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MORGAN KELLY

Do Noise Traders Influence Stock Prices?

This paper tests a smart money-noise trader model directly by comparing its predictions with the behavior of actual investors. It assumes that individual probability of being a noise trader is diminishing in income: high-income households are smart money, lower-income households are noise traders, with passive investors in between. Market data behave as predicted: high participation by the general population is a negative predictor of one-year returns, and is associated with low participation by very high-income groups. The implications for the equity premium puzzle of the low returns earned by noise traders are discussed.

FEW WILL DISAGREE with Black's (1985) assessment that real financial markets differ from their textbook counterparts in comprising noise traders as well as perfectly informed, Bayesian, expected utility maximizers. Although the idea that a subset of agents trade on the basis of extraneous information with no bearing on fundamentals have been formalized in a variety of intuitively reasonable models, most of the empirical evidence offered in support of these models is indirect.¹ It is argued that various return anomalies are more simply explained by noise trading than by efficient market stories of time varying discount rates or the higher fundamental risk of some assets.²

By definition, smart money-noise trader models are concerned with the behavior of different groups of investors. A natural and direct way to test such models is therefore to see how well their behavioral predictions match what investors actually do.³ Suppose that the market comprises smart money, noise traders, and passive

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1. Russell and Thaler (1985) and Haltiwanger and Waldman (1985) analyze general markets; while specific smart money-noise trader models of stock markets include Shiller (1984), DeLong, Shleifer, Summers, and Waldman (1990a), and Campbell and Kyle (1993).

2. For the predictive power of contrarian strategies see DeBondt and Thaler (1985), for the predictive power of E/P and D/P ratios see Campbell and Shiller (1988) and Fama and French (1988). Lee, Shleifer, and Thaler (1991) study co-movements in closed end fund discounts, and Shiller (1981) examines excess volatility. Campbell and Kyle (1993) examine the co-movements between stock prices and dividends when noise is treated explicitly as an unobserved variable, but find that the data cannot distinguish between a model with a high discount rate and little noise, and a noisy model with a low discount rate. Extensive surveys from different perspectives may be found in Fama (1991) and DeBondt and Thaler (1993).

3. Other papers which look directly at the behavior of market participants include Grinblatt, Titman, and Wermers (1993), Haliassos and Bertaut (1992), Lakonishok, Shleifer, and Vishny (1992), Mankiw and Zeldes (1992), and Zeckhauser, Patel, and Hendricks (1991).

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investors. Two behavioral predictions of noise trader models will be tested here. First, market participation by smart money and noise traders should be negatively correlated, and neither should be related to market participation by passive investors. Secondly, high market participation by noise traders (who buy high and sell low) should be a negative predictor of future stock returns,⁴ while participation by smart money should be a positive one, whereas the participation of passive investors should have no predictive power either way.

To test these predictions, the three groups must be identified. To do this, it is assumed that an individual's probability of being a noise trader is declining in income, and conversely for the probability of being smart money. This assumption may be justified by the greater incentives for wealthier investors to acquire reliable information about the market. It follows that low-income groups will be predominantly noise traders, very high-income groups will consist mostly of smart money, and passive investors will dominate intermediate-income groups.

Stock ownership is measured using dividend income data from income tax returns. Two measures of market participation by different income groups are used: the share of dividends going to each group, and the fraction of each group owning any stock. For both measures, the market participation of different income groups behaves almost exactly as the noise trader model predicts. High participation by the general population is a strong negative predictor of one-year stock returns, and is associated with low participation by very high-income households. On the other hand, market participation by intermediate income groups has no power to forecast returns. The paper concludes by looking at the very low returns experienced by households who enter the market during periods of high noise, and the possible implications of this for the equity premium puzzle.

1. SMART MONEY VERSUS NOISE TRADERS

The basic idea behind smart money-noise trader models of financial markets is that some subset of agents trades in response to extraneous variables that convey no information about future dividends or discount rates. These agents occasionally bid the price up, lowering expected returns and causing smarter traders, who can observe both the fundamental and noise processes, temporarily to leave the market.⁵

To derive these predictions consider a variant of Campbell and Kyle (1993), to which the reader should refer for detailed derivations. There is a fixed number of smart money traders, each with instantaneous exponential utility. Assume that the stock price deviates from its fundamental by a zero mean noise variable $Y(t)$. It can be shown that expected return over the risk-free asset is diminishing in Y and that

4. This should not be confused with the important result of DeLong, Shleifer, Summers, and Waldman (1990a) that the *unconditional* expected returns earned by noise traders may be higher than those earned by smart money if the market is made too risky for smart money to participate. We are concerned here with expected return *conditional* on the degree of noise trader participation.

