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Why Has U.S. Stock Ownership Doubled Since the Early 1980s? Equity Participation Over the Past Half Century

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Why Has U.S. Stock Ownership Doubled Since the Early 1980s? Equity Participation Over the Past Half Century*

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Abstract

The U.S. stock ownership rate doubled between 1983 and 2001 but remains below predictions of some equity participation models. Consistent with calibration studies by Heaton and Lucas (2000) and Gomes and Michaelides (2005), mutual fund costs and indicators of background labor risk are significantly related to stock ownership over 1964-2019. Coefficient estimates and continuous data on driving variables can be used to create a continuous proxy for stock ownership, which could help researchers gauge the effects of shocks that are transmitted via equity participation. Typically omitted asset transfer costs can help analyze other aspects of household portfolio behavior.

JEL codes: G11, G02, G23

Keywords: equity participation, stock ownership, transfer costs, labor risk, mutual funds

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I. Introduction

Stock wealth can have large effects on consumption at the aggregate (e.g., Ando and Modigliani, 1963) and individual levels (e.g., Dynan and Maki, 2001, and Mankiw and Zeldes, 1991) and has implications for inequality. Recent research on the latter indicates that inequality-reducing effects of greater stock ownership have been dominated by stock price gains that widen the wealth gap between stockholders and nonstockholders (Favilukis, 2013) and that disproportionately benefit the very wealthy who hold the vast bulk of stock wealth (Bilias, Georgarakos, and Haliassios, 2016). Stock price booms and busts since the 1980s and the Mehra and Prescott (1995) paper on the equity premium puzzle have spurred studies of what determines stock ownership at the individual level and the frequency of household portfolio adjustment (e.g., Cocco, 2004; Gomes and Michaelides 2005; Guo, 2004; Heaton and Lucas (2000), Liu (2004), Longstaff, 2009; and Polkovnichenko, 2007). While the older literature on equity participation focused on why stock ownership was lower amid high equity premiums than what simple theory would imply (e.g., Haliassos and Bertaut 1995), the literature also needs to address why U.S. equity participation rates have doubled (Figure 1). We focus on the role of transfer costs (specifically, mutual fund loads) in this significant shift. Later in this section, we review some of the theoretical literature on limited participation, as well as evidence on other factors that could have contributed to the substantial change in U.S. equity participation.

Calibration studies by Heaton and Lucas (2000) and by Gomes and Michaelides (2005) suggest that the combination of a high equity premium and low participation could stem from background labor market risk and costs of equity participation, and that higher stock ownership rates could stem from lower asset transfer costs, background risk, or risk aversion. However, labor market developments and surveys suggest that households likely face greater risk of job loss compared to several decades ago, while surveys suggest that households are less optimistic about

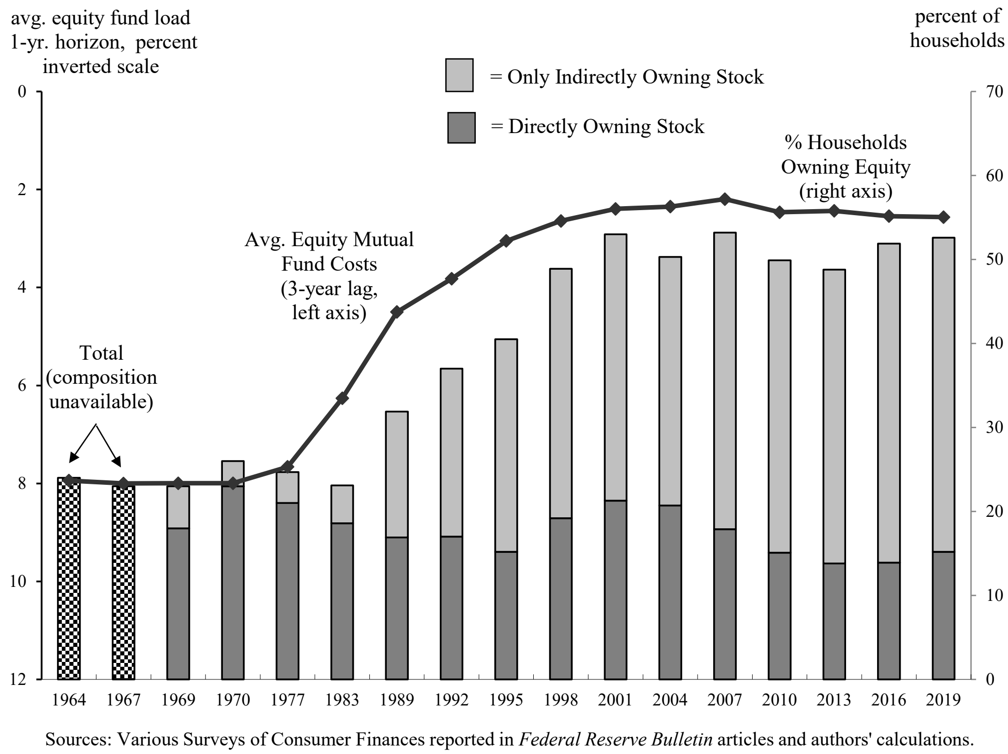

Figure 1: Inverted Stock Mutual Fund Costs Very Correlated with Stock Ownership Rates
(Sources: Surveys of Consumer Finances and authors' calculations.)

future economic conditions and do not suggest an underlying increase in preference toward risk.

This leaves changes in taxes, demographics, or asset transfer costs as possible explanations, with declines in the lattermost consistent with Calvet, et al's (2004) contention of a role for financial innovation. The rise in mutual fund ownership is consistent with changes in tax regulations promoting a shift toward retirement savings in the form of individual retirement accounts and defined contribution (401K/403B) pension plans. However, tax changes alone cannot account for shifts toward mutual fund holdings outside of such accounts and regulatory shift dummies are unable to significantly explain higher stock ownership rates (see Duca, 2005). Also, IRAs were introduced in 1981, but stock ownership only started rising in the 1989 Survey of Consumer Finances. In addition, two other possible long-run factors—an aging of the population and changes in capital gains taxes—have trends that are inconsistent with those in the stock ownership rate (see Appendix A). The role of lower asset transfer costs linked to financial innovation is consistent with Duca's (2005) evidence that information cost declines led large declines in mutual fund load fees, which, in turn, led shifts in the mutual fund share of household equity holdings (with or without IRAs and thrift plan assets). Consistent with Heaton and Lucas (2000), Liu and Lowenstein (2002), Liu (2004), and Gomes and Michaelides (2005) we provide time series evidence that asset transfer costs (see Figure 1) and swings in background labor risk significantly affect stock ownership rates, with estimated long-run relationships closely tracking equity participation over the past half century.

There are possible broader implications of variation in stock ownership for the macroeconomy and wealth inequality. Notable among earlier macroeconomic studies that incorporated limited financial market participation are Christiano and Eichenbaum (1995) and Christiano, Eichenbaum, and Evans (1996) who explored settings in which firms that used finance to produce were more initially exposed to monetary policy changes than households, who did not participate in financial markets and were subject to cash-in-advance constraints. As a result of the asymmetry in participation, monetary policy changes give rise to liquidity effects on short-term interest rates and have short run nonneutral effects. By implication, an increase in participation could lead to monetary policy being less non-neutral in the short run in this framework.

On the other hand, Dynan and Maki (2001) find that the stock wealth effect on consumption was much larger for stockowners than nonowners, suggesting that higher participation could expose more households to monetary and other shocks to stock prices, thereby leading to more pronounced aggregate stock wealth effects on consumption. However, the net aggregate effect could be obscured or different for two possible reasons. First, stock wealth has become more highly concentrated within the set of households owning stock (Bilias, et al., 2016) during the period when stock ownership rates rose. Arguably, the marginal propensity to consume out of stock wealth is lower among the wealthiest, implying that the aggregate sensitivity of consumption to stock wealth may not have risen as the intensive margin effect worked against the impact of higher participation. Second, as stock ownership has risen, the exposure of the median shareholder to shocks to firm valuation are spread out over a larger share of the population and Morelli (2021) argues that this intensive margin effect could more than offset the extensive margin impact of higher participation on the sensitivity of consumption to stock wealth. As a result, the stock wealth effects of monetary policy on consumption could have weakened as the stock ownership rate rose.

Higher equity participation could have distributional effects. Dynan and Maki (2001) and Morelli (2021) find that the consumption of stockowners is more affected by stock prices than the consumption of non-owners. And absent an intensive margin effect, higher participation could help reduce wealth inequality. However, intensive margin effects have effectively countervailed inequality-reducing effects from the extensive margin in practice. As Bilias, et al. (2016) find, the overall inequality of wealth did not fall as the stock ownership rate rose because stock wealth became much more highly concentrated—particularly among the richest 1 percent of households.

Our study focuses on extensive-margin effects, exploring the influence of transaction costs (via mutual fund loads) and background labor risk on broadening access to stock ownership. Fund loads have played a pivotal role in driving the major trends in stock ownership over the past several decades. This is robust even to very conservative upper-bound estimates of standard errors. Further, several measures of background labor risk help to refine predictions of equity participation. We thus find support for the calibration work of Heaton and Lucas (2000) and Gomes and Michaelides (2005), and also Liu and Lowenstein (2002) and Liu (2004). In addition to demonstrating the importance of transfer costs in widening equity participation, our study facilitates further research into stock ownership's macroeconomic implications and importance in two ways. We provide researchers with time series estimates of annual stock ownership and a guide to robust inference using existing irregularly spaced equity participation data.

To present our findings, this paper is organized along the following lines. The second section discusses related literature that helps motivate the stylized time series models later estimated. The third section briefly describes how annual data on stock market mutual fund costs spanning 65 years are constructed, along with discussing other factors affecting equity participation. Section IV uses ARDL models and cointegration tests to link these data to irregular readings on U.S. stock ownership rates and finds that annual mutual fund cost and the gap between the unemployment rate and its natural level help proxy time variation in stock ownership rates.[1]

II. Related Literature

Early theoretical work on asset market participation stressed transaction costs and liquidity (Allen and Gale, 1994 and Williamson, 1994). For tractability, many later papers focus on one of those sources. An exception is Heaton and Lucas (2000), who find that high transfer costs, idiosyncratic labor income risk, and habit formation can lead to low stock ownership and high equity premiums. Consistent with the view that transfer costs matter, Halliassos and Bertarut (1995) find that risk aversion, heterogeneity, habits, investment account minimums, and gaps between borrowing and lending rates are insufficient to account for low equity participation.

Although some research avoids imposing a correspondence between rates of time preference and the degree of risk aversion (Epstein and Zin, 1989), many models deriving utility function parameters in calibrations or simulations assume that the financial architecture (transfer costs and liquidity constraints) are time invariant. However, as Heaton and Lucas (2000) stress, high transfer costs can lead to lower stock ownership rates and higher equity premia, and lower

[1]Related series have helped model substitution between money and bonds (Duca, 2000; Anderson and Duca, 2003).

asset transfer costs would induce greater stock ownership. In a more complicated model in which fixed and proportional asset transfer costs affect the optimal consumption and portfolio behavior of households with constant relative risk aversion, Liu (2004, p.322) finds that portfolio shares reflect differentials in pecuniary yields between safer and risky assets that should be scaled by proportional asset transfer costs,[2] implying that portfolio shares reflect negative linear tradeoffs between expected return differentials and proportional transfer costs. His model and that of Liu and Lowenstein (2002, p. 818) imply that stock ownership is decreasing in transactions costs and increasing in expected stock returns, holding risk and risk aversion constant. Calvet et al. (2004) show how by expanding asset choice, financial innovation can induce greater asset market participation and a lower equity risk premium. In this framework, lower mutual fund costs can be seen as a form of financial innovation, consistent with evidence that lower information costs temporally led lower mutual fund loads and higher household holding of stocks (see Duca, 2005).

Consistent with Heaton and Lucas (2000), Liu (2004), and Gomes and Michaelides (2005), Duca (2005, 2006) shows that average equity fund loads and stock ownership rates from the Surveys of Consumer Finances (SCFs) had a significant negative correlation of about –0.9 for overall and indirect (e.g., mutual fund) stock ownership rates (Figure 1).[3] These SCFs show that higher stock ownership occurred via mutual funds and had risen the most for middle-income families, whose median holdings of transaction accounts and time deposits grew slower relative to total financial assets than did the deposits of high-income families during the transition to higher stock-ownership rates. Consequently, unless researchers control for time series variation in asset

[2] For computational reasons, many studies calibrating asset participation treat investment costs (e.g., brokerage fees and learning about stocks) as an entry cost that is proportional to labor income (Alan, 2006; Gomes and Michaelides, 2005; Guo, 2004; and Guvenen, 2009). This assumption is counter to the role played by proportional mutual fund fees. Brunner and Meltzer (1967) show how proportional costs matter more than fixed costs of transferring between bonds and money in a general version of the Baumol-Tobin money demand model. Duca (2000) finds that bond fund loads—which are proportional transfer costs—account for a large shift in M2 demand in the early 1990s.
[3] The present study more formally investigates factors—not just mutual fund costs—that may affect stock ownership.

transfer costs, making inferences about the average state of risk preferences or the degree of financial frictions from overly simple models is subject to potential omitted variable bias.

