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

Federico Mainardi†

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ABSTRACT

Using high-frequency household-level data—including more than 700 billionaires—I study heterogeneous responses to capital gains taxation. Wealthier households realize more losses and fewer gains, consistent with more effective tax management. A regression kink design shows that this pattern reflects active tax optimization at the top, driven largely by sophisticated financial advisors. Annual tax expenses decline from 1.1% at the bottom to 40 basis points at the top, generating a 70-basis-point tax alpha that is comparable in magnitude to the pre-tax return gap on risky assets estimated in prior work. These differences have sizable effects on the long-run wealth distribution.

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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, financial constraints, or by the choice of sophisticated advisors? And to what extent do these behaviors shape heterogeneity in after-tax performance and wealth accumulation? 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 $9 trillion in assets and more than 1,400 financial advisors. I show that wealthier households are substantially more responsive to tax incentives, resulting in a 70-basis-point annual tax alpha between the top and the bottom of the wealth distribution comparable to pre-tax return gaps documented in the literature. By linking micro-level tax behavior to after-tax return heterogeneity, the paper provides a new empirical foundation for macroeconomic models of wealth dynamics 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 well positioned to study 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. Importantly, the focus on advised wealth is not necessarily restrictive within the top decile: in the SCF, 97–99% of households in the top 10% of the net wealth distribution report using a financial professional or a broker.

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 for causal inference relative to alternative data sources, including administrative datasets, where unrealized returns have to be imputed from market prices and are observed only annually.

Notwithstanding these advantages, Addepar is likely to miss some components of household balance sheets relative to administrative datasets. Comparing the time series of average wealth in Addepar with alternative wealth definitions in the Distributional Financial Accounts (DFA) and the Survey of Consumer Finances (SCF), I show that Addepar tracks financial wealth more closely than gross or net wealth. This motivates the paper's baseline focus on financial wealth and the use of external balance-sheet data in later sections to study implications for net wealth.

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 financial 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 capital gains tax management (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 more effective capital gains tax management and with rational models of portfolio choice featuring capital gains taxes. By contrast, less wealthy households show no such response, and instead often 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 about return persistence, 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 about return persistence.

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 advised by other intermediaries, 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.

I formally test the advisor channel by estimating the regression kink design separately for households in the top quintile of the wealth distribution advised by different types of intermediaries. Focusing on the top quintile isolates the households that are most tax responsive and helps identify what drives the stronger response to tax incentives at the top. Even within this group, the magnitude of the kink varies sharply across advisor types. In particular, the difference between households advised by private banks and those advised by broker/dealers exceeds the difference between households in the top quintile and those in the bottom quintile of the wealth distribution. Moreover, households at the very top investing through broker/dealers, who typically do not provide ongoing fiduciary portfolio advice, are no more responsive than the average household at the bottom of the wealth distribution. More broadly, these results imply that access to—or choice of—effective intermediation, rather than individual financial sophistication alone as proxied by wealth, plays a central role in shaping the response to tax incentives.

I also test alternative mechanisms that could explain the lower response at the bottom of the distribution, such as the possibility that less wealthy households face binding liquidity constraints that prevent them from deferring capital gains taxes over a long investment horizon. If these households must sell securities to finance consumption, they may prefer selling appreciated positions because their higher value generates more liquidity. Under this interpretation, the lower tax responsiveness at the bottom of the wealth distribution reflects financial constraints rather than differences in sophistication or intermediation. I find little evidence that such frictions explain the observed heterogeneity. In particular, the fraction of realized gains and losses across wealth percentiles changes little when I restrict attention to positions with similar values and to households whose portfolios contain both securities with unrealized gains and securities with unrealized losses. In other words, households at the bottom of the distribution that can finance similar consumption by selling securities at a gain or at a loss do not selectively realize more losses than other households with similar wealth.

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 75% of realizations at the bottom to 45% at the top. Effective tax rates decline from 19% to 12% 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 financial wealth, the implied cost falls from 1.1% at the bottom to 40 basis points at the top. This 70-basis-point gap represents an economically significant tax alpha accruing to wealthier households solely from tax management, namely the deferral of realized gains and the active realization of losses. As a point of comparison, the gap in pre-tax returns on risky financial assets documented in the literature is around 60 basis points (Campbell, Ramadorai and Ranish, 2019; Bach, Calvet and Sodini, 2020; Fagereng, Guiso, Malacrino and Pistaferri, 2020). Consistent with this evidence, in the Addepar data the difference in average pre-tax returns between the top and bottom quintiles is 47 basis points and rises to 68 basis points after accounting for differences in capital gains tax expenses, an increase of about 50%. Thus, differences in capital

gains tax expenses exacerbate, rather than attenuate, return gaps across households.

I also show that the tax alpha is genuine: 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 how this tax alpha affects the long-term dynamics of financial and net wealth. Using an accounting framework of household wealth accumulation calibrated with estimates from the Addepar data, I find that, everything else equal, differences in capital gains tax expenses increase the top 1% share of financial wealth by 1.03 to 1.08 percentage points over thirty years, corresponding to 28 to 30% of the historical rise in top-end financial wealth concentration in the DFA over an equivalent horizon. Combining Addepar with external balance-sheet data, I further show that these differences increase the top 1% share of net wealth by 0.68 to 0.80 percentage points over the same horizon, corresponding to 12 to 14% of the increase documented by Smith, Zidar and Zwick (2023) between 1986 and 2016. Accounting additionally for heterogeneity in advisory fees raises these effects to 3.73–3.78 percentage points for financial wealth and 2.74–3.20 percentage points for net wealth, reflecting that wealthier households can access tax-oriented advisory services at a substantial discount relative to less wealthy households. 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 affects long-run wealth dynamics.

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 heterogeneity in after-tax returns, with important implications for the evolution of financial and net 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 are comparable in magnitude to 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 of 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 generate 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 defer gains and 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). Related work also emphasizes the quantitative importance and concentration of capital gains at the top, as well as the gap between realized and accrued gains, in shaping top-end income and wealth dynamics (Campbell, Robbins and Wylde, 2025). By documenting heterogeneity in responses to tax incentives, I identify a mechanism that links the provisions of the U.S. tax code to systematic differences in after-tax performance. 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 dis-

tribution 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 tests the mechanisms behind this heterogeneity. Section 7 links realization behavior to after-tax performance, quantifies the resulting tax alpha, and provides implications for long-run financial wealth concentration. Section 8 complements Addepar with additional data sources to study concentration in net wealth. Section 9 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 first offset realized gains on a dollar-for-dollar basis. If losses exceed gains, individuals can deduct up to $3,000 per year against ordinary income, with any remaining balance carried forward indefinitely to future years (Internal Revenue Code §1211). The main benefit of realizing losses therefore comes from offsetting capital gains, either immediately or through carryforwards, whereas the deduction against ordinary income is comparatively limited, especially for high-net-worth households. For this reason, the paper focuses throughout on the former margin. This asymmetry in the tax treatment of realized gains and losses makes the timing of trades and the choice of which assets to sell central margins of household portfolio choice (Constantinides, 1983).

In particular, these margins are central to tax-loss harvesting (TLH) and, more broadly, to capital gains tax management. In practice, households may reduce tax liabilities both by deferring the realization of gains and by realizing losses when prices fall. 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.

Capital gains tax management has also reshaped 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 tax optimization 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 these benefits are distributed across households remains largely unexplored.

3 Data source and summary statistics

3.1 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 $9 trillion in assets advised by over 1,400 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. In Addepar, realized and unrealized returns are reported by the relevant advisor or custodian using the tax-lot accounting method applied in practice—such as FIFO, LIFO, or specific identification where applicable—rather than being imputed. This makes Addepar uniquely well suited to studying whether and how households optimize capital gains taxes.

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

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 advisors, 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. Moreover, the dataset separately flags positions held through retirement accounts.[2] I classify holdings in equity, fixed income, and derivatives as "liquid", since these asset classes are publicly traded on financial markets. Because the objective is to study how households actively respond to capital gains taxes, I focus throughout on unrealized and realized returns in liquid securities held in taxable (i.e., non-retirement) accounts.

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
Equity	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

[2]Specifically, securities held in retirement accounts are assigned instrument type equal to "Held Away Asset" and reassigned under broad and narrow asset classes "Other".

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

3.2 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 cumulative dollar unrealized return since the purchase of the security, and RR_{iat} the dollar realized return. I define unrealized gains and losses as

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

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

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

Let total financial wealth be $A_{it} = \sum_a A_{iat}$. I scale unrealized returns, gains, and losses by total financial 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: $ug_{it} = \sum_{a\in\mathcal{L}} ug_{iat}$ with analogous definitions for all other variables. I use $\mathcal{L}$ to denote the set of liquid risky asset classes defined in Section 3.1, excluding positions in retirement accounts since gains realized in these accounts are not taxable and losses cannot be used to offset taxable gains.

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. These screens, especially the first one, may introduce selection bias if larger advisors have clients that are systematically different from smaller advisors. As I show below, the time series of the number of portfolios has smooth trends and the distribution of wealth is stable over time. Therefore, these screens are unlikely to introduce meaningful selection. Moreover, the exclusion of concentrated positions, if anything, biases against finding tax alpha since these positions in the portfolios of UHNW households are rarely or never sold and associated capital gains rarely or never realized.

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.[3] 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 financial 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, 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. Together, these steps ensure that the sample is both representative of households' portfolios and free of implausible observations.

3.4 Coverage

Table 3 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

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

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	46	277	708	1,793	4,561	10,706	32,966	267,037
2017	10,426	68	348	882	2,184	5,504	12,532	38,273	253,646
2018	17,588	60	316	795	1,901	4,680	10,767	34,101	264,215
2019	26,675	66	364	936	2,192	5,213	11,048	31,750	296,741
2020	43,319	37	260	752	1,911	4,733	10,318	29,608	259,633
2021	57,904	35	271	786	1,981	4,825	10,429	30,223	281,845
2022	76,536	34	247	709	1,786	4,368	9,406	27,858	248,776
2023	114,387	43	242	663	1,694	4,201	9,121	27,265	232,047
2024	189,610	31	177	508	1,374	3,468	7,625	23,442	223,950

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.

Based on 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 coverage 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 $1.2 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.

Overall, while Addepar oversamples households at the very top—as expected given its focus on advised wealth—it provides broad coverage 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 capital gains tax management—is concentrated.

Table 4: **Average wealth in Addepar and in capitalization methods**
This table compares average household wealth in Addepar to capitalization-based estimates from administrative data in 2016. The second row 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 three to five 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%	1,228	1,224	1,318	1,240
Top 1–0.1%	21,197	6,586	6,339	6,385
Top 0.1%	267,037	65,094	58,873	50,263

While average wealth in Addepar closely matches capitalization-based estimates for the upper tail of the wealth distribution, some components of households' balance sheets—such as owner-occupied housing—may be only partially represented. I therefore turn to the SCF and compare average portfolio wealth in Addepar to alternative definitions of household wealth in the survey. Because the SCF is available only every three years, I focus on 2019 and 2022, the two survey years covered by the Addepar sample. To verify that Addepar indeed captures households in the top decile of the wealth distribution, rather than a different subset of households, I carry out the comparison separately for households in the top 12.5%, top 10%, top 7.5%, and top 5% of the SCF net wealth distribution.

I consider three definitions of wealth in the SCF: financial wealth, gross wealth, and net wealth.[4] For each year, wealth group, and wealth definition, I compute the discrepancy between Addepar and the SCF as the absolute difference in average wealth. I then average the 2019 and 2022 discrepancies by wealth group and wealth definition using the number of unique portfolios in Addepar in each year as weights. This gives greater weight to the year with broader platform coverage.

Table 5 reports the results. The discrepancy is minimized for households in the top 10% of

[4]I construct non-financial wealth in the SCF as the sum of owner-occupied primary residence (SCF variable *houses*), vehicles (*vehic*), and other non-financial assets (*othnfin*). I construct financial wealth as gross wealth (*asset*) minus non-financial wealth. I construct net wealth as gross wealth minus total debt (*debt*).

the SCF net wealth distribution when wealth is measured as financial wealth. This confirms that Addepar is best interpreted as covering households in the top decile of the wealth distribution and that, within this segment, it aligns most closely with the financial component of household balance sheets rather than with gross wealth or net wealth. Tables F2 and F3 in Appendix F confirm this conclusion using more granular wealth definitions in both the SCF and the DFA. Accordingly, the analysis in Sections 4–7 focuses on financial wealth (to which I will refer generically as wealth), while Section 8 uses external data sources to map the estimated effects into implications for net wealth.

Table 5: **Average wealth in Addepar and in the SCF**
This table compares average household wealth in Addepar with alternative definitions of average wealth for households in the top 12.5%, top 10%, top 7.5%, and top 5% of the SCF net wealth distribution. The second column reports the discrepancy between average wealth in Addepar and different definitions of wealth for households in the top 12.5% of the SCF net wealth distribution. Column three focuses on households in the top 10% of the SCF net wealth distribution. Columns four and five focus on households in the top 7.5% and top 5%, respectively. All figures are expressed in thousands of U.S. dollars.

Definitions of wealth	Top 12.5%	Top 10%	Top 7.5%	Top 5%
Financial wealth	1,454	516	1,380	4,256
Gross wealth	558	1,193	2,744	6,010
Net wealth	600	1,025	2,350	5,549

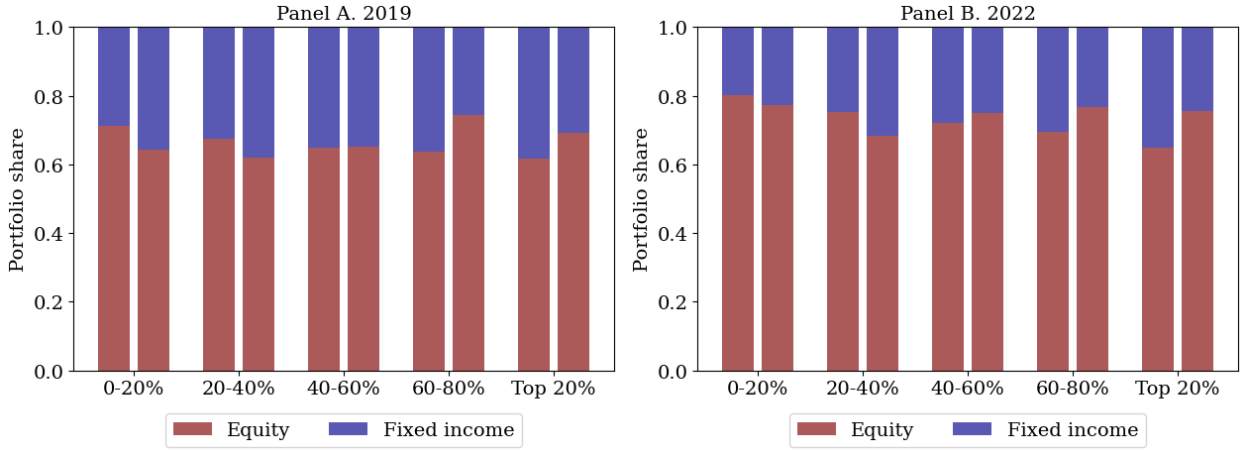
Beyond matching average wealth, it is also useful to compare portfolio composition along the main liquid asset classes that are central to the analysis. Figure 1 plots the shares in equity and fixed income across five quintiles of the Addepar wealth distribution and five corresponding quintiles within the top 10% of the SCF net wealth distribution, separately for 2019 and 2022.[5] The shares in Addepar and in the SCF align remarkably well across quintiles despite the difference in sample size: the top 10% of the SCF net wealth distribution includes 1,562 households in 2019 and 1,279 in 2022, compared with 26,675 and 76,536 unique portfolios in Addepar in the same years. Overall, the differences in wealth shares are small and do not display a systematic pattern.