5. This assumes that the noise process is mean reverting. In cases where the noise is amplified, smart money may react positively to the noise in anticipation of the reaction of the noise traders. DeLong, Shleifer, Summers, and Waldman (1990b) present a model along these lines.

demand for stock of smart money X_S is diminishing linearly in noise. Let X denote the fixed supply of shares for each smart money trader. To close the model, it is assumed that there is a passive investor with fixed share holding X_P , and a noise trader with demand $X_N = X - X_P - X_S$.

In brief, high noise trader participation signals lower expected returns, and lower participation by smart money.

Identifying Smart Money and Noise Traders

To test these predictions, noise traders and smart money must be identified. To do this it is assumed that an individual's probability of being smart money is increasing in wealth, and that the probability of being a noise trader is correspondingly falling.

For an individual with wealth w , define the probability of being a noise trader as $p_N(w)$, the probability of being smart money as $p_S(w)$, and the probability of being a passive trader as $p_P(w) = 1 - p_N(w) - p_S(w)$. In a large group of individuals, assuming that the probabilities are independent across agents, the fraction of the group that belongs to each category will equal the individual probabilities by the Strong Law of Large Numbers. Consider a wealth interval W where a fraction $p_N(W) \equiv \int_W p_N(w)dw$ are noise traders and $p_S(W) \equiv \int_W p_S(w)dw$ are smart money. The change in demand for stocks in response to a change in the noise process Y , given that stock demand is independent of wealth and that the demand of passive traders is unchanged, is

$$\begin{aligned} \frac{dX(W)}{dY} &= p_S(W) \frac{dX_S}{dY} + p_N(W) \frac{dX_N}{dY} \\ &= \{p_S(W) - p_N(W)\} \frac{dX_S}{dY}. \end{aligned} \quad (1)$$

When noise Y rises signaling lower expected returns, stock holdings of very wealthy groups, where smart money predominates, will fall, whereas among less wealthy groups with a preponderance of noise traders, stock ownership will rise. The stock ownership of intermediate groups, where most individuals are passive investors, should be unchanged. Because the probability of owning large financial assets is increasing in income, these predictions also hold for income groups.

2. DATA

To test these predictions, stock ownership of different groups is measured using dividend income in income tax returns from the I.R.S. *Statistics of Income* series. Data from the period 1947 to 1980 are used: before the Second World War only very high-income individuals were required to file tax returns; after 1980 the explosion of money market and bond mutual funds makes dividend income an unreliable proxy for stock ownership. The construction of data series is discussed in the Appendix.⁶

6. The issues involved in using dividend income in tax returns as a measure of stock ownership are treated in the working paper version of this paper (Kelly 1996, Appendix).

TABLE 1
MARKET PARTICIPATION BY INCOME GROUP, 1947 AND 1980

Percentile	1947			1980		
	<i>INC</i>	<i>DIV</i>	<i>NUM</i>	<i>INC</i>	<i>DIV</i>	<i>NUM</i>
100.00	100.0	100	6	100.0	100	16
5.00	18.3	77	38	18.0	59	58
1.00	7.6	57	61	6.5	39	76
0.10	1.8	29	80	1.7	19	88
0.01	0.4	12	90	0.5	8	94

INC: Group's share of total adjusted gross income after federal income tax.

DIV: Group's share of dividend income.

NUM: Percentage of group declaring dividends in tax return.

Two measures of market participation are used. The first, in keeping with the model of the previous section, is the share of dividend income received by each income group. Table 1 gives dividend shares for different quantiles of the income distribution for 1947 and 1980, along with shares of adjusted gross income after tax. Dividend income is much more concentrated than total income: in 1980 the top percentile received almost 40 percent of dividends, while the top 0.01 percentile received 8 percent. These shares are lower than in 1947, reflecting the rise in real income which allowed households lower in the income distribution to accumulate enough savings to consider owning stock.

