A NEW LOOK AT THE EVIDENCE ON LONG-RUN MONETARY NEUTRALITY

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ABSTRACT

A widely held view in macroeconomics is that money is neutral in the long-run. Yet the empirical evidence on monetary neutrality is mixed. Conventional tests for long-horizon predictability may reject the null too frequently when the predictor variable is highly persistent and endogenous and there are overlapping observations creating unintended autocorrelation errors. We use a recently developed econometric technique, designed to overcome these problems, to investigate long-run money neutrality. We conduct extensive examination across a broad spectrum of time horizons and find unambiguous support for long-run monetary neutrality. **JEL Classification**: E42

INTRODUCTION

Classical economics holds that money is neutral. That is a one-time permanent shock to the level of the money supply has no real economic effect in the long-run. While there is considerable debate about the short-run adjustments, it is almost an axiom that money is neutral.

Although well accepted theoretically, the empirical evidence is mixed. Early efforts to test for long-run money neutrality (LRMN) in the 60s and 70s simply regressed the level of the real economic variable on a distributed lag of observations of the money supply. One of the main criticisms of this body of work was that the researchers didn't take into consideration the times series properties of the data, especially the consequences of "permanent" or at least very persistent shocks to the money supply. These shocks are best modeled as a unit root (or near unit root) process, the properties of which were not fully understood at the time. These criticisms initiated a flurry of work in the mid to late 1990s (see Bullard (1999) for a review). Fisher and Seaton (1993) use a relatively structure free ARIMA model to examine LRMN. This model features prominently in that body of research. However, the empirical evidence from these studies has been somewhat mixed with LRMN being weakly supported.

Coe and Nason (2004) point out the long-run regressions in the Fisher and Seater framework is related to and suffers from the same distortions as the long run predictability regressions in Finance. Berkowitz and Giorgianni (2001), Stambaugh

(1999), Mankiw and Shapiro (1986) and Hodrick (1992), among others, show that these distortions may be large. The evidence against LRMN may be due to the econometric difficulties of overlapping observations, highly persistent and endogenous predictor variables and the poor performance of asymptotic distributions in finite samples.

Hjalmarsson (2011) develops new econometric methods for overlapping observations with highly persistent endogenous regressors. He shows that the standard t-statistic can be easily scaled to adjust for the overlapping observations, without the need for robust standard error estimation and that there is a simple modification to the regression that corrects the biasing endogenity effects. He demonstrates through Monte Carlo simulation methods that the asymptotic distributions are able to well approximate the finite sample distributions even when the forecasting horizon is large relative to the sample size.

We apply this newly developed theory to the question of money neutrality. The purpose of this paper is threefold 1) to apply the new econometric techniques to the data, 2) to update the data series for the 10 – 15 years since the major studies on Neutrality were published and 3) to increase the number of real variables used (most earlier studies kept to real output) to include real wages, real consumption expenditures, real interest rate and real output. The findings provide unambiguous support for LRMN. This paper is organized into four sections. The first section is a literature review. The second section describes the econometric methodology. The third section describes the data and presents results, and the fourth section concludes.

PRIOR FINDINGS

Early empirical work on LRMN did not explicitly take into consideration the time-series properties of the data. The 1990s saw a large body of work dedicated to filling this gap. Fisher and Seater (1993), use an almost structure-free ARIMA model, FS hereafter, to test for LRMN. This has become the predominant model in the area. Using their notation, let m be the natural logarithm of the money stock M , and let y be the log of some other real or nominal variable, Y. Let “m *is* $I(a)$" mean “m is integrated of order a” and let $< m >$ represent the order of integration of m. For example, if m is $I(a)$ then $< m > = a$. Let Δ represent a difference operator, so that represents the approximate growth rate of the variable y. The Fisher Seater model is as follows:

$$a(L)\Delta^{<m>}m_t = b(L)\Delta^{<y>}y_t + u_t \qquad (1)$$

$$d(L)\Delta^{<y>}y_t = c(L)\Delta^{<m>}m_t + v_t \qquad (2)$$

where $a(L), b(L), c(L)$, and $d(L)$ are lag polynomials with $a_0 = d_0 = 1$. The error vector is iid with 0 mean and covariance matrix Σ. Now let $x_t \equiv \Delta^i m_t$ and $z_t \equiv \Delta^j y_t$ with $i,j = 0$ or 1. Fisher and Seater define the long-run derivative (LRD) as

$$LRD_{z,x} \equiv \lim_{k\to\infty} \frac{\frac{\partial z_{t+k}}{\partial u_t}}{\frac{\partial x_{t+k}}{\partial u_t}}, \qquad \lim_{k\to\infty} \frac{\partial x_{t+k}}{\partial u_t} \neq 0, \qquad (3)$$

a change in with respect to a permanent change in x. Fisher and Seater define long-run neutrality and superneutrality in this framework. They also use the model to reinterpret the results of earlier studies that did not take into account the time-series properties of the data. They interpret the evidence from these studies as being broadly consistent with long-run neutrality. In their study, they use US data on money, prices, nominal and real income from 1867 to 1975. They conclude that with respect to the nominal variables, long-run monetary neutrality holds, but with respect to real output, long-run monetary neutrality fails.

Haug and Lucas (1997) use FS on Canadian data. They investigate real national income and M2 from 1914 – 1994 and find that they cannot reject neutrality. Olekalns (1996) use FS with Australian data on M1, M3 and real GDP. They find that using M1 they reject long-run neutrality, but with M3 they fail to reject. Coe and Nason (2003), also using FS, examine data from Australia, Canada, the U.S. and the U.K. The data is Australian real GDP and M3, 1900-1993, Canadian real GDP and M2, 1872-1994, U.S. and U.K. real net national income and M2, 1869-1997, and 1871-1993, respectively. They find that "only the U.K. produces an unambiguous failure to reject LRMN." The results for the other three countries are mixed with Canada providing the most evidence against LRMN. Boschen and Otrok (1994) update the time series used by Fisher and Seater through 1992 and find that they reject LRMN for the whole sample, but when the sample is split into a pre-depression, 1869-1929, sample and a post-depression, 1942-1992, sample they cannot reject for either sample. They conclude that there is something inherently different about the Great Depression that leads to the rejection of LRMN in the larger sample.

King and Watson (1997) using a model that is closely related to FS, find that they are unable to reject LRMN. They use real output and M2, 1949-1990, from the United States. Boschen and Mills (1995) use a vector error correction model on US data on real government purchases, taxes, labor supply, M1 and M2 from 1951-1990. They also are unable to reject LRMN. Overall the evidence is broadly supportive of LRMN, but with some notable exceptions.

Coe and Nason (2004) point out that LRMN tests suffer from the same problems as long-horizon prediction regressions in asset returns. First due to the long forecasting horizon relative to the chronological length of the data, overlapping observations must be used i.e. the forecast horizon is longer than the sampling frequency. For 10 year forecasts, 150 years of data would yield only 15 non-overlapping usable observations. This is not practical, and so overlapping observations is the only solution. The problem with overlapping observations is that it induces serial correlation. A forecast horizon of sampling intervals would lead to () order serial correlation in the regression residuals. Standard errors that are unadjusted for this serial correlation will lead to biased inference. Second the forecasting variables are typically endogenous and this leads to a bias in the estimated coefficients in a finite sample. Stambaugh (1999) shows that this bias, can be large. Finally the forecasting variables themselves are highly persistent. Statistical inference is carried out using asymptotic theory, but Richardson and Stock (1989) and Valkanov (2003) show that because of this persistence the asymptotic distributions of the test statistics are poor approximations to the finite sample distributions. This is typically addressed by Monte Carlo simulation of the finite sample distribution as conducted by Mark (1995). However Berkowitz and Giorgianni (2001) demonstrate that these distributions themselves are very sensitive to the specification of the null used to generate the simulations, thus limiting their credibility.

