Who Harvests? Tax Alpha and Heterogeneous Responses to Capital Gains Taxation*

Federico Mainardi†

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ABSTRACT

Capital taxation is a central component of the U.S. fiscal system: realized gains totaled $1.4 trillion in 2024, and their preferential tax treatment amounted to $244 billion in foregone federal revenue. Yet little is known about how households, especially the ultra-wealthy, respond to capital gains taxes. Using granular, high-frequency data on U.S. households—including more than 700 billionaires—I study the response to capital gains taxation across the wealth distribution. Wealthier households realize a smaller fraction of gains but a larger fraction of losses than less wealthy households, consistent with tax-loss harvesting. These differences intensify during market downturns and are concentrated among households supervised by sophisticated advisors, especially private banks. Exploiting a regression kink design around zero unrealized returns, I show that the realization behavior at the top reflects an active response to tax incentives rather than unobserved factors correlated with wealth. The implications for after-tax performance are significant: tax expenses decline from 70 basis points of wealth at the bottom to 20 basis points at the top, generating a 50-basis-points annual tax alpha, equal to over one-third of documented return gaps. Absent this tax alpha, the top 1% aggregate wealth share would grow by 3.54 percentage points less over thirty years, corresponding to 63% of the historical rise in top-end wealth concentration over an equivalent horizon. These findings reveal a policy-relevant channel through which the U.S. tax code amplifies wealth concentration, informing both macroeconomic models of wealth dynamics and normative models of capital taxation.

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†Columbia Business School: fm2913@columbia.edu.

1 Introduction

Capital gains taxation is one of the most consequential and debated components of the U.S. fiscal system. In 2024, realized capital gains reached $1.4 trillion, equivalent to 4.7% of the U.S. GDP. At the same time, the preferential tax treatment of capital gains—through reduced statutory rates and the deductibility of realized losses—constituted a major fiscal subsidy. The Congressional Budget Office estimates that these provisions amounted to $244 billion in foregone federal revenue in 2024 alone, comparable to all subsidies for health insurance and all tax credits for children.

The breadth of these incentives has not gone unnoticed in financial markets. In recent years, the wealth management industry has increasingly marketed tax optimization as a central component of its value proposition. Assets in direct indexing—portfolios that replicate an index while realizing losses for tax purposes—rose fivefold, from $175 billion in 2018 to nearly $1 trillion in 2024. Managed accounts, often used to deliver customized tax strategies, reached a record $13.7 trillion in assets and experienced $800 billion in inflows in 2024. These developments suggest that tax incentives play a first-order role in shaping households' saving behavior.

Yet despite their magnitude, little is known about who actually benefits from these incentives and how. Which households are most responsive to capital gains taxes? Are differences driven by household demographics or by the choice of sophisticated advisors? And to what extent do these behaviors shape heterogeneity in after-tax performance and concentration of aggregate wealth at the top? These questions are central for both macroeconomic models of wealth dynamics (Benhabib, Bisin and Zhu, 2011; Gabaix, Lasry, Lions and Moll, 2016; Greenwald, Leombroni, Lustig and Van Nieuwerburgh, 2021; Catherine, Miller, Paron and Sarin, 2023; Gomez, 2023; Gomez and Gouin-Bonenfant, 2024) and normative models of capital gains taxation (Aguiar, Moll and Scheuer, 2024). Yet empirical progress has been constrained by data limitations: existing U.S. studies rely mainly on surveys or retail brokerage accounts, which miss the ultra-high-net-worth households that earn the majority of capital income and are therefore central to debates on capital taxation.

This paper fills this gap by using new household-level data from Addepar, a wealth management platform covering over $8 trillion in assets and more than 1,300 financial advisors. I show that wealthier households are substantially more responsive to tax incentives, resulting in a tax alpha between the top and the bottom of the wealth distribution comparable to pre-tax return gaps

documented in the literature. Absent this tax alpha, the top 1% aggregate wealth share would grow by 3.54 percentage points less over thirty years—equivalent to 63% of the historical rise in top-end wealth concentration over an equivalent horizon. By linking micro-level tax behavior to aggregate wealth dynamics, the paper provides a new empirical foundation for macroeconomic models of wealth concentration and for the design of optimal capital taxation.

The Addepar dataset offers an unprecedented opportunity to study the incidence of capital gains taxation across households for two reasons. First, average wealth in Addepar closely matches that of the top 10% of households in capitalization-based estimates (Saez and Zucman, 2016, 2020; Smith, Zidar and Zwick, 2023). At the same time, the data oversample ultra-high-net-worth households, including 729 households with wealth higher than $1 billion at some point in the sample and 216 households with a position exceeding $1 billion in a single company (positions removed to preserve confidentiality). These features make Addepar both representative of the top decile, which accounts for almost 90% of total realized capital gains (Balkir, Saez, Yagan and Zucman, 2025a), and uniquely suited to analyze how tax incentives operate among ultra-high-net-worth households that are typically missed in alternative data sources.

Second, the data include monthly realized and unrealized returns at the security level, sourced directly from custodians, and cover a broad range of asset classes, including public and private, direct and indirect positions. Because unrealized and realized returns are central inputs for tax calculations, advisors have incentives to record them with high accuracy. The availability of detailed unrealized and realized returns at high frequency is a key advantage to achieve causal inference over alternative data sources, including administrative datasets, where unrealized returns have to be imputed from market prices and are observed only annually.

Using these data, I start by documenting novel stylized facts on unrealized capital gains and losses across the wealth distribution. In December 2024, the last year-month covered by the data, average unrealized gains rise sharply from 12% of total wealth at the bottom of the wealth distribution to 20% at the top, confirming for the U.S. the positive relationship between wealth and unrealized capital gains previously documented by Fagereng, Holm, Moll and Natvik (2019) for Norway. Symmetrically, unrealized losses decline by a factor of three, from 2.5% to less than 1%.

Over time, unrealized gains and losses move in opposite directions across the wealth distribution: the time-series correlation in average unrealized losses between the top and bottom quintiles is –0.97, and -0.81 for unrealized gains. During market downturns such as late 2018, early 2020,

and 2022, the gap in unrealized losses is as high as 10%. These patterns suggest that households at different wealth levels realize capital gains and losses in systematically different ways.

To confirm this, I study the realization of gains and losses in each wealth percentile. A simple regression of realized gains (losses) on lagged unrealized gains (losses) shows that the fraction of realized gains falls with wealth—from 6% at the bottom to 3% at the top—while the fraction of realized losses rises from near zero to almost 30%. Wealthier households thus engage more actively in tax-loss harvesting (Constantinides, 1983) and benefit more from the realization-based U.S. tax system, which taxes gains only when realized and allows realized losses to offset them.

The difference in loss realization across households is especially pronounced during periods of market turmoil. In those times, wealthier households substantially increase the fraction of realized losses, while less wealthy households remain inert. As a result, less wealthy households lose twice during market declines: they not only suffer lower pre-tax returns but also fail to monetize capital losses when they are most available.

Leveraging the granularity and high-frequency of the data, I then provide evidence that these differences reflect active tax optimization at the top rather than unobserved factors correlated with wealth. Specifically, I exploit the sharp change in marginal tax liability at zero unrealized returns. If households respond to tax incentives, they should discontinuously increase the fraction of realized returns when moving from small gains to small losses. I estimate this slope discontinuity for each wealth quintile using the robust bias-corrected regression kink design in Calonico, Cattaneo and Titiunik (2014b). Among wealthier households, realized returns display a clear kink: the slope is steeper for small losses than for small gains, consistent with tax-loss harvesting and with rational models of portfolio choice featuring capital gains taxes. By contrast, less wealthy households show no such response, and sometimes even realize more gains than losses, in line with earlier evidence from retail brokerage accounts (Odean, 1998).

The identifying assumption in the regression kink design is that, within a narrow neighborhood around zero, securities are quasi-randomly assigned to either side of the cutoff. This is plausible if households cannot manipulate market prices and is reinforced by the use of lagged unrealized returns. Robustness tests, including donut designs that exclude observations closest to zero, confirm that the estimated kink reflects an active response to tax incentives rather than sorting around the cutoff.

I also rule out that the stronger response at the top of the wealth distribution is driven by

households' beliefs of persistent returns, which would induce them to sell securities following a loss (expecting further declines) but would also induce them to purchase securities following a gain (expecting further appreciation). Wealthier households increase sales discontinuously when moving from gains to losses, but they do not increase purchases when moving from losses to gains, which is inconsistent with beliefs of persistent returns.

Beyond wealth, the type of financial advisor is a powerful determinant of realization behavior. At the top of the wealth distribution, households advised by private banks realize substantially more losses than those supervised by other advisors, including family offices, typically regarded as elite advisors. Although perhaps surprising a priori, this pattern is consistent with recent industry developments in which large private banks have invested heavily in tax-optimization infrastructures, including Morgan Stanley's $7-billion acquisition of Eaton Vance, J.P. Morgan's acquisition of 55ip, and Goldman Sachs' acquisition of Folio Financial. More broadly, these results imply that access to—or choice of—effective intermediation, rather than financial sophistication alone as proxied by wealth, plays a central role in shaping the response to tax incentives.

These differences in realization behavior across the wealth distribution have material implications for heterogeneity in after-tax returns. Wealthier households face significantly lower effective tax burdens: taxable gains fall from about 70% of realizations at the bottom to 45% at the top. Effective tax rates decline from 19% to 13% across the distribution, and the share of households with non-positive taxable gains rises from 20% to 40%. When annual tax expenses are scaled by beginning-of-year wealth, the implied cost falls from 70 basis points at the bottom to 20 basis points at the top. This 50-basis-point gap represents an economically significant tax alpha accruing to wealthier households solely from tax management. As a term of comparison, comparable gaps in pre-tax returns on financial wealth documented in the literature range between 55 and 150 basis points (Campbell, Ramadorai and Ranish, 2019; Bach, Calvet and Sodini, 2020; Fagereng, Guiso, Malacrino and Pistaferri, 2020).

This tax alpha is robust and, if anything, understated in the baseline. Allowing for heterogeneity in statutory tax rates across households, imputed from the income distribution in Balkir, Saez, Yagan and Zucman (2025a), and incorporating advisor fee schedules from SEC filings, the gap rises to about 100 basis points. While statutory rates rise with wealth and compress the gradient, fees are strongly regressive and more than offset this decrease in tax alpha. Accounting for advisory fees and heterogeneous tax rates thus strengthens rather than weakens the tax alpha,

suggesting that mechanisms leading to net-of-fee underperformance, such as trust (Gennaioli, Shleifer and Vishny, 2015), are more pronounced among less wealthy households.

I also show that the tax alpha is a genuine alpha as it does not come at the cost of lower pre-tax performance or higher risk. Predictive regressions among top-quintile households reveal that higher realized losses predict higher pre-tax returns net of transaction costs, lower risk, and greater portfolio flexibility (as measured by turnover). The tax alpha is therefore a genuine alpha: households that are more responsive to tax incentives gain twice—first by reducing their tax burden, and second by retaining the ability to rebalance in response to changing investment opportunities without triggering taxable gains.

Finally, I examine the implications of this tax alpha for the long-term dynamics of wealth concentration. Using a simple accounting framework of household wealth accumulation calibrated with estimates from the Addepar data, I find that, absent this tax alpha, the top 1% aggregate wealth share would grow by 0.95 to 3.54 percentage points less over thirty years—corresponding to 17 to 63% of the historical rise in top-end wealth concentration documented by Smith, Zidar and Zwick (2023) over an equivalent horizon. In this sense, heterogeneity in response to capital gains taxation is not only a source of after-tax return dispersion, but also a macro-relevant channel through which the U.S. tax code amplifies long-run wealth concentration.

Taken together, by quantifying heterogeneity in tax responses and their implications for performance, this paper provides new evidence on a mechanism that directly links the tax system to both return heterogeneity and the evolution of wealth concentration. While prior work has emphasized persistent heterogeneity in pre-tax returns, I show that differences in tax management alone generate return differentials that account for at least one third of pre-tax return gaps documented in prior work and can sustain a significant rise in top wealth shares in the long run. Because it arises from the provisions of the U.S. tax code, heterogeneity in response to capital gains taxation is a margin directly actionable through policy, and should be incorporated into both macroeconomic models of wealth dynamics and normative models of optimal capital taxation.

Overall, this paper contributes to three strands of the literature. First, recent work has studied the role diversification (Campbell, Ramadorai and Ranish, 2019), risk tolerance (Bach, Calvet and Sodini, 2020), skills (Fagereng, Guiso, Malacrino and Pistaferri, 2020), and duration (Greenwald, Leombroni, Lustig and Van Nieuwerburgh, 2021; Catherine, Miller, Paron and Sarin, 2023) as drivers of return heterogeneity. I propose and test an alternative but complementary mecha-

nism: heterogeneous responses to tax incentives generates sizable differentials in performance—of comparable magnitude to earlier estimates of pre-tax gaps. In this sense, the paper connects to the broader household finance literature (Campbell, 2006) and to studies using detailed individual-level data to analyze heterogeneity in portfolio allocation (Calvet, Campbell and Sodini, 2007; Fagereng, Gottlieb and Guiso, 2017; Balloch and Richers, 2023), rebalancing (Barber and Odean, 2000; Hoopes, Langetieg, Nagel, Reck, Slemrod and Stuart, 2016; Calvet, Campbell and Sodini, 2009a; Fagereng, Holm, Moll and Natvik, 2019; Gabaix, Koijen, Mainardi, Oh and Yogo, 2025a,b), inertia (Calvet, Campbell and Sodini, 2009b; Andersen, Campbell, Nielsen and Ramadorai, 2020), and savings (Fagereng, Holm, Moll and Natvik, 2019; Mian, Straub and Sufi, 2020).

Second, the paper relates to the literature on households' response to capital taxation. Theoretical work (Constantinides, 1983, 1984; Dammon and Spatt, 1996; Dai, Liu, Yang and Zhong, 2015) micro-founds the asymmetric realization of gains and losses, and empirical studies confirm that aggregate capital gains realizations respond to taxes, though estimates vary (Feldstein, Slemrod and Yitzhaki, 1980; Burman and Randolph, 1994; Agersnap and Zidar, 2021). Yet micro evidence has been more limited: retail brokerage data suggest that households often under-utilize tax incentives (Odean, 1998), while more sophisticated households appear somewhat more responsive around tax reforms (Auerbach and Siegel, 2000). I reconcile these findings by showing that responsiveness is highly heterogeneous: wealthier households harvest losses at scale, while less wealthy households remain largely inert. This aligns with recent evidence of greater tax sophistication at the top (Bach, Bozio, Guillouzouic and Malgouyres, 2023; Balkir, Saez, Yagan and Zucman, 2025b; Boning, Hendren, Sprung-Keyser and Stuart, 2025), but my focus on capital gains taxation and the use of quasi-experimental variation highlights a separate mechanism behind this heterogeneity.

Third, the paper relates to the literature on the dynamics of wealth concentration (Benhabib, Bisin and Zhu, 2011; Gabaix, Lasry, Lions and Moll, 2016; Saez and Zucman, 2016; Hubmer, Krusell, Smith et al., 2017; Saez and Zucman, 2020; Hubmer, Krusell and Smith Jr, 2021; Gomez, 2023; Smith, Zidar and Zwick, 2023; Gomez and Gouin-Bonenfant, 2024; Catherine, Miller and Sarin, 2025), and its implications for welfare (Fagereng, Gomez, Gouin-Bonenfant, Holm, Moll and Natvik, 2025) and asset prices (Kekre and Lenel, 2022; Gomez, 2025). By documenting heterogeneity in the response to tax incentives, I identify a mechanism that directly links the provisions of the U.S. tax code to systematic differences in after-tax performance and long-run wealth concentration. In this sense, the paper provides evidence on a margin that is central for both positive theories of wealth dynamics and normative models of optimal capital gains taxation (Aguiar, Moll

and Scheuer, 2024).

The remainder of the paper is structured as follows. Section 2 provides background on the U.S. capital gains tax system. Section 3 describes the Addepar data and compares the wealth distribution in the sample to external benchmarks. Section 4 documents heterogeneity in realization behavior across the wealth distribution. Section 5 implements the regression kink design to test formally for heterogeneous responses to tax incentives. Section 6 turns to the role of advisors. Section 7 links realization behavior to after-tax performance, quantifies the resulting tax alpha, and provides implications for long-run wealth concentration. Section 8 concludes.

2 Institutional background

In the United States, capital gains on financial assets are taxed on a realization basis rather than an accrual basis. This implies that households may defer capital gains taxes indefinitely by postponing realization, and in many cases may avoid it altogether through the step-up in basis provision at death (Internal Revenue Code §1014). Gains held for less than one year are classified as short-term and taxed at ordinary income rates, while gains realized after one year are classified as long-term and taxed at preferential rates, currently capped at 20% at the federal level.

Realized capital losses are treated asymmetrically. Losses may offset realized gains on a dollar-for-dollar basis, but if losses exceed gains, only up to $3,000 may be deducted annually against ordinary income, with any remaining balance carried forward indefinitely (Internal Revenue Code §1211). The interaction of realization-based taxation, asymmetric loss treatment, and preferential rates creates a tax environment in which the timing of trades and which assets to trade are key margins of household portfolio choice (Constantinides, 1983).

