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Large Estimates of the Elasticity of Intertemporal Substitution Using Aggregate Returns: Is it the aggregate return series or the instrument list?

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Large Estimates of the Elasticity of Intertemporal Substitution Using Aggregate Returns: Is it the aggregate return series or the instrument list?

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Abstract

Estimates of the elasticity of intertemporal substitution that are close to zero have puzzled researchers since the 1980s. Two possible reasons for such results are the use of rates of return that are not representative of the agent's portfolio and inconsistent estimates due to the weak instrument problem. In this paper, we investigate if the aggregate capital return series for the United Sates can still provide large estimates for this elasticity when potential weak instrument problems are addressed and when different instrument lists are used. Our findings indicate that weak instruments remain an important concern and using weak instrument partially and fully robust methods we find the aggregate capital return series is able to deliver above one estimates of the elasticity using different instrument sets.

Keywords: consumption; elasticity of intertemporal substitution; asset return; weak instruments.

JEL Codes: C22, C25, E21.

1. Introduction

The magnitude of the elasticity of intertemporal substitution (EIS) is a crucial question in Macroeconomics and Finance, since it is a key driving force of consumption (and savings) allocation across periods. Moreover, given it is central role in several economic models, consistent estimates of the EIS are extremely useful to researchers in their calibration exercises and to policymakers interested in the aggregate economy.

Nevertheless, several studies using U.S. aggregate data find statistically significant EIS estimates below 0.3, see Patterson and Pesaran (1992), Hahm (1998), and Campbell (2003).[1] These surprisingly low EIS estimates led researchers to carefully examine this important issue using different approaches.

Yogo (2004) investigates if the econometric techniques used in these earlier studies provide consistent EIS estimates. He finds that most estimates of the EIS obtained for the United States and other ten developed countries are plagued by weak instruments. In particular, for the specifications using U.S. data, only those employing T-Bill returns are not plagued by weak instruments; however, their EIS estimates are close to zero.[2] So, the absence of non-weak excluded instruments prevents a definite conclusion regarding the small magnitude of the EIS estimates.

The second approach consists of building an aggregate measure of return, as done by Dacy and Hasanov (2011) and Mulligan (2002), in order to mimic the portfolio of the representative consumer. Studies based on aggregate data usually employ stock returns and government bonds returns as the only assets held by

[1] Small EIS estimates for the U.S. economy have been found in the literature since Hall (1988) and Campbell and Mankiw (1989) seminal studies, which found EIS estimates below 0.3 and barely statistically significant.

[2] Gomes and Paz (2011) further scrutinized Yogo (2004) results, and find that the specifications using the T-Bill returns have the null of the Sargan overidentification test rejected.

consumers. Clearly, those are not the only assets held by the average household in economy—see Dacy and Hasanov (2011). So, a close to zero estimated EIS would not be a surprising result.

Dacy and Hasanov (2011) built a synthetic mutual fund (SMF) that is a share-weighted average of the quarterly returns of the assets held by the representative household. Their EIS estimates using the SMF were statistically significant and close to 0.2.[3] Mulligan (2002) using U.S. national accounts data built an aggregate return series of the total capital stock in the economy that is much more comprehensive than the SMF, and related it to aggregate consumption growth. In contrast to the previous literature, his estimates of the EIS are larger than one and statistically significant.

In this paper, we first follow Yogo's (2004) and Gomes and Paz's (2013) methodology and verify if Mulligan's (2002) estimates are plagued by weak instruments. Second, given that Mulligan (2002) employs a set of excluded instruments that differs from the usual practice in the literature, we also estimate his specifications using Yogo's (2004) and Dacy and Hasanov's (2011) instrument sets. We do so to distinguish between two possible causes for Mulligan's (2002) results. The first is that the EIS estimates are specific to the aggregate return series and instrument set combination. The second is that his aggregate return series is solely driving the above one EIS estimates, therefore other instrument sets would lead to similar estimates.

Our results indicate that Mulligan's (2002) aggregate capital return series is able to deliver statistically significant estimates of the EIS that are larger than one for both nondurable and nondurable plus service consumption series. We find that his

[3] Applying an econometric methodology similar to Yogo (2004), Gomes and Paz (2013) concluded that estimates using SMF returns are plagued by weak instruments and, in some cases, partially robust estimators provided a statistically significant EIS estimate close to 0.2.

original instrument set does not suffer from the weak instrument problem. Interestingly, similar results are obtained when Yogo's (2004) instrument lists are used, even though such instruments sets are weaker. These findings strongly suggest that Mulligan's (2002) aggregate capital return series that is indeed behind the large EIS estimates, and not his instrument sets.

