Slow Belief Updating and the Disposition Effect*

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Abstract

I present a theory of investor selling behavior in which the disposition effect arises because investors are slow to update their beliefs about the values of the assets they hold. I show numerically that the theory generates a disposition effect, propensity to sell functions, and other trading statistics that are in line with empirical estimates. I also show that the theory generates a reversed disposition effect at the end of the tax year, a weaker effect for more sophisticated investors, a stronger effect in more volatile stocks, and a disposition effect in short sales.

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1 Introduction

Over thirty-five years after it was introduced by Shefrin and Statman (1985), the disposition effect—the empirical observation that investors are more likely to sell an asset trading at a gain, rather than an asset trading at a loss—remains one of the most robust stylized facts about investor behavior. It has been documented in numerous countries, a variety of financial decision-making contexts, and in multiple experiments.[1] Researchers have compiled a long list of facts about the effect, from which the literature survey by Kaustia (2010a) identified the following as the key facts that any theory of the disposition effect should explain. First, the typical investor exhibits a disposition effect in all but the last month of the tax year. Second, the disposition effect weakens or reverses in the last month of the tax year. Third, the disposition effect is weaker for more sophisticated investors.[2]

The existing theories of the disposition effect have struggled to explain these facts. As I discuss in more detail in Section 3, the theories have found it difficult to generate disposition effects comparable in magnitude to the disposition effects reported in empirical studies. The theories have also had very little to say about other facets of the disposition effect, such as the relation between the disposition effect and taxes, or the relation between the disposition effect and investor sophistication.

In this paper, I present a theory of investor selling behavior in which the disposition effect arises because investors are slow to update their beliefs about the values of the assets they hold. I show numerically that the theory generates a disposition effect, propensity to sell functions, and other trading statistics that are in line with empirical estimates, as well as a weakened or reversed disposition effect at the end of the tax year,

[1]To mention just a few examples, see Odean (1998), Grinblatt and Keloharju (2001), and Shapira and Venezia (2001) for evidence from equity investors in different countries; see Genesove and Mayer (2001), Frazzini (2006), and Jin and Scherbina (2011) for evidence from other asset classes and contexts; and see Weber and Camerer (1998), Frydman, Barberis, Camerer, Bossaerts, and Rangel (2014), and Fischbacher, Hoffmann, and Schudy (2017) for experimental evidence. For additional references, see the surveys by Kaustia (2010a) and Barber and Odean (2013).

[2]Kaustia (2010a) also suggested a jump in the propensity to sell function at the breakeven point as a fourth key fact. This fact has been challenged by Ben-David and Hirshleifer (2012), and the focus of the literature seems to have shifted to understanding the shape of the propensity to sell function more generally—see, for example, An (2016), Lehtinen (2016), and Peng (2017).

and a weakened disposition effect for more sophisticated investors. I thus show that the theory can simultaneously explain each of the key facts about the disposition effect, while also quantitatively matching several other features of investor selling behavior. In addition, I show how the theory can shed light on other important facts about the disposition effect, such as the disposition effect in short sales (Barber, Lee, Liu, and Odean, 2007; von Beschwitz and Massa, 2020), and the fact that the disposition effect is stronger in more volatile stocks (Kumar, 2009), stronger after shocks to volatility (Vasudevan, 2019), and weaker after stock splits (Birru, 2015).

The intuition behind the theory is illustrated in Figure 1. Suppose an investor who trades for speculative reasons purchases an asset at price P_0 because he believes the true value of the asset is $S_0 > P_0$. Assume, however, that the investor doesn't blindly stick to this initial belief, but instead updates his belief gradually over time based on the market price. Then the time at which the investor sells the asset will depend on the market price. In particular, if the market price of the asset increases (solid blue line),

