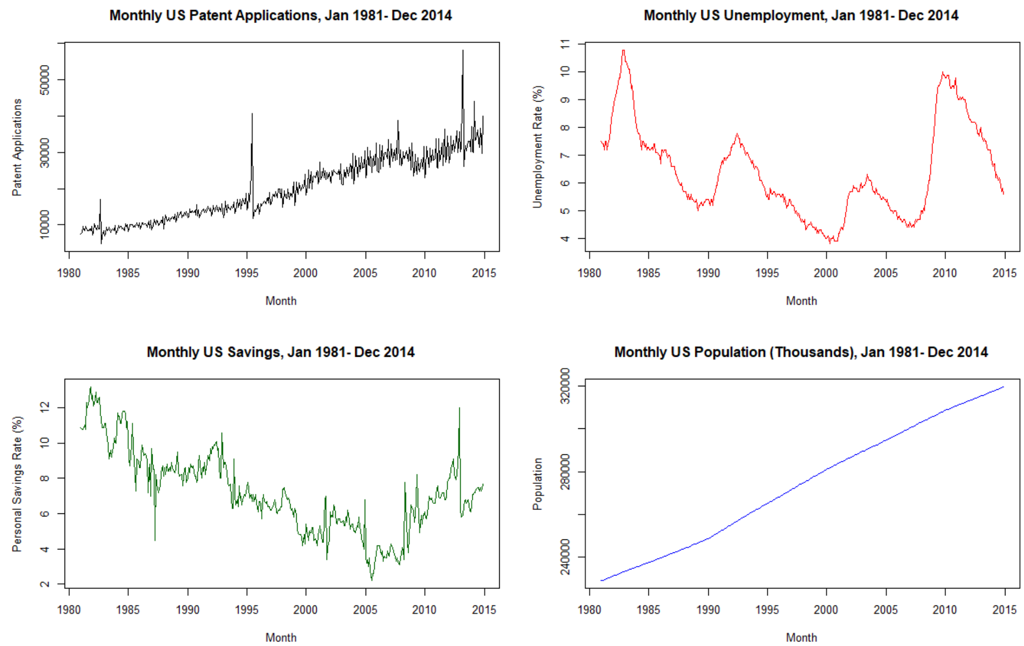

Figure 1: **Plots of US Savings, Patent Applications, Population and Unemployment, Monthly (1981-2014)**

To interpolate these series, I use the method of Forsyth, Malcolm, and Muller (1977). This involves fitting a spline with N knots. To do this, a natural cubic function is fit to the four end points on either side of the data. Assuming smoothness of splines, and the fact that the splines must pass through all N knots, we pin down the curve by equating the third derivative of the spline to the end cubics.

We can see a clear upward trend (possibly non-linear) in both of our imputed series. It is very likely that these two series are non-stationary in their current form. I test this in the next section. Altogether, I now have 6 series, each with 408 observations.

Table 1 shows descriptive statistics for each of our series. In the case of time series variables, the presence of a rough linear trend presents as the