In particular, these margins are central to tax-loss harvesting (TLH), one of the primary mechanisms households use to optimize capital gains taxes. By realizing capital losses when prices fall, households reduce current tax liabilities and reset basis for future gains. These tax savings represent a form of tax deferral that increases after-tax wealth accumulation, particularly when combined with indefinite deferral or the step-up in basis at death. Because TLH does not alter the pre-tax risk–return profile of the underlying portfolio when losses are reinvested in similar assets, it generates a "tax alpha": a systematic increase in after-tax returns without added risk.

The practice of TLH has also shaped the structure of financial intermediation. Over the past

two decades, the demand for tax efficiency has spurred the rapid growth of managed accounts, direct indexing platforms, and robo-advisors that explicitly market TLH strategies. The assets in managed accounts grew to more than $13 trillion in 2024, while direct indexing strategies expanded from niche offerings in the early 2000s to nearly $1 trillion in assets by the same time.[1] The strategic importance of tax optimization for the structure of the wealth management industry is also reflected in the recent wave of acquisitions by major asset managers of firms specializing in TLH and direct indexing. In 2020 alone, the wealth management industry witnessed BlackRock's acquisition of Aperio for $1 billion, Morgan Stanley's acquisition of Eaton Vance for $7 billion, J.P. Morgan's acquisition of 55ip, and Goldman Sachs' acquisition of Folio Financial. At the retail level, robo-advisors such as Wealthfront and Betterment have emphasized automated loss harvesting as a central component of their value proposition.

These institutional developments illustrate that tax optimization is not merely a household-level phenomenon but has become a defining feature of modern wealth management. However, how the benefits of TLH are shared between different households remains largely unexplored.

3 Data source and summary statistics

3.1 Notation

For each household i, security a, and year-month t, let A_{iat} denote the end-of-month dollar holding, $A_{ia,t-1}$ the beginning-of-month dollar holding, F_{iat} the net flow, UR_{iat} the unrealized return, and RR_{iat} the realized return. I define unrealized gains and losses as

$$UG_{iat} = UR_{iat}\mathbb{I}\left(UR_{iat} > 0\right),$$
$$UL_{iat} = -UR_{iat}\mathbb{I}\left(UR_{iat} < 0\right),$$

where $\mathbb{I}\left(\cdot\right)$ is an indicator equal to 1 if the condition holds and zero otherwise. Realized gains and losses are defined analogously as

$$RG_{iat} = RR_{iat}\mathbb{I}\left(RR_{iat} > 0\right),$$
$$RL_{iat} = -RR_{iat}\mathbb{I}\left(RR_{iat} < 0\right).$$

[1] Cerulli Associates, U.S. Managed Accounts Report, 2024.

Let total wealth be $A_{it} = \sum_a A_{iat}$. I scale unrealized returns, gains, and losses by total wealth: $ur_{iat} = \frac{UR_{iat}}{A_{it}}$, $ug_{iat} = \frac{UG_{iat}}{A_{it}}$, and $ul_{iat} = \frac{UL_{iat}}{A_{it}}$, respectively. Similarly, I scale realized returns, gains, and losses by beginning-of-month wealth: $rr_{iat} = \frac{RR_{iat}}{A_{i,t-1}}$, $rg_{iat} = \frac{RG_{iat}}{A_{i,t-1}}$, and $rl_{iat} = \frac{RL_{iat}}{A_{i,t-1}}$. At the household-month level, I aggregate across assets: $ug_{it} = \sum_a ug_{iat}$ with analogous definitions for all other variables.

3.2 Data source

The analysis relies on household-level portfolio data from Addepar, a wealth management platform that provides portfolio aggregation, analytics, and performance reporting for financial advisors. Addepar currently covers more than $8 trillion in assets advised by over 1,300 different financial advisors. The data thus provide an unusually broad coverage of U.S. households' financial activities, including the ultra-high-net-worth (UHNW) segment that is largely absent from survey-based datasets.

The unit of observation is a portfolio. A single household may hold multiple portfolios, which cannot be linked. The data are available at a monthly frequency from January 2016 to December 2024, with a six-month reporting lag. For each portfolio-month, I observe holdings, flows, returns, and—critically—both realized and unrealized returns at the security level. These data are collected directly from custodians at daily frequency, and historical transactions are backfilled for new clients whenever possible. Importantly, realized returns exclude dividends, but include capital gains distributions from pooled investment vehicles such as mutual funds, exchange-traded funds (ETFs), and trusts. Because realized and unrealized returns are central inputs for households' tax reporting, they are recorded with high accuracy.

The combination of high frequency and directly observed returns is a major advantage relative to alternative datasets, which typically report annually and require imputation of unrealized returns based on transaction prices and dates. This makes Addepar uniquely well suited to studying whether and how households optimize capital gains taxes.

The dataset spans a broad range of asset classes (reported in Table 1), and portfolios are managed by a diverse set of advisor types (reported in Table 2). For the purpose of the analysis, I group advisor types other than private banks, single-family offices, multi-family offices, independent registered investment advisors, hybrid registered investment advisors, broker/dealer ad-

visors, national and regional brokers/dealers into a residual category "Other", which includes 12.3% of all households in the dataset. I merge broker/dealer advisors and national and regional brokers/dealers into one category "Brokers/Dealers". I also merge independent registered investment advisors and hybrid registered investment advisors into one category "Registered Advisors".

The dataset includes both direct holdings of individual securities and indirect holdings through pooled investment vehicles such as mutual funds and ETFs. I classify securities in equities, fixed income and derivatives as "liquid", which will play a central role in the analysis. In particular, because the objective is to study how households optimize capital gains taxes, I focus throughout on unrealized and realized returns in liquid securities that are publicly traded on financial markets.

Taken together, these features make the Addepar data uniquely well suited to studying capital gains taxation. The combination of high-frequency realized and unrealized returns, detailed coverage across asset classes, and representation of UHNW households provides an unprecedented setting for analyzing capital gains taxes and after-tax performance across the wealth distribution.

Table 1: **Taxonomy of asset classes**
This table reports the asset classes covered by the dataset. Narrow asset classes are categorized into five broad asset classes and are obtained after imposing adjustments to Addepar internal classification. Details are provided in Appendix A, which summarizes Appendix B.2.1 of Gabaix, Koijen, Mainardi, Oh and Yogo (2025a).

Broad asset classes	Narrow asset classes
Cash	Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Other Currency
Fixed Income	Municipal Bonds, U.S. Government/Agency Bonds, Corporate Bonds, Bond Funds, ABS/MBS, Structured Debt, International Government/Agency Bonds, Other Government/Agency Bonds, Other Debt
Equities	U.S. Equity, Global Equity, Developed Market Equity, Emerging Market Equity, REITs, Other Equity
Alternatives	Private Equity & Venture, Hedge Funds, Direct Real Estate, Direct Private Companies, Fund of Funds, Real Estate Funds, Other Funds, Unknown Alts.
Other	Collectibles, Crypto, Derivatives, Liabilities, Other, Other Non-Financial Assets

Table 2: **Taxonomy of advisors**
This table reports the types of advisors covered by the dataset. For the purpose of the analysis, I group advisor types other than private banks, single-family offices, multi-family offices, independent registered investment advisors, hybrid registered investment advisors, broker/dealers, national and regional brokers/dealers into a residual category "Other".

Broad advisor types	Narrow advisor types
Advisor	Independent Registered Investment Advisor, Hybrid Registered Investment Advisor
Broker Dealer	Private Bank, Broker/Dealer Advisor, National and Regional Broker/Dealer, Wirehouse, Bank Trust, Independent Broker/Dealer
Consolidators	Strategic Acquirer, Platforms, Other
Family Office	Single Family Office, Multi-Family Office
Institutional	Investment Consultant, OCIO, Hedge Fund, Foundation, Endowment, Pension
Other	TAMP, Software/Service Provider, Fund Administrator

3.3 Sample selection

Addepar applies two confidentiality screens before releasing the data. Advisors that account for more than 10% of all portfolios in a given month are removed, and their portfolios do not re-enter in later months. In addition, concentrated positions exceeding $1 billion in equities or in securities that could identify households are suppressed. The platform flags such cases with 216 portfolios being affected.

In addition to these screens, I adapt the construction process in Gabaix, Koijen, Mainardi, Oh and Yogo (2025a) to address occasional anomalies in realized and unrealized returns.[2] First, I drop portfolio-months when at least one liquid security has missing realized or unrealized returns. Second, I drop portfolio-months with non-zero beginning-of-month holdings but zero realized and unrealized returns for at least one liquid security, which cannot occur. Third, I occasionally observe non-zero unrealized returns despite end-of-month holdings are zero. Because this cannot occur, I set unrealized returns to zero whenever end-of-month holdings are zero. This screen affects less than 0.01% of all observations. Fourth, I restrict the dataset to portfolio-months with positive total wealth in either the beginning or the end of the month, which mitigates concerns that the data capture only a narrow slice of a household's wealth. Finally, I winsorize ur_{it} and rr_{it} at the 1^{st} and 99^{th} percentiles by year-month. Because they are positive by construction, I winsorize ug_{it}, ul_{it}, rl_{it}, and rg_{it} at the 99^{th} percentile by year-month. For the security-level analysis in Section 5,

[2] I summarize the data construction process in Gabaix, Koijen, Mainardi, Oh and Yogo (2025a) in Appendix A.

because wealthier households hold a higher number of securities in their portfolios as discussed in the next section, I winsorize ur_{iat} and rr_{iat} by wealth quintile and year-month. These steps altogether ensure that the analysis sample is both representative of households' portfolios and free of implausible observations.

3.4 Summary statistics

Table 2 reports the number of portfolios and average wealth by wealth group for each year in the sample. The size of the sample grows steadily over time, reflecting the rapid expansion of the Addepar platform and its adoption by a broader set of financial advisors. Importantly, this growth has not altered the composition of the data: within each wealth group, average wealth remains stable across years, aside from market-driven fluctuations. This stability suggests that the platform growth did not introduce systematic selection into particular parts of the wealth distribution. Moreover, in the analysis that follows, I account for the unbalanced nature of the dataset by estimating results separately for each year.

Table 3: **Summary statistics**
This table reports, for each year in the sample, the number of unique portfolios and the average household wealth by wealth group. Average wealth is expressed in thousands of U.S. dollars.

Year	N	0–20%	20–40%	40–60%	60–80%	80–90%	90–95%	95–99%	Top 1%
2016	6,581	182	330	712	1,805	4,605	10,762	33,668	272,772
2017	10,426	225	406	943	2,247	5,567	12,615	39,296	255,583
2018	17,588	238	380	845	1,942	4,692	11,149	33,868	262,110
2019	26,675	144	397	955	2,234	5,235	11,026	31,800	298,106
2020	43,319	107	311	775	2,003	4,803	10,406	29,237	258,424
2021	57,904	79	292	817	2,005	5,052	10,386	30,255	278,483
2022	76,536	67	265	733	1,830	4,449	9,438	27,966	247,405
2023	114,387	92	266	686	1,722	4,232	9,190	27,469	231,382
2024	189,610	50	193	519	1,389	3,481	7,797	23,447	223,323

The dataset provides unusually strong coverage of the upper tail of the wealth distribution. Portfolios in the top 1% hold more than $200 million on average, offering a rare window into the behavior of UHNW households that are largely absent from survey-based datasets. The key question is whether this strong upper-tail coverage compromises representativeness.

Consistent with evidence from Smith, Zidar and Zwick (2023), households in the bottom 90% of the wealth distribution hold little equity (3.5% of wealth in 2016) and virtually no fixed-income assets (1.5% in the same year) outside pensions. As a result, the Addepar data should be thought of as covering mostly the top decile of the wealth distribution, where taxable financial assets are concentrated.

To assess representativeness within this segment, the second row of Table 4 compares average wealth across all households in Addepar against estimates for the top 10% of the wealth distribution from Saez and Zucman (2016), Saez and Zucman (2020), and Smith, Zidar and Zwick (2023), based on the capitalization method in administrative data. Average wealth is higher in Addepar—around \$6.8 million, compared with \$2.2–2.4 million in the capitalization-based estimates. This difference is, however, entirely driven by Addepar oversampling UHNW households at the very top.

To confirm this, rows three through five further disaggregate the top decile, and report average wealth from capitalization-based estimates for the top 10–1%, the top 1–0.1%, and the top 0.1%. Because Addepar mostly covers the top 10% of the wealth distribution, these segments correspond to the bottom 90%, the top 10–1%, and the top 1% in the Addepar dataset respectively. For the top 10–1%, average wealth in Addepar is \$1.3 million, precisely in line with capitalization-based estimates of \$1.2–1.3 million. For the top 1%, average wealth is higher in Addepar, reflecting the oversampling of UHNW households relative to administrative datasets. In addition, Gabaix, Koijen, Mainardi, Oh and Yogo (2025a) further compare average holdings in equities, fixed income, and cash for households in Addepar and in the Survey of Consumer Finances (SCF). They find that the two datasets align well, except at the very top, as UHNW households are typically censored in surveys.

Overall, while Addepar overrepresents households at the very top—as expected given its focus on advised wealth—it provides a representative view of the top decile of the wealth distribution, closely matching capitalization-based estimates. This emphasis on the top decile is ideal given the scope of this paper, since it is the segment where taxable capital income—and hence tax optimization—is concentrated.

Table 4 presents descriptive evidence on household portfolios and advisors. The second column reports the average number of distinct securities held by households in different wealth groups. The number of securities increases monotonically with wealth: households in higher

Table 4: **Addepar versus capitalization-based estimates of average wealth**
This table compares average household wealth in Addepar to capitalization-based estimates from administrative data in 2016. Row 2 reports average wealth across all households in Addepar and compares it with estimates for the top 10% from Saez and Zucman (2016), Saez and Zucman (2020), and Smith, Zidar and Zwick (2023). Rows 3–5 further disaggregate the top decile into the top 10–1%, the top 1–0.1%, and the top 0.1%. All figures are expressed in thousands of U.S. dollars. Capitalization-based estimates are from Table I in Smith, Zidar and Zwick (2023).

Wealth group	Addepar	Saez and Zucman (2016)	Saez and Zucman (2020)	Smith, Zidar and Zwick (2023)
Top 10%	6,772	2,345	2,346	2,193
Top 10–1%	1,266	1,224	1,318	1,240
Top 1–0.1%	21,507	6,586	6,339	6,385
Top 0.1%	272,772	65,094	58,873	50,263

wealth groups hold substantially more securities than those in lower groups. This pattern is consistent with wealthier households engaging in strategies such as direct indexing, which consists in replicating an index while holding all the individual underlying securities. This strategy enables households to optimize taxation compared to holding investment vehicles tracking the same benchmark by selectively realizing capital losses as they arise.

Columns three through eight report the average fraction of households advised by different types of financial advisors within each wealth group. The composition shifts markedly with wealth. Among less wealthy households, registered investment advisors and broker-dealers are most common. As wealth increases, their shares decline, while the prevalence of family offices and private banks—typically regarded as more sophisticated intermediaries—rises sharply. This wealth-advisor sorting is central for the subsequent analysis, where I examine how advisors shape heterogeneity in response to tax incentives.

4 Realization behavior across U.S. households

The previous section established the representativeness of the Addepar data and provided summary statistics on wealth, portfolio composition, and advisor market shares across households. I now turn to study the central objects of interest: unrealized and realized capital gains and losses. This section presents novel stylized facts on the incidence of these returns across the wealth distri-

Table 5: **Market shares of advisors**
For each wealth group, the second column reports the number of securities held on average by households in different wealth groups. Columns three through eight further provide the market shares of different types of advisors in each wealth group, computed as the average fraction of households in each group advised by each advisor type.

Wealth group	N	Brokers/Dealers	Multi-Family Offices	Other	Private Banks	Registered Advisors	Single-Family Offices
0–20%	6.81	11.63%	0.89%	3.76%	4.62%	78.27%	0.83%
20–40%	14.52	11.76%	1.07%	3.67%	6.39%	76.14%	0.97%
40–60%	23.94	10.47%	1.20%	3.14%	9.32%	74.92%	0.95%
60–80%	36.3	9.05%	1.33%	3.02%	10.88%	74.41%	1.31%
80–90%	51.24	8.77%	2.43%	3.91%	10.52%	72.65%	1.72%
90–95%	63.19	7.31%	4.11%	5.42%	10.37%	69.86%	2.94%
95–99%	73.87	6.50%	6.12%	5.45%	9.34%	66.15%	6.44%
Top 1%	74.08	7.54%	6.52%	7.98%	7.82%	51.21%	18.92%

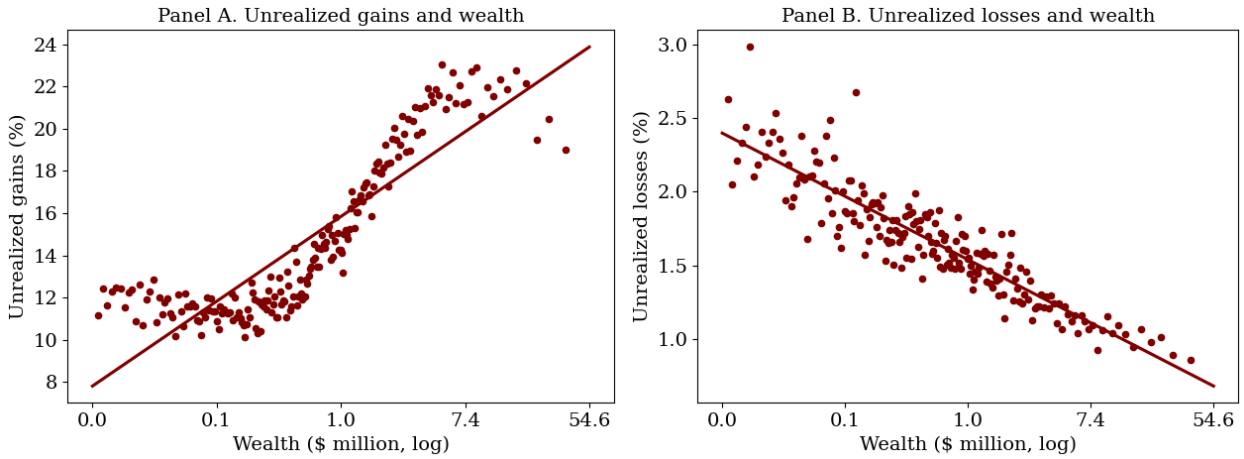
bution and whether households with different levels of wealth display systematic differences in the management of capital gains taxes.