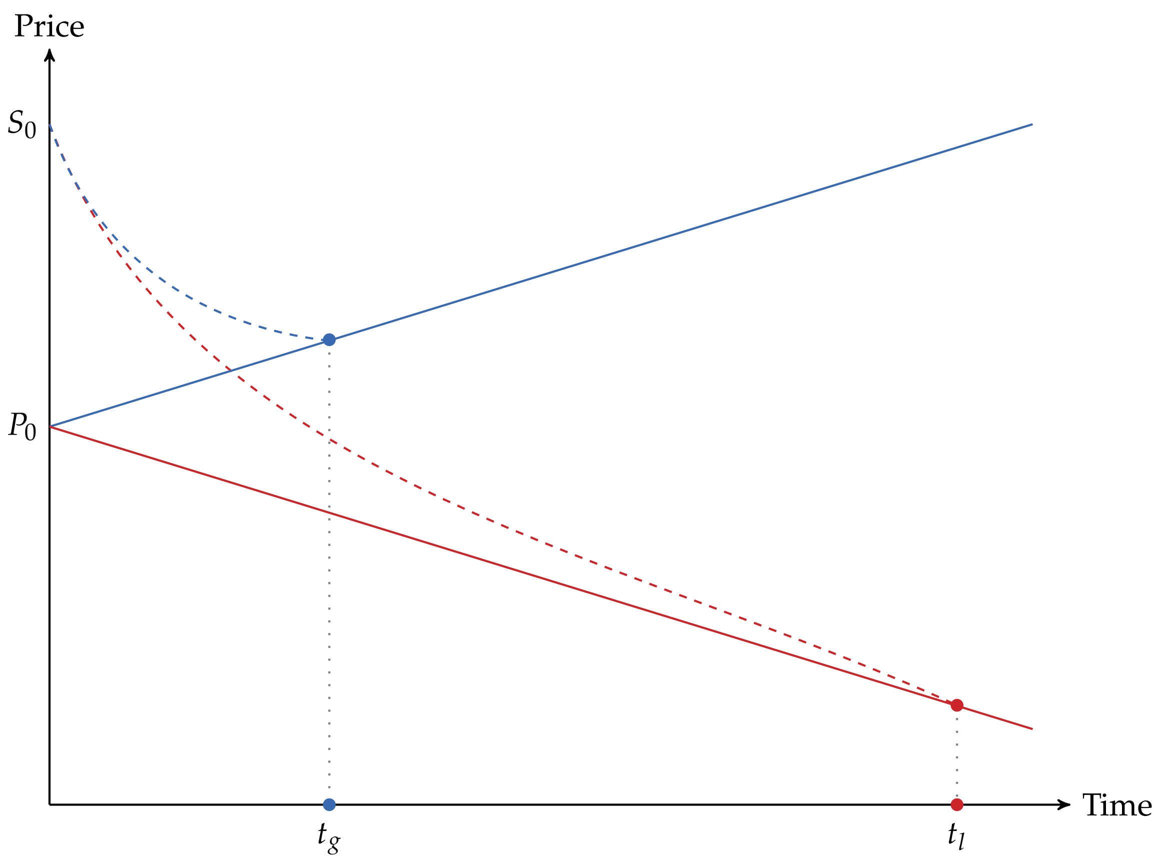

Figure 1: Graphical Intuition

then the investor's belief about the asset's value (dashed blue line) will converge to the market price at time t_g, at which point the investor no longer believes the asset is undervalued, and closes the position. By contrast, if the market price of the asset decreases (solid red line), then the investor's belief about the asset's value (dashed red line) will converge to the market price much more slowly, at time t_l. The investor thus holds losers for much longer than he holds winners, and therefore exhibits a disposition effect.

Closing speculative trades is, of course, not the only reason why investors sell assets. Of other possible reasons, tax-related selling is particularly relevant for the disposition effect. For example, Bazley, Moore, and Vosse (2021) show that reminding traders about the tax consequences of selling an asset causally reduces the disposition effect in an experimental setting, while Birru, Chague, De-Losso, and Giovannetti (2021) utilize a capital gains tax exemption in the Brazilian stock market to show that investors who are inattentive to taxes exhibit a stronger disposition effect. Taxes have also been linked to the weakened or reversed disposition effect in the last month of the tax year, which occurs in taxable trading accounts but not in tax-free accounts (Barber and Odean, 2004; Firth, 2015), and which is related specifically to the tax year and not the calendar year (Brown, Chappel, da Silva Rosa, and Walter, 2006). To account for these facts, I thus incorporate tax-related selling into the theory.