Models of equity participation should be consistent with evidence that liquidity constraints or the costs of obtaining a diversified stock portfolio (e.g., stock mutual fund loads, as in Duca, 2005) have shifted over time. The findings of some studies that ignore such time series variation while trying to infer the average or marginal degree of risk aversion might plausibly be affected by omitted variable bias. In a related study, Duca (2005) shows that trends in mutual fund costs—which lead and drive the mutual fund share of nonIRA/non401K equity holdings by households—are mainly driven by underlying trends in financial technology (e.g., bank productivity is weakly exogenous to mutual fund costs, but not the converse). This implies that mutual fund costs do not mainly reflect the impact of exogenous tax shocks, which push down mutual fund costs indirectly through time invariant economies of scale. That is, financial technology shocks lowered asset transfer costs facing households and thereby raised asset market participation. In runs not shown, a dummy for the advent of 401K plans and individual retirement accounts (=1 since 1983), starting with the IRS's issuance of guidelines for 401K plans in 1981 and the expansion of IRA eligibility rules, was insignificant by itself and if entered interacted with either mutual fund costs or consumer sentiment/equity risk premium variables. Together the above findings are consistent with the interpretation that improvements in technology drove down mutual fund costs, thereby spurring increased equity participation via mutual funds including and excluding 401K accounts.

Some theoretical models of asset participation recognize that the equity risk premium reflects both investors' assessments about the expected differences in returns on stocks versus bonds, as well as the inherent riskiness/uncertainty about stock returns and the degree of risk aversion (e.g., Cao, Wang, and Zhang, 2005). As a result, the sign of the correlation between the equity risk premium and participation rates is, a priori, unclear. Intuitively, if changes in the equity premium are dominated by shifting perceptions of expected risk-adjusted return differentials, then higher equity premiums could be positively correlated with measures of equity risk premiums. If, however, time series movements in equity risk premium are dominated by shifts in investor discount factors (the levels of risk/uncertainty interacted with the degree of risk/uncertainty aversion), then the equity risk premium could be negatively correlated with stock ownership over time. As a result, high levels of measured equity risk premiums can conceivably coincide with low participation if risk or the degree of risk aversion is high (e.g., Basak and Cuoco, 1998; and Cao, Wang, and Zhang, 2005). Thus, without controlling for the degree of risk aversion or confidence, one may observe negative correlations of equity risk premia and participation rates, whereas if adequate controls for time variation in discount factors are included, the remaining or marginal information in equity risk premium measures could be positively correlated with equity participation rates. Thus, in contrast to the negative correlation between stock ownership rates and transactions costs implied in the literature, the sign of the estimated relationship between stock ownership rates and the equity premium is unclear and may turn positive if time series movements in risk aversion or confidence are separately tracked, as summarized in Table 1.

Factor	**Asset Transfer Costs** (proportional mutual fund costs, loads)	**Background Labor Market Risk** (unemployment, labor market confidence)	**Consumer Confidence** (about current or future economy)	**Equity Risk Premium absent controls for risk aversion or confidence)**	**Equity Risk Premium with separate controls for risk aversion, confidence)**
Implied Empirical Correlation	**Negative** (see Heaton & Lucas, 2000; Lin, 2000; Liu & Lowenstein, 2002)	**Negative** (see Heaton & Lucas, 2000)	**Positive** (could reflect expectations of risk or returns in labor or equity markets)	**Ambiguous** (- if premia dominated by Δ's in risk aver-sion, Cao, et al., 2005; + if premia dominated by equity returns)	**Positive** (marginal information in premiums reflects risk-adjusted relative equity returns, see see Cao, et al., 2005, and Liu, 2004)

Table 1: Implied Correlations with Equity Participation Rates

III. Empirical Specification and Data

IIIA. Basic Specification

The literature suggests that equilibrium stock ownership rates reflect several factors aside from proportional asset transfer costs, including background labor market risk (Heaton and Lucas, 2000) and the equity premium, which reflect a confluence of expectations regarding profits, interest rates, and discount factors, where the latter may reflect the uncertainty facing investors (see, e.g., Cao, Wang, and Zhang, 2005). These factors are generally stationary whereas stock ownership rates (*StockOwn*) and loads have unit roots (see Table 2).

This mixture of the order of integration of the main variables suggests estimating long-run cointegrating vectors in a vector–error correction model using the Johansen (1991, 1995) method, where the equilibrium level of equity participation and its change are specified as:

$$\ln StockOwn^{*}_{t} \equiv \alpha_0 + \alpha_1 \ln Sload_t + \mu_t \quad (1)$$

$$\Delta \ln StockOwn_t \equiv \beta_0 + \beta_1 EC_{t-1} + \beta_2 Risk_t + \varepsilon_t \quad (2)$$

respectively, where *Sload* are mutual fund loads, $EC \equiv \ln StockOwn - \ln StockOwn^{*}$, *Risk* is a vector of short-run, stationary risk factors, $\alpha_1 < 0$, and $\beta_1 < 0$ as changes in stock ownership tend to be lower if ownership exceeds equilibrium in t-1. The limited number of stock ownership readings creates a practical n need to limit the number of short-run variables whose correlations could result in multicollinearity. Owing to the irregular spacing of observations on stock ownership, we need to use imputation methods that require calculating standard errors, for which a single-equation autoregressive distributed lag (ARDL) equivalent to (1) and (2) is needed[4]:

$$\Delta \ln StockOwn_t = \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t \quad (3)$$

[4] Essentially, the long-run relationship implied by the ECM term is substituted into the first difference eq. in eq. (2).

In equilibrium, the change in stock ownership is zero (as are all first difference and shock terms) and the long-run equilibrium relationship can be backed out as:

$$\ln StockOwn^{*}_{t} \equiv (-\gamma_0 / \gamma_1) + (-\gamma_2 / \gamma_1) \ln Sload_t \tag{4}$$

IIIB. Addressing Irregularly Spaced Observations; Multiple Imputation Methods

Our main data series has two features that require special consideration: firstly, equity participation is typically observed every three years rather than annually; and secondly, three gaps (1973, 1980, and 1986) are present in the series from 1964 to 2019. Given the first feature, we estimate ARDL models using lag levels from three years prior and differences over the preceding three years. This does require meshing the series around one four-year gap, from 1973 to 1977 instead of to 1976. To address the second issue, we use multiple imputation, a standard technique in the statistical literature (see Rubin (1987), Schenker and Taylor (1996), and Reiter and Raghunathan (2007)). Multiple imputation first generates sets of plausible imputed values, then runs the desired model using each set, and aggregates the results using a form of model averaging.

We use three standard methods to generate imputed values: linear, spline, and the Kalman filter. (Kalman filter results are presented in the main body of this paper; linear and spline results are similar, with some in Appendix D and others available from the authors upon request.) In each, the only input to the imputation process is the stock ownership series itself, so we do not impose any assumptions on relationships the equity participation series may or may not have with other series. However, these imputed values are not necessarily equal to the true value of the series at any or all of our three imputed points in time. We estimate how far our imputed values should be, on average, from the truth; using this estimate, we can establish a range of plausible values the series might truly have taken on at missing points in time. We then ensure that empirical results are robust to this range of plausible variation.

We thus ensure that the core results are robust to potential inaccuracies in the imputed values. The initial imputed values are our "best guess" for the true value of the series at a point in time; in a sense, given a missing equity participation datapoint $EPart_t$, imputed value $\widehat{EPart}_t$, and estimator used for imputation θ, we have

$$\widehat{EPart}_t = E[EPart_t|\theta]. \tag{5}$$

To obtain a better sense of the range of possible values which the true value $EPart_t$ could take, conditional upon $\widehat{EPart}_t$, we need a measure of the variance of our estimate from actual values of the series. This paper uses two main measures of imputed value inaccuracy: the variance of the equity participation series over the entire sample period, used as a (probably rather loose) upper bound on the extent to which our estimates are inaccurate (high variance); and the variance of the residuals formed by comparing the estimates that we would have imputed for any non-missing datapoint with the actual non-missing datapoints (tighter variance).

The variance of the series as a whole is suitable as an upper bound on imputation inaccuracy because, if we had simply imputed the series mean for each missing datapoint, the expected inaccuracy would be at most the series variance. Imputing the overall series mean obviously does not leverage much information about the data, or the fact that it is a time series. Local linear imputation, imputation via spline, and imputation via Kalman filter all utilize more information about the equity participation series, including the fact that it is a time series. Using more information about the data should at least weakly improve our imputation accuracy (so the overall series variance is an upper bound). Non-missing values in the portion of the series where we impute are clustered close to the observed series minimum, and the series trends up relatively smoothly afterwards. These properties suggest that mean imputation would be particularly ill-suited for our application, so the expected variance of its use likely provides a *loose* upper bound. Overstating the inaccuracy of our imputed values in this way may bias our coefficient estimates towards insignificance in model estimation and model averaging.

"Tighter variance" specifications base the anticipated inaccuracy of our imputations on the inaccuracy of modeled or imputed values for *non-missing* datapoints, when we treat these non-missing points as unobserved. Since the three missing datapoints are not missing for any reason related to the rate of equity participation in the relevant years (i.e., they are functionally missing at random, MAR), this method provides a reasonable estimate of the imputed value inaccuracy. In the case of Kalman filtration results presented in the main body of this paper, and for spline results, we use a variance estimate analogous to leave-one-out cross validation (described in greater detail below). For imputed values from simple linear imputation, we take all sets of three non-missing datapoints $t-1,t,t+1$ and perform simple linear imputation to estimate t based on the average of $t-1$ and $t+1$. The variance of the residuals is then computed by averaging the squared deviations of the "imputed values" from the observed time-t datapoints.

In deriving Kalman filter and spline variance estimates, we would ideally like to focus on cases closest to the situation of our actual missing values: at most one consecutive missing value, which is neither the first nor last observation. In light of the limited sample size, we relax the "at most one consecutive missing value" constraint to have variance estimates from a greater variety of points in the series (and in particular, from more points close to the region our truly-missing values lie in). Allowing multiple missing values in a row would generally be expected to increase our estimate of the imputation inaccuracy.

For each data points save the first, last, and seventh,[5] we remove this data point from the series and calculate Kalman or spline imputed values using the resulting four-missing-value version of the data. We then obtain variance estimates by averaging

$$(EPart_t - \widehat{EPart}_t)^2 \tag{6}$$

where $\widehat{EPart}_t$ is the imputed value from the four-missing-value series with $EPart_t$ as the fourth "missing" value.

Since all three imputation methods ultimately yielded similar results, we focus on Kalman filtration models in the main body of this paper, with linear and spline imputation models serving as a proof of results' robustness to variation in imputation method.

After obtaining estimates of imputation inaccuracy to accompany the estimator-conditional means for each missing datapoint, we are able to parameterize a generation process for additional plausible imputed values. For each needed estimate of $EPart_t|\theta$, we match a beta distribution to its estimated mean, $\widehat{EPart}_t$, and standard deviation, σ. That is,

$$EPart_t|\theta \sim Beta(\alpha, \beta) * 100, \tag{7}$$

where α, β are chosen to parameterize a beta distribution with expected value $\widehat{EPart}_t/100$ and variance $\sigma^2/10{,}000$. This rescaling is necessary because, while the beta distribution ranges between 0 and 1, the equity participation series is measured in percentage points and could range 0 to 100. For example, an index value of 24.7 indicates that 24.7 percent of households own equity. We focus on the beta distribution because it, like the series of interest, is bounded. It can therefore

[5] The seventh data point is excluded from being treated as missing since this would create a sequence of three missing values very close to a region where the series trend changes significantly, but we do allow other sequences of three consecutive missing values. Results are robust to variation in the data points, which can be treated as missing to calculate imputation variance.

likely match the series better than a normal distribution, though we have also run models with distribution draws based on the normal distribution $EPart_t|\theta \sim N(\widehat{EPart}_t, \sigma^2)$. These models produced qualitatively similar results. For convenience, the standard equations for a beta distribution's mean and variance in terms of its parameters are provided in Appendix E. To derive the beta distribution parameters, we solve these equations with the appropriate values substituted for mean and variance for each rescaled $EPart_t|\theta$. α and β vary depending on the time- and imputation-method specific "mean" $\widehat{EPart}_t$, and depending on σ, which is constant for all parameterizations within a high-variance or (conditional on imputation method) tighter-variance run of our models.

We next estimate ARDL models using eq. (3) over a variety of plausible completed datasets and average the results. Each dataset is completed by making an independent random draw from the distribution, conditioned on θ, for each missing value of the equity participation series.[6] For each choice of imputation estimator θ and each of the two variance estimates, we generated two sets of 800 completed datasets for each of the 18 ARDL models presented. For each completed dataset, we estimate an ARDL model and record the coefficients, standard errors, and model suitability test statistics (Durbin-Watson, max-lambda, and trace statistics, as well as adjusted R^2). Standard errors are adjusted for between-dataset variation within each block of 800 plausible completed datasets, using an adaptation of the method described in Reiter and Raghunathan (2007) for small-sample multiple imputation. We also apply Reiter and Raghunathan-style penalties to the allowed degrees of freedom in t-distributions for significance testing. Coefficients, non-adjusted error variance, and model suitability test statistics are averaged across completed datasets within the block; then both they and the adjusted error variances are averaged across the two blocks

[6] Since the draws are software generated, we check robustness to changes in the random seed.

of 800 completed datasets. Due to how the adjusted standard errors are calculated, there may be a slight penalty (biasing the coefficients towards insignificance) for adjusting within multiple smaller blocks rather than one larger block.

We report Durbin-Watson, max-lambda, and trace statistics, as well as adjusted R-squares, averaged across 1600 model runs for both tighter and upper-bound variance specifications. Due to the presence of a lagged dependent variable in the models, the information from Durbin-Watson statistics was checked against Durbin's h whenever possible. The two statistics agreed in all cases examined. Durbin's h is not reported for all models because some specifications have too large of coefficient variance on the lagged dependent variable for h to be used.

The imputed stock ownership rates for the "missing" years of 1973, 1980, and 1986 are very similar using the three basic imputation methods. For purposes of illustration, Figure 2 plots the imputed values along with actual observations using the preferred model (Kalman filter using *UGAPSq* as a short-run background labor risk variable), which is discussed in Section IV.