4.1 Stylized facts on unrealized gains and losses

Figure 1 studies the cross-sectional relationship between unrealized returns and wealth. Panel A plots unrealized gains ug_{it} against beginning-of-month log wealth $A_{i,t-1}$ for December 2024, the last month in the sample. Unrealized gains rise sharply with wealth, from 12% among households at the lower end of the distribution to 20% among those with approximately $50 million in wealth. This pattern confirms, for the U.S., the positive relationship between wealth and unrealized capital gains previously documented by Fagereng, Holm, Moll and Natvik (2019) for Norway. Panel B of Figure 1 shows the mirror image for unrealized losses, which decline by a factor of three from 2.5% among less wealthy households to less than 1% at the top.

While Figure 1 provides a static snapshot, unrealized returns are naturally affected by market conditions. The question is whether evolving market conditions affect unrealized returns at the top and bottom in the same way. Figure 2 plots the time series of unrealized gains (Panel A) and losses (Panel B) in the top and bottom quintiles of the Addepar wealth distribution averaged across households after subtracting year-month fixed effects. The difference in unrealized gains

Figure 1: **Unrealized gains and losses across the wealth distribution**
Panel A provides a binned scatterplot of unrealized gains ug_{it} against the log of initial wealth $A_{i,t-1}$ across households. Panel B reports a binned scatterplot of unrealized losses ul_{it} against the log of initial wealth $A_{i,t-1}$ across households. The results are presented for December 2024.

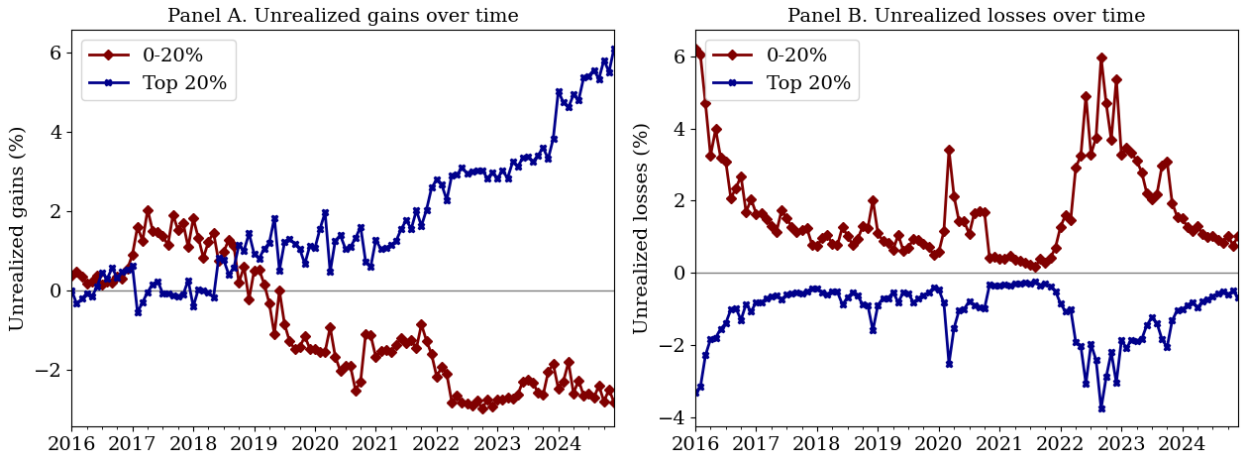


between top and bottom quintiles has widened substantially over time, with a correlation of –0.81 between the two series. Unrealized losses exhibit an even sharper contrast: the top and bottom quintiles move symmetrically in opposite directions, with a correlation of –0.97. This near-perfect negative correlation suggests that households at opposite ends of the wealth distribution manage unrealized returns—and thus their capital gains taxes—in fundamentally different ways. Interestingly, the difference in unrealized losses between the top and bottom quintiles increases precisely during times of market turmoil like the end of 2018, beginning of 2020, and 2022, when it reaches a peak of 10%.

4.2 Fraction of realized capital gains and losses

The stylized facts documented above could reflect mechanisms other than differences in realization behavior across the wealth distribution. For instance, more skilled households successfully select assets that appreciate in the future and, as a result, they become wealthier. If frictions other than capital gains taxes create a disincentive to trade, then skilled households are both wealthier and hold more (less) unrealized gains (losses) in their portfolios. In this section, I provide quantitative evidence that households across the wealth distribution display systematic differences in the realization of capital gains.

Figure 2: **Unrealized gains and losses over time**
Panel A plots average unrealized gains ug_{it} across households in the top and bottom quintiles of the wealth distribution after subtracting year-month fixed effects. Panel B repeats the analysis for average unrealized losses ul_{it}.



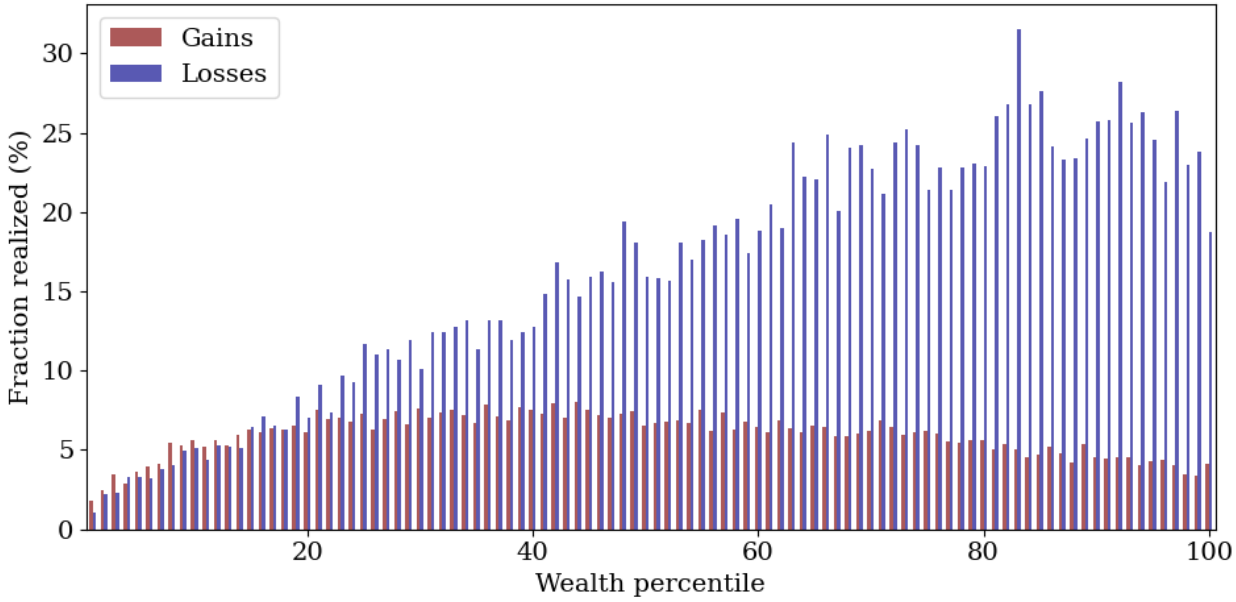
To quantify these differences, for each wealth percentile p, I regress realized losses on initial unrealized losses

$$rl_{it} = \alpha_{lp} + \beta_{lp} ul_{i,t-1} + \varepsilon_{it}. \tag{1}$$

The coefficient β_{lp} measures the fraction of losses realized on average by households in wealth percentile p per dollar of unrealized losses available at the beginning of the month. An analogous regression relates realized gains rg_{it} to initial unrealized gains $ug_{i,t-1}$, yielding β_{gp}, the fraction of realized gains.

Figure 3 plots estimates of β_{gp} and β_{lp} across wealth percentiles. The results highlight starkly different realization behaviors. The fraction of realized gains declines with wealth, from 6% among households in the 20^{th} percentile of the Addepar distribution to around 3% at the top. By contrast, the fraction of realized losses rises monotonically, from near zero at the bottom to almost 30% at the top. As a result, wealthier households benefit more than less wealthy households from the provisions of the U.S. tax code according to which capital gains are taxed when realized and realized losses can be deducted from realized gains.

Figure 3: **The fraction of realized gains and losses**
This figure plots the fraction of gains and losses realized on average by households in each wealth percentile p, summarized by β_{gp} and β_{lp} in equation (1). Estimates are annualized by multiplying each coefficient by 12.



4.3 Robustness

While the evidence so far suggests active tax optimization by wealthier households, I next consider alternative explanations that could confound this interpretation.

4.3.1 Controlling for household characteristics and time fixed effects

Figure D3 in Appendix D controls for households' characteristics including turnover, fraction of wealth allocated to liquid assets, number of months since the household joined the platform, and return on the portfolio of liquid assets.[3] Figure D4 controls for year-month fixed effects to use only variation across households at the same point in time and thereby facing the same market conditions. In both cases, results are unchanged, suggesting that observable households' characteristics correlated with wealth cannot explain the lower (higher) fraction of realized gains (losses). Inter-

[3] I construct turnover in liquid assets for household i in year-month t as $\frac{1}{2}\frac{\sum_a |F_{iat}|}{\sum_a A^{DH}_{ia,t-1}}$, where the sum $\sum_a$ is across liquid securities, $A^{DH}_{ia,t-1} = \frac{1}{2}(A_{iat} - R_{iat} + A_{ia,t-1}) = A_{ia,t-1} + \frac{1}{2}F_{iat}$ denotes the average between beginning-of-period and end-of period holdings depurated by price effects, and R_{iat} is the dollar return (realized and unrealized) on asset a.

estingly, at the bottom of the wealth distribution, households tend to realize a higher fraction of gains than losses, in line with the results in Odean (1998).

4.3.2 Excluding assets likely held in non-taxable accounts

A potential concern is that households at the lower end of the wealth distribution hold a larger share of their wealth in retirement accounts such as 401(k) plans and IRAs. Because capital gains realized in these accounts are not subject to taxation, less wealthy households may have weaker incentives to realize capital losses. The Addepar dataset does not indicate whether securities are held inside or outside retirement accounts, but more than 95% of aggregate assets in retirement accounts are allocated to mutual funds (including balanced funds, target-date funds, and money-market funds).[4]

To address this concern, I re-estimate equation (1) after restricting the sample to directly-held equity and fixed-income securities.[5] Despite losing more than 25% of observations and 30% of households, Figure D5 shows that the results are qualitatively unchanged: wealthier households still realize a substantially higher fraction of losses and a lower fraction of gains than less wealthy households.

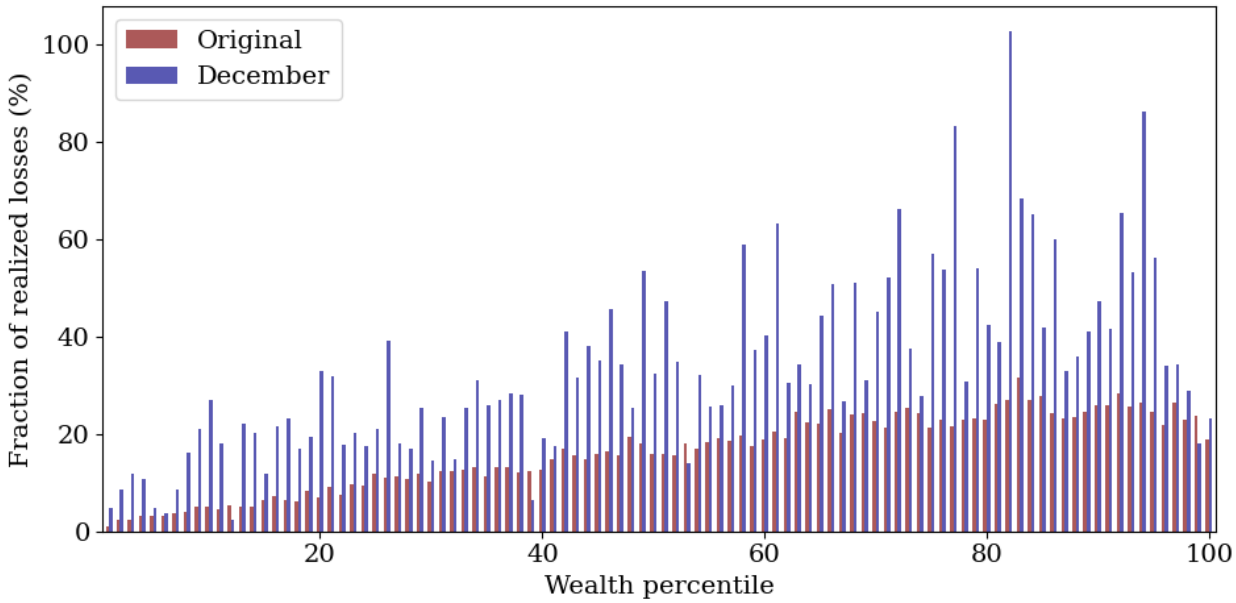
4.3.3 Fraction of realized losses in December

If wealthier households actively optimize taxation, they should have strong incentives to realize capital losses in December if they have realized substantial gains during the rest of the year. To test this hypothesis, I estimate the fraction of losses realized in December by households in each wealth percentile that are above the median of net gains realized until November. I report the results in Figure 4 together with the original estimates discussed in Figure 1. Consistent with wealthier households actively optimizing taxation, the increase in the fraction of realized losses is higher for households at the top of the wealth distribution.

[4] See, for instance, the annual report issued for 2022 by the Investment Company Institute.

[5] I include in the estimation directly held government bonds, corporate bonds, convertible bonds, municipal bonds, ABS/MBS, common stocks, preferred stocks, and convertible stocks. I also include depository receipts on equity and debt that represent stocks and bonds issued by foreign corporations and publicly traded in U.S. markets.

Figure 4: **The fraction of realized losses before the year-end**
This figure plots the fraction of losses realized in the fourth quarter of each year by households above the median of net capital gains realized in the first three quarters. I compare them with the baseline estimates reported in Figure 1 and summarized by β_{lp} in equation (1). Estimates are annualized by multiplying each coefficient by 12.



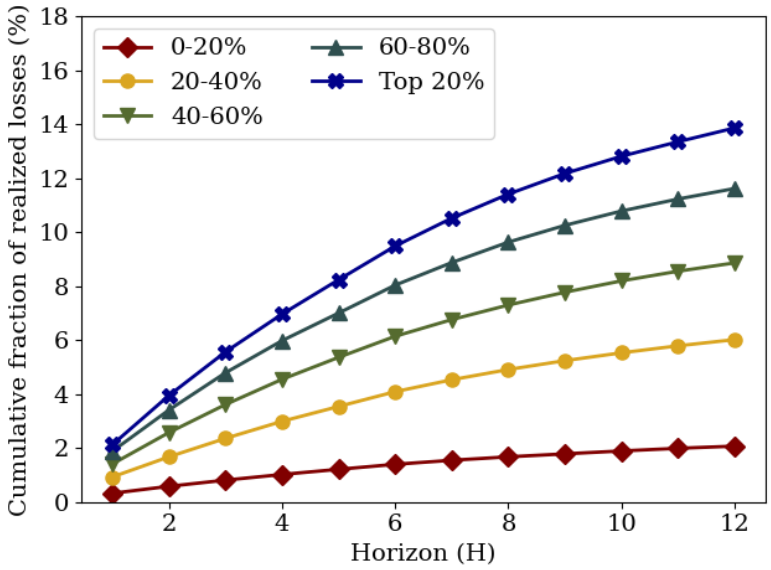
4.3.4 Lagged response of less wealthy households

One alternative explanation of the baseline result is that less wealthy households are more inert and they do optimize capital gains taxes but with a delay. To test this hypothesis, I estimate an analogous version of equation (1) with realized losses $rl_{i,t+h}$ observed h year-months ahead as the outcome variable

$$rl_{i,t+h} = \alpha_{qh} + \beta_{qh} ul_{i,t-1} + \varepsilon_{ith}. \tag{2}$$

In this exercise, I group households into quintiles q of the Addepar wealth distribution to ensure results are easily readable. Figure 5 plots the cumulative fraction of realized losses $\sum_{h=1}^{H} \beta_{qh}$ over different horizons $H \in \{0, 1, .., 11\}$ up to one year ahead. Wealthier households realize a larger fraction of unrealized losses at any horizon H. If anything, the difference between the top and bottom of the wealth distribution increases monotonically over time, confirming that less wealthy households do not optimize capital gains taxes with a delay but are, instead, unconditionally less responsive.

Figure 5: **Dynamic fraction of realized losses**
This figure plots the cumulative fraction of losses realized on average by households in each wealth quintile q over horizon H, summarized by the estimate $\sum_{h=1}^{H} \beta_{qh}$ for $H \in \{0, 1, .., 11\}$.