The paper is organized as follows. In section 2 the consumption model used to motivate the empirical specification is laid out. Section 3 discusses the econometric methodology. Section 4 describes the data used in the estimates. Results are presented in Section 5. Finally, Section 6 reports our conclusions.

2. Consumption Model

Consider a frictionless economy lived by a single representative agent with the Epstein and Zin (1989) non-expected utility. Following Gomes and Paz (2013), the agent's intertemporal optimization problem leads to the following empirical specification.[4]

$$\Delta ln(c_t) = \alpha_i + \frac{\psi(\theta-1)}{\theta} b_t + \frac{\psi}{\theta} r_{i,t} + \varepsilon_{i,t}, \;\; i = 1, \ldots, N \qquad (1)$$

where c_t is the per capita consumption growth in year t, b_t is the return on the portfolio of all invested wealth, $r_{i,t}$ is the return of the *i-th* asset held by the consumer, and $\varepsilon_{i,t}$ is an innovation. The parameter ψ is the EIS, γ is the coefficient of relative risk aversion, and $\theta \equiv (1-\gamma)/(1-\psi^{-1})$. Notice that, by construction, the portfolio of invested wealth is not and cannot be proxied by the returns of any specific asset, like stock market returns.

[4] See Campbell and Viceira (2002, chapter 2) for further details.

Several studies, for example Dacy and Hasanov (2011), adopted the constant relative risk aversion (CRRA) utility function. In the above framework, these preferences are equivalent to restricting the coefficient of relative risk aversion to be equal to the reciprocal of the EIS, this means imposing $\theta = 1$. Therefore, equation (1) becomes:

$$\Delta ln(C_t) = \alpha_i + \psi r_{i,t} + \varepsilon_{i,t}, \;\; i = 1, \dots, N \tag{2}$$

Equation (2) has two interesting properties. The first is that the EIS can be estimated using the return of any asset held by the consumer, as long as valid instruments are available. In this vein, Vissing-Jørgensen (2002) and Gross and Souleles (2002) use microdata to look at specific groups of consumer according to their asset holdings. They find EIS estimates of about 0.7 when they use stock returns for stockholders or credit card interest rate for credit card debtors. Nevertheless, it is unclear that microdata-based EIS estimates are a measure of the EIS faced by the representative consumer in the aggregate economy. Therefore such estimates do not seem appropriate to be used in calibration of representative agent models, for instance. For this reason, we employ the aggregate return measure built by Mulligan (2002) to estimate the EIS using aggregate consumption data.

The second property from equation (2) is the assumption that the EIS is equal to the reciprocal of the coefficient of relative risk aversion, which implies that we can estimate the coefficient of relative risk aversion using the reverse of equation (2). This idea was carried out by Hansen and Singleton (1983) and Campbell (2003), who find puzzling low estimates of the coefficient of relative risk aversion that do not support the $\theta = 1$ assumption.

Yet, even for $\theta \neq 1$, equation (2) can still be a special case of equation (1) if the individual asset return is replaced by the return on the portfolio of all invested wealth, which is the return on the aggregate capital stock (Mulligan, 2002). Then, the sum of the second and third terms in the right-hand side of equation (1) become ψb_t, as seen in equation (3):

$$\Delta ln(c_t) = \alpha_i + \psi b_t + \varepsilon_{i,t}, \;\; i = 1, \ldots, N \tag{3}$$

Consequently, equation (3) implies that consistent estimates of the EIS can be obtained as long as return on total wealth is measured and valid instruments are available. And this is the approach pursued in this paper.

3. Econometric Methodology

In this paper, the EIS will be estimated by means of equation (3) and an instrumental variable estimator. Such estimator requires excluded instruments to be orthogonal to error term and to be correlated with the endogenous regressor, i.e. the aggregate capital rate of return. More precisely, this correlation cannot be small; otherwise the EIS estimate will be biased due to the weak instrument problem.

Following closely Yogo (2004) and Gomes and Paz (2013), we first conduct several econometric pre-tests to assess the weak instrument problem. Next, we employ weak instrument partially robust estimators. And finally, we compute weak instrument robust confidence interval for the EIS.