IIIC. (Risk) Factors Other Than Mutual Fund Costs that May Drive Stock Ownership

Several other plausible factors affecting stock ownership include relative expected returns on stocks, households' tolerance for investment risk, and labor income risk, all of which are stationary and enter as lagged levels (members of the *X* vector in eq. (3)). The first and second factors can be tracked by a measure of the equity premium, for which we tested several. One is Damodaran's (2013) implied equity risk premium (*Eprem*) series, which uses analysts' expectations to form free cash flow estimates of S&P 500 returns relative to the Treasury bill rate and thus is more forward-looking that historical equity risk premium measures. Another stock

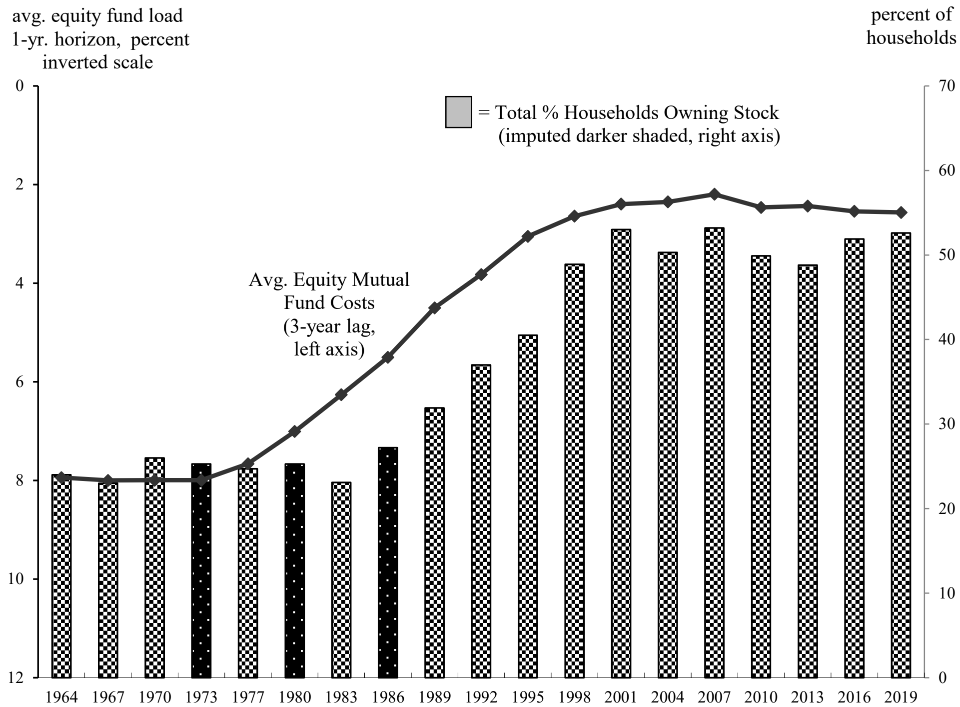

Figure 2: Actual and Imputed Triennial Readings on the U.S. Stock ownership Rate
(Sources: Various Surveys of Consumer Finance and authors' calculations)

market-based risk factor examined is a proxy for volatility, the standard deviation of the daily returns on the Dow Jones Industrial Average over a year (*Volality*), which plausibly could have a negative short-run effect on stock ownership. While not as comprehensive as broader measures, such as the VIX, these data are consistently available into the 1960s.

An alternative to a gauge of the equity risk premium is the overall index of consumer sentiment (*Con*) and its subindex of sentiment about the future (*Conexp*) from the University of Michigan Survey of consumer sentiment. In addition, its subcomponents can separately track household assessments of labor income risk and of future family finances. Labor risk is reflected in household assessments of whether jobs are currently plentiful or hard to get (*Conjob*). Variation in household tolerance for taking financial risk is tracked by the University of Michigan index of households' assessment of their family's future financial condition (*ConExpFn*). For each, more optimistic views are reflected in higher readings (1966=100, Figure 3).[7] While *Conjob* reflects background labor risk, while *ConExpFin* may be more reflective of shifts in discount rates and *Con* likely includes information from both, it is an empirical issue which index better aligns with stock ownership. To conserve space, the tables report results using *Con,* Con*exp*, and *Conjob* which outperformed *ConExpFin*. In models not shown, these sentiment measures outperformed statistically insignificant bond yield spreads, including those between *Baa-* and Aaa-rated corporate bonds and the *Baa* corporate and 10-year Treasury bond yields. As with equity premia measures, it is hard to disentangle how *ConfExp* reflects the effects of risk assessments or shifts in discount rates from those of fundamentals about future income or profit expectations. In addition, *ConfExp* may also reflect household assessments of background labor risk insofar as their answers may reflect perceptions of how robust their wealth and debt positions are to future economic

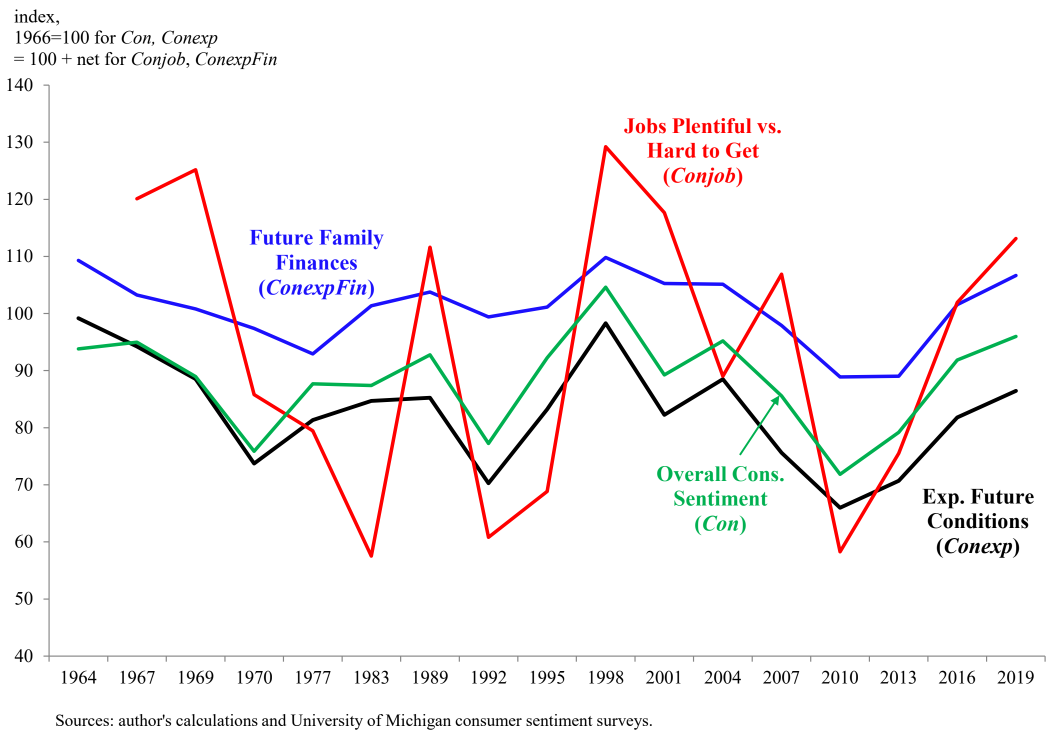

Figure 3: Consumer Confidence Measures Considered
(sources: University of Michigan Survey Research Center and author calculations)

[7] Unlike the Baker-Wurgler (2006) index, *EXPFIN* is nonstationary and can help estimate long-run trends.

shocks. Nevertheless, this index, as with the equity risk premium, can track the combined effect of standard factors, whose movements differ from the trends in mutual fund costs.

Finally, we try to proxy for background labor market risk with the gap (*UGap*) between the actual civilian (H-3) unemployment rate and the CBO's estimate of the noncyclical rate (the "natural rate") of unemployment. This gap abstracts from trends in the unemployment rate associated with trends in demographics (e.g., age and education characteristics of the labor force). Since *UGap* should be increasing in household labor risk, the analysis of Heaton and Lucas (2000) suggests that *UGap* should be negatively associated with stock ownership. The tendency for the unemployment rate to swing half as much as the GDP output gap (Okun's Law) suggests that the risk to labor income could be nonlinear in *UGap* (see Bordo and Duca, 2022). Hence, we also test a specification using *UGap* multiplied by its absolute value ($UGapSq \equiv UGap \times |UGap|$). *UGap* and *UgapSq* are plotted in Figure 4 and have a negative correlation with *Conjob*. A last measure is the output gap (*GDPGap*), calculated as the difference between actual and potential GDP (CBO estimates) scaled by potential GDP. This is similar to the Hodrick-Prescott-based measure of Morelli (2021), who stresses that stock ownership has been procyclical since 1998 (which is after major increases that we find are linked to earlier declines in mutual fund costs).

IIID. Tracking Mutual Fund Costs

Because data before the mid-1980s are sketchy and incomplete, mutual fund costs are based on a sample of large mutual funds (Appendix B). Funds were selected if their assets were at least $1 billion at year-end 1991 if the fund existed before the mid-1980s; were at least $2 billion at year-end 1994 if the fund's inception date occurred after 1983; were at least $5 billion at year-end 2003; or were at least $250 million at year-end 1975. The third criterion reflects whether a fund remained large following the stock market bust of the early 2000s. Given the stock and bond appreciation of the early 1990s, the hurdles for newer funds were higher for the 1994 and 2003

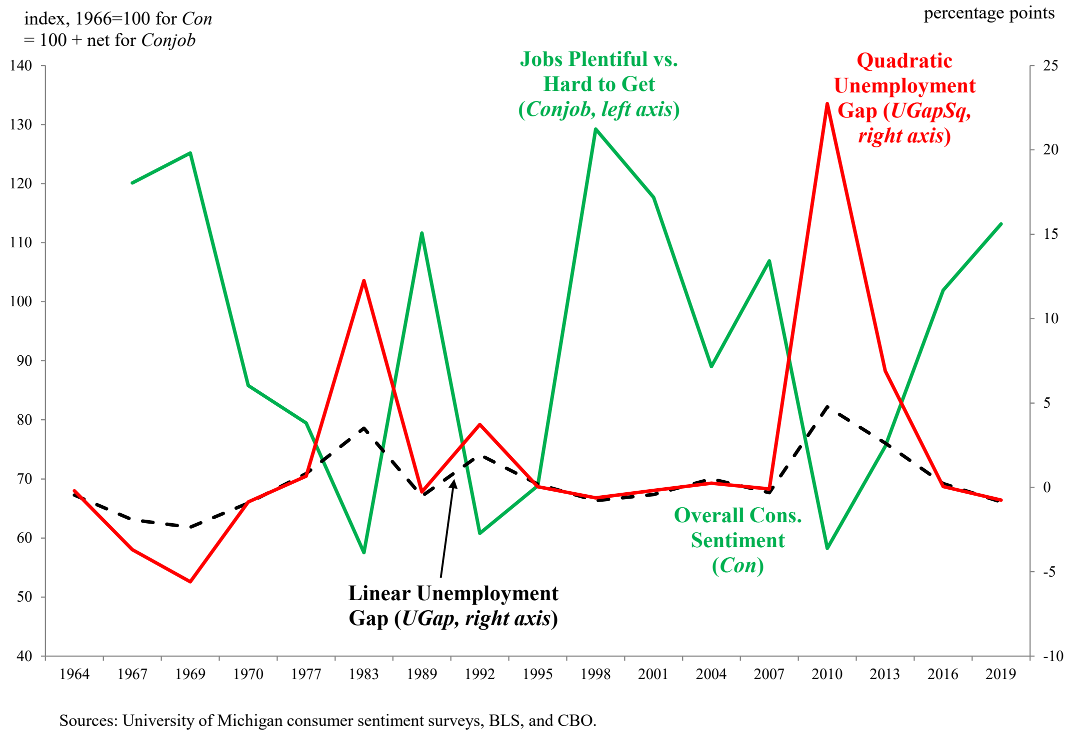

Figure 4: Unemployment Gap Measures of Background Labor Risk
(Sources: CBO, U. Michigan SRC, Bureau of Labor Statistics, and authors' calculations)

cutoff dates to keep data gathering costs from exploding. The fourth criterion avoids excluding funds that were relatively large in 1975 from distorting averages when fewer funds existed. Also excluded were funds that were closed-end, only open to employees of a specific firm, or institutional. One member, the Windsor Fund, became closed-end but was included because its open-end cousin (Windsor II) was started when it became closed-end, and both funds are large. Also omitted are funds with high minimum balances ($100,000 or more) because such high hurdles make such funds less reflective of extensive margin decisions facing middle- and low-income households. 133 equity mutual funds are in the sample (a list is available) using data from funds and various issues of Morningstar, IBC/Donoghue, and CDA/Wiesenberger (a, b).

Four measures of stock mutual fund loads were constructed. *SLoad1* is the average load on stock funds held over a one-year horizon, which counts any front-end load plus any back-end load for withdrawals within 1 year of purchasing a fund. Because fund managers may alter expense ratios along with loads to raise fees from investors, another measure adds the annual expense ratio to the one-year horizon to form an expense-adjusted load (*SELoad1*). Because many investors have longer horizons, such as 5 years, two five-year horizon measures (*SLoad5* and *SELoad5*) were created that annualize the sum of any front-end load and a back-end load for withdrawals within years 4 and 5 following a purchase). As discussed in Duca (2005, 2006), *SELoad1* and *SELoad5* behave very similarly with the annual, industry-side, overall equity fund cost estimates of Rea and Reid (1998, 1999). Which load series best predicts stock ownership is an empirical issue. In general, the measure using a 1-year horizon without an expense ratio adjustment (*SLoad1*) yielded the best fitting and most sensible models of household equity participation.

