

TI 2026-048/IV
Tinbergen Institute Discussion Paper

Investment Targets as Reference Points

Aleksi Pitkälä¹

Matteo Vacca²

Petra Vokata³

¹ Vrije Universiteit Amsterdam and Tinbergen Institute

² Hanken School of Economics

³ Ohio State University and CEPR

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and Vrije Universiteit Amsterdam.

Contact: discussionpapers@tinbergen.nl

More TI discussion papers can be downloaded at <https://www.tinbergen.nl>

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Investment Targets as Reference Points*

Aleksi Pitkäjärvi[†]

Matteo Vacca[‡]

Petra Vokata[§]

July 20, 2026

Abstract

We provide the first evidence of forward-looking reference points in investor behavior. Combining administrative data on option traders with a stacked difference-in-differences design, we show that investors' propensity to sell options spikes precisely when the underlying asset crosses the strike price, which retail investors frequently select to match their target price. The effect is difficult to explain using the standard disposition effect, nominal returns, salience, option Greeks, or complex option trading strategies. Moreover, the effect is present only for options bought out of the money, for which the strike price acts as a natural target, but absent for options bought in the money, for which it does not. The evidence is most consistent with investors evaluating gains and losses relative to a forward-looking target, in sharp contrast with the backward-looking purchase price widely used in the disposition effect literature. Our findings suggest that standard tests of reference dependence in selling decisions are misspecified when investors evaluate outcomes relative to reference points other than the purchase price.

JEL Classification: G11, G40, G41, G50

Keywords: reference dependence, disposition effect, forward-looking reference points, retail trading, options

*We thank Nick Barberis, Justin Birru, Ben Enke, Tobin Hanspal, Rawley Heimer, Matthew Henriksson, Matti Keloharju, Dmitriy Muravyev, Terry Odean, Neil Pearson, Davide Tomio, Michael Ungeheuer, Raman Uppal, Michael Weber, and seminar participants at the Helsinki Finance Summit, Canadian Derivatives Institute, Tilburg Finance Summit, SGF, DGF, MFA, RBFC, IBFC, DAPC, EFA, Young Scholars Nordic Finance Workshop, BFGA, Vrije Universiteit Amsterdam, Aalto University, IIM Ahmedabad, University of Vaasa, University of Nottingham, and Hanken School of Economics for helpful comments. We also thank Alexandra Taranenko for outstanding research assistance. Pitkäjärvi and Vacca gratefully acknowledge financial support from the Foundation for the Advancement of Finnish Securities Markets (grant nos. 20240028 and 20250090) and the OP Group Research Foundation (grant nos. 20220057 and 20220089). This paper subsumes results from an earlier paper titled “Striking Out: Biases and Losses of Retail Option Traders”.

[†]Vrije Universiteit Amsterdam and Tinbergen Institute. Email: a.pitkajarvi@vu.nl.

[‡]Hanken School of Economics. Email: matteo.vacca@hanken.fi.

[§]Fisher College of Business, Ohio State University and CEPR. Email: vokata.1@osu.edu.

1 Introduction

The most widely studied form of reference dependence in finance and economics is the disposition effect, or the tendency to sell gains while holding on to losses.¹ This large empirical and theoretical literature has almost exclusively assumed that the reference point from which investors evaluate gains and losses is an asset’s purchase price.² Much less is known about how investors’ selling decisions respond to forward-looking reference points based on expectations or investment targets (Barberis, 2018, p. 148), as opposed to the backward-looking purchase price. The idea that “there are situations in which gains and losses are coded relative to an aspiration level” is as old as prospect theory (Kahneman and Tversky, 1979, p. 286)³ and has received some support in labor economics. For example, cab drivers tend to stop working after reaching their daily income target.⁴

Because investment decisions are inherently forward-looking, it is natural to expect investors to form aspirations or targets that extend beyond the historical purchase price. In that case, selling decisions would be guided not by expected wealth maximization, as in expected utility theory, nor by gains and losses relative to the purchase price, as in the standard disposition effect, but by comparison with an investment target. Similarly to cab drivers who stop working after reaching their income target, investors should be more likely to exit a position once their target is attained. Yet providing compelling evidence of such forward-looking reference points has proven extremely difficult due to data limitations. Identifying their role requires combining comprehensive trading data with information on the targets investors had in mind when entering each position. Moreover, the setting must support credible causal inference and be free from selection or reporting biases.

In this paper, we fill this gap by exploiting a unique feature of options—the strike price—which

¹Since it was first documented by Shefrin and Statman (1985), the disposition effect has been studied by Odean (1998), Grinblatt and Keloharju (2001), Calvet, Campbell, and Sodini (2009a), Ben-David and Hirshleifer (2012), Heimer (2016), and Frydman and Wang (2020), among many others—see Barber and Odean (2013) and Gomes, Haliassos, and Ramadorai (2021) for surveys. According to the bibliometric analysis by Paule-Vianez, Gómez-Martínez, and Prado-Román (2020), the disposition effect is the second most actively studied topic in behavioral finance.

²An exception is Barberis and Xiong (2009, 2012), who model the reference point as the purchase price compounded at the risk-free rate, arguing that an investor may not view an investment as successful if its return is lower than that of the risk-free asset. We review other types of reference points in Section 5.

³See also “Goals are Reference Points” in Kahneman (2011, pp. 302–304). A formal theory of expectations-based reference points is developed by Köszegi and Rabin (2006, 2007).

⁴See Camerer, Babcock, Loewenstein, and Thaler (1997), Crawford and Meng (2011), and Thakral and Tô (2021). In related work, Mas (2006) shows that employees become dissatisfied when they receive a wage increase that is smaller than they expected.

provides observable variation in investors’ forward-looking motives. Widespread anecdotal evidence from brokers, trading-related websites, and social media shows that investors often select strike prices to match their target price for the underlying asset.⁵ Using 17 years of population-level administrative data and a stacked difference-in-differences design, we show that investors’ propensity to sell options purchased out of the money spikes when the underlying asset crosses the strike. Of course, other contract features may affect both contract choice and selling decisions alongside any target-driven behavior. However, such features do not naturally explain the sharp jump in sales that we document precisely on strike-crossing days. Crucially, this effect is absent for options purchased in the money, for which the strike cannot serve as a forward-looking target because reaching it would imply a loss relative to the purchase price. Overall, the evidence is consistent with investment targets acting as reference points, while being difficult to reconcile with alternative explanations, including the standard disposition effect, salience, or skewness preferences.

We begin by plotting aggregate selling propensity schedules, a common approach in the disposition effect literature. In our setting, the relevant threshold is the strike price, so we plot the propensity to sell as a function of moneyness, defined as the relative distance between the underlying price and the strike. Consistent with investors using the strike as a reference point, the selling schedule exhibits an inverse V shape that peaks at the strike and declines for options that are further in or out of the money. The peak persists after flexibly controlling for holding period returns and holding periods. Because returns vary smoothly around the strike, these controls have little effect on the pattern. The inverse V shape therefore cannot be explained by the standard disposition effect, which predicts that selling responds to realized gains and losses relative to the purchase price.

An obvious concern with interpreting these results is that the strike price may be proxying for other covariates that affect the propensity to sell. For example, the option Greeks gamma and vega peak at the strike, so excess selling at the strike could be explained by investors using them to manage price and volatility risk, or as part of a sophisticated option trading strategy. Similarly, the strike price may serve as a purely salient reference point (O’Donoghue and Sprenger, 2018), rather than reflecting investors’ forward-looking targets. Rather than attempting to control for all possible

⁵See Tables IA.1 and IA.2 for 20 representative quotes from articles and social media posts that relate an option’s strike price to an investor’s target price.

covariates, our preferred approach is to design placebo tests using options that were purchased in the money. Unlike the out-of-the-money option purchases used in our main analyses, the strike price cannot serve as a forward-looking target for in-the-money purchases since reaching the strike would represent a loss relative to the purchase price. If investors respond to the strike price because of option Greeks, salience, or other factors, then this sample should also exhibit a spike in selling propensity at the strike price. This is not what we find. Across all our tests, the elevated selling propensity at the strike is present for options purchased out of the money but absent for options purchased in the money.

Perhaps the cleanest way to identify the effect of the strike on selling behavior is to examine selling decisions around the precise moment the underlying asset crosses the strike. We use an option-level stacked difference-in-differences design that compares options crossing the strike to options that remain out of the money over the entire ± 10 -day event window. In the days prior to the crossing, the estimated coefficients are small and generally statistically insignificant, consistent with the parallel trends assumption. On the crossing day, we observe a sharp spike in selling propensity. In our preferred specification, which compares options written on the same underlying asset on the same day, the probability of selling rises by 6.8 percentage points on the crossing day, a 212% increase relative to the 3.2% unconditional daily selling probability in the event-study sample.

The spike in selling propensity is robust to enriching the option-level design with underlying-by-type-by-day fixed effects, which absorb earnings announcements and other attention-grabbing events in the underlying asset, and to controls for the holding period return, gain status, holding period, and time to expiry of an option's holders. Across all specifications, the crossing-day effect remains positive and highly significant, confirming that it is not explained by the standard disposition effect, return-based motives, or shocks to the underlying.

As before, the effects are confined to options purchased out of the money and are absent in placebo tests using in-the-money purchases. These placebo tests use the same difference-in-differences designs but replace options purchased out of the money with in-the-money purchases for which the strike price cannot plausibly serve as an investment target. In stark contrast to our main results, we find no increase in selling propensity when in-the-money options cross the strike and fall out of

the money. This asymmetry strongly supports the interpretation that the observed selling behavior for out-of-the-money options is driven by target attainment rather than salience, option Greeks, or other strike-related characteristics.

We sharpen the distinction between reference-dependent selling behavior and alternative explanations in another test, where we re-estimate the same design with the propensity to buy additional units of an option as the outcome. If reaching the target triggers a preference to realize the position, the response should be specific to selling. If the crossing instead changes investors' beliefs about the option's prospects or draws their attention to the position, it should affect purchases as well, since beliefs and attention influence buying and selling alike ([Ben-David and Hirshleifer, 2012](#)). We find no strike effect on repurchases: buying does not increase at the crossing. This asymmetry between the two margins is exactly what a selling-specific, target-attainment mechanism predicts and is difficult to reconcile with attention- or belief-based explanations.

We provide further evidence on the mechanism driving the results we document by examining the two primary explanations for reference-dependent selling and the disposition effect considered by the prior literature: (i) reference-dependent preferences (e.g., realization utility; [Barberis and Xiong, 2012](#)), and (ii) belief-based mechanisms, such as a belief in mean reversion ([Odean, 1998](#)). To do so, we exploit settings in which investors simultaneously hold multiple options of the same type on the same underlying asset, so that their beliefs about the future price path of the underlying are plausibly constant across positions. Even in these highly restrictive settings, we show that investors are significantly more likely to sell in-the-money options than otherwise similar out-of-the-money options. This pattern is difficult to reconcile with belief-based explanations. For example, a belief in mean reversion would predict correlated selling across all options of the same type written on the same underlying. Instead, the evidence points to reference dependence centered on forward-looking targets.

We consider and rule out several additional alternative explanations. Our findings are difficult to reconcile with skewness preferences, the rank effect ([Hartzmark, 2015](#)), complex option strategies, rational rebalancing or rollover behavior, hedging motives, transaction costs, liquidity needs, taxes, or rational selling in anticipation of return reversals. For example, the effect of crossing the strike on

selling remains qualitatively and quantitatively unchanged after controlling for the rank of positions within investor portfolios. Skewness preferences are also unlikely to explain the results, as they would predict similar behavior for out-of-the-money and in-the-money purchases, which we do not find. Finally, investors would have earned positive returns by continuing to hold their positions after strike price crossings, which is inconsistent with explanations based on subsequent return reversals.

A natural question is whether our results generalize beyond the option market. We focus on options as a laboratory because their security design makes forward-looking targets observable and enables clean identification. However, there is little reason to believe that this forward-looking behavior is unique to options. Target-driven behavior is widespread among equity investors: traders routinely set limit sell orders at target prices, anchor on analyst price targets, or follow personal rules such as “I’ll sell when the stock hits \$X.”⁶ Similarly, retail brokerage platforms actively encourage investors to set price alerts and exit rules around prespecified targets. The key difference is that in stock markets, researchers typically cannot observe the targets investors use, which makes detecting forward-looking reference dependence in standard equity trading data difficult, even when it is present.

Our results have important implications for the disposition effect literature, asset prices, and investor welfare. Investors who sell options on the strike crossing day forgo average returns of 2.8% over the following day and 4.4% over ten days.⁷ For reference, the costs of the standard disposition effect documented by [Odean \(1998, Table VI\)](#) average 3.4% per year. These results thus imply that the target-driven reference dependence we document imposes large economic costs on investors.

Our results also help reconcile conflicting evidence in the disposition effect literature and inform how reference-dependent selling is measured. In a pair of influential papers, [Odean \(1998\)](#) shows that investors are reluctant to realize losses, whereas [Ben-David and Hirshleifer \(2012\)](#) question this evidence, showing that the propensity to sell stocks displays little discontinuity at zero returns

⁶For example, articles and social media posts frequently describe stock traders who determine a target price before buying and then sell once the stock reaches it, echoing the strike-as-target behavior we document for option traders—see [Table IA.3](#) for ten representative examples. Relatedly, [Kuo, Lin, and Zhao \(2015\)](#) show that retail investors cluster limit orders at round numbers, consistent with round-number price targets in stock trading.

⁷To the extent that target-driven selling generates concentrated, predictable order flow, it may also affect underlying asset prices and generate return predictability analogous to the disposition-driven selling pressure ([Frazzini, 2006](#); [Davis, Knüpfer, Kværner, Sen Dogan, and Vokata, 2026](#)). A growing literature shows that option order flow transmits to equity prices through dealer delta hedging (e.g., [Hu, 2014](#); [Ni, Pearson, Poteshman, and White, 2021](#)) and that stock prices cluster at option strike prices on expiration dates ([Ni, Pearson, and Poteshman, 2005](#)).

and that both selling and buying propensities display a V shape around the purchase price. We provide evidence from a setting that allows for sharper identification of reference-dependent selling behavior and thereby address this critique. More broadly, if a meaningful fraction of investors evaluate outcomes relative to targets that differ from the purchase price, the standard approach of measuring selling propensity as a function of holding period returns is misspecified: gains and losses are computed relative to the wrong benchmark. Our results thus suggest that the widely used PGR–PLR measure (Odean, 1998) and tests of discontinuity in selling around the purchase price (Grinblatt and Keloharju, 2001; Kaustia, 2010; Ben-David and Hirshleifer, 2012) understate the prevalence of reference-dependent behavior in settings where investors hold heterogeneous targets. Ultimately, any test of reference-dependent utility is a joint test of the reference point and the utility specification.

Our main contribution is to provide evidence that investors use investment targets as reference points—an example of forward-looking reference points that have received little attention in finance. Barberis (2018) notes that most implementations of prospect theory in finance adopt “backward-looking” reference points. In contrast, Kőszegi and Rabin (2006, 2007) advocate “forward-looking” reference points, under which investors evaluate gains and losses relative to the wealth they expected to have at a given time. Bordalo, Gennaioli, and Shleifer (2019, 2020) model reference points using associative memory, which mixes both forward- and backward-looking reference points. Our evidence provides new support for models that incorporate forward-looking reference points, although our results do not require the reference point to coincide with an investor’s expectation, but rather with an aspiration or target, a related yet distinct concept. This reference point is also distinct from salient thresholds such as round numbers or 52-week highs (e.g., George and Hwang, 2004; Pope and Simonsohn, 2011; Pope and Schweitzer, 2011). Our results thus enrich our understanding of reference-dependent behavior in the context of investment decisions.

The vast majority of the empirical literature on the disposition effect relies on data from stock investors (e.g., Ivković, Poterba, and Weisbenner, 2005; Grinblatt and Han, 2005; Calvet, Campbell, and Sodini, 2009b; Linnainmaa, 2010; Birru, 2015; An, 2016; Chang, Solomon, and Westerfield, 2016;

An, Engelberg, Henriksson, Wang, and Williams, 2024).⁸ An active literature also studies the role of reference dependence in housing markets (e.g., Genesove and Mayer, 2001; Andersen, Badarinza, Liu, Marx, and Ramadorai, 2022; Badarinza, Ramadorai, Siljander, and Tripathy, 2024). We extend this literature by showing how security design can be leveraged to identify forward-looking reference points.⁹ More broadly, our results suggest that reference points need not be mechanically inherited from the status quo—the purchase price—but can instead be endogenously chosen.¹⁰ Our approach therefore opens new avenues for studying how investors form and revise their reference points.

2 Data

2.1 Data Sources

Euroclear Finland. Our main data source is Euroclear Finland, which acts as the official registry of stock and option holdings in Finland. The data include comprehensive daily holdings and changes in holdings of all stocks and options in Finland from December 2000 to December 2017. We identify retail investors in the data by using the retail investor flag provided by Euroclear Finland. Earlier versions of the data from Euroclear Finland or its predecessor, the Finnish Central Securities Depository, have been used in studies of retail stock investments (Grinblatt and Keloharju, 2000, 2001; Grinblatt, Keloharju, and Linnainmaa, 2012) and employee derivative trading (Vacca, 2026). By contrast, the present study leverages the full sample of retail option trades in Finland.

Technically, the options in our data set are bank-issued warrants. The term “warrant” can be misleading because it typically refers to call options issued by firms on the primary market that, if exercised, lead to the issuance of new shares. By contrast, the warrants in our data set

⁸See also Coval and Shumway (2005) for evidence from futures traders, Heimer (2016) and Heimer and Imas (2022) for evidence from forex traders, Ivković and Weisbenner (2009) for evidence from mutual fund flows, Fischbacher, Hoffmann, and Schudy (2017) and Aristidou, Giga, Lee, and Zapatero (2025) for laboratory experiments, and Andrikogiannopoulou and Papakonstantinou (2020) for evidence from sports bettors. See also Heimer, Iliewa, Imas, and Weber (2025).

⁹The importance of salient product features in retail financial product design has been documented by Célériér and Vallée (2017), who study how issuers of structured products use complexity to offer attractive headline rates, and by Vokata (2025), who shows that issuers strategically set salient features at round numbers. In our setting, the strike price is the salient design feature that reflects investor reference points.

¹⁰Consistent with this view, Gelman, Reiter-Gavish, and Roussanov (2026) show that investors evaluate their portfolio performance against external reference points, such as salient market benchmarks, and adjust their risk-taking accordingly.

are exchange-traded, European-style vanilla call or put options issued by banks and marketed specifically to retail investors.¹¹ To avoid any confusion in terminology, throughout the paper, we refer to the warrants in our data set as options. Unlike in the United States, retail investors in Finland are not permitted to write (short sell) options, and all options are cash-settled at expiry, eliminating the risk of physical settlement.

The data set includes 15 752 unique options written on 42 underlying assets: 27 Finnish stocks, 7 stock indices, and 8 commodities or exchange rates. Stock options account for 85% of all observations, index options for 14%, and the remaining options for 1%.

Stock Exchange Releases. The data from Euroclear Finland do not contain information on option characteristics, such as the expiration date, strike price, underlying asset, or whether an option is a call or a put, so we manually collect data on option characteristics from stock exchange releases prepared by the issuing banks. An excerpt from a representative stock exchange release is presented in Figure [IA.1](#). Due to the limited availability of older stock exchange releases, the proportion of options for which we have data on characteristics increases over time, rising to over 90% in 2010–2013 and reaching 100% in 2014–2017.

Helsinki Stock Exchange. The data from Euroclear Finland also do not contain transaction prices, so we use the price of the asset at market close as the transaction price. Both the option prices and the prices of their underlying assets are from the Helsinki Stock Exchange.

2.2 Terminology and Definitions

We now define key terms and variables that we use throughout the paper. At the outset, we note that many of the variables are calculated at the round-trip level. If an investor combines multiple purchases of the same option within a single round-trip, we calculate round-trip level variables (e.g., returns) as value-weighted averages, where weights correspond to the euro amount invested in each purchase (price $\times$ quantity).

Option Variables. We define the moneyness of a call option as the price of the underlying

¹¹The issuing banks are also required to act as designated market makers, thus guaranteeing liquidity. Table [IA.4](#) shows that over 90% of bid-ask spreads at market close are either one or two cents, which is on the lower end of bid-ask spreads observed in U.S. option markets ([Hendershott, Khan, and Riordan, 2022](#)).

asset minus the strike price, divided by the strike price. The moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. We say that an option is out of the money if its moneyness is less than or equal to zero, and in the money if its moneyness is greater than zero. Option returns are calculated from the respective option close prices, and all return and moneyness variables are adjusted for capital events, such as stock splits. We define the main outcome variable, $Sale_{ijt}$, as an indicator equal to one if investor i sells option j on day t , and zero otherwise. Hence, $Sale_{ijt}$ covers both full and partial sales of a position.

Event Days. In our stacked difference-in-differences analyses, we define “strike crossing days” as the first day on which an option moves from out of the money to in the money, or from in the money to out of the money. The unit of observation is an option-day: an option j that crosses the strike on event date E_c forms a cohort c with control options that do not cross the strike, and the dependent variable $Sale_{jct}$ is the fraction of the option’s holders who sell on day t . When a robustness test restricts the sample on an investor-level characteristic, we apply the restriction at the holder level when forming this option-day outcome, computing the selling fraction over the qualifying holders. The within-investor belief tests of Section 5, by contrast, are estimated at the investor-option level, since they are defined by an investor holding two options at once.

