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Large estimates of the elasticity of intertemporal substitution: is it the aggregate return series or the instrument list?

Fábio Gomes
University of São Paulo, Department of Economics, FEA-RP

Lourenço Paz
Syracuse University

Abstract

Since the 1980s, researchers have been puzzled by close to zero estimates of the elasticity of intertemporal substitution. Two possible causes are rates of return that are not representative of the agent's portfolio return and inconsistent estimates due to the weak instrument problem. We examine if the aggregate capital return series for the United States and several instrument sets can provide large estimates of this elasticity. Our findings indicate that this return series leads to large estimates of the elasticity using different instrument sets. An unusual set of instruments performed well and its use in consumption-model estimates seems promising.

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Contact: Fábio Gomes - fabiogomes@fearp.usp.br, Lourenço Paz - lspaz@maxwell.syr.edu.
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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 its 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.

Since Hall (1988) and Campbell and Mankiw (1989) seminal studies, EIS estimates for the U.S. aggregate data have been found to be small, usually below 0.3 and barely statistically significant. Indeed, Hall (1988) concluded that the EIS is unlikely to be above 0.1 and, more recently, Campbell (2003) could not reject a null EIS. Others studies based on U.S. quarterly or annual aggregate data find statistically significant EIS estimates, but these estimates are still below 0.3 (Patterson and Pesaran, 1992; Hahm, 1998; and Yogo, 2004). These surprisingly low EIS estimates led researchers to carefully examine this important issue using different approaches.[1]

The extant literature employs aggregate consumption and considers stock market and government bond returns as the typical asset return faced by consumers. As pointed out by Dacy and Hasanov (2011), stocks and government bonds are not the only assets held by the average household in economy. Consequently, a close to zero estimated EIS would not be a surprising result.

In response to this remark, one strand of the literature focused on specific groups of consumers in order to use the asset returns that mattered to them. For instance, Vissing-Jørgensen's (2002) results suggest that consumption growth is correlated with expected stock returns in the population of households owning stocks, and her estimated EIS ranges between zero and 0.8. This finding is buttressed by Guvenen's (2006) calibration exercise that shows that when household participation in the stock market is limited, the EIS estimates will be small. This happens because the average investor will be different from the average consumer, which is the agent represented in the aggregate consumption data.

Although studies using household-level data confirm the importance of using the asset returns considered by specific groups of households, there is still the need to estimate the EIS for the representative household in the economy. In response to such needs, another strand of the literature focused on building the representative agent's portfolio rate of return. Mulligan (2002) by means of a state-dependent utility model argued that the expected return on aggregate capital drives the aggregate consumption growth. In this vein, the expected return of an aggregate portfolio gives much more information about consumption growth rate than any particular asset return. Hence, Mulligan (2002) used U.S. national accounts data and built a return series for the aggregate capital stock and a new set of instruments. In contrast to the previous literature, his estimates of the EIS using the aggregate return series are larger than one and statistically significant.[2]

Given that Mulligan's (2002) findings can potentially represent a solution to the low EIS puzzle, in this paper we further scrutinize his results along two lines. First, we investigate if his estimates are plagued by the weak instrument problem, which could make his estimates to be inconsistent. Additionally, we also employ weak instrument partially robust estimators

[1] Although focused on price elasticities, Chetty (2012) suggests that the optimization frictions encountered by agents may lead to a downward bias in the estimated elasticities.

[2] Similarly, 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, which is less comprehensive than Mulligan's (2002) measure. Their EIS estimates using the SMF were statistically significant and close to 0.2. Moreover, 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

and compute weak instrument robust confidence intervals for the EIS. The importance of the weak instrument problem is underscored in Yogo (2004) and in Gomes and Paz (2011). They find that most estimates of the EIS obtained for the United States and other ten developed countries using either quarterly or annual data 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 very close to zero.

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 reasons for Mulligan's (2002) results. The first is that the EIS estimates are specific to the simultaneous use of his aggregate return series and his instrument set. The second reason is that his large EIS estimates are solely due to the use of his aggregate return series, therefore other instrument sets would lead to similar estimates.

Our results indicate that Mulligan's (2002) aggregate capital return series is able to deliver relatively large and statistically significant estimates of the EIS for nondurable and nondurable plus service consumption series. We find that his original instrument set does not suffer from the weak instrument problem. Interestingly, similar estimates are obtained when Yogo's (2004) instrument lists are used, even though such instruments sets are relatively weaker. This can be clearly seen in the wider weak instrument robust confidence intervals for the EIS using Yogo's (2004) instrument list, which contain values close to zero, and indeed below 0.3, whereas the lower bound of the robust confidence interval based on Mulligan's instrument list is 0.67. These findings suggest that Mulligan's (2002) aggregate capital return series is the key factor driving the large EIS estimates

The remainder of this 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 inhabited 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.[3]

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

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, and $\theta \equiv (1-\gamma)/(1-\psi^{-1})$, where γ is the coefficient of relative risk aversion. 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.