In Figure D6, I further report results from estimating equation (2) using realized and unrealized gains. I find that households in the top quintile realize a lower fraction of gains than households in the second to fourth quintiles at any horizon H. Moreover, the difference amplifies over time. This result suggests that wealthier households do not just postpone the realization of capital gains in the short run, but also in the long run.

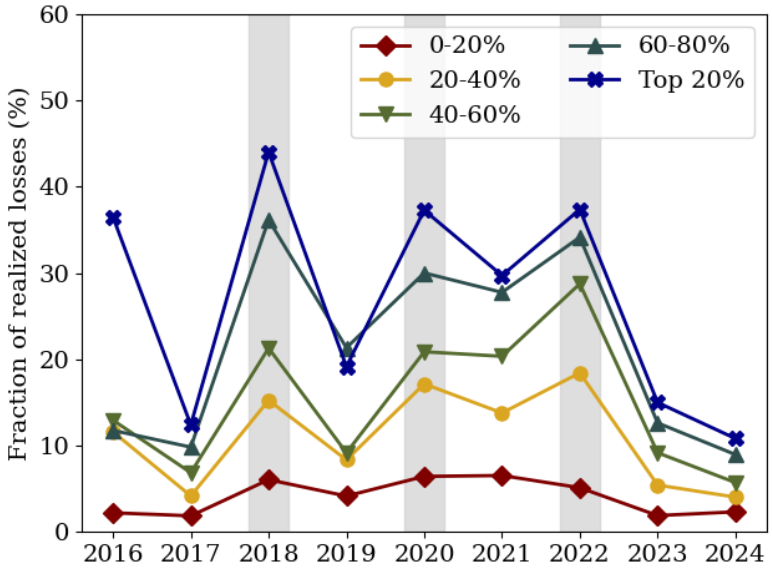
4.3.5 Sample composition over time

Because the Addepar platform has increased rapidly over time, the last years covered by the dataset receive naturally more weight when estimating equation (1). To show that the results are not driven by the final dates but are instead a systematic feature of the data, I estimate equation (1) separately in each year. Results are reported in Figure 6 for each quintile of the Addepar wealth distribution. Wealthier households realize a higher fraction of losses in every year.

More interestingly, consistent with Panel B of Figure 2, the difference between the top and bottom of the wealth distribution visibly increases in periods of market turmoil, highlighted by the shaded gray areas which include the largest monthly drop in the equity market covered by the sample (December 2018, February and March 2020, and September 2022). In those periods, wealth-

ier households substantially increase the fraction of realized losses, while less wealthy households remain inert. As a result, less wealthy households lose twice during times of market turmoil: they not only suffer lower pre-tax returns but also fail to monetize capital losses precisely when they are most available.

Figure 6: **Fraction of realized losses in each year**
This figure plots the fraction of gains and losses realized on average by households in each wealth quintile and in each year covered by the dataset. Estimates are annualized by multiplying each coefficient by 12.



5 Causal evidence from a regression kink design

The reduced-form patterns in Section 4 are consistent with wealthier households actively engaging in TLH, but they do not establish causality. To test whether the realization behavior at the top reflects an active response to tax incentives, I leverage the granularity of the data and variation across individual securities to implement a regression kink design that exploits the sharp change in marginal tax liability when realized returns cross zero. The identifying idea is straightforward: realized losses can be deducted against current or future realized gains to reduce tax liabilities, whereas realized gains increase current tax liabilities. Consequently, the slope of realized returns with respect to unrealized returns should change discontinuously at zero. If households optimize taxation through TLH, they are expected to realize a higher fraction of their unrealized returns

when those returns are negative, producing a steeper slope to the left of zero than to the right.

5.1 Visual evidence in raw data

Before turning to the formal regression kink design, it is useful to examine the raw data. To fix ideas, for each wealth quintile, Figure 7 plots realized monthly returns against unrealized returns for December 2024, the last month of the sample. Each panel is constructed at the household-security level, restricting the running variable to unrealized returns between –10 and +10 basis points.

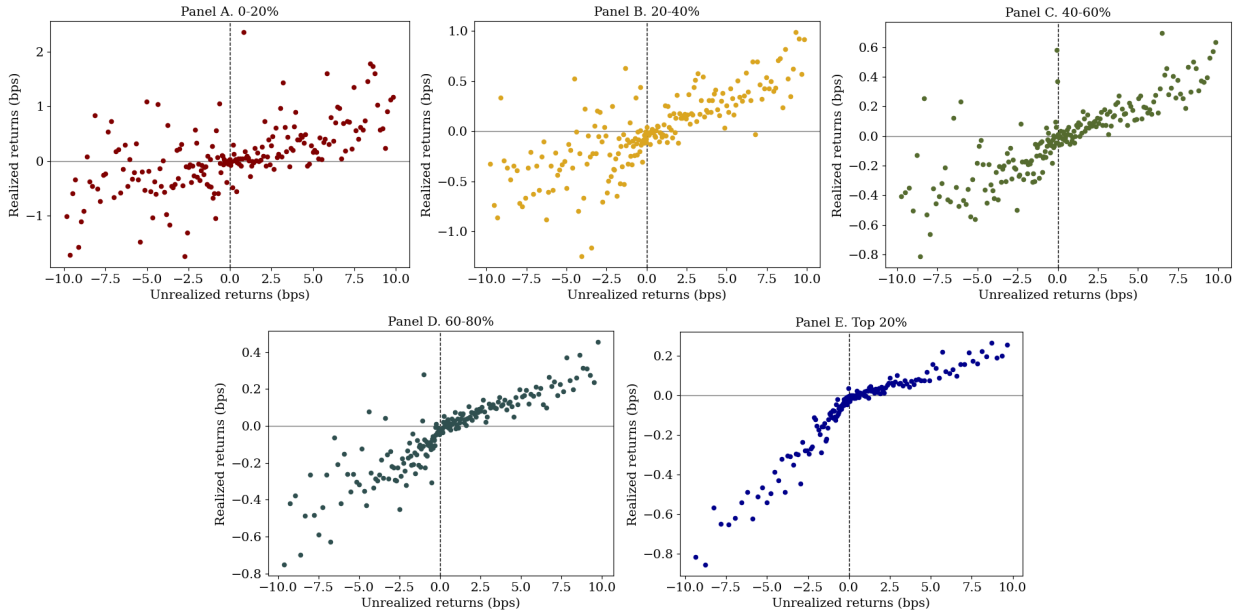
Among households in the bottom 20% of the wealth distribution, realized returns are essentially unrelated to unrealized returns around zero, with no visible kink. As wealth increases, however, a clearer pattern emerges: the slope of realized returns with respect to unrealized returns is steeper for negative values and flattens for positive values, consistent with selective loss realization. For the top quintile, the kink is sharp and closely resembles the theoretical rational benchmark.

Constantinides (1983) shows that, in a rational portfolio choice model with capital gains taxes, households should realize 100% of losses and none of the gains, implying a slope of one on the left of zero and zero on the right. In the data, slopes for wealthier households are smaller in magnitude but move in the predicted direction: approximately 0.1 to the left of zero and 0.02 to the right. This is consistent with subsequent work (e.g., Constantinides, 1984; Dammon and Spatt, 1996; Dai, Liu, Yang and Zhong, 2015) showing that accounting for the differential tax treatment of long- and short-term gains and losses attenuates the stark 100%–0% prediction.

This figure makes two points. First, the kink is already visible in the raw data, particularly among wealthier households, suggesting that the patterns are not artifacts of estimation. Second, the fact that slopes are lower than the theoretical benchmark indicates that real-world frictions—such as trading costs, risk constraints, behavioral inattention, or additional provisions of the tax code—attenuate TLH, but do not overturn its qualitative predictions.

I next formalize this visual evidence using a regression kink design that quantifies the slope discontinuity and establishes its statistical significance.

Figure 7: **Relation between realized and unrealized returns**
Each panel provides a binned scatterplot of realized returns against unrealized returns in a narrow interval around zero for a given quintile of the Addepar wealth distribution. The dataset is restricted to December 2024 and to securities with unrealized returns between –10 and +10 basis points.



5.2 Regression kink design

To formalize the regression kink design, for each year y covered by the dataset and each wealth quintile q, I estimate:

$$rr_{iat} = \alpha_{qy} + \beta_{+,qy} ur_{ia,t-1} \mathbb{I}\left(ur_{ia,t-1} \geq 0\right) + \beta_{-,qy} ur_{ia,t-1} \mathbb{I}\left(ur_{ia,t-1} < 0\right) + \varepsilon_{iat}. \tag{3}$$

The coefficients $\beta_{+,qy}$ and $\beta_{-,qy}$ capture the marginal propensity to realize gains and losses in a neighborhood around zero. The parameter of interest is the difference in slopes, $\Delta_{qy} = \beta_{-,qy} - \beta_{+,qy}$, which measures the change in households' propensity to realize returns when unrealized returns cross zero. If households optimize capital gains taxes and engage in TLH, we expect $\Delta_{qy} > 0$.

The sample is restricted to securities with unrealized returns near zero, with bandwidths selected optimally to minimize the mean-square-error of the estimator Δ_{qy}. In practice, this means that the bandwidth is chosen to balance bias and precision: a narrower window reduces bias

but yields noisier estimates, while a wider window increases precision but risks influence from observations farther from the kink. Because the mean-square-error-optimal bandwidth is often larger than the one that minimizes bias, both the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b).

Identification requires that, within a sufficiently narrow window around zero, securities are as good as randomly assigned to either side of the kink. This condition holds if individual households cannot manipulate the market price of their securities, and it is further reinforced because unrealized returns enter the regression with a one-period lag. Under this assumption, the discontinuity in slope at zero identifies the causal effect of tax incentives on households' realization behavior.

Table 6 reports the estimated kink coefficients Δ_{qy} for each year and wealth quintile, along with the average across years. Additional statistics are reported in Table D2 in Appendix D. The estimates reveal a clear gradient across the wealth distribution: households in the top 20% are consistently more responsive to tax incentives than those at the bottom, increasing the fraction of realized losses relative to gains much more sharply when unrealized returns cross zero. By contrast, coefficients for the bottom quintile are generally small and statistically insignificant; in 2023 they are even significantly negative, indicating that less wealthy households sometimes realize more gains than losses around the kink, in contrast to rational models of portfolio choice with capital gains taxes but in line with Odean (1998).

Averaged across years, the estimates rise monotonically with wealth and closely match the fractions of realized gains and losses discussed in Section 4.2 using the simpler regression approach. For the top quintile, the average effect is both statistically and economically significant: these households realize roughly 40% more losses than gains on average.

5.3 Robustness

While the evidence in the previous section supports active tax optimization by wealthier households, I next consider and test two alternative explanations.

Table 6: **Estimated kink**
This table reports the estimated kink coefficient for each year and wealth quintile. Left and right bandwidths are chosen to minimize the mean-square-error of the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b). Estimates are annualized by multiplying each coefficient by 12. All figures are expressed in percent and standard errors are provided in parenthesis.

Year	0–20%	20–40%	40–60%	60–80%	Top 20%
2016	47.610***	-8.433	14.027	50.720***	50.173***
	(17.241)	(11.669)	(10.931)	(9.789)	(9.501)
2017	16.157	37.774***	24.303**	0.801	18.339**
	(19.820)	(10.982)	(9.583)	(6.986)	(7.548)
2018	9.420	18.534**	7.460	15.692	37.141***
	(10.562)	(9.159)	(9.204)	(10.112)	(11.361)
2019	9.132	13.235**	13.853***	17.261***	34.225***
	(6.776)	(5.788)	(4.977)	(5.860)	(3.881)
2020	0.873	87.384***	86.601***	109.537***	102.188***
	(8.249)	(8.358)	(7.791)	(7.270)	(8.177)
2021	-2.471	0.994	1.334	32.687***	22.545***
	(8.874)	(7.735)	(7.730)	(6.268)	(5.137)
2022	5.306	20.799***	32.471***	51.968***	44.446***
	(3.925)	(3.079)	(2.370)	(2.503)	(2.673)
2023	-8.356***	8.837***	15.594***	7.628***	10.431***
	(3.221)	(2.160)	(1.985)	(1.633)	(1.439)
2024	0.353	8.961***	18.675***	20.975***	26.045***
	(4.456)	(2.477)	(2.747)	(1.910)	(1.591)
Average	8.669	20.898	23.813	34.141	38.393

5.3.1 Sorting and donut regression kink design

A potential concern in regression discontinuity and regression kink designs is that households may endogenously sort around the cutoff. To test for this, for each year and wealth quintile, I implement the local polynomial density discontinuity test of Cattaneo, Jansson and Ma (2020) and I report t-statistics and p-values in Appendix Table D3. The test rejects the null of a continuous distribution at zero: there is statistically significant bunching on the right of the cutoff, i.e. in the region of unrealized gains. This pattern is not surprising: securities are more likely to appreciate rather than depreciate on average. Moreover, if households realize a higher fraction of losses than gains, they mechanically hold a larger fraction of securities with unrealized gains.

An alternative explanation of this bunching, however, is that households strategically position their portfolios in anticipation of future returns. For example, suppose households buy securities they expect to appreciate, then inertia leads them not to sell in the next period, generating few realized gains. To address this concern, I implement a donut regression kink design that, for every year and wealth quintile, excludes the 5% of observations closest to zero on both sides of the cutoff. Results, reported in Table 7, are nearly identical to the baseline, confirming that the estimated kink does not reflect mechanical sorting around the cutoff.

5.3.2 Belief about return persistence

Another alternative explanation for the observed heterogeneity across wealth quintiles is that it reflects differences in beliefs about return dynamics rather than different responses to tax incentives. If wealthier households believe returns are highly persistent, they may sell after they experience small losses (expecting further declines) but not after they experience small gains (expecting continued appreciation). Conversely, if less wealthy households believe in rapid mean reversion, they might avoid realizing small losses, anticipating a rebound.

This interpretation, however, also makes sharp predictions about the buying margin which can be tested directly in the data: if wealthier households expect persistence, they should be more likely to buy after small unrealized gains, while less wealthy households should not. To test this, I estimate the regression kink design in (3) separately for sales and purchases as outcome variables instead of realized returns.[6] The results, reported in Tables D4 and D5, show that wealthier

[6] I construct sales in security a for household i in year-month t as $\frac{-F_{iat}\mathbb{I}(F_{iat}<0)}{\sum_a A^{DH}_{ia,t-1}}$, where the sum $\sum_a$ is across liquid

Table 7: **Estimated donut kink**
This table reports the estimated donut kink coefficient for each year and wealth quintile. I exclude the 5% of observations closest to zero on both sides of the cutoff. Left and right bandwidths are chosen to minimize the mean-square-error of the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b). Estimates are annualized by multiplying each coefficient by 12. All figures are expressed in percent and standard errors are provided in parenthesis.

Year	0–20%	20–40%	40–60%	60–80%	Top 20%
2016	65.534***	-5.504	19.186*	27.417**	48.679***
	(21.191)	(11.559)	(11.216)	(11.482)	(11.764)
2017	0.655	31.651**	28.446***	0.579	22.070***
	(21.648)	(12.410)	(10.553)	(7.603)	(7.189)
2018	-0.267	26.208***	14.277	9.040	28.488**
	(10.730)	(9.822)	(9.900)	(10.298)	(12.731)
2019	-8.149	2.877	15.665***	17.757**	37.909***
	(7.595)	(6.812)	(5.308)	(7.148)	(4.953)
2020	21.559**	75.150***	50.221***	80.104***	108.144***
	(10.411)	(9.516)	(9.316)	(8.127)	(9.476)
2021	-5.109	-34.991***	-9.336	13.871**	9.843*
	(9.252)	(8.260)	(8.022)	(6.585)	(5.125)
2022	5.122	26.927***	33.736***	55.678***	56.085***
	(4.600)	(3.619)	(2.530)	(2.865)	(2.710)
2023	-8.747**	8.500***	7.140***	-2.324	13.152***
	(3.898)	(2.537)	(2.365)	(2.021)	(1.708)
2024	-8.812*	2.970	11.411***	14.601***	26.840***
	(4.876)	(2.886)	(2.656)	(1.991)	(1.607)
Average	6.865	14.865	18.972	24.080	39.023

households increase both sales and purchases following unrealized losses relative to gains. In other words, they do not increase purchases following small gains, as beliefs about persistent returns would require; if anything, they reduce them. Less wealthy households exhibit similar but weaker responses on both margins, suggesting that they do not have different beliefs about return persistence than wealthier households, they are instead less responsive.

Figures D7 and D8 also plot the relation in raw data, confirming the results visually. Altogether, these patterns are inconsistent with heterogeneous beliefs about return persistence and are instead consistent with selective realization in response to tax incentives.

6 Heterogeneity beyond wealth: the role of advisors

The previous analysis established that wealthier households are consistently more responsive to capital gains tax incentives, a pattern robust to alternative specifications and tests of sorting and beliefs. Yet wealth is only one dimension of heterogeneity. In practice, many households rely on financial advisors, and the type of advisor may directly affect the response to tax incentives. I next examine how the propensity to realize gains and losses varies across advisor types, holding wealth fixed.