Because strike crossings are identified using daily closing prices, we do not observe their exact intraday timing relative to sales. While this creates measurement error in event timing, it would, if anything, attenuate the estimated effect on the crossing day by blurring it across nearby days, thus making it more difficult to find a significant effect.

Samples. For our analyses, we generally use two samples of observations. The main sample covers all round-trips that are out of the money at the initial purchase. The placebo sample covers all round-trips that are in the money at the initial purchase. Hence, the placebo sample covers positions for which the strike price cannot act as a target, as it would imply a negative target return.

2.3 Summary Statistics

Table 1 presents summary statistics on our main sample of out-of-the-money purchases, our placebo sample of in-the-money purchases, and investors.

In total, the sample contains 18 570 investors, of whom 10% are female. The average (median) investor is a 38-year-old (36-year-old) male with one year (two months) of option trading experience and 51 (9) executed trades. Consistent with the evidence on retail option trading in the United States presented by [Bryzgalova, Pavlova, and Sikorskaya \(2023\)](#) and [Bogousslavsky and Muravyev \(2024\)](#), we find that retail investors prefer calls over puts, with 80% of out-of-the-money purchases and 73% of in-the-money purchases being calls, and prefer out-of-the-money options to in-the-money options, with 73% of all purchases being out of the money. Compared to options purchased in the money, out-of-the-money option purchases are smaller in value, further away from zero moneyness at the time of purchase, held for longer, and have lower returns.

3 The Propensity to Sell Around the Strike Price

In this section, we examine aggregate patterns in selling behavior around the strike price of an option. Using our main sample of out-of-the-money option purchases, we show that the propensity to sell options as a function of moneyness has an inverse V-shape that peaks at the strike price, consistent with investors using the strike price as a reference point for their out-of-the-money option purchases. We then rule out potential confounding factors and alternative explanations by controlling for the effects that the holding period and holding period return have on selling decisions, and by performing placebo tests with options purchased in the money, for which the strike price cannot act as a target.

3.1 The Inverse V-Shaped Relation Between Option Sales and Moneyness

We begin our examination of how the strike price affects selling propensity by regressing investors' selling decisions on dummy variables for different levels of option moneyness. Our empirical approach is comparable to the propensity to sell functions estimated for stock trades by [Ben-David and Hirshleifer \(2012\)](#) and for real estate transactions by [Andersen et al. \(2022\)](#), except that we plot the selling propensity as a function of moneyness and not as a function of holding period returns.

Specifically, we use our main sample of out-of-the-money purchases to estimate the linear

probability model

$$Sale_{ijt} = \sum_{k=1}^{100} \beta_k \mathbb{1}\{m_{jt} = k\} + \varepsilon_{ijt}. \quad (1)$$

The dependent variable $Sale_{ijt}$ is a dummy variable that equals one if investor i sells option j on day t , and $m_{jt} \in \{1, \dots, 100\}$ denotes the moneyness percentile bin of option j on day t .

The estimated propensity to sell function is plotted in Figure 1. The dots indicate the estimated selling propensities for the moneyness percentile bins. The solid lines are from a nonparametric local quadratic kernel regression fit, estimated separately for out-of-the-money and in-the-money option positions and evaluated on a dense grid. The shaded areas represent 95% pointwise confidence intervals based on the asymptotic standard errors from the local polynomial smoother. Consistent with investors using the strike price of an option as a reference point for their out-of-the-money option purchases, the propensity to sell is close to zero for options that are deep out of the money, increases sharply as the price of the underlying asset approaches the strike price, and then decreases again for options that are in the money. Our results contrast with the puzzling V-shaped selling propensity for stocks documented by Ben-David and Hirshleifer (2012), where the selling propensity is minimized around the purchase price, and which the authors argue is inconsistent with investors holding a simple realization preference with the purchase price as a reference point. By contrast, the inverse V-shape we observe is consistent with investors using the strike price as a reference point.

A potential concern with the results presented in Figure 1 is that investors' selling decisions around the strike price could be driven by factors other than moneyness that are known to influence selling behavior, such as a position's holding period or its holding period return (e.g., Ben-David and Hirshleifer, 2012). As a first piece of evidence against this possibility, in Figures IA.2 and IA.3 we plot average holding period returns and average holding periods for different levels of option moneyness. Neither holding periods nor holding period returns exhibit an inverse V-shaped relation with moneyness, nor do they exhibit any discontinuous behavior at the strike price that could generate the relation observed in Figure 1. As a result, we would not expect the peak in selling propensity at the strike price to be explained by holding periods or holding period returns.

Nonetheless, to rule out this possibility more directly, we re-estimate the regression specification from Equation 1 with flexible and granular controls for the holding period and holding period return

of the position. This empirical approach allows us to isolate the effect that option moneyness has on the propensity to sell in excess of what would be expected purely based on a position’s holding period and holding period return.

Specifically, using the same sample of out-of-the-money purchases, we estimate the linear probability model

$$Sale_{ijt} = \sum_{k=1}^{100} \beta_k \mathbb{1}\{m_{jt} = k\} + \sum_{q=1}^{100} \sum_{p=1}^{20} \gamma_{qp} \mathbb{1}\{r_{ijt} = q\} \mathbb{1}\{h_{ijt} = p\} + \varepsilon_{ijt}, \quad (2)$$

where r_{ijt} denotes the holding period return percentile bin of investor i ’s position in option j on day t , and h_{ijt} denotes the holding period of the same position.¹² The interaction indicators $\mathbb{1}\{r_{ijt} = q\} \mathbb{1}\{h_{ijt} = p\}$ therefore provide a complete set of return-percentile-by-holding-period controls.

The estimated selling propensities in excess of what would be expected purely based on a position’s holding period and holding period return are plotted in Figure 2. Consistent with the strike price exerting a significant influence on the sales of out-of-the-money option purchases, the excess selling propensity again peaks at the strike price and retains the same inverse V-shape as in Figure 1. Holding period returns and the standard disposition effect that operates through them thus cannot explain the peak in selling propensity at the strike price.

The results in Figure 2 are estimated using our main sample of out-of-the-money option purchases, so they do not distinguish between options purchased deep out of the money and options purchased only slightly out of the money. To examine whether the strike price has a consistent effect on the selling of out-of-the-money options with different levels of moneyness at purchase, in Figure IA.4 we plot the results of a subsample analysis where we estimate the model from Equation 2 separately for options purchased between 0% and 10% out of the money and for options purchased more than 10% out of the money. The cutoff of 10% is very close to the median moneyness at purchase of out-of-the-money option purchases in our data set. In both subsamples, we continue to observe a peak in excess selling propensity at the strike price. The strike price thus seems to have a consistent

¹²The holding period is measured in trading days. We winsorize the holding period at 20 days to reduce the risk of overfitting, as our data show that the probability of selling declines steadily from 1 to 20 holding days but remains flat thereafter.

effect on investors' sales of options purchased out of the money, regardless of the precise level of moneyness at purchase, consistent with investors using the strike price as a reference point.

3.2 Placebo Tests Using In-the-Money Options

The analyses presented above have been performed on our main sample of out-of-the-money option purchases, since these are the option purchases for which the strike price can serve as an explicit forward-looking target that investors use. Although the results are consistent with this interpretation, similar results could plausibly be generated by other attributes that can be associated with the strike price. For example, the strike price could be a round number or an otherwise salient price to which investors react, even if they do not use it as an ex ante target (e.g., [Pope and Simonsohn, 2011](#); [Frydman and Wang, 2020](#)). Alternatively, investors could be selling at the strike price because they use sophisticated option trading strategies involving option Greeks like gamma and vega, which peak at the strike.

To rule out these alternative explanations, we repeat the same analyses using our placebo sample of in-the-money option purchases. The attractive feature of these purchases is that the strike price cannot serve as a target price, since reaching the strike would represent a loss relative to the purchase price. As a result, if the peak in selling at the strike for options purchased out of the money is the result of investors using the strike price as a target, then we would not expect to observe a similar peak for options purchased in the money. By contrast, if the peak in selling is driven by other attributes associated with the strike price, such as salience or option Greeks, then we would expect to observe a similar peak at the strike for options purchased in the money.

Figure 3 plots the propensity to sell function derived from estimating Equation 1 with our placebo sample of in-the-money option purchases. For options purchased in the money, the selling propensity is maximized when options remain approximately 3–9% in the money, before decreasing sharply as an option approaches the strike price and falls out of the money. In contrast to options purchased out of the money, the selling propensity does not peak at the strike price. This pattern is consistent with target-driven reference points driving the peak but inconsistent with alternative explanations such as salience or option Greeks.

For completeness, Figure [IA.5](#) plots the excess selling propensities again controlling for a position’s holding period and holding period return, and Figure [IA.6](#) plots the results separately for options purchased between 0% and 10% in the money and for options purchased more than 10% in the money. In both figures, the excess selling propensity is highest for options that remain moderately in the money before decreasing as options approach the strike price and fall out of the money. The subsample plots show that the peak in excess selling propensity does not coincide with the strike price but instead occurs for options whose moneyness has decreased slightly from what it was when the option was purchased.

4 The Propensity to Sell When Crossing the Strike Price

If investors use the strike price of an option as a forward-looking target for their out-of-the-money option purchases, then we would expect to observe a clustering of sales on days when an option first crosses the strike price and investors sell to lock in their profits once their target has been reached.¹³ In this section, we present evidence of such clustering from a stacked difference-in-differences design. This design is particularly appropriate for analyzing staggered treatments as it relies on clean control observations of not-yet-treated or never-treated units within the treatment window (e.g., [Baker, Larcker, and Wang, 2022](#)). We show that there is a significant spike in selling on days when an option purchased out of the money crosses the strike for the first time, but no corresponding spike when in-the-money purchases cross the strike, consistent with investors using the strike price as a target-driven reference point.

4.1 The Clustering of Sales on Strike Price Crossings

To see how investors respond to strike price crossings, we begin by examining selling behavior at the option-day level. Focusing on options that were purchased out of the money, we test whether the probability of selling spikes when options cross from out of the money to in the money for the first time, relative to options purchased out of the money that remain out of the money. For each

¹³Similar examples of clustering around targets have been documented in other settings. For example, [Allen, Dechow, Pope, and Wu \(2017\)](#) document significant clustering in marathon runners’ finishing times around commonly used target times.

strike crossing day E_c , we identify a cohort c of treated options that cross the strike and control options that do not. We then stack the data across strike crossing days and estimate the average treatment effect.

Specifically, we estimate the option-panel regression

$$Sale_{jct} = \alpha_{jc} + \lambda_{tc} + \sum_{\substack{\tau=-10 \\ \tau \neq -5}}^{10} \mu_{\tau} D_{jct}^{\tau} + \varepsilon_{jct}, \quad (3)$$

where $Sale_{jct}$ is the fraction of option holders who sell option j in cohort c on day t , and $D_{jct}^{\tau} = \mathbb{1}[t - E_c = \tau]$ is an indicator for option j in cohort c on day t being τ days away from a strike crossing. The standard two-way fixed effects are at the option-cohort level, α_{jc} , and the day-cohort level, λ_{tc} . The parameters of interest are the event-day coefficients, μ_{τ} , which identify the differences in selling probabilities between options that cross the strike price for the first time on $\tau = 0$ and options that remain out of the money throughout the entire treatment window. We use an event window of ± 10 trading days and include event-day indicators for all leads and lags, omitting $\tau = -5$ as the reference day, so that the μ_{τ} measure selling probabilities relative to day -5 , one trading week before the crossing. Observations are weighted by the number of holders, and standard errors are clustered by option and day.

Figure 4 and Table 2 report the event-day coefficients, μ_{τ} , with 95% confidence intervals shown in the figure. In the days before a strike price crossing, the estimated coefficients are small and generally statistically insignificant, consistent with parallel trends in the selling of treated and control options. The one exception is a modest run-up in the one to two days immediately preceding the crossing, which is expected given the granularity of our data. Because we identify crossings from daily closing prices, an option whose underlying approaches the strike on day -1 or -2 may already have crossed it intraday before falling back out of the money at the close; moreover, investors whose targets lie just below the strike reach them shortly before the measured crossing day. Both forces shift some target-driven sales onto the days just before the crossing and, if anything, attenuate the crossing-day estimate. On the strike crossing day, the probability of selling spikes by 13.0 percentage points relative to the pre-crossing baseline, which is both statistically and economically significant,

corresponding to a 406% increase relative to the 3.2% unconditional daily selling probability in the event-study sample. We thus find significant excess selling of options purchased out of the money precisely on the day when they first cross the strike price, consistent with investors selling to lock in their profits as soon as their target has been reached.

The option-level design in Equation 3 cleanly identifies the discontinuity at the crossing. We next assess its robustness by progressively enriching the fixed-effect structure and adding controls for the determinants of selling. Table 2 reports three specifications: Specification (1) is the baseline design with option-cohort and day-cohort fixed effects; Specification (2) replaces the day-cohort fixed effects with underlying-by-type-by-day-cohort fixed effects, which absorb any selling common to options of the same type written on the same underlying asset on a given day, such as that induced by earnings announcements or other attention-grabbing events; and Specification (3) additionally controls for the option-day averages of the holding period return, gain status, holding period, and time to expiry of an option’s holders. Figure 4 overlays the event-study coefficients from all three specifications.

The crossing-day spike is large and highly significant in all three specifications, with t -statistics of 10.5, 5.9, and 3.7. The magnitude of the spike declines as we add fixed effects and controls—from 13.0 to 6.8 to 3.9 percentage points—which is expected given what each specification absorbs. Moving from Column (1) to Column (2), the underlying-by-type-by-day-cohort fixed effects absorb all selling common to options on the same underlying on a given day, including selling triggered by the very price movement that produces the crossing; the spike that survives is therefore identified purely from variation across options written on the same underlying on the same day. The further decline in Column (3) is driven entirely by the controls for the holding period return and gain status, which are mechanical consequences of crossing the strike: when an out-of-the-money option crosses, its return rises and its gain indicator is more likely to be switched on by construction. Because these are post-treatment variables, conditioning on them absorbs part of the treatment effect itself, and Column (3) is best interpreted as a conservative lower bound rather than as a more credible

estimate.¹⁴ Crucially, what the controls cannot explain is the *discontinuity*: in every specification, the coefficient jumps sharply on the crossing day and lies close to zero on the surrounding days—a pattern that smoothly varying covariates cannot generate and that is absent when in-the-money options cross the strike under the same controls. We conclude that neither shocks to the underlying, the standard disposition effect, nor other observable determinants of selling can account for the spike at the strike.

We view the three specifications as complementary rather than as competing estimates of a single parameter, because each isolates a different economic component of the crossing-day response. Specification (1) captures the total reduced-form spike in selling. Specification (2), our preferred specification, removes the one genuine confounder—selling driven by the underlying’s price movement on the crossing day—by comparing options written on the same underlying on the same day, and therefore provides the cleanest causal estimate that does not condition on consequences of the treatment. In this specification, crossing the strike raises the daily probability of selling by 6.8 percentage points, a 212% increase relative to the unconditional daily selling probability in the event-study sample of 3.2%. Specification (3) strips out even the mechanical return- and gain-based selling that the crossing induces, leaving a conservative lower bound; even then, selling rises by 3.9 percentage points on the crossing day, a 121% increase relative to the same baseline.

4.2 Placebo Tests Using In-the-Money Options

The results of the stacked difference-in-differences analyses presented above are consistent with the interpretation that investors use the strike price of an option as a target-driven reference point and are more likely to sell their positions once their target has been reached. However, as with the propensity to sell functions estimated for out-of-the-money purchases in Section 3, the results could possibly be generated by other attributes associated with the strike price. We thus adopt the same approach as before and perform placebo tests with options that cross the strike price from in the money to out of the money.

¹⁴Adding the controls one at a time to Specification (2) confirms this: the holding period return and gain status account for essentially the entire decline (the crossing-day coefficient falls from 6.8 to 3.8 percentage points when both are included), whereas the holding period and time to expiry leave it unchanged (6.9 percentage points). The latter two are not mechanically tied to the crossing, and their inclusion does not attenuate the effect.

Figure 5 plots the results from the option-level design in Equation 3. The treated options are those that cross the strike price and fall out of the money for the first time, while the control options remain in the money throughout the entire treatment window. The results show that there is no spike in selling propensity when crossing the strike from in the money to out of the money, which is not what we would expect if the clustering of sales around strike price crossings were driven by salience, option Greeks, or other alternative explanations. Instead, the results are consistent with the strike effect being driven by target-driven reference dependence for out-of-the-money purchases.

Table 3 reports the corresponding option-level event study under the same three specifications. Consistent with the figure, we find no evidence of a spike in selling propensity on the crossing day in any specification, including the most demanding one that controls for the holding period return, gain status, holding period, and time to expiry.

4.3 Buying Versus Selling Around the Crossing

If the spike in selling at the strike crossing reflects investors realizing a forward-looking target, it should be specific to the selling margin: reaching a target is a reason to exit a position, not to add to it. This prediction distinguishes our interpretation from belief- and attention-based explanations of reference-dependent trading. Ben-David and Hirshleifer (2012), for instance, document that an investor’s propensity to buy additional units of a position is V-shaped in returns, much like the propensity to sell, and interpret the symmetry of the two margins as evidence that reference-dependent trading reflects beliefs, such as speculation or return chasing, rather than a selling-specific preference such as realization utility. Under such mechanisms, a salient, attention-grabbing event like a strike crossing should draw in additional purchases just as it triggers sales.

To test this, we re-estimate the option-level design of Equation 3 using the propensity to buy as the dependent variable, defined as the fraction of an option’s holders who purchase additional units on a given day. We use the same sample, cohorts, weights, and specifications as in our main analysis. Figure 6 overlays the event-study coefficients from all three specifications on the same scale as Figure 4, and Table 4 reports the corresponding estimates.

The contrast between the two margins is stark. Whereas selling spikes by 13.0 percentage points

on the crossing day, additional buying does not spike at all; if anything, it declines slightly, by 1.2 percentage points (Specification 1). The absence of a buying response is robust: the crossing-day coefficient remains negative and statistically significant under the underlying-by-type-by-day fixed effects of Specification (2), which absorb the attention generated by the price movement itself, and is a precisely estimated zero under the full controls of Specification (3). Pre-crossing coefficients are essentially flat throughout. The two margins thus move in opposite directions at the crossing: investors rush to sell, but are no more likely—indeed slightly less likely—to buy. This asymmetry is what a selling-specific, target-attainment mechanism predicts, and is difficult to reconcile with the symmetric, belief- or attention-based account that [Ben-David and Hirshleifer \(2012\)](#) infer from the parallel behavior of buying and selling in stock data.

5 Interpretation

In this section, we relate our results to the long-standing debate of whether reference-dependent investment behavior is explained by investors’ preferences or their beliefs. We design a novel test to disentangle these two explanations and show that our results are difficult to reconcile with a purely belief-based explanation for reference-dependent selling behavior.

5.1 Reference-Dependent Preferences

The economic literature has considered three types of reference points in models of reference-dependent preferences: backward-looking, forward-looking, and salience-based—see [O’Donoghue and Sprenger \(2018\)](#) for a review. Perhaps the most widespread is the use of backward-looking reference points ([Tversky and Kahneman, 1991](#)). For example, choice may be influenced by a past level of wealth or income, an asset purchase price, or the current endowment ([Thaler, 1980](#); [Kahneman, Knetsch, and Thaler, 1990](#)). The effects of status quo reference points have been well-documented in the housing market ([Andersen et al., 2022](#)) and investment behavior ([Odean, 1998](#); [Barberis and Xiong, 2012](#); [Ben-David and Hirshleifer, 2012](#)).

A second type of reference point is salience-based. Rather than being anchored to past experience, salience-based reference points are determined by the prominence or psychological accessibility of

certain outcomes. For example, choice may be influenced by focal outcomes such as round numbers or other salient thresholds. The effects of salience-based reference points have been documented for golfers (Pope and Schweitzer, 2011) and marathon runners (Allen et al., 2017), as well as in financial markets, where investors anchor to 52-week highs (George and Hwang, 2004; Heath, Huddart, and Lang, 1999a), firms manage earnings to meet salient thresholds (Burgstahler and Dichev, 1997), and consumers’ loan payments (Argyle, Nadauld, and Palmer, 2020) and security design characteristics (Vokata, 2025, 2021) bunch at round numbers.

Finally, forward-looking reference points are based on goals and aspirations (Heath, Larrick, and Wu, 1999b) or future expectations. Target-based reference points, where agents evaluate outcomes relative to a specific goal or aspiration, have been documented, for example, in labor supply decisions (Camerer et al., 1997; Crawford and Meng, 2011; Thakral and Tô, 2021) and among corporate sales teams (Larkin, 2014). Kőszegi and Rabin (2006, 2007) develop a model in which the reference point is determined by rational expectations about future outcomes, distinct from target-based reference points. Bordalo et al. (2020) model reference points using associative memory, where past experiences shape expectations about future outcomes, combining both backward- and forward-looking elements.

Our results are inconsistent with purely backward-looking reference points. The status quo interpretation in our setting would imply that investors use the purchase price as a reference point and react to nominal gains disproportionately more than to nominal losses. Yet, we show that nominal gains are smooth around the strike price, and that across the empirical designs we consider, the results are insensitive to the inclusion of highly flexible controls for holding period returns and the gain status of a position.