The first econometric pre-test conducted is the Kleibergen and Paap (2006) underidentification test (KP). Its null hypothesis is that the excluded instrument has a zero correlation with the endogenous regressor. The next four tests come from Stock and Yogo (2003) and are based on the first-stage *F*-statistic of the two-stage least squares (TSLS) estimator. They have two types of null hypothesis. One is if the size of the bias with respect to OLS estimates is larger than 10% for the TSLS and the Fuller-k estimators. The other type is if the actual size of the 5% level t-test is greater than 10% for the TSLS and the limited information maximum likelihood (LIML) estimators. The use of pre-testing may lead to size distortion in the subsequent estimations that cannot be controlled. For this reason, we now turn to weak instrument partially robust estimators.

The TSLS, the Fuller-k and the LIML estimators have different limiting distributions under weak instruments. Therefore, different EIS estimates across these estimators also indicate the existence of the weak instrument problem. As discussed in Yogo (2004), both the Fuller-k and the LIML are partially robust to the weak instrument problem. Accordingly, if there is evidence of weak instruments, we will focus on Fuller-k and LIML estimates.

Weak instrument robust confidence intervals for the estimated EIS are calculated by inverting econometric tests that test $H_0\colon \beta = \beta_0$. Since these tests are based on the true parameter value, they are not affected by weak instruments. Yogo (2004) employed the following three weak instrument robust tests. The Anderson-Rubin (1949) 'AR' test, the Lagrange multiplier 'LM' test (Kleibergen, 2002), and the conditional likelihood ratio 'CLR' test (Moreira, 2003). We employ the CLR test because Andrews, Moreira, and Stock (2006) showed that the CLR test combines the LM statistic and the J-overidentification restrictions statistic in the most efficient way, thus it is more powerful than the AR and LM tests.[5]

Even if we find that the EIS estimates using Mulligan's (2002) aggregate return series are not plagued by weak instruments, we will re-estimate equation (3)

[5] This J-statistic is calculated at the true parameter value. So, it is different from Hansen's J-statistic that is evaluated at the estimated parameter value, and therefore subject to the weak instrument problem.

using instrument lists that are commonly used in the literature, such as Yogo's (2004) and Dacy and Hasanov's (2011). Given that Mulligan's (2002) instrument set is very different from the commonly used instruments, by conducting these new estimations we can find out if Mulligan's (2002) results are driven by the specific combination of aggregate returns and instrument set or by the aggregate return series alone. The former possibility implies close to zero EIS estimates when using different instrument sets, while the latter implies large EIS estimates using different instrument sets.

4 Data Description

The data used in this paper consists of Mulligan's (2002) and Dacy and Hasanov's (2011) datasets. Mulligan's (2002) data are used in the main estimations and comprise a synthetic real aggregate asset return and a real nondurable consumption per capita (ND) and a real nondurable plus service consumption per capita (NDS) series. To construct the annual aggregate capital return series, Mulligan (2002) used U. S. national accounts data. His measure of capital stock comes from BEA's (2000) fixed assets valued at current cost at the beginning of the year. Next, the direct and indirect taxes were deducted from the capital income net of depreciation per dollar of capital to obtain the after-tax annual aggregate capital rate of return.

Mulligan's (2002) instrument set (hereafter called Mulligan-1st lag) consists of the first lag of the after-tax capital return, nominal promised yield on commercial paper, inflation rate, yield gap between BAA and AAA bonds, and tax rate. Interestingly, Hall's (1988) recommendation for using lags of variables no closer than the second lag because of aggregation problems does not apply here because the

Mulligan's (2002) instrument sets do not contain lagged dependent variables (consumption growth). We construct another instrument set made of the second lag of the aforementioned variables, hereafter called Mulligan-2nd lag.

The Dacy and Hasanov (2011) dataset is used to build four additional instrument sets. The third and fourth sets are based upon Yogo's (2004) instruments. The third set (Yogo-1st lag) is composed of the first lag of the nominal T-Bill rate, inflation, consumption growth (ND or NDS depending on the dependent variable), and log dividend-price ratio. The fourth instrument set (Yogo-2nd lag) consists of the second lag of variables included in Yogo-1st lag set. The last two instrument sets are similar to Dacy and Hasanov's (2011) instruments. The fifth instrument set (DH-1st Lag) consists of one-, two-, and three-period lagged real T-Bill rate and consumption growth rate; one-period lagged bond default yield premium and bond horizon yield premium. And the sixth instrument set (DH-2nd Lag) is comprised of two-, three-, and four-period lagged real T-Bill rate and consumption growth rate; two-period lagged bond default yield premium and bond horizon yield premium. For the sake of comparability across estimates, we restrict the sample to cover 1952–1997 that is the period in which all instrument series are available.[6]

