At the Top of the Mind: Peak Prices and the Disposition Effect

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The disposition effect is the reluctance to sell assets at a loss relative to a salient point of reference, typically assumed to be the purchase price. Using data on stocks and housing sales, we show that the peak price achieved by an asset during the investor's period of holding constitutes

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an additional salient reference point for asset owners that overlaps—and interacts—with the purchase price reference point. Peaks occurring before the investor purchased the asset do not affect future sales, indicating that ownership affects how investors form reference points.

I. Introduction

In part because absolute judgments are difficult, people often evaluate outcomes relative to salient reference points. When we refer to a "small" elephant and a "large" mouse, for example, few people would mistake the ordering of their weights, because we automatically "norm" each descriptor to animals of the same species (Kahneman and Miller 1986). Applied to decision-making, we do not evaluate outcomes in terms of the final levels of wealth they confer (as the expected utility model assumes) but evaluate outcomes as gains or losses depending on whether they exceed or fall short of salient points of comparison.

The most widely documented case of reference dependence in economics and finance is the *disposition effect*, which refers to the reluctance of purchasers of an asset to sell it at a loss (Shefrin and Statman 1985). The disposition effect is a feature of individual financial behavior observed in the sale of both stocks (e.g., Barber and Odean 2000; Shapira and Venezia 2001; Feng and Seasholes 2005; Chang, Solomon, and Westerfield 2016) and housing (Genesove and Mayer 2001; Andersen et al. 2021; Bracke and Tenreyro 2021).[1] Most prior research on the disposition effect has assumed that the relevant price reference point for selling decisions is the purchase price of the owned asset.[2] Both field research focusing on housing sales and field and experimental research involving financial assets have supported the disposition effect prediction that

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[1] Using data from a sample of 5,800 condominium property listings from downtown Boston in the 1990s, Genesove and Mayer (2001) show that owners who experience nominal losses on the original purchase price set higher asking prices to compensate (and attain higher selling prices). Recent studies also show that prevailing market conditions at the time of house purchase influence future selling prices (see Andersen et al. 2021; Bracke and Tenreyro 2021).

[2] With the exception of our own series of contributions on this topic, starting with Quispe-Torreblanca et al. (2024). In that paper, we examined the impact of the price of an asset on the last occasion on which the investor logged in on selling behavior. Also, a few studies have examined the impact of reference points not related to the price history. Hartzmark (2015) finds that investors selling decisions are influenced by their stocks' rank of returns within their portfolio. Frydman, Hartzmark, and Solomon (2018) find that there is a disposition effect when using both a stock's purchase price and the purchase price of a recently sold stock. An et al. (forthcoming) show that the portfolio gain/loss moderates the disposition effect.

people will be reluctant to sell assets at prices below the nominal price at which they were purchased.[3]

However, perhaps as a result of some kind of motivated bias (Bénabou and Tirole 2016) or simply the salience of extreme values (Gagne and Dayan 2021), asset owners often have a distorted view of true value. Casual observation of both homeowners and stockholders suggests that owners often seem to believe that the "true" value of their asset is the highest price it achieved while they have held it, the *peak price*. This might lead to a reluctance to sell at what is perceived to be an unfair lower price (Isoni 2011; Weaver and Frederick 2012) and can also contribute to the belief that the asset's value is likely to regress toward the higher price, corresponding to its perceived true value.

In this paper, we examine whether consideration of the peak historic price an asset achieved while the owner has held it does, indeed, help to predict selling behavior. To do so, we estimate the disposition effect on returns since purchase and returns since peak price in both housing and stock data. Examining decisions for these two distinct asset classes held by individuals (which differ in many features, e.g., length of price cycles, liquidity, divisibility, and trading costs), we show the importance of peak prices in both markets. Our housing data provide population-level coverage of house price sales, providing a substantially larger dataset in which to examine the housing disposition effect compared with previous studies. Our large sample of stock data, in addition to records of trades, provides records of login events allowing us to restrict our sample to days on which investors pay attention to their trading accounts. We define the peak price as the highest price achieved by an asset in the individual's period of ownership that remains the highest price for a persistent period of time (e.g., a period of weeks). We do so for both housing and stock markets, which represent the two largest, and distinct, asset markets in which individuals participate.[4]

Our empirical analysis confirms the importance of peak prices in individual trading decisions for both housing and stocks.[5] Our estimates reveal that the selling probability for stocks and homes more than doubles when returns since a past peak price turn positive. Whereas a stock (home) in gain since purchase but in loss since a past peak price is approximately 50% (40%) more likely to be sold, a stock (home) in gain since purchase *and* in gain since a past peak price is 130% (96%) more likely

[3] Genesove and Mayer (2001), e.g., show that real prices—nominal prices adjusted for inflation—do not predict reluctance to sell.

[4] We calibrate our definition of peak price to the frequency of price movements in each market, with peaks in stock prices occurring at higher frequency than peaks in house prices.

[5] Following the previous literature, our main analysis using the stock trading data focuses on days on which individuals sell at least one stock, though in the appendix (available online) we replicate our results for days on which individuals at least log in to their account.

to be sold. These discontinuities in the sale probability are found regardless of the magnitudes of gains or losses—with respect to either the peak price or the purchase price. In further tests, we show that the peak price result does not arise due to the peak price proxying for extreme observed returns since purchase. We also show that the peak price stands out from a suite of other candidate reference points (e.g., the highest price in the past month, quarter, or year) in explaining individual selling decision.

We evaluate two major psychological mechanisms that could underlie the peak price effect. One involves belief in reversion of prices to the peak. For either motivational reasons or due to the application of a heuristic, people might believe that the peak price represents an asset's true value and hence that an asset that has fallen below its peak value is likely to eventually revert back to it. A second mechanism involves preferences rather than beliefs: Having seen the asset rise to a particular level, then fall, an investor might regret not having sold at the peak and might choose to hold on to the asset in the hope that it would rise to, or go above, that peak level. That is, people might avoid selling an asset that is below its peak to avoid the experience of regret associated with selling the asset at a price lower than they could have sold it at.

Note that these two mechanisms are not mutually exclusive and, indeed, potentially interact with one another. For example, one would likely experience greater regret in selling below the peak if one believed that the asset was more likely to revert to the peak. And, in the opposite direction, an investor would likely be more aware of peak prices occurring while an asset is owned than prior to ownership.

Although not mutually exclusive, the belief-based mechanism does have a prediction that the regret-based one does not, and vice versa. Specifically, the belief-based mechanism predicts that people will be more likely to top-up—that is, purchase more shares of a stock they already own—when the asset is below its peak price and that this effect should occur both for peaks occurring during ownership and (albeit potentially to a lesser extent) peaks occurring prior to ownership. Likewise, the preference-based mechanism predicts a reluctance to sell stocks whose peak occurred during ownership but not stocks whose peaks occurred prior to ownership.

Consistent with the first of these mechanisms, we do find that the probability of an investor topping up their position in the same stock increases as losses since the peak price increase and that this effect occurs for peaks both during ownership and prior to ownership. Likewise, consistent with the preference-based mechanism, peak price events that occurred when the investor owned the asset do have a strong impact on selling decisions, but those occurring before the investor bought the asset do not affect sales. Consistent with other research showing that events that happen to oneself are much more salient to people than those that happen to others or at other times (Kaustia and Knüpfer 2008; Simonsohn et al. 2008; Herz and Taubinsky 2018; Malmendier, Pouzo, and Vanasco 2020; Hartzmark, Hirshman, and Imas 2021), we show that peak prices that predate the individual's purchase of the stock have no bearing on subsequent selling decisions. Hence, it is the individual's experience of the peak price that forms the enduring reference point.

Our main estimates are robust to a variety of econometric specifications and a wide range of controls, including the duration of holding, which has been shown to be important for understanding the disposition effect for stocks (Ben-David and Hirshleifer 2012). In a series of tests, we condition the model to include property (for housing) or investor (for stocks) fixed effects, flexible controls for returns since purchase and returns since the peak price event, and a range of controls for housing and stock characteristics, plus other controls for portfolio and investor characteristics. We conduct additional checks to address particular confounds that might apply specifically to the analysis of housing (e.g., the potential for a home mortgage to be underwater) or to stocks (e.g., effects arising from portfolio rebalancing). We find that the peak price effect does not arise due to these potential confounds.[6] Our results are also very similar when using hazard models to estimate the disposition effect, as in Seru, Shumway, and Stoffman (2010).

We interpret our results in light of a recent framework of the disposition effect in which asset prices experienced by the individual during their period of ownership can generate reference points for future decisions (Quispe-Torreblanca et al. 2024). The key assumption of the framework, motivated by diverse research in psychology, is that asset owners tend to focus on the highest of the different reference points they could pay attention to. Adopting an asset's highest price as one's reference point is self-serving in the sense that it assumes that the true value of an asset one purchased is the highest price that asset achieved, thus giving oneself maximum credit for making a smart purchase decision. Yet at the level of utility maximization, it may not be self-serving since it means that current market valuations will generally fall below one's reference value.[7]

[6] In the analysis of housing sales, we show that our results are not due to market liquidity or individual leverage, which might restrict selling opportunities (Stein 1995; Chan 2001; Ortalo-Magné and Rady 2004) and remain consistent after taking into account the time since purchase and the time since peak. In the analysis of stocks, further tests confirm that our results are not due to portfolio rebalancing; our results also remain consistent after taking into account overall market movements since the purchase of the stock and since the past peak price; and our results are consistent across samples of sell-days and login-days.

[7] The same pattern is evident in many other domains in life in which people tend to make upward social comparisons (Festinger 1954), which could be motivating but entails hedonic costs (Salovey and Rodin 1984). This tendency is probably largely responsible for the hedonic treadmill phenomenon (Lykken and Tellegen 1996), whereby people continually struggle to achieve aspirations but then raise them further the moment they are attained. In general, people do not seem to adopt the reference points that would make them hedonically best-off (Thaler 1985).

As do other theoretical perspectives that assume purchase price as the reference point, ours predicts a disposition effect with respect to gains and losses since purchase. The novel prediction introduced in our theoretical and empirical analysis is an additional disposition effect with respect to the peak price. One way to describe the joint effect of the two reference points is to say that an individual will be reluctant to sell whenever the price falls below the purchase price or the stock's peak price—indicative of an interaction effect. However, another way to interpret the same pattern is to say that there are simply two disposition effects, one on purchase price and one on peak price. The reason these are the same is that peak price can never fall below the purchase price; if it did (e.g., if the stock lost value continuously following purchase), then the purchase price would *be* the peak price. Because there is no situation in which the stock price relative to the purchase price is positive but negative relative to the peak price, the main effect of peak price is identical to the interaction effect between peak price and purchase price. This equivalence is important for our empirical analysis, in which we simply compute the two main effects, with no interaction term.[8]

Our study builds upon a large experimental literature and smaller field literature on the role of peak prices in individual decisions. An experimental literature beginning with Kahneman et al. (1993) presents evidence in support of a "peak-end rule," which states that agents judge an experience or event by how they felt at its peak and end rather than by the sum total, or the average, of every moment of the event (for a review of this literature, see Fredrickson 2000). Peaks play an important role in the subjective evaluation of magnitudes, including economic magnitudes. For example, in range-frequency theory (Parducci 1965, 1995), the range of values encountered—and the top of the range is the peak—provide the context against which magnitudes are evaluated, such that a higher peak makes any given magnitude seem smaller.[9]

Perhaps most relevant to the current research are previous studies in finance showing that peak prices serve as reference points in momentum trading strategies (George and Hwang 2004), as well as in merger and

[8] An illustration of the framework in a basic four-period setting is presented in the appendix.

[9] In laboratory choice experiments, where people choose whether to accept the chance to play mixed gambles (e.g., a 50% chance of gaining $10, otherwise a 50% chance of losing $5), experimentally manipulating the peak gain on offer in earlier choices changes the acceptance of a given gamble (Walasek and Stewart 2015; Walasek, Mullett, and Stewart 2021). For example, when the peak gain is high, which makes any given gain seem smaller, people are less likely to accept mixed gambles. In personnel economics, Heath, Huddart, and Lang (1999) show that employees are more likely to exercise stock options when the stock price exceeds the maximum price attained during the previous year. In strategic games, Anderson and Green (2018) show that chess players stop playing once they pass their previous maximum rating.

acquisition decisions (Baker, Pan, and Wurgler 2012). Furthermore, in popular news media, house price indexes are among the most commonly reported economic data, and turning points in the indexes are newsworthy events. Even just the tone of local housing news is found to be predictive of future house prices (Soo 2018; Ploessl and Just 2022). Price anchors (e.g., the 52-week high) are also commonly published alongside current prices. Hence, homeowners and investors in stocks are exposed to information on peak prices on a regular basis.