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, which means imposing $\theta = 1$. Therefore, Equation 1 becomes:

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

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

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 0.8 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, which at the end of the day 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 becomes 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 unreliable due to the weak instrument problem.

Following 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) under-identification 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 (2005) 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 $H_0: \beta = \beta_0$. Since these tests are based on the true parameter value, they are not impaired 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.[4]

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 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 his specific combination of aggregate returns and instrument set or by his 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 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

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[4] 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.

(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.[5]

Table 1 displays the descriptive statistics of the consumption growth rates 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. In Figure 1 we can see the nondurable and the nondurable plus service consumption growth series over time. They have a similar behavior; however, the nondurable series is more volatile. 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 2, which exhibits the behavior of the Mulligan's (2002) aggregate capital real return, the stock market real return, and the T-Bill real return.

5. Results

In this section, we first conduct the weak instrument tests for the six instrument sets. Next, we report and discuss the EIS estimates obtained using 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 under-identification 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 growth 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 growth series used. We conducted weak instrument tests for nondurable plus service consumption growth, and found *p*-values similar

[5] Mulligan's (2002) estimates refer to the 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.

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 growth 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 (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 a worse performance. The EIS estimates jump wildly across different estimators clearly indicating very weak instruments. Therefore, estimation procedures partially robust to weak instruments lead to larger EIS estimates, even when Mulligan's (2002) original instrument set is not used. In this vein, Mulligan's (2002) aggregate capital return series seems to be the reason behind the large EIS estimates.

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. Notice that 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. These facts do not necessarily weaken our previous conclusion. Intuitively speaking, the weaker the instrument set the wider will be the robust confidence interval. Thus, the interval for the Mulligan-1st lag is the narrowest, as suggested by our weak instrument test results. Therefore, the results for the other instrument sets can be understood as not being very informative due to relatively weaker instruments.

So far our results using aggregate data provide, at least for Mulligan's original instrument set, a larger than one estimated EIS, which is well above the estimates found by studies using aggregate or microdata. It is worth mentioning that our estimates based on Mulligan-1st instrument set are not plagued by weak instruments, but even methods robust to weak instruments corroborate the 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. This indicates the presence of weak instruments. The remaining instrument sets provided positive and statistically significant EIS estimates, which are above 0.87. Focusing on the Mulligan-1st lag instrument set, estimates range from 1.11 (TSLS) to 1.24 (LIML). As before, large EIS estimates are not restrict to Mulligan's original instrument set. The weak instrument robust confidence interval, reported in Table 4, indicate that Mulligan-1st lag set leads to the narrowest interval, ranging from 0.79 to 1.74. The confidence intervals for the Mulligan-2nd lag, Yogo-1st lag, Yogo-2nd lag, and DH-1st lag instrument sets contain only positive numbers, and their lower bound is below 0.5, indicating that EIS could be small and close to zero. And, the confidence interval implied by DH-2nd lag instruments is uninformative.

These results using nondurable plus services consumption also provide large EIS point estimates, and these estimates were not limited to Mulligan's (2002) instrument sets either. Thus, a similar conclusion applies here. It is the Mulligan's (2002) aggregate return rate and not his instruments sets that are leading to large EIS. And again, the same pattern emerges in the weak instrument robust intervals for the EIS. The weaker is the instrument set, the wider will the confidence interval for the EIS.

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 these perspectives. First, we use an aggregate return series that mimics the return on the wealth portfolio of the representative household. Second, 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 found large EIS point estimates which suggests that these large EIS estimates are mostly due to Mulligan's (2002) aggregate return series. The instrument set proposed by Mulligan (2002) performed well and may be useful for researcher interested in estimating consumption models. As expected, the weak instrument fully robust confidence intervals for the EIS became wider when relatively weaker instruments were used. This does not necessarily weaken our conclusions, but it certainly stresses the pitfalls of overlooking the weak instrument problem when estimating the EIS.

In light of our findings, an interesting avenue for future research is estimate the EIS using Mulligan's aggregate return rate for specific consumer groups (for instance, bondholders, stockholders, etc.) and contrast these estimates with those obtained by Vissing-Jørgensen's (2002). Such exercise could shed some light if consumers take into account a benchmark return rate (like Mulligan's) or their portfolio's return rate.

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Figure 1 – Behavior of the consumption growth series over time.