Table 1 displays the descriptive statistics of the consumption growth rate and the aggregate asset returns. Notice that the average growth rate of the NDS is greater than the average growth rate of ND, whereas the former is less volatile than the latter. Among the real return rates considered, the aggregate capital return is always positive and has the lowest volatility. These last two remarks can be clearly seen in Figure 1, which exhibits the behavior of the Mulligan's (2002) aggregate capital real return, the stock market real return, and the T-Bill real return.

[6] Mulligan estimates refers to 1947-1997 period. For Mulligan's instrument sets we also conducted estimates using data covering this period and the results were similar to those reported here in the paper. Such results are available upon request.

5. Results

In this section, we first conduct the weak instrument tests. Next, we report and discuss the EIS estimates obtained using the six instrument sets; the TSLS, Fuller-*k*, and LIML estimators; and the weak instrument robust confidence intervals.

5.1 Weak instrument tests

Table 2 displays the weak instrument tests when the nondurable consumption growth is the dependent variable. The null hypothesis of underidentification of the KP test is rejected at the 5% level of confidence for all instrument sets, except for DH-2nd lag. The Mulligan-1st lag is the only instrument set to exhibit a first-stage *F*-statistic above 10. For this instrument set, the null hypotheses that the coefficient of the TSLS or the Fuller-k estimators is severely biased are rejected. The *p*-value for the LIML size test is below the 1% level, implying that the *t*-test coefficients for the LIML estimates are reliable. Nonetheless, the *p*-value for the TSLS size test is above 10%, indicating that the size of *t*-test for the TSLS estimated coefficient is not reliable. Along these lines, the results suggest taking the TSLS results with a grain of salt, and focusing on the Fuller-*k* and LIML estimates. The other instrument sets show a low first-stage *F*-statistic which do not lead to a rejection of the null hypothesis of the weak instrument tests. Thus, TSLS estimates using these instrument sets are definitely not reliable.

Notice that Mulligan's instruments sets are the same no matter which consumption measure is used. But, Yogo's (2004) and Dacy and Hasanov's (2011) instrument sets include lagged consumption growth as an instrument. Consequently the weak instrument test results change according to the consumption series used. We conducted weak instrument tests for nondurable plus service consumption growth, and found p-values similar to the ones for the nondurable consumption reported in Table 2. For the sake of brevity these results are not reported here but are available upon request.

5.2 EIS estimates and robust confidence intervals

The EIS estimates obtained by means of equation (3) using Mulligan's aggregate rate of return and nondurable consumption are reported in Table 3. Focusing on Mulligan's-1st lag instrument set, the TSLS, Fuller-k, and LIML estimates of the EIS are between 1.34 and 1.37 and are statistically significant at the 5% level. Such results are well above the earlier findings in the literature, and are very similar to the results obtained by Mulligan's (2002) in his Table 3. The fact that our TSLS, Fuller-k, and LIML estimates are close to each other is another result supporting our claim that weak instrument problem is not a concern for this instrument set.

The use of the Mulligan's-2nd lag instrument set leads to larger EIS estimates ranging from 1.26 to 1.27. Yogo's (2004) instruments also provide EIS estimates above one that are statistically significant at the 5% level. The estimates using Dacy and Hasanov's (2011) instrument sets have an even worse performance. The EIS estimates jump wildly across different estimators clearly indicating very weak instruments.

The weak instrument robust confidence intervals are obtained by inverting the CLR test. The calculated intervals indicate a positive EIS for Mulligan's-1st and 2nd lag and Yogo's-1st lag instruments. The confidence intervals for Yogo's-2nd lag and DH-1st lag instrument sets include negative values, while DH-2nd lag instruments provide an uninformative confidence interval. Intuitively speaking, the weaker the instrument set the wider will be the confidence interval. Thus, the interval for the Mulligan-1st lag is the narrowest.

So far our results using aggregate data provide a larger than one estimated EIS, which is well above the estimates found by studies using aggregate or microdata. Our estimates based on Mulligan-1st instrument set are not plagued by weak instruments, but weak instrument partially robust estimators and fully robust confidence intervals of specifications using other instrument lists corroborate our findings. We now turn to the EIS estimates employing nondurable plus service consumption.

