Internet Appendix to “Asset Pricing with Garbage”

Alexi Savov*

Abstract

This document contains supplemental results and derivations for the paper “Asset Pricing with Garbage”. These include cross-sectional results for 25 portfolios formed using a double sort of garbage and expenditure betas, alternative test assets for the Fama MacBeth regressions in the paper, alternative weighting schemes for the cross-sectional GMM test in the paper, a test using a linear stochastic discount factor, a robustness check using a value-weighted garbage index, and a discussion of the differences in the construction of the garbage and expenditure series as they may relate to the results in the paper.

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I. Double-sorted Beta Portfolios

I start by forming portfolios with a spread in consumption betas as proxied either with garbage or NIPA expenditure and checking whether this spread leads to a corresponding spread in average excess returns. This technique was popularized by Fama and French (e.g., Fama and French (1992)) and can be thought of as a local regression of excess returns on betas.

Specifically, I form 25 double-sorted portfolios from all stocks with annual returns from 1960 through 2007. I compute full-sample multivariate garbage growth and expenditure growth betas, calculate a grid of NYSE quintile breakpoints, and assign each stock to a value-weighted portfolio of the stocks in its garbage and expenditure beta quintiles. Requiring 47 years of annual returns introduces strong survivorship bias, but is necessary for computing betas with any precision given the low frequency and short time span of the garbage data. There is also no reason to suspect that this bias will affect the relative performance of the garbage and expenditure models. Also note that, given the forward-looking nature of full-sample betas, the resulting portfolios are not tradable and I therefore exclude them from tests with tradable assets. It is nonetheless still interesting to ask whether they display a spread in returns relative to each other.

Table I presents the average excess returns of the 25 double-sorted portfolios as well as the average returns on long-short strategies between the fifth (highest) and first (lowest) garbage and expenditure beta quintiles. As can be seen from the bottom two panels, garbage betas increase from top to bottom and expenditure betas increase from left to right. To get a sense of the spread in returns across quintiles, it is enough to check for a monotonic increasing pattern from top to bottom or from left to right. Casual inspection suggests that the pattern is more pronounced vertically, as the garbage betas increase.

These patterns suggest that variation in garbage growth betas is more highly compensated than variation in expenditure growth beta, each holding the other fixed. To help visualize this result, Figure **??** shows scatter plots of mean excess returns versus expenditure and garbage growth betas. The garbage growth betas produce a much better fit and a steeper slope. Expenditure growth betas fail to capture the spread in returns across these portfolios. In both graphs, the zero beta rate is high, likely due to the noted survivorship bias endemic to these portfolios. Notice, however, that the zero beta rate is about twice as high in the expenditure beta plot than in the garbage beta plot.

As a formal test, Table II shows the results from Fama and MacBeth (1973) regressions of the returns on the 25 double-sorted portfolios on their garbage growth and expenditure growth betas. Unlike in tests with tradable assets, I include a free constant to allow the regression to ignore the high survivorship bias and focus on the relative fit of the portfolios. Garbage growth betas obtain a statistically significant premium, accounting for 57% of the variation in the average excess returns on the 25 portfolios. In contrast, expenditure growth betas are not priced in this cross-section. In addition, the expenditure-based model leads to a much larger intercept of 10.62%. In unreported tests, the premium on garbage growth is not driven out by the excess market return or the returns on the small-minus-big (SMB) and high-minus-low (HML) Fama and French (1993) factors.

To quantify the risk premium, I plug its estimate into the formula from the linearized Euler equation:

$$\gamma \approx \frac{\lambda}{\beta R_f Var\left(\frac{c_{t+1}}{c_t}\right)}. \tag{1}$$

Calibrating $\beta = 0.95$ and using the sample mean of the Treasury bill return, the estimated premium of 1.04% per unit of garbage growth beta corresponds to a risk aversion of 13, nearly identical to the estimates in the equity premium section of the paper. By contrast, the (insignificant) premium on expenditure growth is many times too low.

The results from the 25 double-sorted beta portfolios suggest that unlike expenditure growth betas, garbage growth betas are compensated with a plausibly large and significant positive risk premium.

II. Fama-MacBeth Regressions

I consider alternative sets of test assets. Table III uses the standard 25 Fama and French (1993) size and book-to-market portfolios as test assets.

Overall, garbage growth obtains a significant positive premium. Expenditure growth does the same. The measure of Parker and Julliard (2005) does particularly well, or about as good as the Fama-French three-factor model. This is a result of the small positive correlation between this measure and HML. Garbage growth survives in the presence of SMB and HML but expenditure growth does not.

Table IV uses the Fama and French (1993) size and book-to-market decile portfolios. Notice that this set of test assets does not lead to model rejection. The factor premia are similar. In this cross-section, garbage growth drives out expenditure growth when the two are matched head-to-head. The other two consumption measures perform well, leading to low pricing errors.

III. GMM Linear Test

In this section I show the derivation of the efficient weighting matrix used in the paper. I conclude with results showing alternative weights.

A. Efficient Weighting Matrix

Recall the set of moments

$$E\begin{bmatrix} R - a - \beta f \\ (R - a - \beta f) \otimes f \\ R - \beta\lambda \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}. \tag{2}$$

A closer look shows that they are linearly dependent. To illustrate, subtract the first set of moments from the third, leaving $a + \beta(f - \lambda)$. If there are N assets and K factors with $N > K$, then β selects N linear combinations of K random variables, so at most K of the moments are linearly independent. This shows that in fact only $N + NK + K$ of the full set of $N + NK + N$ moments are linearly independent. As a result, the covariance matrix of the full set is analytically singular, making standard efficient GMM impossible.

There are three ways to deal with this issue. The first is to only consider one-stage GMM and thus give up on efficiency. The second is to use a pseudo-inverse. In unreported simulations, I find that the pseudo-inverse approach is not efficient. The third approach is to select out of the full set of moments those linear combinations that in some sense produce the most precise estimates.

Along the third approach, consider selecting $N + NK + K$ of the $N + NK + N$ moments in the following way:

$$\begin{bmatrix} I_N & 0 & 0 \\ 0 & I_{NK} & 0 \\ 0 & 0 & L \end{bmatrix} E \begin{bmatrix} R^e - a - \beta f \\ (R^e - a - \beta f) \otimes f \\ R^e - \beta\lambda \end{bmatrix} = E \begin{bmatrix} R^e - a - \beta f \\ (R^e - a - \beta f) \otimes f \\ L(R^e - \beta\lambda) \end{bmatrix}. \tag{3}$$

There is no need to consider alternative weights for the first two sets of moments since given L, the model is just identified.[1] In addition, any off-diagonal terms in the third row or column would lead GMM to push betas away from their OLS estimates in order to fit the cross-section better. The results from such a test would be hard to judge.