This close alignment may appear surprising ex ante, given Addepar's focus on advised wealth. However, in the SCF, 97.4% of households in the top 10% of the net wealth distribution in 2019 and 99.7% in 2022 report either using a financial professional or a broker.[6] This suggests that very

[5] I define equity in the SCF to include both directly-held stocks (variable *stocks*) and equity mutual funds (*stmutf*). I define fixed income to include directly-held bonds (*bond*), directly-held savings bonds (*savbnd*), bond mutual funds (*tfbmutf*, *gbmutf*, and *obmutf*), and cash value of life insurance (*cashli*). Both definitions mirror the definition of equity and fixed income in Addepar.

[6] Specifically, I construct these rates as the share of households in each year in the top 10% of the SCF net wealth distribution that report using a financial planner (*ifinplan = 1*), using another financial professional (*ifinpro = 1*), or holding a brokerage account (*hbrok = 1*).

Figure 1: **Wealth composition in Addepar and in the SCF**
This figure compares the shares in equity and fixed income across five quintiles of the Addepar wealth distribution and five corresponding quintiles within the top 10% of the SCF net wealth distribution, separately for 2019 (Panel A) and 2022 (Panel B). Within each wealth group, the left bar reports the shares in Addepar and the right bar reports the corresponding shares in the SCF. Equity and fixed income are defined in Table 1.



few households in the relevant top-decile segment lie outside the advised or brokered universe captured by Addepar.

3.5 Summary statistics on portfolios and advisors

Table 6 presents descriptive evidence on household portfolios and advisors in Addepar. 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 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 on individual securities 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.

Table 6: **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 to 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%	6.56	11.72%	0.88%	3.76%	4.50%	78.31%	0.83%
20–40%	14.43	11.73%	1.06%	3.67%	6.39%	76.17%	0.98%
40–60%	23.89	10.46%	1.20%	3.14%	9.34%	74.93%	0.94%
60–80%	36.41	9.00%	1.34%	3.01%	10.94%	74.39%	1.32%
80–90%	51.43	8.78%	2.44%	3.92%	10.58%	72.58%	1.71%
90–95%	63.41	7.27%	4.12%	5.41%	10.45%	69.79%	2.96%
95–99%	74.35	6.49%	6.16%	5.45%	9.38%	66.10%	6.42%
Top 1%	74.66	7.55%	6.50%	7.97%	7.85%	51.24%	18.90%

4 Realization behavior across U.S. households

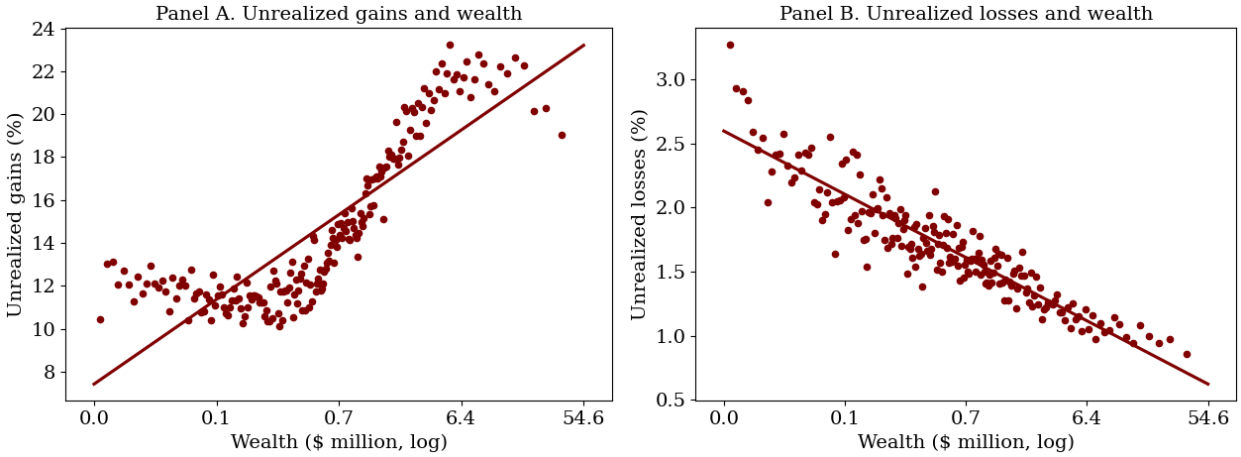
The previous sections established the coverage of the Addepar data and provided summary statistics on wealth, portfolio composition, and advisor market shares across households. I now turn to study the central objects of interest: unrealized and realized capital gains and losses. This section presents novel stylized facts on the incidence of these returns across the financial wealth distribution 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 2 studies the cross-sectional relationship between unrealized returns and wealth. Panel A plots unrealized gains ug_{it} in liquid asset classes 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 2 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. Figure F9 in Appendix F plots unrealized gains and losses in both liquid and illiquid asset classes and finds the same qualitative patterns.

While Figure 2 provides a static snapshot, unrealized returns are naturally affected by market conditions. The question is whether evolving market conditions affect unrealized returns at the

Figure 2: **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.



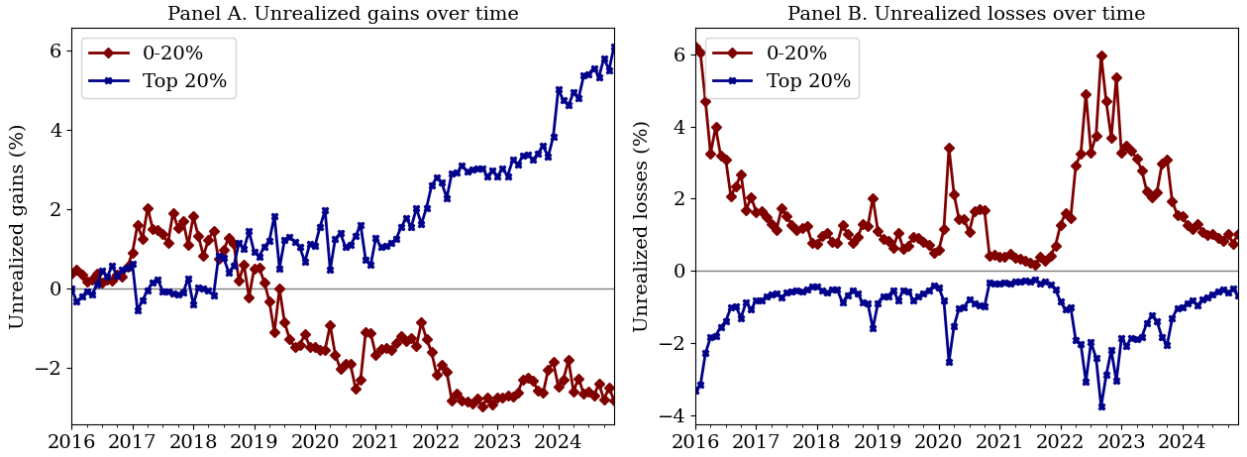
top and bottom in the same way. Figure 3 plots the time series of unrealized gains (Panel A) and losses (Panel B) in the top and bottom quintiles of the Addepar wealth distribution averaged across households after subtracting year-month fixed effects. The difference in unrealized gains between top and 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.

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

Figure 3: **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}.



unrealized losses

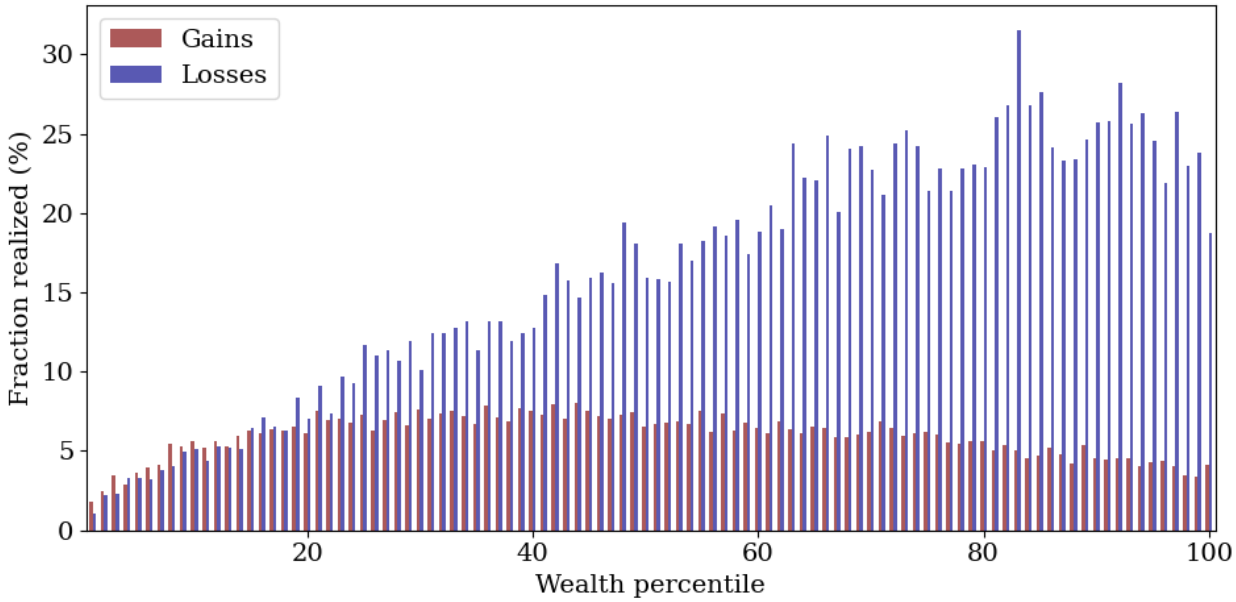
$$rl_{it} = \alpha_{lp} + \beta_{lp} ul_{i,t-1} + \varepsilon_{it}. \tag{1}$$

The coefficient β_{lp} is a reduced-form realization rate: it measures the fraction of unrealized losses available at the beginning of the month that is converted into realized losses, on average, by households in wealth percentile p. As such, it should be interpreted as a summary of realization behavior rather than as a structural elasticity. 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 4 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.

The sharp difference in realization behavior between the bottom and top of the Addepar wealth distribution is also informative about sample composition. If the lower end of the distribution were mostly made up of portfolios managed on behalf of households at the top, one would expect realization behavior to look more similar across the two groups. Instead, the stark differences documented here suggest that the lower end of the Addepar wealth distribution is most likely populated by households with lower wealth within the segment covered by the platform.

Figure 4: **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 F10 in Appendix F controls for households' characteristics, including turnover, fraction of wealth allocated to liquid assets, number of unique securities in the portfolio, number of months since the household joined the platform, and return on the portfolio of liquid assets.[7] Figure F11 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 neither observable households' characteristics, including portfolio complexity as measured by the number of unique securities, nor unobservable time trends can explain the lower (higher) fraction of realized gains (losses).

Interestingly, at the bottom of the wealth distribution, households tend to realize a higher fraction of gains than losses, consistent with Odean (1998). Using brokerage account data, Odean

[7] 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 net of price effects, and R_{iat} is the dollar return (realized and unrealized) on asset a.

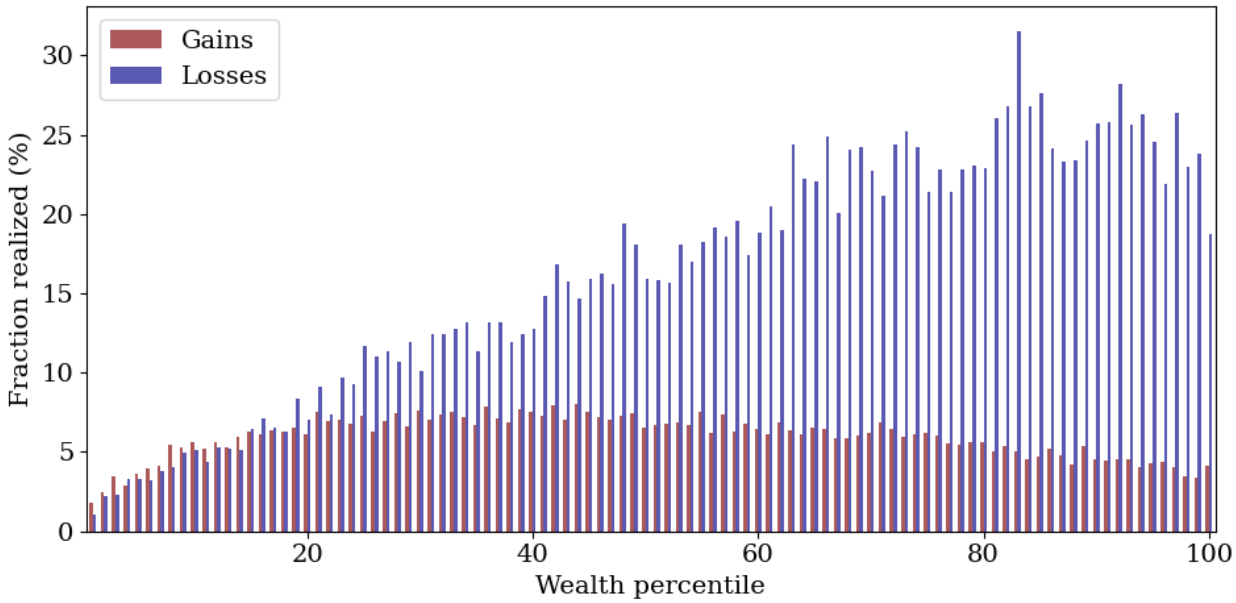
(1998) documents that the fraction of realized gains exceeds the fraction of realized losses by about 5 percentage points. In the Addepar data, households below the 10^{th} percentile realize up to 2.9 percentage points higher gains than losses, indicating a quantitatively similar pattern. More broadly, this result is consistent with the literature on the disposition effect, which documents the reluctance of retail investors to realize losses (Grinblatt and Han, 2005; Frazzini, 2006).

4.3.2 Realization behavior in public equity

An important question is whether the heterogeneity in realization behavior documented in Figure 4 is visible in the asset class that is most central to households' taxable portfolios and to discussions of capital gains taxation: public equity. To address this question, I re-estimate equation (1) after restricting the sample to equity positions only, as defined in Table 1.

Figure 5 reports the results. The pattern is nearly identical to the baseline. The fraction of realized losses rises monotonically with wealth, from essentially zero at the bottom of the wealth distribution to about 30% at the top, while the fraction of realized gains declines from about 6% to 2%. Thus, the heterogeneity in realization behavior documented in Figure 4 is not driven by smaller or less salient asset classes. Instead, it is already fully visible in public equity, the quantitatively most important liquid asset class on households' balance sheets.

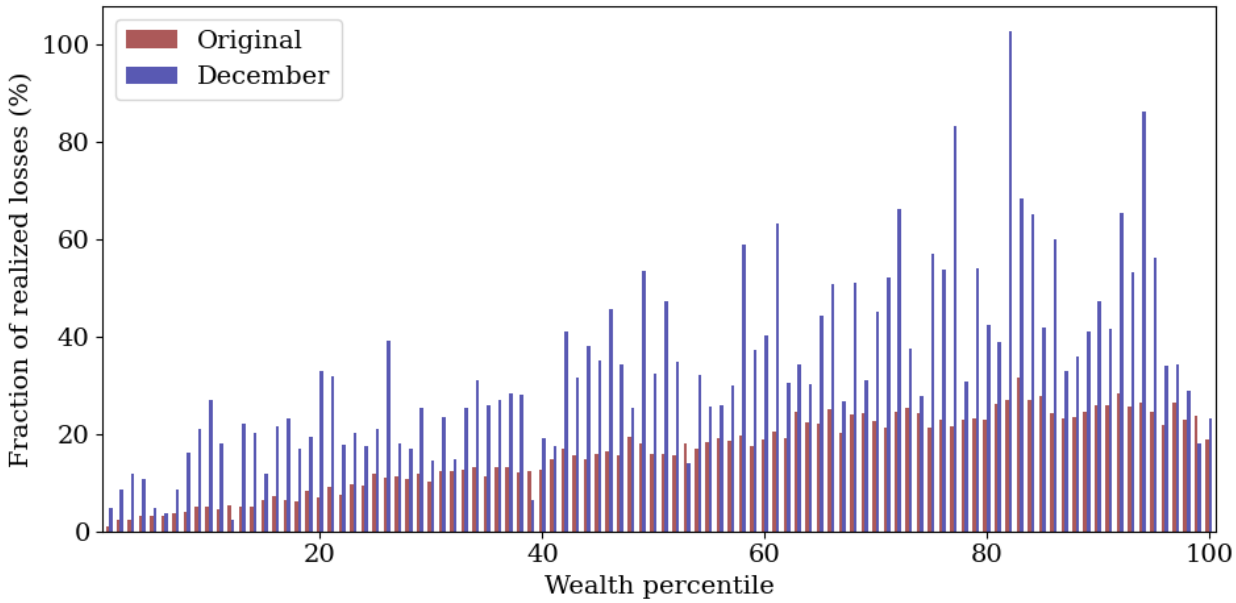
Figure 5: **The fraction of realized gains and losses in public equity**
This figure plots the fraction of gains and losses realized on average by households in each wealth percentile p after restricting the sample to public equity. Estimates are annualized by multiplying each coefficient by 12.