The disposition effect has been observed both in brokerage data across multiple countries and time periods (Grinblatt and Keloharju 2001; Brown et al. 2006; Barber et al. 2007; Calvet, Campbell, and Sodini 2009) and in experiments, for example, Weber and Camerer (1998). Theoretical and empirical research on the disposition effect has highlighted the importance of realization utility and loss aversion (Barberis and Xiong 2009; Frydman et al. 2014) as contributing mechanisms.[10] Odean (1998) shows that the disposition effect cannot be explained by portfolio rebalancing, transaction costs, a preference for realizing gains more frequently than losses, or different beliefs about expected future returns. In a laboratory experiment, Frydman and Rangel (2014) study the role of the salience of prices in the disposition effect and find that the strength of the disposition effect depends on the salience of the purchase price.[11]

Our findings also contribute to the growing literature studying the consequences of salience and attention for individual behaviors. Arkes et al. (2010) study the shift in each subject's reference point following prior gains or losses. Their experimental evidence suggests that reference point adaptation is asymmetric: adaptation following a gain is greater than following a loss. Earlier work suggests that the first and last prices act as reference points. Baucells, Weber, and Welfens (2011) explore the determinants of investor reference points by exposing participants to hypothetical sequences of stock prices in a laboratory experiment. They find that a stock's starting and ending prices are the two most important inputs into an investor's reference point. More generally, research in the psychology literature documents that participants exposed to a series of stimuli tend to remember better the first and the most recent values (Ebbinghaus

[10] Other studies have, however, questioned the importance of these elements (Kaustia 2010; Hens and Vlcek 2011; Henderson 2012).

[11] There is also evidence that the disposition effect tends to be stronger in retail investors, as compared with institutional investors (Genesove and Mayer 2001; Shapira and Venezia 2001), less experienced investors (Feng and Seasholes 2005), and investors who are lower in wealth (Dhar and Zhu 2006). In more recent research, the disposition effect has, however, been shown to not arise for mutual funds (Chang, Solomon, and Westerfield 2016). The focus of our analysis of stock market investors is, however, on sales of individual stocks rather than index funds or mutual funds.

1913; Murdock 1962; Ward 2002). We extend this line of work by empirically testing the effects of another salient reference point, the peak price.

More generally, our study expands a new line of research on how multiple reference points interact to determine individual choices. Very few empirical papers have examined the consequences for decision-making of situations in which specific outcomes are evaluated against multiple reference points, despite evidence of reference-dependent behavior in a variety of settings.[12] Studies documenting the importance of different reference points have tended to examine each in isolation.[13] Prior research has, moreover, typically involved hypothetical choices (see, e.g., Sullivan and Kida 1995; Ordóñez, Connolly, and Coughlan 2000) or stylized laboratory experiments (Koop and Johnson 2012), although one recent empirical study found that purchase price and neighborhood price influenced the length of ownership in Singapore's private housing market (Huang, Lien, and Zheng 2021). A limited number of studies explore how multiple reference points affect choices on separate dimensions, such as income and work hours (Crawford and Meng 2011) or goals and experience (Markle et al. 2018). Another strand of the literature seeks to understand how reference points relate to regret theory in dynamic decisions (Strack and Viefers 2021; Brettschneider, Burro, and Henderson 2025).

The remainder of the paper proceeds as follows. Section II describes the two datasets (home sales and stockbroking data), and section III explains, for each, the methodology we used to calculate returns since purchase and since peak. Section IV presents the econometric specification used in the analysis and describes the sample selection restrictions. Sections V and VI present the main results for housing and stocks. Section VII presents the analysis of ownership and mechanisms for the peak price effect. Section VIII estimates the economic cost of selling at the peak price. Section IX concludes.

[12] Studies of reference-dependent behavior in the context of multiple reference points include consumer products marketing (Hardie, Johnson, and Fader 1993), tax compliance (Yaniv 1999), food choices (Van Herpen, Hieke, and van Trijp 2014), and effort in sports (Allen et al. 2016).

[13] For example, people evaluate the salary they receive from work relative to what they received in the past (Bewley 2009; DellaVigna et al. 2017) but also relative to what they expected to receive (Kőszegi and Rabin 2006; Mas 2006; Crawford and Meng 2011), what others receive (Brown et al. 2008; Card et al. 2012; Bracha, Gneezy, and Loewenstein 2015), and what they would like to receive (aspirations; March and Shapira 1992; Heath, Larrick, and Wu 1999). Neale and Bazerman, in a book describing research on negotiation (cited in Kahneman 1992), identify five possible reference points that might influence worker responses to a wage offer from management: last year's wage, management's initial offer, the union's estimate of management's reservation point, the union's reservation point, and the union's publicly announced bargaining position.

II. Data

A. *Home Sales Data*

We use data on home sales provided by the United Kingdom's principal registry of home sale data, His Majesty's Land Registry (HMLR) Price Paid Dataset (PPD).[14] The price paid data contain entries for the universe of residential property sales in the United Kingdom beginning on January 1, 1995. We draw upon records up to and including December 31, 2019. In total, the dataset covers 25.1 million transactions relating to 14.6 million properties. The data record the date and price of each property purchase, the property's address, and property characteristics, including whether the property is a new-build home or a resale and the type of dwelling.[15] With these data, we can identify property resales, where an individual purchases a property and then sells it at a later date. The vast majority of homes in the dataset are primary family homes, with second and further homes in the United Kingdom accounting for only 3% of the housing stock (English Housing Survey 2021–22). Taxes are not applicable to gains (or tax deductions applicable to losses) on primary family homes, hence tax rules do not affect the decision to sell a home in our data.

Unlike stocks, for which the current market price is continually available, houses have only an up-to-date market price at the time of their sale; consequently, we estimate each property's valuation each calendar quarter from purchase to sale. To do so, we combine the price paid data with a local-level house price index to create property × quarter observations of property values, which is the unit of observation for our analysis of the disposition effect for housing. We draw upon the UK House Price Index (HPI) using records for England and Wales (EW). The index is constructed by the UK Office of National Statistics (ONS) using the price paid data as well as local government property tax and demographic datasets to determine property and location characteristics.[16] The index is a strong predictor of sales prices. The correlation between a property's most recent quarterly valuation prior to sale based upon the index value and the actual sale price achieved is 0.9.[17]

[14] The United Kingdom consists of the four nations of England, Northern Ireland, Scotland, and Wales. Northern Ireland and Scotland, which comprise 7.5% of the UK population, have separate land registries.

[15] Dwelling types are flat, or apartment; detached house, one with no walls shared with neighboring property; semidetached house, shares a common wall on one side; and terraced house, shares common walls on both sides.

[16] The ONS applies a hedonic regression model to the data sources to produce estimates of property price changes for each period (ONS 2016). We use the indexes for each calendar quarter between January 1, 1995, until December 31, 2019, by dwelling type and at the most granular level of geographic area provided, which are the 340 EW local government districts.

[17] This is illustrated in fig. A2 (figs. A1–A19 are available online).

In our analysis, we also use the difference between the price paid for a property (as recorded in the price dataset) and the average value of properties of the same type in the locality as a measure of "quality," following Genesove and Mayer (2001). In addition, we merge in a set of local-level covariates, including the size of the housing stock, volume of property transactions, and average loan-to-value (LTV) ratio.[18]

1. Sample Selection

We apply a number of steps in sample selection. First, as our interest is in the selling behavior of owners of standard residential properties, we drop nonstandard sales (as defined by HMLR). These include commercial transactions, properties purchased specifically to be rented out (where identifiable), gifts, and sales below full market value or under court or compulsory purchase order. At this step, we also drop a very small number of properties sold for token values (less than £250). Second, we drop properties with incomplete address details. A property's address is used to match its purchase with any subsequent sale and to link the property with the other datasets. Properties without full addresses, or that for other reasons cannot be matched to the HPI dataset, are necessarily excluded. Third, we drop a small number of observations with apparent data errors, such as properties owned for less than a week before resale.

Together, these restrictions result in 3.1% of properties being dropped from the dataset. Due to computational limits, we then take a 15% random sample of the total data. We use this baseline (or "full") sample of approximately 3.6 million home purchases and 128.4 million observations for the estimates of the disposition effect based upon returns since purchase. Additionally, observations where there is no peak price achieved that differs from the purchase price (e.g., due to a very recent purchase) are necessarily dropped for the estimates of the disposition effect based upon returns since purchase and since peak, with approximately 2.4 million property purchases and 72.1 million observations retained in this "peak subsample."[19]

[18] The annual estimated housing stock for England and Wales districts is published by the Ministry of Housing, Communities and Local Government (for English districts) and the Welsh Government (for Welsh districts). Data are available from March 31, 2001, to March 31, 2018. Quarterly housing stock is estimated by linear interpolation of the annual figures. The number of property transactions by district and calendar quarter is derived from the PPD dataset. The PPD, HPI, and housing stock datasets are publicly available, online, and free. Additionally, the Financial Conduct Authority (FCA), the conduct regulator for the UK financial services sector, provided to us a private dataset of quarterly LTV ratios for remortgagers by the 10 EW regions between the second quarter 2005 and the fourth quarter of 2019. This is an extension of a table that the FCA makes public as part of their quarterly Mortgage Lenders and Administrators Return. The 10 EW regions are shown in table A5 (tables A1–A45 are available online).

[19] Further details of sample selection are provided in table A2.

2. Summary Statistics

The proportion of properties by dwelling type ranges from 16.2% for flats to 29.7% for terraced houses, with new-build properties representing 10.0% of all transactions. The median purchase price is £250,000, and the corresponding mean is £333,000.[20] The median time to resale (i.e., length of ownership) is 8.8 years, and the corresponding mean is 9.6 years.[21]

B. Stockbroking Data

We use brokerage data provided by Barclays Stockbroking, an execution-only online brokerage service operating in the United Kingdom. The data cover the period from April 2012 to March 2016 and include daily-level records of all trades and quarterly-level records of all positions in the portfolio. Barclays provides brokerage services for both common stocks and mutual funds, although the former are much more common in the portfolios of investors using Barclays Stockbroking. By combining the account-level data with daily stock price data, we can calculate the value of each stock in an investor's portfolio on each day of the sample period. This data construction allows us to track prices at daily frequency, which is the time unit we use in the analysis. The unit of observation used in the analysis is investor $\times$ stock $\times$ day.

We focus on new accounts that open after the beginning of April 2012, as this sample restriction allows us to calculate returns since purchase on all stocks held within the account, which is required for the estimation of the disposition effect. This provides a starting sample of approximately 13,600 accounts and approximately 123,000 observations in which an investor makes a sale.

1. Sample Selection

We apply two stages of sample selection. At the first stage, we drop observations due to data cleaning restrictions. We drop observations for which we cannot match stocks with price data. We also drop observations for which there is an unknown purchase price because the position was transferred into the account after opening (e.g., from a different brokerage

[20] In the summary statistics, prices are adjusted to December 2019 prices, but in our main analysis, we use nominal prices, as the disposition effect is calculated as a gain or loss vs. the nominal purchase price.

[21] North East England has the lowest proportion of property transactions (4.5% of all transactions), whereas London and South East England have the highest proportions (13.4% and 17.0% of all transactions; see table A5). Table A4 provides summary statistics for the baseline sample of property $\times$ quarter observations.

service provider). Together, these restrictions result in 1,196 accounts and 29,700 sales being dropped from the sample.

At the second stage, we apply a series of restrictions necessary for the topic of analysis. First, following Odean (1998), we keep only observations for which we observe at least two stocks in the portfolio on the day of observation. This restriction allows us to analyze selling decisions when investors have the possibility to choose which stock they prefer to sell among the set of stocks they hold in their portfolio. We also drop accounts for which there are missing demographic data. In a third step, we exclude the days in which the stocks were purchased (days when stocks started a positive position) since we are interested in analyzing trades for stocks that have been held at least 1 day in the portfolio—also, note that day-trading is usually performed by professional investors, whose trading strategies differ from those used by retail investors. In a fourth step, we also drop accounts for which there are no sales in the sample period, resulting in a drop of 1,244 accounts but no sales. Finally, we drop observations for which the returns since purchase and/or returns since peak price (defined below) are above the 99th percentile or below the 1st percentile, to remove outliers from the data that might skew the analysis. The resulting baseline sample retains approximately 8,800 accounts and 58,863 observations of sales.[22]

2. Summary Statistics

Approximately 85% of the account holders are male, and the average age of an account holder is 48 years. A similar profile for account holders is observed in the Large Brokerage Dataset used by Barber and Odean (e.g., see Barber and Odean 2001).[23] The average tenure of an account is approximately 1 year. The average portfolio value is approximately £43,000, with a right-skewed distribution with a median portfolio value of approximately £10,000.

The large majority of holdings in the sample are common stocks. By value, investors hold only 5.6% of their position in mutual funds (a small minority of investors hold only mutual funds in their portfolio). Investors also overwhelming hold positions in a few common stocks. On average, investors hold only four stocks, with the median number of stocks held being three.[24]

[22] A breakdown of the steps in sample selection is shown in table A3.

[23] In the large discount brokerage (LDB) dataset used in Barber and Odean (2001), 79% of account holders are male, with an average age of 50 years; see table 1 in Barber and Odean (2001).

[24] Note that in sample selection, we dropped observations in which investors held only one stock in their position. Hence, the unconditional mean of the number of stocks held is lower than four in the starting sample.

They log in once every 4 days (median 6) and make a trade (either a buy or a sell) roughly every 20 market days.[25]

III. Calculation of Returns

Our main analysis uses two calculations of returns: return since purchase and return since peak price. For housing, quarterly returns are calculated via application of the house price index at the locality. Returns since purchase are the difference between the valuation of the property and purchase price. For stocks, returns are calculated using daily prices. Returns since purchase represent gross returns on the asset prices over the holding period and in cases of multiple purchases of a stock, returns are calculated as a weighted average.[26] For housing and stocks, in addition to returns, we also define a dummy variable indicating whether the value of the asset is in gain or loss since purchase (i.e., whether the return since purchase is positive or negative).