Next, I show that

$$L \; = \; \beta' \left[\lambda' Cov(f)^{-1}\lambda \otimes I_N + Cov(R^e - \beta\lambda)\right]^{-1} \tag{4}$$

minimizes the covariance matrix of the estimated factor premia given the betas, and is in this sense optimal. Since betas are not of principal interest here, it makes sense to focus on minimizing error in the λs. Also note that the first term in parentheses naturally incorporates a Shanken (1992)-type factor accounting for the fact that the betas are estimated.

To see how the matrix L is derived, observe that the middle set of NK moments are linearly independent among each other and with the rest. Thus, any selection procedure must preserve these moments (select them with full rank). Consider also preserving the rank of the first N moments and selecting K of the N last moments. This procedure eliminates redundant moments, reducing their number to $N + NK + K$, which is also the number of unknown parameters. Since the resulting model is just identified, there is no need to consider different weighting matrices as there is a unique solution. What is left is to choose exactly which K moments of the last N to keep. Let L be a $K \times N$ selection matrix and form

$$g_T^*(a, \beta, \lambda) \; = \begin{bmatrix} I_N & 0 & 0 \\ 0 & I_{NK} & 0 \\ 0 & 0 & L \end{bmatrix} E \begin{bmatrix} R - a - \beta f \\ (R - a - \beta f) \otimes f \\ R - \beta\lambda \end{bmatrix} \; = \; E \begin{bmatrix} R - a - \beta f \\ (R - a - \beta f) \otimes f \\ L(R - \beta\lambda) \end{bmatrix}. \tag{5}$$

As Cochrane (2005, p.242) points out, OLS sets $L = \beta'$ and GLS sets $L = \beta' Cov(R - a - \beta f)^{-1} \equiv \beta'\Sigma^{-1}$. I will show that in the special case of i.i.d. errors that are also uncorrelated with the factors,

$$L \;=\; \beta' \left(\lambda' \Sigma_f^{-1} \lambda \otimes I_N + \beta \Sigma_f \beta' + \Sigma\right)^{-1} \;=\; \beta' \left(\lambda' Cov(f)^{-1} \lambda \otimes I_N + Cov(R - \beta\lambda)\right)^{-1} \quad (6)$$

is optimal (here $\Sigma_f \equiv Cov(f)$) in that it minimizes the covariance matrix of the λs. Without the i.i.d. assumption, the right-most expression is the correct one.

I find the optimal L by explicitly minimizing the covariance matrix of the estimated λs. The covariance matrix of the parameter vector $\hat{b} = (\hat{a}, \hat{\beta}, \hat{\lambda})$ is

$$\left(\frac{\partial g_T^*}{\partial b}\right)^{-1} Cov(g_T^*) \left(\frac{\partial g_T^*}{\partial b}\right)^{-1'} \quad (7)$$

To see why, note that in GMM with a selection matrix a and moments g,

$$Cov(\hat{b}) \;=\; \left(a \frac{\partial g}{\partial b}\right)^{-1} a Cov(g) a' \left(a \frac{\partial g}{\partial b}\right)^{-1'}. \quad (8)$$

Since the selected model is just identified, I can set $a = I$ or any other invertible matrix and obtain the expression above.

The objective is thus to pick L to minimize $Cov(\hat{b})$. I compute

$$\frac{\partial g_T^*}{\partial b} \;=\; \begin{bmatrix} \begin{bmatrix} 1 & E[f'] \\ E[f] & E[ff'] \end{bmatrix} \otimes I_N & 0 \\ \begin{bmatrix} 0 & \lambda' \end{bmatrix} \otimes L & L\beta \end{bmatrix}. \quad (9)$$

Using the formulas for block-inverting a matrix (and labeling with $*$ terms that are not pertinent),

$$\left(\frac{\partial g_T^*}{\partial b}\right)^{-1} = \begin{bmatrix} * & 0 \\ (L\beta)^{-1}\left(\begin{bmatrix} 0 & \lambda' \end{bmatrix} \otimes L\right)\left(\begin{bmatrix} 1 & E[f'] \\ E[f] & E[ff'] \end{bmatrix} \otimes I_N\right)^{-1} & (L\beta)^{-1} \end{bmatrix} \tag{10}$$

$$= \begin{bmatrix} * & 0 \\ (L\beta)^{-1}\left(\begin{bmatrix} 0 & \lambda' \end{bmatrix} \otimes L\right)\left(\begin{bmatrix} 1 & E[f'] \\ E[f] & E[ff'] \end{bmatrix}^{-1} \otimes I_N\right) & (L\beta)^{-1} \end{bmatrix}. \tag{11}$$

Modifying and rewriting the expression for $S \equiv Cov(g_t)$ in Cochrane (2005, p.243),

$$Cov(g_T^*) = \begin{bmatrix} \begin{bmatrix} 1 & E[f'] \\ E[f] & E[ff'] \end{bmatrix} \otimes \Sigma & \begin{bmatrix} 1 \\ E[f] \end{bmatrix} \otimes \Sigma L' \\ \begin{bmatrix} 1 & E[f'] \end{bmatrix} \otimes L & L\left(\beta\Sigma_f\beta' + \Sigma\right)L' \end{bmatrix}. \tag{12}$$

Note that

$$\begin{bmatrix} 1 & E[f'] \\ E[f] & E[ff'] \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ E[f] \end{bmatrix} = \begin{bmatrix} 1 + E[f']\Sigma_f^{-1}E[f] & -E[f']\Sigma_f^{-1} \\ -\Sigma_f^{-1}E[f] & \Sigma_f^{-1} \end{bmatrix} \begin{bmatrix} 1 \\ E[f] \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \tag{13}$$

Combining and simplifying,

$$\left(\frac{\partial g_T^*}{\partial b}\right)^{-1} Cov(g_T^*) = \begin{bmatrix} * & * \\ (L\beta)^{-1}\left(\begin{bmatrix} 1 & \lambda' + E[f'] \end{bmatrix} \otimes L\right) & (L\beta)^{-1} L\left(\beta\Sigma_f\beta' + \Sigma\right) L' \end{bmatrix} \tag{14}$$

Finally,

$$\begin{aligned} Cov(\hat{b}) &= \left(\frac{\partial g_T^*}{\partial b}\right)^{-1} Cov(g_T^*) \left(\frac{\partial g_T^*}{\partial b}\right)^{-1'} && (15) \\ &= \begin{bmatrix} * & * \\ * & (L\beta)^{-1} L\left(\lambda'\Sigma_f^{-1}\lambda \otimes I_N + \beta\Sigma_f\beta' + \Sigma\right) L' (L\beta)^{-1'} \end{bmatrix}. && (16) \end{aligned}$$