Each of the load series leads stock ownership rates by about three years. Because of the limited number of irregularly spaced observations on stock ownership rates, it is infeasible to incorporate long lag structures in the estimation of long-run coefficients. Accordingly, the long run vectors were estimated using the t-3 lag of log mutual fund costs with an appropriately timed first difference term of mutual fund costs for each. Of these, a lag of 3 yielded the best combination of evidence of cointegration, clean residuals, statistically significant long-run coefficients, and yielded sensible estimates of the speed of adjustment.

IIIE. Calculating Standard Errors with Some Imputed Values of Stock Ownership

Because three of the nineteen stock ownership readings are imputed, standard errors on the coefficients need to be adjusted, for which we investigated three methods. As a lower bound set of standard error estimates, the first method treats the imputed values as wholly accurate estimates of the participation series' value at the time of imputation. For these estimates, we do not generate or average across multiple plausible completed datasets. The second method estimates standard errors based on method-specific inaccuracy. Our missing values are functionally missing at random (i.e., not missing for reasons related to the level of equity participation at the time).

Thus, the typical inaccuracy of an imputation method when used to "impute" a value that is not actually missing, conditional on observed data aside from that value, should be representative of its inaccuracy when used for actually-missing data points. This method provides a plausible set of standard errors. For this method, we generate 1600 completed datasets per model of interest and method of imputation, averaging estimates across these datasets and increasing standard error estimates to reflect between-dataset variation. Our third method of calculating standard errors uses similar averaging and adjustment across 1600 plausible completed datasets per model of interest and imputation method, but this method assumes that our imputed values are, on average, much less accurate. This third method uses the variance of stock ownership over the entire sample (1964-2019) as an upper-bound estimate for the variance between our imputed values and actual series values at a given point in time. The upper bound is loose: using the series mean for all "best guess" imputation values would have this expected variance. We report results for imputation based on the Kalman filter using all three estimates of imputation inaccuracy—no inaccuracy; some inaccuracy; and an overestimate of inaccuracy. Results using linear and spline imputation as a base are qualitatively similar; some are presented in Appendix D and others are available upon request.

IV. Empirical Findings

The main tables report results using a Kalman imputation of the three missing triennial observations, while the Appendix tables report results using the spline and simple linear interpolations, which yielded similar findings. Results favored using mutual fund loads over a one-year horizon. Tables 3 and 4 report results using the mutual fund load series *SLoad1* and *SELoad1*, respectively, across nine versions of eq. (3) using the middle-case estimate of standard errors. Tables 5 and 6 correspond to Tables 2 and 3 except that they use the upper bound S.E. estimates, while the narrowest bands are used in Tables 7 and 8. Model 1 is a baseline model that omits any controls for background labor risk or the equity risk premium, for which the remaining models include one control, each of which is dated at time t. (Lagged measures of risk variables were generally insignificant or less significant.) The next four models focus on background labor market risk, with Models 2-5 adding *UGap, UGapSq*, *GDPGap*, and ln (*Conjob*), respectively. Instead, Models 6 and 7 include the overall consumer sentiment index and the index of expected future conditions, respectively, while Models 8 and 9 only add *Eprem* and *Volatility*, respectively.

There are several noteworthy patterns in the long-run relationships across Tables 3 through 8. First, the trace and max-eigenvalue statistics imply that in all but one case, a unique and statistically significant cointegrating long-run relationship is identified. The exception is Model 2 in Table 2, which uses *Sload1* and *Ugap* to track mutual fund costs and labor risk, respectively.[8] In this model, the statistics rejected that at most one significant vector existed. Second, the lagged level of the stock ownership rate is statistically significant with a negative sign, implying that equity participation changes tend to close the gap between actual and equilibrium equity participation rates and at a speed equal to the third root of the absolute value of the coefficient on $StockOwn_{t-1}$. Third, each load term has a significant and negative long-run relationship, implying that lower mutual funds induce higher stock ownership, consistent with the implications of the theoretical frameworks of Heaton and Lucas (2000) and (Liu, 2004). The lagged log level and its lagged first difference are jointly significant, indicating that stock ownership is not weakly exogenous to mutual fund loads.

Results are less uniform for the impact of short-run risk factors on stock ownership; these display several patterns. First, in the tables using the lower bound and preferred sets of standard errors, (3, 4, 7 and 8), the unemployment gap is always significant, with the expected negative sign. In addition, as reflected in the higher R-square across the models in each of these tables,

[8] In other regressions (see Appendix Table D5) that added the CPI inflation rate, a significant and unique long-run relationship was found in all models and all other results held, but the inflation rate was statistically insignificant.

UGap adds more marginal information (Model 2) than other short-run risk factors, especially the statistically significant output gap (Model 4), the quadratic version of *UGap* (Model 3), and the logged index of consumer assessments of the job market (*Conjob*). As all of these terms reflect background labor risk, they provide support for the emphasis that Heaton and Lucas (2000) place on labor risk. In contrast, the broader measures of overall and future consumer sentiment (*Con* and *Conexp*, respectively), volatility (*Volality*) and—with one exception—the equity premium are always insignificant, irrespective of how standard errors are calculated.[9] With the exception of the volatility measure, the estimated short-run risk coefficients have the expected signs. Together, evidence on risk factors favors the view that variation in background labor risk—and not some much overall expectations or equity risk premia—can have important short-run effects on stock ownership. Overall, models using *UGapSq* perform well, yielding high R-squares, clean residuals, and unique and significant cointegrating vectors with sensible signs.

The qualification to this overview of findings about short-run factors is that none of the short-run risk factors are statistically significant when the widest estimates of standard error bands are applied in contrast to the lagged level of mutual fund loads. Nevertheless, there are good reasons why the set of standard error estimates are too wide, as discussed earlier. That said, a very skeptical interpretation of the findings is that the only truly robust result is that only mutual fund loads have a significant effect on stock ownership rates in time series.

Of the models that implied a unique and significant cointegrating vector, the one using *Sload1* and *UGapSq* (Model 3, Table 3) has a nice combination of a high fit with little evidence of serial correlation in the residuals. As show in Figure 5, the implied long-run equilibrium value from this model plus the estimated short-run effect of *UGapSq* tracks the stock ownership rate

[9] The one exception for *Eprem* is the unrealistic case of treating imputed stock ownership readings as certain using expense-ratio adjusted loads, and *Eprem* is only marginally significant (90% confidence level) in this case.

over the past six decades. Overall, the estimates favor an unemployment-based measure of background labor risk and support Heaton and Lucas' view that labor risk is a key determinant of stock ownership. These patterns hold using the spline and linear imputation alternatives (see Appendix D). Table 9 provides the long-run equilibrium relationships and the implied annual speeds of adjustment from the models in Table 3. For the preferred Model 3, a one percent rise in mutual fund loads lowers long-run stock ownership by approximately 0.64 percent, with an annualized speed of adjustment of approximately 37 percent.

IVB. Proxying Missing Annual Equity Participation Rates with Simulation Results

Earlier literature on equity participation found that stock ownership rates were lower than implied by basic theory. At the same time, annual readings on the stock ownership rate have risen over time, and in line with empirical models, which incorporate asset transfer costs involving mutual funds. Rather than interpolate missing annual readings between irregularly estimated stock ownership rates from various SCFs, missing annual readings can be simulated using the estimated coefficients from the preferred Model 3 from Table 3 in conjunction with actual annual values of mutual fund costs (*SLoad1*) and the quadratic unemployment gap (*UgapSq*). The resulting annual series on stock ownership rates from this model are similar to the triennial estimates plotted in Figure 5. They are listed in Appendix C and are available for use with attribution.

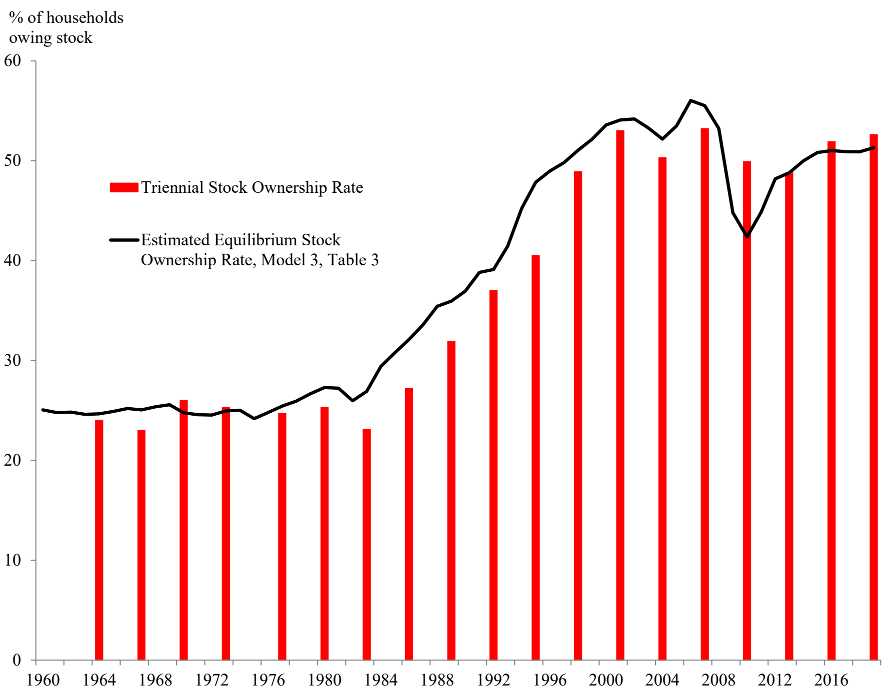

Figure 5: Stock Ownership Rates in Line with Equilibrium Levels Implied by Mutual Fund Costs and Background Labor Risk (Sources: SCF, BLS, and authors' calculations)

V. Concluding Comments and Future Research

This study addresses two gaps in the literature. First, it finds a significant and economically substantial long-run role for variation in asset transfer costs—specifically, the one-year horizon mutual fund loads—in empirical models of equity participation rates. This result is consistent with calibration studies stressing how asset transfer costs influence asset participation (Heaton and Lucas, 2000, and Gomes and Michaelides 2005, *inter alia*) and portfolio choice and composition (Liu and Lowenstein, 2002 and Liu, 2004, *inter alia*). Further increases in equity participation may need to stem from other factors than changes to fund loads, as loads are currently low and may remain so. However, decreasing other sources of transfer costs could broaden future equity participation. For example, automatic enrollment in employer thrift plans—which reduces time and search costs on individuals desiring to transfer assets into equity—has been shown to increase equity participation in individual-level studies (Cribb and Emmerson, 2021, Madrian and Shea, 2001, and Goldin, et al., 2017). Indeed, Yogo et al. (2022) estimate that making employer thrift plans more available would notably increase retirement saving among lower-income middle-aged households.

Results also support a short-run role for labor market risk or slack, as tracked by the gap between the headline unemployment rate and its natural rate, the GDP output gap, or by household assessments of current labor market conditions. In contrast, the measures of the equity premium and stock price volatility did not add significant information. Overall, the time series findings regarding risk premia, expectations, slack, and labor market variables favor Heaton and Lucas' (2000) emphasis on background labor market risk as a determinant of stock ownership and Morelli's (2021) view that stock ownership rates are procyclical. That said, the short-run impacts of labor market risk and slack are not as robust as the long-run effect of mutual fund loads.

This study also addresses another gap in the literature. In particular, the long-run coefficient estimates from the preferred model along with annual mutual fund and unemployment rate data can provide simulated readings on annual stock ownership rates. Such readings could be used in time series studies of stock portfolio, net worth, consumption, and GDP, and could aid research involving the calibration of equity participation or the undertaking of case studies. In addition to providing simulated equity participation series readings, we illustrate methods for robust inference with the existing irregularly spaced participation data that could be applicable to other studies and other economically relevant irregularly spaced series.

Table 2: Unit Root Tests

19 1964 – 2019 Observations

Variable	Dickey-Fuller GLS (ERS) statistic	Reject Unit Root?	KPSS statistic	Reject Stationarity?
ln$STOCKOWNKF_t$	-0.9250	No	0.5240^{**}	Yes
Δln$STOCKOWNKF$	-2.8486^{**}	Yes	0.1217	No
ln$STOCKOWNLin_t$	-0.9018	No	0.5214^{**}	Yes
Δln$STOCKOWNLin_t$	-2.9255^{**}	Yes	0.7390	No
ln$STOCKOWNSpl_t$	-1.0633	No	0.5214^{**}	Yes
Δln$STOCKOWNSpl_t$	-2.5693^{**}	Yes	0.1155	No
ln$SLOAD1_t$	-2.5948^{**}	Yes	0.5153^{**}	Yes
Δln$SLOAD1_t$	-2.0836^{**}	Yes	0.2069	No
ln$SELOAD1_t$	-0.8850	No	0.5268^{**}	Yes
Δln$SELOAD1_t$	-2.6787^{**}	Yes	0.1970	No
$Ugapsq_t$	-3.5147^{***}	Yes	0.1873	No
lnCon_t	-3.3151^{***}	Yes	0.0897	No
ln$Conexp_t$	-3.3606^{***}	Yes	0.0724	No
ln$Conjob_t$	-3.1326^{***}	Yes	0.1105	No
$GDPgap_t$	-3.2922^{***}	Yes	0.2507	No
$EPrem_t$	-1.6436^{***}	Yes	0.1769	No
Volatility	-3.5270^{***}	Yes	0.2890	No

, * denote significant at the 95 and 99 % confidence levels.