6.1 Advisor heterogeneity conditional on wealth

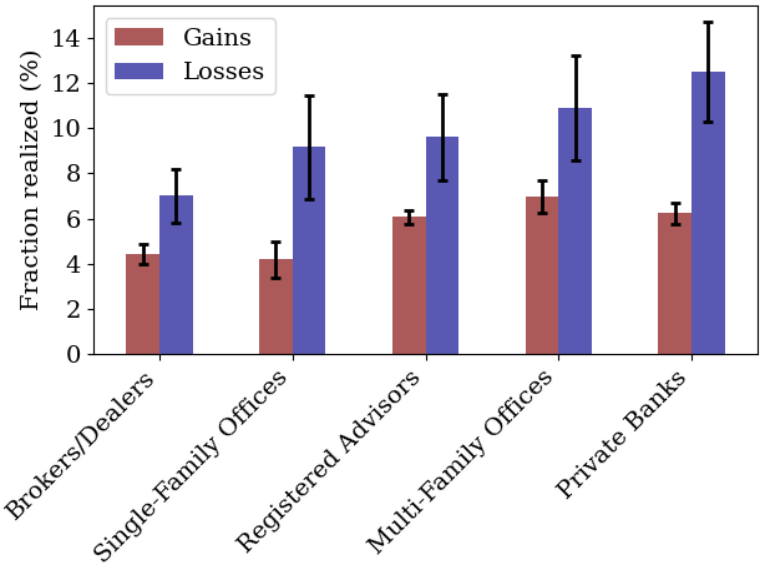
To isolate the role of advisors from differences in household wealth, I estimate an analogous version of equation (1) separately for each advisor type, including wealth-percentile fixed effects. This approach compares households of similar wealth but supervised by different advisors.

Figure 8 plots the fraction of realized gains and losses for each advisor type, revealing substantial heterogeneity even within narrow wealth brackets. Private banks stand out as the most tax-savvy, realizing a markedly higher fraction of losses relative to other advisor types, and outperforming even family offices, often regarded as elite advisors. While this may be unexpected ex-ante, it aligns with recent industry trends: private banks have increasingly positioned themselves as leaders in tax optimization, often through strategic acquisitions of tax-oriented firms such as Morgan Stanley's purchase of Eaton Vance, J.P. Morgan's acquisition of 55ip, and Goldman Sachs'

securities. Similarly, I construct purchases as $\frac{F_{iat}\mathbb{I}(F_{iat}>0)}{\sum_a A^{DH}_{ia,,t-1}}$.

acquisition of Folio Financial.

Figure 8: **Fraction of realized gains and losses by advisor type**
This figure plots the fraction of gains and losses realized on average by households advised by each advisor type, controlling for wealth-percentile fixed effects. Standard errors are clustered at the wealth percentile level and estimates are annualized by multiplying each coefficient by 12.



6.2 Interaction of advisor type and wealth

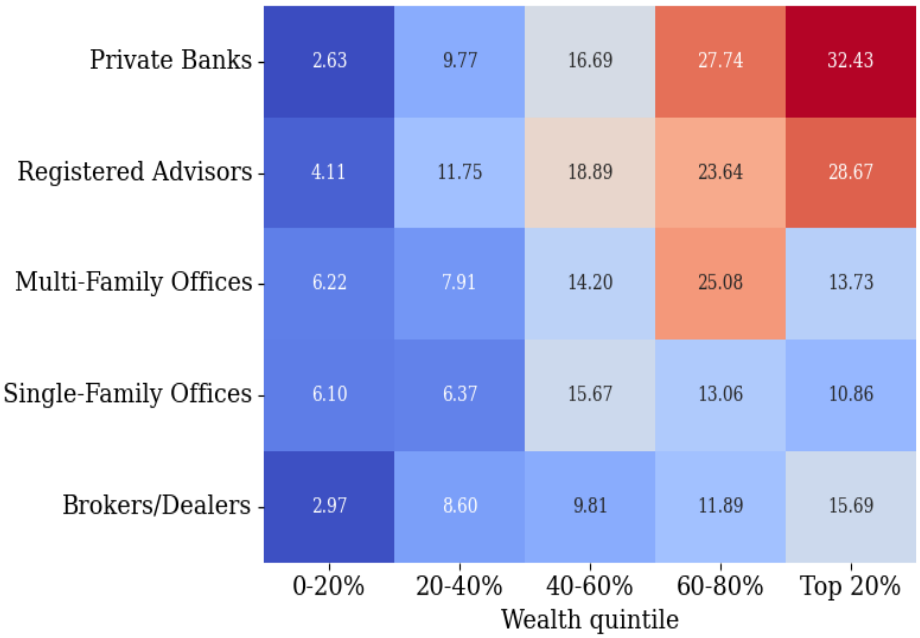
A natural next question is whether private banks deliver uniformly high tax performance across their client base, or whether benefits accrue differently based on households' wealth. To address this, I estimate equation (1) separately for each wealth quintile and advisor type, and report the fraction of realized losses in Figure 9.

Two key patterns emerge. First, less wealthy households underperform regardless of the advisor they use: even those with access to sophisticated advisors realize relatively few losses. Second, higher wealth does not mechanically imply superior tax optimization. For example, households in the top 20% advised by family offices realize a smaller fraction of losses than households around the median of the wealth distribution advised by registered investment advisors.

These findings carry important policy implications. They suggest that the gap between the top and the bottom of the Addepar wealth distribution is not solely driven by intrinsic household sophistication (as proxied by wealth), but also by differential access to or choice of effective advisory

services. Because wealth itself cannot be altered by design, policies or innovations that broaden access to sophisticated tax-optimization advice or improve households' choice of advisors, represent more actionable margins. Interventions along these dimensions could reduce disparities in after-tax portfolio outcomes across the wealth distribution, thereby improving both the equity and the efficiency of the capital gains tax system.

Figure 9: **Fraction of realized losses by advisor type and wealth quintile**
This figure plots the fraction of losses realized on average by households in each wealth quintile advised by each advisor type. Estimates are annualized by multiplying each coefficient by 12.



7 Heterogeneity in after-tax returns

The previous sections established substantial heterogeneity in households' responsiveness to capital gains tax incentives. Wealthier households display sharper realization asymmetries, and access to or choice of sophisticated advisors further amplify these patterns. A natural question is whether such differences carry meaningful implications for after-tax performance and wealth concentration. This section shows that they do: differences in realization behavior translate directly into lower effective tax burdens for wealthier households and into a measurable tax alpha that can sustain sizable concentration of wealth at the top of the distribution in the long run.

7.1 Effective tax rate

I begin by computing the fraction of taxable realized capital gains for each household-year, defined as total realized gains net of total realized losses, divided by total realized gains. If losses exceed gains in a given year, the difference is carried forward to offset future realized gains in accordance with the U.S. tax code.

Panel A of Figure 10 plots the fraction of taxable gains against the log of beginning-of-year wealth and documents a steep gradient: taxable gains decline from roughly 70% at the bottom of the wealth distribution to 45% at the top. In other words, more than half of the gains realized by the wealthiest households are untaxed on average.

Panel B turns to effective tax rates, defined as taxes due in each year divided by total realized gains. Taxes due are calculated by applying the statutory long-term and short-term capital gains rates, while carefully accounting for the ordering rules in the tax code. Short-term losses are first netted against short-term gains, then against long-term gains, with any residual carried forward. Conversely, long-term losses are first netted against long-term gains, then against short-term gains, with any residual carried forward.

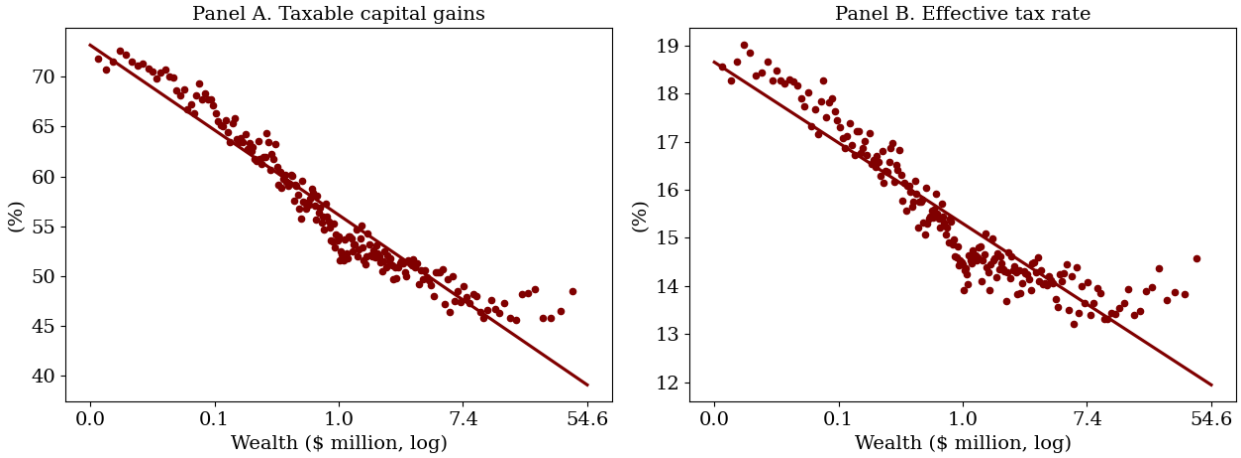
Short-term gains and losses are defined as those realized within one year of purchase; all others are long-term. In the baseline version, I apply the highest marginal tax rates to all households: a 23.8% federal rate on long-term gains (constant during the sample), and a top personal income tax rate of 43.4% until 2017 and 40.8% thereafter on short-term gains, both including the 3.8% Net Investment Income Tax. Under these assumptions, the effective tax rate falls from 19% at the bottom quintile to 13% at the top quintile. These estimates are robust to alternative tax rate assumptions, which I explore below.

Finally, Figure 11 plots the fraction of household-years across the wealth distribution with non-positive taxable gains, i.e. effectively claiming a tax credit. This share increases from 20% at the bottom to 40% at the top of the wealth distribution. Collectively, these findings demonstrate that differences in realization behavior map directly into differences in effective tax burdens.

7.2 Tax alpha

I next assess the implications for after-tax performance. For each household-year, I scale total taxes due by beginning-of-year wealth to obtain an annualized measure of rescaled capital gains

Figure 10: **Taxable capital gains and effective tax rate**
Panel A plots taxable capital gains against the log of beginning-of-year wealth for each household-year in the dataset. Panel B plots the effective tax rate on capital gains.



tax expenses. Figure 12 shows again a pronounced gradient: rescaled tax expenses fall from 70 basis points at the bottom of the wealth distribution to just 20 basis points at the top. The implied difference of 50 basis points per year represents an economically meaningful tax alpha which increases after-tax returns at the top solely through superior tax management.

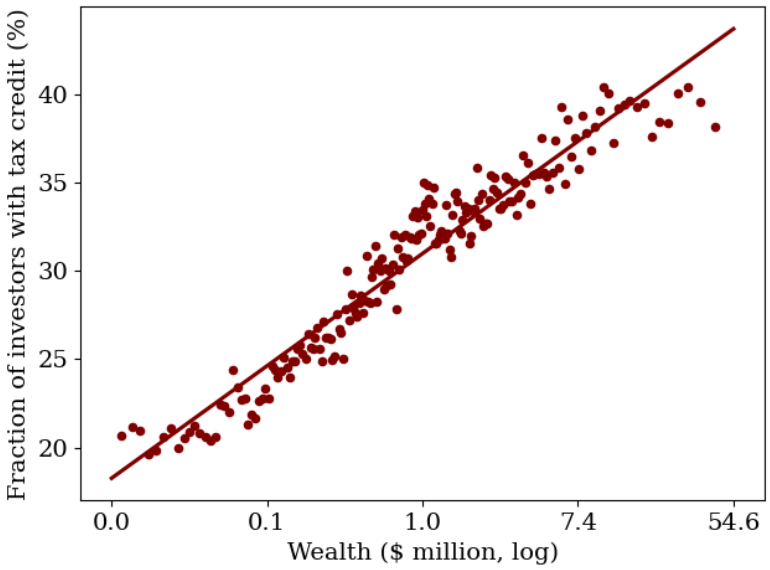
This tax alpha is economically significant. Focusing on returns on financial wealth, Fagereng, Guiso, Malacrino and Pistaferri (2020) estimate a gap of 150 basis points between the top and bottom of the Norwegian wealth distribution, with about 60 basis points attributable to risky assets.[7] Bach, Calvet and Sodini (2020) report a 55-basis-point alpha gap in Sweden, again for financial wealth, similar to the 57-basis-point estimate in Campbell, Ramadorai and Ranish (2019).[8] The tax alpha documented here accounts for at least one-third of these earlier estimates, despite arising purely from heterogeneous response to tax incentives rather than differences in pre-tax performance.

Taken together, these findings show that realization behavior materially shapes households' effective tax burdens and generates a sizable tax alpha. Far from being a minor margin, tax management emerges as a first-order driver of after-tax return heterogeneity across the wealth distribution.

[7] See Panel A of Figure 2 in Fagereng, Guiso, Malacrino and Pistaferri (2020) for the former result and Figure 3 for the latter.

[8] See column (3) of Table 5 in Bach, Calvet and Sodini (2020) and Panel A of Table 2 in Campbell, Ramadorai and Ranish (2019).

Figure 11: **Fraction of investors with tax credit**
This figure plots the fraction of household-years in the dataset with non-positive taxable capital gains against the log of beginning-of-year wealth.



7.3 Robustness: heterogeneous tax rates and advisory fees

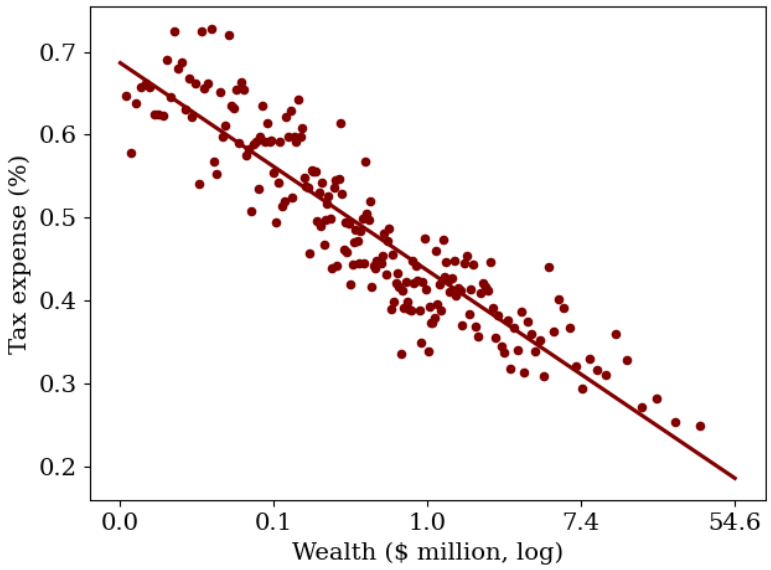
The preceding analysis assumed that all households faced the top statutory tax rates and ignored advisory fees. In this section, I relax both assumptions.

First, I allow tax rates to vary across households based on estimated taxable income. Because Addepar does not report Adjusted Gross Income (AGI), I impute it by combining external tabulations from Balkir, Saez, Yagan and Zucman (2025a) with capitalization factors from Saez and Zucman (2016). I then assign household-specific short- and long-term capital gains rates in every year based on the imputed AGI and the official IRS tax schedules.

Second, I incorporate advisory fees, which could offset the tax alpha if wealthier households pay higher fees to access sophisticated tax-optimization services. Using fee disclosures from SEC Form ADV Part 2, I assign representative fee schedules to each advisor type, while assuming zero fees for broker/dealer accounts. This assumption is conservative and if anything biases against finding a tax alpha at the top, as brokers are most common among less wealthy households. Further details on the construction of tax rates and advisory fees are reported in Appendix B.

Figure 13 plots capital gains tax expenses, inclusive of advisory fees, rescaled by beginning-of-

Figure 12: **Tax alpha**
This figure plots capital gains tax expenses rescaled by beginning-of-year wealth against the log of beginning-of-year wealth for each household-year in the dataset.



year wealth under these relaxed assumptions. The gradient not only persists but becomes steeper: the difference between the bottom and top of the wealth distribution rises from 50 to 100 basis points. The increase reflects two forces. On the one hand, wealthier households face higher statutory tax rates, which compresses the tax alpha. On the other hand, advisory fees are strongly regressive, falling sharply with wealth, which increases the tax alpha. The net result is that the second force dominates and the tax alpha achieved by the wealthiest households is, if anything, understated in the baseline analysis.

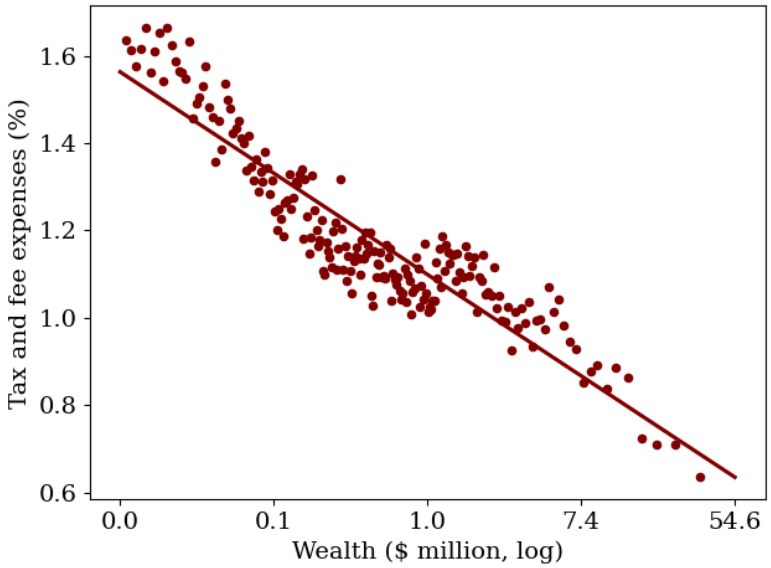
7.4 Is it really alpha?