Our results are also inconsistent with salience-based reference points. The salience-based interpretation of our results would imply that investors react to the strike price because of its prominence, and not because they use it as a target. However, our placebo tests rule out salience as an explanation for our results, since the salience of the strike price is the same regardless of whether an option was purchased in the money or out of the money.

Instead, the evidence we present is most consistent with investors using investment targets as

forward-looking reference points and evaluating the success of a trading episode relative to the target they have set for themselves.

The finance theories most related to our work are models of realization utility, where the act of selling an asset triggers an instantaneous burst of utility relative to a reference point ([Barberis and Xiong, 2012](#); [Ingersoll and Jin, 2013](#)). The sharp increase in selling propensity at the strike price that we document is broadly consistent with the mechanism of realization utility, albeit with a more nuanced specification of the reference point. While existing models of realization utility assume a status quo reference point or its variant compounded by the risk-free rate, our results are most consistent with the idea that investors have investment-specific forward-looking targets that act as reference points. Hence, our results suggest that a fruitful direction for future research is to explore models of realization utility with forward-looking and endogenous reference points.

5.2 Belief-Based Explanations

An alternative class of explanations for reference-dependent selling behavior considered in the disposition effect literature is belief-based explanations. Under this interpretation, investors may be more likely to sell options that have crossed from out of the money to in the money because they believe the price of the underlying asset will mean-revert and re-cross the strike price in the opposite direction, thus decreasing the value of their options and potentially rendering them worthless at expiry.

Disentangling preference- and belief-based explanations is challenging because beliefs are typically unobserved by the researcher. Perhaps the most compelling evidence against belief-based explanations comes from laboratory studies that automatically liquidate positions while attempting to hold beliefs fixed ([Weber and Camerer, 1998](#)). Although the observation that subjects are less likely to repurchase losing stocks after forced liquidation is potentially inconsistent with a belief-based explanation, these results are difficult to interpret because of the confounding effect that ownership has on valuations and belief formation ([Hartzmark, Hirshman, and Imas, 2021](#)), and the evidence that buying and selling decisions are governed by different mental processes ([Barber and Odean, 2013](#); [Akepanidtaworn, Mascio, Imas, and Schmidt, 2023](#)).

In this section, we exploit the unique features of options to design a novel test of reference-dependent selling in a setting where we can plausibly hold beliefs fixed, even without observing them directly. The test we propose takes advantage of the fact that an investor can simultaneously hold multiple options with the same underlying asset. Since all such positions share the same underlying, beliefs about future price movements are common across them. Investors who believe in mean reversion should therefore display correlated selling across options of the same type and underlying, as all positions are adversely affected by the expected price reversal. Alternatively, if investors use the strike price as a forward-looking reference point, they should be more likely to sell options that have crossed into the money and for which the target has been reached, while being less likely to sell out-of-the-money options.

To implement the test, on day t we consider an investor i who simultaneously holds two call options or two put options with the same underlying asset and the same time to expiry. To restrict the setting even further, we can require that the options were purchased on the same day, so that they also have the same holding period. The attractive feature of fixing the holding period, time to expiry, and underlying asset is that both the price path of the underlying asset during the holding period and the investor’s belief about the future price path until the time of expiry are the same for both option positions. As a result, if investors’ reference-dependent selling decisions are driven by their beliefs, we should observe selling behavior that is correlated across the positions, regardless of whether the positions are in the money or out of the money. As we show below, this is not what we find.

Although the setting we exploit is highly restrictive, our data set includes 530 518 investor-option-days that satisfy the option type, underlying asset, and time to expiry requirements, and 76 070 investor-option-days that meet the additional holding period requirement. In total, 2 118 investors—or roughly one in every nine retail option traders in Finland—simultaneously hold two options of the same type with the same underlying asset and the same time to expiry at least once during our sample period. In these scenarios, the typical investor holds two options with a difference of €1 in the strike prices, consistent with investors holding positions at adjacent strikes to accommodate dispersion in target prices. Summary statistics about these investors and their

trades in this restricted setting are presented in Table [IA.5](#).

We test whether an option position being in the money or out of the money influences investors' selling decisions by using the following linear probability model specifications:

$$Sale_{ijt} = \alpha_{it...} + \beta_1 ITM_{jt} + \varepsilon_{ijt}, \quad (4)$$

$$Sale_{ijt} = \alpha_{it...} + \beta_1 ITM_{jt} + \beta_2 Gain_{ijt} + \varepsilon_{ijt}. \quad (5)$$

ITM_{jt} is a dummy variable that equals one if option j is in the money on day t . In Equation [5](#), we add $Gain_{ijt}$, a dummy variable that equals one if the position of investor i in option j on day t is trading at a gain relative to the purchase price, to control for the standard disposition effect. In both specifications, standard errors are clustered by investor and day.

Both specifications are estimated with two sets of fixed effects corresponding to the restricted setting described above. The first set consists of fixed effects at the investor by day by underlying asset by time to expiry level. The identifying variation with these fixed effects comes from situations where one of two options with the same underlying asset and the same time to expiry held by an investor is in the money, while the other is out of the money. The second set consists of fixed effects at the investor by day by underlying asset by time to expiry by holding period level. With these fixed effects, the source of identifying variation is the same as before, except for the additional holding period requirement.

The results from the baseline specification in Equation [4](#) are presented in Columns (1) and (2) of Table [5](#). In both settings, the coefficient on the ITM dummy variable is positive and statistically significant, inconsistent with the explanation based on mean reversion but consistent with investors using the strike price as a reference point. The ITM coefficients remain positive and statistically significant when controlling for the gain or loss status of a position in Columns (3) and (4), so the effect that the strike price has on selling decisions is distinct from the standard disposition effect.

Appendix Section [A](#) further illustrates why the evidence is difficult to reconcile with belief-based explanations. In this same setting, consider a stylized example in which an investor who sells an in-the-money option while retaining an out-of-the-money option plans to hold the latter to expiry and

behaves as if the price of the underlying will reach the retained option’s strike by expiration. Under this assumption, the terminal payoff of the sold in-the-money option when the underlying reaches the retained strike is at least as large as the difference between the two strike prices, which can imply economically large counterfactual returns from continuing to hold the sold option. Empirically, the corresponding counterfactual returns in this illustrative calculation are very large, with an average (median) forgone return of 1 244% (650%) over an average horizon of 33 days. Such magnitudes are difficult to reconcile with belief-based explanations, as they suggest that investors simultaneously expect substantial gains in the underlying asset while liquidating positions that would be especially profitable under those same beliefs.

Overall, these results are consistent with preference-based explanations for reference-dependent selling but inconsistent with a purely belief-based explanation.

6 Alternative Explanations

The results presented above are consistent with investors buying options with a specific target price in mind, and then making their selling decisions by evaluating their performance relative to this forward-looking reference point. In this section, we rule out alternative explanations for our results and provide additional evidence in support of this interpretation.

6.1 Ex Post Rationality

The decision to sell options on the strike crossing day may be rational if options exhibit systematically lower returns after the crossing day. Such behavior could, for example, stem from short-term return reversals in the underlying (Lehmann, 1990; Lo and MacKinlay, 1990), which would cause options that have just crossed into the money to reverse some of their gains. To provide evidence against this interpretation, we evaluate the ex post performance after strike crossing days.

Figure 7 reports average cumulative option returns and their corresponding 95% confidence intervals for the ten days following the crossing of an option from out of the money to in the money. The average 1-day (10-day) option return is 2.8% (4.4%), so investors are forgoing highly attractive short-term returns by selling on strike crossing days. If investors’ sales are explained by a belief in

mean reversion, then, on average, the investors' beliefs are incorrect.

A similar picture emerges in the subsample that we use to test belief-based explanations for reference-dependent selling, when an investor decides to sell an in-the-money option while continuing to hold an out-of-the-money option. Ex post returns calculated from the date on which the in-the-money option was sold to the expiry date of the options show that the out-of-the-money option would have outperformed the in-the-money option in only 10% of cases. Overall, the median return from continuing to hold the in-the-money option until expiry would have been 295%, whereas the median return from the out-of-the-money option would have been -100%.

Overall, the ex post evidence is inconsistent with rational belief-based explanations. Investors who sell on strike crossing days forgo significant short-term returns.

6.2 The Rank Effect

[Hartzmark \(2015\)](#) shows that investors' selling behavior is influenced by the relative performance of holdings within an investor's portfolio, with the best- and worst-performing holdings having higher selling propensities. Since options that cross the strike tend to have more extreme returns than options that do not, the selling behavior around the strike that we document could potentially be driven by this rank effect. To rule out this possibility, Table [IA.6](#) augments the option-level design with controls for the option-day average best- and worst-performer indicators of holders' portfolios. The estimated effects associated with strike price crossings barely change, suggesting that our findings are not driven by the rank effect.

6.3 Skewness Preferences

Selling in-the-money options and holding out-of-the-money options could be consistent with investors having a preference for skewness or levered payoffs, since out-of-the-money options have more skewed return distributions than in-the-money options. However, skewness preferences are unlikely to be a major driver of our results for two reasons. First, it is not clear why skewness preferences would generate a spike in selling when out-of-the-money options cross the strike price, but have no effect when in-the-money options cross the strike. If selling on strike crossing days

is explained by the skewness of the option position changing, then we would expect to observe a decrease in selling propensity for crossings from in the money to out of the money, but we actually observe neither a decrease nor an increase.

Second, in the subsample that we use to test belief-based explanations for reference-dependent selling, when an investor chooses to sell an in-the-money option while continuing to hold an out-of-the-money option, in 93% of cases the sale occurs when the investor also holds other assets in their portfolio. In particular, in 64% of cases the investor also holds one or more stocks. If selling decisions are driven by a preference for skewness, then it is unclear why investors choose to sell in-the-money options rather than stocks, which exhibit considerably less skewed returns.

6.4 Rational Rebalancing or Rollover Strategies

Reinvestment or rollover strategies, defined as sales that are shortly followed by new purchases (e.g., [Grinblatt et al., 2012](#); [Muravyev, 2016](#)), are also unlikely to be driving our results. As shown in Table [IA.7](#), our results continue to hold even when we exclude holders who purchase another option on the strike crossing day or one day after it.

A similar pattern emerges in the tests of belief-based explanations for reference-dependent selling. In that setting, a higher propensity to sell in-the-money options could be rational if investors sell with the intention of reinvesting the proceeds of the sale into positions with even higher expected returns given the investor’s implied beliefs, such as an option on the same underlying asset with a lower moneyness than the sold option. However, we find that after 69% of in-the-money option sales, there is no direct repurchase of another option position on the same day, and 84% of in-the-money option sales are not followed by any rebalancing into an option of the same type and on the same underlying asset that has a lower moneyness than the sold option. Rational rebalancing into options with even higher implied expected returns thus cannot explain the vast majority of the in-the-money option sales we document.

6.5 Transaction Costs

A natural question is whether transaction costs could explain our results. During our sample period, the typical fee structure is €8–9 per trade or 0.20–0.25% of the transaction value, whichever is higher.¹⁵ While the fixed fee component could discourage investors from selling low-value, out-of-the-money options, there are at least three reasons why this mechanism is unlikely to drive our findings. First, transaction costs do not vary systematically around the strike price crossing between our main sample and the placebo sample of options that transition from in the money to out of the money, and thus cannot account for the asymmetry we observe across these samples. Second, the average value of an option position around the strike crossing is €2 352, implying that the fixed fee component is economically small, on average less than 0.4% of position value. Third, Tables IA.8 and IA.9 show that our main results are robust to excluding small option positions, following the definition of Fecht, Hackethal, and Karabulut (2018), where transaction costs are most likely to influence trading decisions.

6.6 Liquidity Needs

Investors may sell in-the-money options because they have a pressing need for liquidity. This explanation is hard to square with our results for three reasons. First, it is not clear why the need for liquidity would spike precisely on days when out-of-the-money options cross the strike for the first time. Second, Tables IA.10 and IA.11 confirm that our main results continue to hold in situations where an investor also holds other assets in their portfolio at the time of selling. In these situations, an investor with a need for liquidity has multiple assets to choose from when making their selling decision. Third, given the positive average returns of continuing to hold in-the-money options sold on strike crossing days reported in Figure 7, investors with liquidity needs would rationally prefer to sell other assets with lower expected returns rather than the more profitable options that became in the money.

¹⁵See <https://osakesijoittaja.fi/osakesijoittaminen/valittajahintavertailu/>.

6.7 Taxes

While tax motives could influence investors' propensity to sell in-the-money options, three pieces of evidence make it unlikely that this is a significant driver of our results. First, 83% of in-the-money options sold on strike crossing days result in realized gains, thus incurring tax liabilities instead of tax benefits. Second, in the subsample that we use to test belief-based explanations for reference-dependent selling, a further 80% of in-the-money options are sold at a gain, again incurring tax liabilities. Moreover, when an in-the-money option is sold at a loss, 93% of the corresponding out-of-the-money options are also trading at a loss, and thus could have been sold instead. Finally, we observe no clustering of in-the-money option sales in December, a month typically associated with tax-loss selling behavior ([Grinblatt and Keloharju, 2004](#)). Overall, we find little evidence that tax motives are a significant driver of our results.

6.8 Hedging Motives

The literature on option trading by retail investors has shown that hedging does not seem to be a primary motivation behind retail investors' option trades ([Lakonishok, Lee, Pearson, and Poteshman, 2007](#)). For example, [Bogousslavsky and Muravyev \(2024\)](#) find that only 0.1% of the option trades in their sample are protective puts, which can be used to limit the downside risk of a long stock position. Table [IA.12](#) shows that protective puts are also very uncommon in our sample: when an investor purchases an option while already owning the underlying stock, 92% of the time they purchase a call option. In other words, investors are far more likely to leverage their long exposure with a call than to limit their downside risk with a put. In total, protective puts make up only 3% of all stock option purchases in our sample. Overall, these results are consistent with the view that hedging is not a primary concern for the investors in our sample.

Nonetheless, to examine whether hedging-motivated trading drives our results, we repeat our analyses excluding put options. Since short selling stocks is very uncommon among retail investors in Finland (e.g., [Grinblatt and Keloharju, 2001](#)), it is highly unlikely that call options are purchased for the purposes of hedging. If our results are driven by hedging motives, then we would expect them to disappear when excluding puts. Tables [IA.13](#) and [IA.14](#) show that this is not the case.

6.9 Avoiding Settlement

An important reason why investors may prefer to sell in-the-money options is to avoid settlement-related frictions, such as the possibility of delivery of the underlying asset or the need to fund an exercise payment. This mechanism, however, does not apply to our setting because all of the options in our data set are cash-settled. For cash-settled contracts, expiration does not require delivery of the underlying asset and does not mechanically trigger a position in the underlying. Instead, the payoff is realized through a cash transfer equal to the contract’s intrinsic value. As a result, there is no need for the investors in our data set to avoid settlement by selling their options.

6.10 Complex Option Trades

Three pieces of evidence speak against our results being attributable to complex option trades. First, because the options in our data set are issued by banks, the investors in our sample cannot write options, which considerably limits their ability to construct complex option trades. For example, [Li, Musto, and Pearson \(2022\)](#) find that between 70% and 85% of complex option trading volume in the U.S. comes from trades that include at least one written option.

Second, while the simultaneous option holdings used in our tests of belief-based explanations for reference-dependent selling could be complex option trades, most option pairs in that sample were purchased on different days. This makes the option pairs less likely to have been purchased as part of a deliberate complex trading strategy.

Finally, we also restrict the option-day selling outcome to holders with a single option on a given underlying asset who do not own the underlying asset itself. Table [IA.15](#) shows that excluding holders that could be part of a complex option trade actually makes the effect of the strike price crossing even stronger.

6.11 Pinning Risk

Investors could sell around strike price crossings because of pinning risk (e.g., [Golez and Jackwerth, 2012](#)). If the price of the underlying asset tends to be pulled toward option strike prices close to option expiration, then small moves in the underlying can generate large changes in an option’s

delta and value. This could, in turn, lead investors to reduce exposure by selling as the price of the underlying asset approaches the strike.

Although the results of our placebo tests are already inconsistent with the pinning risk explanation, since its effect should be the same regardless of whether the price of the underlying asset approaches the strike from out of the money or from in the money, we also perform additional tests to rule it out. In particular, if investors' selling decisions are explained by their concern over pinning risk, then we would expect our main results to be driven by options close to expiry, for which pinning is most relevant. However, Tables [IA.16](#) and [IA.17](#) show that our main results continue to hold even after excluding options with five or fewer days to expiry. Pinning risk thus does not seem to be a significant driver of our results.

6.12 Systematic Differences in Placebo Samples

Our primary empirical strategy for ruling out alternative explanations has been to perform placebo tests using options purchased in the money, since these are options for which the strike price cannot act as a forward-looking target price. A potential concern with the placebo test approach is that the investors who purchase in-the-money options may differ systematically from those who purchase out-of-the-money options in ways that are correlated with selling behavior around the strike. If so, the results of the placebo tests could reflect the selling behavior of different types of investors rather than the effect of the strike as a target price.

To address this concern, in Tables [IA.18](#) and [IA.19](#) we repeat the analyses restricting the option-day outcome to holders who purchase both in-the-money and out-of-the-money options. The results barely change compared to Tables [2](#) and [3](#), consistent with systematic investor differences between the main and placebo samples being unlikely to explain the placebo results.

7 Conclusion

Most empirical work on reference dependence in trading implicitly treats the purchase price as the benchmark against which investors evaluate gains and losses. This paper points to a different, inherently forward-looking benchmark: investment targets. We exploit a distinctive feature of

retail option trading in which investors can choose a strike price that maps naturally to a target price for the underlying asset. Using population-level administrative holdings data and stacked difference-in-differences designs, we document a sharp increase in the propensity to sell precisely when the underlying first crosses the strike price, as well as a peak in the aggregate propensity to sell at the strike.

Our results are consistent with investment targets acting as reference points and investors locking in their gains once their target is reached, but difficult to reconcile with other mechanisms, such as salience or option Greeks. Most importantly, the effect of the strike is absent in placebo settings in which the strike price cannot plausibly represent a gain target, namely for options purchased in the money. In addition, within-investor tests that hold the underlying asset, option type, time to expiry, and holding period fixed are hard to reconcile with belief-based explanations for reference-dependent selling, but are in line with investors evaluating outcomes relative to a position-specific reference point. Taken together, our results are most consistent with reference-dependent preferences centered around forward-looking targets, rather than solely around backward-looking purchase prices.

Our findings are relevant for the debate about whether investors are reluctant to realize their losses. In one of the most influential studies, [Odean \(1998\)](#) uses the purchase price as the reference point, arguing that it is the most natural benchmark and easy to observe in the data. He shows that investors are more likely to sell positions that have appreciated above the purchase price relative to those in the domain of losses, and interprets the results as consistent with investors being reluctant to realize their losses. [Ben-David and Hirshleifer \(2012\)](#) challenge the interpretation of these early results with two empirical observations. First, there is little discontinuity in selling propensity around zero gains. Second, selling propensity displays a V-shape: investors are more likely to sell positions that are further in the gain domain or further in the loss domain. The authors argue that these empirical patterns are more consistent with a mechanism based on belief updating.

Our results imply that tests of discontinuities around the purchase price are misspecified if investors use reference points other than the purchase price. As a result, a lack of discontinuity around the purchase price does not necessarily rule out investors' reluctance to realize losses. More broadly, any test of reference-dependent selling behavior is a joint test of the reference point and

the utility specification. Our results provide new support for the interpretation that investors are reluctant to realize their losses and are faster to sell their gains, but with a more nuanced specification of the reference point. We also demonstrate how the unique features of the options market provide a new laboratory and new results that challenge the belief-based explanation of the empirical patterns.

References

- Akepanidtaworn, Klakow, Rick Di Mascio, Alex Imas, and Lawrence Schmidt, 2023, Selling fast and buying slow: Heuristics and trading performance of institutional investors, *Journal of Finance* 78, 3055–3098.
- Allen, Eric, Patricia Dechow, Devin Pope, and George Wu, 2017, Reference-dependent preferences: Evidence from marathon runners, *Management Science* 63, 1657–1672.
- An, Li, 2016, Asset pricing when traders sell extreme winners and losers, *Review of Financial Studies* 29, 823–861.
- An, Li, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams, 2024, The portfolio-driven disposition effect, *Journal of Finance* 79, 3459–3495.
- Andersen, Steffen, Cristian Badarinza, Lu Liu, Julie Marx, and Tarun Ramadorai, 2022, Reference dependence in the housing market, *American Economic Review* 112, 3398–3440.
- Andrikogiannopoulou, Angie, and Filippas Papakonstantinou, 2020, History-dependent risk preferences: Evidence from individual choices and implications for the disposition effect, *Review of Financial Studies* 33, 3674–3718.
- Argyle, Bronson, Taylor Nadauld, and Christopher Palmer, 2020, Monthly payment targeting and the demand for maturity, *Review of Financial Studies* 33, 5416–5462.
- Aristidou, Andreas, Aleksandar Giga, Suk Lee, and Fernando Zapatero, 2025, Aspirational utility and investment behavior, *Journal of Financial Economics* 163, 103970.
- Badarinza, Cristian, Tarun Ramadorai, Juhana Siljander, and Jagdish Tripathy, 2024, Behavioral lock-in: Housing markets with reference dependent agents, London School of Economics Working Paper.
- Baker, Andrew, David Larcker, and Charles Wang, 2022, How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370–395.
- Barber, Brad, and Terrance Odean, 2013, The behavior of individual investors, in George Constantinides, Milton Harris, and Rene Stulz, eds., *Handbook of the Economics of Finance, Volume 2, Part B*. Elsevier, Oxford, UK.
- Barberis, Nicholas, 2018, Psychology-based models of asset prices and trading volume, in Douglas Bernheim, Stefano DellaVigna, and David Laibson, eds., *Handbook of Behavioral Economics: Foundations and Applications 1*. Elsevier, Oxford, UK.
- Barberis, Nicholas, and Wei Xiong, 2009, What drives the disposition effect? An analysis of a long-standing preference-based explanation, *Journal of Finance* 64, 751–784.
- Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251–271.
- Ben-David, Itzhak, and David Hirshleifer, 2012, Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect, *Review of Financial Studies* 25, 2485–2532.