56 Continuous Annual 1964 – 2019 Observations

Variable	Phillips-Perron Statistic	Reject Unit Root?	KPSS statistic	Reject Stationarity?
ln$SLOAD1_t$	-1.0544	No	0.8125^{**}	Yes
Δln$SLOAD1_t$	-3.5844^{***}	Yes	0.2933	No
ln$SELOAD1_t$	-0.9632	No	0.8302^{**}	Yes
Δln$SELOAD1_t$	-3.7956^{***}	Yes	0.2815	No

Table 3: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*; Kalman Imputation)

Model: $\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$

Model #	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	ln(*Conjob*)	ln(*Con*)	ln(*Conexp*)	*Eprem*	*Volatility*
lnStockOwn(t-1)	-0.912**	-1.142**	-1.203**	-1.096**	-1.051**	-0.862*	-0.851*	-0.757*	-0.832*
Averaged SE	(0.319)	(0.242)	(0.268)	(0.289)	(0.268)	(0.319)	(0.321)	(0.335)	(0.338)
Corrected SE	(0.379)	(0.321)	(0.350)	(0.358)	(0.328)	(0.375)	(0.387)	(0.388)	(0.380)
Eff. df (t-dist.)	7.4	5.3	5.5	6.1	6.3	6.8	6.5	7.0	7.4
ΔlnStockOwn(t-1)	0.221	0.208	0.304	0.132	0.204	0.211	0.217	0.109	0.168
Averaged SE	(0.228)	(0.163)	(0.177)	(0.195)	(0.188)	(0.231)	(0.231)	(0.241)	(0.250)
Corrected SE	(0.270)	(0.201)	(0.211)	(0.223)	(0.230)	(0.259)	(0.260)	(0.276)	(0.293)
Eff. df (t-dist.)	7.4	6.2	6.6	7.2	6.3	7.5	7.4	7.2	6.8
lnSLoad(t-1)	-0.584**	-0.737**	-0.774**	-0.710**	-0.643**	-0.538*	-0.534*	-0.482*	-0.538*
Averaged SE	(0.200)	(0.153)	(0.170)	(0.184)	(0.166)	(0.202)	(0.203)	(0.211)	(0.209)
Corrected SE	(0.238)	(0.211)	(0.225)	(0.230)	(0.208)	(0.238)	(0.246)	(0.246)	(0.238)
Eff. df (t-dist.)	7.3	5.0	5.4	6.0	6.0	6.8	6.4	6.9	7.3
ΔlnSLoad(t-1)	0.411	0.766*	0.939*	0.601	0.646	0.430	0.410	0.426	0.298
Averaged SE	(0.434)	(0.335)	(0.389)	(0.384)	(0.371)	(0.439)	(0.434)	(0.427)	(0.467)
Corrected SE	(0.471)	(0.368)	(0.431)	(0.422)	(0.397)	(0.464)	(0.461)	(0.455)	(0.494)
Eff. df (t-dist.)	8.9	7.8	7.7	7.8	8.3	8.4	8.3	8.3	8.4
S-Run Risk variables		-0.0299**	-0.00786**	0.0206*	0.168**	0.137	0.118	-0.125	5.878
Averaged SE		(0.00887)	(0.00276)	(0.00878)	(0.0662)	(0.177)	(0.158)	(0.103)	(9.005)
Corrected SE		(0.00933)	(0.00288)	(0.0101)	(0.0691)	(0.220)	(0.210)	(0.111)	(9.468)
Eff. df (t-dist.))		8.5	8.6	7.1	8.6	6.1	5.4	8.2	8.5
Constant	4.108**	5.175**	5.452**	4.975**	3.943**	3.257	3.307	3.023	3.704*
Averaged SE	(1.423)	(1.083)	(1.201)	(1.295)	(1.166)	(1.692)	(1.678)	(1.635)	(1.526)
Corrected SE	(1.690)	(1.444)	(1.572)	(1.608)	(1.442)	(2.094)	(2.169)	(1.894)	(1.719)
Eff. Df (t-dist.)	7.4	5.3	5.5	6.1	6.2	6.2	5.6	7.0	7.4
DW test stat.	1.820	2.268	2.140	1.969	2.087	1.900	1.907	2.058	1.698
Max λ, H_0: zero cointegrating vectors	19.255	23.502	24.473	20.627	20.372	20.448	20.482	18.184	21.814
Max λ, H_0: at most 1 cointegrating vector	4.290	10.192	7.700	8.755	3.441	2.787	3.039	3.165	5.020
Trace stat., H_0: zero cointegrating vectors	23.545	33.693	32.173	29.382	23.813	23.235	23.521	21.349	26.834
Trace stat., H_0: at most 1. Cointegrating vector	4.290	10.192	7.700	8.755	3.441	2.787	3.039	3.165	5.020
Adj. R^2	0.490	0.741	0.698	0.643	0.660	0.492	0.497	0.514	0.467

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 4: Models of U.S. Stock Ownership 1970-2019

(Stock loads expense ratio-adjusted (*SELOAD1)*; Kalman Imputation)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	ln(*Conjob*)	ln(*Con*)	ln(*Conexp*)	*ln(Eprem)*	*Volatility*
lnStockOwn(t-1)	-0.870*	-1.106**	-1.135**	-1.052**	-1.030**	-0.832*	-0.819*	-0.729	-0.832*
Averaged SE	(0.335)	(0.264)	(0.290)	(0.298)	(0.289)	(0.340)	(0.335)	(0.340)	(0.340)
Corrected SE	(0.390)	(0.333)	(0.362)	(0.368)	(0.343)	(0.395)	(0.396)	(0.387)	(0.384)
Eff. df (t-dist.)	7.7	5.9	6.0	6.2	6.7	7.0	6.8	7.2	7.4
ΔlnStockOwn(t-1)	0.230	0.219	0.327	0.133	0.228	0.211	0.235	0.0956	0.168
Averaged SE	(0.249)	(0.183)	(0.203)	(0.212)	(0.209)	(0.254)	(0.252)	(0.253)	(0.259)
Corrected SE	(0.301)	(0.229)	(0.245)	(0.246)	(0.260)	(0.291)	(0.289)	(0.298)	(0.317)
Eff. df (t-dist.)	7.1	6.0	6.4	7.0	6.1	7.2	7.1	6.8	6.3
lnSLoad(t-1	-0.677*	-0.869**	-0.887**	-0.830**	-0.764**	-0.630*	-0.623*	-0.566*	-0.654*
Averaged SE	(0.255)	(0.203)	(0.223)	(0.231)	(0.218)	(0.262)	(0.257)	(0.259)	(0.258)
Corrected SE	(0.295)	(0.263)	(0.278)	(0.285)	(0.262)	(0.303)	(0.303)	(0.297)	(0.292)
Eff. df (t-dist.)	7.8	5.6	6.1	6.1	6.5	7.0	6.8	7.2	7.4
ΔlnSLoad(t-1)	0.381	0.813	0.986	0.576	0.712	0.419	0.412	0.439	0.288
Averaged SE	(0.582)	(0.461)	(0.527)	(0.505)	(0.510)	(0.594)	(0.585)	(0.563)	(0.592)
Corrected SE	(0.642)	(0.506)	(0.588)	(0.562)	(0.551)	(0.636)	(0.628)	(0.612)	(0.640)
Eff. df (t-dist.)	8.5	7.8	7.6	7.6	8.1	8.2	8.2	8.0	8.1
S-Run Risk variables (t)		-0.0294**	-0.00730**	0.0211*	0.167**	0.143	0.117	-0.142	7.876
Averaged SE		(0.00916)	(0.00280)	(0.00881)	(0.0684)	(0.179)	(0.161)	(0.0966)	(8.604)
Corrected SE		(0.00964)	(0.00296)	(0.0102)	(0.0717)	(0.222)	(0.210)	(0.102)	(9.079)
Eff. df (t-dist.)		8.5	8.4	7.1	8.6	6.1	5.5	8.4	8.5
Constant	4.199*	5.379**	5.514**	5.125**	4.169**	3.361	3.425	3.081	3.953*
Averaged SE	(1.603)	(1.267)	(1.393)	(1.435)	(1.346)	(1.884)	(1.827)	(1.732)	(1.633)
Corrected SE	(1.864)	(1.606)	(1.739)	(1.769)	(1.609)	(2.298)	(2.309)	(1.972)	(1.842)
Eff. df (t-dist.)	7.7	5.9	6.0	6.2	6.6	6.3	5.9	7.3	7.4
DW test stat.	1.852	2.316	2.171	2.102	2.120	1.937	1.954	2.195	1.738
Max λ, H_0: zero coint. vectors	17.671	21.744	22.865	20.447	19.605	19.816	19.829	16.697	18.010
Max λ, H_0: at most 1 coint. vector	3.546	7.892	5.864	6.507	2.570	2.516	2.706	2.979	4.413
Trace stat., H_0: zero coint. vectors	21.217	29.635	28.729	26.955	22.175	22.332	22.535	19.676	22.423
Trace stat., H_0: at most 1 coint. vector	3.546	7.892	5.864	6.507	2.570	2.516	2.706	2.979	4.413
Adj. R^2	0.471	0.718	0.660	0.636	0.639	0.476	0.477	0.525	0.473

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 5: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*; Kalman Imputation; High variance)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	ln(Conjob)	*ln(Con)*	*ln(Conexp)*	*ln(Eprem)*	*Volatility*
lnStockOwn(t-1)	-1.312**	-1.415**	-1.412**	-1.394**	-1.350**	-1.266*	-1.252*	-1.314*	-1.289*
Averaged SE	(0.393)	(0.414)	(0.416)	(0.404)	(0.410)	(0.406)	(.400)	(0.431)	(0.416)
Corrected SE	(0.509)	(0.506)	(0.510)	(0.533)	(0.510)	(0.532)	(0.546)	(0.561)	(0.532)
Eff. df (t-dist.)	6.2	6.3	6.3	5.4	6.1	5.5	5.1	5.6	5.8
ΔlnStockOwn(t-1)	0.171	0.197	0.211	0.147	0.172	0.130	0.166	0.154	0.160
Averaged SE	(0.255)	(0.254)	(0.256)	(0.245)	(0.265)	(0.279)	(0.273)	(0.271)	(0.271)
Corrected SE	(0.367)	(0.353)	(0.361)	(0.355)	(0.375)	(0.365)	(0.375)	(0.369)	(0.382)
Eff. df (t-dist.)	5.0	4.9	4.7	4.5	4.7	5.5	5.0	5.1	4.7
lnSLoad(t-1)	-0.918*	-0.996*	-0.985*	-0.975*	-0.922*	-0.855*	-0.851*	-0.906*	-0.904*
Averaged SE	(0.293)	(0.312)	(0.313)	(0.303)	(0.305)	(0.302)	(0.298)	(0.312)	(0.307)
Corrected SE	(0.410)	(0.427)	(0.407)	(0.418)	(0.424)	(0.420)	(0.418)	(0.433)	(0.425)
Eff. df (t-dist.)	5.3	5.0	5.6	5.0	4.9	4.8	4.8	4.9	4.9
ΔlnSLoad(t-1)	0.719	1.011	1.064	0.850	0.886	0.742	0.794	0.983	0.686
Averaged SE	(0.995)	(0.977)	(1.056)	(0.898)	(1.020)	(0.987)	(0.975)	(1.132)	(0.963)
Corrected SE	(1.066)	(1.142)	(1.220)	(1.111)	(1.182)	(1.110)	(1.087)	(1.253)	(1.090)
Eff. df (t-dist.)	7.9	6.9	7.1	6.2	7.0	7.5	7.6	7.7	7.4
S-Run Risk variables (t)		-0.0355	-0.00793	0.0222	0.176	0.200	0.277	-0.150	0.578
Averaged SE		(0.0431)	(0.0125)	(0.0338)	(0.307)	(0.667)	(0.593)	(0.365)	(31.029)
Corrected SE		(0.0529)	(0.0137)	(0.0576)	(0.347)	(1.011)	(0.940)	(0.440)	(34.040)
Eff. df (t-dist.)		6.2	7.9	3.2	7.4	4.1	3.8	6.5	7.8
Constant	5.975**	6.486**	6.466**	6.383**	5.331	4.846	4.473	5.505	5.870*
Averaged SE	(1.775)	(1.887)	(1.902)	(1.846)	(2.148)	(3.510)	(3.198)	(2.303)	(1.916)
Corrected SE	(2.292)	(2.304)	(2.305)	(2.402)	(2.804)	(5.365)	(5.019)	(3.056)	(2.455)
Eff. df (t-dist.)	6.2	6.3	6.4	5.6	5.5	4.0	3.8	5.3	5.7
DW test stat.	2.126	2.271	2.210	2.228	2.192	2.056	2.063	2.238	2.101
Max λ, H_0: zero cointegrating vectors	15.555	16.027	16.120	17.213	15.626	15.772	16.121	15.330	15.670
Max λ, H_0: at most 1 cointegrating vector	4.218	5.986	5.724	5.130	2.459	3.585	3.766	3.982	4.575
Trace stat., H_0: zero cointegrating vectors	20.040	22.089	21.942	22.938	17.935	19.478	20.086	19.307	20.245
Trace stat., H_0: at most 1 cointegrating vector	4.299	5.969	5.753	5.473	2.597	3.612	3.773	3.998	4.575
Adj. R^2	0.533	0.570	0.546	0.601	0.544	0.548	0.553	0.514	0.507

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 6: Models of U.S. Stock Ownership 1970-2019