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 6 together with the original estimates discussed in Figure 4. 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.

Figure 6: **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 4 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

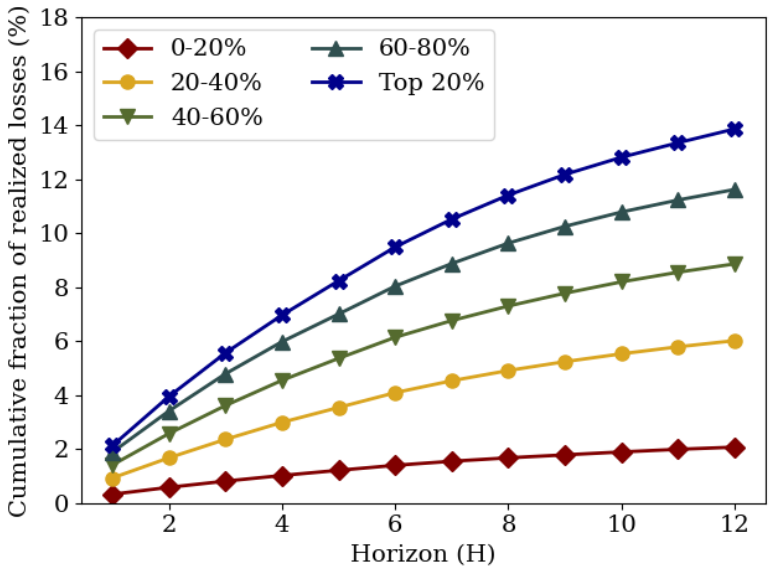
One alternative explanation of the baseline result is that less wealthy households are more inert and they do optimize capital gains taxes but with a delay. To test this hypothesis, I estimate an analogous version of equation (1) with realized losses $rl_{i,t+h}$ observed h months ahead as the outcome 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 7 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 7: **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 F12, 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

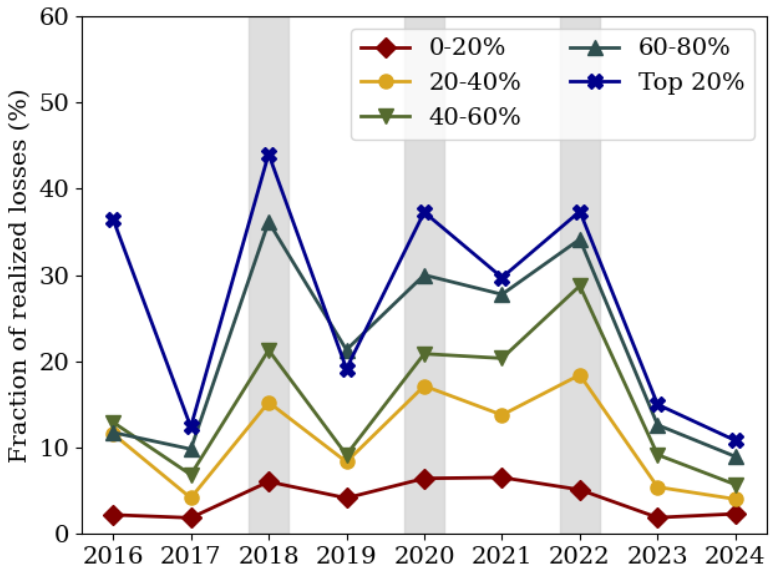
Because the Addepar platform has grown rapidly over time, the last years covered by the dataset receive naturally more weight when estimating equation (1). To show that the results are not driven by the final dates but are instead a systematic feature of the data, I estimate equation (1) separately in each year. Results are reported in Figure 8 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 3, 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, wealthier 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.

Interestingly, the higher fraction of losses realized by wealthier households in turbulent times is unlikely to be driven by wealthier households selling risky assets and reallocating towards safe ones. In fact, Gabaix et al. (2025a) documents that wealthier households, unlike less wealthy ones, do not sell liquid risky assets during market downturns and are even net buyers of U.S. equity.

Figure 8: **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 capital gains tax management, 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, 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 9 plots realized monthly returns rr_{iat} against initial unrealized returns $ur_{ia,t-1}$ 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 gain deferral and 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 but do not overturn the theoretical predictions.

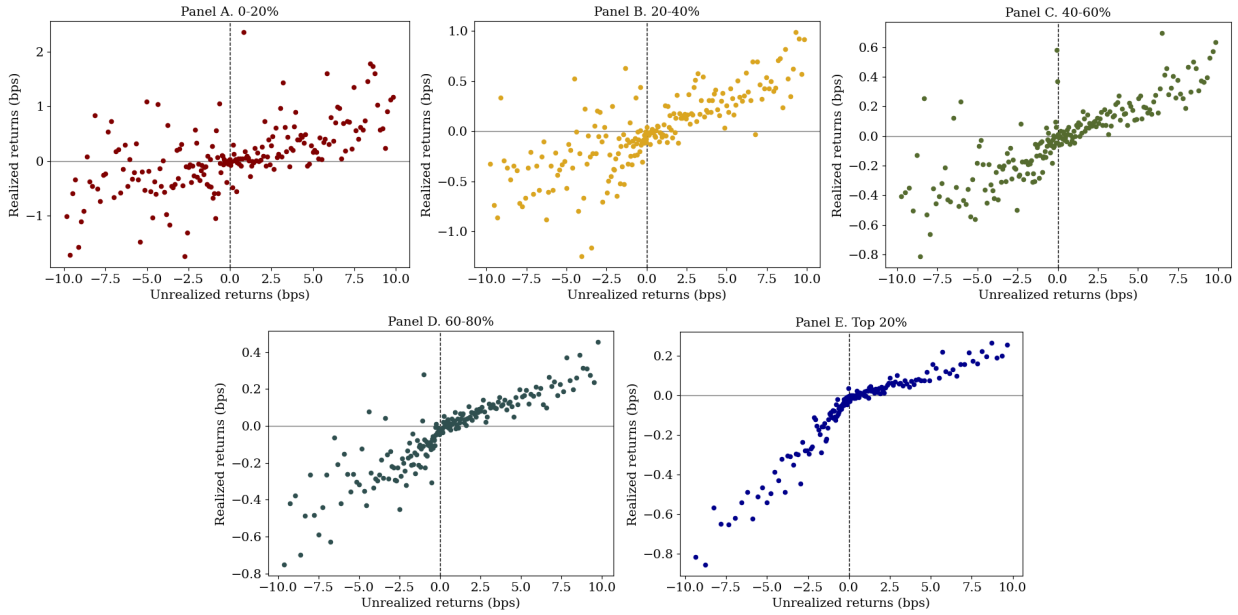
I next formalize this visual evidence using a regression kink design that quantifies the slope discontinuity and establishes its statistical significance.

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:

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

Figure 9: **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.



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, 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 7 reports the estimated kink coefficients Δ_{qy} for each year and wealth quintile, along with

the average across years. Additional statistics, including the number of observations and bandwidths, are reported in Table F4 in Appendix F. 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.

5.3.1 Sorting around the cutoff

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 F5. 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. Inertia then 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 8, are nearly identical to the baseline, confirming that the estimated kink does not reflect mechanical sorting around the cutoff.

Table 7: **Estimated kink**
This table reports the estimated kink coefficient Δ_{qy} for each year and wealth quintile from equation (3). 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

Table 8: **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

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.[8] The results, reported in Tables F6 and F7, show that wealthier 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 F13 and F14 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 Mechanisms behind heterogeneity in tax response

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. This section investigates the mechanisms behind this heterogeneity across the financial wealth distribution. I consider two potential explanations. One emphasizes differences in access to or choice of sophisticated financial intermediation: households advised by certain types of intermediaries may implement tax-optimization strategies more effectively. The other attributes the wealth gradient in tax responsiveness to financial frictions: less wealthy households may face liquidity constraints that force them to realize appreciated assets to finance consumption, thereby limiting their scope to engage in selective loss realization. I evaluate both mechanisms in turn.

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

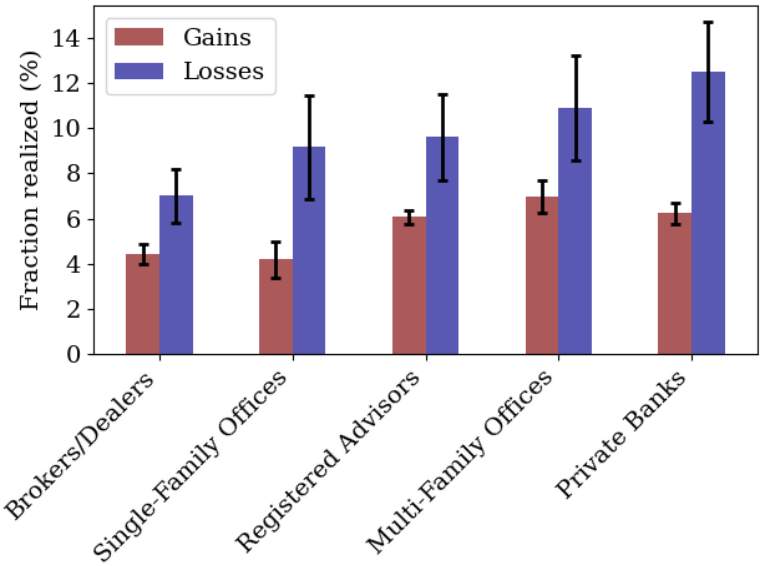
6.1 The role of advisors

6.1.1 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 advised by different advisors.

Figure 10 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' acquisition of Folio Financial.

Figure 10: **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.



6.1.2 Interaction of advisor type and wealth

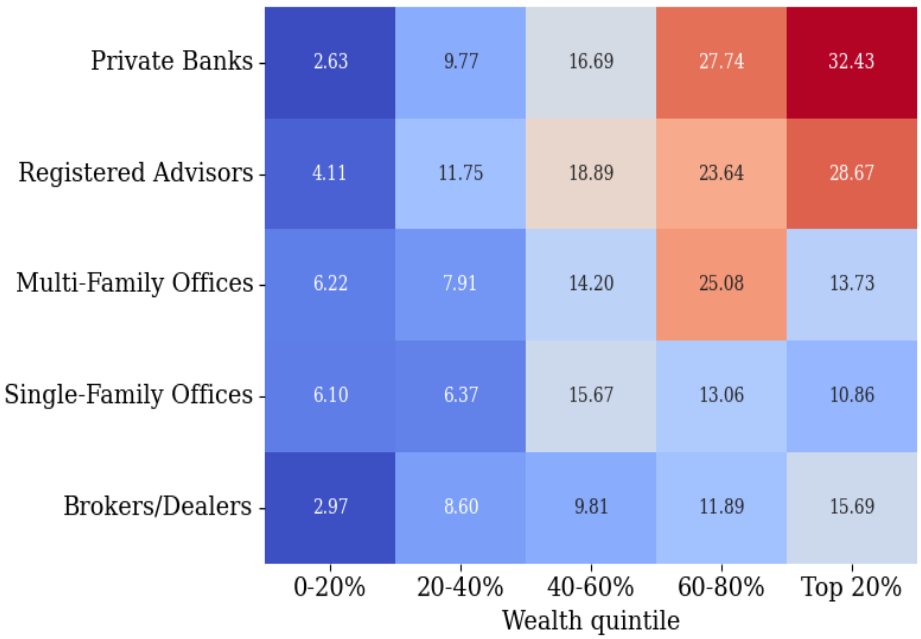
A natural next question is whether private banks deliver uniformly high tax performance across their client base, or whether the benefits accrue differently based on households' wealth. To address this, I estimate equation (1) separately for each wealth quintile and advisor type, and report

the fraction of realized losses in Figure 11.

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 11: **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.



6.1.3 Causal evidence of advisors' role

The evidence so far documents substantial heterogeneity in realization behavior across advisor types, holding wealth fixed. However, the estimates in Sections 6.1.1 and 6.1.2 do not identify causal responses to tax incentives. To assess whether advisors drive the stronger response at the

top, I repeat the regression kink design in Section 5 separately by advisor type after restricting the sample to households in the top quintile of the Addepar financial wealth distribution.

Table 9 reports the estimated kink coefficients.[9] Averaged across years, the slope discontinuity for private banks is 71%, compared to 14% for broker/dealers. The implied difference of 57% between the most and least tax-responsive advisor types exceeds the 30% gap between the top and bottom wealth quintiles reported in Table 7. In other words, differences in advisor type within the top 20% are associated with larger variation in tax responsiveness than differences across the entire wealth distribution. In addition, households at the very top investing through broker/dealers, who typically do not provide ongoing fiduciary portfolio advice, are no more responsive than the average household at the bottom of the wealth distribution: the slope discontinuity is 14% for households in the top 20% that invest via broker/dealers and 21% for the average household in the second quintile of the wealth distribution from Table 7.

These results reinforce the interpretation that intermediation plays a central role in shaping tax optimization. Households in the top quintile of the wealth distribution are generally well above the minimum asset thresholds required by all advisor types in the sample and therefore plausibly face limited barriers to accessing different forms of intermediation. Yet even within this group, there is substantial dispersion in tax responsiveness across advisor types. This pattern suggests that differences in tax responsiveness across the wealth distribution reflect not only wealth itself, but especially the choice of sophisticated and skilled financial advisors at the top.

6.2 The role of liquidity constraints

A complementary mechanism for the wealth gradient in tax responsiveness is that less wealthy households have shorter investment horizons: the payoff to tax optimization is increasing in the horizon over which a household can defer realization, particularly when combined with the step-up in basis at death. One reason less wealthy households may have shorter horizons is that they face binding liquidity needs, forcing them to liquidate positions earlier. If households must sell securities to finance consumption, they may prefer selling appreciated positions because their higher value generates more liquidity, limiting their ability to avoid realizing gains and selectively realize losses. Under this interpretation, lower tax responsiveness at the bottom of the wealth distribution reflects financial constraints rather than differences in sophistication or intermediation.