An innovation of our study is to introduce the concept of return since peak. Return since peak price measures the return since the asset's most recent peak price. "Peak price" requires definition. We define the peak price as the highest price achieved by an asset in the individual's period of ownership that remains the highest price for a persistent period of time. Central to this definition is the idea that a peak price is a price that has persisted as the highest price for some period. For example, an asset that monotonically increases in value in each period could not be said to have formed a "peak" in any period, but an asset that hits a high price from which it then falls for a number of periods could be said to have achieved a peak.[27] Analogous to a series of peaks in a mountain range, peaks are salient price points in the history of the individual's ownership of the asset.[28] This definition captures the idea that a "peak" occurs when an asset reaches a high value that stands out in its recent history. In our main analysis, we define a peak house price as the highest price achieved by the house in the homeowners' holding period that remains the highest price for at least three calendar quarters. We define a peak stock price as the highest price

[25] Full summary statistics for the baseline sample are shown in table A6.

[26] For housing and stocks, gross return is calculated before fees (e.g., real estate fees or brokerage fees). Gross returns for housing are calculated as levels rather than as percentages to be consistent with the way homeowners commonly describe the change in value of their properties, unlike stocks where investors' personal brokerage accounts display the percentage changes.

[27] An extreme case would result if every new high was considered a peak. Under that implementation, in a monotonically increasing price series, every day would see a new peak price.

[28] By constraining the search for peaks to the individual's ownership period, we avoid extreme cases that would result if only the all-time high was considered to be a peak, e.g., a stock that has a historical peak many years earlier but has recent price spikes that would not constitute peaks using the all-time-high definition.

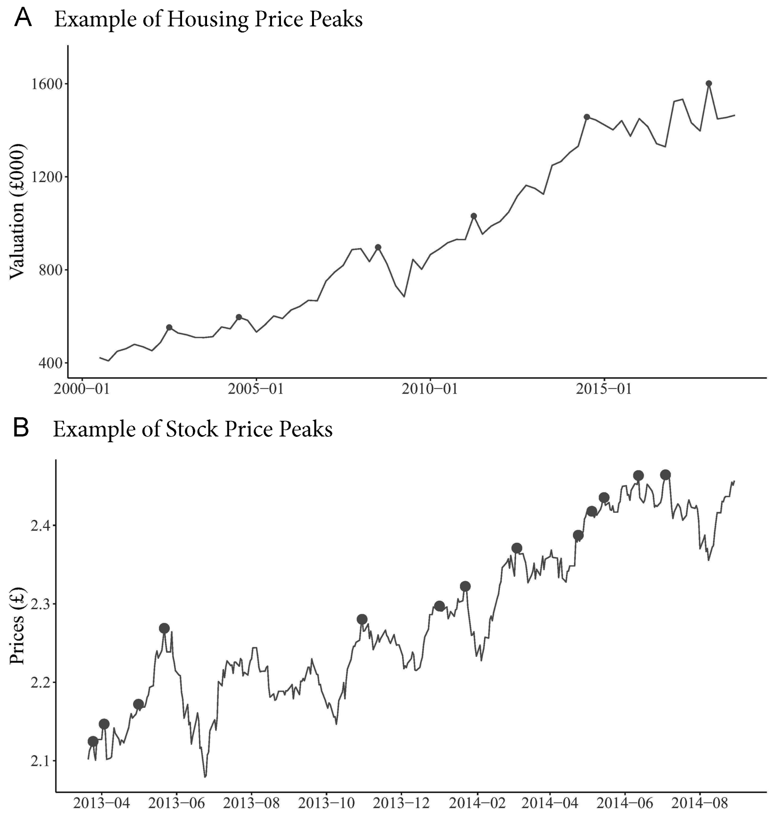

FIG. 1.—Examples of peak prices. The figure illustrates the sequence of peak prices for a single example home (*A*) and a single example stock (*B*). For the case of houses in panel *A*, a peak price is defined as the highest price (since purchase) that lasts for at least three quarters; while for the case of stocks in panel *B*, the peak price must last for a week. In both cases, a new price can only be a peak if it is higher than the purchase price and all previous peaks.

achieved by the stock in the investor's holding period that remains the highest price for at least 1 week.[29]

We illustrate the concept of a peak price using examples for housing and stocks. Figure 1*A* illustrates a quarterly price series for a single property selected from the data. The price series, for the full data period since the property was first purchased, shows the house price drifting upward

[29] This definition of peak price is different from the concept of an all-time high or low price. All-time high or low prices are defined by the day's price breaching the maximum or minimum of the complete to-date series. A peak price, by contrast, is a salient peak within the individual's own personal experience of the asset price. The salience of the peak may arise due to its persistence, whereby the peak remains the highest point in the price series for some period of time.

(with a notable drop in 2009 during the Great Recession). A peak price is defined using the three-quarter persistence criterion. Each circle shows a price that is the highest price since the start of the period and that remains the highest price for at least three quarters.[30] Figure 1*B* illustrates a daily price series of a commonly purchased stock in the data. The price series shown runs from April 2013 to September 2014 and shows the stock price drifting upward. A peak price is defined using the 1-week time horizon. Each circle shows a price that is the highest price since the start of the period and that remains the highest price for at least 1 week.[31] For housing and stocks, in addition to returns since peak, we also define a dummy variable by whether the value of the asset is in gain or loss since peak price.

Using this method, we calculate returns since purchase and returns since peak for observations in the baseline sample. For housing, the distributions of returns since purchase and since past peak price are both positively skewed, reflecting medium-term positive house price growth in the United Kingdom. For stocks, the distributions of returns since purchase and since past peak resemble a normal distribution, reflecting the relatively flat medium-term stock market performance in the United Kingdom.[32]

IV. Econometric Model

We estimate the disposition effect using the standard model in the empirical literature based upon Chang, Solomon, and Westerfield (2016), which we apply to housing and stocks. The standard model takes the form

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + \epsilon_{ijt}, \tag{1}$$

in which the unit of observation for housing is at the property (j) and date (t) level, with quarterly measures of returns since purchase. *Sale* is a dummy equal to 1 if the homeowner sells their property (j) on date (t). *GainSincePurchase* is a dummy variable indicating whether the property (j) had made a gain on date (t) compared with the purchase price. For stocks, the unit of observation is at the account (i), stock (j), and date

[30] In a sensitivity analysis, we widen this to two-quarter and four-quarter time horizons. Each circle in fig. A8 shows a price that is the highest price since the start of the period and that remains the highest price for at least two quarters (fig. A8*A*) or four quarters (fig. A8*B*).

[31] In sensitivity analysis, we widen this to a 1-month time horizon; see fig. A14.

[32] We illustrate and summarize the distributions of returns in more detail in the appendix. For housing, see figs. A3–A7 and tables A7–A9. Additional summary data for a two-quarter time horizon definition of a peak are shown in fig. A9 and table A11 and for the four-quarter definition in fig. A11 and table A12. For stocks, see fig. A13 and table A10, with additional summary data for the 1-month time horizon definition of a peak shown in figs. A14 and A15 and table A13.

(t) level. Note that, given the detailed stock data, we can construct daily measures of returns since purchase. *Sale* is a dummy equal to 1 if the investor holding account (i) sells the stock (j) on date (t). *GainSincePurchase* is a dummy variable indicating whether, for the investor holding account (i), stock (j) had made a gain on date (t) compared with the purchase price.

We modify the baseline specification in equation (1) by adding a dummy variable indicating whether the asset is in gain compared with the peak price. We call this dummy variable *GainSincePeak*. The modified econometric specification is now

$$Sale_{ijt} = b_0 + b_1 GainSincePurchase_{ijt} + b_2 GainSincePeak_{ijt} + \epsilon_{ijt}, \quad (2)$$

in which *GainSincePeak* is a dummy indicating whether property (j) was in gain at date (t) compared with the peak price (housing), or for the investor (i), stock (j) was in gain at date (t) compared with the peak price (stocks).

The variable *GainSincePeak* therefore adds a new element to the estimation of the disposition effect. Note that in the modified econometric specification in equation (2), the dummy variable indicating whether a property $\times$ date (housing) or an account $\times$ stock $\times$ date (stocks) is in gain since peak constitutes an interaction with gain since purchase. This is because, by definition, a gain since the past peak must also be a gain since purchase, as the peak price cannot be lower than the purchase price. If the value continuously fell after purchase, the purchase price would be the peak.

We estimate both equation (1) and equation (2), allowing us first to replicate the standard estimation of the disposition effect from equation (1) before introducing results from the revised specification in equation (2). In subsequent robustness analyses, we also estimate models that add (i) property (housing) or investor (stocks) fixed effects to control for property-specific or individual-specific time-invariant heterogeneity in selling behavior, (ii) continuous measures of returns since purchase above and below the zero threshold, and (iii) a more extensive battery of control variables, including controls for property characteristics and several investment portfolio and account characteristics. In addition, we (iv) show that our results remain consistent when estimating a different econometric estimation approach, a Cox proportional hazard model with time-varying covariates, and (v) show that our results remain consistent when using different time horizons in the definition of a peak price.[33] In the

[33] For the stockholding analysis, results also remain consistent when restricting the analysis to liquidations of entire positions from the portfolio (i.e., excluding partial sells that could occur as a result of portfolio rebalancing strategies).

stockholding analysis, we also perform a placebo test using peak prices that occurred within the past year, instead of peak prices strictly taking place during the holding period.[34] We show that the disposition effect around peak prices is found only when the investor has experienced the peak price (i.e., when the peak occurred during the holding period).

V. Peak Price Effects in Home Sales

A. *Returns since Purchase Price and the Disposition Effect*

The disposition effect based upon the purchase price is not as widely documented among housing sales compared with stock sales. Therefore, we first show results based on purchase price, together with a series of robustness tests, before introducing our results for the disposition effect based upon the peak price.

We draw upon our baseline sample of observations of property × quarters.[35] The unconditional relationship between return since purchase and probability of sale is illustrated in figure 2*A*. The figure is a binned scatterplot, with each point representing a 0.5% bin of observations. Figure 2*A* illustrates the housing disposition effect for returns since purchase; the probability of sale increases sharply when returns since purchase turn positive. In the unconditional plot, the increase in the probability of sale is approximately 0.5%, against a baseline probability of approximately 0.7%, representing a greater than 70% increase in the probability of sale.[36]

This result is confirmed by the ordinary least squares (OLS) regression estimate for equation (1) shown in table 1. Column 1 shows the unconditional relationship between the sale of the property and the dummy for gain since purchase. The coefficient on gain since purchase of 0.0053 is positive and implies that a house that is in gain since purchase is 0.53 percentage points more likely to be sold than a house in loss. Against the base probability of selling a house from the constant in the regression of 0.7% (0.0070), this represents an increase of 75%.

Column 2 adds a set of nonlinear controls for the number of years between purchase and valuation (included as quintics) and controls for

[34] This exercise is possible because stock prices show a higher frequency of peak price dates than peak house prices, which cluster around relatively few dates (fig. A5).

[35] The baseline sample that provides over 128 million property × quarter observations pools together properties and calendar quarters, hence we cluster standard errors at the property and date level.

[36] Figure 2*A* exhibits a small flat portion to the right of zero on the *x*-axis, indicating that over a small interval of the data, the probability of sale does not increase with returns since purchase. This is a feature of the data pre-October 2007, the timing of the onset of the financial crisis in the United Kingdom, which is not present in the data from October 2007 onward (see fig. A6). The flat interval shown in fig. 2*A* contains 4.75% of the observations in the figure and does not materially change the results in the paper.

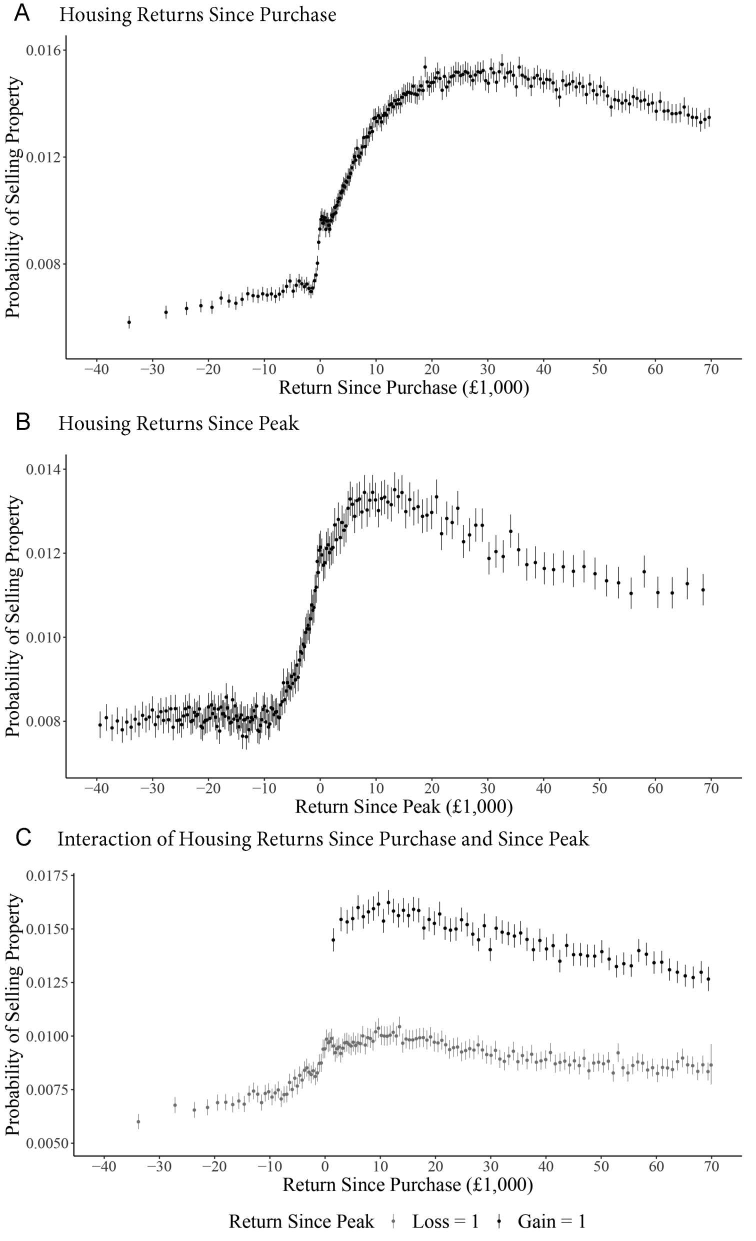

FIG. 2.—Probability of housing sale, returns since purchase, and returns since peak. The figure shows the probability of house sales against return since purchase and return since peak price. Panels display binned scatterplots to illustrate the relationship between the probability of sale and returns since purchase (*A*), returns since peak price (*B*), and the interaction between returns since purchase and returns since peak price (*C*). For visual purposes, returns are restricted to the range of −£40,000 and +£70,000, otherwise observations include all property × quarters in the baseline sample. Vertical lines represent 95% confidence intervals.