(Stock loads expense ratio-adjusted (*SELOAD1)*; Kalman Imputation; High variance)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	*ln(Conjob)*	*ln(Con)*	*ln(Conexp)*	*ln(Eprem)*	*Volatility*
lnStockOwn(t-1)	-1.349**	-1.407**	-1.408**	-1.387*	-1.334**	-1.242*	-1.248*	-1.332*	-1.306*
Averaged SE	(0.401)	(0.423)	(0.422)	(0.408)	(0.415)	(0.410)	(0.406)	(0.434)	(0.415)
Corrected SE	(0.534)	(0.530)	(0.531)	(0.544)	(0.524)	(0.543)	(0.565)	(0.581)	(0.545)
Eff. df (t-dist.)	5.8	6.0	6.0	5.3	5.9	5.4	4.9	5.3	5.5
ΔlnStockOwn(t-1)	0.192	0.192	0.213	0.145	0.177	0.124	0.168	0.161	0.177
Averaged SE	(0.259)	(0.259)	(0.262)	(0.248)	(0.268)	(0.281)	(0.277)	(0.272)	(0.270)
Corrected SE	(0.372)	(0.367)	(0.372)	(0.360)	(0.383)	(0.377)	(0.384)	(0.375)	(0.391)
Eff. df (t-dist.)	5.0	4.7	4.7	4.4	4.6	5.2	4.9	5.0	4.5
lnSLoad(t-1	-1.142*	-1.210*	-1.199*	-1.176*	-1.096*	-1.031	-1.023	-1.134*	-1.109*
Averaged SE	(0.361)	(0.391)	(0.387)	(0.373)	(0.373)	(0.372)	(0.363)	(0.386)	(0.374)
Corrected SE	(0.505)	(0.530)	(0.509)	(0.511)	(0.529)	(0.513)	(0.510)	(0.560)	(0.515)
Eff. df (t-dist.)	5.3	5.1	5.5	5.0	4.7	4.9	4.8	4.5	5.0
ΔlnSLoad(t-1)	0.744	1.084	1.125	0.897	0.967	0.762	0.853	1.118	0.688
Averaged SE	(1.200)	(1.331)	(1.380)	(1.193)	(1.352)	(1.317)	(1.270)	(1.476)	(1.236)
Corrected SE	(1.435)	(1.635)	(1.656)	(1.504)	(1.652)	(1.519)	(1.437)	(1.655)	(1.465)
Eff. df (t-dist.)	7.3	6.2	6.5	5.9	6.3	7.1	7.4	7.5	6.7
S-Run Risk variables (t)		-0.0347	-0.00716	0.0248	0.177	0.198	0.257	-0.183	4.204
Averaged SE		(0.0447)	(0.0124)	(0.0344)	(0.307)	(0.666)	(0.577)	(0.351)	(30.431)
Corrected SE		(0.0559)	(0.0137)	(0.0566)	(0.356)	(1.017)	(0.914)	(0.414)	(33.454)
Eff. df (t-dist.)		6.0	7.8	3.5	7.0	4.0	3.8	6.8	7.8
Constant	6.615**	6.958**	6.947**	6.842**	5.704	5.188	4.965	5.973	6.372*
Averaged SE	(1.955)	(2.087)	(2.086)	(2.015)	(2.289)	(3.618)	(3.250)	(2.367)	(2.042)
Corrected SE	(2.586)	(2.600)	(2.585)	(2.644)	(3.066)	(5.543)	(5.117)	(3.211)	(2.671)
Eff. df (t-dist.)	5.9	6.1	6.1	5.5	5.2	4.0	3.8	5.1	5.5
DW test stat.	2.138	2.287	2.234	2.273	2.201	2.067	2.072	2.285	2.119
Max λ, H_0: zero cointegrating vectors	15.562	15.600	15.730	17.145	15.420	16.265	16.668	15.399	15.420
Max λ, H_0: at most 1 cointegrating vector	3.981	5.504	5.009	4.860	2.495	4.026	4.008	4.014	4.256
Trace stat., H_0: zero cointegrating vectors	19.547	20.982	20.732	22.095	17.622	20.231	20.516	19.647	19.676
Trace stat., H_0: at most 1 cointegrating vector	3.995	5.441	4.986	4.883	2.544	4.047	3.918	4.061	4.256
Adj. R^2	0.539	0.573	0.541	0.604	0.540	0.544	0.550	0.527	0.515

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 7: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*; Kalman Imputation; Treating imputed as certain)

$\Delta\ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta\ln StockOwn_{t-1} + \gamma_4 \Delta\ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$

	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	*ln(Conjob)*	*ln(Conexp)*	*ln(Con)*	*ln(EPrem)*	*Volatilty*
lnStockOwn(t-1)	-0.757**	-1.030***	-1.094***	-0.975***	-0.927***	-0.713**	-0.727**	-0.595*	-0.699**
	(0.281)	(0.188)	(0.211)	(0.244)	(0.223)	(0.286)	(0.281)	(0.287)	(0.298)
ΔlnStockOwn(t-1)	0.279	0.223	0.356**	0.156	0.246	0.272	0.276	0.141	0.217
	(0.216)	(0.137)	(0.149)	(0.183)	(0.167)	(0.217)	(0.215)	(0.224)	(0.237)
lnSLoad(t-1)	-0.482**	-0.662***	-0.699***	-0.629***	-0.563***	-0.443**	-0.447**	-0.377*	-0.450**
	(0.175)	(0.118)	(0.133)	(0.154)	(0.137)	(0.180)	(0.178)	(0.180)	(0.184)
ΔlnSLoad(t-1)	0.295	0.665**	0.865**	0.504	0.549*	0.317	0.344	0.297	0.199
	(0.376)	(0.252)	(0.297)	(0.318)	(0.301)	(0.378)	(0.377)	(0.357)	(0.407)
S-Run Risk var.(t)		-0.0278***	-0.00759***	0.0187**	0.155**	0.126	0.152	-0.130	5.425
		(0.00637)	(0.00198)	(0.00709)	(0.0510)	(0.131)	(0.144)	(0.0849)	(7.569)
Constant	3.404**	4.669***	4.955***	4.424***	3.442***	2.647	2.576	2.276	3.105**
	(1.254)	(0.842)	(0.947)	(1.096)	(0.964)	(1.481)	(1.474)	(1.400)	(1.346)
DW test stat.	1.691	2.162	1.948	1.821	1.970	1.927	1.895	1.921	1.558
Max λ, H_0: zero. cointegrating vectors	31.715	40.669	35.948	39.442	28.383	31.901	31.917	32.439	31.855
Max λ, H_0: at most 1 cointegrating vector	.228	1.390	1.040	.615	.137	.0971	.00526	.384	.263
Trace stat., H_0: zero cointegrating vectors	31.943	42.059	36.989	40.056	28.520	31.998	31.922	32.823	32.118
Trace stat., H_0: at most 1 cointegrating vector	.228	1.390	1.040	.615	.137	.0971	.00526	.384	.263
R^2	0.625	0.863	0.840	0.770	0.797	0.655	0.660	0.691	0.479

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 8: Models of U.S. Stock Ownership 1970-2019

(Stock loads expense ratio-adjusted (*SELOAD1)*; Kalman Imputation; Treating imputed as certain)

Model: $\Delta lnStockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 Risk_t + \varepsilon_t$

	1	2	3	4	5	6	7	8	9
	Baseline	*Ungap*	*UngapSq*	*GDPgap*	*ln(Conjob)*	*ln(Conexp)*	*ln(Con)*	*ln(EPrem)*	*Volatilty*
lnStockOwn(t-1)	-0.739**	-0.999***	-1.034***	-0.934***	-0.913***	-0.698**	-0.707**	-0.577*	-0.710**
	(0.293)	(0.204)	(0.233)	(0.251)	(0.238)	(0.296)	(0.293)	(0.283)	(0.297)
ΔlnStockOwn(t-1)	0.299	0.260	0.391**	0.165	0.285	0.294	0.297	0.138	0.235
	(0.238)	(0.158)	(0.177)	(0.201)	(0.187)	(0.237)	(0.236)	(0.235)	(0.249)
lnSLoad(t-1)	-0.571**	-0.780***	-0.804***	-0.735***	-0.672***	-0.525**	-0.527**	-0.445*	-0.554**
	(0.222)	(0.156)	(0.178)	(0.192)	(0.178)	(0.226)	(0.225)	(0.215)	(0.224)
ΔlnSLoad(t-1)	0.290	0.722*	0.924**	0.475	0.623	0.335	0.359	0.309	0.209
	(0.507)	(0.352)	(0.418)	(0.421)	(0.414)	(0.508)	(0.508)	(0.464)	(0.517)
S-Run Risk var.(t)		-0.0273***	-0.00706***	0.0189**	0.154**	0.135	0.156	-0.144*	6.836
		(0.00674)	(0.00211)	(0.00720)	(0.0529)	(0.132)	(0.146)	(0.0787)	(7.278)
Constant	3.561**	4.853***	5.020***	4.547***	3.660***	2.757	2.689	2.339	3.367**
	(1.402)	(0.980)	(1.118)	(1.207)	(1.100)	(1.604)	(1.614)	(1.447)	(1.424)
DW test stat.	1.762	2.277	2.050	1.970	2.054	2.008	1.958	2.063	1.633
Max λ, H_0: zero cointegrating vectors	31.860	41.733	36.633	41.065	28.943	32.587	33.277	32.563	32.378
Max λ, H_0: at most 1. cointegrating vector	.349	1.565	1.155	.758	.165	.158	.0260	.463	.347
Trace stat., H_0: zero cointegrating vectors	32.209	43.298	37.787	41.823	29.108	32.745	33.303	33.025	32.724
Trace stat., H_0: at most 1 cointegrating vector	.349	1.565	1.155	.758	.165	.158	.0260	.463	.347
R^2	0.611	0.844	0.808	0.761	0.781	0.645	0.648	0.702	0.477

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table 9: Implied Long-Run Relationships of Models in Table 3

Model #	Long-Run Equilibrium Relationship	Short-Run Risk Effect	Annualized Speed of Adjustment
1	ln*StockOwn* = 4.501 – 0.638 ln*Sload1*		27%
2	ln*StockOwn* = 4.531 – 0.643 ln*Sload1*	– 0.0285 *Ugap*	36%
3	ln*StockOwn* = 4.528 – 0.640 ln*Sload1*	– 0.0767 *UgapSq*	37%
4	ln*StockOwn* = 4.535 – 0.645 ln*Sload1*	+ 0.0193 *GDPgap*	37%
5	ln*StockOwn* = 3.721 – 0.608 ln*Sload1*	+ 0.1590 ln*Conjob*	32%
6	ln*StockOwn* = 3.624 – 0.618 ln*Sload1*	+ 0.1480 ln*Con*	26%
7	ln*StockOwn* = 3.775 – 0.623 ln*Sload1*	+ 0.1480 ln*Conexp*	25%
8	ln*StockOwn* = 3.876 – 0.635 ln*Sload1*	- 0.1290 *Eprem*	21%
9	ln*StockOwn* = 4.444 – 0.645 ln*Sload1*	+ 5.562 *Volatility*	25%

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Appendix A: Trends in Capital Gains Taxes and Age Composition Do Not Line Up Well with Stock ownership Rates

In theory, there are two possible explanations for the long-run trends in stock ownership that were unexamined by the referenced theoretical and calibration studies. One is that an aging of the population could induce more households to save for retirement and thereby boost the incentive for more families to own stocks. The second is that cuts in capital gains taxes could induce more households to invest in long-run assets like stocks. With regard to the former, the trends in the age 40 and over share of the adult population are inconsistent with trends in stock ownership rates as illustrated in Figure A1 and as we found in other regressions not shown. In particular, this age share fell in the 1960s when stock ownership was flat. Later the age 40+ share recovered from its 1983 low to its 1964 level by 1998, but the stock ownership share had doubled during the 1980s and 1990s from the flat range that had prevailed from 1964 to 1983.

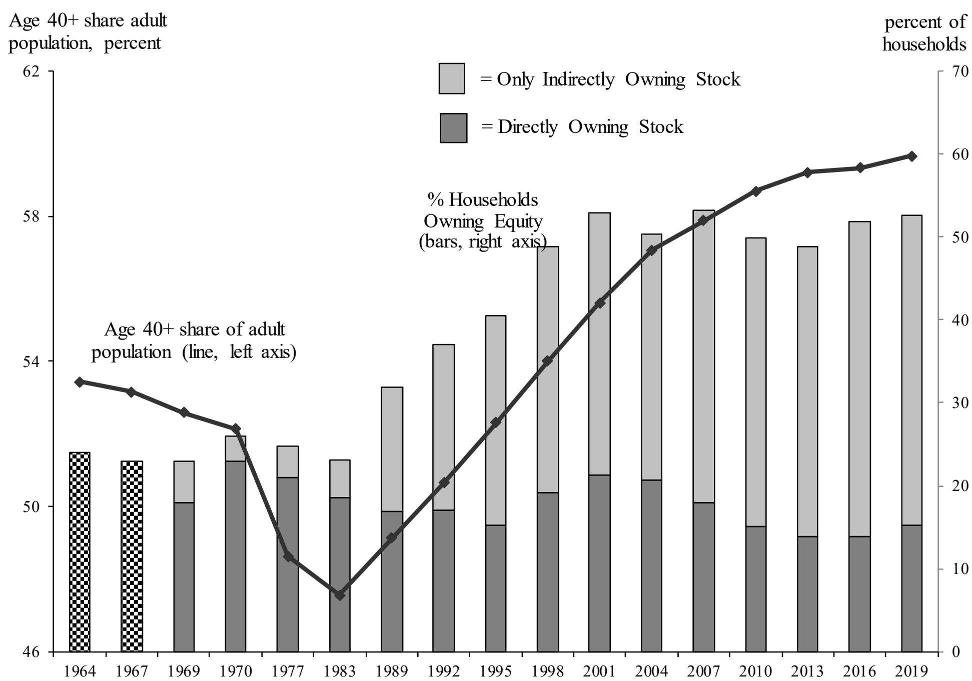

Figure A1: Trends in Age Composition Do Not Line Up With Equity Participation Rates
(Sources: Various SCFs, Census Bureau and authors' calculations)

Trends in the maximum tax rate on long-term capital gains also do not line up consistently with stock ownership, as is illustrated in Figure A2 and as is found in other regressions not shown. For example, even though marginal tax rates on capital gains had risen notably in the 1970s before falling in the early 1980s, the equity participation rate was essentially flat from 1964 to 1983. Then, stock ownership rates rose a good deal between 1983 and 1998 even though capital gains tax rates rose. Finally, the fall in capital gains tax rates following the Bush tax cuts of the early 2000s followed rather than led the sharp run-up of the stock ownership rate from the early 1980s to the late 1990s.