Hjalmarsson (2011) develops new econometric methods for overlapping

observations with highly persistent endogenous regressors. He shows that in the case of exogenous regressors the standard t-statistic can be easily scaled to adjust for the overlapping observations, without the need for robust standard error estimation. The resulting scaled "t-statistic" is normally distributed, leading to easy inference. He also demonstrates that in the case of endogenous regressors, there is a simple modification to the regression that corrects the biasing endogenity effects. The resulting "t-statistic" is again normally distributed. He demonstrates through Monte Carlo simulation methods that the asymptotic distributions are able to well approximate the finite sample distributions even when the forecasting horizon is large relative to the sample size.
The new methodology is applied to test LRMN. Most of the major studies cited above are from the mid to late 1990s and focus on real output. This study updates these data through 2015 to include real interest rates, real consumption expenditures, real wages as well as real output. The results unambiguously reinforce LRMN.

ECONOMETRIC METHODOLOGY

The behavior of Δy_t, and m_t are assumed to satisfy the following:

$$\Delta y_{t+1} = \alpha + \beta m_t + u_{t+1}, \tag{4}$$

$$m_{t+1} = \gamma + \rho m_t + v_{t+1}, \tag{5}$$

where ρ is parameterized local-to-unity as $\rho = 1 + c/T$, where T is the sample size. The joint error process is assumed to satisfy a martingale difference assumption and covariance stationarity with covariance matrix

$$\Omega = \begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{12} & \omega_{22} \end{pmatrix} \tag{6}$$

The errors are endogenous if the correlation $\psi \equiv \frac{\omega_{12}}{\sqrt{\omega_{11}\,\omega_{22}}}$ is non-zero. This research investigates the fitted regression

$$\Delta y_{t+q} = \alpha_q + \beta_q m_t + u_{t+q,t} \tag{7}$$

$$\text{where } \Delta y_{t+q} = \Sigma^{\alpha}_{i=1} \Delta y_{t+i} \tag{8}$$

It should be pointed out that equation (7) is a fitted regression and not the true data generation process for Y which is given in equation (4). Under the null hypothesis of long-rum monetary neutrality, $\beta_q = 0$ for all q. The asymptotic distribution of the OLS estimator β_q is given by Theorem 1 of Hjalmarsson (2011):

Theorem 1

Under the null hypothesis of no predictability, for a fixed q as $T \rightarrow \infty$,

$$\frac{T}{q}\left(\hat{\beta}_q - 0\right) \rightarrow \left(\int_0^1 dB_1 \underline{J_c}\right)\left(\int_0^1 \underline{J_c^2}\right)^{-1} \tag{9}$$

where $B(\bullet) = (B_1(\bullet), B_2(\bullet))'$ denotes a 2-dimensional Brownian motion with variance-covariance matrix:

$$\Omega, J_c(r) = \int_0^r e^{(r-s)c} dB_2(s), and\ J_{\underline{c}} = J_c - \int_0^1 J_c \tag{10}$$

In the very special case of exogenous regressors i.e. $\Psi = 0, B_1$ and J_c are orthogonal to each other and the limiting distribution becomes

$$\frac{T}{q}\left(\hat{\beta}_q - 0\right) \to MN\left(0, \omega_{11}\left(\int_0^1 J_{\underline{c}}^2\right)^{-1}\right) \tag{11}$$

where $MN(\bullet)$ denotes a mixed normal distribution i.e. $\hat{\beta}_q$ is asymptotically normally distributed with a random variance. This means that $\hat{\beta}_q$ is asymptotically conditionally normal (conditional on the variance) and so regular test statistics have standard distributions.