- Birru, Justin, 2015, Confusion of confusions: A test of the disposition effect and momentum, *Review of Financial Studies* 28, 1849–1873.
- Bogousslavsky, Vincent, and Dmitriy Muravyev, 2024, An anatomy of retail option trading, Michigan State University Working Paper.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2019, Memory and reference prices: An application to rental choice, *AEA Papers and Proceedings* 109, 572–576.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2020, Memory, attention and choice, *Quarterly Journal of Economics* 135, 1399–1442.
- Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2023, Retail trading in options and the rise of the big three wholesalers, *Journal of Finance* 78, 3465–3514.
- Burgstahler, David, and Ilia Dichev, 1997, Earnings management to avoid earnings decreases and losses, *Journal of Accounting and Economics* 24, 99–126.
- Calvet, Laurent, John Campbell, and Paolo Sodini, 2009a, Fight or flight? Portfolio rebalancing by individual investors, *Quarterly Journal of Economics* 124, 301–348.
- Calvet, Laurent, John Campbell, and Paolo Sodini, 2009b, Measuring the financial sophistication of households, *American Economic Review* 99, 393–398.
- Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler, 1997, Labor supply of New York City cabdrivers: One day at a time, *Quarterly Journal of Economics* 112, 407–441.
- Célérier, Claire, and Boris Vallée, 2017, Catering to investors through security design: Headline rate and complexity, *Quarterly Journal of Economics* 132, 1469–1508.
- Chang, Tom, David Solomon, and Mark Westerfield, 2016, Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect, *Journal of Finance* 71, 267–302.
- Coval, Joshua D, and Tyler Shumway, 2005, Do behavioral biases affect prices?, *Journal of Finance* 60, 1–34.
- Crawford, Vincent, and Juanjuan Meng, 2011, New York City cab drivers’ labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income, *American Economic Review* 101, 1912–1932.
- Davis, Carter, Samuli Knüpfer, Jens Soerlie Kværner, Bahar Sen Dogan, and Petra Vokata, 2026, Do households matter for asset prices?, Fisher College of Business Working Paper.
- Fecht, Falko, Andreas Hackethal, and Yigitcan Karabulut, 2018, Is proprietary trading detrimental to retail investors?, *Journal of Finance* 73, 1323–1361.
- Fischbacher, Urs, Gerson Hoffmann, and Simeon Schudy, 2017, The causal effect of stop-loss and take-gain orders on the disposition effect, *Review of Financial Studies* 30, 2110–2129.
- Frazzini, Andrea, 2006, The disposition effect and underreaction to news, *Journal of Finance* 61, 2017–2046.
- Frydman, Cary, and Baolian Wang, 2020, The impact of salience on investor behavior: Evidence from a natural experiment, *Journal of Finance* 75, 229–276.

- Gelman, Michael, Liron Reiter-Gavish, and Nikolai Roussanov, 2026, FOMO economics: External reference-dependence and risk-taking in household portfolios, Wharton School Working Paper.
- Genesove, David, and Christopher Mayer, 2001, Loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics* 116, 1233–1260.
- George, Thomas, and Chuan-Yang Hwang, 2004, The 52-week high and momentum investing, *Journal of Finance* 59, 2145–2176.
- Golez, Benjamin, and Jens Carsten Jackwerth, 2012, Pinning in the S&P 500 futures, *Journal of Financial Economics* 106, 566–585.
- Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, *Journal of Economic Literature* 59, 919–1000.
- Grinblatt, Mark, and Bing Han, 2005, Prospect theory, mental accounting, and momentum, *Journal of Financial Economics* 78, 311–339.
- Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: a study of Finland’s unique data set, *Journal of Financial Economics* 55, 43–67.
- Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.
- Grinblatt, Mark, and Matti Keloharju, 2004, Tax-loss trading and wash sales, *Journal of Financial Economics* 71, 51–76.
- Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa, 2012, IQ, trading behavior, and performance, *Journal of Financial Economics* 104, 339–362.
- Hartzmark, Samuel, 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* 28, 1024–1059.
- Hartzmark, Samuel, Samuel Hirshman, and Alex Imas, 2021, Ownership, learning, and beliefs, *Quarterly Journal of Economics* 136, 1665–1717.
- Heath, Chip, Steven Huddart, and Mark Lang, 1999a, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601–627.
- Heath, Chip, Richard Larrick, and George Wu, 1999b, Goals as reference points, *Cognitive Psychology* 38, 79–109.
- Heimer, Rawley, 2016, Peer pressure: Social interaction and the disposition effect, *Review of Financial Studies* 29, 3177–3209.
- Heimer, Rawley, Zwetelina Iliewa, Alex Imas, and Martin Weber, 2025, Dynamic inconsistency in risky choice: Evidence from the lab and field, *American Economic Review* 115, 330–363.
- Heimer, Rawley, and Alex Imas, 2022, Biased by choice: How financial constraints can reduce financial mistakes, *Review of Financial Studies* 35, 1643–1681.
- Hendershott, Terrence, Saad Ali Khan, and Ryan Riordan, 2022, Option auctions, University of California Berkeley Working Paper.

- Hu, Jianfeng, 2014, Does option trading convey stock price information?, *Journal of Financial Economics* 111, 625–645.
- Ingersoll, Jonathan, and Lawrence Jin, 2013, Realization utility with reference dependent preferences, *Review of Financial Studies* 26, 723–767.
- Ivković, Zoran, James Poterba, and Scott Weisbenner, 2005, Tax-motivated trading by individual investors, *American Economic Review* 95, 1605–1630.
- Ivković, Zoran, and Scott Weisbenner, 2009, Individual investor mutual fund flows, *Journal of Financial Economics* 92, 223–237.
- Kahneman, Daniel, 2011, *Thinking, Fast and Slow* (Farrar, Straus and Giroux, New York, USA).
- Kahneman, Daniel, Jack Knetsch, and Richard Thaler, 1990, Experimental tests of the endowment effect and the Coase theorem, *Journal of Political Economy* 98, 1325–1348.
- Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–292.
- Kaustia, Markku, 2010, Prospect theory and the disposition effect, *Journal of Financial and Quantitative Analysis* 45, 791–812.
- Kőszegi, Botond, and Matthew Rabin, 2006, A model of reference-dependent preferences, *Quarterly Journal of Economics* 121, 1133–1165.
- Kőszegi, Botond, and Matthew Rabin, 2007, Reference-dependent risk attitudes, *American Economic Review* 97, 1047–1073.
- Kuo, Wei-Yu, Tse-Chun Lin, and Jing Zhao, 2015, Cognitive limitation and investment performance: Evidence from limit order clustering, *Review of Financial Studies* 28, 838–875.
- Lakonishok, Josef, Inmoo Lee, Neil Pearson, and Allen Poteshman, 2007, Option market activity, *Review of Financial Studies* 20, 813–857.
- Larkin, Ian, 2014, The cost of high-powered incentives: Employee gaming in enterprise software sales, *Journal of Labor Economics* 32, 199–227.
- Lehmann, Bruce, 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1–28.
- Li, Su, David Musto, and Neil Pearson, 2022, A simple role for complex options, University of Pennsylvania Working Paper.
- Linnainmaa, Juhani, 2010, Do limit orders alter inferences about investor performance and behavior?, *Journal of Finance* 65, 1473–1506.
- Lo, Andrew, and Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175–205.
- Mas, Alexandre, 2006, Pay, reference points, and police performance, *Quarterly Journal of Economics* 121, 783–821.
- Muravyev, Dmitriy, 2016, Order flow and expected option returns, *Journal of Finance* 71, 673–708.

- Ni, Sophie Xiaoyan, Neil D. Pearson, and Allen M. Poteshman, 2005, Stock price clustering on option expiration dates, *Journal of Financial Economics* 78, 49–87.
- Ni, Sophie Xiaoyan, Neil D. Pearson, Allen M. Poteshman, and Joshua White, 2021, Does option trading have a pervasive impact on underlying stock prices?, *Review of Financial Studies* 34, 1952–1986.
- Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1798.
- O’Donoghue, Ted, and Charles Sprenger, 2018, Reference-dependent preferences, in Douglas Bernheim, Stefano DellaVigna, and David Laibson, eds., *Handbook of Behavioral Economics: Foundations and Applications 1*. Elsevier, Oxford, UK.
- Paule-Vianez, Jessica, Raúl Gómez-Martínez, and Camilo Prado-Román, 2020, A bibliometric analysis of behavioural finance with mapping analysis tools, *European Research on Management and Business Economics* 26, 71–77.
- Pope, Devin, and Maurice Schweitzer, 2011, Is Tiger Woods loss averse? Persistent bias in the face of experience, competition, and high stakes, *American Economic Review* 101, 129–157.
- Pope, Devin, and Uri Simonsohn, 2011, Round numbers as goals: Evidence from baseball, SAT takers, and the lab, *Psychological Science* 22, 71–79.
- Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.
- Thakral, Neil, and Linh Tô, 2021, Daily labor supply and adaptive reference points, *American Economic Review* 111, 2417–2443.
- Thaler, Richard, 1980, Toward a positive theory of consumer choice, *Journal of Economic Behavior & Organization* 1, 39–60.
- Tversky, Amos, and Daniel Kahneman, 1991, Loss aversion in riskless choice: A reference-dependent model, *Quarterly Journal of Economics* 106, 1039–1061.
- Vacca, Matteo, 2026, Insider trading with options: Evidence from rank-and-file employees, *Journal of Corporate Finance* 102963.
- Vokata, Petra, 2021, Engineering lemons, *Journal of Financial Economics* 142, 737–755.
- Vokata, Petra, 2025, Juicing the coupon yield: How banks extract rents from behavioral biases, Fisher College of Business Working Paper.
- Weber, Martin, and Colin Camerer, 1998, The disposition effect in securities trading: An experimental analysis, *Journal of Economic Behavior & Organization* 33, 167–184.

Figure 1. Propensity to Sell Options by Moneyness: Out-of-the-Money Purchases.

Plotted is the propensity to sell function estimated by regressing the dummy variable *Sale* on a set of dummy variables corresponding to moneyness percentile bins. We overlay a nonparametric local quadratic kernel regression fit, estimated separately for out-of-the-money and in-the-money option positions and evaluated on a dense grid. The shaded areas represent 95% pointwise confidence intervals based on the asymptotic standard errors from the local polynomial smoother. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. The sample contains 3 130 682 investor-option-day observations from Dec-2000 to Dec-2017.

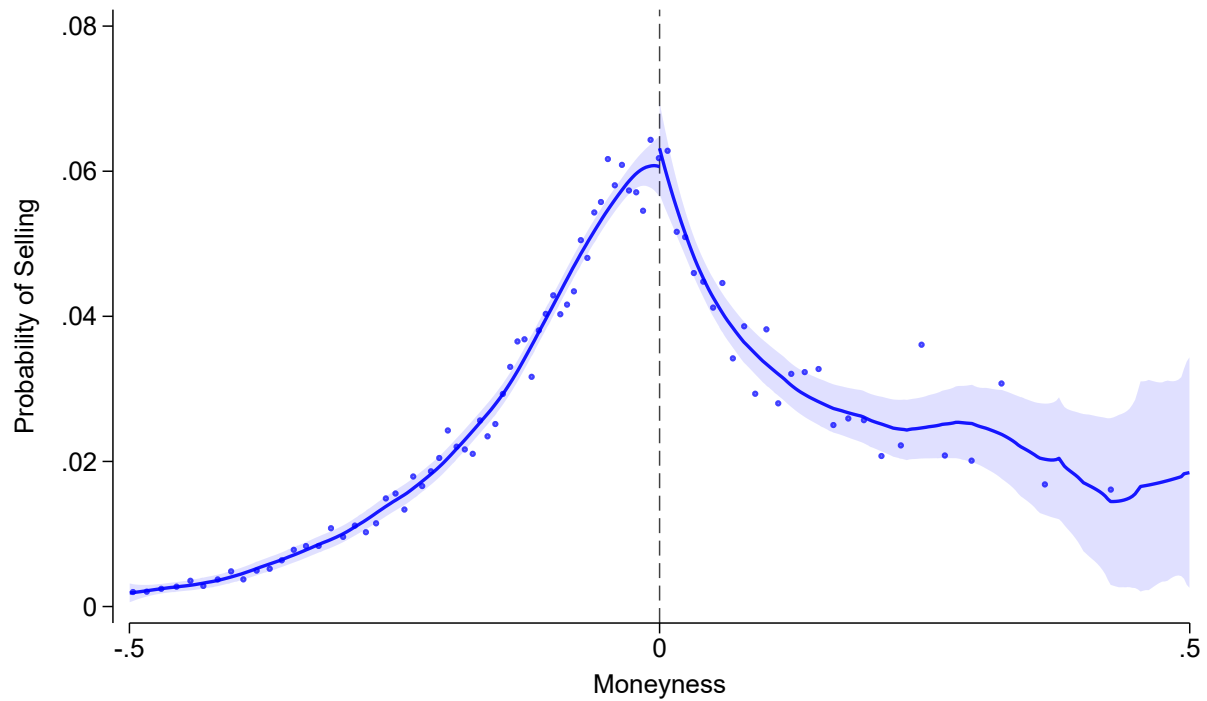


Figure 2. Excess Propensity to Sell Options by Moneyness: Out-of-the-Money Purchases.

Plotted is the excess propensity to sell function estimated by regressing the dummy variable *Sale* on a set of dummy variables corresponding to moneyness percentile bins and on interacted controls for holding period return percentile bins and the holding period. The holding periods are winsorized at 20 days. We overlay a nonparametric local quadratic kernel regression fit, estimated separately for out-of-the-money and in-the-money option positions and evaluated on a dense grid. The shaded areas represent 95% pointwise confidence intervals based on the asymptotic standard errors from the local polynomial smoother. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. The sample contains 3 130 682 investor-option-day observations from Dec-2000 to Dec-2017.

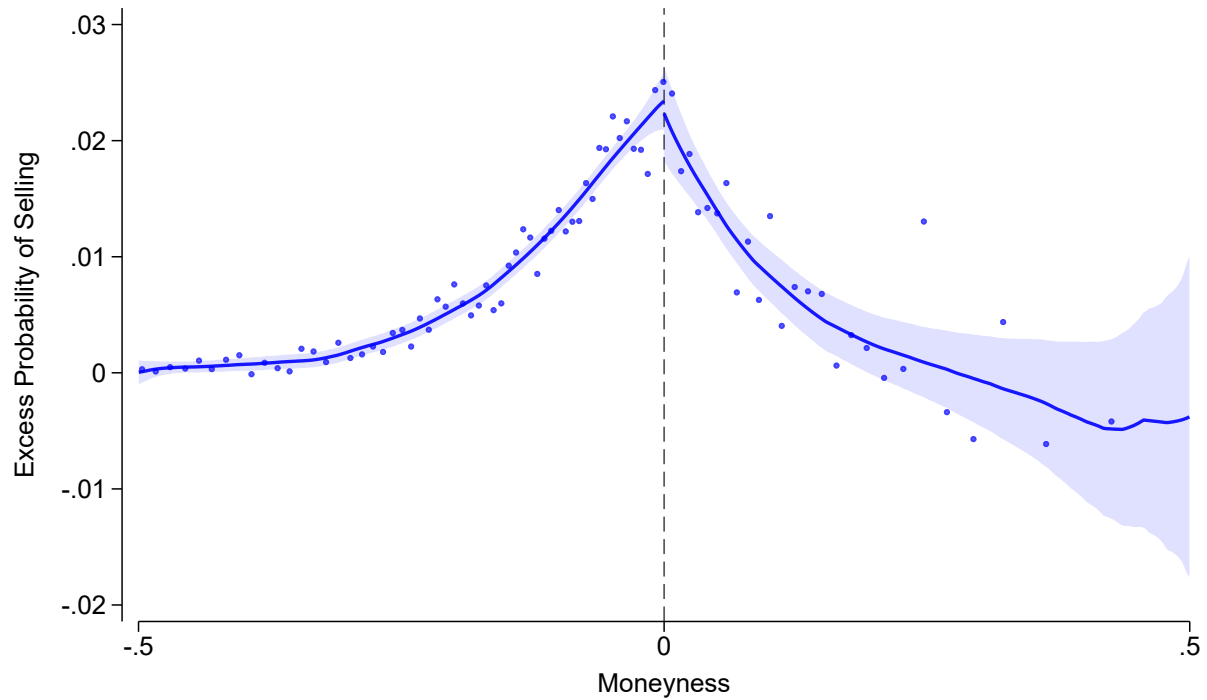


Figure 3. Propensity to Sell Options by Moneyness: In-the-Money Purchases.

Plotted is the propensity to sell function estimated by regressing the dummy variable *Sale* on a set of dummy variables corresponding to moneyness percentile bins. We overlay a nonparametric local quadratic kernel regression fit, estimated separately for out-of-the-money and in-the-money option positions and evaluated on a dense grid. The shaded areas represent 95% pointwise confidence intervals based on the asymptotic standard errors from the local polynomial smoother. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. The sample contains 736 078 investor-option-day observations from Dec-2000 to Dec-2017.

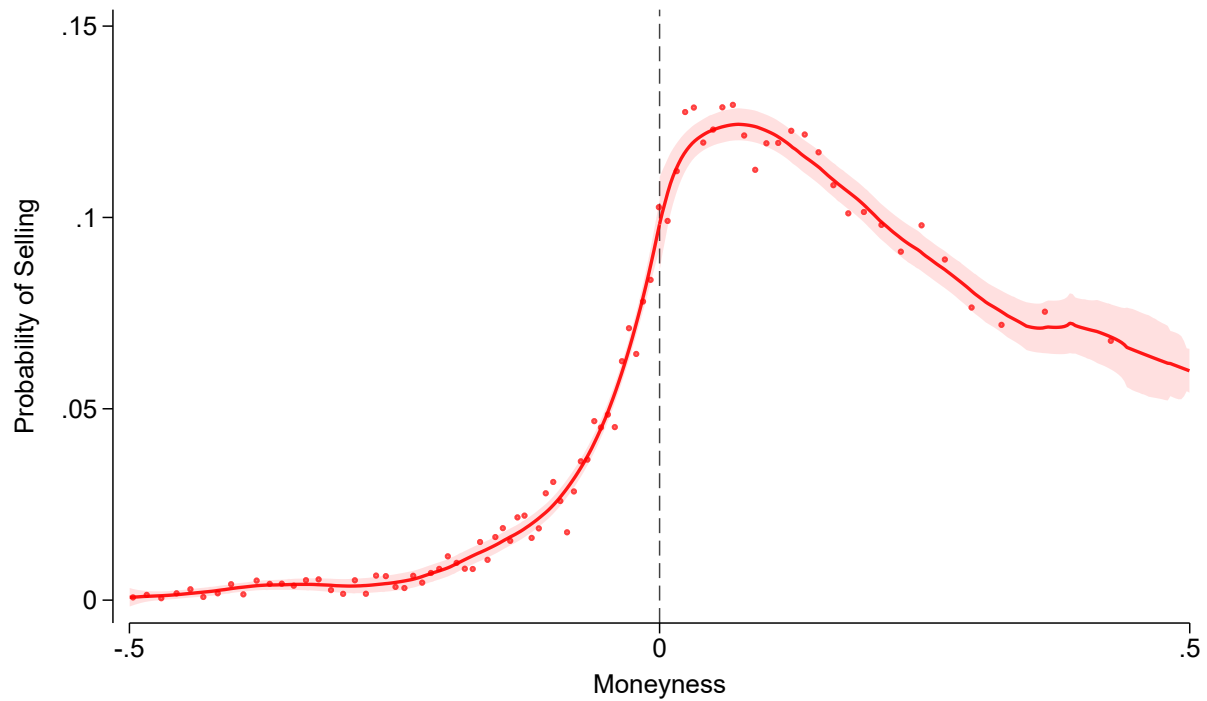


Figure 4. Propensity to Sell Options Around Strike Price Crossings: OTM to ITM.

Plotted are the option-level event-study coefficients around strike price crossings from out of the money to in the money under the three specifications of Table 2: (1) option-cohort and day-cohort fixed effects; (2) option-cohort and underlying-by-type-by-day-cohort fixed effects; and (3) the latter plus option-day controls for the holding period return, gain status, holding period, and time to expiry of an option's holders. Event-day coefficients from equation 3 are estimated over a ± 10 -day window with day -5 as the omitted reference day, and the dashed vertical line marks the crossing day. The unit of analysis is an option-day and the dependent variable is the fraction of option holders who sell on a given day, weighted by the number of holders. The sample is constructed from 2 197 strike price crossings from out of the money to in the money from Dec-2000 to Dec-2017. The shaded areas represent 95% confidence intervals based on standard errors clustered by option and day.