Table 4 reports the estimates of equation (3) for nondurable plus service consumption growth. The estimated EIS is not very different from Table 3 results. The estimates using DH-1st lag and DH-2nd lag instrument sets varied substantially. The remaining instrument sets provided positive and statistically significant EIS estimates above 0.87. Focusing on the Mulligan-1st lag instrument set, estimates range from 1.11 (TSLS) to 1.24 (LIML). The weak instrument robust confidence interval, reported in Table 4, indicate that Mulligan-1st lag set leads to the narrowest interval. The confidence intervals for the Mulligan-2nd lag, Yogo-1st lag, Yogo-2nd lag, and DH-1st lag instrument sets contain only positive numbers. Last, the confidence interval implied by DH-2nd lag instruments is uninformative.

These results using nondurable plus services consumption also provide large EIS estimates, and these estimates were not limited to Mulligan's (2002) instrument sets either. Thus, we can conclude that it is the Mulligan's (2002) aggregate return rate and not his instruments sets that are leading to large EIS, which in some cases are above 1.

6. Conclusions

In the literature, the estimated elasticity of intertemporal substitution is usually close to zero when aggregate data is used. Such puzzling result led researchers to investigate this issue from different perspectives. Following Gomes and Paz (2013), in this paper we combine two of those approaches. On the one hand, we use an aggregate return series that mimics the return on the wealth portfolio of the representative household. On the other hand, we employ several econometric techniques to verify and address the presence of the weak instrument problem in the EIS.

The empirical evidence amassed in this paper indicate that Mulligan's (2002) aggregate rate of return provide statistically significant estimates of the EIS that are not plagued by the weak instrument problem and are above one. By estimating the EIS using different instrument sets, we are able to determine that this important result is due to the Mulligan's (2002) aggregate return series and not the instrument sets used is indeed leading to large EIS estimates.

The question is then why Mulligan's aggregate return rate leads to larger EIS estimates? The consumption model discussed earlier suggests that this happens because Mulligan's (2002) aggregate capital return mimics more closely the typical return faced by the representative (or aggregate) consumer. Nevertheless, we believe this hypothesis deserves additional scrutiny in the future because to a certain degree, our results are sensitive to the instrument set and the consumption growth measure used.

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Figure 1 – Behavior of the real asset returns over time.