The second measure of market participation is the percentage of households in each group that owned any stock. Although expected utility maximization implies that all households should own stock (cf. Haliassos and Bertaut 1992), Table 1 shows that only one household in six received dividends in 1980, up from 6 percent in 1947. Even in the top percentile, where brokerage fees and minimum investment requirements are less of an impediment to stock ownership, nearly one quarter of households owned no stock in 1980.⁷

Stock Ownership

Figure 1 plots the time series of the percentage of households owning stock (orthogonal to income) for the bottom 95 percent and top 0.01 percent of households from 1947 to 1980. The first group rises steadily, while the second group is volatile, tending to move in the opposite direction.

Table 2 reports the results of a regression of one- and three-year stock returns on the percentage of households in different income groups owning stock in the previous year, and a constant. The dependent variable is the log of one plus the real return on the S&P index.⁸

Noise apart, stock ownership can be expected to have increased over the sample

7. Looking at wealth rather than income, Haliassos and Bertaut (1992) find that many households with large financial assets own no stock, either directly or indirectly.

8. Data are taken from Shiller (1989, Appendix). Returns are deflated by the producer price index to allow comparison with results in later sections. Using the excess return on stocks over the commercial paper rate produced almost identical results.

FIG. 1. Percentage of Households Owning Stock (orthogonal to income), 1947–1980. Solid line: bottom 98 percent; dashed line: top 0.01 percent

period as a result of rising real income. To control for this, the explanatory variable used is the component of each group's stock ownership orthogonal to its real, after-tax income (that is, the least squares residual from a regression of the percentage of a group owning stock on the group's mean income).

For one- and three-year return regressions there are two columns of results. The first, labeled "Total," uses the stock ownership of the entire population above a given quantile as the explanatory variable. The second, labeled "Interval," uses the population above each reported quantile and below the next one.

Table 2 reports the sign of the coefficient on stock ownership, and the R^2 and (two-sided) nominal p value of each regression. The standard errors used to derive the p values were estimated using a MacKinnon-White jackknife (cf. Davidson and MacKinnon 1993, pp. 553–54) for one-year return regressions; and a QS kernel (cf.

TABLE 2
PERCENTAGE OWNING STOCK AS A PREDICTOR OF RETURNS

Percentile		1-year returns				3-year returns		
		Total		Interval		Total		Interval
100.00	—	0.141 (0.035)	—	0.148 (0.035)	—	0.493 (0.002)	—	0.500 (0.002)
5.00	—	0.003 (0.736)	—	0.007 (0.617)	—	0.082 (0.149)	—	0.082 (0.093)
1.00	+	0.054 (0.219)	+	0.021 (0.403)	+	0.033 (0.433)	+	0.021 (0.456)
0.50	+	0.099 (0.111)	+	0.040 (0.338)	+	0.076 (0.222)	+	0.017 (0.625)
0.10	+	0.162 (0.016)	+	0.065 (0.225)	+	0.208 (0.006)	+	0.057 (0.384)
0.05	+	0.169 (0.012)	+	0.141 (0.030)	+	0.235 (0.010)	+	0.142 (0.035)
0.01	+	0.156 (0.012)			+	0.271 (0.025)		

NOTES: Sample period: 1948–1981.

Dependent variable: log of one plus real S&P return.

Explanatory variable: percentage of households in each income group owning stock in previous year (component orthogonal to real income). Columns labeled "Total" correspond to all households above the given quantile; columns labeled "Interval" correspond to households above each given quantile, but below the next highest one.

The sign (+ or —) gives the sign of the regression coefficient. The number is the regression R^2 , and the number in brackets below it is the p value of the regression. For the one-year regression this is calculated using MacKinnon-White jackknife standard errors, for the three-year regression it is estimated using a QS kernel.

Andrews 1991) for three-year regressions.⁹ Monte Carlo simulations indicate that the reported nominal significance levels are reliable.¹⁰

The pattern of results is simple and striking. The percentage of lower-income households (the bottom 95 percent of the income distribution) owning stock is a significant negative predictor of one-year stock returns. Market participation by intermediate households (between the top 5 percent and 0.05 percent of the income distribution) has no predictive power for returns. Participation by very high-income households (the top 0.05 percent) is a significant positive predictor. These patterns of significance repeat for three-year returns, but there are too few independent observations for strong inferences to be drawn.