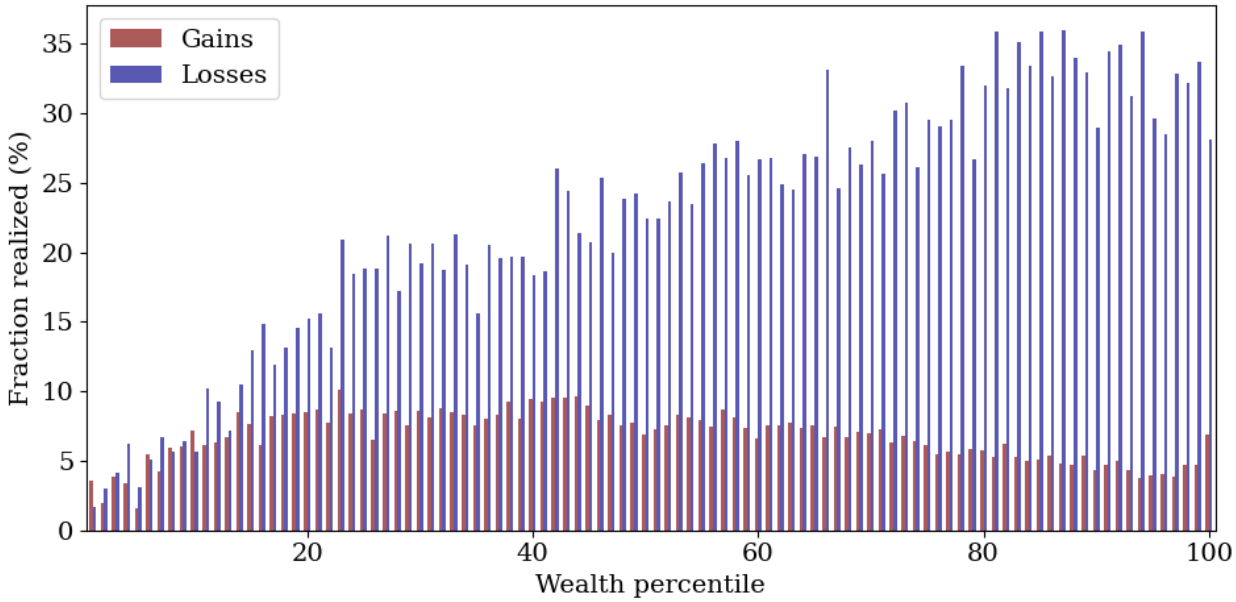
To evaluate this hypothesis, I estimate equation (1) after restricting attention to securities of similar dollar size within each household's portfolio. For each household and year-month, I compute the mean and standard deviation of initial dollar holdings across securities and retain only positions within one standard deviation of the household-specific mean. This restriction ensures that selling different securities generates comparable liquidity. I further restrict the sample to household–month observations in which at least one security exhibits unrealized gains and at

[9] I report additional statistics in Table F8 in Appendix F.

Table 9: **Estimated kink across advisors**
This table reports the estimated kink coefficient for each year and advisor type after restricting the dataset to households in the top 20% of the Addepar financial wealth distribution. 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	Brokers/ Dealers	Single-Family Offices	Registered Advisors	Multi-Family Offices	Private Banks
2016	-9.709	40.567	56.678***	213.800**	181.154***
	(36.857)	(39.501)	(8.066)	(101.944)	(69.778)
2017	-8.803	-21.501	13.012*	34.217	77.704
	(31.149)	(17.705)	(6.751)	(35.434)	(50.846)
2018	38.667	19.115	33.425**	136.955	66.685*
	(40.738)	(20.396)	(14.259)	(86.326)	(37.269)
2019	14.801	30.342	41.312***	9.062	83.622***
	(19.623)	(22.451)	(6.539)	(45.262)	(23.865)
2020	106.518***	128.320***	100.595***	54.610	125.650***
	(35.958)	(38.492)	(10.784)	(40.886)	(14.441)
2021	-56.284*	38.211	36.229***	57.445**	-5.798
	(32.547)	(42.419)	(6.694)	(27.724)	(12.031)
2022	27.914**	31.797	44.980***	-58.096***	67.137***
	(13.276)	(23.003)	(2.863)	(21.597)	(5.272)
2023	-12.487	6.633	4.415**	43.120***	14.839***
	(9.774)	(12.745)	(1.725)	(7.766)	(3.901)
2024	26.106***	-1.947	22.140***	46.034***	28.351***
	(9.268)	(11.049)	(1.968)	(8.658)	(3.655)
Average	14.080	30.171	39.198	59.683	71.038

Figure 12: **The fraction of realized gains and losses on similar holdings**
This figure plots the fraction of gains and losses realized on average by households in each wealth percentile p after restricting the sample to securities of similar dollar size within each household's portfolio. For each household and year-month, I compute the mean and standard deviation of initial dollar holdings across securities and retain only positions within one standard deviation of the household-specific mean. I further restrict the sample to household–month observations in which at least one security exhibits unrealized gains and at least one exhibits unrealized losses. Estimates are annualized by multiplying each coefficient by 12.



least one exhibits unrealized losses. Once position sizes are comparable, a liquidity-constrained household can generate similar liquidity by selling either a gaining or a losing security. In that case, selective loss realization should no longer be mechanically limited by liquidity constraints.

Figure 12 reports the results. The wealth gradient in realization behavior remains quantitatively similar to the baseline and, if anything, becomes steeper. Wealthier households continue to realize a substantially higher fraction of losses and a significantly lower fraction of gains than less wealthy households.

I also re-estimate the regression kink design in (3) under the same restriction and report results in Table 10.[10] The slope discontinuity remains economically large for wealthier households and smaller for less wealthy households. Averaged across year-months, the difference between the top and bottom quintiles remains on the order of 20%, compared with 30% in the baseline specification in Table 7. Thus, the cross-quintile gap persists under the liquidity restriction.

Taken together, these findings provide little evidence that liquidity constraints are the primary driver of heterogeneous tax responses across the wealth distribution. Instead, the results in Section 6.1 highlight differences in financial intermediation as a central mechanism.

[10] I report additional statistics in Table F9 in Appendix F.

Table 10: **Estimated kink on similar holdings**
This table reports the estimated kink coefficient for each year and wealth quintile after restricting the sample to securities of similar dollar size within each household's portfolio. For each household and year-month, I compute the mean and standard deviation of initial dollar holdings across securities and retain only positions within one standard deviation of the household-specific mean. I further restrict the sample to household-month observations in which at least one security exhibits unrealized gains and at least one exhibits unrealized losses. 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	54.005***	71.060***	46.721***	23.180**	41.309***
	(20.846)	(18.509)	(17.327)	(11.680)	(9.521)
2017	46.678	28.591**	25.307**	-7.933	15.955*
	(32.592)	(13.228)	(10.972)	(9.064)	(8.378)
2018	3.834	17.777	21.259**	14.127	48.755***
	(16.170)	(12.625)	(10.397)	(10.994)	(15.310)
2019	-5.083	6.420	7.837	26.076***	26.694***
	(8.249)	(7.938)	(5.418)	(6.402)	(5.780)
2020	66.665***	84.979***	74.648***	107.526***	107.153***
	(13.249)	(10.496)	(8.938)	(9.358)	(8.455)
2021	-18.564	-31.970***	-11.726	3.833	15.695***
	(15.934)	(8.754)	(7.736)	(6.441)	(5.867)
2022	0.710	6.147	29.513***	53.014***	49.567***
	(6.657)	(4.284)	(3.613)	(2.783)	(2.695)
2023	10.984**	10.717***	12.700***	10.128***	25.033***
	(4.555)	(3.042)	(1.950)	(2.160)	(1.939)
2024	13.445**	10.707***	16.041***	13.595***	27.297***
	(5.806)	(3.577)	(2.601)	(2.223)	(1.602)
Average	19.186	22.714	24.700	27.061	39.718

7 Heterogeneity in after-tax returns

The previous sections document substantial heterogeneity in households' responsiveness to capital gains tax incentives. Wealthier households display sharper realization asymmetries, mostly driven by differences in financial intermediation. An important question is whether these differences translate into economically meaningful implications for after-tax performance and, ultimately, the distribution of wealth. This section shows that they do: differences in realization behavior lower the effective tax burden of wealthier households and generate a measurable tax alpha that can sustain sizable concentration of wealth at the top of the distribution. Because the focus here is on heterogeneity in portfolio performance, the analysis centers on financial wealth, which is the component of household balance sheets directly subject to realization-based capital gains taxation and for which Section 3.4 shows that the Addepar data provide the broadest coverage. Section 8 then uses external data sources to translate these effects into implications for net wealth.

7.1 Effective tax rate

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

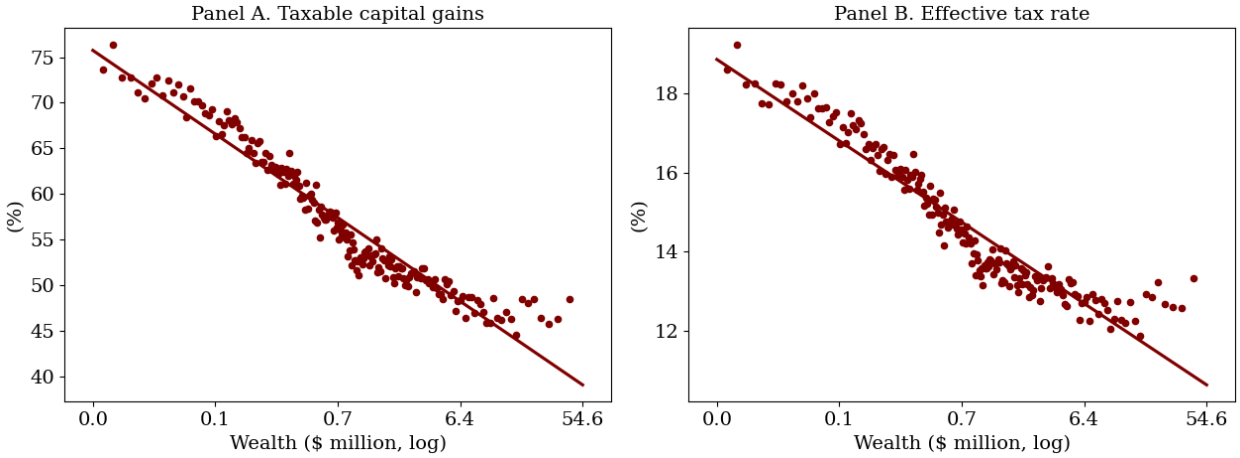
Panel A of Figure 13 plots the fraction of taxable gains against the log of beginning-of-year wealth and documents a steep gradient: taxable gains decline from roughly 75% at the bottom of the wealth distribution to 45% at the top. In other words, more than half of the gains realized by the wealthiest households are effectively untaxed.

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 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 specification, I apply the highest marginal tax rates to all households so that I can later assess whether and how specific provisions of the tax code (e.g., progressive marginal capital gains tax rates) affect these results. I therefore apply 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 declines from 19% at the bottom of the distribution

to 12% at the top.

Figure 13: **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.



Finally, Figure 14 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 show that differences in realization behavior translate directly into substantial differences in effective tax burdens across the wealth distribution.

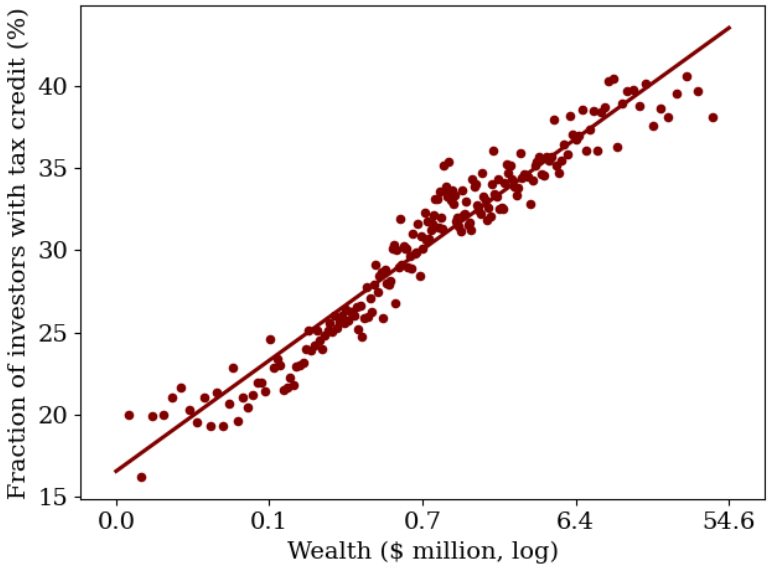
7.2 Tax alpha

I next assess the implications for after-tax performance. For each household-year, I scale total capital gains taxes due by beginning-of-year wealth to obtain an annualized measure of capital gains tax expenses. To account for the growth of the sample over time, I first average annualized tax expenses across households by wealth percentile and year and subsequently across years by wealth percentile. A lower tax burden can arise both because households realize fewer taxable gains and because they realize more losses that offset realized gains. Both margins are central to effective tax management.[11][12] Figure 15 reveals a pronounced gradient: annual capital gains tax

[11] Under the U.S. wash-sale rule, a realized capital loss cannot be used to offset realized gains if the taxpayer purchases the same or a substantially identical security within 30 days after realizing the loss. Because my data are monthly, I cannot observe the exact 30-day window and therefore construct a conservative proxy for potential wash-sale activity. Specifically, for each household-year-month, I flag a security if the household buys it in month t after realizing a loss on the same security in month $t-1$. I then compute the share of flagged securities in each household-year-month, average this share across households within year-month, and then across year-months. The resulting fraction is 0.25%. This estimate is likely an upper bound, since monthly data cannot distinguish purchases within 30 days from purchases just outside the statutory window. Moreover, the flagged share is identical across wealth groups not only unconditionally but in every year-month, suggesting that wash-sale behavior cannot explain the estimated tax alpha or its gradient across the wealth distribution.

[12] One additional margin that may differ across households is the donation of appreciated assets. Under U.S. tax law, direct donations of appreciated property to qualified charitable organizations generally do not require the donor to

Figure 14: **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.



expenses decline from 1.4% of initial financial wealth at the bottom of the distribution to 40 basis points at the top. The implied difference of roughly 100 basis points per year represents a sizable tax alpha which increases after-tax returns through more effective tax management.

This tax alpha is economically significant. Focusing on returns on financial wealth, Fagereng, Guiso, Malacrino and Pistaferri (2020) estimate a gap of 1.5 percentage points between the top and bottom of the Norwegian wealth distribution, with about 60 basis points attributable to differences in returns on risky assets.[13] Bach, Calvet and Sodini (2020) report a 53-basis-point alpha gap in Sweden, again for financial wealth, similar to the 57-basis-point estimate in Campbell, Ramadorai and Ranish (2019).[14] The tax alpha documented here is directly comparable to these earlier estimates, despite arising purely from heterogeneous responses to tax incentives rather than differences in pre-tax performance.

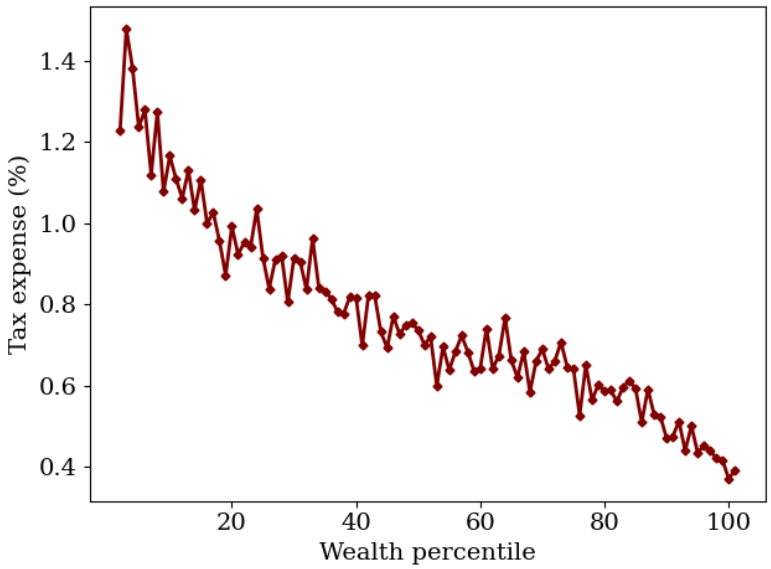
Taken together, these findings show that realization behavior materially shapes households' effective tax burdens and generates a sizable tax alpha. These results indicate that tax management is a first-order driver of after-tax return heterogeneity across the wealth distribution.

recognize the accrued capital gain. If such transfers are appropriately recorded in the data without a taxable realized gain, they will correctly appear as lower realized gains. If instead some donated assets are incorrectly recorded as disposals with realized gains, the estimated tax alpha will be biased downward—that is, the paper will understate the true tax alpha—since such donations are more common at the top of the wealth distribution.

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

[14]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 15: **Tax alpha**
This figure plots average capital gains tax expenses, rescaled by beginning-of-year wealth, by wealth percentile. I first average rescaled tax expenses across households by wealth percentile and year and subsequently across years by wealth percentile.