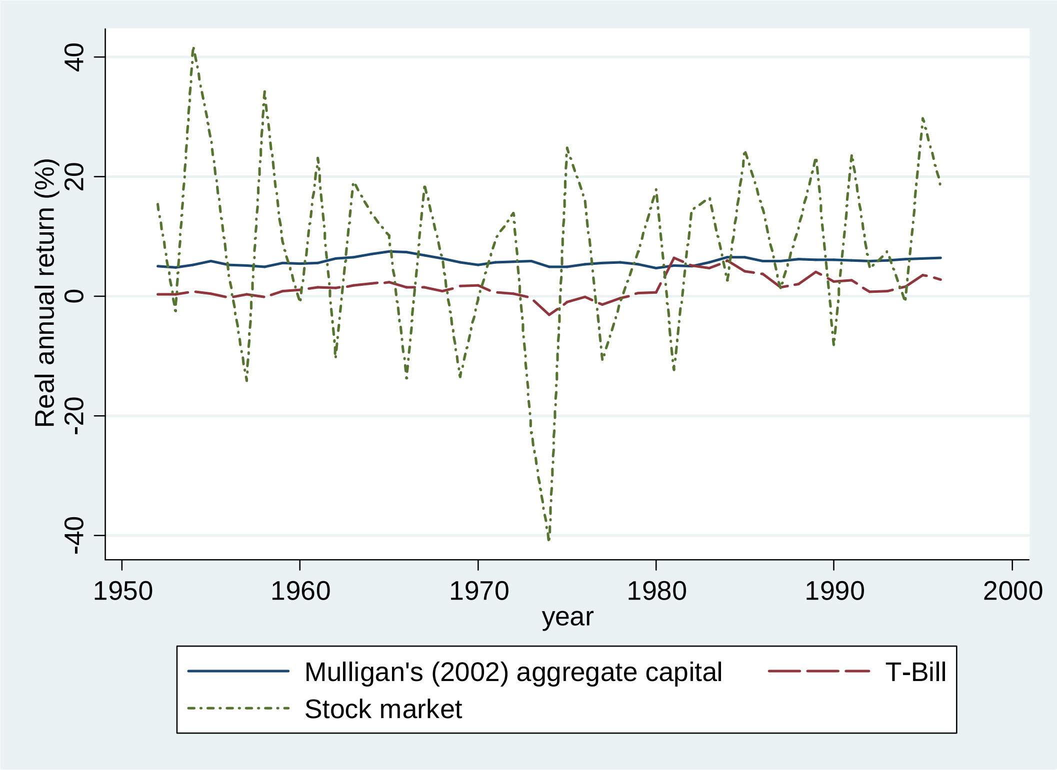

Table 1: Descriptive Statistics

Variable	Number of Obs.	Mean	Standard error	Min	Max
Δ Log Nondurable consumption	46	0.008	0.016	-0.035	0.041
Δ Log Nondurable plus Service consumption	46	0.021	0.012	-0.006	0.037
Log(1+ aggregate capital return)	46	0.058	0.007	0.047	0.075
Log(1 + real T-Bill return)	46	0.016	0.019	-0.031	0.064
Log(1+ real Stock return)	46	0.082	0.162	-0.412	0.419

Note: Data is annual frequency. Nondurable consumption, nondurable plus service consumption and aggregate capital return comes from Mulligan (2002) and cover the 1947–1997 period. T-Bill and Stock returns come from Dacy and Hasanov (2011) and cover the 1952–1997 period.

Table 2 – Weak instrument tests for Mulligan's aggregate rate of return using Nondurable consumption

Instrument set	Mulligan 1st Lag	Mulligan 2nd Lag	Yogo 1st Lag	Yogo 2nd Lag	DH 1st Lag	DH 2nd Lag
1st stage F-statistic	24.337	7.255	8.348	8.944	2.599	1.351
Weak Instrument Tests (p-value)						
TSLS bias	0.000	0.949	0.810	0.748	0.999	0.999
TSLS size	0.769	1.000	1.000	0.999	1.000	1.000
Fuller-k bias	0.000	0.327	0.325	0.255	0.488	0.919
LIML size	0.000	0.231	0.205	0.151	0.320	0.837
KP	0.000	0.000	0.000	0.000	0.038	0.240
Observations	45	44	45	44	43	42

Notes: All specifications include a constant. Fuller-k estimates used k=1.

Table 3 –Equation (1) estimated using Nondurable Consumption and Mulligan's aggregate rate of return

Instrument set	Mulligan 1st Lag	Mulligan 2nd Lag	Yogo 1st Lag	Yogo 2nd Lag	DH 1st Lag	DH 2nd Lag
EIS Estimates						
TSLS	1.34**	1.27**	1.22**	1.08**	0.78	0.84
Fuller-k	1.36**	1.26**	1.18**	1.03**	-0.03	-1.64
LIML	1.37**	1.26**	1.19**	1.02**	-0.20	-4.59
Observations	45	44	45	44	43	42
Weak instrument Robust confidence interval						
CLR	[0.67, 2.09]	[0.13, 2.38]	[0.01, 2.30]	[-0.13, 2.01]	[-7.65, 1.47]	(-∞,+∞)

Notes: All specifications include a constant. **, * means statistically significant at the 5% and 10% level respectively. Fuller-k estimates used k=1. Weak instrument robust confidence intervals are calculated using the rivtest command in Stata, developed by Finlay and Magnusson (2009).

Table 4 –Equation (1) estimated using Nondurable plus Service Consumption and Mulligan's aggregate rate of return

Instrument set	Mulligan 1st Lag	Mulligan 2nd Lag	Yogo 1st Lag	Yogo 2nd Lag	DH 1st Lag	DH 2nd Lag
EIS Estimates						
TSLS	1.11**	1.03**	0.97**	0.94**	1.37**	1.78**
Fuller-k	1.23**	1.01**	0.96**	0.88**	0.93**	-1.00
LIML	1.24**	1.00**	0.95**	0.87**	1.55**	4.01**
Observations	45	44	45	44	43	42
Weak instrument Robust confidence interval						
CLR	[0.79, 1.74]	[0.21, 1.75]	[0.16, 1.72]	[0.06, 1.55]	[0.45, 3.64]	(-∞,+∞)

Notes: All specifications include a constant. **, * means statistically significant at the 5% and 10% level respectively. Fuller-k estimates used k=1. Weak instrument robust confidence intervals are calculated using the rivtest command in Stata, developed by Finlay and Magnusson (2009).