Corollary 1

Hjalmarsson (2011): Let denote the standard t-statistic corresponding to $\hat{\beta}_q$. Under the null of LRMN and an exogenous regressor, for a fixed as

$$\frac{t_q}{\sqrt{q}} \to N(0,1) \tag{12}$$

Thus the effects of the overlapping data are controlled by standardizing the t-statistic by the square root of the forecast horizon.
Exogenous regressors are not the usual case. The innovations to m_t and $y_{t+q} - y_t$ are typically very correlated. However Hjalmarsson shows how the regression equation 3 can be transformed to take advantage of the above results. The idea is to remove the part of u_t that is correlated to v_t from the regression residuals. By doing so, the regressor m_t acts as if it were exogenous and so the results of corollary 1 apply.
If ρ is known, the innovation v_t can be obtained by $v_t = m_t - \rho m_{t-1}$. Consider the augmented regression of Phillips (1991) using v_t

$$\Delta y_{t+1} = \alpha + \beta m_t + \gamma v_{t+1} + u_{t\bullet v} \tag{13}$$

where $u_{t\bullet v} = u_{t\bullet v} - \gamma v_t$,and $\gamma = \omega_{12}(\omega_{22})^{-1}$. By construction $u_{t\bullet v}$ and v_t are uncorrelated and so can be treated as exogenous and the result of corollary 1 can be used for inference. This correction can be easily extended to the q period horizon. The augmented long-horizon regression becomes

$$\Delta y_{t+q} = \alpha_q + \beta_q m_t + \gamma_q v_{t+q}(q) + u_{t+q\bullet v}(q) \tag{14}$$

where $v_t(q) = \Sigma_{j=1}^q v_{t-q+j}$ The results of theorem 1 and corollary 1 can now be extended. Let $\hat{\beta}_q+$ be the OLS estimator of $\hat{\beta}_q$ in equation 14.

Theorem 2

Hjalmarsson (2011): Under the null hypothesis of no predictability, for a fixed q as $T \to \infty$,

$$\frac{T}{q}\left(\hat{\beta}_q^{+}-0\right) \rightarrow MN\left(0, \omega_{11.2}\left(\int_0^1 \underline{J_c^2}\right)^{-1}\right) \tag{15}$$

Given the conditional asymptotic normality of the estimator, the scaled t-statistic will be asymptotically distributed as a standard normal. Let t^{+}_{q} denote the standard t-statistic corresponding to $\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}{}^{+}$.

Corollary 2

Hjalmarsson (2011): Under the null of no predictability and an exogenous regressor, for a fixed q as $T \longrightarrow \infty$,

$$\frac{t_q^{+}}{\sqrt{q}} \rightarrow N(0,1) \tag{16}$$

The above results depend on knowledge of the parameter or, for a given sample size, ρ. In general is unknown and not estimable. Although not estimable it is possible to form a confidence interval for c. Haljmarsson (2011) suggests using the unit-root test of Chen and Deo (2009). By calculating the t-statistic for each value of c within the interval, the most conservative value for the test of the null hypothesis can be chosen. If the confidence interval for c has a coverage of 100(1- θ_1)% and the size of the t-test is θ_2 then, by Bonferroni's inequality, the final conservative test will have a size no greater than $\theta_1 + \theta_2$. For the results presented here the confidence interval for c is set at 95% and so if the nominal size of the resulting t-test is 5%. The final test has a size no greater than 10%.

DATA AND RESULTS

The money measure is the St. Louis Adjusted Monetary Base (AMBSL). Real output is measured by the Industrial Production Total Index (IPB50001SQ). Both series run from 1919:Q1 – 2015:Q1. The real interest rate, real wages and real consumption expenditure are calculated from the 3-Month Treasury Bill: Secondary Market Rate (TB3MS), Gross Domestic Income: Compensation of Employees, Paid: Wages and salaries (A4102C1Q027SBEA), Personal Consumption Expenditure (PCEC), and the Consumer Price Index (CPI). The real interest rate runs from 1934:Q1-2015:Q1, real wages and real consumption expenditure run from 1947:Q1 – 2015:Q1. All data come from the Federal Reserve Economic Database (FRED) maintained by the Federal Reserve Bank of St. Louis. For the case of real interest rates, Δy_{t+1} is replaced with r_{t+1} which is the natural log of 1+ the real rate of interest.