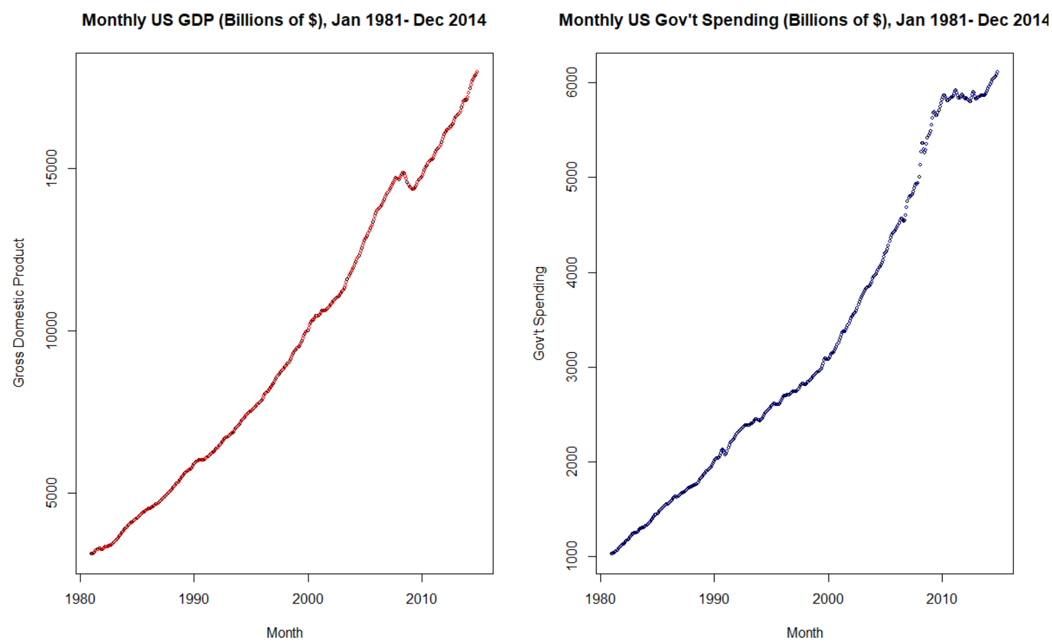

Figure 2: **Plots of US GDP and Gov't Spending (Billions), Monthly (1981-2014)**

Table 1: **Summary Statistics**

Stats	GDP	Gov't	Patents	Savings	Unemp	Pop
Min	2121	1023	4761	2.200	3.800	229004
1st Quart.	5690	1912	12363	5.675	5.200	247401
Median	8850	2818	18426	7.000	6.000	274616
Mean	9495	3265	19748	7.213	6.433	273979
3rd Quart.	13835	4543	26540	8.625	7.400	298717
Max	17941	6109	58214	13.20	10.80	319742
N(original)	159	159	408	408	408	408
N(imputed)	249	249	-	-	-	-
St. Dev	4381.33	1588.24	8552.40	2.296	1.652	27809

median or mean of the series being roughly halfway between min and max. Notice then, that we have an approximate linear trend for GDP and Government Spending. The presence of such linearity is a rough indicator of at least trend stationarity, but may also indicate non-stationarity. The patents series appears to be a bit more exponential in its growth. The population, unemployment and savings rate series also appear to have upward trends.

Analysis

Recall one of the conditions for the use of a Granger causality framework is that all variables need to be stationary. Until now, this has not been proven for our data, but I will now test for it. One of the ways to test for stationarity of a time series is using a unit root test, which examines the possibility that at least one of the roots of the variable in its characteristic equation is one (which implies the series may never return to its mean). The two types of unit root test I will use are the *Augmented Dickey-Fuller*(ADF) Test, and the *Phillips-Perron* (PP) Test.

The ADF Test evaluates the random time series variable y_t according to the following regression equation:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_t + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_h \Delta y_{t-h+1} + \epsilon_t$$

The intuition is as follows: If the series is unit root, then the lagged level should have no effect on the first difference, so we would expect $\alpha_2 = 0$. Thus the null hypothesis for the test is that a unit root is present (ie. the series is not stationary). Notice what happens if we add back the lagged value of y_t:

$$\Delta y_t + y_{t-1} = y_t = \alpha_0 + \alpha_1 t + (1+\alpha_2) y_t + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_h \Delta y_{t-h+1} + \epsilon_t$$

Since we know that for a stationary process, $-1 < 1 + \alpha_2 < 1$, we have $-2 < \alpha_2 < 0$. Thus, the ADF t-statistic is always negative, because the coefficient is always negative. So our test is one-tailed. The alternative hypothesis is that there is stationarity. The number of lags to be included is a hyperparameter, but here I choose h based on the rule of thumb provided by Schwert 1989:

$$h_{max} = \lfloor 12 \cdot (\frac{T}{100})^{1/4} \rfloor$$

The Phillips-Perron Test is very similar to the ADF, following a slightly simpler regression equation:

$$y_t = \alpha_0 + \alpha_1 t + (1 + \alpha_2) y_t + u_t$$

This is essentially the same t-statistic as the ADF test, but there is a difference in the error estimation. In the ADF setting, we use lagged values of the difference to account for serial correlation in the error terms. In the PP test, we simply use Newey-West standard error estimates, which are robust to both serial correlation and heteroskedasticity. The null and alternative are again unit root and no unit root.

Recall that a non-stationary time series can be made stationary by applying a first (or higher) order difference operator. I run these tests in order to A) identify which of the current series needs differencing in order to induce stationarity, and B) to ensure that first-differencing is all that is needed. Note that, in the case of some variables, I take the log of the difference, which is equivalent to the percentage change.