The previous section documented that wealthier households achieve a tax alpha of at least 50 basis points per year. But for this to be considered a genuine alpha, it must not come at the expense of lower pre-tax returns, higher portfolio risk, or excessive trading costs.

To test this, I focus on households in the top quintile of the wealth distribution, where TLH is most pronounced, and I estimate predictive regressions of the form:

$$y_{i,t+1\to t+h} = \alpha_{th} + \beta_h rl_{i,t-11\to t} + \gamma_h X_{it} + \varepsilon_{ith}$$

Figure 13: **Tax alpha under heterogeneous tax rates and advisory fees**
This figure plots capital gains tax expenses rescaled by beginning-of-year wealth against the log of beginning-of-year wealth for each household-year in the dataset after accounting for heterogeneous tax rates and advisory fees.



where $y_{i,t+1\to t+h}$ denotes the average of an outcome variable over an horizon of h months ahead, α_{th} denotes year-month fixed effects, $rl_{i,t-11\to t}$ is the average of rescaled realized losses over the previous 12 months, and X_{it} includes contemporaneous values of the outcome variables to account for persistence in y. The outcome variables include: (i) pre-tax returns, measured gross of taxes but net of other trading costs; (ii) risk, measured as returns net of household fixed effects and subsequently squared; (iii) turnover.[9]

Table 8 reports the results for each outcome variable and for $h \in \{1, 3, 6, 12\}$. The estimates show three key findings. First, households that realize more losses subsequently earn higher pre-tax returns. This indicates that superior tax management is not achieved at the cost of lower pre-tax performance; if anything, these households outperform even before taxes. Second, there is no evidence of elevated portfolio risk: realized losses predict lower rather than higher volatility of returns. Third, greater loss realization predicts higher turnover, consistent with greater trading flexibility.

Taken together, these results suggest that the tax alpha is indeed a genuine alpha. House-

[9] I construct returns on security a for household i in year-month t as $\frac{R_{iat}}{\sum_a A^{DH}_{ia,t-1}}$, where R_{iat} is measured before taxes but after other transaction costs. The sum $\sum_a$ is across liquid securities.

Table 8: **Realized losses, pre-tax performance, and risk**
This table reports estimates from a predictive regression of pre-tax returns, portfolio risk, and turnover against past average realized losses. Standard errors are clustered at year-month times advisor type level and are provided in parenthesis.

	h			
	1	3	6	12
Panel A. Pre-tax returns				
$rl_{i,t-11\to t}$	0.251**	0.217***	0.163***	0.083*
	(0.113)	(0.070)	(0.059)	(0.045)
R-squared Adj.	0.573	0.487	0.492	0.496
N	174,205	141,729	107,391	65,267
Panel B. Risk				
$rl_{i,t-11\to t}$	-0.037**	-0.037***	-0.054***	-0.068***
	(0.016)	(0.009)	(0.009)	(0.009)
R-squared Adj.	0.258	0.301	0.299	0.255
N	174,205	141,729	107,391	65,267
Panel C. Turnover				
$rl_{i,t-11\to t}$	2.489***	2.145***	2.057***	2.1297***
	(0.369)	(0.272)	(0.274)	(0.250)
R-squared Adj.	0.064	0.107	0.140	0.153
N	174,203	141,723	107,387	65,267

holds that are more responsive to tax incentives do not simply save taxes; they also benefit from enhanced portfolio flexibility, gaining twice—first by reducing their tax burden, and second by retaining the ability to rebalance in response to changed investment opportunities without triggering large taxable gains.

7.5 Implications for wealth concentration

The previous sections showed that heterogeneous responses to capital gains taxation generate an economically significant tax alpha earned by wealthier households. In this section, I study the implications of this tax alpha for the long-term dynamics of the wealth distribution.

Let $s_{pt} = \frac{\sum_{i \in p} A_{it}}{\sum_{i \in p} A_{it} + \sum_{p' \neq p} \sum_{i \in p} A_{it}}$ denote the share of aggregate wealth held by households in percentile p at time t, and let T_{it} denote capital gains taxes paid by household i at time t. Starting from the intertemporal budget constraint governing household wealth dynamics and applying a first-order Taylor expansion of s_{pt}, Appendix C shows that the change in the wealth share of percentile p satisfies

$$s_{pt} - s_{p0} = t s_{p0} \sum_{p' \neq p} s_{p'0} \left(\bar{\tau}_{p'} - \bar{\tau}_p \right) + \varepsilon_{pt}, \tag{4}$$

where $\bar{\tau}_p = \frac{1}{t} \sum_{s=1}^{t} \tau_{ps} = \frac{1}{t} \sum_{s=1}^{t} \frac{\sum_{i \in p} T_{is}}{\sum_{i \in p} A_{i,s-1}}$ is the average capital gains tax expense in percentile p, expressed as a share of beginning-of-year wealth, and s_{p0} is the initial wealth share.

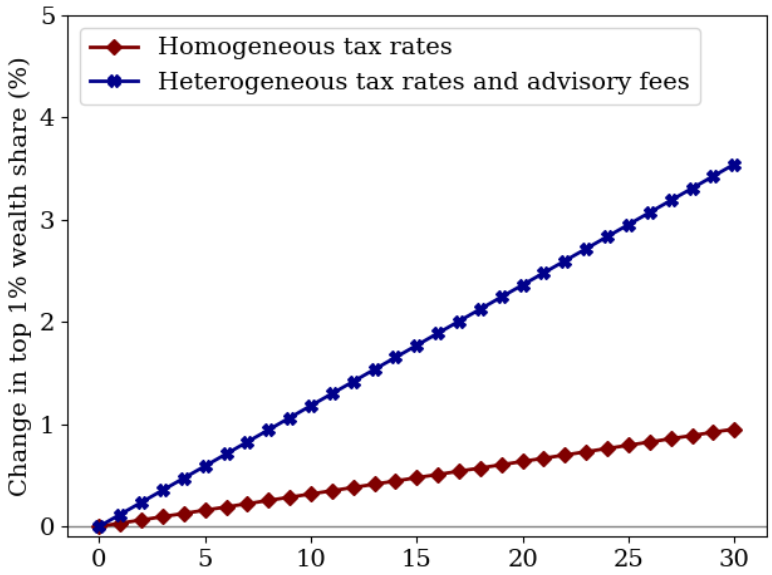
The first term on the right hand-side represents the change in wealth share attributable to differences in capital gains taxes across percentiles. The residual term ε_{pt} captures all other determinants of wealth share dynamics—such as heterogeneity in savings rates, pre-tax returns or higher-order terms that are small in magnitude. Equation (4) is intuitive: to first order, the wealth share of percentile p grows faster when the gap between tax expenses in other percentiles $\bar{\tau}_{p'}$ and its average tax expense $\bar{\tau}_p$ is larger.

I evaluate the contribution of the first term in (4) for the change in the wealth share of the top percentile of households in the Addepar data. I set s_{p0} to match the wealth share of the top 1% in December 2024—the last year covered by the dataset—and compute $\bar{\tau}_p$ as the average annual capital gains tax expense scaled by beginning-of-year wealth. I construct $\bar{\tau}_p$ under both the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates and advisory fees. The same procedure is applied to obtain $s_{p'0}$ and $\bar{\tau}_{p'}$ for the remaining percentiles.

Figure 14 plots the results over an horizon t from one to thirty years. Differences in capital gains tax expenses increase the wealth share of households in the top 1% of the Addepar dataset by 0.95 to 3.54 percentage points over thirty years, everything else equal. For comparison, Smith, Zidar and Zwick (2023) estimate that the share of the top 0.1% rose by 5.63 percentage points over the past thirty years, relative to aggregate wealth in the top decile—the segment of the distribution covered by the Addepar data. If these differences in tax expenses were to persist, they would then raise top-end wealth concentration by 17 to 63% of this historical increase.

Taken together, these findings highlight that heterogeneous responses to capital gains taxes are not only transforming the financial industry but they are also a macroeconomically relevant channel through which the U.S. tax system shapes long-run wealth dynamics.

Figure 14: **Capital gains taxes and growth in the top 1% wealth share**
This figure plots the growth in the top 1% wealth share explained by differences in capital gains tax expenses across the wealth percentiles, which corresponds to the sum of the first two terms on the right hand-side of equation (4). Results are reported over an horizon of one to thirty years. Capital gains tax expenses are computed both under the assumption of homogeneous statutory tax rates (red) and under the assumption of heterogeneous tax rates and advisory fees (blue).



8 Conclusion

This paper provides the first systematic evidence on heterogeneity in response to capital gains taxes across U.S. households. Using granular, high-frequency data on U.S. households, I show that wealthier households are more responsive to capital gains taxes, realizing a smaller fraction of gains and a larger fraction of losses than less wealthy households, consistent with tax-loss harvesting. These patterns are amplified during market downturns and are concentrated among households supervised by sophisticated financial advisors, especially private banks. Exploiting quasi-experimental variation around zero unrealized returns, I establish that these differences reflect an active response to tax incentives rather than unobserved factors correlated with wealth.

The implications for after-tax performance and the evolution of aggregate wealth shares are economically significant. Effective tax burdens decline with wealth, generating a 50-basis-point annual tax alpha for wealthier households—a differential amounting to at least one third of pre-tax return gaps previously documented in the literature. This tax gain does not come at the expense of lower pre-tax performance or higher risk and represents therefore a genuine alpha. Absent this tax alpha, I estimate that the growth in the aggregate wealth share of the top 1% of households would be 3.5 percentage points lower over an horizon of thirty years—equivalent to 63% of the historical rise in top-end wealth concentration documented by Smith, Zidar and Zwick (2023) over an equivalent horizon.

By documenting this channel, the paper identifies a mechanism that links tax policy design to return heterogeneity and long-run wealth concentration. While prior work has emphasized heterogeneity in pre-tax returns due to skill, risk-taking, diversification, or duration, I show that heterogeneity in tax management represents an equally important and policy-relevant margin. These findings suggest that models of wealth dynamics and optimal taxation should explicitly account for heterogeneity in households' response to tax incentives.

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ONLINE APPENDIX

A Details on data construction

A.1 Details on screening process

This section summarizes the construction of the dataset before imposing the screening steps discussed in Section 3.3. Additional details can be found in Appendices B and C of Gabaix, Koijen, Mainardi, Oh and Yogo (2025a).

First, for a small number of portfolios, I observe that the last date of the incubation period is later than the first month in which the portfolio appears in dataset. For these portfolios, I drop any month that predates the last historical date. Similarly, for a minority of portfolios, I observe positions classified as historical segments. To avoid focusing on incubation periods where investors do not trade then, for each investor, I drop all months that predate the last date on which an historical segment was present in the portfolio.

Second, dollar flows F_{iat} in Addepar are measured net of dividends and distributions, which I observe separately. To ensure that dollar flows properly measure investors' rebalancing, I add dividends and distributions back to dollar flows and I subtract them from dollar returns R_{iat}.

Third, I observe a small number of investors that have either zero beginning-of-month holdings or zero end-of-month holdings in all securities other than securities with narrow asset class "Other". To avoid considering historical segments where investors do not trade, I drop any portfolio-month when two conditions are met: (i) in the previous month, the investor had either zero beginning-of-month holdings or zero end-of-month holdings in all securities other than securities with narrow asset class "Other"; (ii) in the current month, the investor had zero beginning-of-month holdings in all securities other than securities with narrow asset class "Other".

Fourth, I remove the year-month in which a household onboards the platform as flows tend to be more volatile during this period (for example, as the beginning-of-period assets are unknown for some or all of the asset classes). I also remove the last year-month in which I observe a given household for the same reason.

Fifth, I remove household-month observations when an item from the budget constraint is missing for at least one liquid security—that is, the beginning-of-month holding, $A_{ia,t-1}$, the end-

of-month holding, A_{iat}, the dollar flow, F_{iat}, or the dollar return, R_{iat}.

Sixth, I remove household-month observations if the budget constraint does not hold for at least one liquid security. I allow for a small margin of error of $1,000 or 0.5% of the average (absolute value) of the end-of-month and beginning-of-month holdings.

Seventh, for a small fraction of all observations, beginning-of-month and end-of-month holdings coincide. While this can happen for cash accounts, this is unlikely to be correct for risky assets. Therefore, I set dollar returns and dollar flows to zero for such observations in liquid asset classes that are not cash.

A.2 Details on asset class assignment

Addepar employs an internal algorithm to impute the narrow and broad asset classes based on the following input variables: *cfi_code*, a universal six letter code provided by ISO 10962 and attributed to the entity at the time of issue; *instrument_type*, directly derived from *cfi_code*; *fund_asset_class*, which describes the broad type of fund based on *morningstar_us_asset_class*; *fund_category*, which describes the type of fund based on *morningstar_category*; *bond_term*, which assigns a bond as short-term if the time-to-maturity is lower than one year and long-term otherwise; *domcile_country_class*, which maps the country of domicile into United States, Developed or Emerging; *business_country_class*, which maps the country in which the entity has its headquarter into United States, Developed or Emerging; *currency*, which provides the native currency of the security. For each broad asset class, I report below the criteria used by Addepar for the assignment of narrow asset classes. A summary of broad and narrow asset classes observed in the raw data, before I perform any adjustment to the original classification, is provided in Table A1 .

A.2.1 Cash

Positions in Addepar are assigned narrow asset class equal to: CAD if *instrument_type* is Bank Account and *currency* is CAD; Certificate of Deposit if *instrument_type* is Certificate of Deposit; CHF if *instrument_type* is Bank Account and *currency* is CHF; Commercial Paper if *instrument_type* is Commercial Paper; EUR if *instrument_type* is Bank Account and *currency* is EUR; Money Market Fund if *instrument_type* is Money Market Fund or if *instrument_type* is ETF/Mutual Funds and *fund_category* is Money Market Taxable or Money Market-Tax Free or Prime Money Market or

Ultrashort Bond; Other Currency if *instrument_type* is Bank Account; Other Short Term Government Bonds if *instrument_type* is Government/Agency Bonds and *bond_term* is Short; Short Term U.S. Government Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is Short and either *domicile_country_class* or *business_country_class* is United States; USD if *instrument_type* is Bank Account and *currency* is USD.

A.2.2 Fixed Income

Positions in Addepar are assigned narrow asset class equal to: ABS/MBS if *instrument_type* is ABS/MBS; Bond Funds if *instrument_type* is ETF/Mutual Funds and *fund_asset_class* is Taxable Bond or if *instrument_type* is ETF/Mutual Funds and *fund_category* is either Intermediate Core-Plus Bond or Intermediate Core Bond or Short-Term Bond or Multisector Bond; Corporate Bonds if *instrument_type* is either Corporate Bonds or Depository Receipts on Debt; International Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is either Long or Unknown and *business_country_class* (or *domicile_country_class*) is either Developed or Emerging; Municipal Bonds if *instrument_type* is Municipal Bonds or if *instrument_type* is Mutual Funds/ETF and *fund_asset_class* is Municipal Bond; Other Debt if *instrument_type* is Other Debt; Structured Debt if *instrument_type* is either Structured Debt or Convertible Bonds; U.S. Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is either Long or Unknown and *business_country_class* (or *domicile_country_class*) is United States; U.S. Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is Long and both *business_country_class* and *domicile_country_class*) are unavailable;

A.2.3 Equity

Positions in Addepar are assigned narrow asset class equal to: Call Option if *instrument_type* is Call Option; Developed Market Equity if *instrument_type* is Depository Receipts on Equity or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is Developed; Emerging Market Equity if *instrument_type* is Depository Receipts on Equity or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is Emerging; Global Equity if *instrument_type* is ETF

or Mutual Funds and *fund_asset_class* is International Equity; Other Equity if *instrument_type* is Depository Receipts on Equity or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity or Rights/Warrants or Acquisition Company; Other Funds if *instrument_type* is either Mutual Funds or ETF; Put Option if *instrument_type* is Put Option; REITs if *instrument_type* is REITs; U.S. Equity if *instrument_type* is Depository Receipts on Equity or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is United States; U.S. Equity if *instrument_type* is either ETF or Mutual Funds and *fund_asset_class* is U.S. Equity.

A.2.4 Alternatives

Positions in Addepar are assigned narrow asset class equal to: Direct Private Companies if *instrument_type* is Direct Private Companies; Fund of Funds if *instrument_type* is Fund of Funds; Hedge Funds if *instrument_type* is Hedge Funds; Private Equity & Venture if *instrument_type* is Private Equity & Venture; Real Estate Funds if *instrument_type* is Real Estate Funds; Unknown Alts if *instrument_type* is Unknown Alts.

A.2.5 Real Estate

Positions in Addepar are assigned narrow asset class equal to Direct Real Estate if *instrument_type* is either Other Direct Real Estate or Direct Residential Real Estate.

A.2.6 Other

Positions in Addepar are assigned narrow asset class equal to: Collectibles if *instrument_type* is Collectibles; Crypto if *instrument_type* is Crypto; Liabilities if *instrument_type* is Loans/Liabilities; Other Derivatives if *instrument_type* is either Other Derivative or Forwards/Futures; Other Non-Financial Assets if *instrument_type* is Other Non-Financial Assets.