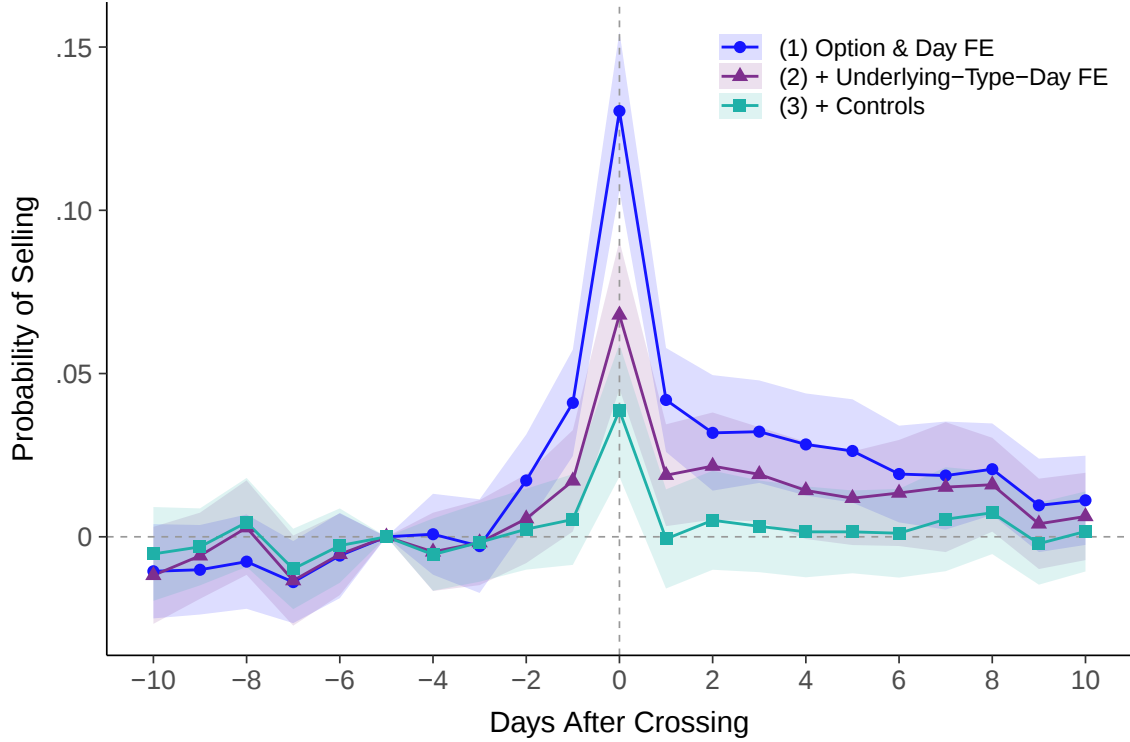


Figure 5. Propensity to Sell Options Around Strike Price Crossings: ITM to OTM.

Plotted are the option-level event-study coefficients around strike price crossings from in the money to out of the money under the three specifications of Table 3: (1) option-cohort and day-cohort fixed effects; (2) option-cohort and underlying-by-type-by-day-cohort fixed effects; and (3) the latter plus option-day controls for the holding period return, gain status, holding period, and time to expiry of an option's holders. Event-day coefficients from equation 3 are estimated over a ± 10 -day window with day -5 as the omitted reference day, and the dashed vertical line marks the crossing day. Consistent with the placebo interpretation, no crossing-day spike is present in any specification. The unit of analysis is an option-day and the dependent variable is the fraction of option holders who sell on a given day, weighted by the number of holders. The sample is constructed from 597 strike price crossings from in the money to out of the money from Dec-2000 to Dec-2017. The shaded areas represent 95% confidence intervals based on standard errors clustered by option and day.

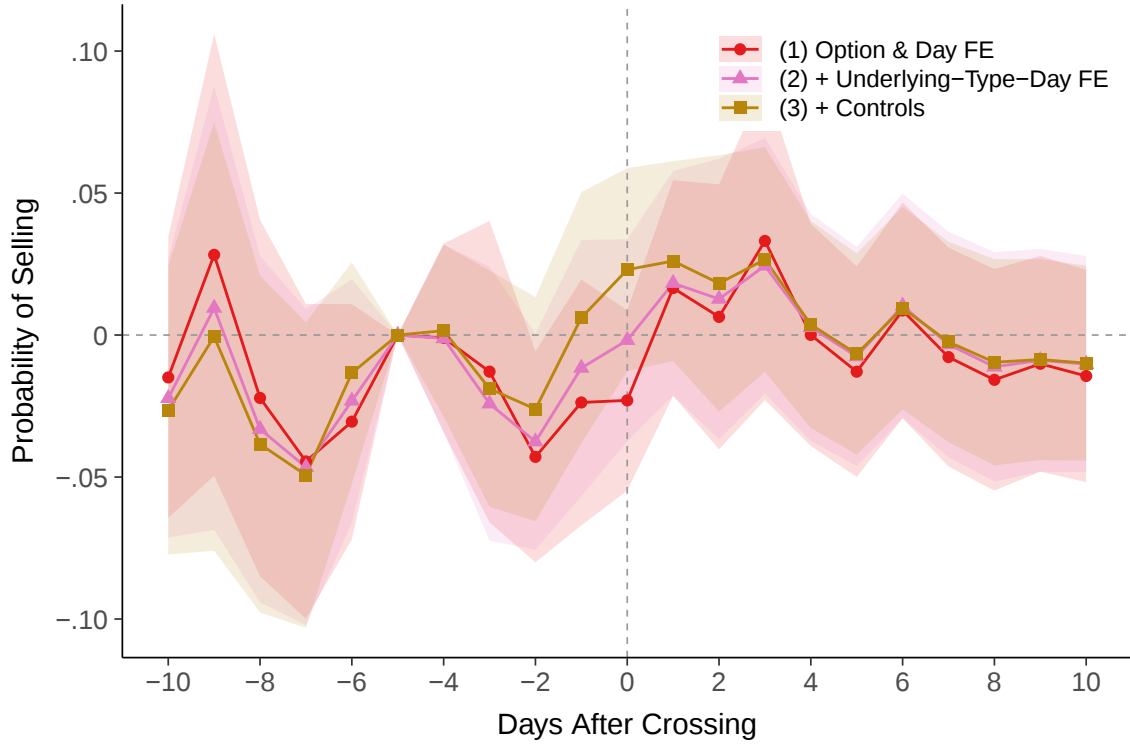


Figure 6. Propensity to Buy Options Around Strike Price Crossings: OTM to ITM.

Plotted are the option-level event-study coefficients for the propensity of an option's existing holders to *buy* additional units around strike price crossings from out of the money to in the money, under the same three specifications as Table 4 and Figure 4: (1) option-cohort and day-cohort fixed effects; (2) option-cohort and underlying-by-type-by-day-cohort fixed effects; and (3) the latter plus option-day controls for the holding period return, gain status, holding period, and time to expiry of an option's holders. Event-day coefficients from equation 3 are estimated over a ± 10 -day window with day -5 as the omitted reference day, and the dashed vertical line marks the crossing day. The vertical axis is drawn on the same scale as Figure 4 to ease comparison. The unit of analysis is an option-day and the dependent variable is the fraction of holders who buy additional units on a given day, weighted by the number of holders. The sample is constructed from 2 197 strike price crossings from out of the money to in the money from Dec-2000 to Dec-2017. The shaded areas represent 95% confidence intervals based on standard errors clustered by option and day.

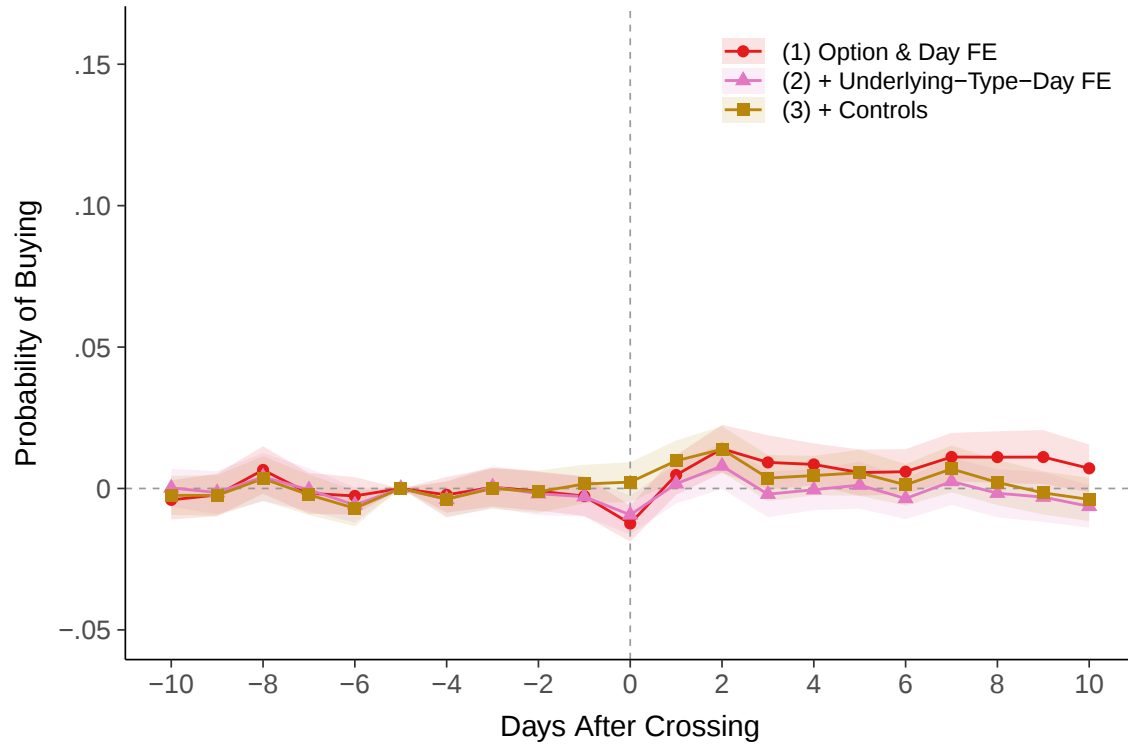


Figure 7. Realized Option Returns After Strike Price Crossings.

Plotted are the average cumulative returns of holding an option for one to ten days after it crosses from out of the money to in the money for the first time. Options with a price below €0.10 on the strike price crossing day are excluded. The sample consists of 1 807 strike price crossings from out of the money to in the money from Dec-2000 to Dec-2017. The shaded areas represent 95% confidence intervals based on standard errors clustered by underlying asset and day.

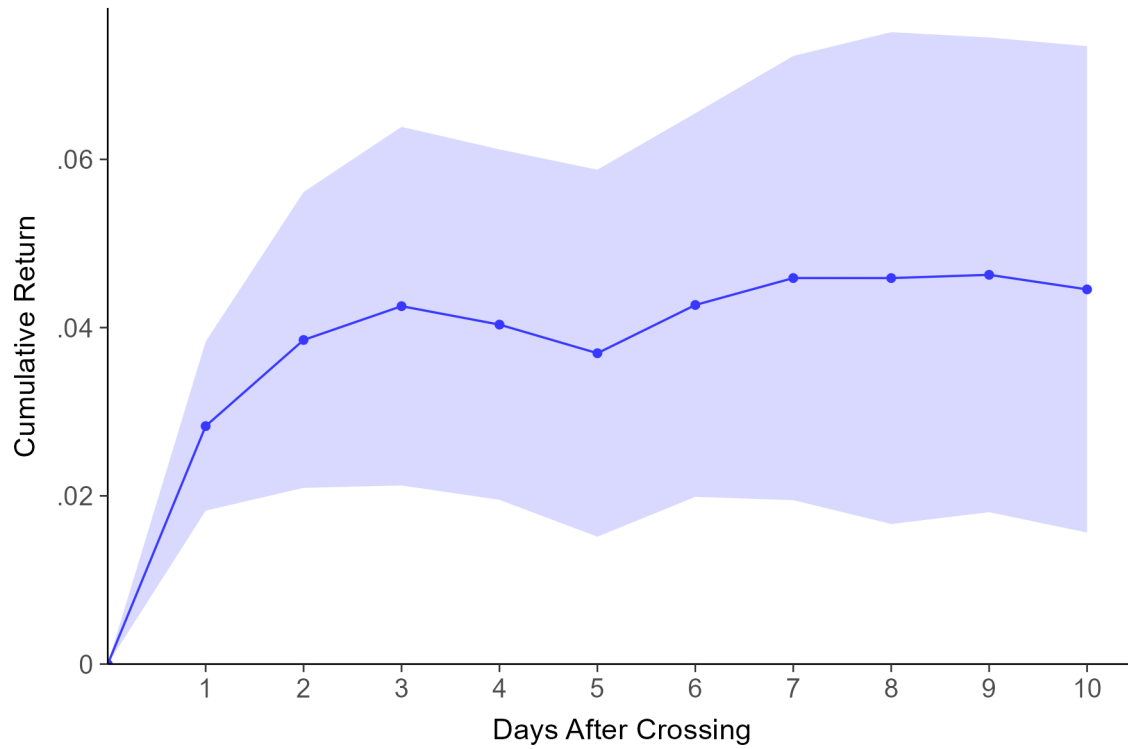


Table 1. Summary Statistics.

Reported are summary statistics about out-of-the-money purchases, in-the-money purchases, and investors. For the investor characteristics, we first calculate the average value of a characteristic separately for each investor and then report the distribution of the investor-level averages, with investor age and trading experience measured at the beginning of each new trade. The daily selling probability is the unconditional probability that an investor sells an option on a given day. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. The round-trip return is the total return from the first purchase which opens a new position to the final sale which fully closes the position. The data set contains the option trades of all retail investors in Finland from Dec-2000 to Dec-2017.

Panel A: Main Sample, Out-of-the-Money Purchases ($N = 122\,525$)					
	Mean	SD	25 th Pct.	Median	75 th Pct.
Call Option (%)	80.34				
Daily Selling Probability (%)	2.62				
Moneyness at Purchase (%)	-12.77	11.28	-17.50	-9.73	-4.67
Days to Expiry at Purchase	94.32	131.80	26.00	49.00	93.00
Value at Purchase (euros)	1 352	4 860	200	500	1 200
Round-Trip Return (%)	-11.68	90.56	-100.00	-6.67	26.51
Holding Period (days)	45.65	92.83	3.00	13.00	45.00
Panel B: Placebo Sample, In-the-Money Purchases ($N = 44\,556$)					
	Mean	SD	25 th Pct.	Median	75 th Pct.
Call Option (%)	72.81				
Daily Selling Probability (%)	5.88				
Moneyness at Purchase (%)	9.34	20.61	2.41	5.78	11.78
Days to Expiry at Purchase	54.85	80.46	17.00	34.00	59.00
Value at Purchase (euros)	2 171	7 385	300	750	1 950
Round-Trip Return (%)	-3.79	61.71	-37.08	2.33	23.53
Holding Period (days)	19.50	44.48	2.00	5.00	19.00
Panel C: Investor Characteristics ($N = 18\,570$)					
	Mean	SD	25 th Pct.	Median	75 th Pct.
Female (%)	10.46				
Age (years)	37.88	13.04	28.50	35.50	45.94
Experience (years)	1.00	1.64	0.00	0.17	1.34
Total Trades	51.38	175.51	3.00	9.00	33.00

Table 2. Option Sales Around Strike Price Crossings: OTM to ITM.

Reported are option-level probabilities of selling around strike price crossings from out of the money to in the money, estimated with a stacked difference-in-differences design in Equation 3. The unit is an option-day; the dependent variable is the fraction of holders who sell. Spec. (1) includes option-cohort and day-cohort fixed effects; (2) replaces day-cohort with underlying-by-type-by-day-cohort fixed effects; (3) adds option-day controls (holding-period return, holding days, days to expiry, gain). All fixed effects are interacted with cohort. Option-days are weighted by number of holders. Standard errors clustered by option and day in parentheses. ***, **, * denote significance at 1%, 5%, 10%.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0106 (0.0074)	-0.0118 (0.0076)	-0.0052 (0.0073)
t_{-9}	-0.0101 (0.0070)	-0.0058 (0.0067)	-0.0031 (0.0060)
t_{-8}	-0.0076 (0.0074)	0.0028 (0.0074)	0.0044 (0.0069)
t_{-7}	-0.0139** (0.0064)	-0.0134* (0.0070)	-0.0098 (0.0063)
t_{-6}	-0.0058 (0.0067)	-0.0054 (0.0064)	-0.0027 (0.0058)
t_{-4}	0.0008 (0.0063)	-0.0046 (0.0061)	-0.0055 (0.0056)
t_{-3}	-0.0029 (0.0073)	-0.0018 (0.0066)	-0.0017 (0.0061)
t_{-2}	0.0172** (0.0072)	0.0055 (0.0069)	0.0023 (0.0063)
t_{-1}	0.0410*** (0.0083)	0.0171** (0.0079)	0.0053 (0.0071)
t_0	0.1304*** (0.0124)	0.0680*** (0.0116)	0.0387*** (0.0104)
t_1	0.0419*** (0.0081)	0.0189** (0.0080)	-0.0007 (0.0077)
t_2	0.0318*** (0.0090)	0.0217*** (0.0084)	0.0051 (0.0077)
t_3	0.0322*** (0.0080)	0.0191*** (0.0074)	0.0032 (0.0072)
t_4	0.0283*** (0.0080)	0.0142* (0.0076)	0.0015 (0.0071)
t_5	0.0263*** (0.0081)	0.0118 (0.0073)	0.0015 (0.0065)
t_6	0.0192** (0.0076)	0.0134 (0.0083)	0.0011 (0.0069)
t_7	0.0188** (0.0084)	0.0152 (0.0102)	0.0054 (0.0081)
t_8	0.0207*** (0.0072)	0.0159** (0.0073)	0.0074 (0.0065)
t_9	0.0096 (0.0073)	0.0040 (0.0071)	-0.0021 (0.0064)
t_{10}	0.0112 (0.0070)	0.0062 (0.0068)	0.0016 (0.0063)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.363	0.477	0.508
Observations	2 086 392	1 913 642	1 896 902

Table 3. Option Sales Around Strike Price Crossings: ITM to OTM.

Reported are option-level probabilities of selling around strike price crossings from in the money to out of the money, estimated with a stacked difference-in-differences design in Equation 3. The unit is an option-day; the dependent variable is the fraction of holders who sell. Spec. (1) includes option-cohort and day-cohort fixed effects; (2) replaces day-cohort with underlying-by-type-by-day-cohort fixed effects; (3) adds option-day controls (holding-period return, holding days, days to expiry, gain). All fixed effects are interacted with cohort. Option-days are weighted by number of holders. Standard errors clustered by option and day in parentheses. ***, **, * denote significance at 1%, 5%, 10%.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0149 (0.0252)	-0.0223 (0.0250)	-0.0265 (0.0259)
t_{-9}	0.0283 (0.0397)	0.0095 (0.0399)	-0.0005 (0.0385)
t_{-8}	-0.0222 (0.0320)	-0.0331 (0.0311)	-0.0384 (0.0302)
t_{-7}	-0.0445 (0.0283)	-0.0465 (0.0284)	-0.0493* (0.0274)
t_{-6}	-0.0305 (0.0211)	-0.0232 (0.0219)	-0.0134 (0.0199)
t_{-4}	-0.0010 (0.0169)	-0.0012 (0.0169)	0.0015 (0.0154)
t_{-3}	-0.0129 (0.0271)	-0.0242 (0.0246)	-0.0189 (0.0212)
t_{-2}	-0.0429** (0.0189)	-0.0375* (0.0194)	-0.0261 (0.0201)
t_{-1}	-0.0237 (0.0221)	-0.0116 (0.0230)	0.0061 (0.0225)
t_0	-0.0230 (0.0162)	-0.0018 (0.0181)	0.0230 (0.0182)
t_1	0.0165 (0.0194)	0.0183 (0.0201)	0.0261 (0.0180)
t_2	0.0064 (0.0238)	0.0127 (0.0252)	0.0182 (0.0230)
t_3	0.0331 (0.0286)	0.0244 (0.0229)	0.0266 (0.0202)
t_4	0.0000 (0.0199)	0.0027 (0.0204)	0.0037 (0.0186)
t_5	-0.0129 (0.0189)	-0.0076 (0.0197)	-0.0066 (0.0181)
t_6	0.0087 (0.0194)	0.0103 (0.0202)	0.0095 (0.0182)
t_7	-0.0078 (0.0197)	-0.0033 (0.0202)	-0.0024 (0.0180)
t_8	-0.0158 (0.0199)	-0.0112 (0.0206)	-0.0096 (0.0185)
t_9	-0.0101 (0.0194)	-0.0089 (0.0200)	-0.0086 (0.0181)
t_{10}	-0.0144 (0.0191)	-0.0102 (0.0194)	-0.0099 (0.0175)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.369	0.496	0.530
Observations	1 189 117	1 118 907	1 112 701

Table 4. Option Purchases Around Strike Price Crossings: OTM to ITM.