The intuition behind the effect of taxes is illustrated in Figure 2. In particular, taxes affect investor behavior differently in the gain and loss domains. Because realized losses can be offset against realized gains to lower an investor's overall tax burden, in the loss domain the investor will sell the asset when his belief converges to a threshold (dotted red line) that reflects the combined value of the asset and this tax benefit, at time $t_{l'} < t_l$. By contrast, because realized gains incur a tax cost, in the gain domain the investor will wait to sell the asset until his belief converges to a threshold (dotted blue line) that reflects the combined value of the asset and this tax cost, at time $t_{g'} > t_g$. In other words, taxes make the investor hold winners for longer while selling losers more quickly, thus reducing the magnitude of his disposition effect.

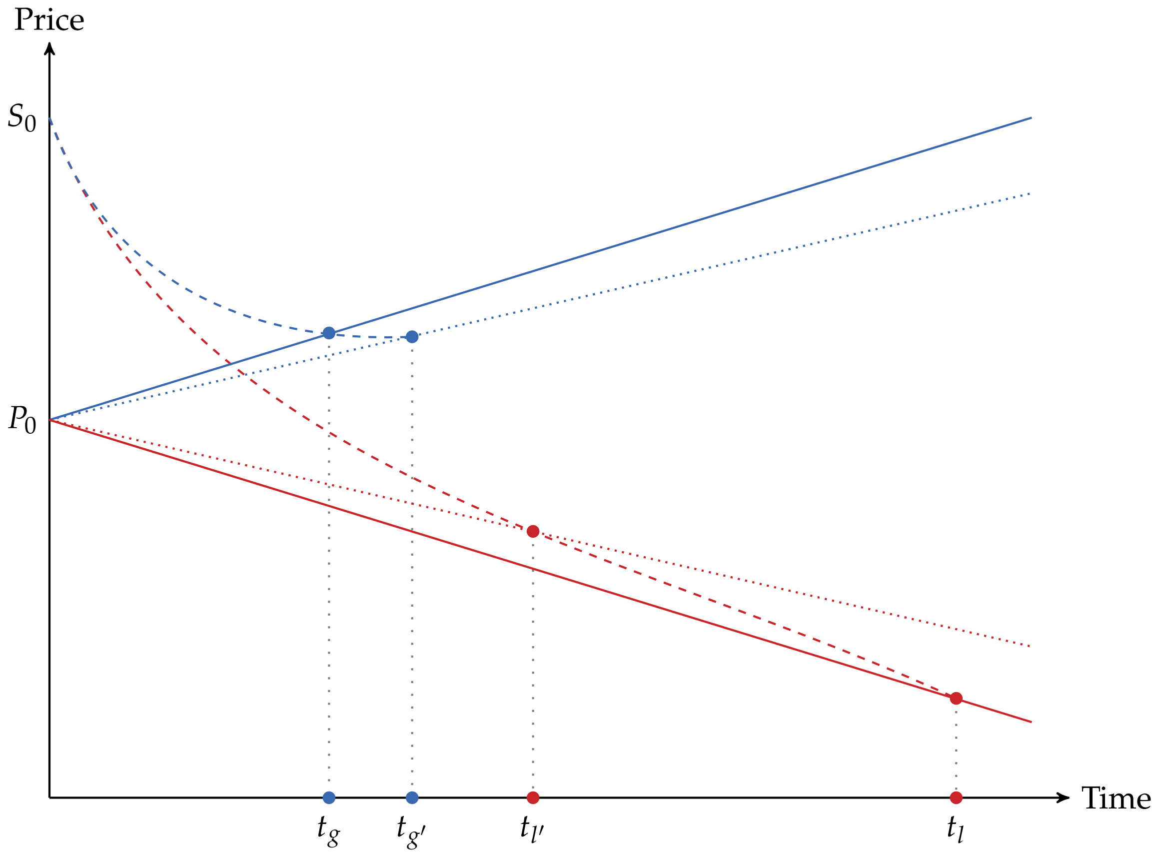

Figure 2: Graphical Intuition with Taxes

I formalize this intuition in a simple and stylized model, where a risk-neutral investor who updates his beliefs slowly is endowed with an asset, and must decide when to sell it. To make his decision, the investor balances two potentially conflicting trading motives. On one hand, he trades for speculative reasons, and wants to hold assets for as long as he believes them to be undervalued. On the other hand, he trades for tax-related reasons, and wants to sell assets in such a way that his overall tax burden is minimized. I extract the trading rule suggested by the investor's problem, and use simulations to study its implications for the disposition effect, and for other dimensions of investor selling behavior.

The main result of the simulations is that the investor exhibits a disposition effect that is comparable in magnitude to the disposition effects reported in earlier empirical studies. In the baseline simulation specification, the model generates an Odean (1998) Proportion of Gains Realized/Proportion of Losses Realized (PGR/PLR) measure of the disposition effect equal to 2.11, which is very close to the value of 2.06 reported by Dhar and Zhu (2006).[3] In the same specification, the model also generates other trading statistics that are consistent with empirical estimates, such as the percentage of trades sold at a gain, the average holding period return conditional on selling at a gain or loss, and the average holding period length, as well as a propensity to sell function that is consistent with the empirical estimates from Seru, Shumway, and Stoffman (2010) and Lehtinen (2016). The results are also robust to different simulation specifications. Despite the simplicity of the modeling approach, the model is thus able to match all of these dimensions of investor selling behavior not just qualitatively, but also quantitatively.