TABLE 1
PURCHASE PRICE DISPOSITION EFFECT FOR HOUSING: OLS ESTIMATES

	$Sale_{it}$	
	(1)	(2)
Gain since purchase = 1	.0053***	.0074***
	(.0005)	(.0006)
Years from purchase		.0074***
		(.0005)
Detached = 1		−.0055***
		(.0004)
Semidetached = 1		−.0040***
		(.0003)
Terraced = 1		−.0017***
		(.0002)
New-build = 1		.0016***
		(.0002)
Quality (£100,000)		−.0005***
		(.0000)
Constant	.0070***	.0030***
	(.0003)	(.0004)
Years from purchase quintics	No	Yes
Region	No	Yes
Observations	128,444,588	128,444,588
R^2	.0002	.0017

NOTE.—Ordinary least squares (OLS) regression estimates. The dependent variable takes a value of 1 if the homeowner sold their property and zero otherwise. Column 1 displays the baseline specification. Column 2 adds controls for year since purchase and property characteristics. Years from purchase constitute the length of the property's ownership at valuation and are evaluated as quintics. Property characteristics include detached, semidetached, and terraced, which take the value of 1 if the property is of that type, otherwise zero (for the case of apartments). New-build takes a value of 1 if the property was acquired as a new development, otherwise zero if acquired as a resale. Quality is a proxy measure of the caliber of the property (computed following Genesove and Mayer 2001). Region is the official England and Wales region where the property is located. Observations include all property × quarters in the baseline sample. Standard errors (in parentheses) are clustered by property and year-quarter.
*** $p < .01$.

property characteristics. Property characteristics are the property's type, whether it is new-build, its regional location, and its quality.[37] The coefficient of 0.74% (0.0074) in column 2 implies that a property in gain since purchase is twice as likely to be sold than a property in loss (the latter value defined by the unconditional probability of selling a house at a loss, given by the constant in col. 1, of 0.7%).

[37] Quality is proxied by the difference between the purchase price and the price at purchase predicted by the house price index, a measure of the quality suggested by Genesove and Mayer (2001).

TABLE 2
Purchase Price Disposition Effect for Housing: Liquidity, Market Size, Leverage, and Time since Purchase Tests

	Gain Since Purchase		Constant	
Liquidity (sales):				
Above median	.0051***	(.0005)	.0063***	(.0004)
Below median	.0043***	(.0004)	.0047***	(.0003)
Size (stock):				
Above median	.0064***	(.0007)	.0043***	(.0004)
Below median	.0059***	(.0006)	.0039***	(.0004)
Leverage (LTV%):				
Above median	.0024***	(.0005)	.0043***	(.0004)
Below median	.0052***	(.0008)	.0024***	(.0007)
Time since purchase:				
Above median	.0028***	(.0005)	.0246***	(.0077)
Below median	.0066***	(.0005)	.0062***	(.0005)

Note.—Ordinary least squares regression estimates for our baseline specification for separate samples divided by liquidity, market size, leverage, and time since purchase. The full estimates are presented in tables A14–A17. Each row reports coefficients and standard errors (in parentheses) from a single regression in which the dependent variable takes a value of 1 if the homeowner sold their property and zero otherwise. There are covariates for continuous returns since purchase; the years from purchase and property characteristics are equivalent to those in col. 1 of table A28. Column 1 displays the main coefficient of interest for the gain since purchase dummy. Column 2 shows the intercept to enable a better interpretation of the effect size of the gain since purchase dummy. Observations include all property × quarters in the baseline sample. Standard errors are clustered by property and year-quarter.
*** $p < .01$.

This result is robust to a range of additional tests to account for market conditions, including liquidity, market size, and leverage, as well as time since purchase; see table 2. These tests are important as, for example, highly levered mortgagors (at the limit, 100% levered) may be unable to sell at any price below the purchase price. We measure housing market liquidity using the number of housing transactions per quarter; housing market size, using housing stock volumes per quarter; and homeowner's leverage, using quarterly LTV percentages. Then, for each case, we split the dataset at the median value of the variable of interest (housing transactions, housing stock, LTV percentage, or time since purchase) and estimate the OLS regression models specified by equation (1) for the "high" (above-median) and "low" (below-median) subsets. The pattern of positive coefficients demonstrates that the disposition effect for gain since purchase exists in above- and below-median samples in each case.[38]

[38] Across the above- and below-median splits, the coefficient estimates on the gain since purchase dummy in table 2 are consistent in magnitude when evaluated relative to the model constants, also shown in the table. Full results for these tests relating to liquidity, size, leverage, and time since purchase are shown in tables A14–A17.

B. *Returns since Peak Price and the Disposition Effect*

Our main result is the existence of a disposition effect arising from a past peak price. We use the baseline sample of observations of property × quarters with a peak price.[39] Figure 2*B* is a binned scatterplot illustrating the relationship between the probability of sale and returns since peak price. It reveals the existence of a housing disposition effect for returns since the peak price. Similar to figure 2*A*, here we also observe a sharp increase in the probability of sale when returns since peak price turn positive (i.e., when the property price crosses its previous peak). Given we define peak prices as the highest prices achieved by the asset during the holding period, any gains since a past peak price inherently suggest a gain since purchase. Conversely, any loss since purchase also implies a loss from a past peak price.[40] Figure 2*C* shows the interaction of returns since purchase and returns since a past peak. There is a strong interaction effect: the disposition effect for returns since purchase doubles its magnitude when the house price is in gain since a past peak.

Table 3 shows the results from OLS regression models. Columns 1–3 show unconditional estimates for coefficients on the *GainSincePeak* and *GainSincePurchase*, independently in columns 1 and 2, and combined in column 3. The coefficients in column 3 are positive for both gain since purchase and gain since peak. Column 4 introduces control variables including years from purchase, property-type controls, and the quality measure used previously. The model also includes nonlinear controls (quintics) for the length of period since purchase and region fixed effects. Coefficients for gain since peak and gain since purchase are positive and precise.

Unconditional estimates in column 3 suggest that a home in gain since purchase but in loss since peak price is approximately 0.10 percentage points more likely to be sold (representing a 13% increase), whereas a home in gain since purchase and in gain since peak price is 0.41 percentage points more likely to be sold (representing a 55% increase, both effects evaluated against a baseline probability of 0.75%, given by the intercept), an effect size consistent with the patterns observed in figure 2*C*. Including controls in column 4 leads to even larger effects. A home in gain since purchase but in loss since peak price is approximately 0.36 percentage points more likely to be sold (representing a 48% increase), whereas a home in gain since purchase and in gain since peak price is approximately 0.72 percentage points more likely to be sold (representing a 96% increase, with both effects evaluated against the same baseline probability of 0.75%, given by the intercept of col. 3).

[39] This baseline subsample provides more than 72 million property × quarter observations.

[40] In the analysis of stock sales where we define peak prices as the highest prices achieved in the past year—regardless of the investment holding period—there might be instances where the peak price may be lower than the purchase price. Such cases are exceptionally rare, making up fewer than 1% of our observations.

TABLE 3
Purchase and Peak Price Disposition Effects for Housing: OLS Estimates

	$Sale_{it}$			
	(1)	(2)	(3)	(4)
Gain since purchase = 1	.0024***		.0010***	.0036***
	(.0004)		(.0003)	(.0004)
Gain since peak = 1		.0033***	.0031***	.0036***
		(.0005)	(.0005)	(.0005)
Years from purchase				.0053***
				(.0007)
Detached = 1				−.0039***
				(.0003)
Semidetached = 1				−.0034***
				(.0003)
Terraced = 1				−.0020***
				(.0002)
New-build = 1				.0013***
				(.0001)
Quality (£100,000)				−.0002***
				(.0000)
Constant	.0075***	.0084***	.0075***	.0021**
	(.0003)	(.0003)	(.0003)	(.0009)
Years from purchase quintics	No	No	No	Yes
Region	No	No	No	Yes
Observations	72,113,609	72,113,609	72,113,609	72,113,609
R^2	.0001	.0003	.0003	.0011

Note.—Ordinary least squares regression estimates for our modified baseline specification that incorporates gain since peak price. The dependent variable takes a value of 1 if the homeowner sold their property and zero otherwise. Years from purchase constitute the length of a property's ownership at valuation and are evaluated as quintics. Property characteristics include detached, semidetached, and terraced, which take the value of 1 if the property is of that type, otherwise zero (for the case of apartments). New-build takes a value of 1 if the property was acquired as a new development, otherwise zero if acquired as a resale. Quality is a proxy measure of the caliber of the property (computed following Genesove and Mayer 2001). Region is the official England and Wales region where the property is located. Observations include all property × quarters in the baseline sample with a peak price. Standard errors (in parentheses) are clustered by property and year-quarter.

** $p < .05$.

*** $p < .01$.

In the following subsection, we test the robustness of our main result with additional tests.

C. *Robustness Tests*

1. Controls for Continuous Returns and Property Fixed Effects

In tables A27 and A29, we add further covariates to the main specification. Both tables show estimates for the coefficients on the *GainSincePeak* and *GainSincePurchase*, independently in columns 1 and 2, and combined in column 3. Table A27 includes all the controls from column 4 of table 3, plus continuous measures of returns since purchase, with separate linear controls for returns on either side of zero. Estimates show positive coefficients on both gain since purchase and gain since peak. In table A29, we add property and year-quarter fixed effects to account for unobserved heterogeneity across properties and time periods. The estimates again show positive and precisely defined coefficients for gain since purchase and gain since peak.

2. Liquidity, Market Size, Leverage, Time since Purchase, and Time since Peak

In table 4, we replicate the robustness tests for market liquidity, market size, leverage,[41] and time since purchase described earlier, and carry out a similar robustness test for time since peak. All the above- and below-median samples show the disposition effect for gain since purchase and gain since peak, except for the above-median sample of time since purchase. Here there is no gain since purchase disposition effect. A small percentage of observations (9.5%) in this sample are in loss since purchase, suggesting collinearity between the gain since purchase dummy and the model's intercept, thus resulting in larger standard errors.

We note that our results highlight a stronger effect of peak prices after a short period of time has passed since a previous peak price. It may be that homeowners refinance at a peak, thus reducing their ability to sell their properties (Genesove and Mayer 1997). This mechanism, however, will result in homeowners being less able to sell their homes when losses from a previous peak are substantial. However, a closer inspection of figure 2*B* rules out this possibility. Figure 2*B* shows that the extent of losses since peak does not alter selling patterns.

3. Additional Robustness Tests

Additional robustness and sensitivity tests are presented in the appendix. To better account for the effects of the holding period, we estimate a Cox proportional hazard model that exploits the duration dimension of the data, which is an important determinant of asset-selling decisions (Ben-David and Hirshleifer 2012). The hazard model allows us to estimate the time-varying probability of a sell event without imposing any structure on the baseline hazard (i.e., without specifying the exact form of the distribution of the sell event times).

The three-quarter time horizon used to define peak prices was selected as a pragmatic lower bound. The quarter following a high price is required

[41] Similar to Andersen et al. (2021), we find a stronger disposition effect in low-leveraged households. Detailed models estimates are provided in the appendix; see tables A18–A22.