7.3 Institutional features of the tax code and advisory industry

The analysis so far documented a sizable tax alpha arising from heterogeneous realization behavior. I now assess whether this tax alpha survives after incorporating institutional features of the tax code and the advisory industry. Two considerations are particularly relevant. First, less wealthy households may face lower statutory capital gains tax rates, which could reduce their capital gains tax expenses. Second, capital gains realized in retirement accounts are exempt from capital gains taxation. Because Addepar separately flags positions held in retirement accounts and I exclude both realized and unrealized gains and losses on these positions from the analysis throughout, I already account for this exemption in the construction of tax expenses. The remaining question is therefore whether the tax alpha survives once capital gains tax rates are allowed to vary across households.

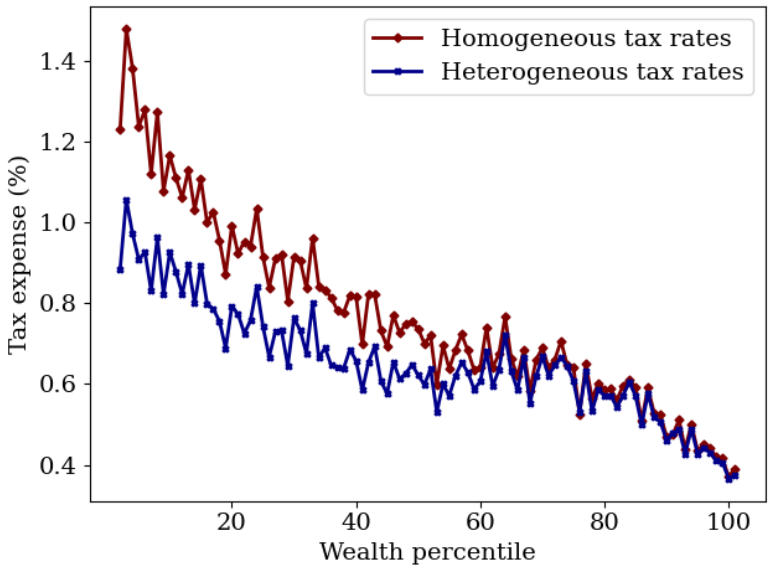
I begin by allowing capital gains tax rates to vary across households based on estimated taxable income. Because Addepar does not report Adjusted Gross Income (AGI), I estimate it by combining external tabulations from Balkir, Saez, Yagan and Zucman (2025a) with capitalization factors from Saez and Zucman (2016). For each household and year, I then construct taxes on short- and long-term capital gains based on the estimated AGI and the official IRS tax schedules. Further details are reported in Appendix B.1.

Figure 16 reports tax expenses across the wealth distribution after allowing tax rates to vary across households. To facilitate comparison, I also report tax expenses under homogeneous tax

rates, as in Figure 15. Allowing tax rates to vary across households reduces annual capital gains tax expenses at the bottom of the wealth distribution from 1.4% to 1.1%, while leaving the top essentially unchanged because households there already face the top statutory tax rate. Although progressive tax rates reduce the gradient, a sizable tax alpha of 70 basis points per year remains. In Appendix E, I repeat the exercise after estimating income from the SCF rather than external capitalization-based tabulations and obtain a similar tax alpha of 60 basis points.

Overall, even after accounting for progressive tax rates, the tax alpha remains comparable in magnitude to the 60-basis-point gap in pre-tax returns on risky financial assets documented in the household finance literature (Campbell, Ramadorai and Ranish, 2019; Bach, Calvet and Sodini, 2020; Fagereng, Guiso, Malacrino and Pistaferri, 2020). Consistent with this evidence, in the Addepar data the difference in average pre-tax returns between the top and bottom quintiles is 47 basis points and rises to 68 basis points after accounting for differences in capital gains tax expenses, an increase of about 50%. Thus, differences in capital gains tax expenses exacerbate, rather than attenuate, return gaps across households.

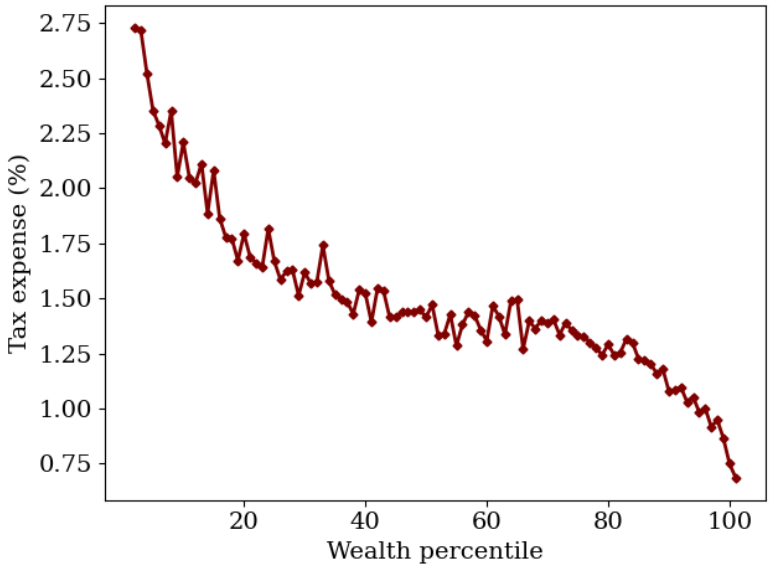
Figure 16: **Tax alpha after incorporating heterogeneous tax rates**
This figure plots average capital gains tax expenses, rescaled by beginning-of-year wealth, by wealth percentile after accounting for heterogeneous capital gains tax rates. To facilitate comparisons, I also report average capital gains tax expenses under the assumption of homogeneous capital gains tax rates discussed in Figure 15.



As a second exercise, 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 advisory fees are reported in Appendix B.2.

Figure 17 plots annual capital gains tax expenses after accounting for heterogeneous tax rates and advisory fees. The gradient not only persists but becomes steeper: the difference between the bottom and top of the wealth distribution rises to about 2 percentage points. This increase reflects the fact that advisory fees are strongly regressive, falling sharply with wealth. Ignoring advisory fees therefore likely understates the net-of-fee tax alpha achieved by wealthier households.

Figure 17: **Tax alpha after incorporating heterogeneous tax rates and advisory fees**
This figure plots average capital gains tax expenses net of advisory fees, rescaled by beginning-of-year wealth, by wealth percentile after accounting for heterogeneous capital gains tax rates and heterogeneous advisory fees.



7.4 Is it really alpha?

The previous section documented that wealthier households achieve a tax alpha of 70 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 tax optimization is most pronounced, and I estimate predictive regressions of the form:

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

where $y_{i,t+1\to t+h}$ denotes the average of an outcome variable over a 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

Table 11: **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***	2.130***
	(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

subsequently squared; (iii) turnover.[15]

Table 11 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. Households 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 trig-

[15] I construct returns for household i in year-month t as $\frac{\sum_{a\in\mathcal{L}} R_{iat}}{\sum_{a\in\mathcal{L}} A^{DH}_{ia,t-1}}$, where R_{iat} is measured before taxes but after other transaction costs.

gering large taxable gains.

7.5 Implications for concentration in financial wealth

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 financial 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 financial 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 $\bar{\tau}_p$ both under the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates. I also consider heterogeneous advisory fees separately in the discussion below, since this channel reflects differences in intermediation costs rather than taxation per se. The same procedure is applied to obtain $s_{p'0}$ and $\bar{\tau}_{p'}$ for the remaining percentiles.

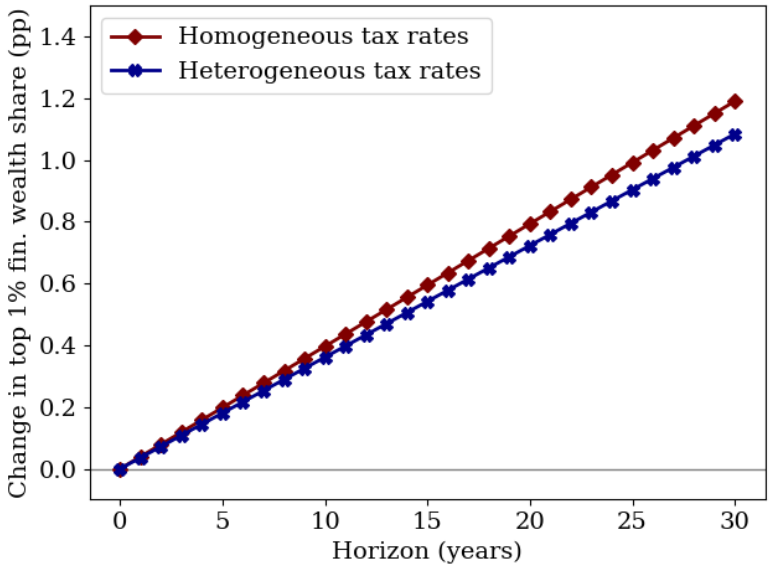
Figure 18 plots the first two specifications for horizons t from one to thirty years. After accounting for heterogeneous tax rates, differences in capital gains tax expenses increase the financial wealth share of households in the top 1% of the Addepar dataset by 1.08 percentage points over thirty years, everything else equal. Adding heterogeneity in advisory fees further raises the implied increase to 3.78 percentage points. For comparison, in the DFA, the share of financial wealth held by the top 0.1% rose by 3.62 percentage points over the past thirty years, relative to aggregate financial 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 concentration in fi-

nancial wealth by 30% of this historical increase. Further accounting for heterogeneity in advisory fees would raise top-end concentration by nearly all of the historical increase.

Using estimated income from the SCF, Appendix E shows that these results are robust: differences in capital gains taxes increase the financial wealth share of the top 1% by 1.03 percentage points after accounting for heterogeneous tax rates and by 3.73 percentage points after further accounting for heterogeneous advisory fees. These correspond to 28% and to virtually all of the historical increase, respectively.

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

Figure 18: **Capital gains taxes and growth in the top 1% financial wealth share**
This figure plots the change in the top 1% financial wealth share explained by differences in capital gains tax expenses, corresponding to the first term on the right hand-side of equation (4). Results are reported for horizons from one to thirty years. Capital gains tax expenses are computed both under the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates.



8 From financial wealth to net wealth

Section 7 focused on financial wealth because Addepar is most likely to provide broad coverage of that component of household balance sheets, as discussed in Section 3.4. This focus is natural not only because of coverage, but also because concentration in financial wealth shapes asset demand, risk bearing, and the transmission of shocks through capital markets. At the same time, many questions about household balance sheets are naturally stated in terms of net wealth. In this

section, I therefore study whether the differences in capital gains taxes documented above are large enough to sustain concentration in net wealth.

To move from financial wealth to net wealth, I estimate non-financial wealth and liabilities for each household-year-month in Addepar using the DFA. Appendix D provides details on the procedure, and Appendix E shows that repeating the exercise using the SCF leads to similar results. Because the SCF separately reports the value of private businesses, in that robustness exercise I classify private business wealth as non-financial wealth, allowing for the possibility that privately held businesses are only partially reported on advisory platforms.

I construct net wealth for each household-year-month in Addepar by adding estimated non-financial wealth to observed financial wealth and subtracting estimated liabilities. Figure 19 repeats the analysis of Section 7.5 after replacing financial wealth with net wealth in the definition of wealth shares and scaling capital gains tax expenses by beginning-of-year net wealth. After accounting for heterogeneous tax rates, differences in capital gains tax expenses increase the net wealth share of households in the top 1% of the Addepar net wealth distribution by 0.68 percentage points over thirty years, everything else equal. Adding heterogeneity in advisory fees further raises the implied increase to 2.74 percentage points. For comparison, Smith, Zidar and Zwick (2023) estimate that the share of the top 0.1% rose by 5.63 percentage points over a thirty-year horizon between 1986 and 2016, relative to net 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 net wealth concentration by 12% of this historical increase. Accounting as well for heterogeneity in advisory fees would raise this figure to 49%.

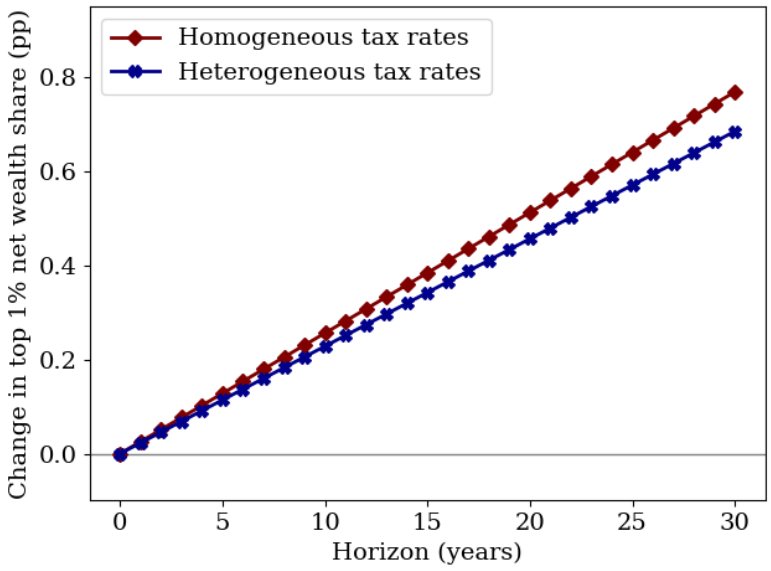
Using estimated income, non-financial wealth, and liabilities from the SCF, Appendix E shows that these results are robust: differences in capital gains taxes increase the net wealth share of the top 1% by 0.80 percentage points after accounting for heterogeneous tax rates and by 3.20 percentage points after further accounting for heterogeneous advisory fees. These correspond to 14% and 57% of the historical increase, respectively.

Taken together, these findings highlight that heterogeneous responses to capital gains taxes are a meaningful driver of both financial and net wealth concentration.

9 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. These patterns are amplified during market downturns and are concentrated among households advised by sophisticated financial intermediaries, especially private banks. Exploiting quasi-experimental variation around

Figure 19: **Capital gains taxes and growth in the top 1% net wealth share**
This figure plots the change in the top 1% net wealth share explained by differences in capital gains tax expenses, corresponding to the first term on the right hand-side of equation (4). Results are reported for horizons from one to thirty years. Capital gains tax expenses are computed both under the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates.



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 heterogeneity in after-tax performance are economically significant. Effective tax burdens decline with wealth, generating a 70-basis-point annual tax alpha for wealthier households that is comparable in magnitude to pre-tax return gaps previously documented in the household finance literature. This tax gain does not come at the expense of lower pre-tax performance or higher risk and therefore represents a genuine alpha. I estimate that differences in capital gains tax expenses increase the aggregate financial (net) wealth share of the top 1% of households by 28–30% (12–14%) of the historical increase, everything else equal.

By documenting this channel, the paper identifies a mechanism that links tax policy design to return heterogeneity. 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 hold-

ings 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.

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

A.2.7 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 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 Estimation 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, realized capital gains, and pension benefits by wealth group in 2019. Second, I construct a measure of taxable financial income by subtracting wages and pension benefits from AGI. This measure includes capital income, business income, and realized capital gains. Third, I convert financial income into financial wealth using the capitalization factor reported in Table A.13 of Saez and Zucman (2016), which is designed for taxable capital and business income. Specifically, I multiply taxable financial income by 12.5, the midpoint of the 10–15 range observed since 2000. Results are similar when I instead use 10 or 15.

Fourth, I interpolate log AGI net of realized capital gains as a function of log financial wealth using cubic splines, and I apply the resulting function to end-of-year log wealth in Addepar for each household-year. I then compute capital gains tax liabilities using the statutory tiered schedule. Starting from estimated AGI net of realized capital gains, I first tax short-term capital gains as ordinary income, filling the ordinary-income brackets in sequence. I then tax long-term capital gains under the preferential long-term capital gains schedule, stacking them on top of income inclusive of short-term gains. This procedure follows the ordering prescribed by the tax code and captures the nonlinear mapping from realizations to tax liabilities. For each year, I use the statutory schedules for short- and long-term capital gains published by the IRS. I apply the income brackets for married filing separately because the unit of observation in Addepar is a portfolio, and different members of the same family may manage separate portfolios that I cannot link.