Related Literature. The theory of investor selling behavior I present assumes that investors buy assets for speculative reasons, and that they slowly update their beliefs during the holding period. The theory is thus very much in the spirit of the Barber and Odean (2013) view that "buying is forward-looking and selling backward-looking," and that investors "buy stocks because of what they hope will happen and sell stocks because of what has already happened." The theory is also in line with the recent working paper by Andersen, Hanspal, Martínez-Correa, and Nielsen (2021), in which the authors use experiments and administrative data from Denmark to show that more optimistic beliefs are associated with a higher incidence of the disposition effect. They thus provide empirical support for the link between investors' speculative trading motives and the disposition effect.[4]

More broadly, this paper belongs to the literature on theories of investor selling behavior and the disposition effect. The first explanation for the disposition effect was the combination of prospect theory, mental accounting, regret aversion, and limited self-control proposed by Shefrin and Statman (1985), while other early explanations for the effect included transaction cost minimization, portfolio rebalancing, a general belief in mean-reverting returns, and trading based on private information (Kaustia,

[3]The Ben-David and Hirshleifer (2012) Probability of Selling Winners/Probability of Selling Losers (PSW/PSL) measure of the disposition effect is equal to 2.82, which is within the range of 1.61–3.73 reported by earlier papers.

[4]Speculative trading motives have also been linked to the disposition effect by Ben-David and Hirshleifer (2012).

2010a). These other explanations were subsequently rejected by Odean (1998), Dhar and Zhu (2006), and other papers in the first wave of large-scale empirical studies of the disposition effect, while explanations related to prospect theory have been challenged both theoretically and empirically by Barberis and Xiong (2009), Kaustia (2010b), Hens and Vlcek (2011), and Ebert and Strack (2015, 2018).

The failure of these early explanations has led to the development of several formal theories of the disposition effect. These have been based on realization preferences (Barberis and Xiong, 2012; Henderson, 2012; Ingersoll and Jin, 2013), cognitive dissonance (Chang, Solomon, and Westerfield, 2016), and the belief in the law of small numbers (Peng, 2017). There has also been a revival of interest in theories based on prospect theory (Li and Yang, 2013; Henderson, Hobson, and Tse, 2018; Meng and Weng, 2018), while some authors have even proposed rational theories of the disposition effect (Dorn and Strobl, 2009; Dai, Jiang, Liu, and Xu, in press).