The extreme returns experienced in the early 1970s suggest that the significance of these least squares regressions might be generated solely by one or two extreme outliers. To test this, the regressions were rerun using least median of squares which is highly robust to groups of outliers. To calculate significance levels outlying observations which lie more than five adjusted standard errors from the least median squares line are omitted, and the regression run using standard least squares.¹¹ The patterns of significance in Table 2 were unchanged by this procedure. As a second

9. To calculate the standard errors, the least squares residuals were first weighted using the diagonal of the projection matrix, as in the jackknife procedure. Andrews and Monahan's (1993) pre-whitening of residuals with a VAR produced identical standard errors.

10. Ten thousand iterations were carried out assuming real stock returns to be normally distributed with mean and variance equal to those for the period 1871–1991. See Hodrick (1992) for a survey of the literature on exact significance levels in rate of return regressions.

11. The exact procedure used is Rousseeuw's (1984) least trimmed squares which has slightly better numerical and asymptotic properties.

TABLE 3
CORRELATION OF STOCK OWNERSHIP OF DIFFERENT GROUPS

	100.00	5.00	1.00	0.50	0.10	0.05
5.00	0.588					
1.00	-0.149	0.265				
0.50	0.165	0.365	0.896			
0.10	-0.290	0.285	0.812	0.904		
0.05	-0.525	-0.033	0.650	0.709	0.870	
0.01	-0.727	-0.534	0.119	0.131	0.335	0.705

NOTES: Rank order correlations. 5 percent significance: 0.34. 1 percent significance: 0.45.

test of robustness, observations after 1969 were omitted. Running standard least squares, market participation of the top 0.05 percent is still significant at 1 percent with an R^2 of 0.30, but market participation of the entire population is no longer significant. If least median squares is used to identify outliers, market participation by the entire population again becomes significant when these are omitted.

The rank order correlations between the percentage of different income groups owning stock are given in Table 3. Each income group represents household above some percentile of the income distribution and below the percentile of the next reported group: for instance the 5.00 group represents households between the fifth and first percentiles of the income distribution. It is notable that the market participation of the bottom 95 percent is positively correlated with the participation of the fifth to first percentiles, is uncorrelated with the next three groups, and is significantly negatively correlated with the market participation of the top 0.05 percent of the population.

An alternative explanation for these results is that changing stock ownership by lower income groups reflects changing discount factors, whereas changing market participation by a small number of very high-income individuals reflects their access to private information about fundamentals, such as future corporate dividend policy. If true, stock ownership by high income households should have ability to forecast returns beyond that contained in the market participation of the general population. Regressing one-year returns on the stock ownership of both groups shows that this is not so: neither variable is individually significant, reflecting their strong negative correlation.

Dividend Share

The same analysis is repeated in Tables 4 and 5 using each group's share of total dividends to measure market participation. To control for the effect of economic growth in allowing households lower in the income distribution to hold stock, each group's dividend share is first regressed on the mean real after-tax income for the entire population, and the residual is used in the return regressions.

Table 4 shows that dividend shares of all groups above the fifth percentile are significant predictors of future one-year returns, with no tendency for predictive power to rise noticeably with income above the 0.5 percent group. Market participation of the bottom 95 percent is a negative predictor of returns, but is only signifi-

TABLE 4
SHARE OF DIVIDENDS AS A PREDICTOR OF RETURNS

Percentile	1-year returns				3-year returns			
	Total		Interval		Total		Interval	
100.00			—	0.041 (0.207)			—	0.121 (0.012)
5.00	+	0.224 (0.011)	+	0.175 (0.020)	+	0.565 (0.000)	+	0.541 (0.000)
1.00	+	0.226 (0.010)	+	0.197 (0.030)	+	0.547 (0.000)	+	0.527 (0.001)
0.50	+	0.227 (0.008)	+	0.226 (0.007)	+	0.541 (0.000)	+	0.572 (0.000)
0.10	+	0.225 (0.010)	+	0.220 (0.014)	+	0.517 (0.000)	+	0.511 (0.000)
0.05	+	0.222 (0.010)	+	0.145 (0.021)	+	0.508 (0.000)	+	0.423 (0.001)
0.01	+	0.223 (0.011)			+	0.421 (0.002)		

NOTES: Sample period: 1948–1981.

Dependent variable: log of one plus real S&P return.

Explanatory variable: group's share of total dividend income in previous year (component orthogonal to real income). Columns labeled "Total" correspond to all households above the given percentile; columns labeled "Interval" correspond to households above each given percentile, but below the next highest one.

