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FINANCIAL WINDFALLS, PORTFOLIO ALLOCATIONS, AND RISK PREFERENCES

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ABSTRACT

We investigate the impact of financial windfalls on household portfolio choices and risk exposure. Exploiting the randomized assignment of lottery prizes in three Swedish lotteries, we find a windfall gain of \$100K leads to a 5-percentage-point decrease in the risky share of household portfolios. We show theoretically that negative wealth effects are consistent with both constant and decreasing relative risk aversion and analyze how our empirical estimates help distinguish between competing models of portfolio choice. We further show our results are quantitatively aligned with the predictions of a calibrated dynamic portfolio choice model with nontradable human capital and consumption habits.

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A data appendix is available at <http://www.nber.org/data-appendix/w31864>

1 Introduction

Models of portfolio choice in finance and macroeconomics often differ in their assumptions about risk preferences. A common strategy is to assume preferences with constant relative risk aversion (CRRA). Absent any frictions, models with CRRA utility predict that the share of a household’s portfolio invested in risky assets (hereon, the *risky share*) will not depend on the level of wealth (Samuelson, 1969). A variety of modifications to the CRRA assumption have been proposed and explored. For example, decreasing relative risk aversion (DRRA) preferences have been invoked to generate procyclical stock prices and countercyclical risk premia in consumption-based asset pricing (Constantinides, 1990; Campbell and Cochrane, 1999) and to explain the positive cross-sectional relationship between household wealth and the risky share (Wachter and Yogo, 2010; Meeuwis, 2022).

Credible evidence on how the risky share is impacted by financial windfalls would be valuable for distinguishing between competing models. Despite a vast literature, substantial uncertainty remains about the range of plausible effects and estimates reported in the literature vary substantially in both sign and magnitude. For example, Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011) do not find that changes in a household’s wealth over time are associated with changes in its risky share. In contrast, Calvet, Campbell and Sodini (2009) and Calvet and Sodini (2014) find positive effects in their analyses of Swedish data using different identification strategies. The apparent lack of consensus about how exogenous wealth shocks impact the risky share remains a roadblock hampering progress in the literature.

The fundamental challenge in identifying wealth effects is that even the most sophisticated quasi-experimental studies conducted to date rely on identifying assumptions that are difficult to stringently evaluate given the available data. Carroll (2002, p. 420) notes that the “ideal experiment” to examine the causal relationship between wealth and risk tolerance would be to “exogenously dump a large amount of wealth on a random sample of households and examine the effect on both their expressed risk preferences and their risk-taking behavior.” In this paper, we use a research design that, in the spirit of Imbens, Rubin and Sacerdote (2001), approximates this ideal experiment closer than any previous work. Specifically, we leverage the randomized assignment of lottery prizes among players from three separate Swedish lotteries. The players have been matched to government registers with detailed information about numerous characteristics, including year-end household finances. For each lottery, we observe the factors conditional on which the lottery prizes

were randomly assigned and can therefore control for these factors in our empirical analyses. Our study thus has several methodological strengths that bolster the credibility of our causal estimates.

Our headline finding is that among lottery players who owned stocks before the lottery event, a windfall gain of \$100K causes the risky share to fall by approximately five percentage points. The effect is immediate, precisely estimated, and appears to persist for at least four years (the longest horizon over which we estimate wealth effects). We show that the negative effect is robust to alternative definitions of the risky share and shows up reliably across all subsamples considered in our heterogeneity analyses. In additional analyses, we find little evidence that the negative effects are explained by (i) risky investments in alternative assets (e.g., real estate) that crowd out some investments in stocks, (ii) household inaction/sluggishness in investing the lottery wealth after it is deposited in the winner's bank account, or (iii) our use of a potentially unrepresentative estimation sample composed of lottery players.

Under the common convention in the literature to interpret the risky share as a proxy for relative risk aversion, our findings would suggest that relative risk aversion *increases* in wealth. However, such inferences are only valid under restrictive assumptions that do not align well with the empirical environment in which households make financial decisions. To clarify the basic argument, we formulate and analyze a static portfolio choice model that incorporates human capital and incomplete markets (Campbell and Viceira, 2002). A key feature of the model is that human capital – defined as the expected present discounted value of all future income – is assumed to be nontradable: agents cannot borrow against anticipated future income flows. We show that this simple model is consistent with negative wealth effects on the risky share even when the underlying risk preferences are CRRA or DRRA. Intuitively, in a model with nontradable human capital, a large windfall mechanically causes the share of a household's total wealth held in human capital to fall. This, in turn, dampens the household's incentives to over-invest in equities to offset its nontradable (and relatively less risky) position in human capital. The household thus reacts by reducing its exposure to equity, leading to a decline in the risky share.

We derive and test three additional predictions of the static model. First, the elasticity of the risky share with respect to a financial wealth shock should diminish (in absolute magnitude) with the size of the shock. Second, the elasticity should be increasing (in magnitude) in the ratio of human capital to pre-existing financial wealth. Third, the effect of an increase in future income (as opposed to an increase in financial wealth) on the risky share should

be positive. Our unique empirical setting allows us to exploit variation in prize sizes, pre-win human-capital-to-wealth ratios, and differences in the mode of payment (lump-sums versus monthly installments) to test these predictions. Overall, our evidence aligns quite closely with all three predictions. While previous theoretical work has recognized human capital as an important determinant of asset allocations (Bodie, Merton and Samuelson, 1992; Heaton and Lucas, 1997; Viceira, 2001) and has inspired the development of so-called target-date funds (Parker, Schoar and Sun, 2022), empirical evidence consistent with the human-capital channel in the previous literature is relatively scant.

In further analyses, we find that a richer, dynamic portfolio choice model yields predictions consistent with our quasi-experimental estimates.¹ Under a standard calibration, our baseline model with nontradable human capital predicts that a \$100K windfall causes the risky share to decline by over 10 percentage points, a reduction twice the size of our preferred quasi-experimental estimate. Extending the model to incorporate realistic consumption habits, as in Campbell and Cochrane (1999) and Polkovnichenko (2007), results in a predicted reduction of 5.2 percentage points per \$100K won, closely matching the quasi-experimental estimate. Thus, the negative wealth effect we report is both qualitatively and quantitatively consistent with predictions from a broad class of models that incorporate human capital and incomplete markets.

Even though our results point to nontradable human capital as a potentially important mechanism, our results do not contradict previous studies that emphasize the significance of consumption habits and DRRA preferences. For example, the lifecycle model that best matches our quasi-experimental estimates allows for both consumption habits and nontradable human capital. This finding suggests that any model that incorporates only one of these factors is likely to be misspecified. Accordingly, inferences about risk preferences from the financial wealth elasticity of the risky share are more credible when they are based on an augmented model that adequately accounts for both nontradable human capital and consumption habits in a quantitative manner.

Finally, our paper contributes to the broader literature on how wealth impacts households' saving and investment behaviors.² Our rich data allows us to characterize the dy-

¹Our model is based on Gomes and Michaelides (2005) and Cocco, Gomes and Maenhout (2005), and is comparable to the models used in other quantitative studies of household portfolio choice, including Fagereng, Gottlieb and Guiso (2017) and Calvet, Campbell, Gomes and Sodini (2021).

²There is an active literature studying the effect of wealth on household finances. In recent work, Andersen and Nielsen (2011) and Briggs, Cesarini, Lindqvist and Östling (2021) estimate the effect of wealth on stock market participation, Hankins, Hoestra and Skiba (2011) estimate the effect on bankruptcy, Cookson, Gilje and Heimer (2022) estimate the effect on household debt, Paiella and Pistaferri (2017) and Fagereng,

dynamic effects of lottery wealth on multiple asset and liability classes up to four years after the lottery. To set the stage for these analyses, we first analyze how winning the lottery impacts a player’s year-end net wealth. These estimates provide potentially informative bounds on the marginal propensities to spend and save.³ We find that a \$100K windfall increases year-end net wealth by approximately \$60K in the year of win, with the effect dissipating to \$35K four years later. Next, we decompose the estimated increase in net wealth into three components: financial assets, real assets, and debt. We find that 80-90% of the estimated increase in net wealth is explained by an increase in financial assets, with the remaining share accounted for by real estate investments and reductions of debt. Lastly, we decompose the estimated effect on financial wealth into five subcomponents: equities, bonds, interest funds, bank account balances, and other. These analyses provide information about households’ marginal propensities to invest in specific assets and to take risk. Our results suggest that investments in risky assets account for a relatively modest share of the total increase in financial wealth, with point estimates ranging from 14% to 31%. The causal estimates presented in our study could be further utilized in future work to test and refine different theories of investment and saving behavior.

The organization of the paper is as follows. Section 2 presents our simple, static, portfolio choice model and analyzes its predictions. Section 3 describes our data, the construction of our estimation sample, and our identification strategy. Section 4 presents our reduced-form empirical results and robustness analyses. Section 5 introduces a dynamic lifecycle model of portfolio choice and compares the model predictions with our empirical estimates. Finally, Section 6 discusses the implications of our findings and concludes.

2 A Simple Model of Portfolio Choice

This section examines a static model of portfolio choice that follows [Campbell and Viceira \(2002\)](#).⁴ In a baseline model with CRRA, we examine the main implications of nontradable labor income for a household’s portfolio allocation decision. We analyze how a windfall gain impacts the risky share and derive four predictions that we evaluate empirically in Section 4. A key insight is that in the presence of nontradable labor income,

Holm and Natvik (2021) estimate the effect on consumption, and [Juster, Lupton, Smith and Stafford \(2006\)](#) and [Druedahl and Martinello \(2020\)](#) estimate the effect on saving.

³While we can accurately estimate the saving response, we can only bound the spending response because we do not fully observe transfers, donations, and durable purchases in administrative tax records.

⁴See Chapter 6 of [Campbell and Viceira \(2002\)](#) for additional details and derivations.

estimates of how exogenous wealth shocks impact the risky share may be less informative about risk preferences than the prior literature has tended to acknowledge. We later extend the model to incorporate consumption habits and show that a similar conclusion holds in a model with DRRA. Since the primary purpose of this section is to clarify key mechanisms and concepts in the simplest possible way, the model is purposefully kept simple. In Section 5, we examine to what extent the key insights and conclusions from the static model hold in a richer, dynamic setting.