As mentioned earlier, these theories have found it difficult to generate disposition effects that are of comparable magnitude to the disposition effects reported in empirical studies. Moreover, very few of the theories report results for trading statistics other than the disposition effect, thus making it difficult to evaluate the implications that the theories have for other dimensions of investor selling behavior. The theories have also had very little to say about the numerous other facts about the disposition effect that have been documented in the empirical literature. The main contribution of this paper is thus to present a theory of investor selling behavior that not only generates a disposition effect, but also quantitatively matches other important dimensions of investor selling behavior, while also shedding light on numerous other facts about the disposition effect, such as the reversed disposition effect at the end of the tax year, the weakened disposition effect for more sophisticated investors, the disposition effect in short sales, the stronger disposition effect in more volatile stocks and after shocks to volatility, and the weaker disposition effect after stock splits.

Finally, this paper is also related to the literature on slow belief updating. The notion that people are often slow to update their beliefs when presented with new information has a long history in psychology—see, for example, the early surveys by Edwards (1968) and Slovic and Lichtenstein (1971)—but in finance this idea has not received much attention.[5] One notable recent exception is Bouchaud, Krüger, Landier, and Thesmar (2019), who use a model of slow belief updating to explain the profitability anomaly. More broadly, economists have studied slow belief updating in the context of inflation expectations (Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2015) and, more recently, in general studies of belief formation (Kučinskas and Peters, 2019; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2020).

The rest of the paper is structured as follows. Section 2 presents the theory. Section 3 presents the simulation setting and establishes some empirical and theoretical benchmarks that the simulation results can be compared to. Section 4 presents the main simulation results, structured around the key facts about the disposition effect identified by Kaustia (2010a) and Ben-David and Hirshleifer (2012). Section 5 presents additional results and applications of the theory. Section 6 concludes.

2 Theory

In this section, I introduce the form of slow belief updating that I adopt in this paper, and briefly review its psychological foundations. I then set up and discuss a simple trading problem where a risk-neutral investor who trades for speculative and tax-related reasons is endowed with an asset, and must decide when to sell it.

2.1 Slow Belief Updating

The fact that people are often slow to update their beliefs is well-established in the psychology literature (Edwards, 1968). In a typical example of an experiment used to demonstrate this fact, participants are given the prior probabilities of two possible states of the world, and a sequence of informative signals, before being asked to evaluate the posterior probabilities of the states. For example, a participant could be presented with

[5] See, however, Slovic (1972) for an early discussion of slow belief updating in the context of making investment decisions, and Barberis (2018, pp. 119–121) for a brief survey.

two urns containing red and blue balls in different proportions, and a sequence of balls drawn randomly from one of the urns, before having to determine the probability that the balls were drawn from the first urn. As summarized in the survey and meta-analysis by Benjamin (2019), the general finding in these experiments is that people update their beliefs too slowly, where slowness is defined relative to the normative benchmark of Bayesian updating.

It is worth emphasizing that this form of slow belief updating is different from a form of slow updating that is sometimes assumed in finance and economics, and that arises because of agents' limited attention, or because of other frictions in information acquisition. For example, Mankiw and Reis (2002) present a model where only some firms receive new information about the state of the economy, while the rest of the firms continue to set prices based on stale information from earlier periods. As a result, even if each firm updates their prices rationally, the aggregate price level will be updated slowly because of this informational friction. Similarly, Ben-David and Hirshleifer (2012) argue that if investors are inattentive, then they may only update their beliefs after extreme positive or negative returns grab their attention. Because extreme returns are rare, it follows that investors' beliefs will be updated slowly because of this inattention. In contrast with these examples, the evidence from the psychology literature shows that people can update their beliefs slowly even when they are fully attentive and fully informed.

Why would a fully attentive and fully informed person update their beliefs slowly? According to Benjamin (2019), the three main theories that have been proposed as explanations are the biased sampling-distribution beliefs theory, the conservatism bias theory, and the extreme-belief aversion theory. Stated informally, the biased sampling-distribution beliefs theory posits that people update their beliefs according to Bayes' Theorem, but they make systematic errors when evaluating the information contained in the signals they observe. By contrast, the conservatism bias theory maintains that people correctly identify the information contained in the signals, but they systematically underweight that information when updating their beliefs. Finally, the extreme-belief aversion theory states that people are simply averse to holding extreme beliefs, and thus update their beliefs more conservatively than what Bayes' Theorem would predict.