TABLE 4
Purchase and Peak Price Disposition Effects for Housing: Liquidity, Market Size, Leverage, Time since Purchase, and Time since Peak Sensitivity Tests

	Gain Since Purchase		Gain Since Peak		Constant	
Liquidity (sales):						
Above median	.0031***	(.0004)	.0036***	(.0005)	.0021*	(.0012)
Below median	.0020***	(.0003)	.0031***	(.0004)	.0039***	(.0008)
Size (stock):						
Above median	.0027***	(.0004)	.0041***	(.0006)	.0008	(.0010)
Below median	.0025***	(.0004)	.0036***	(.0007)	.0042***	(.0012)
Leverage (LTV%):						
Above median	.0015***	(.0004)	.0020***	(.0004)	.0040***	(.0008)
Below median	.0027***	(.0005)	.0036***	(.0006)	.0034***	(.0010)
Time since purchase:						
Above median	−.0002	(.0015)	.0017***	(.0002)	−.0054	(.0237)
Below median	.0021***	(.0004)	.0057***	(.0007)	.0038**	(.0019)
Time since peak:						
Above median	.0023***	(.0002)	.0021***	(.0003)	.0153**	(.0064)
Below median	.0031***	(.0005)	.0049***	(.0008)	.0011	(.0008)

Note.—Ordinary least squares regression estimates for our modified baseline specification for separate samples divided by liquidity, market size, leverage, time since purchase, and time since peak. The full estimates are presented in tables A18–A22. Each row reports coefficients and standard errors (in parentheses) from a single regression in which the dependent variable takes a value of 1 if the homeowner sold their property and zero otherwise. There are covariates for return since purchase, return since peak, years from purchase quintics, and property characteristics equivalent to col. 3 of table A27. Columns 1 and 2 display the main coefficient of interest for the gain since purchase and gain since peak price dummies. Column 3 shows the intercept to enable a better interpretation of the effect size of the gain dummies. Observations include all property × quarters in the baseline sample with a peak price. Standard errors are clustered by property and year-quarter.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

to establish that this price is indeed a peak, rather than part of a monotonically increasing series. Additionally, the homeowner needs some time to become aware of the peak. As a sensitivity analysis, we also estimated peak prices using two- and four-quarter definitions of peak price and found consistent results across these alternative definitions.

VI. Peak Price Effects in Stock Sales

The existence of a disposition effect among stock trading based upon the purchase price is widely documented and replicated in our data. We therefore focus on our main result for the existence of a disposition effect around the peak price. This is illustrated in figure 3. The figure is a binned scatterplot, illustrating the relationship between the probability of sale and returns since purchase price (fig. 3*A*), returns since peak price (fig. 3*B*), and the interaction between returns since purchase price and peak price (fig. 3*C*). Following the previous literature on stockholding and the

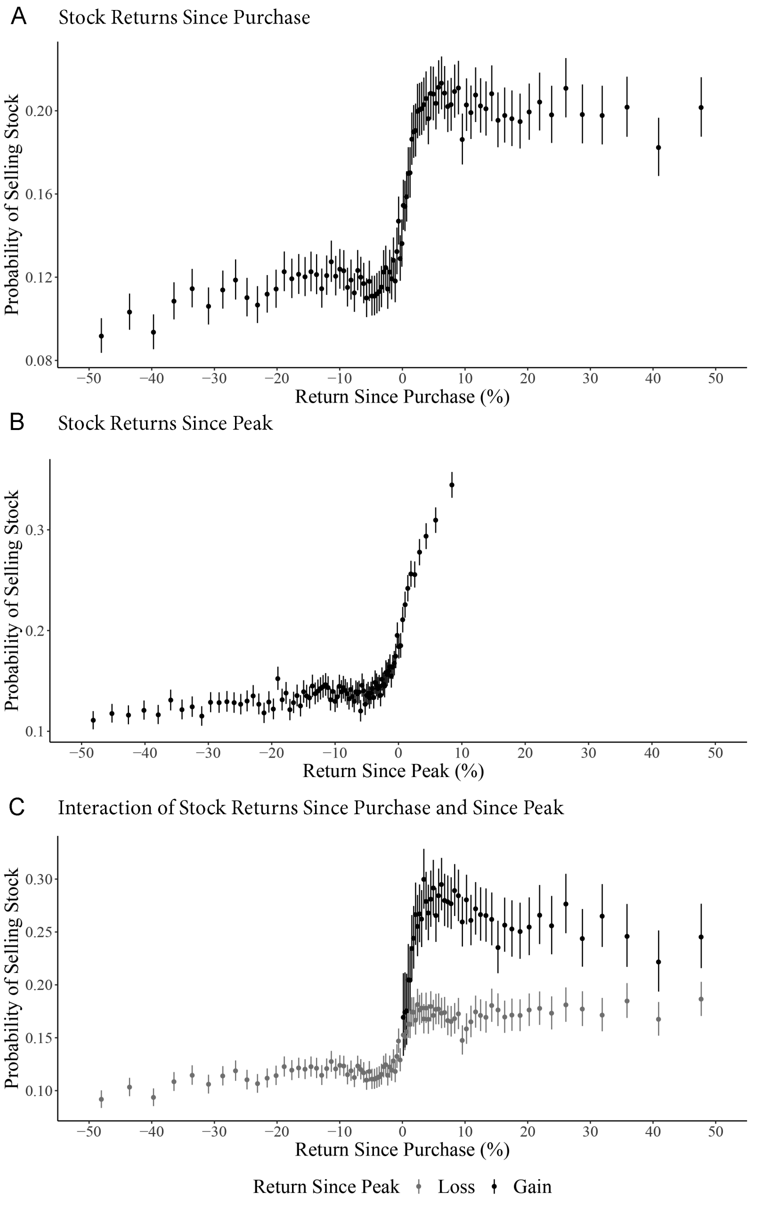

FIG. 3.—Probability of stock sale, returns since purchase, and returns since peak. The figure shows the probability of stock sales against return since purchase and return since peak price. Panels display binned scatterplots to illustrate the relationship between the probability of sale and returns since purchase (*A*), returns since peak price (*B*), and the interaction between returns since purchase and returns since peak price (*C*). For visual purposes, returns are restricted to the range of −50% and 50%. The sample includes all investor × stock × days on which the investor sold at least one stock in his portfolio. Vertical lines represent 95% confidence intervals.

disposition effect, we present main estimates from models using the subsample of observations of account × stock × days on which the investor made a sale of at least one stock.[42]

Figure 3*A* illustrates the standard disposition effect results for returns since purchase. The probability of sale increases sharply when returns since purchase turn positive; in the unconditional plot, the increase in the probability of sale is approximately 8 percentage points against a baseline probability of 12% (an increase in the probability of sale of two-thirds).

Figure 3*B* reveals the existence of a disposition effect for returns since the peak price. Again, here we observe a sharp increase in the probability of sale when returns since peak price turn positive (i.e., when the stock price crosses its previous peak). In the plot, the increase in the probability of sale is large, with the probability more than doubling when returns since peak turn positive.[43]

These patterns are confirmed by OLS regression estimates of equations (1) and (2), which are shown in table 5. Column 1 shows the estimate of equation (1). The coefficient of the gain since purchase dummy is positive and implies that a stock that is in gain since purchase is approximately 8.3 percentage points more likely to be sold compared with a stock in loss. Against the base probability of selling a stock from the constant in the regression of 11.4%, this represents an increase of 73%.

The model in column 2 replaces the gain since purchase dummy from equation (1) with the gain since peak price. The coefficient of this dummy variable is again positive and precisely defined. The coefficient of the gain

[42] As discussed by Chang, Solomon, and Westerfield (2016), on days with no sales, we cannot tell whether the absence of a sale is a deliberate choice on the part of the investor or whether it is due to inattention. Consequently, previous studies (beginning with Odean 1998) restrict the sample to account × stock × time units on which the investor sold at least one stock in their portfolio. This sample restriction ensures that the investor was paying attention to the portfolio at those points in time and there was some risk that the investor would sell any stock. We also show results from a login-day sample: the subsample of observations of account × stock × days on which the investor made a login to their account. The rationale for this sample is that on login days, investors pay attention to their accounts and hence have some nonzero likelihood of making a sale. The sell-day sample provides approximately 396,000 account × stock × days for investors who sold at least one stock on the day, whereas the login sample is much larger (because login days are much more common than sale days). The login-day sample provides approximately 6,259,000 account × stock × days for investors who made at least one login on the day. Both data samples pool together investors and days, hence we cluster standard errors at the account and date level.

[43] The plot has fewer observations to the right in consistency with the underlying distribution of returns observed in fig. A13 and table A10 (where returns since peak are on average −16.2%, median −9.6%, while returns since purchase are −4.8%, median −2.2%). Also note that because of the higher volatility in stock prices, compared with house prices, peak prices in the stock data are updated frequently, as observed in fig. 1*A*, which implies that gains since peaks last a shorter time and are therefore of small magnitude. In fig. A16, we replicate the plots using peak prices that should be the highest prices for at least a month, instead of a week, and we observe in fig. A16*B* a larger frequency of gains since peak.

TABLE 5
Purchase and Peak Price Disposition Effect for Stocks: OLS Estimates

	$Sale_{ijt}$		
	(1)	(2)	(3)
Gain since purchase = 1	.0828***		.0572***
	(.0045)		(.0039)
Gain since peak = 1		.1281***	.0906***
		(.0063)	(.0050)
Constant	.1135***	.1332***	.1135***
	(.0042)	(.0040)	(.0042)
Observations	396,186	396,186	396,186
R^2	.0132	.0137	.0188

Note.—Ordinary least squares regression estimates. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors (in parentheses) are clustered by account and day.

*** $p < .01$.

since peak price dummy in column 2 implies that a stock that is in gain since peak price is approximately 12.8 percentage points more likely to be sold compared with a stock in loss. Against the base probability of selling a stock of 13.3%, this represents a 96% increase in the likelihood of a sale.

Figure 3*C* shows the interaction of returns since purchase and returns since peak. Similar to houses, the disposition effect since purchase is stronger when the price is above a past peak. Estimates of equation (2), the corresponding regression, are shown in column 3. Results show a positive coefficient on both the gain since purchase and the gain since peak price dummies, which are both precisely estimated. A stock in gain since purchase but in loss since peak price is 5.7 percentage points more likely to be sold. When the stock is also in gain since the peak price, this probability increases further by 9.1 percentage points. Hence, evaluated against a baseline probability of 11.4%, a stock in gain since purchase but in loss since peak price is approximately 50% more likely to be sold, whereas a stock in gain since purchase and gain since peak price is 130% more likely to be sold.

We examine the robustness of this main result with a series of additional tests. Previous studies have shown that particular covariates may be important for explaining the disposition effect, including the length of the holding period and the magnitude of returns. We therefore include these controls in additional robustness tests, together with other control variables, such as the time elapsed since a past peak, investor demographics, and several portfolio characteristics. We also estimate fixed effects regressions and a modified econometric specification that employs a Cox proportional hazard model.

A. *Robustness Tests*

1. Individual Fixed Effects

The first robustness test adds individual fixed effects to control for individual-specific time-invariant heterogeneity in selling behavior. Results are shown in table A31. The table reports results for the same four specifications as those shown in table 5. With the inclusion of individual fixed effects, the coefficient values are very similar to those in table 5.

2. Controls for Continuous Returns

A second robustness test adds linear controls for returns to the econometric models in equation (1) and equation (2). Separate linear controls are added for returns on either side of zero, for both returns since purchase and returns since peak price. Results are shown in table A32, which reports estimates both without individual fixed effects (shown in cols. 1–3) and with the addition of individual fixed effects (shown in cols. 4–6). The coefficient values are again very similar to those in the baseline OLS models, slightly attenuated by the linear controls for returns, which are precisely defined in the majority of models and imply that investors have a higher probability of sale when experiencing greater returns since purchase and greater returns since peak price.

3. Additional Controls

Table A33 shows estimates from models with additional controls. Previous studies suggest important control variables in econometric specifications of the disposition effect, including the stockholding period (see Ben-David and Hirshleifer 2012) and investor experience (see Da Costa et al. 2013). In a series of econometric models presented in the table, we control for the holding period (days since purchase), days since peak, and portfolio and account characteristics (portfolio value, number of stocks in the portfolio, and account tenure), plus individual controls for account-holder gender and account-holder age. We also show specifications that include account and stock fixed effects. Coefficient estimates for gain since purchase and gain since peak are stable across a wide range of specifications incorporating these additional controls.[44]

[44] The fullest pooled model (col. 8 of table A33) returns coefficient values of 0.0637 and 0.0779 on the gain since purchase and gain since peak dummies, respectively, which show little change in a model that includes account and stock fixed effects (col. 10) in which the values are 0.0724 and 0.0769. These estimates are again very similar to the OLS estimates reported in table 5: the increased probability of sale for a stock in gain since purchase and gain since peak is 14.9 percentage points in col. 10 of table A33, compared with 14.8 percentage points in col. 3 of table 5.

4. Additional Robustness Tests

Additional robustness and sensitivity tests are presented in the appendix. We find consistent results when using (i) a hazard model specification instead of a linear probability model (following Seru, Shumway, and Stoffman 2010), (ii) excluding partial sales to rule out confounds arising from portfolio rebalancing strategies, and (iii) using month periods to define peak prices instead of week periods. We also replicate our results using (iv) the sample of login-days (which encompasses the sample of sell-days used in the main analyses, since investors have to log in to trade).

These additional checks also include sensitivity analyses that include estimates of interaction effects with (v) market movements (daily market movements as well as market movements since the purchase of the stock and since past peak prices), (vi) the time elapsed since purchase and since the past peak price event, and (vii) investor and account characteristics (e.g., gender, age, account tenure, portfolio value, and portfolio size).

These additional tests reveal that while the disposition effect on gains since purchase and gains since peak price is present across various demographic groups, including both females and males and younger and older individuals, smaller coefficient estimates are observed for older investors and for those who have held their accounts for longer periods, suggesting a weaker disposition effect among more experienced investors. These tests also indicate that the strength of the disposition effect varies with time since purchase and time since the peak price event. Specifically, the coefficient of gains since purchase is weakest when the peak price event is more recent, indicating that recent peak price events may diminish the influence of the purchase price as a reference point.