Baseline Model

Consider an agent who must allocate some fraction $\alpha \in [0, 1]$ of initial financial wealth W_0 into a risk-free asset that yields a guaranteed return R_f , with $r_f = \log(1 + R_f)$, and the remaining fraction $(1 - \alpha)$ into a risky asset that yields a stochastic return R that is log-normally distributed with expected excess return $\mathbb{E}[r - r_f] = \mu$ and variance σ_r^2 . The agent makes the allocation decision knowing that her terminal wealth will be the sum of the realized value of her financial assets and the realized value of her non-negative stochastic labor income H , where $h = \log(H) \sim N(\eta, \sigma_h^2)$. After the allocation decision is made, the value of the labor income is realized, along with the return on the risky investment. The agent then consumes her terminal wealth. We allow for arbitrary correlation between the risky labor income and the return on the risky asset, denoting their covariance by $\sigma_{h,r}$, and assume that the agent cannot borrow against future income to pay for the initial investments: human capital is nontradable. The agent's optimization problem is to maximize the expected utility of her consumption,

$$\max_{\alpha \in [0, 1]} \mathbb{E} \left[\frac{C^{1-\gamma}}{1-\gamma} \right], \quad (1)$$

subject to the budget constraint,

$$C = W_0(1 + R_p) + H, \quad (2)$$

where γ is the coefficient of relative risk aversion and $R_p = \alpha(R - R_f) + R_f$ denotes the portfolio return on total financial wealth. The optimal portfolio rule is given by:

$$\alpha^* \approx \underbrace{\left(1 + \overline{H/W}\right)}_{\text{Upward adjustment}} \left(\frac{\mu + \sigma_r^2/2}{\gamma\sigma_r^2}\right) - \underbrace{\overline{H/W} \left(\frac{\sigma_{h,r}}{\sigma_r^2}\right)}_{\text{Hedging demand}}, \quad (3)$$

where $\overline{H/W}$ captures the ratio of expected human capital to expected financial wealth.⁵ As a special case, without nontradable labor income, the optimal share is $\alpha^* \approx \frac{\mu + \sigma_r^2/2}{\gamma\sigma_r^2}$, which is independent of the level of wealth (Samuelson, 1969).

Equation (3) highlights the factors that affect portfolio choice in the presence of nontradable labor income. The first term represents the optimal share when labor income risk is idiosyncratic and uncorrelated with the risky asset. The optimal portfolio share absent labor income, $\frac{\mu + \sigma_r^2/2}{\gamma\sigma_r^2}$, is distorted by the nontradability of labor income. Because future labor income is a source of positive wealth and is relatively safe compared to equity investments, the agent increases her equity exposure to offset this nontradable position, with the size of the distortion increasing in the ratio of human capital to financial wealth. The second term reflects the hedging demand arising from the covariance between labor income and the risky asset. For example, a negative covariance ($\sigma_{h,r} < 0$) makes equity investments more attractive as they help the agent hedge her consumption risk against bad realizations of labor income. Consequently, a negative covariance increases the risky share by $-\overline{H/W} (\sigma_{h,r}/\sigma_r^2)$, with the size of the adjustment increasing in the ratio of human capital to financial wealth.

While the direction of the total impact of nontradable labor income on the risky share depends on the sign of the covariance term $\sigma_{h,r}$, the analyses in Section 5.2 show that as an empirical matter, $\frac{\mu + \sigma_r^2/2}{\gamma\sigma_r^2} \gg \left| \frac{\sigma_{h,r}}{\sigma_r^2} \right| \approx 0$. That is, the covariance between equity returns and labor income is very small, both in absolute value and relative to the first term. Thus, the overall impact of nontradable labor income on the risky share is always positive.

⁵More formally,

$$\overline{H/W} \equiv \frac{\exp\{\eta\}}{\exp\{w_0 + r_p\}}, \quad (4)$$

where $\eta = \mathbb{E}[\log(H)]$ denotes expected log labor income, $w_0 = \log(W_0)$ denotes log initial wealth, and $r_p = \mathbb{E}[\log(1 + R_p)]$ denotes expected log return on wealth. See Campbell and Viceira (2002) for derivation.

2.1 Model Predictions

Equation (3) can be used to derive a clear, qualitative prediction of how a change in financial wealth impacts α^* . For simplicity, we set $\sigma_{h,r} = 0$ for the purpose of deriving model predictions.

Model Prediction 1. *The risky share decreases after a financial wealth shock.*

Analytically, the prediction follows from the fact that the derivative of α^* with respect to W_0 is everywhere negative. The main intuition behind this result is that the windfall gain reduces the proportion of total wealth held in nontradable human capital. As a result, the household's incentive to offset its nontradable position in future labor income through equity investments is weakened, leading to a decline in equity exposure.

Next, we turn to three additional testable predictions made by the model.

Model Prediction 2. *The elasticity of the risky share with respect to a financial wealth shock diminishes (in absolute magnitude) with the size of the shock.*

Model Prediction 3. *The elasticity of the risky share with respect to a financial wealth shock is larger (in magnitude) when the human-capital-to-financial-wealth ratio is higher.*

Model Prediction 4. *The risky share rises after an exogenous increase in future income.*

Prediction 2 follows from the fact that the second derivative of the portfolio share with respect to financial wealth is everywhere positive. Because the portfolio distortion is hyperbolic in financial wealth, the marginal effect of a dollar-increase becomes smaller as the size of the shock becomes larger. Prediction 3 follows from the sign of the cross-partial with respect to financial wealth and the human-capital-to-financial-wealth ratio. Intuitively, the financial wealth elasticity of the risky share depends on the baseline level of distortions created by the nontradability of human capital. When the initial distortion is large due to a high human-capital-to-financial-wealth ratio, the financial wealth shock induces a stronger unraveling of this distortion, which generates a larger effect. Lastly, Prediction 4 follows from the first derivative of the portfolio share with respect to future income. The intuition for this result is similar to the one underlying Prediction 1 but in the opposite direction. In Section 4, we empirically test each of the four predictions in our sample of Swedish lottery players.

2.2 Incorporating Habit Formation

Even though human capital is a key determinant of households' portfolio choices (Bodie et al., 1992; Viceira, 2001; Benzoni, Collin-Dufresne and Goldstein, 2007), much of the focus in the empirical literature has been on models with habit-formation preferences. Here, we consider an extension of our model that incorporates consumption habits.⁶ We denote the consumption habit by $X > 0$ and define surplus consumption as $C_h \equiv C - X$. The optimization problem can then be expressed as:

$$\max_{\alpha_h \in [0,1]} \mathbb{E} \left[\frac{C_h^{1-\gamma}}{1-\gamma} \right] \quad (5)$$

subject to the budget constraint,

$$C_h = W_0(1 + R_p) + H - X, \quad (6)$$

where $R_p = \alpha_h(R - R_f) + R_f$ denotes the portfolio return on total financial wealth. If $H = 0$ with non-zero probability, the problem is well-defined only if $W_0(1 + R_p) > X$. The reason is that the utility costs of failing to meet the subsistence level are unbounded. To ensure next period's consumption habit is met, a utility-maximizing agent will first allocate the discounted value of consumption habit, $X/(1 + R_f)$, to the risk-free asset and then invest the surplus wealth, $W_0 - X/(1 + R_f)$, using the formula for the baseline model derived in the previous section. Hence, we have:

$$\alpha_h^* = \underbrace{\left(1 - \frac{X}{W_0(1 + R_f)} \right)}_{\text{Downward adjustment}} \alpha^* \quad (7)$$

$$= \left(1 + \frac{\overline{H}}{W} \right) \left(1 - \frac{X}{W_0(1 + R_f)} \right) \left(\frac{\mu + \sigma_r^2/2}{\gamma\sigma_r^2} \right) - \frac{\overline{H}}{W} \left(1 - \frac{X}{W_0(1 + R_f)} \right) \frac{\sigma_{h,r}}{\sigma_r^2}. \quad (8)$$

Equation (7) shows that the optimal allocation in the extended model, α_h^* , is proportional to the optimal share in the baseline model, α^* . Since the adjustment factor is strictly less than one, the adjustment is always toward zero and we have $\alpha_h^* < \alpha^*$. Moreover, the adjustment-factor is increasing in financial wealth, a fact that provides insight into why

⁶Alternatively, incorporating subsistence levels (Rubinstein, 1976; Litzenberger and Rubinstein, 1976) or consumption commitments (Chetty and Szeidl, 2007) into the model can yield similar effects as consumption habits.

habit-formation models are often invoked to explain empirical evidence suggesting positive wealth effects on the risky share (e.g., Wachter and Yogo, 2010; Calvet and Sodini, 2014).

In the extended model incorporating nontradable human capital and consumption habits, a wealth shock thus influences the risky share through two distinct channels, which work in opposite directions. Heuristically, consumption habits can be viewed as negative labor income. Just as human capital is a nontradable asset that provides resources beyond the current financial wealth to generate utility in the future, consumption habits are a nontradable liability that withholds resources from the financial wealth available in future periods. Thus, human capital and consumption habits have opposite implications for the financial wealth elasticity of the risky share, as shown in Equation (8). Whereas human capital induces negative wealth effects on the risky share, consumption habits induce positive wealth effects. Consequently, the net effect is ambiguous and depends on the relative strengths of the two channels.

Despite the ambiguity, our analysis above makes two simplifying assumptions that are likely to cause the model to overstate the quantitative importance of consumption habits. First, our analysis implicitly assumes that the lower bound on the realized labor income is zero. Second, we assume that the worst-case equity returns is -100%, implying that all wealth not invested in the safe asset could be depleted entirely. These assumptions jointly imply that the investor will always choose to allocate the maximally conservative amount in the risk-free asset to fund the consumption habit. Under more realistic assumptions about the worst-case scenario,⁷ the mandatory investment in the risk-free asset would be smaller, and accordingly, the positive relationship between financial wealth and the risky share induced by the consumption-habit channel would be weaker.

In Section 5, we conduct a quantitative analysis of an enriched lifecycle portfolio choice model featuring calibrated income profiles and consumption habits, and show that the human-capital channel indeed dominates the habit channel in this more realistic setting, as evidenced by the negative overall effect of financial wealth on the risky share.

⁷For instance, social insurance programs in Sweden, such as unemployment insurance, provide a safety net equivalent to 70-80% of a household's previous average earnings in Sweden (<https://www.oecd.org/social/soc/29736100.pdf>). The largest historical annual market downturns on the Swedish equity markets occurred in 1918 and 2008. In both years, the index declined by about 43% (Waldenström, 2014).