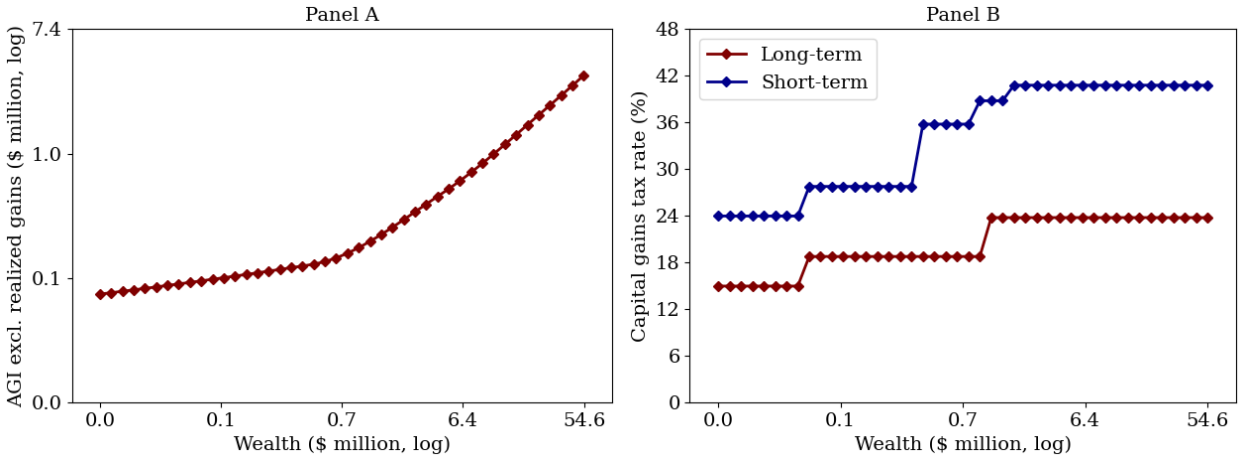
Panel A of Figure B1 plots interpolated log AGI net of realized capital gains against log financial wealth. Panel B plots the corresponding estimated marginal tax rates on short-term and long-term capital gains as a function of log financial wealth.

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.

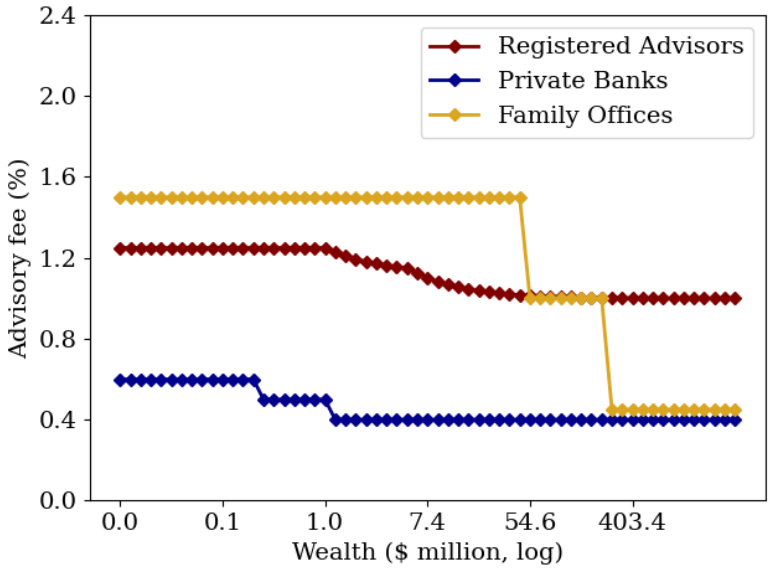
For each household-year, I apply the schedule of the relevant advisor type to the household's end-of-year wealth to compute annual advisory fees. Broker/dealer accounts are assigned a zero

Figure B1: **Estimated AGI net of realized capital gains and marginal tax rates**
Panel A plots the interpolated log AGI net of realized capital gains as a function of log financial wealth. Panel B plots the estimated marginal tax rates on long-term and short-term capital gains.



fee, a conservative choice that biases against finding a tax alpha since these accounts are disproportionately held by less wealthy households (see Table 6 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, wealth A_{it} satisfies the following intertemporal budget constraint

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

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

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

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

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

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

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

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

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

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

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

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 Estimation of non-financial wealth and liabilities

To move from financial wealth to net wealth, I impute non-financial wealth and liabilities for households in Addepar using the DFA. The DFA report aggregate financial wealth, non-financial wealth, liabilities, and the number of households for five segments of the wealth distribution at quarterly frequency: the bottom 50%, 50–90%, 90–99%, 99–99.9%, and the top 0.1%. Financial wealth includes equity and fixed-income securities, mutual fund shares, deposits and money market funds, loans, equity non-corporate businesses, and positions held in defined-benefit and defined-contribution retirement accounts. Non-financial wealth includes real estate, including owner-occupied housing, and consumer durables such as vehicles.

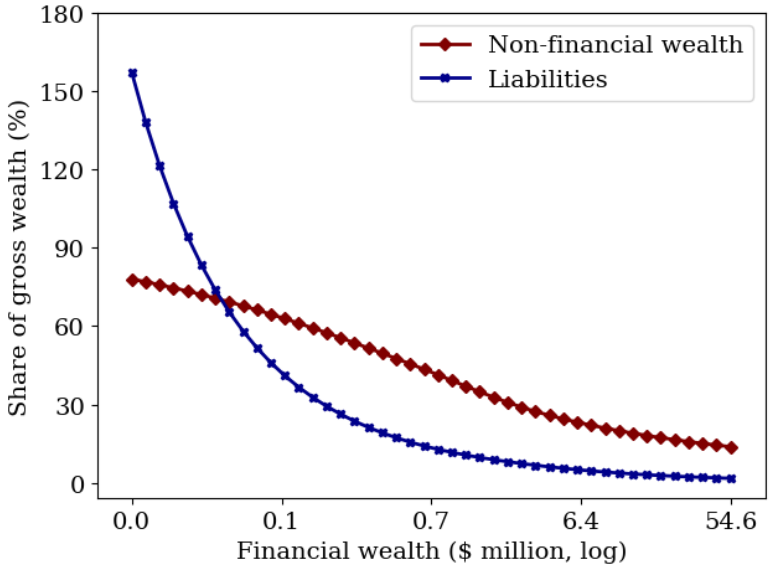
I begin with non-financial wealth. For each wealth segment and year-quarter, I compute the share of gross wealth held in non-financial assets, where gross wealth is the sum of financial and non-financial wealth. I also compute average financial wealth as aggregate financial wealth divided by the number of households in the segment. I then take the logit transformation of the non-financial wealth share and interpolate it as a function of log average financial wealth using cubic splines across wealth segments for each year-quarter.

For each household-year-month in Addepar, I apply the interpolated relationship for the corresponding year-quarter to the household's observed financial wealth and recover the implied share of gross wealth held in non-financial assets using the inverse logit transformation. Because this share is expressed relative to gross wealth, I convert it into a ratio of non-financial wealth to financial wealth by dividing the share by one minus the share. Multiplying this ratio by observed financial wealth in Addepar yields an estimate of household non-financial wealth.

I next impute liabilities using a similar procedure. For each wealth segment and year-quarter, I compute liabilities relative to gross wealth and interpolate this ratio as a function of log average financial wealth across DFA groups. Unlike the non-financial wealth share, this ratio is not necessarily bounded above by one, so I do not apply a logit transformation. I then apply the resulting relationship to households in Addepar to obtain household-level liabilities.

Figure D3 plots the interpolated share of non-financial wealth and liabilities over gross wealth as a function of the log of financial wealth. Using these estimates of non-financial wealth and liabilities, I construct gross wealth for each household and year-month in Addepar as the sum of observed financial wealth and estimated non-financial wealth, and I construct net wealth as gross wealth minus estimated liabilities.

Figure D3: **Estimated share of non-financial wealth and liabilities**
This figure plots the estimated share of non-financial wealth and liabilities over gross wealth as a function of log financial wealth.



E Robustness using the SCF

To assess the robustness of the results in Sections 7 and 8, I repeat the estimation of heterogeneous tax rates, non-financial wealth, and liabilities using the SCF rather than the baseline external sources.

E.1 Variables definition

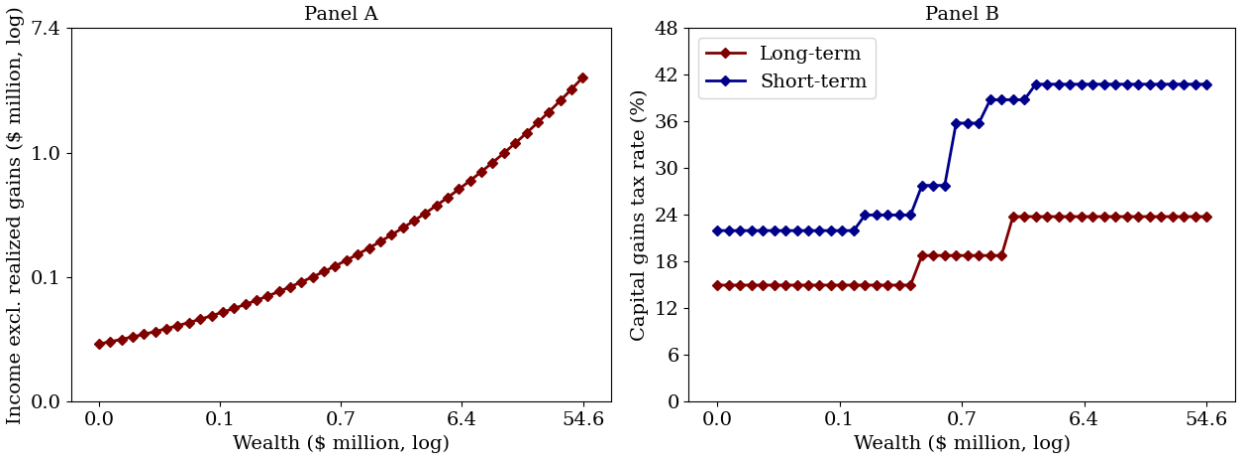
I use the 2019 summary SCF to estimate these objects for years in Addepar up to and including 2019, and the 2022 summary SCF for all subsequent years. In all regressions, observations are weighted using the SCF population weight (variable *wgt*).

I begin by constructing the relevant balance-sheet and income variables in the SCF. Financial wealth is defined as the sum of cash, cash-equivalent securities, directly hold stocks and bonds, mutual funds, securities held in retirement accounts, real estate other than owner-occupied housing (variables *liq*, *cds*, *nmmf*, *savbnd*, *stocks*, *bond*, *cashli*, *othma*, *retqliq*, *othfin*, *oresre*, and *nnresre*). Non-financial wealth, is defined as the sum of vehicles, owner-occupied housing, private businesses, and other non-financial assets (*vehic*, *houses*, *bus*, and *othnfin*). The inclusion of private businesses allows for the possibility that they are only partially reported to advisors in Addepar, especially at the lower end of the wealth distribution. Finally, I construct income net of realized capital gains, as total income (*income*) minus realized capital gains (*kginc*).

E.2 Estimation procedure

To estimate household income net of realized gains, I regress log income net of capital gains on a constant and a cubic polynomial in log financial wealth in the SCF. I save the estimated coefficients and apply them to log financial wealth in each household-year-month of the Addepar data. I then use the resulting imputed income measure to assign household-specific statutory tax rates on short- and long-term capital gains following the same tiered tax-code procedure described in Appendix B.1. Panel A of Figure E4 plots the estimated log income net of realized capital gains as a function of log financial wealth. Panel B plots the corresponding estimated marginal tax rates on short-term and long-term capital gains as a function of log financial wealth.

Figure E4: **Estimated income net of realized capital gains and marginal tax rates in the SCF**
Panel A plots the estimated log income net of realized capital gains as a function of log financial wealth. Panel B plots the estimated marginal tax rates on long-term and short-term capital gains.

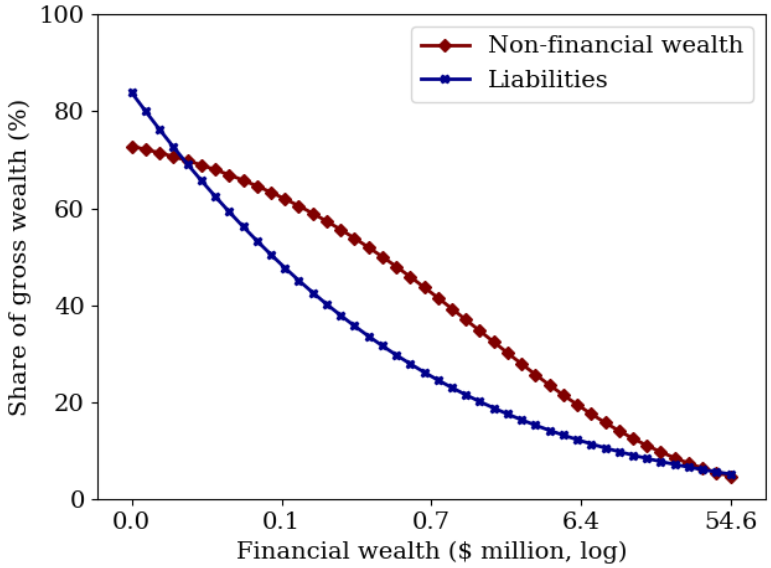


To estimate non-financial wealth, I run binomial generalized linear model. The dependent variable is the share of gross wealth held in non-financial assets, computed as non-financial wealth divided by gross wealth (defined as financial plus non-financial wealth). Regressors again include a constant and a cubic polynomial in log financial wealth. I then apply the estimated coefficients to observed log financial wealth of Addepar households and recover shares using the inverse logit transformation. Because the resulting object is a share of gross wealth rather than a share of financial wealth, I convert it into a ratio of non-financial wealth to financial wealth and multiply that ratio by observed financial wealth in Addepar to obtain household-level non-financial wealth.

Finally, I estimate liabilities using a gamma generalized linear model with log link. The dependent variable is liabilities, constructed as gross wealth minus net wealth (*networth*) relative to gross wealth in the SCF, and regressors again include a constant and a cubic polynomial in log financial wealth. I apply the estimated coefficients to the observed log financial wealth of each household-year-month in Addepar and recover the liabilities-to-gross-wealth ratio by exponentiating the fitted values.

Figure E5 plots the estimated share of non-financial wealth and liabilities over gross wealth as a function of the log of financial wealth. Using these estimates of non-financial wealth and liabilities, I construct gross wealth for each household and year-month in Addepar as the sum of observed financial wealth and estimated non-financial wealth, and I construct net wealth as gross wealth minus estimated liabilities.

Figure E5: **Estimated share of non-financial wealth and liabilities in the SCF**
This figure plots the estimated share of non-financial wealth and liabilities over gross wealth as a function of log financial wealth.



E.3 Results

Figure E6 repeats the analysis in Section 7.3 using the SCF-based estimates of heterogeneous tax rates described in Appendix E.2. I find that, after accounting for heterogeneous tax rates, the gap in capital gains tax expenses between the top and bottom of the wealth distribution remains equal to 60 basis points. This estimate is close to the 70 basis-point gap reported in Section 7.3 under the baseline approach, and it is still comparable in magnitude to the 60 basis-point gap in pre-tax returns estimated in the household finance literature (Campbell, Ramadorai and Ranish, 2019; Bach, Calvet and Sodini, 2020; Fagereng, Guiso, Malacrino and Pistaferri, 2020).

Figure E7 repeats the analysis in Section 7.5 to evaluate how heterogeneous capital gains taxes affect concentration in financial wealth. After accounting for heterogeneous tax rates, differences in capital gains tax expenses increase the financial wealth share of households in the top 1% of the Addepar dataset by 1.03 percentage points over thirty years, everything else equal. Adding heterogeneity in advisory fees further raises the implied increase to 3.73 percentage points.