The appendix also reproduces the analysis on the triple interaction between gains since purchase, gains since the past peak price, and gains since the most recent login to the account, we document in Quispe-Torreblanca et al. (2024).[45] Losses on any of these margins reduce the probability that the investor will sell, even when other margins show gains. This further shows the importance of other reference points in creating a reluctance to realize losses.

B. Controlling for Nonlinearities in Returns

In addition to the robustness checks presented in the previous sections, we address potential nonlinear return effects. The previous literature has shown how the disposition effect is in part driven by extreme returns (see Ben-David and Hirshleifer 2012) and peak prices could potentially proxy for extreme gains. To control for this, we conduct an analysis presented

[45] In Quispe-Torreblanca et al. (2024), we show that the price observed on the last login day constitutes another important reference point that influences investors selling decisions.

in table 6, where the sample is divided into 10 deciles based on stock returns, with each column representing a decile. By dividing the sample into 10 deciles and allowing for distinct response gradients for positive and negative returns within each, we capture nonlinear return effects across the entire sample. The regression model for each decile includes covariates for the magnitudes of returns.

Accordingly, for the first six deciles, the constants in the regressions indicate the selling probabilities for stocks with returns just below zero since purchase (stocks that are at a loss since the last peak price date, as the peak price is by definition above the purchase price). For the last four deciles, the constants indicate the selling probabilities for stocks with returns just above zero since purchase. The "gain since peak" coefficients indicate the increase in selling probability when a stock surpasses a previous peak price. The sign of the gain-since-peak coefficients is consistent with the main findings displayed in figures 2*C* and 3*C*. This shows a rapid increase in the probability of selling when prices exceed a previous peak, which slightly diminishes when returns are very large. This demonstrates that peak price effects remain significant, even when accounting for nonlinearities in returns.

Estimates from the same econometric specifications estimated on the housing data are shown in table 7. In the case of housing, returns are positive across a greater majority of the distribution. The rightmost eight columns show positive returns since purchase, with the gain since peak coefficient indicating that the increase in selling probability when a home surpasses a previous speak is positive and statistically significant across the full distribution of returns since purchase. From this analysis, we can therefore be confident that the gain since peak dummy is not simply proxying for nonlinearities in returns.

C. *Peak Prices versus Additional Reference Points*

The purchase price and peak price might be two among many potential reference points of interest in this research. Therefore, in additional analysis, we test for selling responses by investors in response to a large suite of gain measures. In addition to gain since purchase and gain since peak, these are gain since yesterday, gain since past week, gain since past month, gain since past quarter, and year-to-date gain (i.e., gain from the beginning of the current year to the present date). Results are shown in table 8, which contains a set of specifications in which each gain measure enters independently alongside gain since purchase and gain since peak (cols. 2–6), as well as specifications in which all gain measures enter simultaneously, both without (col. 7) and with (col. 8) investor fixed effects.

Results from the fullest models in columns 7 and 8 reveal that the coefficients of gain since purchase and gain since peak are statistically

TABLE 6

Purchase and Peak Price Disposition Effects for Stocks: Splitting the Sample into 10 Deciles Based on Returns since Purchase

	Deciles of Stock Returns since Purchase									
	D1 −83.32% to −33.59%	D2 −33.59% to −18.29%	D3 −18.29% to −10.58%	D4 −10.58% to −5.78%	D5 −5.78% to −2.24%	D6 −2.24% to .67%	D7 .67% to 3.94%	D8 3.94% to 8.60%	D9 8.60% to 17.51%	D10 17.51% to 87.22%
Gain since purchase = 1						.0067				
						(.0084)				
Return since purchase > 0 (%)						.0066	.0078***	−.0033**	−.0003	−.0001
						(.0193)	(.0025)	(.0016)	(.0009)	(.0002)
Return since purchase < 0 (%)	.0006*	.0002	.0007	−.0006	.0037**	.0122***				
	(.0003)	(.0006)	(.0009)	(.0014)	(.0016)	(.0031)				
Gain since peak = 1						.0151	.0541***	.0593***	.0173**	.0324***
						(.0142)	(.0102)	(.0091)	(.0086)	(.0091)
Returns since peak > 0 (%)						.0414***	.0218***	.0206***	.0235***	.0134***
						(.0152)	(.0044)	(.0023)	(.0020)	(.0019)
Returns since peak < 0 (%)	.0007**	.0002	−.0003	−.0007**	−.0014***	−.0020***	−.0012**	−.0016***	−.0018***	−.0010***
	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0005)	(.0004)	(.0004)	(.0004)
Constant	.1565***	.1244***	.1240***	.1030***	.1165***	.1275***	.1462***	.1801***	.1588***	.1702***
	(.0108)	(.0122)	(.0133)	(.0112)	(.0080)	(.0060)	(.0078)	(.0119)	(.0132)	(.0076)
Observations	39,619	39,619	39,618	39,619	39,618	39,619	39,619	39,618	39,619	39,618
R^2	.0033	.0001	.0001	.0004	.0012	.0041	.0097	.0202	.0233	.0103

Note.—Ordinary least squares regression estimates of our main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. The sample is divided into 10 subsamples, each represented by a decile based on stock returns, with each decile subject to a separate regression. The regression model for each decile includes covariates for the magnitudes of returns. Accordingly, for the first six deciles, the constants in the regressions indicate the selling probabilities for stocks with returns just below zero since purchase. For the last four deciles, the constants indicate the selling probabilities for stocks with returns just above zero since purchase. Standard errors (in parentheses) are clustered by account and day.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

TABLE 7

Purchase and Peak Price Disposition Effects for Housing: Splitting the Sample into 10 Deciles Based on Returns since Purchase

	Deciles of House Returns since Purchase									
	D1 −3,739,680 to −66	D2 −66 to 11,184	D3 11,184 to 25,866	D4 25,866 to 43,971	D5 43,971 to 64,338	D6 64,338 to 86,815	D7 86,815 to 114,363	D8 114,363 to 154,860	D9 154,860 to 235,927	D10 235,927 to 77,548,936
Gain since purchase = 1		−.0000								
		(.0005)								
Return since purchase > 0 (£100,000)		.0000	−.0067***	−.0014	.0024**	.0012*	.0005	−.0000	.0001	−.0000
		(.0032)	(.0025)	(.0012)	(.0012)	(.0007)	(.0006)	(.0004)	(.0002)	(.0000)
Return since purchase < 0 (£100,000)	.0055***									
	(.0016)									
Gain since peak = 1		.0027***	.0023***	.0026***	.0026***	.0019***	.0019***	.0016***	.0018***	.0016***
		(.0005)	(.0005)	(.0006)	(.0006)	(.0006)	(.0006)	(.0005)	(.0005)	(.0004)
Return since peak > 0 (£100,000)		.0584***	.0245***	.0091***	.0026	.0008	−.0012*	−.0013***	−.0014***	−.0003***
		(.0126)	(.0056)	(.0030)	(.0016)	(.0010)	(.0007)	(.0005)	(.0004)	(.0001)
Return since peak < 0 (£100,000)	.0012	.0118***	.0089***	.0064**	.0068**	.0072***	.0066***	.0056***	.0040***	.0013**
	(.0017)	(.0028)	(.0026)	(.0026)	(.0027)	(.0026)	(.0022)	(.0019)	(.0014)	(.0005)
Years from purchase	.0085***	.0063***	.0042*	.0034	.0045*	.0061***	.0061***	.0050**	.0055***	.0046**
	(.0024)	(.0015)	(.0022)	(.0025)	(.0024)	(.0023)	(.0022)	(.0020)	(.0020)	(.0018)
Constant	−.0014	.0038**	.0092***	.0123***	.0105***	.0089**	.0079**	.0091**	.0063	.0044
	(.0021)	(.0016)	(.0031)	(.0036)	(.0037)	(.0036)	(.0037)	(.0036)	(.0038)	(.0035)
Years from purchase quintics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,211,444	7,211,362	7,211,417	7,211,284	7,211,592	7,211,271	7,211,331	7,211,310	7,211,261	7,211,337
R^2	.0005	.0010	.0013	.0014	.0014	.0012	.0010	.0007	.0007	.0005

Note.—Ordinary least squares regression estimates for our modified baseline specification. The dependent variable takes a value of 1 if the homeowner sold their property and zero otherwise. The controls added correspond to table A27. Observations include all property × quarters in the baseline sample with a peak price. The sample is divided into 10 subsamples, each represented by a decile based on property returns, with each decile subject to a separate regression. The regression model for each decile includes covariates for the magnitudes of returns. Accordingly, the constant in the regressions indicates the selling probability for properties with returns just below zero since purchase is in the first two deciles and just above zero for the remaining eight deciles, each isolated from the effects of property characteristics. Standard errors (in parentheses) are clustered by property and year-quarter.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

significant at the 1% level. In contrast, all other measures of gain since other time points are smaller in magnitude, in some cases negative, and at longer time horizons not statistically significant (e.g., the gain since past quarter and year-to-date gain in col. 8). We therefore conclude that the purchase price and the peak price are important reference points compared with a wide set of alternative reference points.

D. *Timing of Peaks*

Peak price effects may be more apparent if the peak price is more salient to the investor. This salience could be higher if the peak price lasted through the end of the month, a time when most investors receive statements or updates about the value of their portfolios. In table 9, we explore how the timing of the peaks relative to when investors typically review their portfolios might influence their decision-making. Columns categorize sales based on the recency of the last peak: columns 1 and 2 represent sales following peaks in the current month, columns 3 and 4 for the previous month, and columns 11 and 12 for sales from 5 months ago or earlier. The first four columns compare peaks that occurred in the past calendar month (and remain the highest) versus peaks in the current calendar month (which investors may not have recognized yet). While the magnitude of the effects is similar, our analysis of peaks from earlier months shows that the longer the peak persists, the larger its effect. For instance, a peak in the current month increases the selling probability by approximately 40%, while a peak occurring 5 months ago or earlier increases the selling probability by approximately 55%.

VII. Explanations for the Peak Price Effect

In the remainder of the paper, we evaluate explanations for the existence of a peak price effect. We consider two main explanations. First, a belief in "peak reversion": Owners of assets might optimistically infer from the fact that an asset at one point achieved a particular price that its true value corresponds to that peak price and, hence, expect the market price to evolve toward the peak price. Anticipation of such an increase in price would lead to a reluctance to sell the asset at its current, lower price. This explanation is related to an explanation for the disposition effect proposed by Shefrin and Statman (1985) and Odean (1998)—that investors hold on to losing stocks because they expect higher future returns from losing stocks compared with winning stocks; that is, they expect losing stocks to outperform in the future as they rebound in price.

Second, regret avoidance: The peak price can be a source of regret for owners who wish they had sold at the peak. Asset owners may resist selling, therefore, to avoid converting the paper loss of not having sold at the peak

TABLE 8

Purchase and Peak Price Disposition Effects for Stocks: Controlling for Alternative Reference Points

	$Sale_{ijt}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gain since purchase = 1	.0453***	.0453***	.0450***	.0450***	.0436***	.0433***	.0428***	.0505***
	(.0039)	(.0039)	(.0038)	(.0038)	(.0040)	(.0040)	(.0039)	(.0034)
Return since purchase > 0 (%)	−.0001	−.0001	−.0001	−.0001	−.0001	−.0001	−.0002	.0001
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0001)
Return since purchase < 0 (%)	.0016***	.0015***	.0016***	.0017***	.0017***	.0017***	.0016***	.0018***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Gain since peak = 1	.0413***	.0388***	.0345***	.0363***	.0390***	.0383***	.0314***	.0254***
	(.0055)	(.0054)	(.0054)	(.0054)	(.0055)	(.0055)	(.0054)	(.0049)
Return since peak > 0 (%)	.0179***	.0173***	.0176***	.0178***	.0179***	.0177***	.0173***	.0154***
	(.0013)	(.0013)	(.0013)	(.0013)	(.0013)	(.0013)	(.0013)	(.0012)
Return since peak < 0 (%)	−.0008***	−.0005**	−.0004*	−.0005**	−.0006***	−.0007***	−.0002	−.0007***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Gain since yesterday = 1		.0344***					.0282***	.0240***
		(.0022)					(.0021)	(.0019)
Return since yesterday > 0 (%)		−.0000					−.0000	−.0000
		(.0000)					(.0000)	(.0000)
Return since yesterday < 0 (%)		−.0139***					−.0101***	−.0085***
		(.0008)					(.0006)	(.0006)
Gain since past week = 1			.0334***				.0204***	.0187***
			(.0021)				(.0020)	(.0018)
Return since past week > 0 (%)			−.0000*				−.0000	.0000
			(.0000)				(.0000)	(.0000)
Return since past week < 0 (%)			−.0073***				−.0039***	−.0031***
			(.0004)				(.0003)	(.0003)