3 Data and Identification Strategy

Our analyses are conducted in a sample of lottery players who have been matched to administrative demographic and financial records using players’ personal identification numbers (PINs). This section describes the key features of the administrative lottery samples, the government registers, and our identification strategy.⁸

3.1 Portfolio and Register Data

All financial variables used in our analyses are derived from the Swedish Wealth Register. The register is maintained by Statistics Sweden and contains detailed information about the year-end financial portfolios of the entire Swedish population from 1999 until 2007. These data have been used in a number of influential studies beginning with Calvet, Campbell and Sodini (2007) and are generally of very high quality. Despite its comprehensive coverage, however, we acknowledge a limitation of our data, namely that defined-contribution retirement wealth and private businesses are not reported (Bach, Calvet and Sodini, 2020; Calvet et al., 2021) and thus are excluded from our analyses. See Section 4.3 for additional details on the dataset and a discussion of possible limitations.

The Wealth Registry contains disaggregated measures of debt and multiple types of assets, including bank account balances,⁹ mutual funds, directly held stocks, bonds, interest funds, debt, residential and commercial real estate, and other financial and real assets. Throughout the paper, we refer to several portfolio measures constructed from these underlying assets. Similar to Calvet and Sodini (2014), we refer to *cash* as the sum of bank account balances and interest funds, whereas *risky financial assets* refer to directly held stocks and mutual funds. *Equity market participants* are those who own risky financial assets. We measure *financial wealth* as the sum of cash, risky financial assets, capital insurance products, and directly held bonds. In our preferred specification, the *risky share* is defined as the year-end share of a household’s total financial wealth that is held in risky financial assets. In addition to the financial variables, we use administrative records of demographics and income from Statistics Sweden.

⁸Our data and empirical strategy are similar to those of Cesarini, Lindqvist, Östling and Wallace (2016), Cesarini, Lindqvist, Notowidigdo and Östling (2017), and Briggs et al. (2021), with Cesarini et al. (2016) providing the most thorough description of our lottery samples.

⁹We impute bank account balances which fell below the required reporting threshold. We discuss our imputation procedure in detail in Appendix C.

Our baseline analyses are conducted at the household level, where a household is defined as the lottery player and, if present, his or her spouse. We limit all analyses to players aged at least 18 at the time of the lottery and who are known to have participated in equity markets in the year prior to the lottery.¹⁰ Since we only observe equity-market participation annually from 1999 until 2007, the participation restriction effectively limits the sample to players whose lottery event occurred between 2000 and 2007.

3.2 Lottery Data

Our final estimation sample consists of players from three separate Swedish lotteries – Triss, Kombi and PLS – whose lottery events took place between 2000 and 2007. Our empirical strategy is to use the available data and institutional knowledge about each lottery to assign players to groups within which we know the prizes were randomly assigned under the rules of the lottery. We then control for group-identifier fixed effects in all analyses. Doing so ensures all identifying variation comes from players in the same group. Because the process by which we assign players to groups varies across lotteries, we briefly describe each lottery separately below.¹¹ Throughout the paper, lottery prizes and all other variables originally measured in units of SEK are converted to units of year-2010 USD before analyses. To convert each monetary variable, we first convert each value to units of year-2010 SEK using Statistics Sweden’s annual consumer price index normalized so its value is 1 in 2010. We then convert the inflation-adjusted SEK amount to USD using the exchange rate on December 31, 2010 (6.72 SEK/USD). Except where explicitly noted otherwise, we restrict all analyses to prizes paid as lump sums.

Kombi

Kombi is a monthly subscription lottery used to raise funds for the Swedish Social Democratic Party, Sweden’s largest political party. Participants specify how many tickets to purchase each month, and usually pay via direct debit. Kombi provided us with a longitudinal dataset containing the number of tickets purchased, information about any prizes won that are greater than or equal to 1M SEK, and the PIN for each participant between

¹⁰Households that did not participate in the equity market prior to the lottery can only weakly increase their risky share through the previously studied extensive-margin participation decision (Briggs et al., 2021), and thus are excluded from analysis for interpretational clarity in this paper.

¹¹For a more detailed description of the data, we refer the reader to Section 2 and the Online Appendix of Cesarini et al. (2016), where the data was first introduced, pre-processed, and quality controlled.

1998 and 2011.

Prizes are awarded by randomly sampling a ticket from the set of tickets purchased for each monthly draw. Because all tickets have an equal probability of being selected, individuals with the same number of tickets are equally likely to win any given prize. To construct the group identifiers, each winner is therefore matched to (up to) 100 non-winning players with the same age, gender, and number of tickets in the month of the draw. This matching procedure leaves a sample of 199 large-prize winners, matched to a total of 18,078 controls.

Triss

Triss is a scratch-ticket lottery run by Svenska Spel, the government-owned gambling company. Since 1994, a subset of Triss lottery winners are entitled to appear on a TV show where she can win a monetary prize. There are two ways to qualify for the show.

The first is to present a ticket with three matching television symbols. Each player in possession of such a ticket is invited to a live TV show where they win a lump-sum prize. At the show, the player draws a prize by selecting a ticket from a stack of scratch-off tickets that are indistinguishable (before they are scratched). The chosen ticket is then scratched to reveal the size of the lump-sum prize. The distribution of prizes in each stack of tickets is determined by a regulatory document called a prize plan. Since there is no element of skill or strategy in the ticket selection, the magnitude of the lump-sum prize won is random conditional on the prize plan (which is occasionally revised). We therefore assign two players to the same group if they appeared on the TV show exactly once in the same year and drew a lump-sum prize under the same prize plan. In our sample, the lump-sum prizes, measured net of taxes in year-2010 USDs, range in value from 8K to 866K.

The second way is to present a ticket with three matching clover symbols. Each player in possession of such a ticket wins a monthly installment prize, the value of which is determined on live television, this time by having the player draw two tickets. The first determines the size of the monthly installment to be paid out (range: \$1,500 to \$8,000) and the second the duration of the monthly installments (10 to 25 years). The two draws are independent, again with underlying distributions determined by the prize plan.

Svenska Spel provided us with demographic information about all TV show participants between 1994 and 2011. Using this information, we were able to identify the PINs of 99% of participants and match them to the government registers. In our main analyses, we only include the 1,065 lumpsum winners. We exclude monthly-installment winners

since the purpose of our main analyses is to test theoretical predictions about the effect of a sudden windfall that increases initial wealth W_0 , as described in Section 2. Since monthly prizes cannot be easily liquidated into a net present value, it is not appropriate to use them to test predictions about the effects of windfalls that increase the amount of liquid, financial wealth. Rather, they are conceptually more similar to a change in human capital, H . Therefore, we include the monthly prizes in testing the prediction that shocks to future income and initial financial wealth have opposite effects on the risky share. In this comparison, we include a sample of 227 participants who received prizes paid in monthly installments. To facilitate comparability, we convert each monthly prize to a net present value and exclude Triss monthly prizes with an estimated net present value above \$1M. The latter restriction is intended to make the prize distributions more comparable.

Prize-Linked Savings

Prize-linked savings (PLS) accounts are savings accounts with a lottery element that randomly award monetary prizes to some accounts instead of (or sometimes in addition to) paying interests. PLS accounts were initially subsidized by the Swedish government. Although the subsidies ended in 1985, banks were authorized to continue offering PLS products to retail consumers. Participation was widespread across broad strata of Swedish society, with every other Swede owning an account in the late 1980s.

The PLS sample was obtained by combining prize records and account information from the PLS accounts maintained by commercial banks and the state bank. These data allow us to identify the account owner, account balance, and amount won for each prize paid between 1986 and 2003. The probability of winning was proportional to the number of tickets associated with an account, where one ticket was assigned for each 100 SEK in the account balance at the times of draws. PLS lotteries paid both odds prizes, which were awarded as a multiple of the account balance, and fixed prizes whose magnitude was independent of account balance. However, because we lack information on account balances after 1994, we only consider fixed prizes in this paper.

Following [Imbens et al. \(2001\)](#) and [Hankins et al. \(2011\)](#), our identification strategy for PLS exploits the fact that the prize distribution is independent of account balance among players who won the same number of fixed prizes in a given draw. Hence, we assign two individuals to the same group if they won an identical number of fixed prizes in that draw. This matching procedure leaves a sample of 30,613 PLS lottery winners for the period 2000 through 2007.

Table 1: Prize Distribution. This table shows the number of lottery prizes in the indicated prize-size categories for the pooled sample and the three lottery subsamples. Prize amounts are in year-2010 USD and net of taxes.

| Prize Amount | (1) Pooled | (2) Kombi | (3) Triss | (4) PLS |
|------------------------|---------------|--------------|--------------|------------|
| $L_i = 0$ | 18,078 | 18,078 | 0 | 0 |
| $0 < L_i \leq 1K$ | 30,345 | 0 | 0 | 30,345 |
| $1K < L_i \leq 10K$ | 478 | 0 | 212 | 266 |
| $10K < L_i \leq 100K$ | 801 | 0 | 801 | 0 |
| $100K < L_i \leq 250K$ | 202 | 188 | 12 | 2 |
| $250K < L_i$ | 51 | 11 | 40 | 0 |
| Total | 49,955 | 18,277 | 1,065 | 30,613 |

3.3 Identification

Normalizing the time of the lottery to $s = 0$, our main estimating equation is given by

$$Y_{i,s} = \beta_s L_{i,0} + \mathbf{X}_i \mathbf{M}_s + \mathbf{Z}_{i,-1} \boldsymbol{\gamma}_s + \eta_{i,s}, \quad (9)$$

where i indexes households, $L_{i,0}$ denotes the prize size (in 100K USD), \mathbf{X}_i is a vector of group-identifier fixed effects, and $\mathbf{Z}_{i,-1}$ is a vector of controls that include a wide range of demographic characteristics (age, sex, marital status, higher education, household size, household income, Nordic born) as well as financial characteristics (net wealth, gross debt, real estate ownership, risky share). The control variables are measured in the year before the lottery and are included only to improve the precision of our estimates. Standard errors are clustered at the level of the player. The key identifying assumption needed for β_s to have a causal interpretation is that the prize amount won is independent of $\eta_{i,s}$ conditional on the group-identifier fixed effects.