Finally, Figure E8 repeats the analysis in Section 8 using the SCF-based estimates of non-

financial wealth and liabilities described in Appendix E.2. I find that differences in capital gains tax expenses, after accounting for heterogeneous tax rates, increase the net wealth share of households in the top 1% of the Addepar dataset by 0.80 percentage points over thirty years, everything else equal. Adding heterogeneity in advisory fees further raises the implied increase to 3.20 percentage points.

Taken together, these results show that the main findings on tax alpha and on the implications of heterogeneous capital gains taxes for concentration in financial wealth and net wealth are robust to using the SCF instead of the DFA to impute tax rates, non-financial wealth, and liabilities.

Figure E6: **Tax alpha after incorporating heterogeneous tax rates using the SCF**
This figure plots average capital gains tax expenses, rescaled by beginning-of-year financial wealth, by wealth percentile after accounting for heterogeneous capital gains tax rates. To facilitate comparisons, I also report average capital gains tax expenses under the assumption of homogeneous capital gains tax rates discussed in Figure 15.

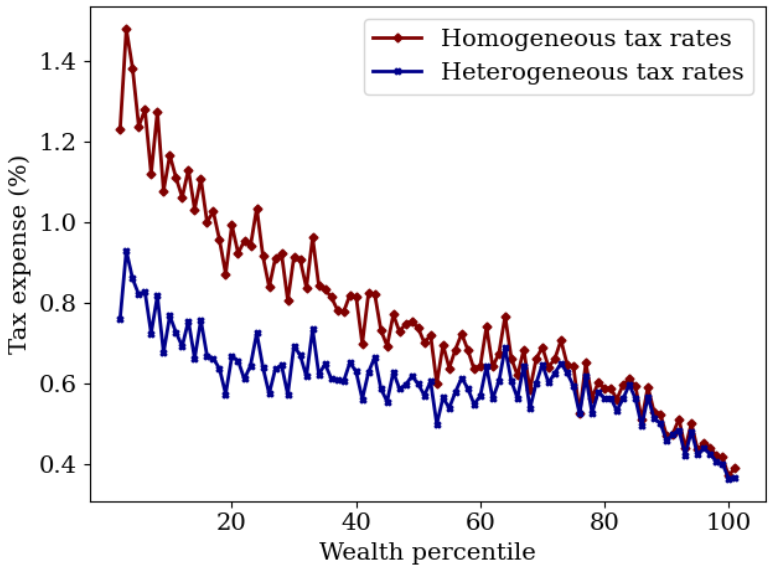


Figure E7: **Top 1% financial wealth share using estimates from the SCF**
This figure plots the change in the top 1% financial wealth share explained by differences in capital gains tax expenses, corresponding to the first term on the right hand-side of equation (4). Results are reported for horizons from one to thirty years. Capital gains tax expenses are computed both under the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates.

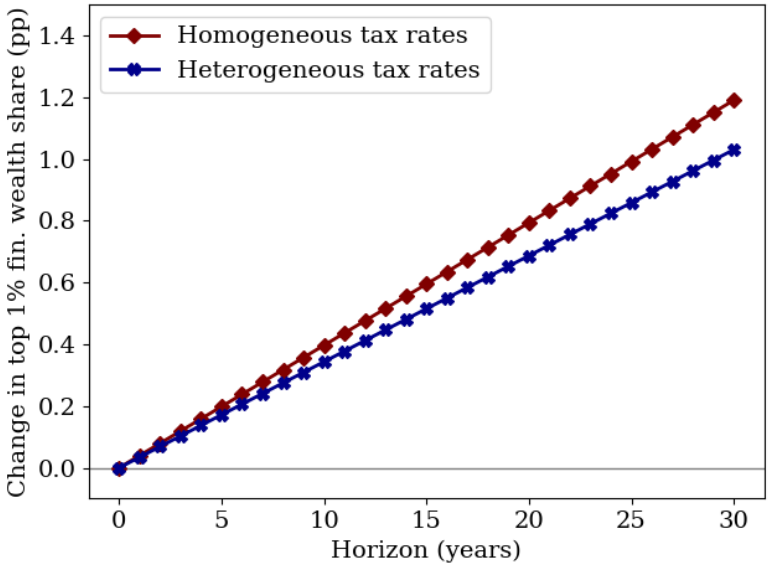
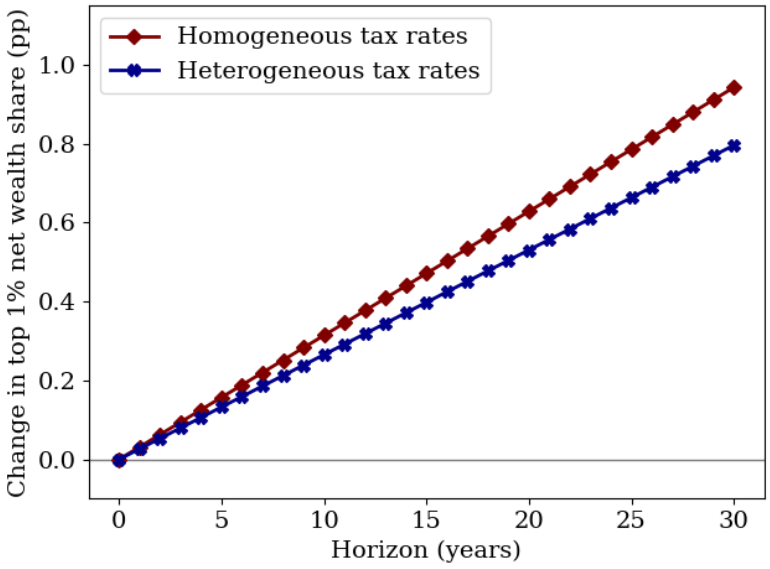


Figure E8: **Top 1% net wealth share using estimates from the SCF**
This figure plots the change in the top 1% net wealth share explained by differences in capital gains tax expenses, corresponding to the first term on the right hand-side of equation (4). Results are reported for horizons from one to thirty years. Capital gains tax expenses are computed both under the baseline assumption of homogeneous statutory tax rates and allowing for heterogeneous tax rates.



F Additional figures and tables

Figure F9: **Unrealized gains and losses in liquid and illiquid asset classes across the wealth distribution**
Panel A provides a binned scatterplot of unrealized gains against the log of initial wealth $A_{i,t-1}$ across households. Panel B reports a binned scatterplot of unrealized losses against the log of initial wealth $A_{i,t-1}$ across households. The results are presented for December 2024.

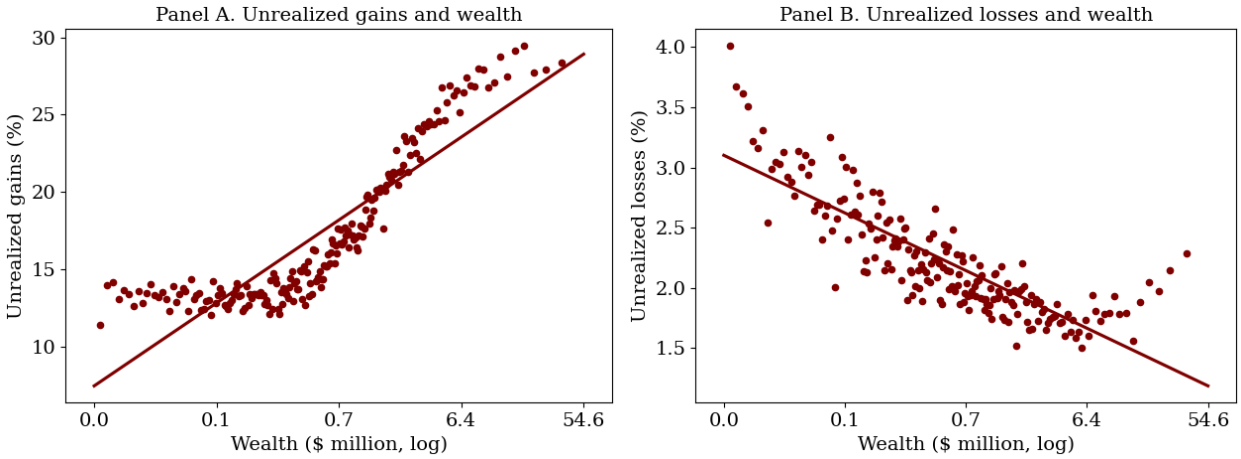


Table F2: **Average wealth in Addepar and in the SCF**
This table compares average household wealth in Addepar with alternative definitions of average wealth for households in the top 10% of the SCF net wealth distribution. The second column reports the discrepancy between average wealth in Addepar and different definitions of wealth in the SCF. I define non-financial wealth in the SCF as the sum of owner-occupied primary residence (variable *houses*), vehicles (variable *vehic*), and other non-financial assets (variable *othnfin*). I define financial wealth as gross wealth (variable *asset*) minus non-financial wealth. I define net wealth as gross wealth minus total debt (variable *debt*). Column three excludes positions in retirement accounts (variable *retqliq*) from all definitions of SCF wealth and column four excludes private businesses (variable *bus*). All figures are expressed in thousands of U.S. dollars.

Definitions of wealth	All items	Net of retirement accounts	Net of private businesses
Financial wealth	516	1,529	2,459
Gross wealth	1,193	557	1,171
Net wealth	1,025	585	1,515

Table F3: **Average wealth in Addepar and in the DFA**
This table compares average household wealth in Addepar with alternative definitions of average wealth for households in the top 10% of the DFA net wealth distribution. The second column reports the discrepancy between average wealth in Addepar and different definitions of wealth in the DFA. Financial wealth includes equity and fixed-income securities, mutual fund shares, deposits and money market funds, loans, equity non-corporate businesses, and positions held in defined-benefit and defined-contribution retirement accounts. Non-financial wealth includes real estate, including owner-occupied housing, and consumer durables such as vehicles. Gross wealth is defined as the sum of financial and non-financial wealth, while net wealth is defined as gross wealth minus liabilities. Column three excludes positions in retirement accounts (both defined-benefit and defined-contribution plans) from all definitions of DFA wealth and column four excludes non-corporate businesses. All figures are expressed in thousands of U.S. dollars.

Definitions of wealth	All items	Net of retirement accounts	Net of non-corporate businesses
Financial wealth	918	1,199	1,165
Gross wealth	1,898	1,252	1,216
Net wealth	1,652	1,116	1,063

Figure F10: **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 unique securities in the portfolio, 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.

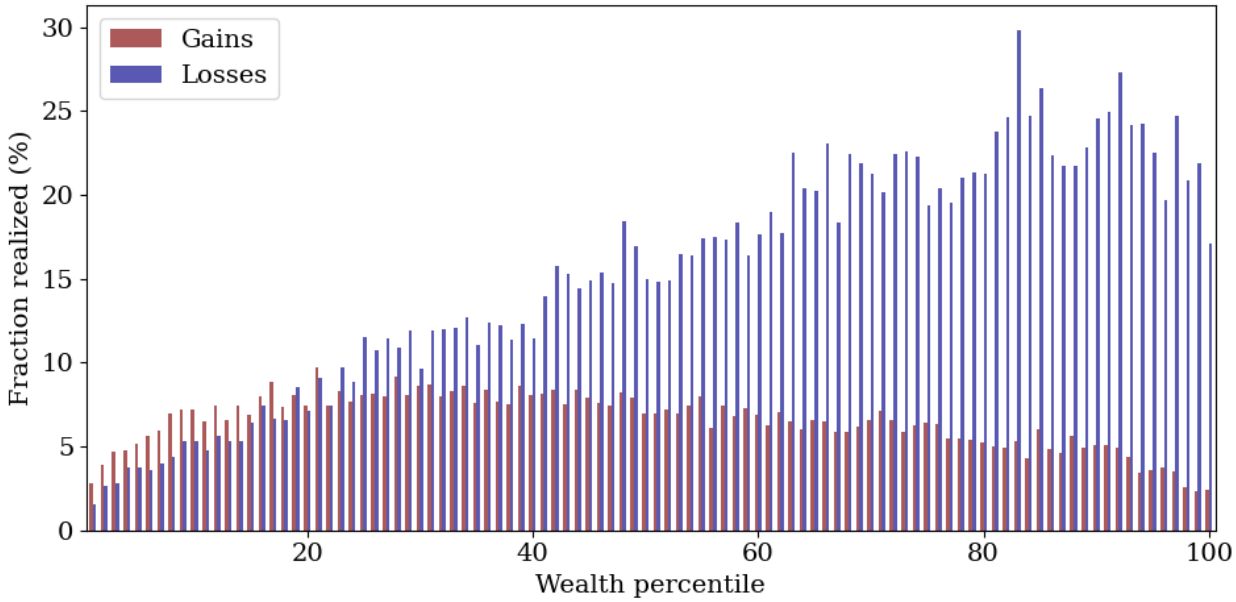


Figure F11: **The fraction of realized gains and losses conditional on year-month fixed effects** This figure plots the fraction of unrealized gains and losses that households in each wealth percentile p realize on average after controlling for year-month fixed effects. Estimates are annualized by multiplying each coefficient by 12.

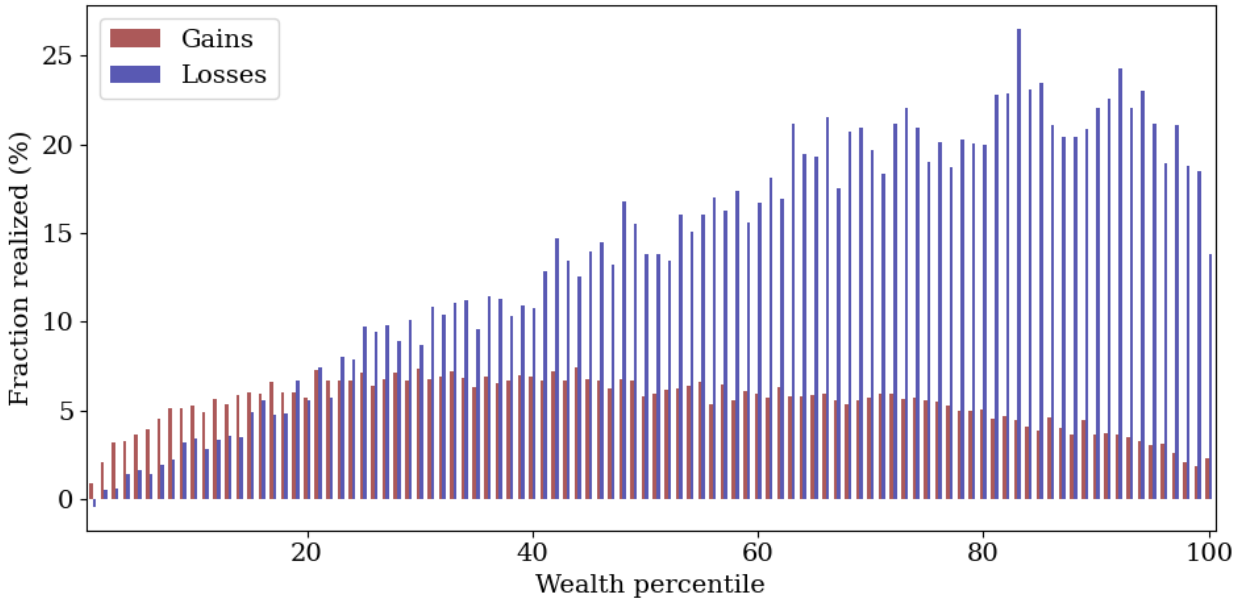


Figure F12: **Dynamic fraction of realized gains**
This figure plots the cumulative fraction of gains realized on average by households in each wealth quintile q over horizon H.