Gain since past month = 1				.0197***			.0050**	.0072***
				(.0023)			(.0021)	(.0018)
Return since past month > 0 (%)				−.0000*			.0000*	.0000*
				(.0000)			(.0000)	(.0000)
Return since past month < 0 (%)				−.0027***			−.0006***	−.0004***
				(.0002)			(.0002)	(.0001)
Gain since past quarter = 1					.0165***		.0051**	.0002
					(.0026)		(.0025)	(.0021)
Return since past quarter > 0 (%)					.0000		.0000**	.0000*
					(.0000)		(.0000)	(.0000)
Return since past quarter < 0 (%)					−.0012***		−.0003**	−.0001
					(.0001)		(.0001)	(.0001)
Year-to-date gain = 1						.0130***	.0041	−.0039*
						(.0030)	(.0030)	(.0021)
Year-to-date return > 0 (%)						−.0000	−.0000**	−.0000**
						(.0000)	(.0000)	(.0000)
Year-to-date return < 0 (%)						−.0008***	−.0001	.0000
						(.0001)	(.0001)	(.0001)
Constant	.1207***	.0984***	.0984***	.1068***	.1095***	.1118***	.0805***	
	(.0045)	(.0046)	(.0046)	(.0047)	(.0046)	(.0051)	(.0056)	
Account fixed effects	No	No	No	No	No	No	No	Yes
Observations	396,186	396,176	396,175	395,679	393,562	390,397	387,990	387,990
R^2	.0220	.0293	.0279	.0243	.0233	.0221	.0313	.1593

NOTE.—Ordinary least squares regression estimates of our main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. Standard errors (in parentheses) are clustered by account and day.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

TABLE 9

Purchase and Peak Price Disposition Effects for Stocks: Impact of Peak Timing

	$Sale_{ijt}$											
	Current Month		Past Month		2 Months Ago		3 Months Ago		4 Months Ago		5+ Months Ago	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gain since purchase = 1	.0349***	.0612***	.0319***	.0489***	.0495***	.0468***	.0601***	.0519***	.0644***	.0517***	.0703***	.0585***
	(.0064)	(.0067)	(.0052)	(.0049)	(.0060)	(.0060)	(.0072)	(.0070)	(.0084)	(.0087)	(.0057)	(.0051)
Return since purchase > 0 (%)	−.0002	.0010***	.0000	.0010***	−.0001	.0002	−.0007**	−.0004	−.0003	−.0007*	−.0005**	−.0007***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0003)	(.0002)	(.0003)	(.0003)	(.0003)	(.0004)	(.0002)	(.0002)
Return since purchase < 0 (%)	.0020**	.0010	.0014***	.0019***	.0016***	.0018***	.0012***	.0011***	.0017***	.0020***	.0014***	.0014***
	(.0008)	(.0007)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0003)	(.0002)
Gain since peak = 1	.0497***	.0341***	.0384***	.0222***	.0758***	.0534***	.0735***	.0443***	.0505**	.0358	.0562***	.0521***
	(.0084)	(.0076)	(.0066)	(.0060)	(.0132)	(.0120)	(.0172)	(.0166)	(.0244)	(.0239)	(.0201)	(.0194)
Return since peak > 0 (%)	.0205***	.0118***	.0175***	.0132***	.0104***	.0035	.0135***	.0052	.0285***	.0169**	.0331***	.0283***
	(.0021)	(.0020)	(.0015)	(.0014)	(.0032)	(.0027)	(.0042)	(.0041)	(.0068)	(.0069)	(.0066)	(.0062)
Return since peak < 0 (%)	−.0044***	.0001	−.0022***	−.0003	−.0017***	−.0001	−.0010***	.0007*	−.0010***	−.0001	−.0008***	−.0010***
	(.0006)	(.0006)	(.0004)	(.0004)	(.0003)	(.0003)	(.0003)	(.0004)	(.0004)	(.0004)	(.0003)	(.0002)
Gain since yesterday = 1		−.0007		.0246***		.0095**		.0046		.0246***		.0220***
		(.0045)		(.0028)		(.0042)		(.0044)		(.0048)		(.0026)
Return since yesterday > 0 (%)		.0086***		.0000		.0079***		.0055***		−.0000*		−.0000
		(.0015)		(.0000)		(.0012)		(.0011)		(.0000)		(.0000)
Return since yesterday < 0 (%)		−.0111***		−.0113***		−.0084***		−.0055***		−.0039***		−.0061***
		(.0014)		(.0011)		(.0012)		(.0013)		(.0011)		(.0007)
Gain since past week = 1		−.0057		.0192***		.0040		.0036		.0144***		.0163***
		(.0052)		(.0031)		(.0048)		(.0049)		(.0050)		(.0024)
Return since past week > 0 (%)		.0038***		−.0000		.0020**		.0018***		−.0001***		.0000*
		(.0008)		(.0000)		(.0008)		(.0005)		(.0000)		(.0000)
Return since past week < 0 (%)		−.0049***		−.0042***		−.0028***		−.0025***		−.0026***		−.0017***
		(.0008)		(.0005)		(.0006)		(.0007)		(.0008)		(.0003)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gain since past month = 1		−.0070		−.0036		−.0041		−.0083		.0076		.0096***
		(.0050)		(.0034)		(.0046)		(.0051)		(.0062)		(.0026)
Return since past month > 0 (%)		−.0002		.0000		.0024***		.0019***		.0014***		.0000
		(.0001)		(.0000)		(.0005)		(.0004)		(.0005)		(.0000)
Return since past month < 0 (%)		.0006		−.0003		−.0012***		−.0011***		−.0011***		−.0004**
		(.0004)		(.0002)		(.0003)		(.0004)		(.0004)		(.0002)
Gain since past quarter = 1		−.0017		−.0174***		−.0072		.0138**		.0224***		.0184***
		(.0056)		(.0039)		(.0047)		(.0062)		(.0073)		(.0030)
Return since past quarter > 0 (%)		.0000		.0000		−.0000		−.0002**		−.0001		.0000
		(.0000)		(.0000)		(.0000)		(.0001)		(.0006)		(.0000)
Return since past quarter < 0 (%)		.0002		.0004**		−.0002		−.0006**		−.0006**		−.0005***
		(.0003)		(.0002)		(.0002)		(.0003)		(.0003)		(.0001)
Year-to-date gain = 1		−.0092		−.0085**		−.0060		−.0110**		−.0101		.0106***
		(.0057)		(.0038)		(.0043)		(.0051)		(.0064)		(.0029)
Year-to-date return > 0 (%)		−.0001***		−.0000		−.0000		−.0000		.0001		−.0000
		(.0000)		(.0000)		(.0000)		(.0000)		(.0001)		(.0000)
Year-to-date return < 0 (%)		−.0001		.0000		.0003**		.0001		−.0002		.0000
		(.0002)		(.0002)		(.0002)		(.0002)		(.0002)		(.0001)
Constant	.1266***		.1232***		.1041***		.1035***		.1056***		.1019***	
	(.0062)		(.0054)		(.0054)		(.0059)		(.0064)		(.0047)	
Account fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	53,667	51,609	111,543	107,446	54,735	53,530	35,259	34,797	25,717	25,503	115,265	115,105
R^2	.0197	.2869	.0163	.2134	.0186	.2902	.0178	.3379	.0241	.3657	.0207	.2261

Note.—Ordinary least squares regression estimates of our main specification. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. Columns categorize sales based on the recency of the last peak: cols. 1 and 2 for sales following peaks in the current month, cols. 3 and 4 for the previous month, and cols. 11 and 12 for sales from 5 months ago or earlier. Standard errors (in parentheses) are clustered by account and day.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

to the real loss of actually selling "too late." Such an account would be consistent with research on "inaction inertia," which finds that "when an attractive action opportunity has been forgone, individuals tend to decline a substantially less attractive current opportunity in the same action domain, even though, in an absolute sense, it still has positive value" (Tykocinski and Pittman 1998, 206).

Note that these explanations are not mutually exclusive—for example, an individual could regret not having sold at the peak, could want to wait for the asset price to rise back to the peak before selling, and could also be overoptimistic that this opportunity will arise, as a result of belief in peak reversion.

We evaluate these explanations via additional analysis of the role of ownership in generating the peak price effect and the role of top-up purchases. If the peak price effect arises due to regret, we would expect to see a stronger effect among those who held the asset at the point in time of reaching the peak price (as only this group would experience greater regret). If the peak price effect arises due to belief in reversion to the peak, we would expect to observe individuals making top-up purchases when the price falls below the peak price (in expectation of future gains as the price reverts to the peak). We examine both issues using the stock trading data.[46]

A. *Ownership and the Peak Price Effect*

We first examine the relationship between ownership and the peak price effect. Recent studies suggest that ownership is itself important for attention and belief formation (Hartzmark, Hirshman, and Imas 2021; Kindermann et al. 2021; Medina, Mittal, and Pagel 2021; Carney et al. 2022). For each investor $\times$ stock $\times$ day observation, we first identify the peak price for that stock within the past year (defined as the highest price achieved over the past year). We then divide the sample into observations for which the investor held the stock on the peak price day and observations for which the investor did not hold the stock on the peak price day.

Figure 4 provides examples of scenarios in which investors held (fig. 4*A*) and did not hold (fig. 4*B*) a stock on the peak price day. In figure 4*A*, the investor purchased the stock prior to the peak day event and, in this case, has experienced a gain since purchase and a gain since the peak price day. In figure 4*B*, the investor purchased the stock after the peak price day event (which occurred approximately 6 months prior to the purchase day) and has also experienced a gain since purchase and a gain since peak price day.

[46] It is not feasible to conduct the analysis on the housing data, as "top-up" purchases of a residential house are typically not possible.

FIG. 4.—Examples of stocks price trajectories for the placebo analysis. The figure illustrates the test that contrasts the effect of peak prices that occurred before the purchase of the stock with those that occurred after the purchase of the stock. Across panels, peak prices are defined over the past year. The panels display examples of days with a gain since the past peak day and a gain since purchase (the day of evaluation is *Day t*, 2015–06–25) but distinguishing the case when the investor has held the stock during the past peak (*A*) or has not held it (*B*).

Using this approach, we find much weaker evidence for a disposition effect around peak price events that predate the investor's holding of the stock. We estimate equation (2) on both samples, with results shown in table 10. Panel A reports results for the sample of observations in which the investor did not hold the stock on the peak price day. Estimates show a positive and precisely defined coefficient of the gain since purchase dummy. The coefficient of the gain since peak dummy is imprecisely defined in column 1 and negative in column 2 (statistically significant at the 5% level). The coefficient remains negative in column 3 after adding account and stock fixed effects to account for heterogeneity across investors and assets.

TABLE 10
Estimates of the Stocks Disposition Effect, Placebo Analysis

	$Sale_{ijt}$		
	(1)	(2)	(3)
	A. No Holding Stock		
Gain since purchase = 1	.1582***	.1431***	.1502***
	(.0073)	(.0071)	(.0064)
Gain since peak = 1	−.0161	−.0249**	−.0015
	(.0102)	(.0102)	(.0081)
Days from purchase day (100 days)		−.0450***	−.0053***
		(.0025)	(.0017)
Constant	.1268***	.1723***	
	(.0052)	(.0066)	
Account fixed effects	No	No	Yes
Stock fixed effects	No	No	Yes
Observations	242,536	242,536	242,536
R^2	.0383	.0480	.2397
	B. Holding Stock		
Gain since purchase = 1	.0361***	.0350***	.0322***
	(.0043)	(.0043)	(.0040)
Gain since peak = 1	.0320***	.0290***	.0298***
	(.0054)	(.0055)	(.0050)
Days from purchase day (100 days)		−.0033***	.0054***
		(.0009)	(.0007)
Constant	.1172***	.1289***	
	(.0047)	(.0062)	
Account fixed effects	No	No	Yes
Stock fixed effects	No	No	Yes
Observations	169,800	169,800	169,800
R^2	.0045	.0050	.1998

Note.—Ordinary least squares regression estimates for the placebo test that compares the effect of peak prices that took place before the holding period of the stock with those that occurred during the holding period. Peak prices are defined over the past year. The dependent variable takes a value of 1 if the investor made a sale of the stock and zero otherwise. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. However, panel A includes the set of days in which past peak prices occurred before the purchase of the stock and panel B the set of days in which peak prices occurred after the purchase of the stock. Standard errors (in parentheses) are clustered by account and day.

** $p < .05$.

*** $p < .01$.

Panel B reports results for the sample of observations in which the investor did hold the stock on the peak price day. In this sample, in contrast with panel A, estimates show positive and precisely defined coefficients for both the gain since purchase and gain since peak price dummies.[47] The coefficient values are smaller than in the main analysis, as expected—given that a peak price in the past year is likely less salient than a peak price

[47] The coefficient on gain since peak in panel B is 0.0298 (95% confidence interval [CI] 0.0200, 0.0396). In panel A, the coefficient is −0.0015 (95% CI −0.017376, 0.014376).

since purchase—but show the existence of both forms of the disposition effect as expected. Hence, this test adds evidence that peak prices affect trading behaviors through returns experienced by the investor.