Reported are option-level probabilities of an existing holder buying additional units of the option around strike price crossings from out of the money to in the money, estimated with the same stacked difference-in-differences design in Equation 3 as the selling results in Table 2. The unit is an option-day; the dependent variable is the fraction of an option's holders who buy additional units on a given day. Spec. (1) includes option-cohort and day-cohort fixed effects; (2) replaces day-cohort with underlying-by-type-by-day-cohort fixed effects; (3) adds option-day controls (holding-period return, holding days, days to expiry, gain). All fixed effects are interacted with cohort. Option-days are weighted by number of holders. Standard errors clustered by option and day in parentheses. ***, **, * denote significance at 1%, 5%, 10%.

	Dependent Variable: Share Buying		
	(1)	(2)	(3)
t_{-10}	-0.0040 (0.0035)	0.0002 (0.0035)	-0.0024 (0.0035)
t_{-9}	-0.0023 (0.0038)	-0.0014 (0.0039)	-0.0025 (0.0036)
t_{-8}	0.0065 (0.0043)	0.0041 (0.0043)	0.0035 (0.0040)
t_{-7}	-0.0017 (0.0037)	-0.0005 (0.0039)	-0.0022 (0.0037)
t_{-6}	-0.0026 (0.0034)	-0.0058* (0.0032)	-0.0070** (0.0032)
t_{-4}	-0.0022 (0.0032)	-0.0039 (0.0033)	-0.0038 (0.0032)
t_{-3}	0.0004 (0.0035)	0.0006 (0.0038)	0.0000 (0.0037)
t_{-2}	-0.0009 (0.0035)	-0.0019 (0.0039)	-0.0011 (0.0038)
t_{-1}	-0.0027 (0.0036)	-0.0029 (0.0036)	0.0016 (0.0035)
t_0	-0.0124*** (0.0033)	-0.0093*** (0.0035)	0.0023 (0.0036)
t_1	0.0048 (0.0036)	0.0016 (0.0036)	0.0098*** (0.0037)
t_2	0.0140*** (0.0043)	0.0079* (0.0041)	0.0139*** (0.0041)
t_3	0.0092* (0.0049)	-0.0020 (0.0041)	0.0037 (0.0042)
t_4	0.0085** (0.0038)	-0.0004 (0.0037)	0.0046 (0.0036)
t_5	0.0056 (0.0042)	0.0012 (0.0043)	0.0056 (0.0042)
t_6	0.0059 (0.0041)	-0.0036 (0.0037)	0.0013 (0.0037)
t_7	0.0111** (0.0043)	0.0025 (0.0043)	0.0069 (0.0042)
t_8	0.0111** (0.0047)	-0.0017 (0.0044)	0.0021 (0.0041)
t_9	0.0111** (0.0049)	-0.0031 (0.0045)	-0.0016 (0.0039)
t_{10}	0.0071* (0.0043)	-0.0063 (0.0039)	-0.0039 (0.0039)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.207	0.285	0.297
Observations	2 086 392	1 913 642	1 896 902

Table 5. Option Sales by Moneyness: Within Investor-Day-Underlying Analyses

Reported are the results from regressing the dependent variable *Sale* on dummy variables for the moneyness status and gain status of an option in situations where a given investor on a given day simultaneously holds two options of the same type with the same underlying asset, the same time to expiry, and, in a second specification, the same holding period. The sample contains 530 518 investor-option-day observations from Dec-2000 to Dec-2017. Standard errors clustered by investor and day are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Sale			
	(1)	(2)	(3)	(4)
ITM	0.0204*** (0.0018)	0.0261*** (0.0046)	0.0084*** (0.0017)	0.0190*** (0.0045)
Gain			0.0281*** (0.0029)	0.0373*** (0.0065)
	Fixed Effects			
	Yes	No	Yes	No
Investor $\times$ Day $\times$ Underlying $\times$ Expiry	No	Yes	No	Yes
Investor $\times$ Day $\times$ Underlying $\times$ Expiry $\times$ Hold				
Observations	530 518	76 070	530 518	76 070
Adjusted R^2	0.3406	0.5309	0.3446	0.5334

Internet Appendix to Investment Targets as Reference Points

Alexi Pitkäjärvi, Matteo Vacca, Petra Vokata

July 20, 2026

Table of Contents

A	Counterfactual Returns Implied by In-the-Money Option Sales	3
----------	--	----------

Additional Figures

IA.1	Excerpt From a Representative Stock Exchange Release	5
IA.2	Average Holding Period Returns by Moneyiness	6
IA.3	Average Holding Periods by Moneyiness	7
IA.4	Excess Propensity to Sell Options by Moneyiness: Out-of-the-Money Subsamples	8
IA.5	Excess Propensity to Sell Options by Moneyiness: In-the-Money Purchases .	9
IA.6	Excess Propensity to Sell Options by Moneyiness: In-the-Money Subsamples	10

Additional Tables

A.1	Counterfactual Returns Implied by In-the-Money Option Sales	4
IA.1	Illustrative Social Media Posts on Strike Prices as Targets	11
IA.2	Illustrative Online Articles on Strike Prices as Targets	12
IA.3	Illustrative Online Quotes on Targets in Stock Trading	13
IA.4	Distribution of Bid-Ask Spreads	14
IA.5	Summary Statistics for Within Investor-Day-Underlying Analyses	15
IA.6	Option Sales Around Strike Price Crossings: Rank Effect	16
IA.7	Option Sales Around Strike Price Crossings: Rollover Strategies	17
IA.8	Option Sales Around Strike Price Crossings: Excluding Small Positions . . .	18
IA.9	Option Sales by Moneyiness When Investor Beliefs are Fixed: Excluding Small Positions	19
IA.10	Option Sales Around Strike Price Crossings: Liquidity	20
IA.11	Option Sales by Moneyiness When Investor Beliefs are Fixed: Liquidity . . .	21
IA.12	Stock Option Purchases and Ownership of the Underlying Stock	22
IA.13	Option Sales Around Strike Price Crossings: Hedging	23
IA.14	Option Sales by Moneyiness When Investor Beliefs are Fixed: Hedging	24

IA.15	Option Sales Around Strike Price Crossings: Complex Strategies	25
IA.16	Option Sales Around Strike Price Crossings: Pinning Risk	26
IA.17	Option Sales by Moneyness When Investor Beliefs are Fixed: Pinning Risk .	27
IA.18	Option Sales Around Strike Price Crossings: OTM and ITM Buyers	28
IA.19	Option Sales Around Strike Price Crossings: ITM to OTM, OTM and ITM Buyers	29

A Counterfactual Returns Implied by In-the-Money Option Sales

The results of Table 5 show that in situations where an investor simultaneously holds two options of the same type with the same underlying asset and the same time to expiration, with one of the options being in the money and the other out of the money, they are more likely to sell the in-the-money option. Specifically, when an investor sells one of the options but not the other, 79% of the time they sell the in-the-money option. Could these sales of in-the-money options be rationalized by investors’ beliefs, and what do they reveal about the determinants of investors’ selling decisions? To shed light on these questions, we examine whether selling in-the-money options is consistent with the beliefs implied by the fact that investors continue to hold their out-of-the-money options.

To illustrate the economic tension in a belief-based interpretation, consider a simple example in which an investor who sells an in-the-money option while retaining an out-of-the-money option plans to hold the latter to expiry and behaves as if the price of the underlying will reach the retained option’s strike by expiration.¹ Under this stylized assumption, the terminal payoff of the sold in-the-money option when the underlying reaches the retained strike is equal to the difference between the two strike prices. Relative to the current price of the sold in-the-money option, this implies economically large forgone returns from selling that option rather than continuing to hold it.

Specifically, the counterfactual return from continuing to hold the in-the-money option until expiry under the stylized assumption described above is given by:

$$r_t^{ITM,cf} = \frac{\text{Payoff}_T^{ITM} \mid S_T = K^{OTM}}{P_t^{ITM}} - 1, \quad (6)$$

where the numerator is the terminal payoff conditional on the price of the underlying asset being equal to the strike price of the out-of-the-money option, and the denominator is the current price of the in-the-money option.² We view this calculation as an illustrative benchmark rather than as a general revealed-belief bound.

Table A.1 reports summary statistics of the counterfactual returns implied by investors’ sales of in-the-money options in this restricted setting and in subsamples based on option type, trade size, time to expiry, and moneyness. In each instance, the forgone returns implied by investors’ selling decisions are extraordinarily high. Across all options, the average (median) forgone return is 1 244% (650%) over an average investment horizon of 33 days. If investors’ selling decisions were explained by such beliefs, then they would be making highly contradictory trading decisions by selling in-the-money positions and continuing to hold out-of-the-money positions. These decisions are very difficult to reconcile with a purely belief-based explanation for investors’ reference-dependent selling.

¹Empirically, we find that 52% of the unsold out-of-the-money positions are held until expiry.

²For example, if an investor sells an in-the-money call with a price of 10 and a strike of 100 while continuing to hold an out-of-the-money call with a strike of 120, then the counterfactual return from continuing to hold the in-the-money option is $(120 - 100)/10 - 1 = 100\%$.

Table A.1. Counterfactual Returns Implied by In-the-Money Option Sales.

Reported are summary statistics on the counterfactual returns implied by investors' sales of in-the-money options while continuing to hold out-of-the-money options in the sample of option trades where investors' beliefs are fixed described in Section 5.2. The sample is constructed from our data set which contains the option trades of all retail investors in Finland from Dec-2000 to Dec-2017.

Characteristic	Category	N	Mean	St. Dev.	25th Pct.	Median	75th Pct.
All Options	–	1 340	1 243.95%	3 144.45%	400.00%	650.00%	1 233.33%
Option Type	Call	1 238	1 240.38%	3 050.09%	400.00%	650.00%	1 233.33%
	Put	102	1 287.34%	4 140.24%	337.20%	669.23%	925.86%
Trade Size (euros)	Below 250	141	1 697.12%	3 572.78%	376.19%	809.09%	1 566.67%
	250–1 000	364	1 325.59%	2 636.01%	391.18%	677.78%	1 400.00%
	1 000–10 000	649	1 192.40%	3 625.95%	408.47%	650.00%	1 180.00%
	Above 10 000	186	920.55%	1 390.89%	404.31%	531.91%	823.02%
Time to Expiry	0–5 days	239	1 579.89%	2 712.57%	559.42%	900.00%	1 900.00%
	1–4 weeks	302	1 257.71%	2 985.26%	400.00%	614.29%	1 150.00%
	1–3 months	374	772.73%	1 011.90%	294.12%	500.00%	891.94%
	3–12 months	299	1 726.68%	5 234.00%	478.27%	680.49%	1 453.98%
Moneyness	Above 10%	527	834.77%	1 997.26%	387.15%	525.00%	763.47%
	1% to 10%	704	1 488.30%	3 904.41%	433.33%	769.57%	1 400.00%
	0% to 1%	109	1 644.13%	1 600.36%	525.00%	1 100.00%	2 087.50%

Figure IA.1. Excerpt From a Representative Stock Exchange Release.

Presented is an excerpt from a stock exchange release by Nordea Bank AB dated 9 February 2009. For each option issued by a bank, the stock exchange release generally contains information on option characteristics such as the expiration date, strike price, underlying asset, and whether the option is a call or a put. For illustrative purposes we only include the first two rows from each table. In this example, the stock exchange release was retrieved from [GlobeNewsWire](#).

Nordea Bank AB (publ) issues 77 new warrant series on 10 February 2009

February 09, 2009 05:00 ET| Source: [Nordea Bank AB \(publ.\)](#)

[Follow](#)

Nordea Bank AB (publ) will launch 77 new warrant series on 10 February 2009 under its warrant programme. The underlying asset of the warrants is the Fortum Oyj (FUM1V), Metso Oyj (ME01V), Nordea Bank AB (NDA1V), Neste Oil Oyj (NES1V), Nokian Renkaat Oyj (NRE1V), Outotec Oyj (OTE1V), Outokumpu Oyj (OUT1V), Sampo Oyj (SAMAS), Stora Enso Oyj (STERV), UPM-Kymmene Oyj (UPM1V), Wärtsilä Oyj (WRT1V), Nokia Oyj (NOK1V) shares and Dow Jones Euro Stoxx 50-index and OMXH25-index. The warrants are call and put warrants. The warrants are redeemed by cash payment. Upon expiry of a warrant, the possible net value is paid in cash to the holder of the warrant.

Warrant specific terms and conditions

All Warrants are issued under the warrant programme of Nordea Bank AB (publ) dated 6 October 2008. The base prospectus for the warrant programme and the final terms for each warrant serie are available at the issuer's website: www.nordea.fi/warrantit. The following terms only summarize the final terms and the base prospectus.

Table 1

Warrant Trading code	Warrant ISIN code	Underlying instrument	Underlying instrument ISIN code	Underlying Currency	Additional Information on the underlying
9RFUMEW130	FI0009654149	Fortum Oyj	FI0009007132	EUR	www.fortum.com
9RFU1EW150	FI0009654156	Fortum Oyj	FI0009007132	EUR	www.fortum.com

Table 2

Warrant Trading code	Strike price	Type	Multiplier	Total number of warrants	Issue date	Expiration Date	Settlement Date
9RFUMEW130	13	P	0,2	1 500 000	10.2.2009	18.6.2009	26.6.2009
9RFU1EW150	15	P	0,2	1 500 000	10.2.2009	18.6.2009	26.6.2009

Figure IA.2. Average Holding Period Returns by Moneyness.

Plotted are the average holding period returns of option positions within moneyness percentile bins. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price.

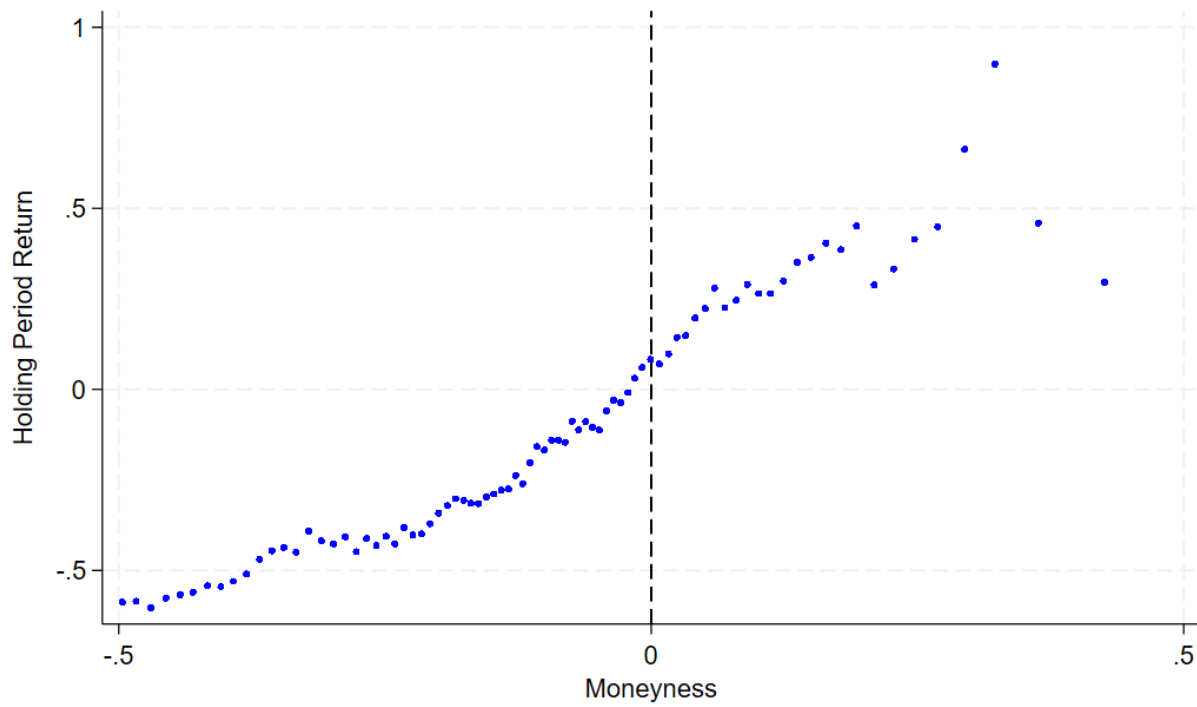


Figure IA.3. Average Holding Periods by Moneyness.

Plotted are the average holding periods of option positions within moneyness percentile bins. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price.

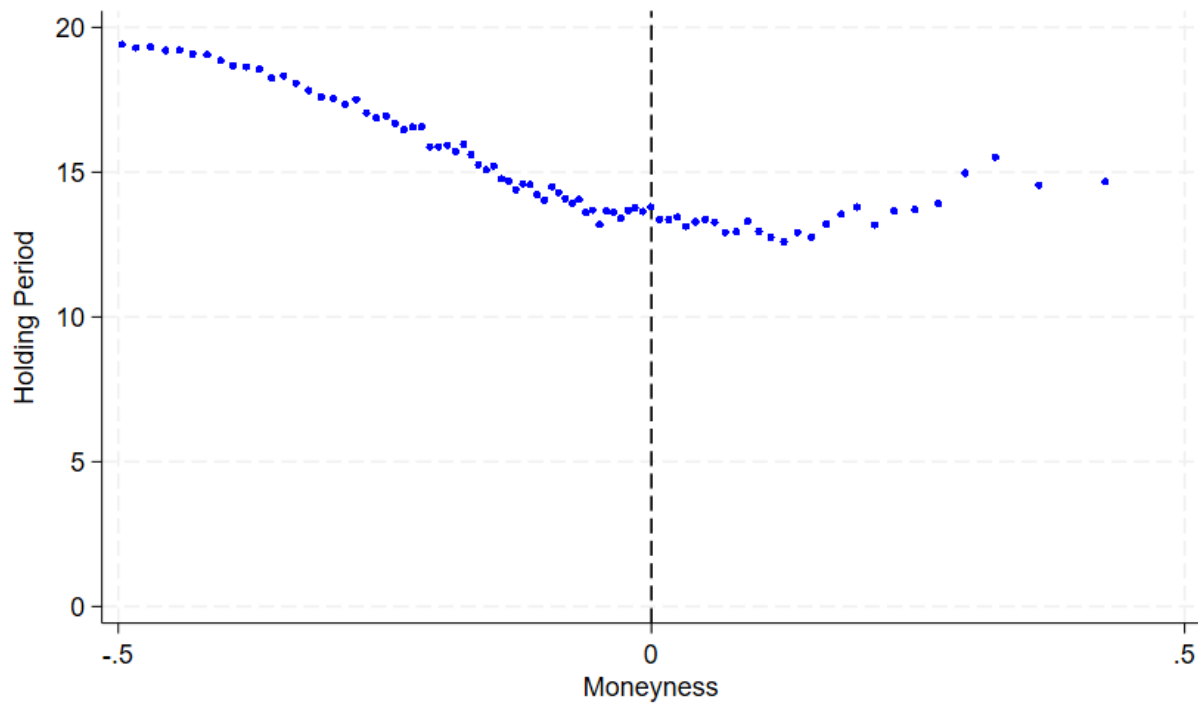
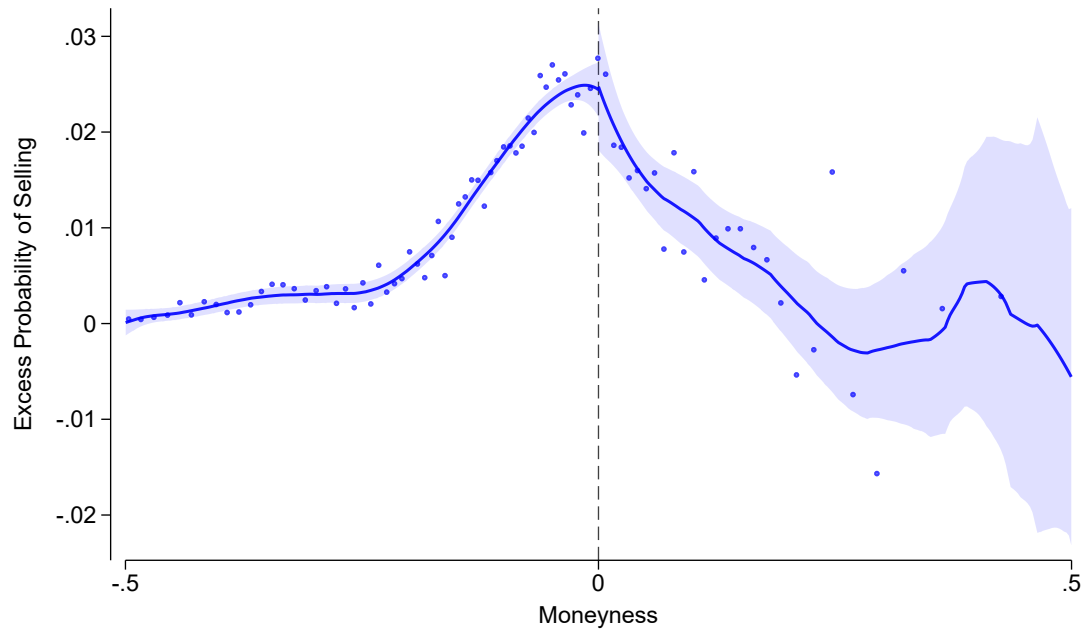


Figure IA.4. Excess Propensity to Sell Options by Moneyness: Out-of-the-Money Subsamples.

Plotted are subsample analyses corresponding to Figure 2 for options purchased (a) between 0% and 10% out of the money and (b) more than 10% out of the money.