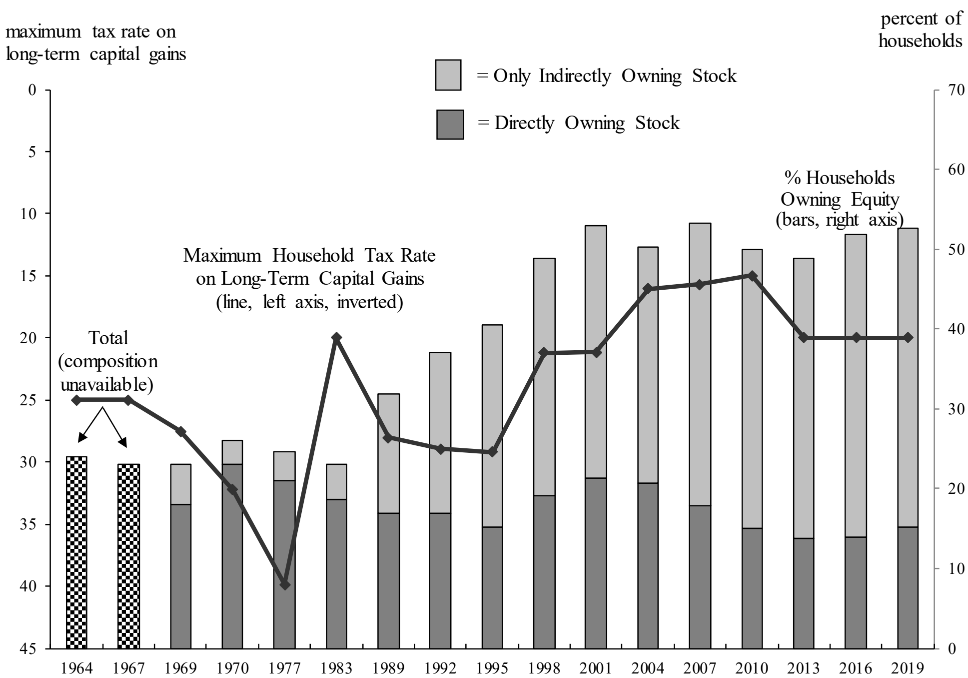

Figure A2: Trends in Capital Gains Tax Rates Do Not Line Up With Stock ownership Rates
(Sources: Various SCFs and Tax Policy Institute)

Appendix B: Mutual Fund Data

Because data before the mid-1980s are sketchy and incomplete, mutual fund cots were based on a sample of large mutual funds. Funds were selected if their assets were at least $1 billion at year-end 1991 if the fund existed before the mid-1980s; were at least $2 billion at year-end 1994 if the fund's inception date occurred after 1983; were at least $5 billion at year-end 2003; or were at least $250 million at year-end 1975. The first criterion reflects whether a fund was sizable during early missing M2 period of the early 1990s. The second criterion reflects whether a growing but new fund was large near the end of the missing M2 period. The third criterion reflects whether a fund remained large following the stock market bust of the early 2000s. Given the stock and bond appreciation of the early 1990s, the hurdles for newer funds were higher for the 1994 and 2003 cutoff dates to keep data gathering costs from exploding. The fourth criterion avoids excluding funds that were relatively large in 1975 from distorting averages when fewer funds existed. Also excluded were funds that were closed-end, only open to employees of a specific firm, or institutional. One member, the Windsor Fund, became closed-end but was included because its open-end cousin (Windsor II) was started when it became closed-end, and both funds are large. Also omitted are funds with high minimum balances (100,000 or more) because such high hurdles make such funds poor substitutes for M2, which is predominantly held by middle income households. 46 non-municipal bond and 133 equity mutual funds are in the sample (a list is available from the author) using data from the funds and various issues of Morningstar, IBC/Donoghue, and CDA/Wiesenberger (a, b).

Because only year-end asset data for many equity funds are available, quarterly asset weights are interpolated from a year-end data and quarterly inception dates of the funds. Using annual data for benchmark weights is common and is used in at least one of the conventional money variables (*OC*). Given the lack of large year-to-year changes in asset weights and the more important impact of load cuts in year-end to year-end changes in weighted-average loads, the series track quarterly load changes well. As discussed in Duca (2005, 2006), if expense ratios are added to *Sload* and if they were redefined using a 5-year horizon, the resulting overall mutual fund cost variables would behave very similarly with the annual, industry-side, overall equity fund cost estimates of Rea and Reid (1998, 1999).

Appendix C: Equilibrium Stock Ownership Readings Implied by Model 3, Table 3

Year	Stock Owner-ship Rate	Year	Stock Owner-ship Rate
1960	25.06	1990	36.93
1961	24.79	1991	38.83
1962	24.83	1992	39.12
1963	24.61	1993	41.43
1964	24.67	1994	45.24
1965	24.90	1995	47.85
1966	25.20	1996	48.96
1967	25.06	1997	49.81
1968	25.37	1998	51.05
1969	25.58	1999	52.15
1970	24.77	2000	53.58
1971	24.57	2001	54.07
1972	24.54	2002	54.18
1973	24.95	2003	53.26
1974	25.03	2004	52.16
1975	24.19	2005	53.49
1976	24.79	2006	56.03
1977	25.44	2007	55.51
1978	25.93	2008	53.24
1979	26.68	2009	44.79
1980	27.29	2010	42.37
1981	27.22	2011	44.84
1982	25.98	2012	48.18
1983	26.91	2013	48.79
1984	29.42	2014	49.97
1985	30.79	2015	50.82
1986	32.10	2016	51.02
1987	33.59	2017	50.91
1988	35.42	2018	50.89
1989	35.94	2019	51.30

Appendix D: Additional Results

Table D1: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*, linear imputation)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1	2	3	4	5	6	7	8
	Baseline No risk	*Ungap*	*UngapSq*	*GDPgap*	*ln(Conjob)*	*ln(Con)*	*ln(Conexp)*	*ln(EPrem)*
lnStockOwn(t-1)	-0.933**	-1.175**	-1.245**	-1.116**	-1.091**	-0.909*	-0.883*	-0.806*
Averaged SE	(0.324)	(0.244)	(0.269)	(0.292)	(0.273)	(0.327)	(0.327)	(0.349)
Corrected SE	(0.393)	(0.337)	(0.362)	(0.366)	(0.351)	(0.395)	(0.405)	(0.419)
Eff. df (t-dist.)	7.0	4.9	5.2	6.0	5.7	6.5	6.2	6.6
ΔlnStockOwn(t-1)	0.209	0.194	0.303	0.123	0.196	0.204	0.207	0.0982
Averaged SE	(0.229)	(0.163)	(0.177)	(0.196)	(0.189)	(0.234)	(0.233)	(0.245)
Corrected SE	(0.273)	(0.202)	(0.214)	(0.225)	(0.236)	(0.265)	(0.264)	(0.281)
Eff. df (t-dist.)	7.3	6.1	6.4	7.1	6.0	7.4	7.3	7.2
lnSLoad(t-1)	-0.597**	-0.754**	-0.798**	-0.721**	-0.666**	-0.566*	-0.554*	-0.512
Averaged SE	(0.202)	(0.154)	(0.171)	(0.185)	(0.169)	(0.206)	(0.207)	(0.219)
Corrected SE	(0.245)	(0.221)	(0.232)	(0.234)	(0.224)	(0.250)	(0.256)	(0.265)
Eff. df (t-dist.)	7.1	4.5	5.1	5.9	5.4	6.4	6.1	6.4
ΔlnSLoad(t-1)	0.423	0.786*	0.976*	0.614	0.675	0.462	0.431	0.455
Averaged SE	(0.439)	(0.334)	(0.389)	(0.388)	(0.375)	(0.445)	(0.441)	(0.437)
Corrected SE	(0.482)	(0.371)	(0.436)	(0.428)	(0.405)	(0.475)	(0.474)	(0.471)
Eff. df (t-dist.)	8.6	7.6	7.5	7.7	8.1	8.3	8.2	8.1
S-Run risk variables (t)		-0.0302**	-0.00800**	0.0207*	0.170**	0.122	0.110	-0.120
Averaged SE		(0.00880)	(0.00275)	(0.00884)	(0.0671)	(0.181)	(0.161)	(0.106)
Corrected SE		(0.00936)	(0.00289)	(0.0104)	(0.0707)	(0.226)	(0.216)	(0.114)
Eff. df (t-dist.)		8.3	8.5	6.8	8.5	6.0	5.2	8.1
Constant	4.202**	5.321**	5.640**	5.062**	4.109**	3.533	3.490	3.256
Averaged SE	(1.443)	(1.091)	(1.208)	(1.307)	(1.191)	(1.729)	(1.709)	(1.701)
Corrected SE	(1.753)	(1.519)	(1.625)	(1.642)	(1.552)	(2.181)	(2.272)	(2.040)
Eff. df (t-dist.)	7.0	4.9	5.2	6.0	5.5	5.9	5.3	6.6
DW test stat.	1.828	2.286	2.166	1.987	2.110	1.922	1.916	2.069
Max λ, H_0: ≤ 0 coint.	19.034	23.624	24.619	20.692	20.513	20.092	20.147	17.697
Max λ, H_0: ≤ 1 coint.	4.321	9.886	7.591	8.599	3.374	2.883	3.114	3.233
Trace stat., H_0: ≤ 0 coint.	23.355	33.511	32.210	29.291	23.887	22.975	23.261	20.930
Trace stat., H_0: ≤ 1 coint.	4.321	9.886	7.591	8.599	3.374	2.883	3.114	3.233
Adj. R^2	0.492	0.749	0.708	0.647	0.667	0.493	0.500	0.516

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table D2: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*, spline imputation)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1 Baseline No risk	2 *Ungap*	3 *UngapSq|*	4 *GDPgap*	5 *ln(Conjob)*	6 *ln(Con)*	7 *ln(Conexp)*	8 *ln(EPrem)*
lnStockOwn(t-1)	-0.826**	-1.047***	-1.104**	-1.020**	-0.969**	-0.792**	-0.778*	-0.683*
Averaged SE	(0.293)	(0.222)	(0.256)	(0.258)	(0.249)	(0.294)	(0.293)	(0.305)
Corrected SE	(0.328)	(0.269)	(0.308)	(0.306)	(0.286)	(0.329)	(0.333)	(0.333)
Eff. df (t-dist.)	8.3	6.4	6.5	6.7	7.1	7.5	7.3	7.9
ΔlnStockOwn(t-1)	0.284	0.261	0.354	0.181	0.280	0.271	0.284	0.171
Averaged SE	(0.223)	(0.159)	(0.178)	(0.187)	(0.185)	(0.226)	(0.225)	(0.232)
Corrected SE	(0.262)	(0.196)	(0.213)	(0.214)	(0.226)	(0.254)	(0.253)	(0.267)
Eff. df (t-dist.)	7.5	6.2	6.6	7.2	6.3	7.5	7.4	7.1
lnSLoad(t-1)	-0.525**	-0.671***	-0.705**	-0.6578**	-0.583**	-0.487**	-0.482*	-0.430*
Averaged SE	(0.183)	(0.141)	(0.162)	(0.164)	(0.154)	(0.186)	(0.185)	(0.192)
Corrected SE	(0.204)	(0.174)	(0.195)	(0.196)	(0.179)	(0.206)	(0.209)	(0.210)
Eff. df (t-dist.)	8.4	6.2	6.5	6.6	7.0	7.7	7.4	7.9
ΔlnSLoad(t-1)	0.384	0.744*	0.908*	0.597	0.641	0.423	0.400	0.434
Averaged SE	(0.422)	(0.328)	(0.396)	(0.363)	(0.368)	(0.426)	(0.419)	(0.412)
Corrected SE	(0.452)	(0.357)	(0.434)	(0.400)	(0.392)	(0.451)	(0.444)	(0.443)
Eff. df (t-dist.)	9.0	8.0	7.9	7.8	8.3	8.4	8.4	8.2
S-Run risk variables (t)		-0.0310**	-0.00782**	0.0227*	0.172**	0.150	0.120	-0.142
Averaged SE		(0.00934)	(0.00302)	(0.00904)	(0.0703)	(0.185)	(0.164)	(0.107)
Corrected SE		(0.00982)	(0.00316)	(0.0102)	(0.0733)	(0.225)	(0.215)	(0.112)
Eff. df (t-dist.)		8.5	8.6	7.4	8.7	6.4	5.5	8.6
Constant	3.713**	4.746***	5.000**	4.629**	3.550**	2.877	2.968	2.633
Averaged SE	(1.306)	(0.996)	(1.149)	(1.157)	(1.080)	(1.621)	(1.586)	(1.508)
Corrected SE	(1.462)	(1.210)	(1.381)	(1.375)	(1.255)	(1.911)	(1.963)	(1.636)
Eff. df (t-dist.)	8.3	6.4	6.5	6.7	7.0	6.8	6.1	8.0
DW test stat.	1.845	2.273	2.163	1.970	2.086	1.900	1.902	2.116
Max λ, H_0: ≤ 0 coint.	20.827	24.561	25.465	22.437	22.003	22.369	22.367	19.828
Max λ, H_0: ≤ 1 coint.	4.001	9.897	7.325	8.879	3.173	2.505	2.774	2.814
Trace stat., H_0: ≤ 0 coint.	24.829	34.458	32.790	31.316	25.176	24.874	25.141	22.643
Trace stat., H_0: ≤ 1 coint.	4.001	9.897	7.325	8.879	3.173	2.505	2.774	2.814
Adj. R^2	0.468	0.729	0.665	0.647	0.641	0.473	0.479	0.507