Prize Variation

To provide a better sense of the source of our identifying variation, Table 1 summarizes the prize distribution in our final estimation sample. The total value of the after-tax prize money disbursed to the winners in our sample is approximately 90M USD (610M SEK), with 84% of the identifying variation coming from prizes whose value exceeds the median Swedish household income in 1999 of 21K USD (143K SEK). Even though small prizes

account for a relatively large fraction of prizes won, most of the identifying variation comes from the larger prizes, especially in Kombi and Triss.¹²

Testing for Random Assignment

To test our key identifying assumption, we again normalize the time of lottery to $s = 0$ and run the following regression:

$$L_{i,0} = \mathbf{X}_{i,0}\boldsymbol{\Gamma}_0 + \mathbf{Z}_{i,-1}\boldsymbol{\rho}_{-1} + \varepsilon_i. \quad (10)$$

Under the null hypothesis of conditional random assignment, the characteristics determined before the lottery ($\mathbf{Z}_{i,-1}$) should not predict the lottery outcome ($L_{i,0}$) conditional on the group-identifier fixed effects ($\mathbf{X}_{i,0}$). We run these quasi-randomization tests in our pooled sample and in each lottery subsample separately. As expected, Appendix Table A.2 shows the lagged characteristics overall have no statistically significant predictive power once we control for group-identifier fixed effects in the analyses.¹³ When the fixed effects are omitted, the null hypothesis is rejected. This finding illustrates the importance of controlling for factors conditional on which the lottery prizes are randomly assigned.

Representativeness of the Lottery Sample

Table 2 compares our lottery sample to a random sample of adult Swedish stock-market participants matched on sex and age. Columns (1) and (2) compare our pooled sample to the random sample. For most demographic characteristics, the distributions are very similar. The main difference is that players in our sample are ten percentage points less likely to have attended college. In terms of financial characteristics, players in our sample have lower net wealth on average, but the differences in other characteristics are quite small. For example, the average risky share in the pooled lottery sample is 0.41, compared to 0.43 in the representative sample. Columns (3)-(5) provide descriptive statistics separately by lottery.

¹²Our main results are robust to excluding PLS prizes, most of which are relatively small prizes.

¹³We reject the joint significance of the lagged characteristics in 10 of the 12 F -tests conducted. The two exceptions occur in the PLS subsample, with p -values of 0.08 and 0.035.

Table 2: Representativeness of the Lottery Sample. This table compares our lottery sample to a representative sample of stock market participants matched on age and sex. The pooled sample is generated by weighting each lottery sample by its share of the identifying variation. The summary statistics shown are all means and are measured at $s = -1$. All variables except female, age, and Nordic born are measured at the household level. Continuous financial variables are winsorized at the 0.5 and 99.5 percentiles.

| | (1) | (2) | (3) | (4) | (5) |
|------------------------------------|----------------|--------|--------|-------|--------|
| | Representative | Pooled | Kombi | Triss | PLS |
| <u>Demographic Characteristics</u> | | | | | |
| Female | 0.479 | 0.479 | 0.421 | 0.511 | 0.539 |
| Age (years) | 56.1 | 56.1 | 62.2 | 52.8 | 62.1 |
| Nordic born | 0.952 | 0.971 | 0.986 | 0.963 | 0.968 |
| Household size (#) | 2.269 | 2.264 | 2.010 | 2.408 | 2.012 |
| Household income (\$K) | 63.0 | 60.2 | 59.9 | 60.4 | 54.6 |
| Married | 0.617 | 0.592 | 0.624 | 0.575 | 0.581 |
| College | 0.385 | 0.284 | 0.255 | 0.300 | 0.314 |
| <u>Financial Characteristics</u> | | | | | |
| Net wealth (\$K) | 220.5 | 162.6 | 174.2 | 155.7 | 257.1 |
| Gross debt (\$K) | 62.6 | 56.8 | 45.4 | 63.2 | 37.9 |
| Homeowner | 0.800 | 0.807 | 0.851 | 0.783 | 0.780 |
| Risky share | 0.434 | 0.413 | 0.428 | 0.405 | 0.455 |
| <i>N</i> | 208,916 | 49,955 | 18,277 | 1,065 | 30,613 |

4 Empirical Analysis

4.1 Baseline Estimates of Wealth Effects on Risky Share

Figure 1 displays our estimates of how wealth impacts the year-end risky share at $s = 0, 1, \dots, 4$. Our estimates suggest that a \$100K windfall leads to an immediate decrease in the share of financial wealth allocated to risky assets: in the year of win, the risky share declines by 4.8 percentage points (SE = 0.6). Figure 1 also illustrates that this reduction persists for at least four years, the longest post-lottery event horizon we consider in our analyses.¹⁴

¹⁴As shown in Appendix Table A.1, the confidence intervals widen as the the time horizon is extended. Two factors contribute to this widening. First, the pre-lottery characteristics absorb less and less residual variance. Second, the size of the estimation sample falls as the time horizon is extended.

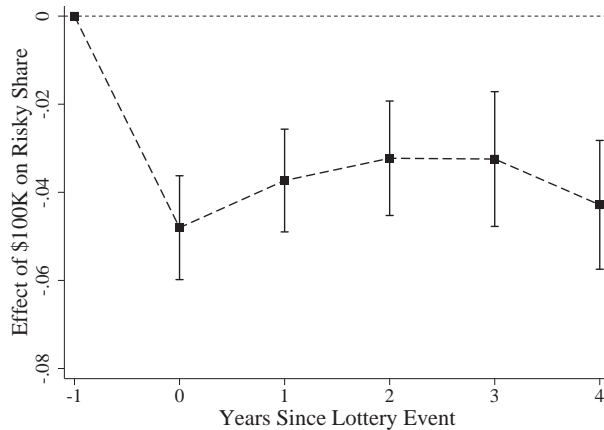


Figure 1: Effect of 100K USD of Lottery Wealth on Risky Share. Coefficients and 95% confidence intervals are obtained by estimating Equation (9) in our pooled sample. See Appendix Table A.1 for the underlying estimates.

4.2 Evaluating Model Predictions

Our next analyses are designed to empirically test predictions 2, 3, and 4 of the static model described in Section 2.

Prediction 2: Diminishing Marginal Wealth Effects on Risky Share

The model predicts that the risky share is everywhere decreasing in the magnitude of the lottery prize, but at a decreasing rate. To test this hypothesis, we derive five indicator variables from the lottery-wealth variable used in our main analyses. Each indicator variable takes on the value 1 if the prize falls within a given prize range and 0 otherwise. The five ranges are (i) 0 to 1K USD, (ii) 1K to 10K, (iii) 10K to 100K, (iv) 100K to 250K, and (v) 250K and more. We then re-run our main analyses using four of these indicator variables in lieu of the original treatment variable (the omitted category is the one with prizes less than \$1K).

Figure 2 displays the estimated coefficients at year-end in $s = 0$. In the figure, the x -coordinate for each coefficient is the average prize won by players in the category. The results are broadly consistent with the theoretical prediction. Although the first two coefficient estimates are not statistically distinguishable from zero, the latter two coefficients provide supporting evidence that the marginal effect of wealth is larger (in absolute value) in the smaller category than the larger one.

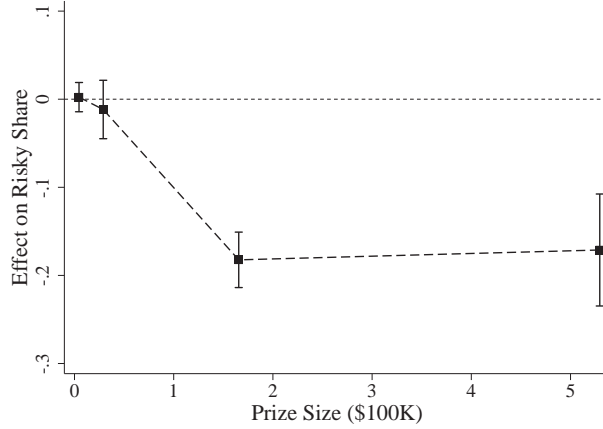


Figure 2: Effect of Lottery Wealth on Risky Share by Prize Size. Coefficients are obtained by estimating Equation (9) with the lottery-wealth variable replaced by indicators for five mutually exclusive prize categories: 0 to 1K USD, 1K to 10K, 10K to 100K, 100K to 250K, and 250K+ . The smallest prize category is omitted in the regression. Coefficient estimates and the 95% confidence intervals are plotted for each category. See Appendix Table A.3 for the underlying estimates.

Prediction 3: Wealth Effects by Human-Capital-to-Wealth Ratio

Next, we evaluate the prediction that the impact of a wealth shock should be larger in absolute value (i.e. more negative) when a larger share of total (pre-lottery) wealth is accounted for by human capital. To test this prediction, we first define a measure of each household’s expected human capital, following Calvet and Sodini (2014). Household h ’s human capital at time t is given by:

$$HC_{h,t} = \sum_{n=1}^{T_{h,t}} \pi_{h,t,t+n} \frac{\mathbb{E}_t(H_{h,t+n})}{(1+r)^n}, \quad (11)$$

where $H_{h,t}$ denotes the household’s period- t labor income, $\pi_{h,t,t+n}$ denotes the probability that household h is alive at date $t+n$ conditional on being alive at date t , and $T_{h,t}$ is the difference between 100 and the age of household h at date t . We use the observed income of household h at date t , together with the estimated labor income process specified in Equation (14), to compute the expected trajectory of future income $H_{h,t}$ over the life cycle.¹⁵ We then use Equation (9) to estimate separate wealth effects for households with human-capital-to-wealth ratios below and above the median.

¹⁵For a more detailed description of the human capital calculation, we refer the reader to Appendix B.5.



Figure 3: Effect of Lottery Wealth on Risky Share by $s = -1$ HC/W Ratio. Coefficients and 95% confidence intervals are obtained by estimating Equation (9) in our pooled sample stratified by pre-lottery human-capital-to-wealth ratio (above or below median). See Appendix Table A.4 for the underlying estimates.

The results, depicted in Figure 3, provide some support for the prediction. For every $s = 0, 1, \dots, 4$, our point estimate is consistently larger (in absolute value) for households with above-median ratios of human capital to wealth, as predicted by the theory. However, these differences are not statistically significant, indicating that the evidence is at most suggestive. Another potential limitation of our test is that human-capital-to-wealth ratios are not randomly assigned. It is therefore possible that the patterns displayed in the figure partly reflect differential selection into the two groups.