Table 2: Dickey-Fuller and Phillips-Perron Unit Root Tests

Series	Dickey-Fuller		Phillips-Perron	
	Level	First Difference	Level	First Difference
GDP	1.640	4.382***	3.953	52.378***
Gov't $	2.443	3.175*	3.040	67.757***
Patents	2.877	6.286***	811.13***	465.42***
Savings	1.552	5.857***	42.888***	390.09***
Unemp	2.844	3.963**	8.836	844.29***
Pop	2.276	2.1507	3.735	24.994**

Note: *, $p \leq 0.10$; **, $p \leq 0.05$;***,$p \leq 0.01$.

All reported statistics contain both a constant and trend term. Numbers presented are absolute values.

The results of the unit root tests are promising. For both GDP and government spending, we see that the level itself is not stationary, but both tests confirm that the percentage change is. Patent applications is already a flow variable (unlike, say total number of outstanding patents or applications per outstanding patent), so it causes some confusion in our test. The ADF statistic indicates that there is some evidence that it is first-difference stationary, whereas the PP test indicates level stationarity. Because the evidence is stronger in favor of stationarity, I use the level of the patents series.

Savings and unemployment rates are first-difference stationary as expected, with strong evidence in favor of rejecting the null for both test types. One unexpected result is the failure to reject the null hypothesis for the ADF test of population change. However, given the strong evidence from the PP test, I use percentage change in population for the Granger causality specification. With modifications made according to the test results, I now have stationary series for each of the six variables.

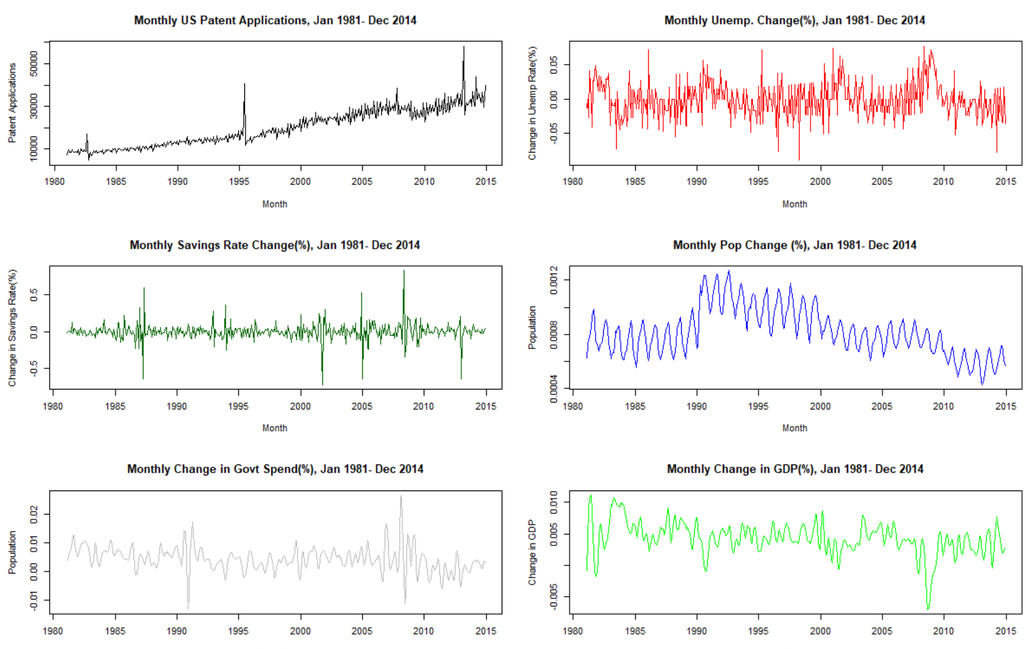

Figure 3: **Plots of First-difference Stationary Series, Monthly (1981-2014)**

Figure 3 shows variables with first differences applied to induce stationarity. The exception is the patents series, which serves as a proxy to technological innovation, and requires no differencing per the unit root tests.

These series are what I use to test for Granger Causality. The multivariate regression takes the form of a Vector Auto-regression (VAR), using lags of the dependent variable as well as lags of other series. Formally, the system of equations is defined below:

$$\begin{aligned}\Delta GDP_t = {} & \alpha_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \alpha_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \alpha_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \alpha_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \alpha_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \alpha_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{1i}\end{aligned}$$

$$\begin{aligned}\Delta GOV_t = {} & \beta_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \beta_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \beta_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \beta_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \beta_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \beta_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{2i}\end{aligned}$$

$$\begin{aligned}PAT_t = {} & \gamma_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \gamma_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \gamma_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \gamma_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \gamma_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \gamma_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{3i}\end{aligned}$$