When $L = \beta'\left(\lambda'\Sigma_f^{-1}\lambda \otimes I_N + \beta\Sigma_f\beta' + \Sigma\right)^{-1}$, the lower right term in $Cov(\hat{b})$, that is $Cov(\hat{\lambda})$, attains its lower bound, which is

$$Cov(\hat{\lambda}) = \left[\beta'\left(\lambda'\Sigma_f^{-1}\lambda \otimes I_N + \beta\Sigma_f\beta' + \Sigma\right)^{-1}\beta\right]^{-1}.$$

To see why, let $S = \lambda'\Sigma_f^{-1}\lambda \otimes I_N + \beta\Sigma_f\beta' + \Sigma$ and follow the proof in Hansen (1982, p.1052) to find the lower bound for $(L\beta)^{-1}LSL'(L\beta)^{-1'}$. Specifically, let $S = CC'$ and $A = (L\beta)^{-1}LC - \left(\beta'S^{-1}\beta\right)^{-1}\beta'C^{-1'}$. It follows that

$$\begin{aligned} AA' &= (L\beta)^{-1}LSL'(L\beta)^{-1'} - \left(\beta'S^{-1}\beta\right)^{-1} && (17) \\ (L\beta)^{-1}LSL'(L\beta)^{-1'} &= AA' + \left(\beta'S^{-1}\beta\right)^{-1}. && (18) \end{aligned}$$

Thus, the matrix to minimize, $(L\beta)^{-1}LSL'(L\beta)^{-1'}$, is equal to the sum of a positive-definite matrix that does not depend on L and another positive definite matrix, AA'. This shows that the minimizing L must satisfy $A = 0$, which gives

$$L = \beta' S^{-1} = \beta' \left(\lambda' \Sigma_f^{-1} \lambda \otimes I_N + \beta \Sigma_f \beta' + \Sigma\right)^{-1} = \beta' \left(\lambda' \Sigma_f^{-1} \lambda \otimes I_N + Cov(R - \beta\lambda)\right)^{-1}. \tag{19}$$

This L is the optimal selection matrix for minimizing the covariance matrix of the estimated factor premia.

B. Alternative Weighting Matrices

Results using the efficient matrix discussed above are in the paper. In this section, I present results using alternative weights for comparison. Specifically, the different weights are cross-sectional OLS, one-stage GMM, and pseudo-inverse GMM.

The cross-sectional OLS results in Table V are very similar to the Fama and MacBeth (1973) and efficient selection matrix results presented int eh main paper. Garbage growth obtains a significant positive premium of about 2.32% that is in line with the risk aversion estimates in the equity premium tests. In addition, garbage growth drives out the premium on expenditure growth when the two factors are included together. Also as before, the premium on expenditure growth is unstable.

These inferences are challenged by the results in Table VI and Table VII. Here garbage growth is borderline significant whereas expenditure growth is once significant and once insignificant but its premium switches to negative in the presence of garbage growth. Notice that expenditure growth seems to do well when paired up with the market factor. This result illustrates the main pitfall of these two tests. Both the one-stage and the pseudo-inverse tests allow GMM to deviate from OLS betas (sample covariance over sample variance) in order to fit the cross-section better. As a result, the tiny positive correlation between HML and expenditure growth and the tiny negative correlation between HML and garbage growth are heavily exploited, inducing a larger-than-OLS spread in expenditure betas and a smaller-than-OLS spread in garbage betas among the six Fama and French (1993) portfolios. Phrased differently, the betas estimated in these models are not exactly betas; they are deviations from betas designed to better fit the cross-section. This leads to the suspiciously small pricing errors shown in the tables. It also leads to the unstable premia across specifications: as betas are stretched out or pushed in, the premia they obtain in the cross-section rise or fall. These properties limit the usefulness of the one-stage and pseudo-inverse GMM tests.

IV. Linear Stochastic Discount Factor

Having verified that garbage growth is priced in the cross-section of returns, I now check whether garbage growth helps to price other assets. As Cochrane (2005, p.260) points out, these two questions are related but distinct. The latter can be answered by checking whether garbage growth appears significantly in an estimated stochastic discount factor.

The nonlinear power utility stochastic discount factor $\beta\left(c_{t+1}/c_t\right)^{-\gamma}$ can be approximated with the linear one

$$m_{t+1} = \frac{1}{R^f} - b\left(\frac{c_{t+1}}{c_t} - E\left[\frac{c_{t+1}}{c_t}\right]\right), \tag{20}$$

where

$$b = \frac{\gamma/R^f}{1+\gamma\left(1-E\left[\frac{c_{t+1}}{c_t}\right]\right)}. \tag{21}$$

Notice that I set $E[m] = 1/R^f$ by construction. This forces the model to fit the sample risk-free rate. Without this normalization, a discount of the form $m = 1 - bf$ uncorrelated with returns can satisfy the Euler equation $0 = E[mR^e]$ by setting $E[m] = 0$. This would not only imply an infinite risk-free rate but it would also produce large estimates of b. Such a model cannot be judged solely on the basis of the coefficient b. By contrast, forcing $E[m] = 1/R^f$ makes $E[m] = 0$ impossible. The resulting bs will be estimated to fit the cross-section as well as possible while also matching the sample risk-free rate.

To derive this linearization, observe that a first-order Taylor approximation around $c_{t+1}/c_t = 1$ gives

$$m_{t+1} \approx \beta\left[1-\gamma\left(\frac{c_{t+1}}{c_t}-1\right)\right]. \tag{22}$$

Since the level of the discount factor is not identified when only excess returns are used, I rewrite this expression and divide by $\beta R^f\left[1+\gamma\left(1-E\left[\frac{c_{t+1}}{c_t}\right]\right)\right]$:

$$m_{t+1} \approx \frac{1}{R^f} - \frac{\gamma/R^f}{1+\gamma\left(1-E\left[\frac{c_{t+1}}{c_t}\right]\right)}\left(\frac{c_{t+1}}{c_t} - E\left[\frac{c_{t+1}}{c_t}\right]\right). \tag{23}$$

Letting

$$b \equiv \frac{\gamma/R^f}{1+\gamma\left(1-E\left[\frac{c_{t+1}}{c_t}\right]\right)}, \tag{24}$$

the implied risk aversion coefficient is

$$\gamma = \frac{bR^f}{1-bR^f\left(1-E\left[\frac{c_{t+1}}{c_t}\right]\right)}. \tag{25}$$

As before, the formula for b suggests an implied risk aversion estimate against which to judge the robustness of the results. To implement this approach, I write the set of moments

$$E\begin{bmatrix} \left[\frac{1}{\mu_{R^f}} - b\left(\frac{c_{t+1}}{c_t} - \mu_{\Delta c}\right)\right] R^e_{t+1} \\ R^f_{t+1} - \mu_{R^f} \\ \frac{c_{t+1}}{c_t} - \mu_{\Delta c} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}. \tag{26}$$

This formulation takes into account the fact that the mean risk-free rate and the mean level of consumption growth are estimated. To make these estimates fit the sample means exactly and thus rule out $E[m] = 0$, I select the second and third moments independently with the selection matrix

$$a = \begin{bmatrix} d'W & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{27}$$

where d is a consistent estimate of the matrix of partial derivatives of the moments with respect to the parameters evaluated at the true parameter vector. I run two stages, setting $W = I_N$ in the first and $W = S^{-1}$ in the second, with S a consistent estimate of the spectral density matrix of the top moments (the pricing errors). I use the same test assets as in the Fama and MacBeth (1973) section, namely, the 25 Fama and French (1993) size and book-to-market portfolios and the 10 industry portfolios.