(a) Options Purchased 0–10% Out of the Money



(b) Options Purchased More Than 10% Out of the Money

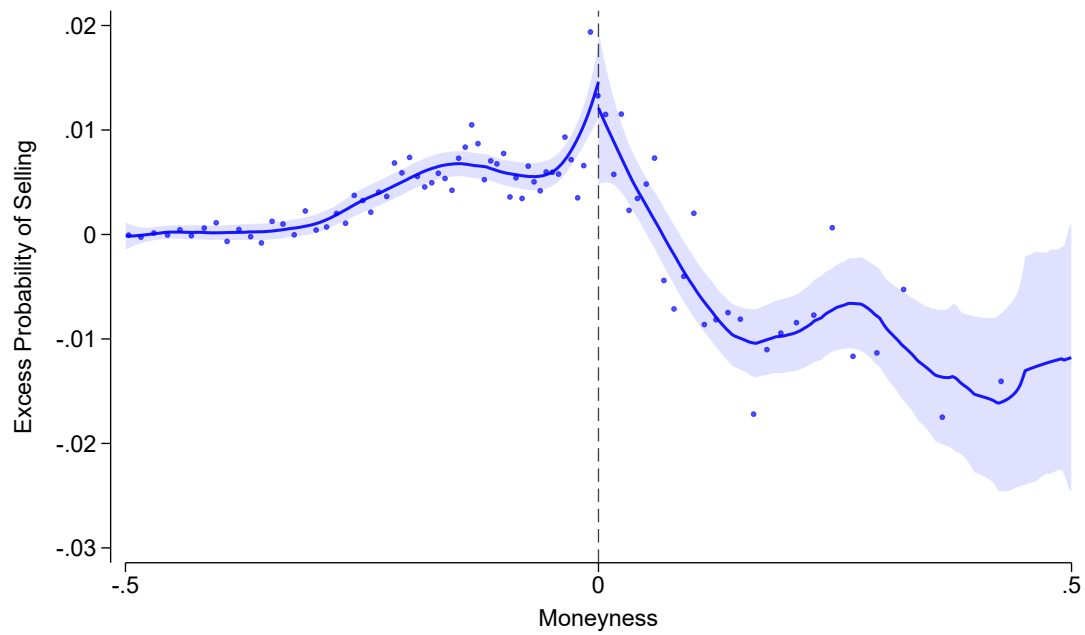


Figure IA.5. Excess Propensity to Sell Options by Moneyness: In-the-Money Purchases.

Plotted is the excess propensity to sell function estimated by regressing the dummy variable *Sale* on a set of dummy variables corresponding to moneyness percentile bins and on interacted controls for holding period return percentile bins and the holding period. The holding periods are winsorized at 20 days. We overlay a nonparametric local quadratic kernel regression fit, estimated separately for out-of-the-money and in-the-money option positions and evaluated on a dense grid. The shaded areas represent 95% pointwise confidence intervals based on the asymptotic standard errors from the local polynomial smoother. The moneyness of a call option is the price of the underlying asset minus the strike price, divided by the strike price, and the moneyness of a put option is the strike price minus the price of the underlying, divided by the strike price. The sample contains 736 078 investor-option-day observations from Dec-2000 to Dec-2017.

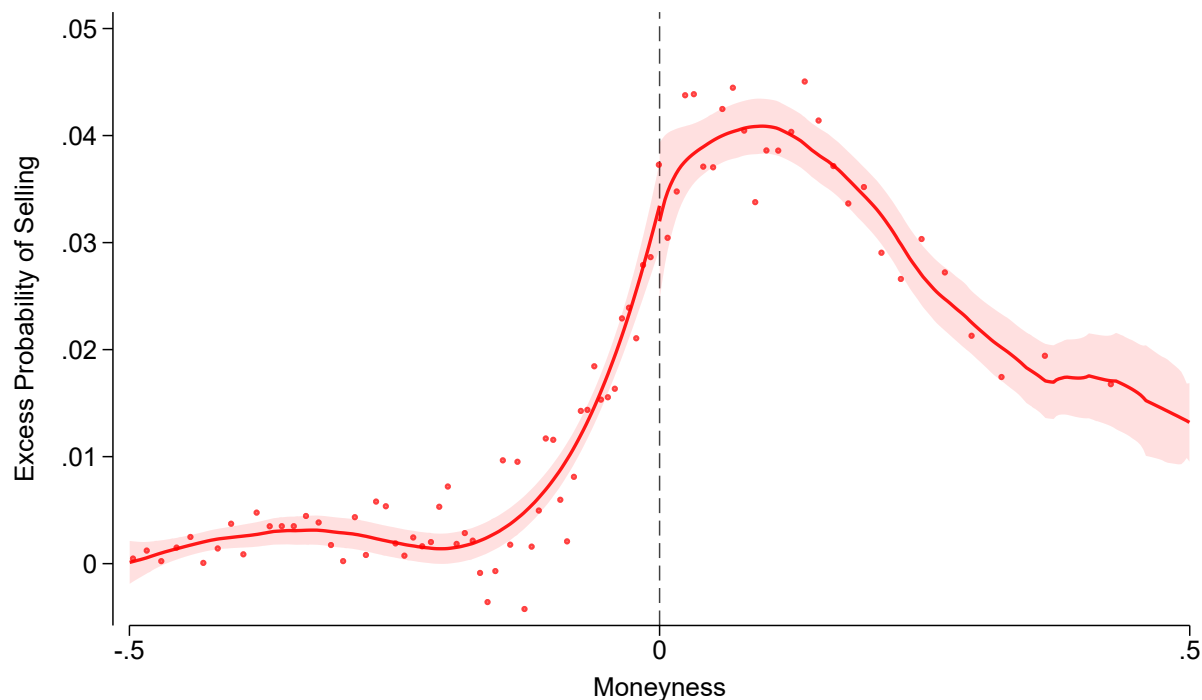
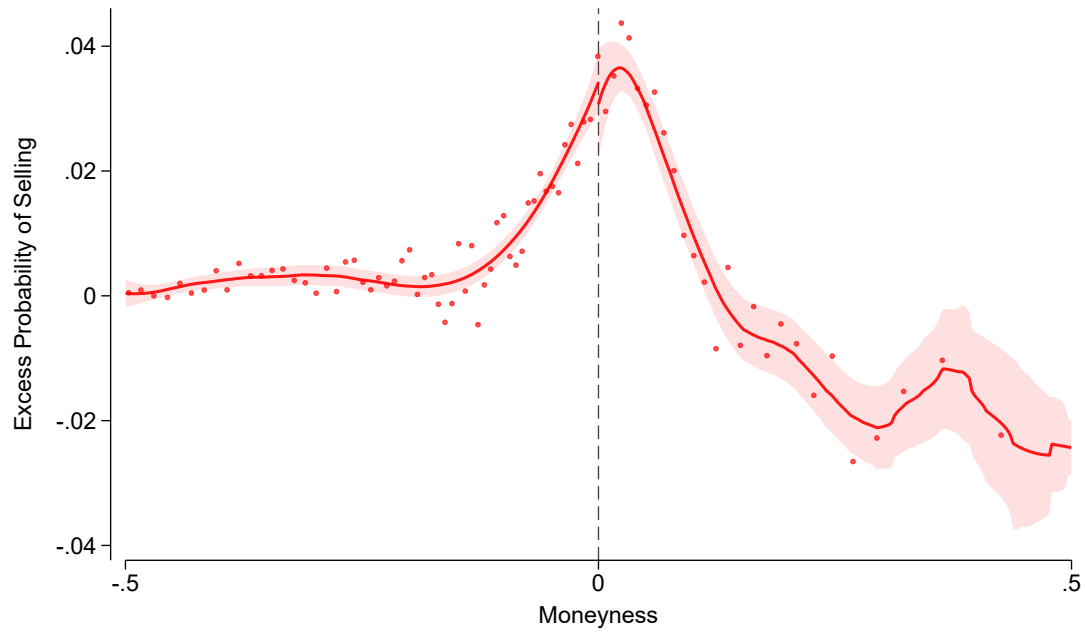


Figure IA.6. Excess Propensity to Sell Options by Moneyness: In-the-Money Subsamples.

Plotted are subsample analyses corresponding to Figure IA.5 for options purchased (a) between 0% and 10% in the money and (b) more than 10% in the money.

(a) Options Purchased 0–10% in the Money



(b) Options Purchased More Than 10% in the Money

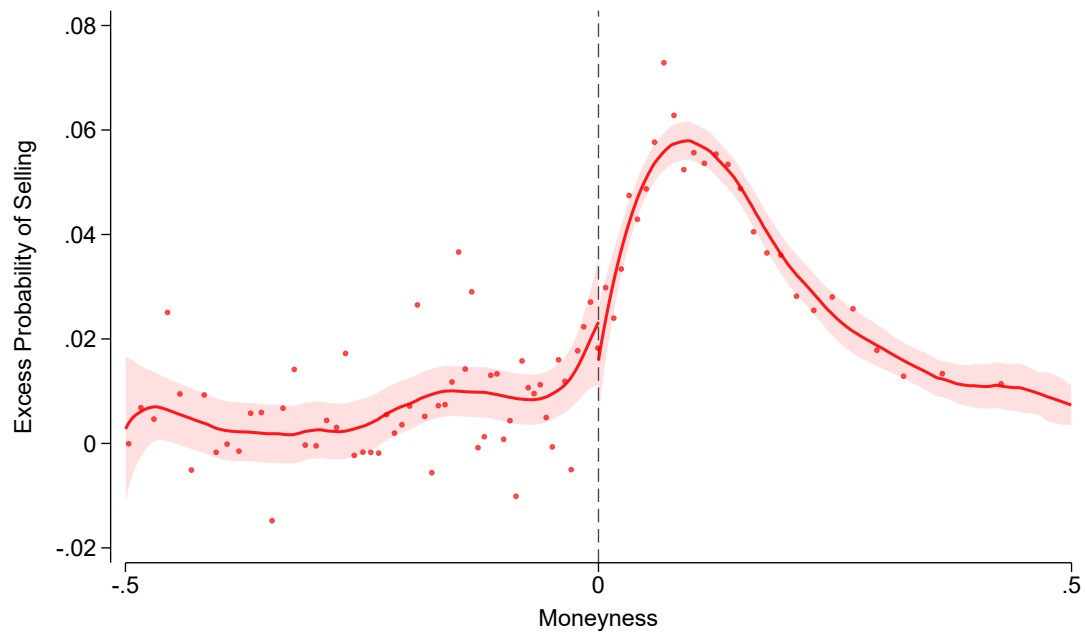


Table IA.1. Illustrative Social Media Posts on Strike Prices as Targets.

Reported are examples of retail option traders' social media posts that treat the strike price of an option as a target price for the underlying asset. Excerpts were retrieved in February 2026.

ID	Source	Excerpt
1	EliteTrader	"For certain moves (i.e. range bound oscillation) I will purchase an OTM strike that is my target price to sell when it is ATM."
2	EliteTrader	"The [special] Elite Trader who always times everything perfectly should buy the OTM strike near the target price and enjoy the leveraged return."
3	EliteTrader	"[...] if that's your modus operandi, the most bang for the buck will come from the call with the closest expiration and just under your target price."
4	Reddit	"For me I'll usually buy calls with a strike price just above the current price and sell when it hits my strike. [...] When price hits that target sell. [...] I make my targets based off the underlying asset price, not the option price."
5	Reddit	"Typically you buy a few strikes OTM and sell as the price approaches the strike."
6	Reddit	"Always buy the nearest ITM of your expected value. For example, if you buy at \$600 and expect a \$20 move buy the \$615 call."
7	Reddit	"Are there any cons to selling right away once strike price is reached, before expiration? Say a \$40 stock call is bought for \$50 on 12/1 with expiry 12/18. Are there any cons to selling the call right away once it hits \$50.2 [on] 12/5?"
8	Reddit	"Let's assume a stock is currently trading at \$250 and you believe the stock will reach \$300 (ignore theta for now). My understanding is that it's most efficient to buy the \$300 OTM call when the underlying is \$250 and sell it when the underlying's price is near the strike (\$300) to maximize the change in delta."
9	X (formerly Twitter)	"I target a strike that coincides with my chart level target price or I trade in the money."
10	Worden forum	"If [I am] expecting a big move, [I will] normally buy out the money by 1 strike, ABC is at \$100 and [I am] expecting a move to \$110 today, [I] would look to buy the 110 calls.. if [I] expect a move to 106, i would probably buy the 105 calls"

Table IA.2. Illustrative Online Articles on Strike Prices as Targets.

Reported are examples of articles that treat the strike price of an option as a target price for the underlying asset. Excerpts were retrieved in February 2026.

ID	Source	Excerpt
11	B2Prime	“The strike price is just the target price for the stock.”
12	CBOE	“Suppose each of the stocks A, B, C, D, and E were trading at €100/share, and we expect that at least one of these five stocks will rise to at least €150/share by the Dec 2025 expiry date.”
13	Forex.com	“You will need to choose a strike price close to where you expect the stock to trade by expiration.”
14	IndiaBulls Securities	“The strike price is the cost at which the buyer of the option can buy (in a call option) or sell (in a put option) the underlying asset. You can think of it as a price target.”
15	Insider Finance	“For a Long Call, select a strike price based on your price target for the stock and an expiration date that gives the stock enough time to move.”
16	Interactive Brokers	“Are you expecting the price of a security to rise, and you have a target price in mind? In this article, you will learn how to choose the right strike price to optimize your return if the security reaches your target price by the time your call option expires.”
17	Investing Daily	“People trade options with a price target in mind. That price target is the strike price.”
18	National Bank Direct Brokerage	“When you turn on a GPS, you must tell it where you want to go and then it will give you the optimal route. The same thing is true of options (this applies to calls and puts): you need to have an expected target price.”
19	Option Samurai	“To make the most of a strike price in options, align it with: • Your price target • The time you expect the move to happen • Current volatility conditions”
20	Saxo Bank	“After the stock has moved to your target level, the sooner you sell the put option then the more money you will be able receive for it, as you are minimizing time decay.”

Table IA.3. Illustrative Online Quotes on Targets in Stock Trading.

Reported are quotes related to stock trading using target prices. Excerpts were retrieved in March 2026.

ID	Source	Excerpt
21	Bogleheads	“The market has dropped, and we all know to buy stocks when the market has dropped big and hold for the long term (+1 to 5 years or when a target price is reached).”
22	Cabot Wealth	“If you set price targets on your stocks, you’ll be entering a trade with a head start over most investors because your exit strategy is already halfway done.”
23	Elite Trader	“SHORT GOOGL. Price target \$660-680.”
24	E*TRADE	“When you’re preparing a new trade, you should consider both the profit and the loss potential. It’s important to have a strategy for evaluating profit with price targets.”
25	Fidelity	“The price target following the breakout can be estimated by measuring the distance from the right top of the cup to the bottom of the cup and adding that number to the buy point. This should be used only as a guideline.”
26	Investopedia	“The target-price sell method uses a specific stock value to trigger a sell. This is one of the most widely used ways by which investors sell a stock [...]”
27	Reddit	“What do you do when share price reaches your target price? The obvious answer is "sell" and most of the big name investors I follow talk about selling when the share price reaches their target price.”
28	Reddit	“I always look at TipRanks for stocks’ target prices from analysts. I was doing this blindly, and that is wrong. So, I want to start educating myself on the topic of determining my own target price for a stock.”
29	Reddit	“Personally, my PT for the stock [...] is \$150. This would give the company a valuation of around \$70 billion which seems reasonable to me.”
30	Warrior Trading	“Thanks to price targets, traders and investors know when to exit a position. As a result, they will sell a number of shares in their possession thus earning a profit.”

Table IA.4. Distribution of Bid-Ask Spreads.

Reported is the distribution of bid-ask spreads at market close for 749 067 option-day observations. The data set contains all options traded in Finland from Dec-2000 to Dec-2017.

Bid-Ask Spread (€)	N	Proportion
0.01	511 981	68.35%
0.02	168 575	22.50%
0.03	35 194	4.70%
0.04	13 858	1.85%
0.05	6 952	0.93%
> 0.05	12 507	1.67%

Table IA.5. Summary Statistics for Within Investor-Day-Underlying Analyses.

Reported are summary statistics about investor, trade, and sample characteristics for the within investor-day-underlying analyses described in Section 5.2. The sample contains 530 518 investor-option-day observations from Dec-2000 to Dec-2017.

Panel A: Investor Characteristics					
	Mean	SD	25th Pct.	Median	75th Pct.
Female (%)	5.20				
Age (years)	41.02	12.28	32.00	39.50	49.59
Experience (years)	2.43	2.21	0.76	1.83	3.59
Total Trades	224.35	438.31	31.00	81.00	232.00
Panel B: Trade Characteristics					
	Mean	SD	25 th Pct.	Median	75 th Pct.
Call Option (%)	88.86				
Value at Purchase (euros)	1 400	3 504	224	530	1 266
Days to Expiry at Purchase	100.04	148.53	18.00	40.00	92.00
Holding Period (days)	74.35	105.04	10.75	31.00	88.00
Panel C: Sample Characteristics					
	N				
Investors	2 118				
Observations	530 518				

Table IA.6. Option Sales Around Strike Price Crossings: Rank Effect.

Reported is the option-level analysis corresponding to Table 2 controlling for the option-day average best- and worst-performer indicators of holders' portfolios. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0066 (0.0068)	-0.0094 (0.0073)	-0.0046 (0.0073)
t_{-9}	-0.0074 (0.0064)	-0.0050 (0.0064)	-0.0028 (0.0060)
t_{-8}	-0.0048 (0.0066)	0.0036 (0.0071)	0.0049 (0.0069)
t_{-7}	-0.0131** (0.0059)	-0.0137** (0.0068)	-0.0100 (0.0063)
t_{-6}	-0.0046 (0.0062)	-0.0050 (0.0061)	-0.0027 (0.0058)
t_{-4}	0.0001 (0.0058)	-0.0042 (0.0058)	-0.0053 (0.0056)
t_{-3}	-0.0039 (0.0066)	-0.0016 (0.0063)	-0.0019 (0.0061)
t_{-2}	0.0138** (0.0066)	0.0054 (0.0067)	0.0026 (0.0064)
t_{-1}	0.0319*** (0.0075)	0.0152** (0.0076)	0.0053 (0.0071)
t_0	0.1056*** (0.0112)	0.0592*** (0.0111)	0.0373*** (0.0103)
t_1	0.0243*** (0.0074)	0.0141* (0.0077)	-0.0013 (0.0077)
t_2	0.0166** (0.0082)	0.0186** (0.0080)	0.0048 (0.0077)
t_3	0.0182** (0.0071)	0.0162** (0.0070)	0.0031 (0.0071)
t_4	0.0152** (0.0072)	0.0115 (0.0072)	0.0013 (0.0071)
t_5	0.0142** (0.0070)	0.0103 (0.0069)	0.0012 (0.0065)
t_6	0.0082 (0.0068)	0.0113 (0.0078)	0.0009 (0.0069)
t_7	0.0094 (0.0075)	0.0142 (0.0092)	0.0052 (0.0080)
t_8	0.0133** (0.0064)	0.0156** (0.0067)	0.0071 (0.0065)
t_9	0.0038 (0.0065)	0.0037 (0.0067)	-0.0024 (0.0064)
t_{10}	0.0066 (0.0062)	0.0072 (0.0066)	0.0016 (0.0063)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.391	0.489	0.510
Observations	2 086 392	1 913 642	1 896 902

Table IA.7. Option Sales Around Strike Price Crossings: Rollover Strategies.

Reported is the option-level analysis corresponding to Table 2 excluding holders who purchase another option on the crossing day or the following day. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0093 (0.0066)	-0.0112 (0.0069)	-0.0059 (0.0067)
t_{-9}	-0.0083 (0.0064)	-0.0042 (0.0062)	-0.0016 (0.0055)
t_{-8}	-0.0073 (0.0067)	0.0016 (0.0067)	0.0035 (0.0062)
t_{-7}	-0.0124** (0.0058)	-0.0127* (0.0066)	-0.0096 (0.0060)
t_{-6}	-0.0056 (0.0057)	-0.0062 (0.0056)	-0.0038 (0.0050)
t_{-4}	0.0010 (0.0057)	-0.0027 (0.0056)	-0.0035 (0.0052)
t_{-3}	-0.0020 (0.0063)	-0.0001 (0.0059)	0.0002 (0.0055)
t_{-2}	0.0141** (0.0068)	0.0046 (0.0067)	0.0017 (0.0060)
t_{-1}	0.0333*** (0.0075)	0.0148* (0.0078)	0.0047 (0.0071)
t_0	0.1179*** (0.0117)	0.0673*** (0.0116)	0.0429*** (0.0105)
t_1	0.0402*** (0.0077)	0.0195** (0.0078)	0.0027 (0.0074)
t_2	0.0308*** (0.0082)	0.0196*** (0.0076)	0.0041 (0.0067)
t_3	0.0325*** (0.0071)	0.0199*** (0.0068)	0.0053 (0.0066)
t_4	0.0242*** (0.0067)	0.0131** (0.0066)	0.0014 (0.0062)
t_5	0.0246*** (0.0072)	0.0111* (0.0067)	0.0015 (0.0060)
t_6	0.0168** (0.0066)	0.0113 (0.0073)	0.0000 (0.0062)
t_7	0.0211*** (0.0078)	0.0173* (0.0096)	0.0076 (0.0077)
t_8	0.0202*** (0.0066)	0.0139** (0.0070)	0.0053 (0.0062)
t_9	0.0089 (0.0065)	0.0058 (0.0067)	-0.0008 (0.0061)
t_{10}	0.0110* (0.0062)	0.0062 (0.0065)	0.0014 (0.0060)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.360	0.452	0.478
Observations	1 953 177	1 779 921	1 764 971

Table IA.8. Option Sales Around Strike Price Crossings: Excluding Small Positions.