Prediction 4: Heterogeneity by Mode of Payment (Lump Sum vs. Installments)

Finally, we test the prediction that an exogenous increase in future income should have a *positive* impact on the risky share. Our test takes advantage of the fact that some players in our Triss sample won lump-sum prizes, whereas others won prizes paid out as monthly installments. Conditional on winning exactly one Triss prize, the type of prize is random and outside the control of the player. Lump-sum prizes generate an immediate increase in liquid financial wealth that is predicted to generate a negative effect on the risky share (per *Prediction 1*). Prizes paid as monthly installments, by contrast, have no impact on short-run liquidity but increase future income flows. For these prizes, the model predicts a positive effect on the risky share (per *Prediction 4*), provided there is no mechanism for liquidating the future income flows into a lump-sum payment approximately equal to the net-present

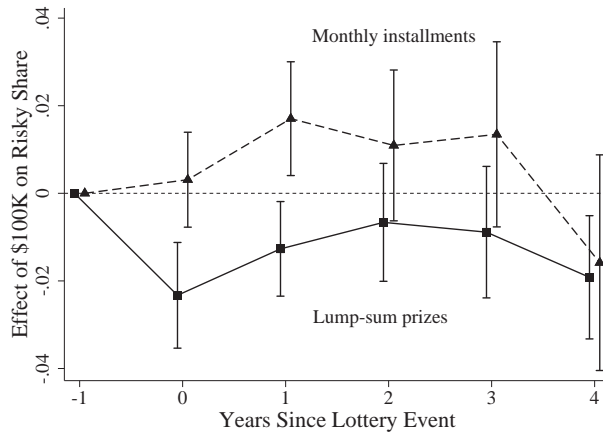


Figure 4: Effect of Lottery Wealth on Risky Share by Mode of Payment. Coefficients and 95% confidence intervals are obtained by estimating Equation (9) among Triss winners stratified by type of payment plan (lump sum or monthly installments). See Appendix Table A.4 for the underlying estimates.

value of the anticipated income flows. We therefore estimate separate treatment effects for the two types of windfalls.

To facilitate comparisons, we convert each monthly-installment prize into a lump-sum equivalent by calculating its net present value before running any analyses. We also restrict the set of monthly prizes to ensure that the distribution of prizes (measured either as lump-sums or lump-sum equivalents) are similar in the two samples. Figure 4 displays the results. For winners of monthly installments, the estimated effects are indeed weakly positive (though not always statistically significant) in all post-lottery years except $s = 4$. This is in sharp contrast to the sizable decline in the risky share observed for winners of lump-sum prizes. A standard F -test rejects the null of identical effects at $s = 0$ (p -value = 0.002) and $s = 1$ (p -value < 0.001) but not at later time horizons, where the differences in treatment effects are estimated less precisely.

Heterogeneity by Household Characteristics

We conduct a number of additional analyses to examine how wealth effects vary by a range of demographic and financial characteristics. In each analysis, we stratify our pooled sample along some dimension of interest, and then compare the estimated wealth effects in the two subsamples. We estimate wealth effects for two time horizons: $s = 0$ and $s = 3$. Table 3 presents the results for $s = 0$ (see Appendix Table A.5 for the $s = 3$ results,

Table 3: Heterogeneous Effects of Lottery Wealth on Risky Share. Coefficients are obtained by estimating Equation (9) at time $s = 0$ in our pooled sample stratified by various demographic and financial characteristics. Hetero p is obtained from an F -test of the null hypothesis that the two lottery-wealth coefficients are identical. Income risk is proxied by the standard deviation of annual income changes prior to the lottery. Equity returns are based on the MSCI Sweden Index in the calendar year prior to the lottery.

| | Demographic Characteristics | | | | | | | |
|------------|-----------------------------|--------|-----------|--------|---------|--------|---------------|--------|
| | Sex | | Age | | College | | Self-employed | |
| | Male | Female | ≤ 45 | > 45 | No | Yes | No | Yes |
| Effect | -0.068 | -0.040 | -0.061 | -0.051 | -0.061 | -0.036 | -0.058 | -0.016 |
| SE | 0.011 | 0.009 | 0.019 | 0.008 | 0.008 | 0.013 | 0.007 | 0.018 |
| p | <0.001 | <0.001 | 0.001 | <0.001 | <0.001 | 0.006 | <0.001 | 0.365 |
| Hetero p | 0.051 | | 0.603 | | 0.116 | | 0.027 | |
| N | 25,218 | 24,737 | 6,115 | 43,840 | 35,371 | 14,584 | 46,861 | 3,094 |

| | Financial Characteristics | | | | | | | |
|------------|---------------------------|--------|-----------|--------|-------------|--------|----------------|--------|
| | Gross Debt | | Homeowner | | Income Risk | | Equity Returns | |
| | ≤ 0 | > 0 | No | Yes | Low | High | ≤ 0 | > 0 |
| Effect | -0.068 | -0.048 | -0.088 | -0.049 | -0.071 | -0.042 | -0.076 | -0.042 |
| SE | 0.012 | 0.008 | 0.020 | 0.007 | 0.011 | 0.009 | 0.013 | 0.008 |
| p | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Hetero p | 0.173 | | 0.070 | | 0.041 | | 0.030 | |
| N | 20,051 | 29,904 | 9,679 | 40,276 | 25,006 | 24,949 | 29,584 | 20,371 |

which are broadly similar in terms of magnitude, but with larger standard errors). Table 3 shows that across all subsamples analyzed, the estimated wealth effects are negative. The analyses also suggest that wealth effects may be larger in magnitude in some groups, including winning players who (i) are male, (ii) are not self-employed, (iii) do not own a home, (iv) face lower income risks, and (v) win the lottery at a time when equities have recently been generating negative returns.

Many of these findings are readily reconcilable with findings of other studies. For example, smaller wealth effects among homeowners are in line with a prior literature that finds that homeownership reduces households' appetite for risk (Grossman and Laroque, 1990; Cocco, 2005; Flavin and Yamashita, 2011). In particular, if we view homeownership as a proxy for committed consumption (Chetty and Szeidl, 2007), it would generate an offsetting effect to nontradable human capital and weaken the negative relationship between

financial wealth and the risky share, as discussed in Section 2. Similarly, if households hold less equity ex ante to compensate for background risk from more volatile income (Viceira, 2001) or entrepreneurial risk from self-employment (Heaton and Lucas, 2000), the scope for financial wealth shocks to reduce the risky share might be relatively limited for such households, which results in a smaller decrease in the risky share. Lastly, households being less willing to invest in risky assets in years following poor equity returns is consistent with findings that expectations about the stock market reflect extrapolation of recent realized returns into the future (Vissing-Jørgensen, 2003; Greenwood and Shleifer, 2014).

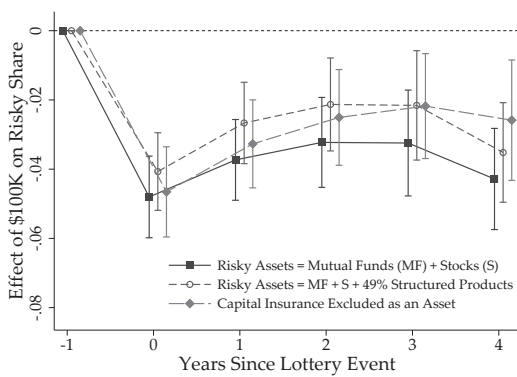
4.3 Robustness Analyses

In this section, we probe the robustness of our main results. We examine the sensitivity of our headline estimates to alternative definitions of the risky share, further discuss the external validity of our estimates, and investigate the concern that the negative wealth effects are an artifact explained by household inaction/sluggishness. We conclude by discussing the broader relevance of some of the treatment effects reported in this section for household-finance and macro-finance literatures.

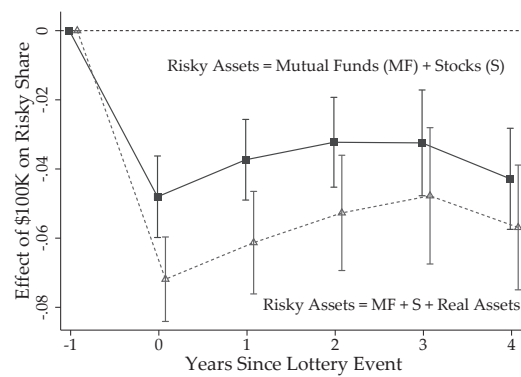
Definition of Risky Share

In our main analyses, we follow the convention of defining a household's risky share as the proportion of its total financial wealth held in directly held stocks or mutual funds. In practice, not all types of financial assets can be straightforwardly categorized as either risky or risk-free. We examine how robust our results are to three alternative definitions of the risky share. First, we follow Calvet, C  lerier, Sodini and Vall  e (2023) by classifying structured products as partially risky, assuming a risk exposure of 49%. Second, we follow Calvet et al. (2007) by excluding capital insurance products altogether when calculating the risky share.¹⁶ Third, we classify real estate as a risky asset and define the risky share as the proportion of a household's portfolio – defined as the sum of financial wealth and real estate wealth – that is held in risky financial assets or in real estate. Figure 5 compares our original results to the three alternatives. Classifying structured products as partially risky or dropping capital insurance products produces similar results, albeit with coefficient

¹⁶The Wealth Register records the total value of capital insurance products but not the asset allocation within these products. Dropping capital insurance from the calculation of the risky share is equivalent to assuming that the total amount in capital insurance is allocated between safe and risky assets in the same proportion to all other assets in a household's portfolio with determinable risk exposure.



(a) Alternative Financial Assets



(b) Real Estate Assets

Figure 5: Robustness to Alternative Definitions of Risky Share. Coefficients and 95% confidence intervals are obtained by estimating Equation (9) using an alternative definition of the risky share. Panel (a) categorizes structured products as partially risky assets with a risk exposure of 49%, and excludes capital insurance products in calculating the risky share. Panel (b) classifies real estate as risky assets. See Appendix Table A.1 for the underlying estimates.

estimates that are smaller in magnitude. Treating real estate wealth as a risky asset instead gives coefficients further away from zero.