Table VIII shows the second-stage estimates of the linear stochastic discount factor. Taken by themselves, both garbage growth and expenditure growth play a significant role in pricing the test assets. The pricing errors for the garbage model are somewhat smaller than those of the expenditure model. Perhaps surprisingly, the measures of Parker and Julliard (2005) and Jagannathan and Wang (2007) do not come in significantly. Also note that *cay* comes in positively when scaling expenditure but negatively when scaling garbage.

Using the formula for b, the coefficient on garbage growth implies a risk aversion estimate of 21, which is well inside the range estimated in the paper. The coefficient on expenditure growth, on the other hand, implies a risk aversion coefficient of 20, which is much lower than the previous estimates. At this level of risk aversion, the expenditure growth leaves unexplained 5% of the 6% sample equity premium.

V. Value-weighted Garbage Index

One advantage of expenditure is that it is measured in dollars. If goods are indivisible and demand locally insatiable, market prices reveal marginal values and might therefore give a better basis for measuring consumption. Note, however, that once levels are converted to growth rates, the units are less important. To the extent that measurement in tons might bias garbage as a measure of consumption, it is likely that garbage underweighs expensive luxury goods in favor of necessities. Ait-Sahalia, Parker, and Yogo (2004) show that luxury goods purchases are more volatile and more procyclical, so in this sense garbage may actually be biased towards understating the true covariance between consumption and the market return.

In this section, I use a shorter 30-year set of garbage data that includes a detailed breakdown of the waste stream. I match as many of the components as possible to categories of NIPA expenditure to obtain a measure of the price per ton of waste generated for each component. I use 1990 as the base year for this calibration. I then use the relative prices thus obtained to create a value-weighted garbage index stretching back to the beginning of the sample in 1960. Finally, I run the same GMM equity premium test as before, this time using the value-weighted index.

Table IX shows the category matches I use to create a value-weighted garbage index. Since the EPA waste components are largely commodity-based, there is not a unique correspondence between them and the NIPA expenditure categories. However, the matching in Table IX was the only matching considered, and so it does not suffer from pre-test bias.

Table X shows summary statistics for the value-weighted garbage index. At 50%, the growth in value-weighted garbage index is still one and a half times more correlated with the excess market return than expenditure growth, although its correlation is lower than that of the weight-based index. With a standard deviation of 5%, the value-weighted garbage growth is also much more volatile than both expenditure and the weight-based garbage growth. Once again, these features allow for a lower risk aversion estimate and a more reasonable implied risk-free rate.

The results of a GMM equity premium test using the value-weighted garbage index are in Table XI. The value-weighted garbage index leads to a risk aversion estimate of 11, which is seven times smaller than that for the NIPA expenditure model and roughly equal to that for the weight-based garbage index used in the main part of the paper. The results from this exercise suggest that value-weighting does not have a significant impact on my results.

VI. A Comparison of Two Measures

In this section, I compare the statistical and economic differences between the two measures of consumption, National Income and Product Accounts (NIPA) expenditure and garbage. I focus on the relative differences that can explain the central result in this paper, namely, that garbage growth, by virtue of being more volatile and more correlated with stock returns, can match the equity premium with a coefficient of relative risk aversion that is significantly lower than that with NIPA expenditure.

A. Expenditure

The statistical properties of NIPA expenditure are often overlooked. Triplett (1997) offers a good review of the main issues. These include benchmarking, non-reporting bias, and the residual method. NIPA expenditure is benchmarked once every five years,[2] drawing on the

Economic Census from the U.S. Census Bureau. The benchmarking process is described in the latest methodology paper from the Department of Commerce (U.S. Department of Commerce (1990)). In the intervening non-benchmark years, the Retail Trade Survey[3] from the Census Bureau forms the backbone of the annual and higher-frequency updates. Types of expenditure not in the survey are interpolated from the benchmark years or forecast since the last benchmark year of 2002.

The high sample autocorrelation of 39% in the expenditure growth series may be evidence of interpolation. Another possibility is time aggregation, but it should also induce a positive autocorrelation in garbage growth, which is not the case.

Benchmarking creates a serious problem when it comes to measuring the volatility of consumption growth. Interpolation naturally smoothes the path from one benchmark year to the next. In addition, it is reasonable to suppose that the most volatile sectors of the economy will be the ones most likely to be interpolated or forecast. This is because the Retail Trade Survey focuses on large, long-established retail firms.

The Retail Trade Survey and consequently the NIPA expenditure measure also suffer from selection bias due to non-reporting. Non-reporting occurs when a survey participant fails to fill out parts or all of the survey. The Census Bureau estimates that around 7% of the annual data currently suffers from this problem, down from 14% 10 years ago, and likely more in the preceding decades. In addition, there is no fixed method for the discovery and inclusion of new retail establishments. Again, it is likely that the non-reporting and newly formed retailers are precisely the ones with the most volatile sales, causing the annual volatility of expenditure growth to be understated.

Finally, for most commodities, personal expenditure is computed residually. This is done by subtracting government and business purchases from total estimated domestic supply. But as stated by the U.S. Department of Commerce (1990, p. 33), "Estimates of business purchases are derived in part from Census Bureau data on purchased materials and services, but because such data are not available for all business, most business purchases must be estimated using other data and, where necessary, judgment in place of data." The data on government purchases are also known to be unreliable. Having to use estimates or "judgment" to compute the expenditures of businesses and government agencies could be another reason why NIPA personal expenditure appears too smooth and not highly correlated with stocks.

In addition to the statistical issues of benchmarking, non-reporting bias, and the residual method, expenditure data by definition also fail to capture non-market consumption. Aguiar and Hurst (2005) refer to this problem in the context of measuring the drop in consumption at retirement. By accounting for non-market activities like the extra time seniors spend looking for cheaper goods and collecting coupons, they are able to show that in spite of the observed precipitous drop in expenditure, food consumption does not fall at all at retirement. This suggests that non-market consumption is as important as Becker (1965) argued.