$$\begin{aligned}\Delta SAV_t = {} & \kappa_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \kappa_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \kappa_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \kappa_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \kappa_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \kappa_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{4i}\end{aligned}$$

$$\begin{aligned}\Delta UNEMP_t = {} & \tau_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \tau_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \tau_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \tau_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \tau_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \tau_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{5i}\end{aligned}$$

$$\begin{aligned}\Delta POP_t = {} & \theta_1 \Sigma_{i=1}^{n} \Delta GDP_{t-i} + \theta_2 \Sigma_{i=1}^{n} \Delta GOV_{t-i} + \theta_3 \Sigma_{i=1}^{n} PAT_{t-i} + \\ & \theta_4 \Sigma_{i=1}^{n} \Delta SAV_{t-i} + \theta_5 \Sigma_{i=1}^{n} \Delta UNEMP_{t-i} + \theta_6 \Sigma_{i=1}^{n} \Delta POP_{t-i} + \epsilon_{6i}\end{aligned}$$

Recall that A Granger-causes B if:

i) current or past information about A has strong predictive power over future information of B, accounting for other factors, including past or current values of B.

ii) The opposite relationship does not hold.

What this means for our VAR is that if, for example, technological innovation Granger-causes income growth, we should find significant evidence of a positive coefficient α_3, but a coefficient γ_1 that is not statistically significant from zero. This would imply that past patent applications have strong pre-

Table 3: **Multivariate Regression Coefficients**

Pred/Resp	GDP_t	GOV_t	PAT_t	SAV_t	$UNEMP_t$	POP_t
GDP_{t-1}	2.691***	-0.119**	-11.66	0.011	0.002	-0.005
GOV_{t-1}	0.041	2.274***	-12.68	-0.002	0.006	-0.006
PAT_{t-1}	0.001	0.002	-0.104*	0.001	0.001	0.044*
SAV_{t-1}	0.170	0.421	-0.015	0.545***	0.025*	-0.621
$UNEMP_{t-1}$	0.303	1.943	0.011	-0.156	0.828	0.629
POP_{t-1}	0.069*	0.013	25.98*	0.002	0.008	2.623***

a Note: *, $p \leq 0.10$; **, $p \leq 0.05$;***,$p \leq 0.01$.

b All reported statistics contain both a constant and trend term.

dictive power over income growth, meaning technological innovation drives growth (not the other way around).

Unfortunately, the results to not seem to indicate Granger causality in either of the two directions we might expect (GDP growth predicting technology or vice-versa). The coefficients on (GDP_t, PAT_{t-2}) and (PAT_t, GDP_{t-1}) in Table 3 are both statistically insignificant from zero. This means that past values of patent applications do not strongly predict GDP growth. Also past values of GDP growth do not strongly predict future values of patent applications. We do notice, however, that for each variable, the strongest predictors of future value are current values of that variable itself. Given the solid theoretical basis for opposite findings, it is likely that the model of Granger causality has simply failed to untangle the endogeneity of the variables in our dataset. In the next section, I formally test for this, using two different portmanteau tests designed to evaluate goodness of fit.

Note that although the lag structure of the VAR above was chosen according to the Akaike Information Criteria, similar results are present when using fewer and more lags. Results also do not change when the population variable is excluded, and I instead model GDP per capita. Results again do not change regardless of whether I use the level or the change in each of the six components.

Table 4: **Portmanteau Tests for Residual Serial Correlation (Ljung-Box and Box-Pierce)**

Result	ϵ_{1t}	ϵ_{2t}	ϵ_{3t}	ϵ_{4t}	ϵ_{5t}
BP χ^2	0.84	4.14	0.29	84.33	40.30
LB χ^2	0.83	4.18	0.29	85.30	40.80
BP p-value	0.84	0.25	0.96	0.000	0.000
LB p-value	0.84	0.24	0.96	0.000	0.000

Evaluation

One way to evaluate whether any model is a good fit for the data is to examine the residuals to see if they match the original assumptions. Although I did not state it in the formal system of equations, fitting the VAR should result in error terms (ϵ_{it}) that have no serial correlation. In fact, these errors should, in theory, be Gaussian White Noise, which means, in addition to no serial correlation, they should also be Gaussian distributed with zero mean and constant variance. To evaluate goodness of fit of the model calculated earlier, I use Ljung-Box and Box Pierce portmanteau tests to look for serial correlation in the residuals.