External Validity

A commonly voiced concern about lottery studies is their results may be hard to generalize. The concern is usually grounded in widespread beliefs that lottery players tend to be strongly negatively selected on factors such as financial sophistication and educational background. These popular beliefs are often reinforced by reports in the popular press about lottery winners who went on to quickly squander their wealth and claim to regret the experience of winning. However, a prior literature starting with [Kaplan \(1987\)](#) generally rejects these popular beliefs as inaccurate. Differences between lottery players and the general population tend to be smaller than common stereotypes might suggest. It is also rare for players to completely squander the financial windfalls within a matter of years, contrary to what the common stereotype suggests. For example, previous analyses of the sample of Swedish lottery players analyzed here provide no evidence that lottery winnings have deleterious long-run effects on winners' financial and emotional well-being ([Lindqvist, Östling and Cesarini, 2020](#)).

Here, we conduct additional analyses designed to test different explanations for the dis-

parities between our results and those reported in the earlier literature. Our basic approach is to examine if large differences in results persist when the methodology of previous quasi-experimental papers is applied in our sample (as closely as possible). Our main analysis compares the estimates reported in Brunnermeier and Nagel (2008) to those we obtain when we follow their methodology as closely as possible in our data. Brunnermeier and Nagel (2008) use the following estimating equation in their analysis of the Panel Study of Income Dynamics (PSID):

$$\Delta_k \alpha_t = \beta q_{t-k} + \gamma \Delta_k h_t + \rho \Delta_k w_t + \varepsilon_t, \quad (12)$$

where α_t is the share of stocks or mutual funds in the financial portfolio, q_{t-k} is a vector of household characteristics (e.g., age, gender, marital status, household composition, unemployment, log income, union employment, vehicle ownership, and inheritances), $\Delta_k h_t$ is a vector containing changes in family composition or asset ownership (e.g., changes in number of children, homeownership, business ownership), and $\Delta_k w_t$ is the change in log wealth. To address concerns about measurement error, Brunnermeier and Nagel (2008) run additional analyses with quantile dummies for income growth from $t - k$ to t and inheritance receipts as instruments, and estimate Equation (12) using a two-stage least squares procedure.

We sought to replicate their original analyses as closely as possible in our sample of Swedish lottery players.¹⁷ The results are summarized in Figure 6. At the $k = 2$ year horizon, the estimates for both OLS and 2SLS are statistically indistinguishable from zero and/or economically small.¹⁸ Estimates are similarly indistinguishable from zero at the $k = 5$ year horizon. For three out of four coefficients, a test of the null that the parameters are identical in the PSID sample and the Swedish lottery sample fails to reject. Overall, the results are consistent with the hypothesis that most of the original differences in results disappear under a common methodology.

Our findings of robust negative wealth effects on portfolio risk also conflict with those reported in Calvet and Sodini (2014) and Calvet et al. (2009), both of whom analyzed large samples of Swedes. Although data limitations do not allow us to directly apply ei-

¹⁷Our specification is identical to the one originally used by Brunnermeier and Nagel (2008) except that we exclude four controls that are not available in the register data. To avoid contamination from lottery winnings, we restrict our analysis to households that won the lottery at least $k + 1$ years after 1999. Hence, the estimation sample used in the $k = 2$ (5) is restricted to players who won in 2002 (2005) or later.

¹⁸The OLS coefficient of -0.039 reported by Brunnermeier and Nagel (2008) implies that 10% growth in wealth leads to a tiny reduction in the share of risky assets by 0.0039, for example, from 50% to 49.61%.

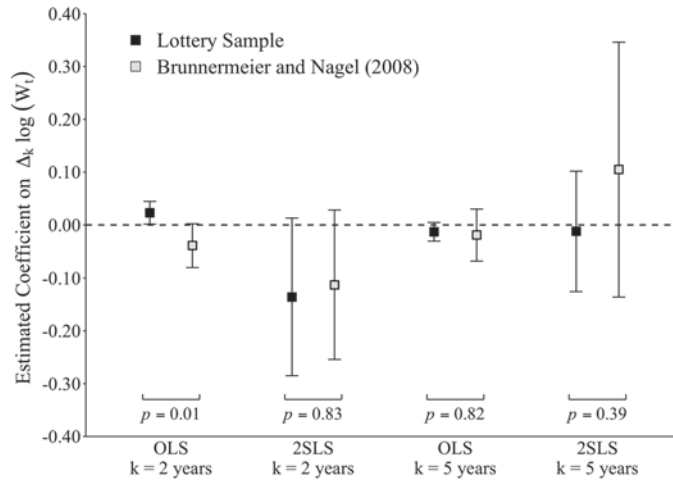
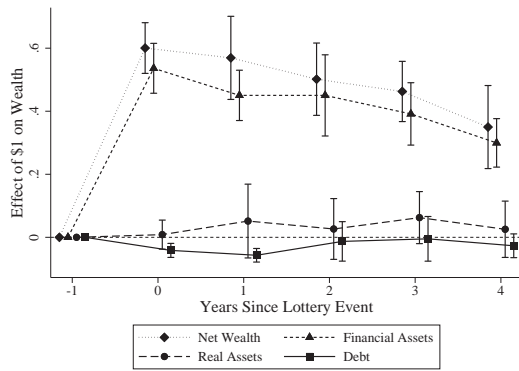


Figure 6: Non-Experimental Estimates of Financial Wealth Elasticity of Risky Share. Coefficients are obtained by estimating Equation (12) in our pooled sample with an end date the year prior to the lottery win. Regressions are estimated at 2- and 5-year horizons using both OLS and 2SLS. This estimation closely replicates Table 4 of Brunnermeier and Nagel (2008). Observations are weighted by their respective contribution to the identifying variation in the lottery regressions. p -value is obtained from a test of the null that the two coefficients are identical. See Appendix Table A.6 for underlying estimates.

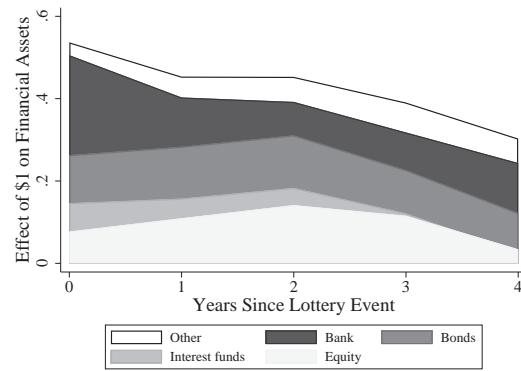
ther study’s methodology in our lottery sample, Calvet et al. (2007) reported an analysis of the cross-sectional relationship between stock market participation and a number of demographic and financial characteristics. Briggs et al. (2021) show that when a similar specification is used in our sample of Swedish lottery players, the results are strikingly similar. In Appendix D, we provide a more detailed discussion of the assumptions underlying the identification strategies by Calvet et al. (2009) and Calvet and Sodini (2014). Overall, the available evidence thus points to methodological differences as a plausible explanation for the observed differences between our findings and those in the previous literature.

Household Inaction and Sluggish Reinvestment

We next explore the hypothesis that the negative wealth effects are an artifact of households’ inaction and sluggishness in investing the prize money after it is deposited into players’ bank accounts. Such inaction could cause the risky share to fall mechanically for reasons unrelated to risk preferences (e.g., procrastination or status quo bias causes the prize money to sit in a checking account for a long time before it is invested). To investigate this hypothesis, we analyzed how the lottery windfalls impact a number of specific asset



(a) Wealth Categories



(b) Financial-Asset Categories

Figure 7: Allocation of Lottery Wealth across Asset Classes. Coefficients and 95% confidence intervals are obtained by estimating Equation (9) where various asset classes are used as outcome variables. Panel (a) shows the allocation of lottery winnings across broad wealth categories. Panel (b) shows the allocation within financial assets. All outcome variables reflect year-end market values. See Appendix Table A.7 for the underlying estimates.

and liability subcategories.

The results from these analyses are summarized in Figure 7. The coefficients depicted are scaled as proportions, so an estimate of 0.10 implies that the total value of the asset class rises by 10 cents for each dollar won. In Panel (a), we plot the estimated coefficients for net wealth and its decomposition into financial assets, real assets, and debt. In Panel (b), we show a further decomposition of the financial assets into five mutually exclusive categories: equity, interest funds, bonds, bank account balances, and other financial assets.

Under widespread inaction, a considerable portion of the lottery winnings is expected to remain in the bank accounts, where the prizes are initially deposited, for an extended period of time. The $s = 0$ estimates in Panel (b) indicate that there is some initial tendency to keep the winnings in the bank accounts: in the year of win, each \$100 won is estimated to increase the year-end bank account balance by \$24 (SE = \$4.3). However, this effect diminishes quickly, and in all subsequent periods, it remains in the range of \$8 to \$12. Importantly, we also find that most of the prize money is actively reallocated to other financial assets, with much of the investments directed towards bonds and interest funds that carry low risks. These findings thus suggest that the reduction in the risky share cannot be attributed to inaction or a general aversion to investing the windfalls in financial assets.

Broader Relevance

The estimates depicted in Figure 7 are likely to prove valuable beyond the specific setting of this paper.¹⁹ For example, credible and statistically precise estimates of how windfalls impact various asset and liability classes could help improve evaluations and calibrations of a wide range of household-finance and macro-finance models.

Consider the estimates in Panel (a) of the per-dollar effect of lottery winnings on net wealth. At the end of the year of win, we estimate that net wealth increases by \$60 per \$100 won, whereas the analogous estimate four years after the lottery is \$35. These estimates provide information about the average household’s marginal propensity to save (MPS) out of a wealth shock, whereas the residual effect (i.e., $1 - \text{MPS}$) can be interpreted as an upper bound on the household’s marginal propensity to spend (MPX), a crucial determinant of fiscal and monetary policies in heterogeneous-agent models (Kaplan, Moll and Violante, 2018; Auclert, 2019; Laibson, Maxted and Moll, 2022).²⁰ Furthermore, the panel nature of our data allows us to estimate dynamic saving responses over time, providing valuable information about *intertemporal* marginal propensities that are essential inputs for the general-equilibrium amplification of shocks (Auclert, Rognlie and Straub, 2023).