B. Top-Up Purchases and the Peak Price Effect

If investors believe that stocks that have performed poorly since their peak price will eventually return to that level, they may be more likely to make additional purchases of those stocks the larger the loss since the past peak event. To explore this, figure 5 shows binned scatterplots of the

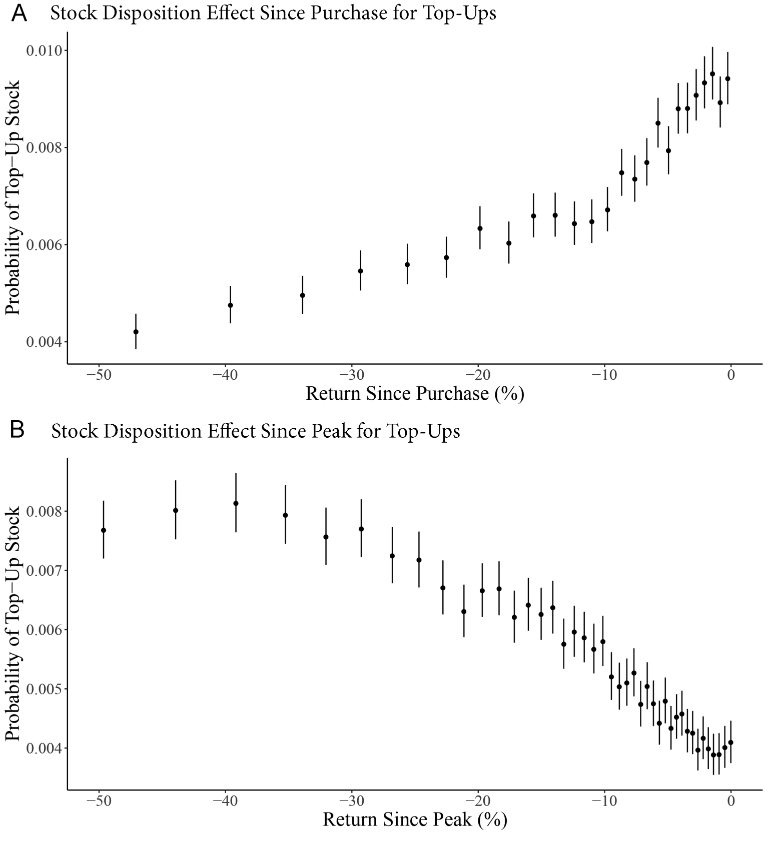

FIG. 5.—Stock top-ups, returns since purchase, and return since peak. The figure displays binned scatterplots to illustrate the relationship between the probability of sale and returns since purchase (*A*) and returns since peak price (*B*). Plots intend to test potential beliefs in reversion to the purchase price and peak price, respectively. As such, returns are restricted to the range of −50% and 0%. The sample includes all investor × stock × days on which the investor made at least one login to his account. Vertical lines represent 95% confidence intervals.

relationships between losses since purchase, losses since peak, and the propensity of investors to top-up current positions with new purchases of the same stock. The proportion of observations with top-ups is shown on the y-axis, with loss since purchase (fig. 5*A*) and since peak (fig. 5*B*) shown on the x-axis. Results in figure 5*A* show that the probability of top-up decreases as losses since purchase increase. However, in figure 5*B*, we observe the opposite relationship for losses since peak price: the probability of top-up increases as losses since peak price increase. These relationships are confirmed by regression analysis, with the former showing a positive coefficient of the loss since purchase variable and the latter showing a negative coefficient of the loss since peak variable.[48]

While our analysis has shown that observations with higher losses since peak price display a higher probability of top-up purchases, which is consistent with the idea of belief in reversion to the past peak price, one might expect that a similar relationship would hold when the reference point is the purchase price. That is, one would expect that higher losses since purchase would be related to a higher probability of a top-up purchase. However, our analysis did not find this relationship in the data. This suggests that investors may not necessarily be chasing losses in general but rather only chasing losses relative to certain reference points that are independent of the time they purchase the stock. These higher reference points, such as the peak price, may be more salient for investors and may influence their decision-making more significantly. This indicates that the peak price may serve as a particularly influential reference point for investors and may shape their perceptions of the value of an asset in a way that the purchase price does not.

In combination, these results provide strong support for a peak-reversion account—we should not expect to observe elevated top-ups when prices are below peak unless investors anticipate that prices will rise—and also positive but less strong support for regret avoidance. Support for regret avoidance comes from the observation that peak prices occurring when the asset is owned have a much greater impact than peak prices before the asset was owned, consistent with an account in which people, naturally, only regret not selling assets they actually owned. However, the latter finding could also be consistent with a peak-reversion account if people pay more attention to—and hence have a stronger belief in peak reversion to—peaks occurring when they hold an asset.

[48] See tables A40 and A41. In an extension, in table A42, we also test whether the negative slope found in fig. 5*B* is different for the cases in which the investor has not held the stock during the past peak price, following the same spirit of our earlier test but this time analyzing topping-up decisions. We, however, find that the slopes are quantitatively similar for peaks occurring before the purchase of the stocks and peaks occurring after the purchase. These findings provide additional support to the notion of beliefs in reversion to the peak.

VIII. Future Returns and Economic Costs of Selling

In this section, we estimate the economic costs to individual stock and housing investors resulting from their decisions to sell at the purchase price and at the peak price. Following Odean (1998), we use data on the future returns to calculate the paper returns investors would have achieved had they held on to the stocks and housing.

First, we present calculations for stocks, which are shown in table 11. Panel A shows calculations of the excess (of the FTSE100) postsale returns

TABLE 11
Ex Post Returns for Stocks and Housing

	A. Stocks		
	Performance over		
	Next Month	Next 166 Days	Next Year
Returns since purchase (%):			
Average excess return on winning stocks sold	.5653	.3417	.4540
Average excess return on paper losses	.0049	−.5208	−3.1676
Difference in excess returns	.5603**	.8625	3.6216***
Returns since peak price date (%):			
Average excess return on winning stocks sold	.6054	1.3750	1.9935
Average excess return on paper losses	.0874	−.1508	−1.2712
Difference in excess returns	.5180	1.5258*	3.2647***
	B. Housing		
	Performance over		
	Next 6 Months	Next Year	Next 2 Year
Returns since purchase (%):			
Average return on winning homes sold	3.86	7.67	14.81
Average return on paper losses	1.41	2.79	6.31
Difference in average returns	2.45***	4.87***	8.50***
Returns since peak price date (%):			
Average return on winning homes sold	3.26	6.62	12.50
Average return on paper losses	.99	2.63	6.53
Difference in average returns	2.28***	3.99***	5.97***

Note.—Panel A presents excess postsale returns for periods subsequent to the sale of a winning stock or the observation of an unrealized loss, relative to the FTSE100. Returns are calculated over three periods: the month following the sale, 166 days (which is the average holding period), and 1 year after the sale for realized winnings, and similarly after occasions when stocks with paper losses were retained. The sample includes all investor × stock × days on which the investor sold at least one stock in the portfolio. Panel B presents excess postsale returns for periods following the sale of a winning property or the observation of an unrealized loss. Returns are calculated over three periods: 6 months, 1 year, and 2 years following the sale for realized winnings, and similarly after occasions when properties with paper losses were retained.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

for periods subsequent to the sale of a winning stock or the observation of an unrealized paper loss. These returns are evaluated over three periods: the month following the sale, 166 days (which corresponds to the average holding period), and 1 year after the sale for realized winnings and similarly after occasions when stocks with paper losses were retained. Each instance of a stock sold at a profit is treated as a separate observation in our analysis, whether it involves sales on different dates or by different investors on the same date. This approach is also applied to paper losses.

To provide an approximate estimate of the economic costs associated with the disposition effect and the peak price effect, we can use the analogy proposed by Odean (1998). Let us consider a hypothetical investor who is deciding whether to sell one of two stocks, each worth £1,000 after commissions. Initially, imagine that this investor has only one reference point, which is the purchase price of the stock. The first stock has gained since purchase, while the second stock has lost since purchase. Suppose this investor is averse to realizing losses and decides to sell the winning stock. Results in table 11 show that, on average, winning stocks sold achieve higher subsequent returns compared with losing stocks not sold. Over the next year, the difference is 3.62 percentage points. Hence, if the investor had retained the winning stock sold and instead sold the stock showing paper losses, they would have achieved an on-paper gain over the next year of £36.22. In addition, selling the winning stock incurs a capital gain, while selling the losing stock would incur a capital loss that could be offset against future capital gains for tax purposes.[49]

An analysis of future returns for stocks sold at the peak shows a similar pattern. The excess return on winning stocks sold at the peak is higher than that for paper losses not sold (which, as with paper losses for returns since purchase, show negative future returns over the 1-year horizon). Moreover, by choosing to retain the winning stock, the investor would have benefited from an additional £32.65 over the following year, in comparison to the losing stock. An additional consideration, however, is that an investor who makes selling decisions based upon peak prices is less likely to sell compared with an investor who makes selling decisions based on purchase prices (because the peak price is by definition higher than

[49] For example, based on the average investor's experience, the return on this sale of a winning stock is 0.1312 (see table A43 for calculations of average returns), which translates to a capital gain of £116. With a purchase price of £884$(=(1{,}000/1 + 0.1312))$. If the investor sells the losing stock instead, they can expect a return of -0.1816, with a purchase price of £1,222$(=(1{,}000/1 - 0.1816))$ and a capital loss of £222. Assuming the investor's marginal tax rate is 18% (for basic rate taxpayers) and they have taxable gains to offset losses, choosing to sell the winning stock means giving up an immediate tax saving of £60.84$(= .18 \times (116 + 222))$. Moreover, delay in the realization of gains for a year or more may increase the benefits of saved taxes for the investor since they would pay taxes at a later date.

the purchase price).[50] In additional analysis, we show that when investors use peak price as a reference point, holding highly volatile assets exhibiting an above-average number of peaks leads to more significant losses. This occurs because of momentum in volatile stocks that surpass previous peaks and then tend to perform well in the following year and because volatility leads to more occasions in which the stock is above its past peak price, increasing the investor's trading frequency.[51]

An analysis of future returns for homes sold at the purchase price and the peak price again shows a very similar pattern. Panel B of table 11 shows calculations of the postsale returns for periods subsequent to the sale of a winning home or observation of an unrealized paper loss over three periods: the next 6 months, next year, and next 2 years (these time periods are longer than those for stocks, due to the much lower frequency of trades of housing compared with stocks). The difference in returns for winning homes sold versus paper losses over the 2 years following the sale of a home at the purchase price is 8.5 percentage points. In the case of homes sold at peak price, the difference in returns is 5.97 percentage points. These results indicate that vendors would have achieved higher future returns had they not sold at the point where the price rose through the purchase price or peak price. Hence the same pattern of economic costs from selling at the purchase price and the peak prices exists for housing as for stocks, though the tax implications differ between the two.[52] For housing, unlike stocks, there are of course reasons for buying and selling unrelated to the financial return, however, it is striking that the same pattern of foregone future returns through selling is seen in both asset types.

IX. Conclusion

Using data on the buying and selling behavior of individual asset-owners—both for housing and stocks—we show a new disposition effect for returns based upon the peak price reached by the asset during the individual's period of ownership. This disposition effect arising from the peak price experienced by the asset owner exists over and above the disposition effect arising from the purchase price. We show that this effect is robust to a range of econometric tests and also sensitivity analyses. For the stock data, whose prices are more volatile and therefore contain a larger frequency of peak prices, we were also able to perform a placebo test that exploits peak price events that occur before investors purchase stocks.

[50] Additionally, the tax savings from using the peak prices as a reference are smaller, since stocks below that peak price that are retained do not exhibit as significant losses compared with stocks below the purchase price that are kept.

[51] See the appendix for further analysis.

[52] Unlike in the case of stocks in panel A, in panel B, the future returns on winning homes sold and paper loss homes remaining unsold are both positive.

Our study contributes to the expanding literature on how multiple reference points affect individual decisions. Research has documented the operation and consequences for economic behavior of diverse reference points.[53] In the setting we analyze, evidence from testing the peak price versus other reference points indicates that, alongside the purchase price, the peak price is most important for individual choices. However, reference prices may be asset- or context-dependent, and relevant reference points may differ for institutional versus individual investors. For example, financial news outlets and information services commonly refer to a wide range of reference prices. Li and Yu (2012) find that nearness to the 52-week high positively predicts future aggregate market returns, while nearness to the historical high negatively predicts future market returns.

The current research also contributes to the growing literature showing that an individual's personal history can affect their economic behavior (see, e.g., Malmendier and Nagel 2011; Malmendier, Tate, and Yan 2011; Malmendier and Nagel 2016; Andersen, Hanspal, and Nielsen 2019) and that, more specifically, the history of an individual's ownership of an object—for example, how they came to acquire the object—can affect valuations (Loewenstein and Issacharoff 1994; Strahilevitz and Loewenstein 1998). One dimension of understanding the consequences of individual experience for future behavior, the current research suggests, is to understand the reference points that experience makes salient.

Data Availability

The code required to replicate the tables and figures in this paper can be found in Quispe-Torreblanca et al. (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/UNKWEP. The investor data from Barclays Stockbroking is proprietary and accessible only with prior approval; details on the process are provided in the replication package. The housing data are publicly available from multiple sources: the Price Paid Dataset (His Majesty's Land Registry), the UK House Price Index (Office for National Statistics), housing stock estimates (Ministry of Housing, Communities, and Local Government), and Loan-to-Value ratios (Financial Conduct Authority). Instructions on accessing and preparing these datasets, as well as constructing the variables used in the analysis, are included in the replication package.

[53] For example, past wages (Bewley 2009; DellaVigna et al. 2017), other people's wages (Brown et al. 2008; Card et al. 2012; Bracha, Gneezy, and Loewenstein 2015), and what people expect to receive (Kőszegi and Rabin 2006; Mas 2006; Crawford and Meng 2011) in settings as varied as consumer products marketing (Hardie, Johnson, and Fader 1993), tax compliance (Yaniv 1999), food choices (Van Herpen, Hieke, and van Trijp 2014), sports (Pope and Schweitzer 2011; Allen et al. 2016), and rental choices (Bordalo, Gennaioli, and Shleifer 2019). Very few of these papers, however, have examined the interplay between different reference points in situations in which multiple natural points of comparison are operative.

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