Household and other non-market consumption can only help rationalize risk prices if they covary with stock returns more strongly than does market expenditure. This requires that for non-market consumption, the income effect from a shock to wealth must dominate the substitution effect. Thus, if household activities are cut more than market activities in bad times, and increased more in good times, total consumption will be more volatile than market expenditure. Intuitively, a loss of income could be accompanied by a more-than-commensurate loss in leisure. Along these lines, Aguiar and Hurst (2005) note that total consumption (not just expenditure) seems to respond more when income shocks are unanticipated, as with job loss, than when it is anticipated, as with retirement. To the extent that stock market downturns are unanticipated, this evidence suggests that consumption might indeed fall substantially with the stock market. The data in this paper do not allow me to identify whether this intuition holds. Although the results in this paper indicate that garbage works better than market expenditure for understanding asset prices, I do not take a stand on whether my results are due to data problems, or to the omission of household production in expenditure.

B. Garbage

No published methodology paper details the construction of the garbage data from the EPA. Data collection is in part from surveys of landfills, incinerators, and recycling plants, and also in part from industry commodity flow estimates; the relative use of these two methods is unspecified. Benchmarking and forecasting are not an issue since data collection is equally detailed each year. This could explain why garbage growth exhibits a lower sample autocorrelation than NIPA expenditure. Survey bias may exist in the garbage data but it is not clear how the survey responses of disposal facilities would correlate with economic conditions. Finally, there is no residual method to speak of in this data.

The major criticism of the EPA's garbage measure refers to the level of waste generation. Kaufman, Goldstein, Millrath, and Themelis (2004) find that the only alternative comprehensive measure of garbage generation in America, a biennial survey by the journal *Biocycle*, arrives at much higher total waste numbers.[4] This discrepancy may be due to the EPA's incentive to report improving environmental conditions or to *Biocycle*'s incentive to do the opposite. In either case, any bias in the level of consumption is peripheral to this study since asset pricing is concerned with growth rates, not levels.

Interestingly, *Biocycle*'s measure exhibits the same stock market correlation (59%) as the EPA's measure but is even more volatile (its standard deviation is 4.1% versus 2.9% for the EPA measure). *Biocycle*'s garbage measure thus matches the equity premium with a lower risk aversion estimate of 11 versus 17 for the EPA's measure. In this study, I use the EPA's data because they cover a 47-year range, whereas there are only 10 years of *Biocycle* data available. Nevertheless, *Biocycle*'s measure confirms the result that the consumption model has an easier time with the equity premium when consumption is measured with garbage growth as opposed to NIPA expenditure. Furthermore, to the extent that *Biocycle*'s measure is more volatile and produces lower risk aversion estimates, the equity premium results in this paper may be conservative.

On the conceptual side, it may be the case that garbage provides a truer measure of consumption than expenditure. One reason is in the timing of garbage relative to consumption. For one thing, goods are only disposed of right after their usefulness is exhausted, providing a tight link between consumption and waste generation. In contrast, expenditure may be incurred well ahead of consumption. This could happen if, for example, consumers continue to purchase goods in a recession only to consume them later when times are good. Clearly, such a "precautionary spending" effect would have to be small, or there would not be a recession in the first place.

Perhaps more importantly, it is likely that garbage accounts at least in part for the household production sector of the economy. Given some economies of scale in market production, a good produced at home will generate waste at a higher rate than its closest market substitute, which in turn typically costs more in dollar terms. This argument holds true for the informal economy as a whole.

For example, a restaurant meal may generate waste at a lower rate per calorie served than a home-cooked meal if all waste-generating activities associated with cooking a meal are included. For example, home-cooked ingredients are packaged separately whereas restaurants buy supplies in bulk. In addition, the restaurant meal likely costs more in dollar terms than its home-cooked counterpart. This is because market expenditure does not account for the opportunity cost of the time spent cooking that meal. In sum, expenditure is likely to overemphasize the restaurant meal whereas garbage will weigh the home-cooked meal more heavily, thus picking up household production as posited by Becker (1965).

Together, this line of reasoning offers some possible explanations for why garbage growth performs better than expenditure growth in standard asset pricing tests. Which explanation is the relevant one remains to be seen.

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Footnotes

[1]As an example, the set of moments in Pastor and Stambaugh (2003, eq. 17) can be viewed as a special case of this approach. In that paper, the third set of moments is essentially $\lambda - E[f]$, which can be obtained here by imposing the restriction under the null $a = 0$ (the factors are traded portfolios), subtracting the top set of moments from the bottom ones before L is applied, and finally letting $L = (\beta'\beta)^{-1}\beta'$.

[2]The last several benchmark years were 2002, 1997, 1992, and so on.

[3]See http://www.census.gov/svsd/www/artstbl.html.

[4]The EPA's response to this criticism is that *Biocycle*'s characterization of municipal solid waste includes construction debris and some industrial wastes that are not considered by the EPA (see Horinko (2003)).

Figure captions

Figure 1. Betas against average excess returns for the 25 double-sorted garbage and expenditure beta portfolios. The betas are from a multivariate regression of portfolio returns on garbage growth and expenditure growth. The portfolios are created using sorts on full-sample multivariate garbage growth and expenditure growth betas. Specifically, after regressing the return series of every firm in the CRSP database jointly on garbage growth and expenditure growth, the firms are independently sorted into garbage beta and expenditure beta quintiles using NYSE breakpoints. The dots in this figure are the 25 portfolios obtained from this double sort. Note that due to data limitations, only stocks with a full series of annual returns over the 1960–2007 period are used, which leads to survivorship bias in the construction of these portfolios. The vertical intercepts should not be used to draw inferences.

Table I
Summary Statistics: The 25 Double-sorted Garbage and Expenditure Beta Portfolios

The table presents average excess returns, Newey-West t-statistics, and betas for the 25 double-sorted beta portfolios and the high beta minus low beta long-short strategies. LG is low garbage growth beta, HE is high expenditure growth beta, and H−L is high beta minus low beta. The portfolios are created using full-sample multivariate garbage growth and expenditure growth betas. Specifically, after regressing the return series of every firm in the CRSP database jointly on garbage growth and expenditure growth, the firms are independently sorted into garbage beta and expenditure beta quintiles using NYSE breakpoints. Note that due to data limitations, only stocks with a full series of annual returns over the 1960 through 2007 period are used. Reported betas are multivariate. Portfolio returns are value-weighted.