The sign (+ or –) gives the sign of the regression coefficient. The number is the regression R^2 , and the number in brackets below it is the p value of the regression. For the one-year regression this is calculated using MacKinnon-White jackknife standard errors, for the three-year regression it is estimated using a QS kernel.

cant for three-year returns. Table 5 shows that the dividend of the bottom 95 percent of the population is negatively correlated with that of the rest of the population. Dividend shares of other groups show a strong positive correlation.

Turning to resistance, the results of Table 4 still hold if outliers are removed using least median of squares. If the sample is truncated in 1969, dividend shares of the top 0.01 percent are no longer significant, even when outliers are removed. Dividend shares of other groups remain significant however.

The fact that the dividend share of some groups in Table 4 is a significant, positive predictor of future returns, whereas their stock ownership in Table 2 is not, is to be expected if the individuals in each group with the largest stock holdings are more likely to be smart money or passive investors than noise traders. Consider a group where one smart money investor has \$1 million in stock. He believes the market to be overvalued and sells his entire holding in equal lots to ten noise traders, none of

TABLE 5
CORRELATION OF DIVIDEND SHARE OF DIFFERENT GROUPS

	100.00	5.00	1.00	0.50	0.10	0.05
5.00	–0.473					
1.00	–0.772	0.774				
0.50	–0.748	0.831	0.926			
0.10	–0.648	0.839	0.884	0.929		
0.05	–0.673	0.821	0.882	0.818	0.786	
0.01	–0.641	0.637	0.862	0.873	0.885	0.565

NOTES: Rank order correlations. 5 percent significance: 0.34. 1 percent significance: 0.45.

whom currently owns stock. One of these noise traders is in his income group, the other nine are in a lower income group. Looking at the smart trader's group, the number of stock owners is unchanged, whereas the group's share of dividends has fallen. Similarly, consider a group with no smart money where most stock is owned by passive investors; and where a large influx of noise traders occurs, each of whom buys a small amount of stock from smart money in higher income brackets. This group will show a large increase in stock ownership, but a smaller change in its share of dividends.

3. THE EQUITY PREMIUM PUZZLE

The tendency for new investors to enter the market during periods of high noise may help to explain part of the low demand for stocks which Mehra and Prescott (1985) identified, and termed the equity premium puzzle. Stocks historically have earned an average real return of 8 percent, versus 1 percent for bonds. Over a thirty-year investment horizon this implies an average return of 35 percent on a bond portfolio, versus 900 percent on stocks.

To consider why demand for stock might be so low, consider an individual who, like most American households, owns no stock, and has little idea of the distribution of stock returns.¹² This individual observes a strong noise and decides to buy some stock. Three years later he evaluates this investment, comparing it with the return on risk-free bonds. To extend the analysis beyond the short period for which we have stock ownership, it is necessary to identify a noise variable.

Experimental data (cf. Andreassen 1990, p. 156) suggest that individuals extrapolate using distributed lags of past data. Define the innovation in stock prices as $u_t = p_t - p_{t-1}$ where p_t is the log of the real stock price. A candidate noise variable is therefore extrapolated price growth, measured as

$$\begin{aligned} g_t &= (1 - \lambda) \sum_{i=0}^{\infty} \lambda^i u_{t-i} \\ &= \lambda g_{t-1} + (1 - \lambda) u_t \end{aligned} \quad (2)$$

where $\lambda < 1$.

The series g is constructed using the January S&P series and producer price index beginning in 1871 from Shiller (1989, Appendix) updated to 1992. The value of g for 1871, and the average innovation $\bar{u}$, are set equal to the average value of u over the entire sample period and it is assumed that $\lambda = 0.99$ (similar results were obtained using values of λ in the range 0.98 to 0.995). This variable seems a good candidate as a noise variable: the correlation between g and fraction of the bottom 95 percent of households owning stock (adjusted for income) is significant at 1 per-

12. As a case in point, how many economists knew the average real return on stock before reading Mehra and Prescott?

FIG. 2. Three-year Returns versus Noise g , 1890–1989

cent, and if g is added to the regressions in Table 2, neither variable is individually significant.

Figure 2 gives boxplots summarizing the distribution of three-year average real returns for the hundred-year period 1890–1989.¹³ Three plots are shown. The middle one represents all three-year returns over the century, while the left- and right-hand plots summarize returns in the twenty-five years with the lowest and highest values of noise g respectively. The middle plot shows a median return on stocks of approximately 8 percent, and that stocks earned a positive return approximately three quarters of the time: the lower part of the interquartile box lies at zero.