The results of the regression of changes in real output on the money supply are given in table 1 below. The forecast horizons used are 1, 2, 3, 4, 5, 10, 15, 20 and 30 years. The entire sample is used which includes the Great Depression. LRMN cannot be rejected for any of the regressions.

The results for real wages, real personal consumption expenditure, and real interest rates are given in tables 2 – 4. They are all carried out at the same horizons and the results are qualitatively similar. No evidence against LRMN can be found for any series at any horizon considered.

CONCLUSION

Most economists would be very surprised to find that long-run monetary neutrality does not hold, yet the empirical work, while providing general support, does contain some notable exceptions. Conventional tests for LRMN are plagued by the serial correlation induced by overlapping observations, bias due to the endogenity of the regressors and the poor finite sample performance of the asymptotic distributions due to the high persistence of the regressors. Recently developed econometric techniques designed for cases of overlapping observations, endogenous and persistent regressors are used to examine LRMN. Once these features are taken into consideration, the research reveals there is no evidence against LRMN.

Future research will move along two strands. First, the next step is to test for superneutrality, which claims that changes to the money growth rate has no real economic effect in the long-run. The other direction is to attempt a cross country analysis, although since we are testing the long-run, with some series running for 30 years, this will limit the choice of countries.

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TABLE 1: REAL OUTPUT

(quarters)				
4	0.0771	0.0143	0.0774	0.0143
8	-1.5580	-0.1767	-1.5574	-0.1766
12	-0.3579	-0.0363	-0.3573	-0.0362
16	0.8274	0.0717	0.8278	0.0717
20	3.1652	0.2291	3.1654	0.2291
40	9.9107	0.4736	9.9106	0.4736
60	13.8727	0.5474	13.8728	0.5475
80	32.7342	0.8955	32.7317	0.8955
120	82.6816	1.3061	82.6746	1.3061

TABLE 2: REAL WAGES

(quarters)				
4	-0.3274	-0.1863	-0.3270	-0.1861
8	-0.5203	-0.1635	-0.5198	-0.1634
12	-0.4643	-0.1267	-0.4637	-0.1265
16	0.6938	0.1471	0.6943	0.1472
20	2.0047	0.3608	2.0051	0.3609
40	6.6114	0.7067	6.6115	0.7068
60	7.4663	0.4522	7.4669	0.4523
80	15.6195	0.5274	15.6191	0.5275
120	45.0361	0.7770	45.0332	0.7771

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TABLE 3: REAL PERSONAL CONSUMPTION EXPENDITURE				
(quarters)				
4	0.6086	0.4529	0.6088	0.4531
8	0.5028	0.2168	0.5031	0.2169
12	0.3081	0.1197	0.3085	0.1199
16	0.3753	0.1170	0.3758	0.1171
20	0.8592	0.2338	0.8596	0.2339
40	3.0892	0.5409	3.0896	0.5410
60	5.0745	0.5140	5.0749	0.5141
80	9.6847	0.5742	9.6847	0.5744
120	27.8851	0.8941	27.8838	0.8943

TABLE 4: REAL INTEREST				
(quarters)				
4	0.0199	0.7301	0.0204	0.7534
8	-0.0085	-0.1459	-0.0075	-0.1307
12	-0.0204	-0.2570	-0.0192	-0.2446
16	-0.0578	-0.4906	-0.0561	-0.4820
20	-0.0861	-0.5803	-0.0843	-0.5741
40	-0.2231	-0.6426	-0.2197	-0.6410
60	-0.3933	-0.6073	-0.3997	-0.6068
80	-0.7789	-0.6662	-0.7930	-0.6643
120	-2.6350	-1.1102	-2.6827	-1.1088