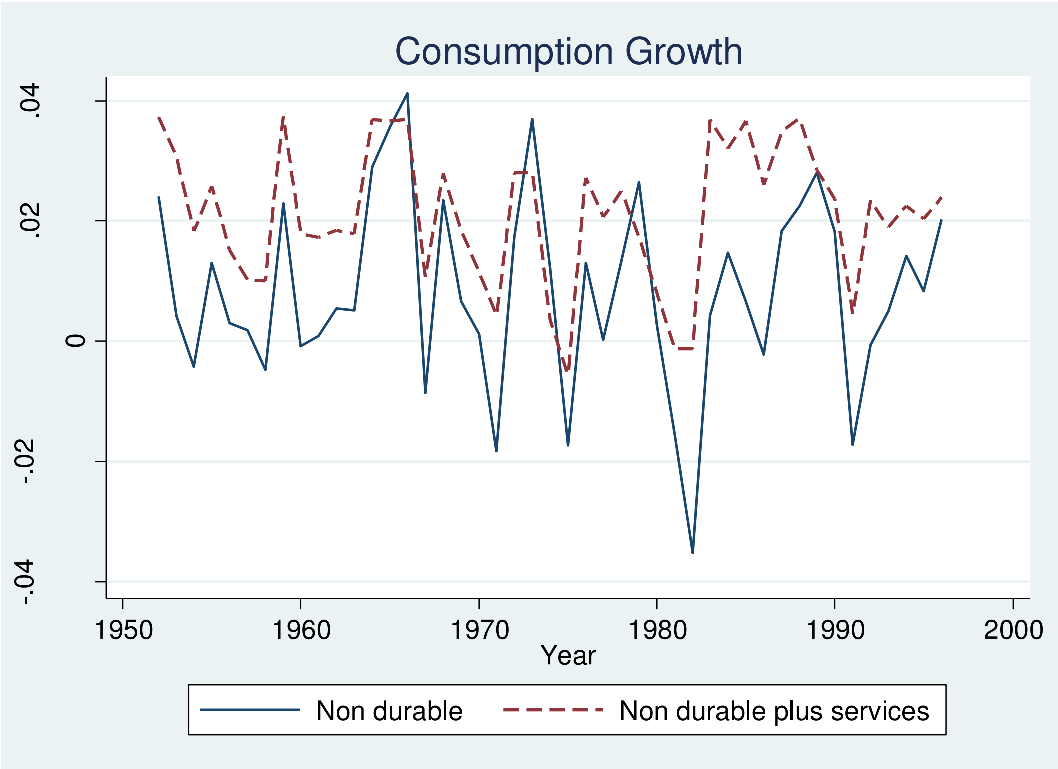

Figure 2 – Behavior of the real asset returns over time.

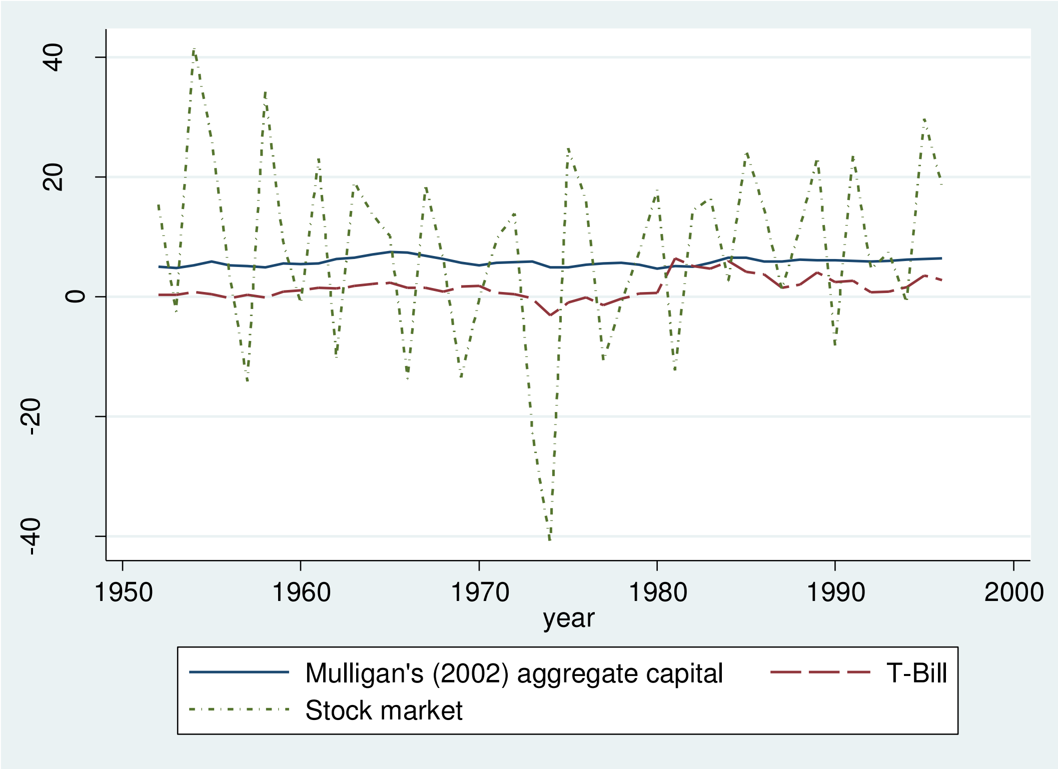

Table 1: Descriptive Statistics

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 in annual frequency. Nondurable consumption, nondurable plus service consumption and aggregate capital return comes from Mulligan (2002). T-Bill and Stock returns come from Dacy and Hasanov (2011).

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 use k=1.

Table 3 –Equation 3 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 use k=1. Weak instrument robust confidence intervals are calculated using the rivtest command in Stata, developed by Finlay and Magnusson (2009).

Table 4 –Equation 3 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]	$(-\infty,+\infty)$

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