Adjustments to the Addepar classification I make several adjustments to the assignment of asset classes imputed by Addepar. First, I merge Short Term U.S. Government Bonds into U.S. Government/Agency Bonds. Similarly, I merge Other Short Term Government Bonds into Unknown

Table A1: **Initial asset class definitions**
This table summarizes broad and narrow asset classes observed in the dataset, before any correction is made. Narrow asset classes are categorized into six broad asset classes. The broad and narrow asset classes are obtained from Addepar's internal classification.

Broad asset classes	Narrow asset classes
Cash	Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Short Term U.S. Government Bonds, Other Short Term Government Bonds, Other Currency
Fixed Income	Municipal Bonds, U.S. Government/Agency Bonds, Corporate Bonds, Bond Funds, ABS/MBS, Structured Debt, International Government/Agency Bonds, Unknown Government/Agency Bonds, Other Debt
Equity	U.S. Equity, Global Equity, Developed Market Equity, Emerging Market Equity, REITs, Call Option, Put Option, Other Equity, Other Funds
Alternatives	Private Equity & Venture, Hedge Funds, Real Estate Funds, Direct Private Companies, Fund of Funds, Unknown Alts.
Real Estate	Direct Real Estate
Other	Collectibles, Crypto, Liabilities, Other, Other Derivatives, Other Non-Financial Assets

Government/Agency Bonds and relabel the narrow asset class as Other Government/Agency Bonds. Third, I merge Call Option, Put Option, and Other Derivatives into a single narrow asset class Derivatives to which I assign broad asset class Other. Fourth, I combine Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Other Currency into a single narrow asset class Cash. Fifth, when holdings are classified as Other Funds and the fund asset class is Sector Equity, I relabel the narrow asset class to U.S. Equity if either the business country class or the domicile country class is United States. For the remaining observations in Other Funds, I change the broad asset class from Equity to Alternatives. Lastly, I perform several adjustments to holdings classified as Bond Funds: if the fund category is either Intermediate Government or Long Government, I modify the narrow asset class to U.S. Government/Agency Bonds if either the business country class or the domicile country class is United States; if the fund category is Corporate Bond or High Yield Bond, I relabel the narrow asset class to Corporate Bonds; if the fund category is Preferred Stock, I reclassify the asset class to the equity category Other Equity; finally, I reclassify positions to Cash when the fund category is Ultrashort Bond.

These adjustments lead to the assignment of broad and narrow asset classes reported in Table 1 of the paper.

B Imputation of tax rates and advisory fees

B.1 Tax rates

To map household wealth in Addepar to taxable income, I proceed in several steps.

First, I use Table 1 of Balkir, Saez, Yagan and Zucman (2025a), which reports average Adjusted Gross Income (AGI), wages, and pension benefits for various wealth groups in 2019. Second, I construct a notion of taxable financial income by subtracting wages and pension benefits from AGI. This definition of taxable financial income includes capital income, business income, and realized capital gains. Third, I translate financial income into financial wealth using the capitalization factor in Table A.13 of Saez and Zucman (2016) which is specifically designed for taxable capital and business income. Specifically I multiply taxable financial income income by a factor of 12.5, which is the midpoint of the 10–15 range observed since 2000. Results are robust to using 10 or 15.

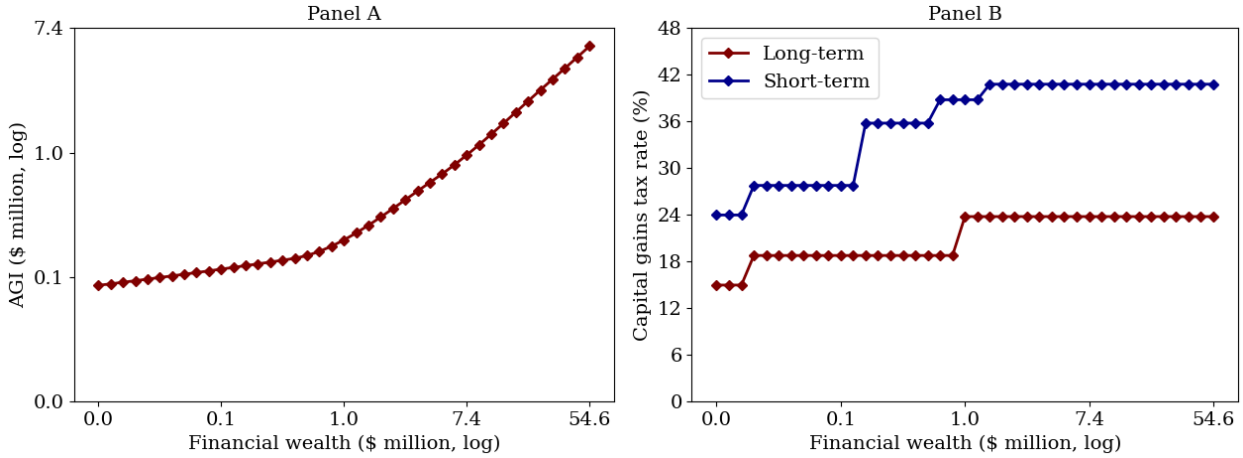
Third, I interpolate log AGI as a function of log financial wealth using cubic splines and apply the interpolated function to Addepar end-of-year log wealth for each household-year. Finally, I assign household-specific statutory rates for short- and long-term gains based on the official tax schedules published every year by the IRS. I use the brackets that apply to married individuals filing separately because the unit of observation in Addepar is a portfolio and multiple members of the same family could manage different portfolios which I cannot link.

Panel A of Figure B1 plots the interpolated log AGI as a function of log financial wealth. Panel B reports the imputed statutory tax rates on long-term and short-term capital gains again as a function of log financial wealth.

B.2 Advisory fees

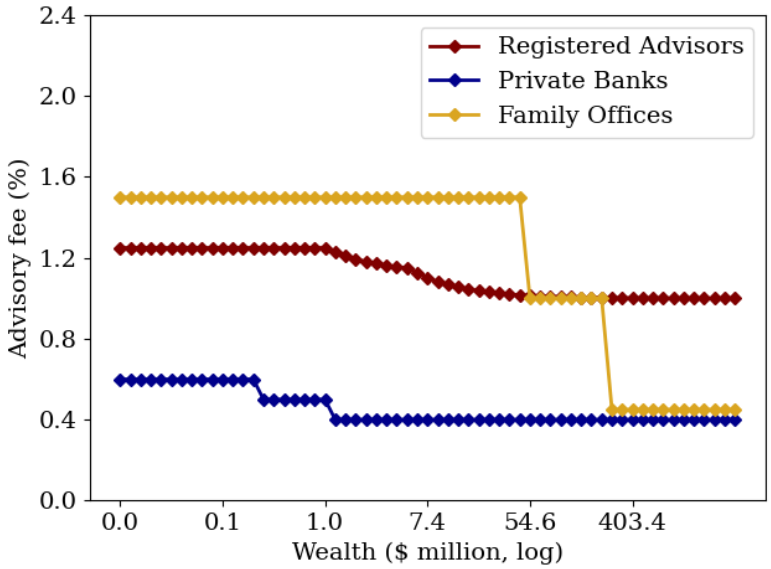
I obtain representative fee schedules from Form ADV Part 2 filed with the SEC by leading firms in each category: Fisher Investments for registered advisors, WE Family Offices for multi- and single-family offices, and J.P. Morgan Securities LLC for private banks. These advisors managed $299, $18, and $353 billion in assets at the end of 2024. Importantly, each advisor reports separate fees charged on households in different wealth brackets. Fees are always reported in the form as a fraction of invested wealth.

Figure B1: **Imputed AGI and statutory tax rates**
Panel A plots the interpolated log AGI as a function of log financial wealth. Panel B plots the imputed statutory tax rates on long-term and short-term capital gains.



For each household-year, I apply the schedule of the relevant advisor type to the household's end-of-year wealth to compute annual advisory fees. Broker/dealer accounts are assigned a zero fee, a conservative choice that biases against finding a tax alpha since these accounts are disproportionately held by less wealthy households (see Table 5 in the main body of the paper).

Figure B2: **Advisory fees**
This figure plots advisory fees as a function of log wealth for different advisory types.



C A framework of wealth dynamics

For each household i and time t, total wealth A_{it} satisfies the following intertemporal budget constraint

$$A_{it} = A_{i,t-1} + R_{it} + F_{it} - T_{it} - C_{it},$$

where R_{it} denotes dollar returns, F_{it} savings, T_{it} dollar capital gains taxes, and C_{it} any additional cost. Summing across all households in wealth percentile p

$$A_{pt} = A_{p,t-1} + R_{pt} + F_{pt} - T_{pt} - C_{pt},$$

where $X_{pt} \equiv \sum_{i \in p} X_{it}$ for a generic variable X, and factoring out initial wealth $A_{p,t-1}$

$$A_{pt} = A_{p,t-1} \left(1 + r_{pt} + f_{pt} - \tau_{pt} - c_{pt}\right), \tag{C1}$$

where I used lower case letters to denote dollar variables rescaled by initial wealth and τ_{pt} to denote rescaled capital gains tax expenses. We can iterate equation (C1) backwards to obtain

$$A_{pt} = A_{p0} \prod_{s=1}^{t} \left(1 + r_{ps} + f_{ps} - \tau_{ps} - c_{ps}\right). \tag{C2}$$

The share of aggregate wealth held by households in a given wealth percentile p at time t, can then be written as

$$\begin{aligned} s_{pt} &\equiv \frac{A_{pt}}{A_{pt} + \sum_{p' \neq p} A_{p't}} \\ &= \frac{A_{p0} \prod_{s=1}^{t} \left(1 + r_{ps} + f_{ps} - \tau_{ps} - c_{ps}\right)}{A_{p0} \prod_{s=1}^{t} \left(1 + r_{ps} + f_{ps} - \tau_{ps} - c_{ps}\right) + \sum_{p' \neq p} A_{p'0} \prod_{s=1}^{t} \left(1 + r_{p's} + f_{p's} - \tau_{p's} - c_{p's}\right)}. \end{aligned} \tag{C3}$$

I take a Taylor expansion of the right hand-side in (C3) around each term in parenthesis equal to zero to obtain

$$s_{pt} = s_{p0} + \sum_{s=1}^{t} \frac{-A_{p0}\left[A_{p0} + \sum_{p' \neq p} A_{p'0}\right] + A_{p0}^2}{\left(A_{p0} + \sum_{p' \neq p} A_{p'0}\right)^2} \tau_{ps} + \sum_{p' \neq p} \sum_{s=1}^{t} \frac{A_{p'0} A_{p0}}{\left(A_{p0} + \sum_{p' \neq p} A_{p'0}\right)^2} \tau_{p's} + \varepsilon_{pt}, \tag{C4}$$

where ε_{pt} includes first-order terms independent of capital gains taxes as well as higher-order terms. Using $s_{p0} \equiv \frac{A_{p0}}{A_{p0}+\sum_{p' \neq p} A_{p'0}}$ in (C4) and rearranging

$$\begin{aligned} s_{pt} &= s_{p0} + \sum_{s=1}^{t} \left(-s_{p0} + s_{p0}^2\right) \tau_{ps} + \sum_{p' \neq p} \sum_{s=1}^{t} s_{p0} s_{p'0} \tau_{p's} + \varepsilon_{pt} \\ &= s_{p0} + \left(-s_{p0} + s_{p0}^2\right) \sum_{s=1}^{t} \tau_{ps} + s_{p0} \sum_{p' \neq p} s_{p'0} \sum_{s=1}^{t} \tau_{p's} + \varepsilon_{pt} \\ &= s_{p0} - s_{p0} \left(1 - s_{p0}\right) \sum_{s=1}^{t} \tau_{ps} + s_{p0} \sum_{p' \neq p} s_{p'0} \sum_{s=1}^{t} \tau_{p's} + \varepsilon_{pt}. \end{aligned} \tag{C5}$$

Finally, let $\bar{\tau}_p$ denote the average rescaled capital gains tax expenses in wealth percentile p. From equation (C5), the change in wealth share in wealth percentile p becomes

$$s_{pt} - s_{p0} = -t s_{p0} \left(1 - s_{p0}\right) \bar{\tau}_p + t s_{p0} \sum_{p' \neq p} s_{p'0} \bar{\tau}_{p'} + \varepsilon_{pt},$$

and substituting $1 - s_{p0} = \sum_{p' \neq p} s_{p'0}$

$$s_{pt} - s_{p0} = t s_{p0} \sum_{p' \neq p} s_{p'0} \left(\bar{\tau}_{p'} - \bar{\tau}_p\right) + \varepsilon_{pt},$$

corresponding to equation (4) in the main text. To first order, the change in the share of wealth in percentile p is higher the lower is the average tax expense $\bar{\tau}_p$ in that percentile and the higher are the average tax expenses in other wealth percentiles.

D Additional figures and tables

Figure D3: **The fraction of realized gains and losses conditional on households' observable characteristics**
This figure plots the fraction of unrealized gains and losses that households in each wealth percentile p realize on average after controlling for households' observable characteristics (turnover, fraction of wealth allocated to liquid assets, number of months since the household joined the platform, and return on the portfolio of liquid assets). Estimates are annualized by multiplying each coefficient by 12.

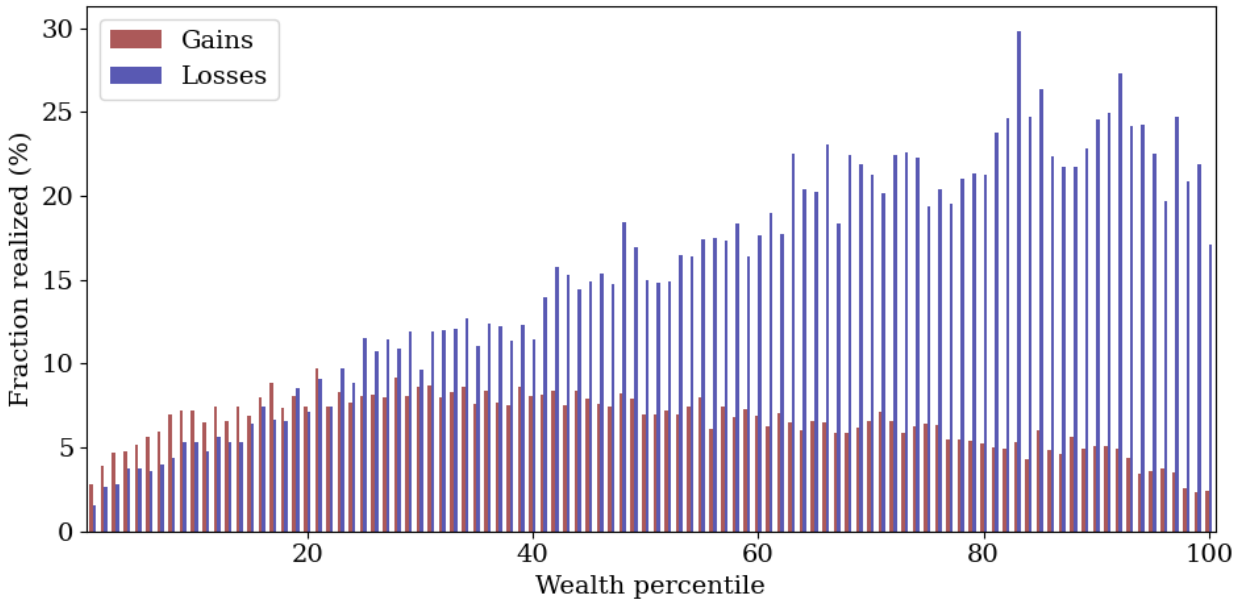


Figure D4: **The fraction of realized gains and losses conditional on year-month fixed effects** This figure plots the fraction of unrealized gains and losses that households in each wealth percentile p realize on average after controlling for year-month fixed effects. Estimates are annualized by multiplying each coefficient by 12.

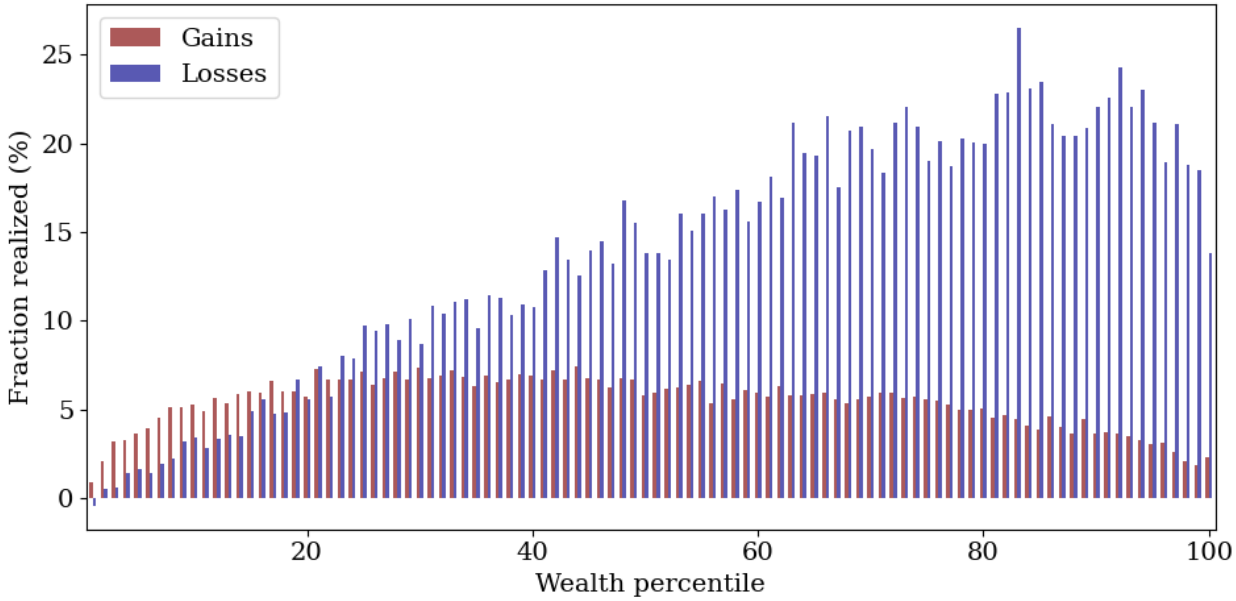


Figure D5: **The fraction of realized gains and losses on directly-held securities**
This figure plots the fraction of unrealized gains and losses that households in each wealth percentile p realize on average, after restricting the dataset to directly held equity and fixed-income securities. Estimates are annualized by multiplying each coefficient by 12.