Our data also allow us to decompose the total saving response into allocations across different components of household balance sheets. In Panel (a), among broad wealth categories, financial assets account for 80-90% of the net wealth increase, whereas no more than 10-20% is used to invest in real estate or to pay off debt.²¹ Among the financial assets, in Panel (b), investment in risky assets represents 14% of the total savings in financial assets in the year of win, which then rises to 31% after two years before declining to 30% (11%) by year 3 (year 4). Such a decomposition enables us to infer households’ marginal propensities to invest in various asset classes and to take risk (MPR), which are proposed to be an important parameter shaping asset prices and investment dynamics in macro-finance models (Kekre and Lenel, 2022).

¹⁹The estimates presented in this paper are for households who already owned stocks before the lottery event. We refer the reader to Briggs et al. (2021) for similar results among households that do not participate in the stock market before the lottery event.

²⁰We can only bound the *spending* response because we do not observe inter-household transfers and donations in our data. Relatedly, we can only bound the *consumption* response because we cannot distinguish between durable and nondurable expenditures.

²¹The small fraction of wealth invested in real estate suggests that housing investments are unlikely to explain the negative wealth effects in our baseline analyses. This conclusion is further bolstered by our finding (in Panel (b) of Figure 5) that re-classifying real estate as a risky asset leads to an even greater decline in the risky share.

5 Structural Analysis

Patterns in our reduced-form results suggest our estimates are qualitatively consistent with a model in which nontradable human capital induces households to hold a larger share of their financial assets in equity, and that as financial wealth increases, this distortion becomes smaller and the share of risky assets in the financial portfolio decreases. In this section, we turn to a lifecycle portfolio choice model to demonstrate *quantitatively* that the nontradable human-capital channel can explain our results in an enriched environment featuring lifecycle income profiles calibrated to the Swedish data. We also consider an extended model that incorporates a realistic level of consumption habits to numerically assess whether the portfolio distortion induced by the nontradable human capital is large relative to that induced by the consumption habits in the opposite direction.

The workhorse model we study is based on [Gomes and Michaelides \(2005\)](#) and [Cocco et al. \(2005\)](#) and is similar in structure to other models of lifecycle portfolio choice including [Cocco \(2005\)](#), [Fagereng et al. \(2017\)](#) and [Calvet et al. \(2021\)](#). We briefly introduce the main model features and calibration before introducing the main results, and refer the reader to [Appendix B](#) for details of the model solution.

5.1 Model

Each period, an agent of age t chooses how much to consume C_t and what fraction of her savings α_t to invest in equity, with returns realized at age $t + 1$. We assume agents cannot hold short positions, so $\alpha_t \in [0, 1]$.

Demographics Each agent in our model is a single household with a fixed marital status $m \in \{0, 1\}$. Households in our model fall into one of three education groups: high school education ($e = 0$), some post-secondary education ($e = 1$), and college degree or higher ($e = 2$). Households have a maximum lifespan of $T = 100$, but prior to reaching age T , face an age-dependent mortality risk with an exogenous probability of surviving from period t to $t + 1$, denoted by π_t .

Preferences Agents have Epstein-Zin preferences (Epstein and Zin, 1991) defined over consumption C_t and wealth W_t ,

$$V_t = \left\{ (1 - \beta \pi_t) C_t^{1-1/\psi} + \beta \mathbb{E} \left[\pi_t V_{t+1}^{1-\gamma} + (1 - \pi_t) b W_{t+1}^{1-\gamma} \right]^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}, \quad (13)$$

where γ is the coefficient of relative risk aversion, ψ is the intertemporal elasticity of substitution, β is the discount factor, and b is the bequest multiplier.

Income The labor income process H_t has both a permanent component P_t and a transitory component U_t . The log of the permanent component follows a random walk with innovation N_t . All innovations are assumed to be lognormally distributed with mean zero and education group-specific variances, $\sigma_{n,e}^2$ and $\sigma_{u,e}^2$. Formally, the labor income process before retirement is given by

$$H_t = \exp(f(t, m, e)) P_t U_t, \quad (14)$$

$$P_t = P_{t-1} N_t, \quad (15)$$

where $f(t, m, e)$ is a deterministic function of age, marital status, and education. Hence, the labor income process is summarized by parameters $\sigma_{n,e}$, $\sigma_{u,e}$, and the coefficients that define $f(t, m, e)$.

At retirement age $t_R = 65$, all future labor income becomes non-stochastic. For any age greater than 65, income is defined by a replacement rate $\lambda_{m,e}$ of the age-65 permanent component of income, where $\lambda_{m,e}$ varies with education and marital status. Thus, $H_t = \lambda_{m,e} \cdot \exp(f(t_R, m, e)) P_{t_R}$ for all $t \geq t_R$.

Housing We do not formally model housing but follow Gomes and Michaelides (2005) in modeling housing expenditures as an age-dependent share of income $h(t)$. Thus, housing expenditures of amount $h(t)H_t$ are subtracted from income each period.

Assets Agents can invest in two assets: a risk-free asset that pays out certain return R_f and a risky equity that pays stochastic return $R_{s,t}$. Equity returns are assumed to be lognormally distributed, with mean excess return μ_s . Log equity returns are given by

$$r_{s,t} - r_f = \mu_s + \varepsilon_{s,t}, \quad (16)$$

where $\varepsilon_{s,t}$ is distributed normally with mean zero and variance σ_s^2 . Innovations to excess returns are correlated with innovations to the permanent component of the labor income, and we denote the correlation coefficient as $\text{corr}(\ln N_t, \varepsilon_{s,t}) = \rho_{n,s}$. Note that because in our sample of interest, all households already participate in the equity market, we do not require entry costs that are common in similar models.

Wealth Accumulation and Lottery Prizes The intertemporal budget constraint is given by

$$W_{t+1} = (1 + R_f)(W_t - C_t) + \alpha_t(R_{s,t+1} - R_f)(W_t - C_t) + H_{t+1}(1 - h_{t+1}) + L_{t+1}. \quad (17)$$

To align the model with our empirical setting, households can receive unanticipated lottery winnings L_t . Households do not form expectations over the prize distribution, meaning prizes are exogenous and unexpected. Accordingly, we set $L_t = 0$ when solving the model. Whenever lottery winnings L_t are positive, they enter additively into the budget constraint.

Household Problem Households' decision problem can be summarized as follows:

$$V_t(W_t, P_t) = \max_{C_t, \alpha_t} \left\{ (1 - \beta \pi_t) C_t^{1-1/\psi} + \beta \mathbb{E} \left[\pi_t V_{t+1}^{1-\gamma} + (1 - \pi_t) b W_{t+1}^{1-\gamma} \right]^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}},$$

$$W_{t+1} = (1 + R_f)(W_t - C_t) + \alpha_t(R_{s,t+1} - R_f)(W_t - C_t) + H_{t+1}(1 - h_{t+1}), \quad (18)$$

$$0 \leq \alpha \leq 1,$$

where the process for labor income H_t is given by Equations (14) and (15), and the asset returns $R_{s,t}$ are given by Equation (16). The policy function for α_t is the key object of interest for our purpose, which characterizes the optimal allocation of financial wealth to risky assets.²²

²²We focus on the optimal portfolio allocation (conditional on the amount saved) and do not explicitly address the consumption response for two reasons. First, from an empirical standpoint, we cannot accurately estimate the consumption response and only bound it from above due to data limitations, as discussed in Section 4.3. Second, from a modeling standpoint, standard lifecycle portfolio choice models (including the one used in this paper) are admittedly not well-suited to jointly address the elevated consumption response and the portfolio response, as the former typically requires the modeling of assets with different degrees of liquidity with costly adjustment (e.g., Laibson, Lee, Maxted, Repetto and Tobacman, 2023; Kaplan and Violante, 2014), whereas the latter requires the modeling of assets with different risk characteristics.

Table 4: Calibration of Parameters. This table presents our baseline calibration of model parameters. Panel A presents our calibration of preference parameters from [Gomes and Michaelides \(2005\)](#) and asset returns from [Waldenström \(2014\)](#). Panel B shows the estimated income process parameters for each education group, including the standard deviation of transitory and permanent income innovations, the correlation of equity returns and permanent income innovations, and the replacement rates of retirement income for single and married households.

| A. Structural Model Parameters | | B. Income Process by Education Group | | | |
|----------------------------------|------|--------------------------------------|---------|---------|---------|
| Discount factor, β | 0.96 | | No | Some | |
| Relative risk aversion, γ | 5 | | College | College | College |
| IES, ψ | 0.2 | Transitory risk, σ_u | 0.156 | 0.163 | 0.172 |
| Bequest multiplier, b | 2.5 | Permanent risk, σ_n | 0.089 | 0.081 | 0.088 |
| Risk-free return, r_f | 0.02 | Equity correlation, $\rho_{n,s}$ | -0.024 | -0.022 | -0.025 |
| Mean excess return, μ_s | 0.06 | Rep. rate (single), λ | 0.685 | 0.641 | 0.617 |
| Return std. dev., σ_s | 0.21 | Rep. rate (married), λ | 0.644 | 0.608 | 0.589 |

5.2 Calibration

We calibrate the model with standard preference parameters from [Gomes and Michaelides \(2005\)](#) and calibrate the labor income and equity return processes to reflect historical Swedish data. The resulting calibration is presented in Table 4. We assume an annual discount rate of $\beta = .96$, the coefficient of relative risk aversion $\gamma = 5$, the intertemporal elasticity of substitution $\psi = .2$, and the bequest multiplier $b = 2.5$. Equity returns are calibrated with $\mu_s = .06$ and $\sigma_s = .21$ to match the historical Swedish stock market returns ([Waldenström, 2014](#)). Additionally, agents are assumed to die with certainty at age 100, and we solve for policy functions beginning at age 18, the minimum age in our sample.

The labor income process described in Equation (14) is estimated from pre-lottery labor income realizations from our sample of lottery players. The estimation procedure follows [Cocco et al. \(2005\)](#) and [Carroll and Samwick \(1997\)](#), and Appendix B.3 summarizes the exact procedure used to estimate the parameters of the income process. Appendix Figure B.2 presents the resulting estimates of $f(t, m, e)$ for both single and married households.

We estimate the standard deviations of transitory and permanent risks, σ_u and σ_n , in the range of 0.156 – 0.172 and 0.081 – 0.089, respectively, which are comparable to values estimated in the US by [Carroll \(1997\)](#), [Gourinchas and Parker \(2002\)](#), and [Cocco et al.](#)

(2005). Furthermore, we estimate the correlations between equity returns and permanent labor income shocks in the range of -0.022 to -0.025, which are not significantly different from zero both statistically and economically.^{23,24} This implies that income is fairly safe and not highly correlated with equity market returns in Sweden. Finally, we calibrate the income replacement rate after retirement λ to 0.589 – 0.685 to reflect the Swedish pension system (Laun and Wallenius, 2015) (see Appendix B.4).