Reported is the option-level analysis corresponding to Table 2 excluding holders with positions worth less than €100. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0103 (0.0079)	-0.0123 (0.0079)	-0.0055 (0.0077)
t_{-9}	-0.0107 (0.0074)	-0.0080 (0.0068)	-0.0050 (0.0062)
t_{-8}	-0.0076 (0.0079)	0.0028 (0.0076)	0.0051 (0.0073)
t_{-7}	-0.0149** (0.0065)	-0.0130* (0.0068)	-0.0090 (0.0062)
t_{-6}	-0.0061 (0.0071)	-0.0047 (0.0067)	-0.0018 (0.0061)
t_{-4}	0.0001 (0.0067)	-0.0046 (0.0063)	-0.0050 (0.0059)
t_{-3}	-0.0043 (0.0078)	-0.0029 (0.0068)	-0.0025 (0.0064)
t_{-2}	0.0190** (0.0078)	0.0052 (0.0073)	0.0029 (0.0068)
t_{-1}	0.0429*** (0.0087)	0.0149* (0.0082)	0.0045 (0.0074)
t_0	0.1280*** (0.0129)	0.0561*** (0.0116)	0.0301*** (0.0106)
t_1	0.0381*** (0.0084)	0.0142* (0.0080)	-0.0024 (0.0077)
t_2	0.0292*** (0.0092)	0.0193** (0.0086)	0.0051 (0.0080)
t_3	0.0313*** (0.0083)	0.0156** (0.0076)	0.0021 (0.0073)
t_4	0.0263*** (0.0084)	0.0103 (0.0076)	-0.0005 (0.0073)
t_5	0.0253*** (0.0082)	0.0095 (0.0075)	0.0009 (0.0068)
t_6	0.0164** (0.0079)	0.0113 (0.0084)	0.0004 (0.0072)
t_7	0.0179** (0.0087)	0.0143 (0.0101)	0.0062 (0.0083)
t_8	0.0200*** (0.0075)	0.0143* (0.0074)	0.0072 (0.0066)
t_9	0.0080 (0.0075)	0.0026 (0.0071)	-0.0022 (0.0066)
t_{10}	0.0107 (0.0074)	0.0043 (0.0070)	0.0014 (0.0065)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.375	0.501	0.526
Observations	1 889 168	1 720 469	1 705 182

Table IA.9. Option Sales by Moneyness When Investor Beliefs are Fixed: Excluding Small Positions.
Reported are analyses corresponding to Table 5 excluding option positions worth less than €100.

	Dependent Variable: Sale			
	(1)	(2)	(3)	(4)
ITM	0.0181*** (0.0017)	0.0248*** (0.0049)	0.0074*** (0.0018)	0.0177*** (0.0048)
Gain			0.0255*** (0.0029)	0.0368*** (0.0072)
	Fixed Effects			
	Yes	No	Yes	No
Investor $\times$ Day $\times$ Underlying $\times$ Expiry	No	Yes	No	Yes
Investor $\times$ Day $\times$ Underlying $\times$ Expiry $\times$ Hold				
Observations	429 509	59 550	429 509	59 550
Adjusted R^2	0.3557	0.5325	0.3591	0.5348

Table IA.10. Option Sales Around Strike Price Crossings: Liquidity.

Reported is the option-level analysis corresponding to Table 2 restricted to holders who simultaneously hold other assets in their portfolio. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0114 (0.0075)	-0.0113 (0.0077)	-0.0047 (0.0075)
t_{-9}	-0.0117* (0.0071)	-0.0057 (0.0070)	-0.0028 (0.0062)
t_{-8}	-0.0099 (0.0070)	0.0007 (0.0073)	0.0025 (0.0070)
t_{-7}	-0.0149** (0.0065)	-0.0143** (0.0071)	-0.0110* (0.0065)
t_{-6}	-0.0058 (0.0068)	-0.0049 (0.0065)	-0.0025 (0.0060)
t_{-4}	-0.0039 (0.0061)	-0.0084 (0.0060)	-0.0093* (0.0055)
t_{-3}	-0.0064 (0.0073)	-0.0048 (0.0067)	-0.0048 (0.0062)
t_{-2}	0.0139* (0.0074)	0.0028 (0.0070)	-0.0006 (0.0064)
t_{-1}	0.0414*** (0.0084)	0.0191** (0.0081)	0.0078 (0.0074)
t_0	0.1253*** (0.0127)	0.0644*** (0.0118)	0.0367*** (0.0107)
t_1	0.0401*** (0.0083)	0.0179** (0.0080)	-0.0007 (0.0079)
t_2	0.0269*** (0.0087)	0.0189** (0.0081)	0.0032 (0.0075)
t_3	0.0312*** (0.0081)	0.0188** (0.0075)	0.0035 (0.0073)
t_4	0.0246*** (0.0081)	0.0121 (0.0077)	0.0001 (0.0073)
t_5	0.0221*** (0.0080)	0.0081 (0.0072)	-0.0019 (0.0065)
t_6	0.0183** (0.0077)	0.0142* (0.0085)	0.0026 (0.0072)
t_7	0.0159* (0.0083)	0.0135 (0.0100)	0.0046 (0.0081)
t_8	0.0168** (0.0071)	0.0143* (0.0075)	0.0061 (0.0067)
t_9	0.0081 (0.0072)	0.0031 (0.0069)	-0.0026 (0.0064)
t_{10}	0.0079 (0.0070)	0.0043 (0.0067)	0.0003 (0.0063)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.352	0.467	0.496
Observations	2 013 687	1 841 138	1 825 091

Table IA.11. Option Sales by Moneyness When Investor Beliefs are Fixed: Liquidity.

Reported are analyses corresponding to Table 5 excluding investors who hold no other assets in their portfolio.

	Dependent Variable: Sale			
	(1)	(2)	(3)	(4)
ITM	0.0197*** (0.0018)	0.0262*** (0.0049)	0.0081*** (0.0018)	0.0191*** (0.0047)
Gain			0.0272*** (0.0030)	0.0358*** (0.0065)
	Fixed Effects			
	Yes	No	Yes	No
Investor $\times$ Day $\times$ Underlying $\times$ Expiry	No	Yes	No	Yes
Investor $\times$ Day $\times$ Underlying $\times$ Expiry $\times$ Hold				
Observations	500 104	70 958	500 104	70 958
Adjusted R^2	0.3418	0.5295	0.3457	0.5320

Table IA.12. Stock Option Purchases and Ownership of the Underlying Stock.

Reported are the total number of purchases of calls and puts, and the total euro value of call and put purchases, based on whether an investor owns the underlying stock at the time of purchase or not. The data set contains the stock option purchases of all retail investors in Finland from Dec-2000 to Dec-2017 for which we can determine the underlying stock.

	Purchases		Value (€)	
	Call	Put	Call	Put
Owens Underlying	47 190	4 350	63 579 058	4 559 199
Does Not Own Underlying	88 891	26 691	144 477 833	38 048 115

Table IA.13. Option Sales Around Strike Price Crossings: Hedging.

Reported is the option-level analysis corresponding to Table 2 restricted to call options. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0142* (0.0074)	-0.0148** (0.0074)	-0.0084 (0.0069)
t_{-9}	-0.0117* (0.0066)	-0.0115* (0.0066)	-0.0086 (0.0058)
t_{-8}	-0.0085 (0.0073)	-0.0012 (0.0074)	0.0009 (0.0069)
t_{-7}	-0.0124* (0.0064)	-0.0147** (0.0071)	-0.0113* (0.0062)
t_{-6}	-0.0091 (0.0067)	-0.0089 (0.0062)	-0.0063 (0.0056)
t_{-4}	-0.0040 (0.0061)	-0.0108* (0.0059)	-0.0115** (0.0053)
t_{-3}	-0.0097 (0.0068)	-0.0111* (0.0065)	-0.0108* (0.0059)
t_{-2}	0.0123 (0.0076)	0.0022 (0.0070)	-0.0004 (0.0062)
t_{-1}	0.0242*** (0.0077)	0.0120 (0.0081)	0.0024 (0.0072)
t_0	0.0996*** (0.0124)	0.0639*** (0.0123)	0.0410*** (0.0111)
t_1	0.0213*** (0.0076)	0.0098 (0.0080)	-0.0055 (0.0078)
t_2	0.0196** (0.0082)	0.0129 (0.0086)	-0.0002 (0.0079)
t_3	0.0216*** (0.0076)	0.0104 (0.0073)	-0.0022 (0.0070)
t_4	0.0140** (0.0070)	0.0074 (0.0076)	-0.0024 (0.0070)
t_5	0.0185** (0.0077)	0.0083 (0.0074)	0.0007 (0.0064)
t_6	0.0131* (0.0076)	0.0039 (0.0086)	-0.0057 (0.0071)
t_7	0.0127 (0.0091)	0.0100 (0.0109)	0.0028 (0.0089)
t_8	0.0079 (0.0070)	0.0056 (0.0073)	-0.0009 (0.0062)
t_9	0.0063 (0.0072)	-0.0017 (0.0071)	-0.0061 (0.0063)
t_{10}	0.0041 (0.0065)	-0.0000 (0.0066)	-0.0030 (0.0059)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.381	0.473	0.501
Observations	840 355	785 934	775 405

Table IA.14. Option Sales by Moneyness When Investor Beliefs are Fixed: Hedging.
Reported are analyses corresponding to Table 5 excluding put options.

	Dependent Variable: Sale			
	(1)	(2)	(3)	(4)
ITM	0.0192*** (0.0018)	0.0220*** (0.0044)	0.0078*** (0.0017)	0.0156*** (0.0043)
Gain			0.0266*** (0.0028)	0.0323*** (0.0062)
	Fixed Effects			
	Yes	No	Yes	No
Investor $\times$ Day $\times$ Underlying $\times$ Expiry	No	Yes	No	Yes
Investor $\times$ Day $\times$ Underlying $\times$ Expiry $\times$ Hold				
Observations	513 548	72 178	513 548	72 178
Adjusted R^2	0.3238	0.5166	0.3277	0.5188

Table IA.15. Option Sales Around Strike Price Crossings: Complex Strategies.

Reported is the option-level analysis corresponding to Table 2 restricted to holders with a single option on the underlying who do not own the underlying asset. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0081 (0.0101)	-0.0111 (0.0137)	-0.0033 (0.0134)
t_{-9}	-0.0056 (0.0095)	0.0067 (0.0128)	0.0075 (0.0121)
t_{-8}	0.0008 (0.0115)	0.0264** (0.0134)	0.0266** (0.0127)
t_{-7}	-0.0159* (0.0084)	-0.0184 (0.0114)	-0.0136 (0.0112)
t_{-6}	0.0009 (0.0095)	0.0065 (0.0126)	0.0123 (0.0119)
t_{-4}	0.0097 (0.0094)	0.0027 (0.0115)	0.0040 (0.0113)
t_{-3}	0.0104 (0.0105)	0.0103 (0.0125)	0.0122 (0.0119)
t_{-2}	0.0268*** (0.0097)	0.0142 (0.0124)	0.0139 (0.0118)
t_{-1}	0.0554*** (0.0109)	0.0203 (0.0127)	0.0041 (0.0119)
t_0	0.1768*** (0.0144)	0.0979*** (0.0163)	0.0578*** (0.0157)
t_1	0.0576*** (0.0102)	0.0295** (0.0132)	0.0022 (0.0131)
t_2	0.0487*** (0.0127)	0.0365*** (0.0137)	0.0139 (0.0134)
t_3	0.0598*** (0.0114)	0.0470*** (0.0133)	0.0229* (0.0132)
t_4	0.0479*** (0.0107)	0.0333** (0.0132)	0.0124 (0.0126)
t_5	0.0456*** (0.0111)	0.0347*** (0.0130)	0.0200* (0.0120)
t_6	0.0376*** (0.0099)	0.0375*** (0.0134)	0.0226* (0.0125)
t_7	0.0280*** (0.0106)	0.0242* (0.0140)	0.0116 (0.0127)
t_8	0.0375*** (0.0102)	0.0251** (0.0119)	0.0155 (0.0113)
t_9	0.0285*** (0.0108)	0.0195 (0.0123)	0.0112 (0.0116)
t_{10}	0.0260*** (0.0098)	0.0240** (0.0120)	0.0158 (0.0113)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.314	0.413	0.448
Observations	1 571 789	1 394 684	1 389 403

Table IA.16. Option Sales Around Strike Price Crossings: Pinning Risk.

Reported is the option-level analysis corresponding to Table 2 excluding options with five or fewer days to expiry. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0099 (0.0074)	-0.0122 (0.0076)	-0.0069 (0.0073)
t_{-9}	-0.0098 (0.0069)	-0.0064 (0.0067)	-0.0043 (0.0060)
t_{-8}	-0.0075 (0.0072)	0.0022 (0.0069)	0.0034 (0.0066)
t_{-7}	-0.0131** (0.0065)	-0.0113 (0.0070)	-0.0087 (0.0063)
t_{-6}	-0.0055 (0.0068)	-0.0047 (0.0064)	-0.0023 (0.0058)
t_{-4}	0.0009 (0.0065)	-0.0042 (0.0061)	-0.0051 (0.0057)
t_{-3}	-0.0019 (0.0074)	-0.0013 (0.0067)	-0.0015 (0.0065)
t_{-2}	0.0188** (0.0076)	0.0080 (0.0071)	0.0041 (0.0065)
t_{-1}	0.0408*** (0.0084)	0.0173** (0.0080)	0.0053 (0.0073)
t_0	0.1172*** (0.0123)	0.0586*** (0.0117)	0.0315*** (0.0104)
t_1	0.0287*** (0.0076)	0.0062 (0.0071)	-0.0126* (0.0071)
t_2	0.0189** (0.0081)	0.0106 (0.0074)	-0.0050 (0.0067)
t_3	0.0215*** (0.0076)	0.0095 (0.0068)	-0.0040 (0.0067)
t_4	0.0201*** (0.0076)	0.0084 (0.0070)	-0.0041 (0.0068)
t_5	0.0225*** (0.0081)	0.0086 (0.0072)	-0.0008 (0.0064)
t_6	0.0134* (0.0076)	0.0098 (0.0083)	-0.0018 (0.0072)
t_7	0.0097 (0.0069)	0.0082 (0.0072)	-0.0004 (0.0067)
t_8	0.0135* (0.0070)	0.0095 (0.0068)	0.0028 (0.0065)
t_9	0.0039 (0.0074)	0.0004 (0.0068)	-0.0037 (0.0065)
t_{10}	0.0042 (0.0068)	0.0010 (0.0065)	-0.0018 (0.0062)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.362	0.483	0.512
Observations	1 922 862	1 747 818	1 747 753

Table IA.17. Option Sales by Moneyness When Investor Beliefs are Fixed: Pinning Risk.
Reported are analyses corresponding to Table 5 excluding options with five or fewer days to expiry.

	Dependent Variable: Sale			
	(1)	(2)	(3)	(4)
ITM	0.0163*** (0.0016)	0.0217*** (0.0042)	0.0051*** (0.0016)	0.0152*** (0.0041)
Gain			0.0262*** (0.0028)	0.0354*** (0.0066)
	Fixed Effects			
	Yes	No	Yes	No
Investor $\times$ Day $\times$ Underlying $\times$ Expiry	No	Yes	No	Yes
Investor $\times$ Day $\times$ Underlying $\times$ Expiry $\times$ Hold				
Observations	509 072	71 982	509 072	71 982
Adjusted R^2	0.3427	0.5296	0.3464	0.5321

Table IA.18. Option Sales Around Strike Price Crossings: OTM and ITM Buyers.

Reported is the option-level analysis corresponding to Table 2 restricted to holders who purchase both in-the-money and out-of-the-money options. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0107 (0.0079)	-0.0118 (0.0083)	-0.0059 (0.0082)
t_{-9}	-0.0098 (0.0079)	-0.0040 (0.0078)	-0.0024 (0.0071)
t_{-8}	-0.0072 (0.0082)	0.0054 (0.0086)	0.0064 (0.0081)
t_{-7}	-0.0127* (0.0070)	-0.0104 (0.0079)	-0.0075 (0.0074)
t_{-6}	-0.0061 (0.0075)	-0.0050 (0.0073)	-0.0030 (0.0069)
t_{-4}	0.0012 (0.0069)	-0.0030 (0.0070)	-0.0040 (0.0065)
t_{-3}	-0.0028 (0.0082)	-0.0013 (0.0078)	-0.0013 (0.0073)
t_{-2}	0.0183** (0.0079)	0.0079 (0.0079)	0.0043 (0.0075)
t_{-1}	0.0448*** (0.0088)	0.0211** (0.0086)	0.0072 (0.0080)
t_0	0.1412*** (0.0127)	0.0738*** (0.0124)	0.0416*** (0.0114)
t_1	0.0482*** (0.0087)	0.0255*** (0.0088)	0.0045 (0.0088)
t_2	0.0353*** (0.0099)	0.0247*** (0.0094)	0.0072 (0.0090)
t_3	0.0371*** (0.0088)	0.0218*** (0.0083)	0.0057 (0.0082)
t_4	0.0329*** (0.0088)	0.0185** (0.0086)	0.0054 (0.0082)
t_5	0.0279*** (0.0087)	0.0124 (0.0083)	0.0017 (0.0076)
t_6	0.0206** (0.0082)	0.0142 (0.0091)	0.0021 (0.0080)
t_7	0.0194** (0.0089)	0.0159 (0.0106)	0.0066 (0.0091)
t_8	0.0214*** (0.0076)	0.0165** (0.0078)	0.0087 (0.0072)
t_9	0.0108 (0.0080)	0.0042 (0.0077)	-0.0008 (0.0073)
t_{10}	0.0115 (0.0076)	0.0057 (0.0076)	0.0020 (0.0072)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.351	0.472	0.504
Observations	1 983 361	1 810 364	1 795 991

Table IA.19. Option Sales Around Strike Price Crossings: ITM to OTM, OTM and ITM Buyers.

Reported is the placebo (in the money to out of the money) option-level analysis corresponding to Table 3, restricted to holders who purchase both in-the-money and out-of-the-money options. Each investor-level restriction is applied at the holder level when forming the option-day outcome: the dependent variable is the fraction of qualifying holders who sell, and option-days are weighted by the number of qualifying holders. Specifications follow Table 2 (option-cohort and day-cohort fixed effects; then underlying-by-type-by-day-cohort fixed effects; then option-day controls). Standard errors clustered by option and day.

	Dependent Variable: Share Selling		
	(1)	(2)	(3)
t_{-10}	-0.0177 (0.0258)	-0.0251 (0.0250)	-0.0293 (0.0259)
t_{-9}	0.0248 (0.0400)	0.0043 (0.0400)	-0.0063 (0.0388)
t_{-8}	-0.0197 (0.0320)	-0.0307 (0.0311)	-0.0369 (0.0303)
t_{-7}	-0.0475* (0.0278)	-0.0505* (0.0278)	-0.0537** (0.0268)
t_{-6}	-0.0308 (0.0206)	-0.0217 (0.0217)	-0.0108 (0.0198)
t_{-4}	-0.0012 (0.0181)	-0.0017 (0.0179)	0.0013 (0.0162)
t_{-3}	-0.0114 (0.0273)	-0.0204 (0.0251)	-0.0140 (0.0213)
t_{-2}	-0.0443** (0.0191)	-0.0390* (0.0199)	-0.0260 (0.0212)
t_{-1}	-0.0270 (0.0214)	-0.0140 (0.0221)	0.0057 (0.0217)
t_0	-0.0275* (0.0162)	-0.0034 (0.0183)	0.0233 (0.0183)
t_1	0.0142 (0.0193)	0.0180 (0.0203)	0.0259 (0.0180)
t_2	0.0047 (0.0240)	0.0131 (0.0255)	0.0186 (0.0234)
t_3	0.0307 (0.0281)	0.0230 (0.0228)	0.0248 (0.0199)
t_4	-0.0017 (0.0199)	0.0024 (0.0207)	0.0029 (0.0187)
t_5	-0.0137 (0.0191)	-0.0065 (0.0200)	-0.0058 (0.0184)
t_6	0.0091 (0.0195)	0.0116 (0.0204)	0.0104 (0.0184)
t_7	-0.0081 (0.0197)	-0.0012 (0.0205)	-0.0005 (0.0181)
t_8	-0.0161 (0.0202)	-0.0097 (0.0211)	-0.0082 (0.0189)
t_9	-0.0104 (0.0195)	-0.0070 (0.0203)	-0.0069 (0.0182)
t_{10}	-0.0132 (0.0191)	-0.0079 (0.0195)	-0.0080 (0.0176)
Fixed Effects			
Option $\times$ Cohort	Yes	Yes	Yes
Day $\times$ Cohort	Yes	No	No
Underlying $\times$ Type $\times$ Day $\times$ Cohort	No	Yes	Yes
Controls	No	No	Yes
Adjusted R^2	0.356	0.489	0.524
Observations	1 137 087	1 066 249	1 061 218