No consensus exists regarding which of the three theories is the best explanation (Benjamin, 2019). As a result, I choose to remain agnostic on the question of why investors update their beliefs slowly, and opt not to give precedence to any particular theory. Instead, inspired by Coibion and Gorodnichenko (2015) and Bouchaud, Krüger, Landier, and Thesmar (2019), I adopt a simple form of belief updating where an investor's belief in the current period is a weighted average of his belief in the previous period and the market price in the current period. While simple, this approach is flexible enough to allow for considerable heterogeneity in the speeds at which investors update their beliefs, and general enough to arguably be a reasonable reduced-form representation of many possible theories of slow belief updating.[6]

Formally, given an initial belief about the true value of an asset S_0, at each $t = 1, 2, \ldots$ the investor updates his belief according to

$$S_t = \lambda S_{t-1} + (1 - \lambda) P_t, \tag{1}$$

where $0 < \lambda < 1$. In other words, at each $t = 1, 2, \ldots$ the investor first observes the new market price P_t, and then updates his belief about the true value of the asset, where his new belief S_t is a weighted average of his previous belief S_{t-1} and the market price, with weight λ determining how stubbornly the investor sticks to his previous belief, and weight $1 - \lambda$ determining how much he defers to the market price. The parameter λ thus determines how quickly the investor's belief converges to the market price.

2.2 The Investor's Problem without Taxes

If the investor only trades for speculative reasons, then the trading problem he faces is particularly simple. At $t = 0$ he has purchased an asset with initial price P_0 because

[6] A potential microfoundation for this approach is provided by Epstein (2006), who presents an axiomatic model of non-Bayesian updating that nests a similar form of slow belief updating as a special case.

he believes the true value of the asset is $S_0 > P_0$. At each $t = 1, 2, \ldots$ he must decide whether or not to sell the asset, and because he only trades for speculative reasons the only factor he considers when making his decision is whether or not he believes the asset is under- or overvalued. He thus holds the asset for as long as $S_t > P_t$, sells the asset as soon as $S_t < P_t$, and is indifferent between holding and selling when $S_t = P_t$.

Two comments are in order. First, in line with the Barber and Odean (2013) view that buying and selling are largely distinct phenomena governed by different processes, I do not model the investor's initial buying decision, and I do not take a stand on why the investor believes the asset is initially undervalued. In this respect, my approach is very general and allows for many possible reasons, such as the investor being overconfident about his ability to analyze and identify undervalued assets (Moore and Healy, 2008), the investor extrapolating the asset's future performance from its past performance (Barberis, Greenwood, Jin, and Shleifer, 2015), or the investor unwittingly reacting to stale news about the asset (Tetlock, 2011). The only implicit restriction I impose on the buying decision is that it must be consistent with the form of belief updating in Equation 1.

Second, in line with the Barber and Odean (2013) view that selling is backward-looking, I model the investor's selling decision as backward-looking in the sense that the investor does not forecast how his belief may evolve in the future. Instead, at any given time his decision only depends on the current market price and his current belief, which—by iterating Equation 1—can be written in terms of his initial belief and the full price history of the asset during the holding period:

$$S_t = \lambda^t S_0 + (1 - \lambda) \sum_{j=0}^{t-1} \lambda^j P_{t-j}. \tag{2}$$

More broadly, the investor does not form any plans about how he will trade in future periods, but instead makes his selling decision by myopically comparing his current belief with the current price. While this assumption may be a simplification of real investor behavior, it has the benefit of avoiding the dynamic inconsistency between planned and actual behavior documented in the context of the disposition effect by Barberis (2012), Fischbacher, Hoffmann, and Schudy (2017), and Heimer, Iliewa, Imas, and Weber (2021). Concretely, what these papers show is that investors do not start out with the intention of exhibiting the disposition effect. Instead, their initial plan—either explicitly stated or inferred from their actions—is to continue holding their winning positions while quickly selling their losing positions. However, when it comes time to act on their initial plan, investors do the exact opposite, and sell their winning positions while holding on to their losing positions. The investor in the model thus more closely reflects the actual behavior of investors, rather than their planned behavior.