Other calibrated parameters include survival probabilities (π_t), which are calibrated to observed mortality rates (see Appendix B.2), and housing expenditures (h_t), which are calibrated to be 30% of income while working and 20% of income in retirement.

5.3 Results

Using the above calibration, we solve for optimal portfolio allocation decisions and explore how windfall gains affect the share of financial wealth allocated to risky assets. In solving for the optimal policy function, we observe that the optimal risky share in the financial portfolio is increasing in permanent income but decreasing in financial wealth. Because income is not positively correlated with equity returns and not easily tradable, a household tilts their financial portfolio toward equity to offset this position, as reviewed in Section 2. The degree to which households overweight equity is increasing in the ratio of human capital to financial wealth, causing the risky portfolio share to increase in permanent income and decrease in financial wealth.

After solving the model, we simulate lottery winnings and portfolio decisions for a sample that has identical characteristics to lottery winners in our data. We then record the resulting portfolio allocations and estimate Equation (9) on the simulated dataset. This procedure provides a set of model-implied coefficients $\tilde{\beta}$ comparable to the causal estimates presented in Section 4. In particular, we focus on comparing the overall effect of the windfall on the risky share, the non-linear effects by prize size, and the effects by the (pre-lottery) human-capital-to-wealth ratio, all in the year of win $s = 0$.

²³Following Campbell, Cocco, Gomes and Maenhout (2001), we use the excess stock returns lagged one year in estimating the correlation between stock returns and labor income shocks to allow for potential lags in the realization of labor income.

²⁴While these estimates are comparable to similarly low values estimated in the US (e.g., Cocco et al., 2005; Davis and Willen, 2013), the evidence on the correlations between equity returns and labor income shocks in the literature remains mixed. Hence, we later perform sensitivity analyses around these values by assuming a commonly used correlation coefficient of 0.15, as in Campbell et al. (2001) and Gomes and Michaelides (2005).

Baseline Model

Column (1) of Table 5 displays our empirical estimates in the year of win, and column (2) presents the corresponding model-implied estimates under our baseline calibration. The first striking feature of the model-implied effects is that the model overpredicts the negative wealth effects on the risky share. The model predicts each \$100K received causes a 10.9-percentage-point decrease in the risky share, which is twice the size of our preferred quasi-experimental estimate. Thus, the model suggests that the negative wealth effects we estimate in the data are not only theoretically plausible, but also possibly less negative than expected.

Additionally, the model broadly matches the patterns of heterogeneity by prize size and the human-capital-to-wealth ratio. The model generally overpredicts the effects but matches the qualitative pattern of diminishing marginal effects by prize size. The model also well captures the heterogeneity by the human-capital-to-wealth ratio, because those with a higher ratio reduce the risky share of their financial portfolio by more. Overall, the qualitative patterns implied by the model align closely with our empirical estimates, providing support for our interpretation of the estimated negative effects.

We next undertake a series of exercises to investigate how alternative calibrations and assumptions might affect the model-implied estimates. Appendix Table A.8 presents the results from these analyses. In columns (2) and (3), we examine the sensitivity to preference parameters by increasing the relative risk aversion to $\gamma = 8$ and increasing the intertemporal elasticity of substitution to $\psi = 0.5$. In columns (4) and (5), we vary our structural model assumptions by removing the bequest motive ($b = 0$) and allowing for a positive correlation between stock returns and income innovations ($\rho_{n,s} = 0.15$). Finally, Calvet et al. (2007) show the historical equity premium is larger than the return realized by most households. In column (6), we thus impose a 2% management fee and vary the expected excess returns on equity to $\mu_s = 0.04$. In all cases, we find that the model-implied estimates are robust and remain largely unchanged.

Extended Model with Consumption Habits

Human capital and habit formation mechanisms impact the financial wealth elasticity of the risky share in opposite direction. To assess the relative strength of each factor, we therefore extend our baseline model to also incorporate consumption habits. We do so by mandating a compulsory consumption expense equivalent to 50% of the previous period's

Table 5: Comparison of Empirical Estimates with Model-Predicted Effects. This table compares our empirical estimates with the model-predicted estimates of wealth on the risky share, the effects stratified by prize size, and the effects stratified by the human-capital-to-wealth ratio. Column (1) presents our empirical estimates from Section 4. Column (2) displays the model-implied estimates from our baseline model. Column (3) shows the model-implied estimates from our extended model incorporating consumption habits, where consumption habits are approximated as 50% of the previous period’s average household income.

| | | (1) | (2) | (3) |
|------------------|--------------|-----------|------------|---------|
| | | Empirical | Model | Model |
| | | Estimate | (Baseline) | (Habit) |
| Effect of \$100K | | -0.048 | -0.109 | -0.052 |
| Prize Size | 1K to 10K | 0.002 | -0.010 | 0.016 |
| | 10K to 100K | -0.012 | -0.063 | -0.012 |
| | 100K to 250K | -0.182 | -0.314 | -0.103 |
| | 250K+ | -0.171 | -0.504 | -0.274 |
| HC/W Ratio | Low | -0.035 | -0.087 | -0.060 |
| | High | -0.055 | -0.121 | -0.048 |

average disposable income in each period.²⁵ Incorporating habits into the model this way confers two methodological advantages. First, it captures a realistic level of consumption habits without imposing any additional computational burden in solving the model. This is in contrast to modeling a fixed subsistence level that remains constant throughout the life cycle, which is an unrealistic assumption. It also differs from explicitly modeling an internal consumption habit as a function of the agent’s own past consumption, which would require an additional state space. Second, our approximation allows for micro-founded interpretations, because the previous period’s average income can be viewed as a noisy proxy of the agent’s own past consumption or as the average consumption of the agent’s demographic group. While there is no consensus in the literature on how consumption habits are formed, our approximation captures elements of the two leading theories that habits are formed internally through one’s own past consumption (Constantinides, 1990;

²⁵We consider 50% of the previous period’s disposable income to be a reasonable approximation of consumption habits. This level aligns with the existing literature, which often estimates consumption habits to be within the range of 30% to 60% of the agent’s past consumption (Polkovnichenko, 2007). Additionally, the agent’s disposable income is commonly used as a proxy for consumption (Calvet and Sodini, 2014).

Polkovnichenko, 2007) or externally influenced by the consumption of the peer group (Bakshi and Chen, 1996; Chan and Kogan, 2002).

Column (3) of Table 5 presents the model-implied estimates from our extended model incorporating consumption habits. The extended model predicts each \$100K received causes a 5.2-percentage-point decrease in the risky share, which well matches our empirical estimate of a 4.8-percentage-point reduction. In comparison to our baseline model, the inclusion of consumption habits in our extended model generates decreasing relative risk aversion and thus results in less negative wealth effects on the risky share. Nonetheless, the overall effect on the risky share remains negative, indicating that the nontradable human capital channel quantitatively dominates the habit channel in this enriched framework featuring both calibrated income profiles and realistic consumption habits.

The extended model also well matches the heterogeneity by prize size, although it does less well in matching the heterogeneity by the human-capital-to-wealth ratio. Although the patterns of heterogeneity remain broadly comparable to the baseline, the overall magnitude of the effects is better aligned in this extended specification. While we primarily focus on the nontradable human capital as a plausible mechanism underlying our empirical findings, these results also highlight the importance of consumption habits or DRRA preferences, because the model best matches our empirical estimates in the presence of such factors. Lastly, we conduct a series of robustness checks on model parameters and assumptions and find that the results are not too sensitive to alternative calibrations (see Appendix Table A.9).

In summary, under a wide range of specifications and assumptions, our structural analyses suggest that the effect of a windfall gain on the risky share is negative, and that the magnitude of our estimated effect is quantitatively plausible. Importantly, we confirm our analyses in Section 2 that nontradable human capital generates negative wealth effects that seemingly imply increasing relative risk aversion, even when relative risk aversion is constant or decreasing in financial wealth. This finding highlights that carefully accounting for nontradable human capital and the full household decision problem is critical before observed portfolio shares can be used to inform risk preferences.

6 Conclusion

Better evidence on the impact of financial windfalls on risky shares can help distinguish between competing theories of investment behavior. Our study provides such evidence by

analyzing the randomized assignment of lottery prizes among a sample of Swedish lottery players who have been matched to government registers with demographic and financial information. We study how financial windfalls impact the risky share up to four years after the lottery event, and conduct a number of follow-up analyses aimed at exploring the ability of different models to explain our new findings, both qualitatively and quantitatively.

The main finding in our quasi-experimental analyses is that wealth effects on the risky share are negative. This conclusion is robust across specifications and subsamples. We attribute the discrepancy between our findings and those of the prior literature to our use of a natural experiment that better approximates the “ideal experiment” suggested by [Carroll \(2002, p. 420\)](#). While not our primary focus, we also analyze how lottery wealth impacts a number of specific asset and liability subcategories. These estimates provide moments that could prove informative for model calibration or validation in settings that go well beyond our study.

We demonstrate that negative wealth effects are consistent with the *qualitative* predictions of a static portfolio choice model featuring nontradable human capital. We also derive three additional predictions from the static model and find that each aligns well with the empirical evidence. In further analyses, we show that a richer, dynamic lifecycle portfolio choice model predicts wealth effects that *quantitatively* match our results. Our findings do not imply that the previous literature’s emphasis on consumption habits and DRRA preferences was incorrect or misplaced. However, they suggest that a productive direction for future work may be to extend the workhorse models in much of the current literature to ones that additionally allow for the nontradable human capital mechanism to operate ([Bodie et al., 1992](#); [Heaton and Lucas, 1997](#); [Viceira, 2001](#)).

Finally, our results may have implications for the optimal design of target date funds, which have become increasingly popular among retail investors. Currently, these funds allocate assets solely based on information about the investor’s age. However, our theoretical and empirical analyses indicate that the optimal allocation depends not just on age, but also on human capital and accumulated financial wealth, suggesting that incorporating these additional factors may lead to more effective asset allocations ([Dahlquist, Setty and Vestman, 2018](#)).

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