	Average excess returns						t-statistics					
	LE	(2)	(3)	(4)	HE	H−L	LE	(2)	(3)	(4)	HE	H−L
LG	9.06	7.42	8.61	9.61	16.41	7.67	4.24	3.51	4.55	3.17	2.61	1.17
(2)	9.61	8.91	7.53	10.12	14.27	4.66	4.40	4.03	3.85	3.49	3.71	1.13
(3)	8.67	9.61	9.01	11.11	13.35	4.68	3.70	4.20	4.02	4.08	3.62	1.23
(4)	11.81	13.29	10.44	12.87	15.69	3.88	3.66	3.22	3.89	3.93	4.03	0.87
HG	15.45	13.06	14.89	12.06	21.54	6.09	3.39	2.33	3.75	2.95	3.81	0.98
H−L	6.33	6.04	6.28	2.45	5.13		1.55	1.04	1.89	0.59	0.88	

	Garbage growth betas					Expenditure growth betas				
	LE	(2)	(3)	(4)	HE	LE	(2)	(3)	(4)	HE
LG	0.75	0.78	0.99	0.88	-1.29	-3.56	1.31	2.74	7.18	19.10
(2)	2.49	2.42	2.21	2.65	2.67	-5.78	-0.99	0.88	5.73	9.42
(3)	3.63	3.59	3.70	3.44	3.65	-6.24	-3.68	0.77	4.52	11.71
(4)	4.86	5.10	5.17	4.90	5.54	-10.23	-8.69	-2.43	3.35	7.19
HG	8.60	9.25	8.69	8.35	8.83	-20.64	-10.56	-8.27	-3.67	5.62

Table II
Fama-Macbeth Regressions: The 25 Double-sorted Garbage Beta and Expenditure Beta Portfolios

The portfolios are created using sorts on full-sample multivariate garbage growth and expenditure growth betas. Specifically, after regressing the return series of every firm in the CRSP database jointly on garbage growth and expenditure growth, the firms are independently sorted into garbage beta and expenditure beta quintiles using NYSE breakpoints. The test assets in this table are the 25 portfolios obtained from this double sort. Note that due to data limitations, only stocks with a full series of annual returns over the 1960 through 2007 period are used, which leads to survivorship bias in the construction of these portfolios. As a result, the intercepts in these regressions should not be used to draw inferences. The table shows factor premia, Newey-West t-statistics, and cross-sectional R^2.

Constant	Garbage beta	Expenditure beta	R^2
7.61	1.04		57
(4.07)	(2.14)		
10.62		0.22	22
(4.75)		(1.00)	
7.66	1.03	0.25	58
(4.07)	(2.13)	1.17	

Table III
Fama-Macbeth Regressions: The 25 Fama-French Portfolios

The test assets are the 25 Fama and French (1993) size and book-to-market portfolios. There is no cross-sectional intercept. The estimates follow the Fama and MacBeth (1973) cross-sectional procedure. R.m.s is the root-mean-squared pricing error with an associated p-value for the hypothesis that all pricing errors are zero in parentheses. Three-lag Newey-West t-statistics are also in parentheses. P−J is three-year expenditure growth as in Parker and Julliard (2005); Q4−Q4 is the fourth-quarter year-over-year growth in expenditure as in Jagannathan and Wang (2007); and *cay* is the consumption-to-wealth ratio proxy from Lettau and Ludvigson (2001).

Garbage	Garbage × *cay*	Expen-diture	Expen-diture × *cay*	P-J	Q4-Q4	MRF	SMB	HML	r.m.s. (p)
2.56									3.64
(3.53)									(0.00)
2.83	-0.16								3.46
(2.95)	(0.39)								(0.00)
		1.35							3.33
		(3.55)							(0.00)
		1.24	0.08						3.19
		(2.54)	(0.16)						(0.00)
1.81		1.38							3.33
(2.69)		(2.87)							(0.00)
				6.06					1.54
				(4.03)					(0.00)
					2.18				2.11
					(3.87)				(0.00)
						8.41			3.88
						(3.49)			(0.00)
5.71						7.86			3.45
(5.17)						(3.29)			(0.00)
		1.62				6.92			3.30
		(3.14)				(3.08)			(0.00)
						5.85	3.18	6.36	1.49
						(2.69)	(1.44)	(3.48)	(0.00)
1.82						5.86	3.24	6.23	1.44
(3.10)						(2.69)	(1.46)	(3.41)	(0.00)
		0.47				5.97	3.10	6.32	1.48
		(1.54)				(2.75)	(1.40)	(3.45)	(0.00)

Table IV
Fama-Macbeth Regressions: Size and Book-to-market Decile Portfolios

The test assets are the Fama and French (1993) 10 size decile and 10 book-to-market decile portfolios. There is no cross-sectional intercept. The estimates follow the Fama and MacBeth (1973) cross-sectional procedure. R.m.s is the root-mean-squared pricing error with an associated p-value for the hypothesis that all pricing errors are zero in parentheses. Three-lag Newey-West t-statistics are also in parentheses. P−J is three-year expenditure growth as in Parker and Julliard (2005); Q4−Q4 is the fourth-quarter year-over-year growth in expenditure as in Jagannathan and Wang (2007); and *cay* is the consumption-to-wealth ratio proxy from Lettau and Ludvigson (2001).

Garbage	Garbage × *cay*	Expenditure	Expenditure × *cay*	P-J	Q4-Q4	MRF	SMB	HML	r.m.s. (p)
2.42									1.73
(3.59)									(0.22)
2.31	0.12								1.52
(2.66)	(0.25)								(0.48)
		1.34							1.88
		(3.58)							(0.08)
		0.76	0.61						1.50
		(1.51)	(1.10)						(0.14)
2.25		0.76							1.69
(3.14)		(1.38)							(0.17)
				2.02					1.00
				(3.74)					(0.01)
					5.69				1.01
					(3.66)				(0.12)
						8.01			1.87
						(3.57)			(0.05)
3.26						7.74			1.71
(2.64)						(3.48)			(0.14)
		0.77				7.68			1.72
		(1.45)				(3.50)			(0.06)
						6.50	2.83	4.36	0.46
						(2.99)	(1.25)	(2.32)	(0.25)
1.75						6.50	2.78	4.34	0.35
(1.96)						(2.99)	(1.24)	(2.31)	(0.51)
		0.41				6.56	2.77	4.46	0.43
		(1.24)				(3.02)	(1.23)	(2.38)	(0.25)

Table V
GMM Estimates Using Cross-sectional OLS Weighting

Each row corresponds to a different specification. The moment restrictions are

$$E\left[\begin{array}{c} R^e - a - \beta f \\ (R^e - a - \beta f) \otimes f \\ R^e - \beta\lambda \end{array}\right] = 0.$$

The βs, as, and λs are all set to their OLS estimates. The test assets are the six Fama and French (1993) size and book-to-market portfolios and five industry portfolios. The table shows factor premia (λs) with three-lag GMM t-statistics in parentheses. The last column shows root-mean-squared pricing errors.