The *Ljung-Box test* has a null hypothesis of independence; that is, any serial correlation in the errors is entirely due to randomness in the DGP. The alternative hypothesis is that there is serial correlation in the residuals. The Box-Pierce test is very similar with regards to the null hypothesis, but tends to have worse properties in small sample sizes. Following the suggested number of lags based on the AIC from the VAR above, I use a maximum lag of 3 for both types of tests.

Looking at Table 4, we can see that the assumption of serially uncorrelated errors appears to hold well for the first 3 equations (these are the regression lines with GDP, government spending and patent applications as response variables). However, we can see that for the remaining equations, there is significant evidence that the residuals to exhibit serial correlation. In other words, for these variables, the VAR model has failed to account for some of the explanatory power. So what about the assumptions of normality and constant variance?

To determine whether the normality assumption holds, I simply plot density estimates of the residuals. Figure 4 shows the shape of the residuals. Although we can see that they each appear to be mean zero, there is an abnormally large presence of outliers, in both the positive and negative directions. This indicates a heavier tailed distribution than we should expect from Gaussian Noise. Moreover, there is skewness in equations 1 and 4, which is a sign that our model is missing a key component. Overall, it appears as though the linear relationship defined by the VAR system does not fully explain the data. The leading cause for this would be a confounding variable that was not included in this analysis. Alternatively, patent applications as a proxy for technological growth may not be as effective as intuition tells us.

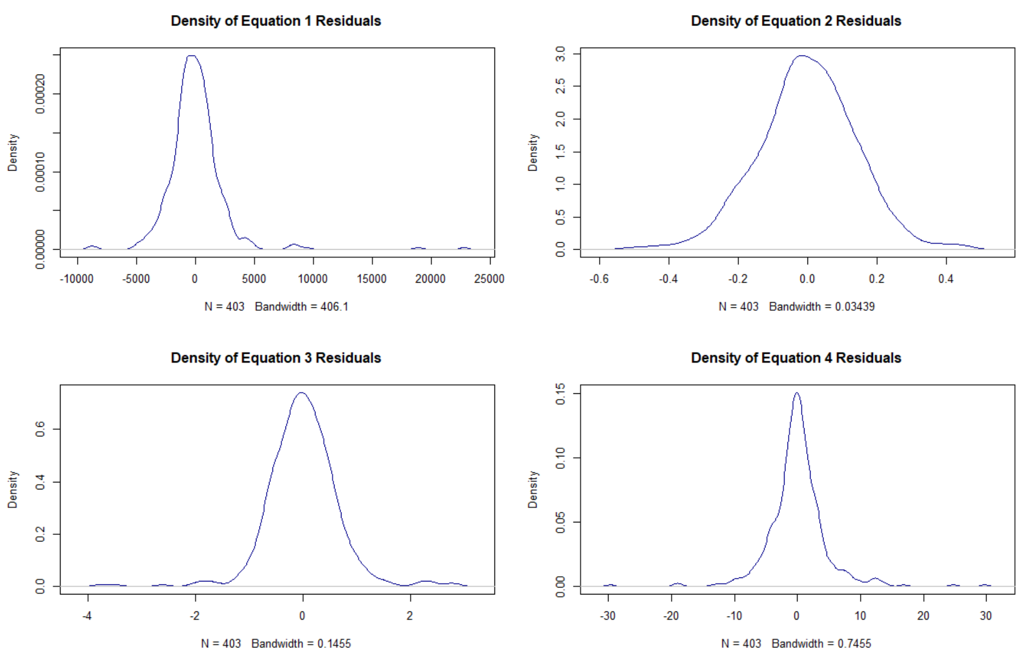

Figure 4: **Plots of VAR Residuals**

Conclusions

I analyze macroeconomic trend data from several sources to determine A) if there is a causal relationship between technological change and economic growth, and B) in what direction the causality runs (if there is any). Data are collected monthly from the beginning of 1981 to the end of 2014. Where data are not available monthly (e.g. for GDP), I use cubic spline interpolation to convert quarterly estimates into monthly frequency. Using GDP growth as a proxy for economic growth, and patent applications as a proxy for technological development, I fit a vector autoregressive model that infers correlations between past values of dependent variables and future values of responses.

Significance of a future-on-past regression, but not on the corresponding past-future regression would thus indicate that the dependent variable 'Granger-causes' or 'G-causes' the response. Finding no evidence of significance in either direction, I cannot definitively suggest a direction of causality between the two variables of interest. Moreover, testing for goodness of fit reveals that the linear VAR model does not strongly predict any of the responses. The most likely cause for this is a confounding variable not included in the study; theoretical models may be able provide candidates for this omitted variable.

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