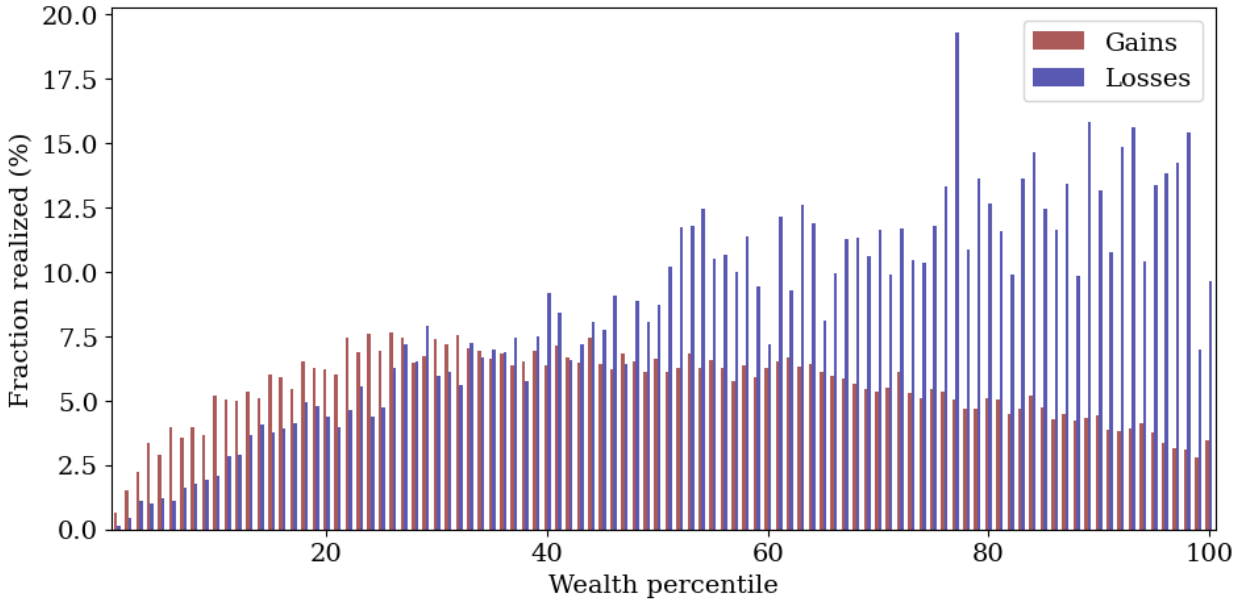


Figure D6: **Dynamic fraction of realized gains**
This figure plots the cumulative fraction of gains realized on average by households in each wealth quintile q over horizon H.

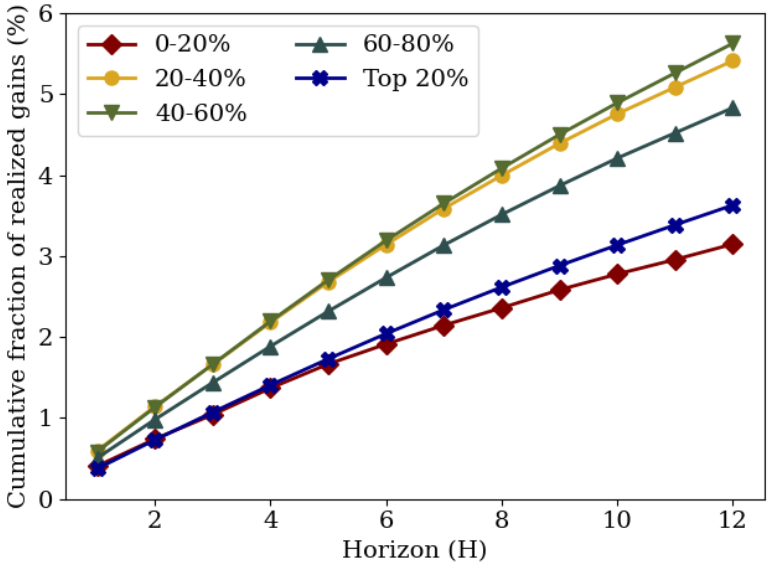


Table D2: **Estimated kink**
This table reports additional statistics about the regression kink design presented in Table 6. For each year, the first and second rows provide the number of observations at the rightLeft and right bandwidths are chosen to minimize the mean-square-error of the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b).

Year	Statistic	0–20%	20–40%	40–60%	60–80%	Top 20%
2016	Left N	15,238	25,808	38,166	53,898	73,209
	Right N	19,320	38,179	62,505	97,182	149,914
	Left bandwidth (estimation, %)	3.217	0.522	0.414	0.324	0.072
	Right bandwidth (estimation, %)	3.217	0.522	0.414	0.324	0.072
	Left bandwidth (bias, %)	8.330	1.671	1.451	0.984	0.274
	Right bandwidth (bias, %)	8.330	1.671	1.451	0.984	0.274
2017	Left N	18,696	34,696	51,387	81,348	134,403
	Right N	46,206	63,210	89,001	130,003	240,968
	Left bandwidth (estimation, %)	2.780	0.355	0.184	0.116	0.083
	Right bandwidth (estimation, %)	2.780	0.355	0.184	0.116	0.083
	Left bandwidth (bias, %)	8.214	1.821	0.724	0.397	0.271
	Right bandwidth (bias, %)	8.214	1.821	0.724	0.397	0.271
2018	Left N	48,670	90,547	120,060	200,518	311,141
	Right N	57,733	105,324	123,462	194,194	307,090
	Left bandwidth (estimation, %)	1.847	0.740	0.292	0.196	0.103
	Right bandwidth (estimation, %)	1.847	0.740	0.292	0.196	0.103
	Left bandwidth (bias, %)	5.782	1.956	0.748	0.464	0.317
	Right bandwidth (bias, %)	5.782	1.956	0.748	0.464	0.317
2019	Left N	68,387	114,223	159,062	215,086	323,845
	Right N	131,350	213,553	322,963	473,973	827,754
	Left bandwidth (estimation, %)	2.366	0.725	0.402	0.184	0.185
	Right bandwidth (estimation, %)	2.366	0.725	0.402	0.184	0.185
	Left bandwidth (bias, %)	5.994	2.033	1.131	0.609	0.733
	Right bandwidth (bias, %)	5.994	2.033	1.131	0.609	0.733

(continued)

Year	Statistic	0–20%	20–40%	40–60%	60–80%	Top 20%
2020	Left N	109,637	182,059	274,791	381,584	484,320
	Right N	181,241	358,899	581,793	962,427	1,487,691
	Left bandwidth (estimation, %)	1.837	0.933	0.494	0.314	0.161
	Right bandwidth (estimation, %)	1.837	0.933	0.494	0.314	0.161
	Left bandwidth (bias, %)	4.744	2.268	1.334	0.827	0.489
	Right bandwidth (bias, %)	4.744	2.268	1.334	0.827	0.489
2021	Left N	89,009	190,586	362,498	508,941	652,339
	Right N	190,128	505,402	878,424	1,344,967	2,182,195
	Left bandwidth (estimation, %)	1.830	0.701	0.237	0.147	0.088
	Right bandwidth (estimation, %)	1.830	0.701	0.237	0.147	0.088
	Left bandwidth (bias, %)	5.975	1.980	0.684	0.352	0.257
	Right bandwidth (bias, %)	5.975	1.980	0.684	0.352	0.257
2022	Left N	284,930	643,260	1,068,188	1,342,216	1,841,247
	Right N	171,335	487,126	911,486	1,278,053	1,978,528
	Left bandwidth (estimation, %)	2.738	0.757	0.376	0.207	0.110
	Right bandwidth (estimation, %)	2.738	0.757	0.376	0.207	0.110
	Left bandwidth (bias, %)	6.874	1.964	1.044	0.608	0.383
	Right bandwidth (bias, %)	6.874	1.964	1.044	0.608	0.383
2023	Left N	360,723	792,182	1,312,055	1,766,635	2,450,051
	Right N	320,024	801,081	1,371,777	1,914,549	3,115,947
	Left bandwidth (estimation, %)	1.444	0.523	0.283	0.181	0.114
	Right bandwidth (estimation, %)	1.444	0.523	0.283	0.181	0.114
	Left bandwidth (bias, %)	4.066	1.598	0.732	0.483	0.411
	Right bandwidth (bias, %)	4.066	1.598	0.732	0.483	0.411
2024	Left N	350,878	720,774	980,688	1,492,212	2,542,193
	Right N	804,842	1,637,109	2,036,194	3,085,803	4,996,134
	Left bandwidth (estimation, %)	1.015	0.792	0.305	0.205	0.122
	Right bandwidth (estimation, %)	1.015	0.792	0.305	0.205	0.122
	Left bandwidth (bias, %)	3.046	2.115	0.919	0.714	0.354
	Right bandwidth (bias, %)	3.046	2.115	0.919	0.714	0.354

Table D3: **Local polynomial density test**
This table reports t-statistics and p-values from the local polynomial density test in Cattaneo, Jansson and Ma (2020) on $ur_{ia,t-1}$ for each year in the dataset.

	0–20%		20–40%		40–60%		60–80%		Top 20%	
Year	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value
2016	5.285	0.000	8.889	0.000	17.087	0.000	28.104	0.000	114.843	0.000
2017	19.043	0.000	11.775	0.000	4.225	0.000	38.648	0.000	80.324	0.000
2018	-46.651	0.000	-35.506	0.000	-43.558	0.000	-76.665	0.000	-118.156	0.000
2019	35.596	0.000	20.612	0.000	19.578	0.000	41.585	0.000	156.946	0.000
2020	36.213	0.000	23.509	0.000	35.146	0.000	78.201	0.000	271.844	0.000
2021	12.458	0.000	0.896	0.370	5.988	0.000	27.754	0.000	271.557	0.000
2022	-63.245	0.000	-29.497	0.000	-26.196	0.000	-35.753	0.000	1.695	0.090
2023	-33.007	0.000	5.173	0.000	1.724	0.085	9.334	0.000	116.639	0.000
2024	122.399	0.000	74.823	0.000	77.788	0.000	120.271	0.000	255.801	0.000

Table D4: **Estimated kink for sales**
This table reports the estimated kink coefficient for each year and wealth quintile when sales $f_{iat}^{(s)}$ are used as outcome variable. Left and right bandwidths are chosen to minimize the mean-square-error of the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b). Standard errors are provided in parenthesis.

Year	0–20%	20–40%	40–60%	60–80%	Top 20%
2016	0.579***	1.207***	1.440***	1.165***	1.103***
	(0.142)	(0.116)	(0.143)	(0.151)	(0.155)
2017	0.894***	1.340***	1.261***	1.526***	1.862***
	(0.169)	(0.137)	(0.184)	(0.188)	(0.162)
2018	0.498***	0.599***	0.782***	0.702***	1.606***
	(0.088)	(0.087)	(0.108)	(0.106)	(0.139)
2019	0.301***	0.544***	0.553***	0.520***	1.295***
	(0.066)	(0.062)	(0.062)	(0.074)	(0.092)
2020	1.083***	0.929***	0.815***	0.732***	0.952***
	(0.073)	(0.068)	(0.056)	(0.054)	(0.059)
2021	1.771***	1.294***	1.018***	0.792***	0.953***
	(0.085)	(0.097)	(0.082)	(0.064)	(0.084)
2022	0.490***	0.625***	0.745***	0.583***	1.061***
	(0.039)	(0.032)	(0.031)	(0.022)	(0.034)
2023	0.711***	1.064***	1.178***	1.680***	2.153***
	(0.041)	(0.046)	(0.053)	(0.058)	(0.063)
2024	2.015***	1.930***	1.494***	1.277***	1.573***
	(0.066)	(0.061)	(0.059)	(0.050)	(0.045)
Average	0.927	1.059	1.032	0.997	1.395

Table D5: **Estimated kink for purchases**
This table reports the estimated kink coefficient for each year and wealth quintile when purchases $f_{iat}^{(b)}$ are used as outcome variable. Left and right bandwidths are chosen to minimize the mean-square-error of the estimator and standard errors are bias-corrected following the robust approach in Calonico, Cattaneo and Titiunik (2014b). Standard errors are provided in parenthesis.

Year	0–20%	20–40%	40–60%	60–80%	Top 20%
2016	0.023	-0.117***	-0.006	0.129***	0.349***
	(0.043)	(0.030)	(0.025)	(0.038)	(0.063)
2017	-0.133***	-0.098***	-0.039	0.248***	0.506***
	(0.033)	(0.029)	(0.037)	(0.060)	(0.087)
2018	0.049**	-0.050*	0.151***	0.234***	0.338***
	(0.022)	(0.026)	(0.033)	(0.042)	(0.052)
2019	-0.030	-0.056***	0.042**	0.148***	0.270***
	(0.021)	(0.021)	(0.018)	(0.023)	(0.029)
2020	-0.051***	-0.254***	-0.206***	0.011	0.229***
	(0.018)	(0.023)	(0.021)	(0.017)	(0.024)
2021	1.028***	0.076**	0.050*	0.115***	0.473***
	(0.056)	(0.032)	(0.027)	(0.028)	(0.044)
2022	0.013	-0.007	-0.049***	-0.078***	0.079***
	(0.013)	(0.006)	(0.008)	(0.010)	(0.009)
2023	-0.026*	0.016***	0.063***	0.078***	0.203***
	(0.014)	(0.005)	(0.007)	(0.007)	(0.012)
2024	-0.457***	-0.794***	-0.308***	0.024***	0.245***
	(0.020)	(0.020)	(0.014)	(0.009)	(0.012)
Average	0.046	-0.143	-0.034	0.101	0.299

Figure D7: **Relation between sales and unrealized returns**
Each panel provides a binned scatterplot of sales against unrealized returns in a narrow interval around zero for a given quintile of the Addepar wealth distribution. The dataset is restricted to December 2024 and to securities with unrealized returns between –10 and +10 basis points.

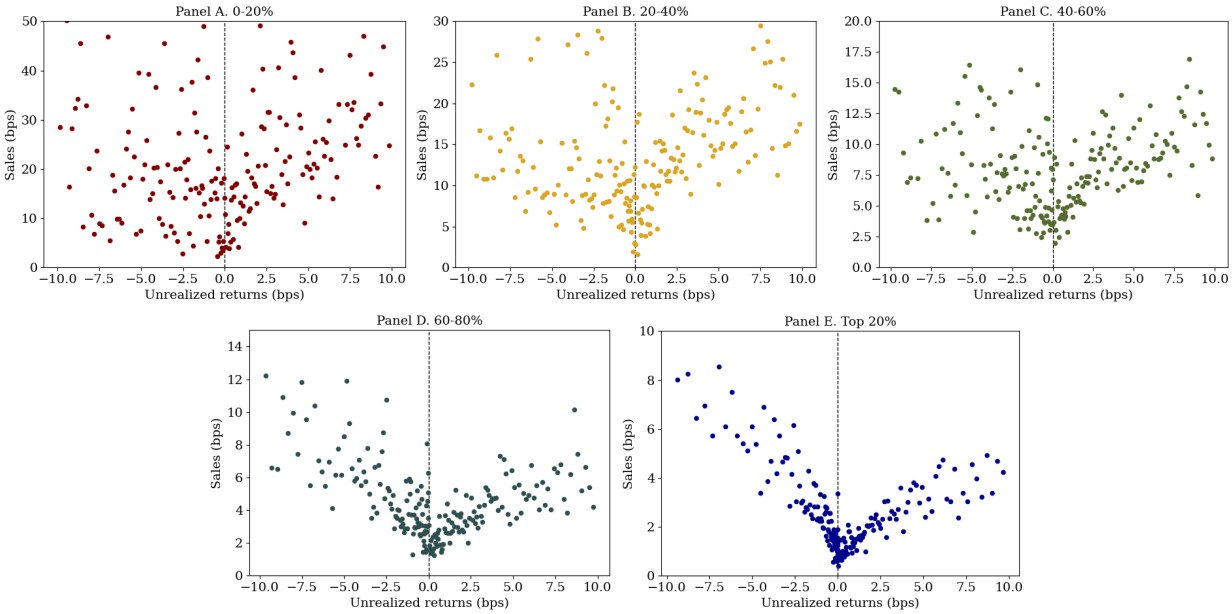


Figure D8: **Relation between purchases and unrealized returns**
Each panel provides a binned scatterplot of purchases against unrealized returns in a narrow interval around zero for a given quintile of the Addepar wealth distribution. The dataset is restricted to December 2024 and to securities with unrealized returns between –10 and +10 basis points.