Garbage	Garbage × *cay*	Expen-diture	Expen-diture × *cay*	P-J	Q4-Q4	MRF	SMB	HML	r.m.s.
2.32									2.88
(2.63)									(0.00)
2.88	-0.36								2.73
(2.26)	(0.38)								(0.00)
		1.26							3.04
		(2.11)							(0.00)
		0.64	0.71						2.76
		(1.47)	(0.97)						(0.00)
2.21		0.65							2.87
(2.18)		(1.61)							(0.00)
				5.55					3.24
				(1.35)					(0.00)
					1.99				2.17
					(1.66)				(0.03)
						7.75			2.93
						(3.51)			(0.00)
2.11						7.57			2.88
(1.59)						(3.46)			(0.00)
		0.60				7.47			2.87
		(1.54)				(3.38)			(0.00)
						6.91	1.78	4.66	1.64
						(3.10)	(0.81)	(2.24)	(0.00)
-0.21						6.97	1.76	4.81	1.60
(0.16)						(3.11)	(0.82)	(2.33)	(0.00)
		0.42				6.85	1.84	4.88	1.62
		(1.14)				(3.07)	(0.85)	(2.47)	(0.00)

Table VI
GMM Estimates Using One-stage Weighting

Each row corresponds to a different specification. The moment restrictions are

$$E \begin{bmatrix} R^e - a - \beta f \\ (R^e - a - \beta f) \otimes f \\ R^e - \beta\lambda \end{bmatrix} = 0.$$

The estimation uses an identity weighting matrix. The test assets are the six Fama and French (1993) size and book-to-market portfolios and five industry portfolios. The table shows factor premia (λs) with three-lag GMM t-statistics in parentheses. The last column shows root-mean-squared pricing errors.

Garbage	Garbage × *cay*	Expen- diture	Expen- diture × *cay*	P-J	Q4-Q4	MRF	SMB	HML	r.m.s.
2.68									0.00
(2.77)									
9.30	-5.03								0.00
(0.84)	(0.68)								
		2.50							0.00
		(1.44)							
		-4.31	6.56						0.00
		(0.35)	(0.44)						
5.29		-3.33							0.00
(1.32)		(0.83)							
				8.42					0.00
				(0.98)					
					3.04				0.00
					(1.27)				
						8.74			0.24
						(3.83)			
-6.89						10.11			0.00
(1.61)						(2.71)			
		1.54				7.59			0.00
		(3.32)				(3.28)			
						7.04	0.70	6.73	0.04
						(3.11)	(0.32)	(3.13)	
-3.31						7.19	0.99	6.99	0.00
(1.82)						(2.95)	(0.44)	(3.17)	
		1.65				6.50	1.41	8.17	0.00
		(3.20)				(2.87)	(0.60)	(3.71)	

Table VII
GMM Estimates Using a Pseudo-inverse of the Moment Covariance Matrix

Each row corresponds to a different specification. The moment restrictions are

$$E\begin{bmatrix} R^e - a - \beta f \\ (R^e - a - \beta f) \otimes f \\ R^e - \beta\lambda \end{bmatrix} = 0.$$

The estimation uses a Moore-Penrose (Moore (1920)) pseudo-inverse of the analytically singular moment covariance matrix as the weighting matrix. The test assets are the six Fama and French (1993) size and book-to-market portfolios and five industry portfolios. The table shows factor premia (λs) with three-lag GMM t-statistics in parentheses. The last column shows root-mean-squared pricing errors.

Garbage	Garbage × *cay*	Expenditure	Expenditure × *cay*	P-J	Q4-Q4	MRF	SMB	HML	r.m.s.
2.73									0.17
(2.80)									
9.79	-4.90								1.93
(2.54)	(2.37)								
		2.52							0.09
		(4.04)							
		-3.93	6.81						3.44
		(0.89)	(0.90)						
5.53		-3.24							0.90
(3.21)		(3.97)							
				8.46					0.05
				(0.98)					
					3.08				0.09
					(4.09)				
						8.74			3.90
						(3.83)			
-7.09						8.89			1.24
(1.64)						(2.51)			
		1.61				8.03			0.48
		(4.45)				(3.65)			
						7.05	0.58	6.75	0.16
						(3.11)	(0.26)	(2.19)	
-3.23						7.15	1.01	6.91	0.06
(1.74)						(3.05)	(0.45)	(1.48)	
		1.66				6.53	1.40	8.11	0.04
		(2.53)				(2.62)	(0.35)	(1.93)	

Table VIII
Linear Stochastic Discount Factor Estimates

The test assets are the 25 Fama and French (1993) size and book-to-market portfolios and 10 industry portfolios. The discount factor is constructed to match the sample average risk-free rate (see text for details), that is $m = 1/R^f - b'(f - E[f])$. Reported coefficients are estimates of the loadings b. $E[f]$ and R^f are restricted to their simple sample averages. R.m.s is the root-mean-squared pricing error for each model with an associated p-value for the joint test that all pricing errors are zero directly below. Three-lag GMM t-statistics are in parentheses.

Garb.	cay×Garb.	Expend.	cay×Exp.	P-J	Q4-Q4	MRF	SMB	HML	r.m.s. (p)
29.67									3.25
7.57									0.00
51.30	-115.88								3.04
9.38	7.94								0.00
		34.44							3.55
		3.53							0.00
		60.60	59.76						3.07
		6.96	6.63						0.00
14.47		32.05							3.25
2.82		2.64							0.00
				-3.06					2.93
				0.61					0.00
					25.51				2.21
					1.59				0.00
						9.39			3.28
						11.57			0.00
49.95						1.69			3.24
8.60						1.62			0.00
		53.99				6.66			3.25
		4.97				7.48			0.00
						5.26	0.43	8.31	1.86
						7.51	0.46	9.18	0.00
-9.32						5.30	1.66	5.79	1.83
2.25						6.14	1.88	6.94	0.00
		-25.43				6.39	-0.73	7.57	1.85
		2.08				7.80	0.81	8.76	0.00

Table IX
Personal Consumption Expenditure Categories Matched to Components of the Waste Stream

This table shows the mapping between garbage and NIPA consumption expenditure categories. This mapping allows for the construction of a value-weighted garbage index, taking into account the relative value of the different components. While there are many other possible matchings, no other combinations were considered.