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table D3: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*, linear imputation, high variance)

$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$

Model #	1 Baseline No risk	2 *Ungap*	3 *UngapSq*	4 *GDPgap*	5 *ln(Conjob)*	6 *ln(Con)*	7 *ln(Conexp)*	8 *ln(EPrem)*
lnStockOwn(t-1)	-1.328**	-1.407**	-1.417**	-1.396**	-1.382**	-1.256*	-1.258*	-1.329*
Averaged SE	(0.395)	(0.415)	(0.417)	(0.407)	(0.404)	(0.405)	(0.402)	(0.432)
Corrected SE	(0.513)	(0.504)	(0.506)	(0.531)	(0.506)	(0.532)	(0.549)	(0.571)
Eff. df (t-dist.)	6.2	6.4	6.4	5.6	6.0	5.4	5.1	5.4
ΔlnStockOwn(t-1)	0.172	0.187	0.208	0.148	0.193	0.126	0.158	0.161
Averaged SE	(0.255)	(0.255)	(0.256)	(0.246)	(0.261)	(0.278)	(0.272)	(0.271)
Corrected SE	(0.359)	(0.349)	(0.358)	(0.356)	(0.371)	(0.368)	(0.370)	(0.365)
Eff. df (t-dist.)	5.2	5.0	4.8	4.5	4.7	5.4	5.1	5.2
lnSLoad(t-1)	-0.919*	-0.988*	-0.990*	-0.979*	-0.927*	-0.855*	-0.846*	-0.919*
Averaged SE	(0.292)	(0.312)	(0.313)	(0.307)	(0.298)	(0.302)	(0.296)	(0.313)
Corrected SE	(0.410)	(0.428)	(0.412)	(0.421)	(0.428)	(0.420)	(0.413)	(0.447)
Eff. df (t-dist.)	5.3	5.0	5.4	5.0	4.6	4.9	4.8	4.6
ΔlnSLoad(t-1)	0.741	0.979	1.029	0.825	0.880	0.723	0.773	0.961
Averaged SE	(0.926)	(0.968)	(1.038)	(0.917)	(0.953)	(0.982)	(0.967)	(1.124)
Corrected SE	(1.055)	(1.141)	(1.218)	(1.134)	(1.117)	(1.106)	(1.078)	(1.242)
Eff. df (t-dist.)	8.0	6.8	6.9	6.2	6.9	7.4	7.6	7.7
S-Run risk variables (t)		-0.0345	-0.00758	0.0204	0.171	0.210	0.238	-0.140
Averaged SE		(0.0428)	(0.0122)	(0.0349)	(0.289)	(0.664)	(0.586)	(0.361)
Corrected SE		(0.0528)	(0.0135)	(0.0584)	(0.334)	(0.991)	(0.930)	(0.430)
Eff. df (t-dist.)		6.2	7.6	3.4	7.1	4.2	3.7	6.6
Constant	6.040**	6.444**	6.486**	6.392**	5.484	4.764	4.660	5.606
Averaged SE	(1.781)	(1.891)	(1.902)	(1.859)	(2.116)	(3.497)	(3.160)	(2.289)
Corrected SE	(2.304)	(2.294)	(2.290)	(2.394)	(2.829)	(5.292)	(4.972)	(3.081)
Eff. df (t-dist.)	6.2	6.4	6.5	5.7	5.3	4.1	3.8	5.2
DW test stat.	2.136	2.272	2.217	2.220	2.203	2.057	2.057	2.240
Max λ, H_0: ≤ 0 coint.	15.555	16.027	16.120	17.404	15.626	15.772	16.121	15.330
Max λ, H_0: ≤ 1 coint.	4.218	5.986	5.724	5.396	2.459	3.585	3.766	3.982
Trace stat., H_0: ≤ 0 coint.	19.772	22.013	21.843	22.800	18.085	19.358	19.887	19.312
Trace stat., H_0: ≤ 1 coint.	4.218	5.986	5.724	5.396	2.459	3.585	3.766	3.982
Adj. R^2	0.533	0.573	0.551	0.601	0.555	0.546	0.557	0.516

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table D4: Models of U.S. Stock Ownership 1970-2019

(Stock loads not expense ratio-adjusted (*SLOAD1)*, spline imputation, high variance)

$$\Delta \ln StockOwn_t \equiv \gamma_0 + \gamma_1 \ln StockOwn_{t-1} + \gamma_2 \ln Sload_{t-1} + \gamma_3 \Delta \ln StockOwn_{t-1} + \gamma_4 \Delta \ln Sload_{t-1} + \gamma_5 Risk_t + \varepsilon_t$$

Model #	1	2	3	4	5	6	7	8
	Baseline No risk	*Ungap*	*UngapSq*	*GDPgap*	*ln(Conjob)*	*ln(Con)*	*ln(Conexp)*	*ln(EPrem)*
lnStockOwn(t-1)	-1.298**	-1.395**	-1.383**	-1.358**	-1.328**	-1.213*	-1.229*	-1.290*
Averaged SE	(0.391)	(0.413)	(0.416)	(0.407)	(0.405)	(0.401)	(0.400)	(0.430)
Corrected SE	(0.507)	(0.503)	(0.508)	(0.523)	(0.497)	(0.520)	(0.538)	(0.559)
Eff. df (t-dist.)	6.2	6.4	6.3	5.7	6.3	5.6	5.2	5.6
ΔlnStockOwn(t-1)	0.174	0.188	0.201	0.137	0.179	0.109	0.149	0.152
Averaged SE	(0.255)	(0.255)	(0.257)	(0.247)	(0.265)	(0.276)	(0.272)	(0.272)
Corrected SE	(0.366)	(0.352)	(0.361)	(0.352)	(0.375)	(0.367)	(0.368)	(0.365)
Eff. df (t-dist.)	5.0	5.0	4.8	4.6	4.7	5.3	5.1	5.2
lnSLoad(t-1)	-0.896*	-0.980*	-0.959*	-0.955*	-0.888*	-0.817*	-0.826*	-0.876*
Averaged SE	(0.289)	(0.312)	(0.312)	(0.309)	(0.300)	(0.302)	(0.297)	(0.310)
Corrected SE	(0.395)	(0.418)	(0.401)	(0.422)	(0.416)	(0.404)	(0.408)	(0.430)
Eff. df (t-dist.)	5.5	5.3	5.7	5.1	4.9	5.3	5.0	4.9
ΔlnSLoad(t-1)	0.774	1.033	1.113	0.884	0.965	0.787	0.820	1.009
Averaged SE	(0.948)	(1.016)	(1.098)	(0.967)	(1.039)	(1.036)	(0.986)	(1.156)
Corrected SE	(1.076)	(1.179)	(1.245)	(1.167)	(1.201)	(1.162)	(1.098)	(1.283)
Eff. df (t-dist.)	8.1	7.0	7.3	6.5	7.1	7.5	7.6	7.6
S-Run risk variables (t)		-0.0373	-0.00853	0.0261	0.202	0.224	0.293	-0.151
Averaged SE		(0.0447)	(0.0129)	(0.0369)	(0.315)	(0.692)	(0.600)	(0.374)
Corrected SE		(0.0545)	(0.0139)	(0.0585)	(0.354)	(1.066)	(0.978)	(0.449)
Eff. df (t-dist.)		6.3	8.1	3.8	7.5	4.0	3.5	6.6
Constant	5.902**	6.398**	6.332**	6.232**	5.096	4.502	4.291	5.387
Averaged SE	(1.763)	(1.886)	(1.899)	(1.858)	(2.146)	(3.629)	(3.250)	(2.339)
Corrected SE	(2.271)	(2.282)	(2.293)	(2.365)	(2.737)	(5.558)	(5.198)	(3.077)
Eff. df (t-dist.)	6.3	6.4	6.5	5.8	5.8	4.0	3.7	5.4
DW test stat.	2.124	2.277	2.208	2.235	2.200	2.052	2.052	2.241
Max λ, H_0: ≤ 0 coint.	15.753	15.986	16.042	17.022	15.250	15.804	16.023	15.261
Max λ, H_0: ≤ 1 coint.	4.242	5.991	5.715	5.501	2.535	3.612	3.714	3.916
Trace stat., H_0: ≤ 0 coint.	19.995	21.977	21.757	22.523	17.785	19.416	19.737	19.177
Trace stat., H_0: ≤ 1 coint.	4.242	5.991	5.715	5.501	2.535	3.612	3.714	3.916
Adj. R^2	0.520	0.562	0.534	0.584	0.531	0.532	0.545	0.503

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Table D5: Models of U.S. Stock Ownership 1970-2019 Adding CPI Inflation
Kalman Filter imputations, middle-case estimate of standard errors

	Unadjusted (SLOAD1)			**Expense-Adjusted (SELOAD1)**		
Model #	1	2	3	1	2	3
	Ungap	*UngapSq*	*GDPgap*	*Ungap*	*UngapSq*	*GDPgap*
lnStockOwn(t - 1)	-0.989**	-1.038**	-0.935**	-0.937**	-0.970**	-0.870**
Averaged SE	(0.235)	(0.262)	(0.304)	(0.263)	(0.296)	(0.321)
Corrected SE	(0.277)	(0.309)	(0.338)	(0.306)	(0.349)	(0.359)
Eff. df (t-dist.)	6.1	6.1	6.8	6.2	6.1	6.8
Δ *lnStockOwn(t - 1)*	0.190	0.315	0.127	0.208	0.333	0.118
Averaged SE	(0.147)	(0.162)	(0.193)	(0.173)	(0.195)	(0.216)
Corrected SE	(0.161)	(0.176)	(0.201)	(0.191)	(0.216)	(0.227)
Eff. df (t-dist.)	7.0	7.1	7.8	6.9	6.9	7.6
lnSLoad(t - 1)	-0.625**	-0.651**	-0.593**	-0.718**	-0.738**	-0.670*
Averaged SE	(0.160)	(0.178)	(0.207)	(0.218)	(0.244)	(0.267)
Corrected SE	(0.192)	(0.213)	(0.234)	(0.259)	(0.291)	(0.303)
Eff. df (t-dist.)	5.8	5.9	6.7	6.0	5.9	6.6
Δ *lnSLoad(t - 1)*	0.602	0.781*	0.444	0.607	0.799	0.359
Averaged SE	(0.304)	(0.355)	(0.383)	(0.431)	(0.503)	(0.514)
Corrected SE	(0.333)	(0.397)	(0.409)	(0.476)	(0.570)	(0.554)
Eff. df (t-dist.)	7.0	6.8	7.4	6.9	6.6	7.3
S-Run Risk var. (t)	-0.0280***	-0.00753***	0.0187**	-0.0273***	-0.00701**	0.0188**
Averaged SE	(0.00683)	(0.00216)	(0.00755)	(0.00724)	(0.00227)	(0.00765)
Corrected SE	(0.00696)	(0.00223)	(0.00789)	(0.00738)	(0.00235)	(0.00799)
Eff. df (t-dist.)	8.2	7.9	7.8	8.1	7.9	7.8
CPI (t)	-0.00300	-0.00348	-0.00280	-0.00347	-0.00369	-0.00348
Averaged SE	(0.00548)	(0.00601)	(0.00707)	(0.00600)	(0.00668)	(0.00737)
Corrected SE	(0.00768)	(0.00808)	(0.00895)	(0.00840)	(0.00890)	(0.00952)
Eff. df (t-dist.)	4.3	4.7	5.3	4.3	4.8	5.1
Constant	4.480**	4.699**	4.239**	4.547**	4.700**	4.230**
Averaged SE	(1.055)	(1.179)	(1.369)	(1.273)	(1.432)	(1.558)
Corrected SE	(1.765)	(1.393)	(1.525)	(1.485)	(1.691)	(1.744)
Eff. df (t-dist.)	6.0	6.1	6.8	6.2	6.1	6.8
DW test stat.	2.175	2.000	1.878	2.254	2.072	2.005
Max λ, H_0: zero cointegrating vectors	23.215	26.252	20.288	21.471	23.933	19.444
Max λ, H_0: at most 1 cointegrating vector	5.416	3.304	4.141	3.287	2.069	2.467
Trace stat., H_0: zero cointegrating vectors	28.631	29.556	24.429	24.758	26.002	21.911
Trace stat., H_0: at most 1 cointegrating vector	5.416	3.304	4.141	3.287	2.069	2.467
Adj. R^2	0.789	0.747	0.651	0.761	0.703	0.640

*,**, *** denote significant at the 90, 95, and 99 % confidence levels.

Appendix E: Statistical reference information

Beta parameter formulae

$$\alpha = \left(\frac{1-\mu}{\sigma^2} - \frac{1}{\mu}\right)\mu^2$$

$$\beta = \alpha\left(\frac{1}{\mu} - 1\right)$$

Critical values for rejection of H_0, Lambda and Trace (must exceed)

	Max-Lambda	Trace
H_0: ≤ 0 coint.	15.67	19.96
H_0: ≤ 1 coint.	9.24	9.24