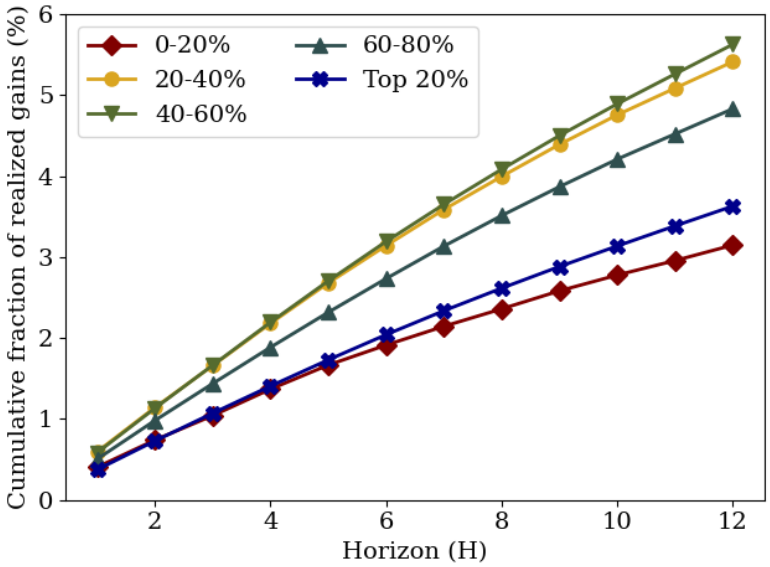


Table F4: **Additional statistics for regression kink design**
This table reports additional statistics about the regression kink design presented in Table 7. For each year, the first and second rows provide the number of observations on the left and right of the cutoff. Left and right bandwidths (reported on rows three to six for each year) 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 F5: **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 F6: **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 F7: **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 F13: **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.

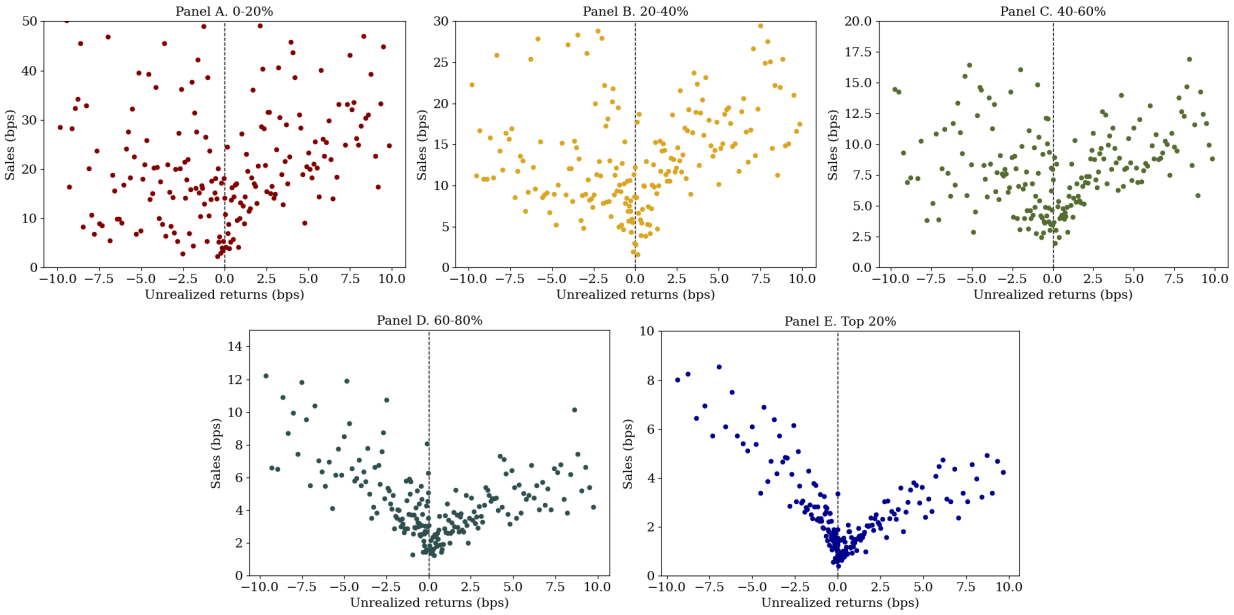


Figure F14: **Relation between purchases and unrealized returns**
Each panel provides a binned scatterplot of purchases against unrealized returns in a narrow interval around zero for a given quintile of the Addepar wealth distribution. The dataset is restricted to December 2024 and to securities with unrealized returns between –10 and +10 basis points.

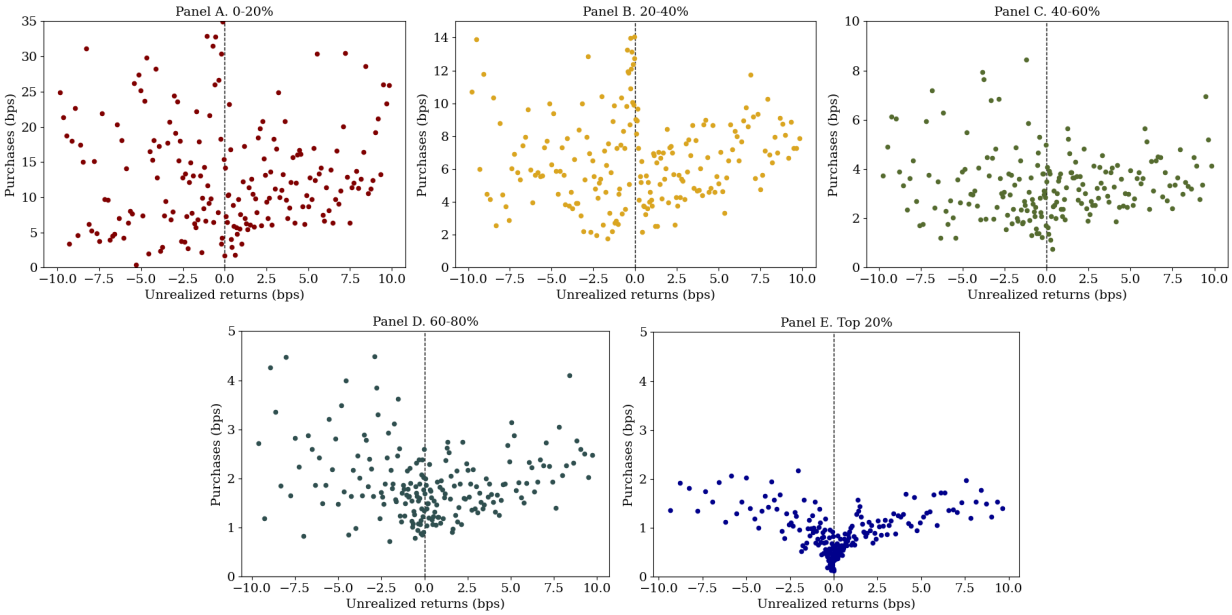


Table F8: **Additional statistics for regression kink design across advisors**
This table reports additional statistics about the regression kink design presented in Table 9. For each year, the first and second rows provide the number of observations on the left and right of the cutoff. Left and right bandwidths (reported on rows three to six for each year) 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	Brokers/ Dealers	Single-Family Offices	Registered Advisors	Multi-Family Offices	Private Banks
2016	Left N	5,977	1,107	66,729	616	607
	Right N	10,122	1,713	141,058	1,124	932
	Left bandwidth (estimation, %)	0.206	0.055	0.078	0.017	0.132
	Right bandwidth (estimation, %)	0.206	0.055	0.078	0.017	0.132
	Left bandwidth (bias, %)	0.735	0.140	0.286	0.092	0.273
	Right bandwidth (bias, %)	0.735	0.140	0.286	0.092	0.273
2017	Left N	12,921	6,526	112,011	614	1,828
	Right N	21,869	11,254	200,748	2,910	2,730
	Left bandwidth (estimation, %)	0.157	0.044	0.080	0.013	0.141
	Right bandwidth (estimation, %)	0.157	0.044	0.080	0.013	0.141
	Left bandwidth (bias, %)	0.469	0.186	0.281	0.048	0.315
	Right bandwidth (bias, %)	0.469	0.186	0.281	0.048	0.315
2018	Left N	30,161	15,021	245,471	1,150	13,991
	Right N	28,320	13,305	233,535	4,586	15,311
	Left bandwidth (estimation, %)	0.149	0.037	0.084	0.074	0.159
	Right bandwidth (estimation, %)	0.149	0.037	0.084	0.074	0.159
	Left bandwidth (bias, %)	0.445	0.123	0.270	0.232	0.321
	Right bandwidth (bias, %)	0.445	0.123	0.270	0.232	0.321
2019	Left N	14,713	12,272	215,545	2,317	19,336
	Right N	29,602	18,766	505,216	6,849	46,920
	Left bandwidth (estimation, %)	0.203	0.054	0.076	0.126	0.244
	Right bandwidth (estimation, %)	0.203	0.054	0.076	0.126	0.244
	Left bandwidth (bias, %)	0.574	0.193	0.297	0.335	0.547
	Right bandwidth (bias, %)	0.574	0.193	0.297	0.335	0.547

(continued)

Year	Statistic	Brokers/ Dealers	Single-Family Offices	Registered Advisors	Multi-Family Offices	Private Banks
2020	Left N	25,005	17,764	292,790	7,059	78,476
	Right N	63,295	44,075	938,417	36,388	228,302
	Left bandwidth (estimation, %)	0.321	0.055	0.155	0.156	0.158
	Right bandwidth (estimation, %)	0.321	0.055	0.155	0.156	0.158
	Left bandwidth (bias, %)	0.912	0.228	0.450	0.578	0.537
	Right bandwidth (bias, %)	0.912	0.228	0.450	0.578	0.537
2021	Left N	30,271	20,729	385,466	15,859	128,344
	Right N	89,840	66,738	1,306,203	71,839	342,939
	Left bandwidth (estimation, %)	0.115	0.081	0.096	0.100	0.058
	Right bandwidth (estimation, %)	0.115	0.081	0.096	0.100	0.058
	Left bandwidth (bias, %)	0.397	0.232	0.290	0.338	0.187
	Right bandwidth (bias, %)	0.397	0.232	0.290	0.338	0.187
2022	Left N	59,977	52,233	1,161,655	43,209	374,639
	Right N	53,335	47,905	1,192,622	75,718	397,517
	Left bandwidth (estimation, %)	0.218	0.126	0.138	0.213	0.096
	Right bandwidth (estimation, %)	0.218	0.126	0.138	0.213	0.096
	Left bandwidth (bias, %)	0.595	0.411	0.437	0.706	0.333
	Right bandwidth (bias, %)	0.595	0.411	0.437	0.706	0.333
2023	Left N	81,205	54,532	1,693,718	73,514	346,206
	Right N	99,974	82,023	2,041,220	199,566	390,207
	Left bandwidth (estimation, %)	0.150	0.168	0.117	0.123	0.075
	Right bandwidth (estimation, %)	0.150	0.168	0.117	0.123	0.075
	Left bandwidth (bias, %)	0.502	0.506	0.361	0.431	0.283
	Right bandwidth (bias, %)	0.502	0.506	0.361	0.431	0.283
2024	Left N	107,616	51,527	1,753,235	70,786	332,704
	Right N	226,062	104,195	3,222,253	266,025	578,873
	Left bandwidth (estimation, %)	0.263	0.152	0.105	0.125	0.114
	Right bandwidth (estimation, %)	0.263	0.152	0.105	0.125	0.114
	Left bandwidth (bias, %)	0.698	0.460	0.335	0.422	0.382
	Right bandwidth (bias, %)	0.698	0.460	0.335	0.422	0.382

Table F9: **Additional statistics for regression kink design on similar holdings**
This table reports additional statistics about the regression kink design presented in Table 10. For each year, the first and second rows provide the number of observations on the left and right of the cutoff. Left and right bandwidths (reported on rows three to six for each year) 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	8,911	16,712	27,787	38,622	63,609
	Right N	9,773	24,746	44,607	65,483	129,917
	Left bandwidth (estimation, %)	1.164	0.336	0.264	0.142	0.059
	Right bandwidth (estimation, %)	1.164	0.336	0.264	0.142	0.059
	Left bandwidth (bias, %)	2.925	0.956	0.633	0.403	0.174
	Right bandwidth (bias, %)	2.925	0.956	0.633	0.403	0.174
2017	Left N	12,986	25,615	41,193	67,275	116,912
	Right N	22,830	41,494	67,658	100,725	208,363
	Left bandwidth (estimation, %)	1.533	0.276	0.162	0.084	0.067
	Right bandwidth (estimation, %)	1.533	0.276	0.162	0.084	0.067
	Left bandwidth (bias, %)	4.264	0.974	0.487	0.307	0.185
	Right bandwidth (bias, %)	4.264	0.974	0.487	0.307	0.185
2018	Left N	30,096	63,598	92,023	166,741	258,548
	Right N	27,550	69,432	91,322	157,533	244,446
	Left bandwidth (estimation, %)	0.753	0.473	0.208	0.146	0.057
	Right bandwidth (estimation, %)	0.753	0.473	0.208	0.146	0.057
	Left bandwidth (bias, %)	2.339	1.168	0.559	0.378	0.197
	Right bandwidth (bias, %)	2.339	1.168	0.559	0.378	0.197
2019	Left N	43,834	76,800	120,791	183,008	259,366
	Right N	65,154	121,300	220,962	387,066	587,032
	Left bandwidth (estimation, %)	0.789	0.301	0.220	0.145	0.062
	Right bandwidth (estimation, %)	0.789	0.301	0.220	0.145	0.062
	Left bandwidth (bias, %)	2.125	0.877	0.653	0.377	0.183
	Right bandwidth (bias, %)	2.125	0.877	0.653	0.377	0.183

(continued)

Year	Statistic	0–20%	20–40%	40–60%	60–80%	Top 20%
2020	Left N	72,073	137,989	222,078	303,343	408,801
	Right N	94,914	235,681	429,747	696,967	1,184,503
	Left bandwidth (estimation, %)	0.844	0.585	0.327	0.158	0.086
	Right bandwidth (estimation, %)	0.844	0.585	0.327	0.158	0.086
	Left bandwidth (bias, %)	2.263	1.431	0.963	0.462	0.243
	Right bandwidth (bias, %)	2.263	1.431	0.963	0.462	0.243
2021	Left N	51,817	145,425	304,242	424,793	576,295
	Right N	73,508	306,589	657,893	978,385	1,828,341
	Left bandwidth (estimation, %)	0.761	0.409	0.165	0.087	0.061
	Right bandwidth (estimation, %)	0.761	0.409	0.165	0.087	0.061
	Left bandwidth (bias, %)	2.446	1.666	0.509	0.233	0.187
	Right bandwidth (bias, %)	2.446	1.666	0.509	0.233	0.187
2022	Left N	127,865	419,900	760,099	1,105,337	1,592,522
	Right N	97,482	329,194	646,240	1,064,248	1,742,290
	Left bandwidth (estimation, %)	1.293	0.391	0.182	0.151	0.083
	Right bandwidth (estimation, %)	1.293	0.391	0.182	0.151	0.083
	Left bandwidth (bias, %)	3.212	1.117	0.579	0.379	0.206
	Right bandwidth (bias, %)	3.212	1.117	0.579	0.379	0.206
2023	Left N	210,264	552,249	1,077,895	1,356,664	1,986,993
	Right N	191,411	549,653	1,115,751	1,423,193	2,515,678
	Left bandwidth (estimation, %)	0.734	0.271	0.203	0.091	0.057
	Right bandwidth (estimation, %)	0.734	0.271	0.203	0.091	0.057
	Left bandwidth (bias, %)	1.954	0.825	0.600	0.312	0.160
	Right bandwidth (bias, %)	1.954	0.825	0.600	0.312	0.160
2024	Left N	230,848	517,243	816,099	1,223,368	2,210,991
	Right N	385,568	953,635	1,594,670	2,372,395	4,172,780
	Left bandwidth (estimation, %)	0.562	0.391	0.272	0.136	0.082
	Right bandwidth (estimation, %)	0.562	0.391	0.272	0.136	0.082
	Left bandwidth (bias, %)	1.761	0.912	0.653	0.418	0.239
	Right bandwidth (bias, %)	1.761	0.912	0.653	0.418	0.239