	Expenditure Category	Garbage Category
1	Tires, tubes, accessories, and other parts	Tires
2	Furniture, including mattresses and bedsprings	Furniture
3		Carpets
4	Kitchen and other household appliances	Major Appliances
5		Small Appliances
6	Video and audio goods, and computer goods	Electronics
7		Batteries
8	Other durable house furnishings	Towels and Sheets
9	Other durable goods	Corrugated
10		Wood packaging
11	Books and maps	Books and Magazines
12	Food	Beer and Soft Drink
13		Wine and Liquour
14		Food and Other
15		Paper Plates, Cups
16		Plastic Plates, Cups
17		Milk Cartons
18		Bags and Sacks
19		Other Paper
20		Milk Bottles
21		Alluminum Foil and Closures
22		Soft Drinks
23	Clothing and shoes	Clothing, Footwear
24	Other nondurable goods	Folding Cartons
25		Other Paperboard
26		Other Plastic
27	Toilet articles and preparations	Tissue Towels
28	Magazines, newspapers, and sheet music	Newspapers
29	Services excluding transportation	Office Papers

Table X
Summary Statistics: The Value-weighted Garbage Index

Expenditure is the annual growth in NIPA personal consumption expenditure on nondurable goods and services. Garbage is the annual growth in per capita waste generation. Value-Weighted uses a match between garbage and NIPA consumption categories to create a relative price-weighted garbage index. The table shows descriptive statistics using the annual growth in this index. The data cover the years from 1960 through 1990.

	Market	Expenditure	Garbage	Value-Weighted
Corr. R^M		34	71	50
Cov. R^M		7	38	44
St. dev.	17	1	3	5

Table XI
GMM Test and Estimates of Relative Risk Aversion Using the Value-weighted Garbage Index

VW Garbage uses the annual growth in the relative price-weighted garbage index as a measure of consumption growth. The moment restriction is

$$E\left[\left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} R^e_{t+1}\right] \; = \; 0.$$

RRA is the GMM estimate of relative risk aversion coefficient γ. The implied risk-free rate is evaluated at the GMM estimate of the RRA coefficient. The data in this table cover the years from 1960 through 1990.

	Expenditure	Garbage	VW Garbage
RRA	77	11	10
St. err.	(460)	(35)	(34)
Implied R_f	327	22	34

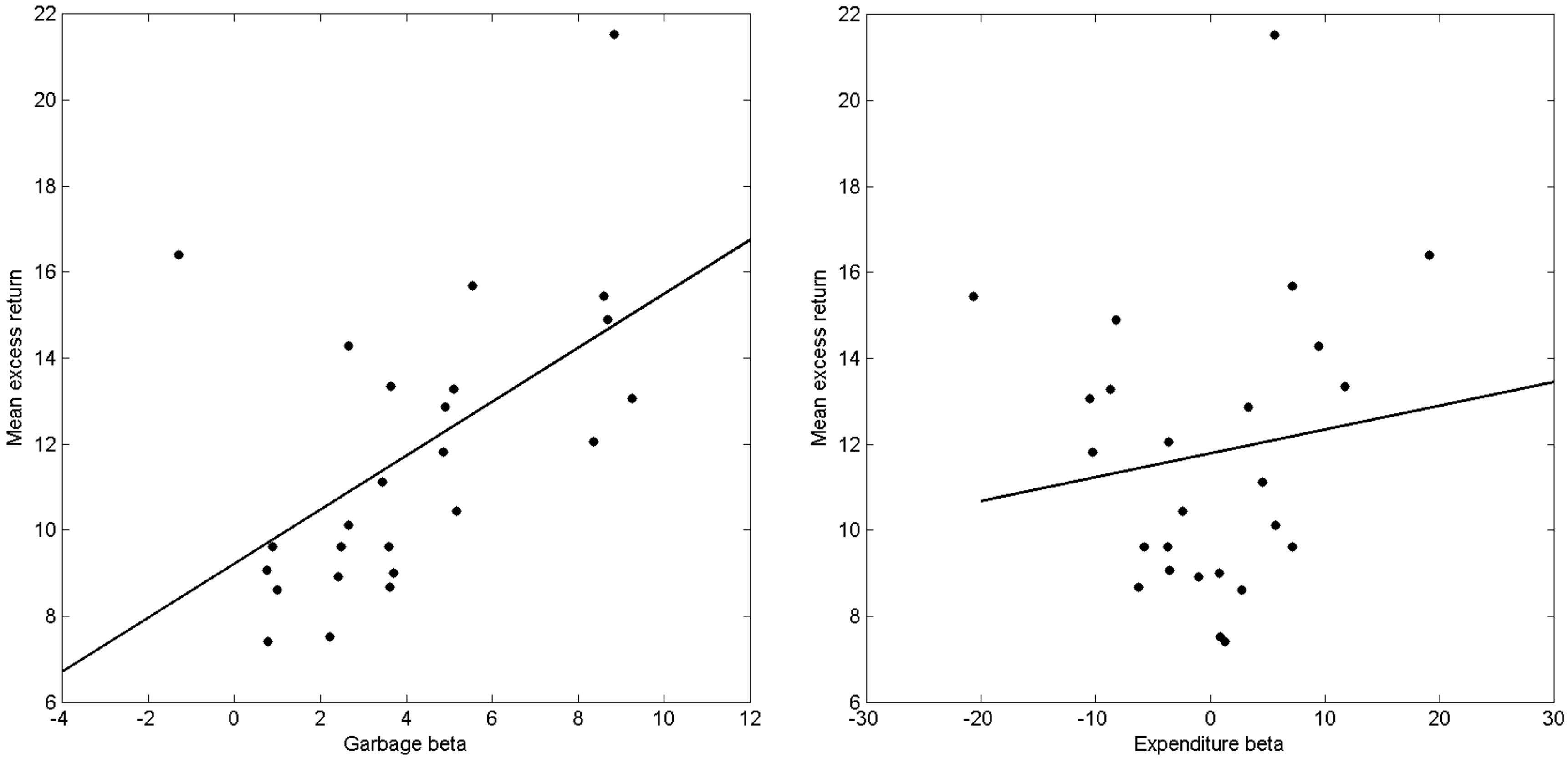

Figure IA.1. Betas against average excess returns for the 25 double-sorted garbage and expenditure beta portfolios. The betas are from a multivariate regression of portfolio returns on garbage growth and expenditure growth. The portfolios are created using sorts on full-sample multivariate garbage growth and expenditure growth betas. Specifically, after regressing the return series of every firm in the CRSP database jointly on garbage growth and expenditure growth, the firms are independently sorted into garbage beta and expenditure beta quintiles using NYSE breakpoints. The dots in this figure are the 25 portfolios obtained from this double sort. Note that due to data limitations, only stocks with a full series of annual returns over the 1960 through 2007 period are used, which leads to survivorship bias in the construction of these portfolios. The vertical intercepts should not be used to draw inferences.