The right-hand boxplot shows that the experience of those who enter the market when noise is high (as many households seem to do) is very much worse than the unconditional distribution of stock returns would suggest. In only four of the twenty-five years does the individual attain the average market return of 8 percent or higher. The median return is 0.9 percent, slightly less than the average return on bonds, even before brokerage fees are paid. In eight of the years a negative return is experienced, and often a very large one, with the result that the mean return earned is -0.5 percent. Most investors who enter the market in periods of strong noise will regret their decision three years later. If they place more weight on their own experiences than on the advice of brokers, academics, and other pundits, they will conclude that stocks are an unwise investment and will hold risk-free assets instead.

The experience of investors who buy stock when noise is low is quite different. As the left-hand boxplot shows, they earned the average market return or higher about three quarters of the time, and in only one year did they earn a return substantially below the return on bonds.

13. Each box gives the interquartile range of returns, and the line across its middle gives the median return. The whiskers extending from the top and bottom of each box represent an approximate 99 percent confidence interval. Outliers beyond this range are represented by individual horizontal lines.

4. CONCLUSIONS

This paper attempted a direct test of the smart money-noise trader model by considering its implications for the behavior of different groups of investors. It was assumed that an individual's probability of being a noise trader was diminishing in income, and conversely for the probability of being smart money.

The empirical results support the model strongly. Market participation by the general population (where noise traders are assumed to predominate) was a strong negative predictor of returns. Participation by very high-income households was a strong positive predictor, and changed in direct response to noise trader participation. Changing participation by intermediate households, who were identified as predominantly passive investors, had no power to forecast returns.

These results are not easily amenable to an efficient markets interpretation. It is not obvious why so many expected utility maximizers with common expectations of returns should not own stock, and why the number doing so should fluctuate widely through time, independently of income. Even if it could be argued that this changing participation reflects an optimal response to some fundamental that is negatively correlated with individual discount rates, it is implausible that the optimal response of very high-income households to this variable should be opposite to that of ordinary households, while the optimal response of intermediate households is to do nothing at all.

Several extensions are possible. The first is to investigate the noise variables to which households are reacting more thoroughly. Secondly, one direct implication of the smart money-noise trader model of section 1 which was not explored here is the positive relationship between changing levels of noise Y and trading volume. As the noise variable increases smart traders sell to noise traders, and this process is reversed as noise falls. Campbell, Grossman, and Wang (1993) find that the serial correlation of returns falls with volume, and show that this is in keeping with trading by "non-informational" traders. Although their formal model considers changing risk aversion as the source of non-informational trading, it would be useful to know if the noise variables used here could be the source of variations in trading volume.

APPENDIX: CONSTRUCTING DATA SERIES

For households above given nominal incomes $\{y_1, \dots, y_N\}$, tax tables give the average gross income per taxpayer, the average federal tax rate paid, the percentage of households owning stock, and the fraction of dividends they received. However, we require these data for different percentiles of the income distribution.

Suppose that the tables tell the number of individuals with incomes between y_1 and y_2 , and that the fraction of returns with income below these values is F_1 and F_2 respectively. To calculate the fraction of taxpayers between some cutoff value y and y_2 it is assumed that income obeys a Pareto distribution with parameters κ and α (cf. Feenberg and Poterba 1992):

$$\Pr(Y < y) = 1 - (\kappa/y)^\alpha. \quad (3)$$

Given the empirical distributions F_1 and F_2 the parameters are estimated as

$$\hat{\alpha} = \ln \left(\frac{1 - F_1}{1 - F_2} \right) / \ln \left(\frac{y_2}{y_1} \right),$$

$$\hat{\kappa} = y_1(1 - F_1)^{1-\alpha}. \quad (4)$$

Given these estimates one can calculate the cutoff income y from (3).

Suppose that for taxpayers above nominal incomes $\{y_1, \dots, y_N\}$ the fraction owning stock is $\{s_1, \dots, s_N\}$. To obtain the fraction s for individuals above income y two interpolation methods were used: a cubic spline and linear interpolation. This procedure was repeated to estimate average income per taxpayer, average federal tax rates, and share of dividend income. Each of the series interpolated was very smooth and these procedures produced essentially identical results. Average income per taxpayer was deflated using the GDP deflator.

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