2.3 The Investor's Problem with Taxes

In keeping with the simplicity of the modeling approach adopted above, I incorporate taxes into the investor's problem by modeling the investor's selling decision as a straightforward trade-off between two trading motives. On one hand, the investor trades for speculative reasons, and wants to hold assets for as long as he believes them to be undervalued. On the other hand, the investor trades for tax-related reasons, and wants to sell assets in such a way that his overall tax burden is minimized. Because these trading motives can be in conflict, the investor must balance them based on their relative importance to him.[7]

Concretely, at time t the investor's belief about the under- or overvaluation of the asset that he has purchased is $S_t - P_t$, while the tax cost or credit that could be realized by selling the asset is $\tau(P_0 - P_t)$, where τ is the capital gains tax rate. The investor balances these quantities by the weights $1 - \phi$ and ϕ, which capture the importance the investor places on the speculative trading motive and the tax-related trading motive, respectively. In deciding whether or not to sell the asset, the investor compares the weighted under- or overvaluation to the weighted tax cost or credit. He thus holds the

[7]See Barberis, Greenwood, Jin, and Shleifer (2018) for an example of a model where the investor's problem involves this kind of balance between two potentially conflicting signals.

asset for as long as

$$(1-\phi)(S_t - P_t) > \phi\tau(P_0 - P_t), \tag{3}$$

and sells the asset as soon as

$$(1-\phi)(S_t - P_t) < \phi\tau(P_0 - P_t). \tag{4}$$

Three more comments are in order. First, the assumption that the tax consequences of selling an asset are fully described by the tax cost or credit $\tau(P_0 - P_t)$ is, of course, a simplification of real capital gains tax systems, where short- and long-term sales may be taxed at different rates, and where realized losses are valuable only if an investor has realized gains that they can be offset against. Nevertheless, it is a useful simplifying assumption that is often made in the optimal tax trading literature (e.g., Constantinides, 1983, 1984; Dammon and Spatt, 1996).

Second, it is informative to consider how the investor trades at the extreme values of ϕ. If $\phi = 0$, the investor only sells for speculative reasons, and the investor's problem simplifies to the case without taxes outlined previously. By contrast, if $\phi = 1$ the investor only sells for tax-related reasons. In this case, he holds the asset for as long as $P_t > P_0$, and sells the asset as soon as $P_t < P_0$. In other words, he holds winners indefinitely while selling losers immediately, as in Constantinides (1983). Despite the simplicity of the modeling approach, the model thus nests this seminal result from the optimal tax trading literature as a special case.

Third, the parameter ϕ can be interpreted in multiple ways. On one hand, a high ϕ could reflect fixed investor characteristics related to wealth, culture, investment experience, tax status, or other factors that determine the extent to which an investor considers the tax consequences of their actions when making their trading decisions. On the other hand, a low ϕ could reflect fixed investor characteristics related to gambling preferences, sensation seeking, overconfidence, or other factors that have been associated with speculative trading behavior. In addition to these fixed characteristics, a high or low ϕ could also reflect seasonal or news-driven variation in the salience of capital gains taxes, with investors paying more attention to taxes around important tax deadlines, and before the end of the tax year (Hoopes, Reck, and Slemrod, 2015). The parameter ϕ can thus be thought of as a simplified way of aggregating all the factors that determine how an investor balances the speculative and tax-related trading motives at a given moment in time, without imposing any specific structure on the relative contributions of the underlying drivers.

3 Simulation Setting and Benchmark Results

In this section, I first describe the simulation procedure and the disposition effect measures used in this paper. I then present empirical and theoretical estimates of the disposition effect and other trading statistics collected from the prior literature, in order to establish empirical and theoretical benchmarks to which the simulation results can be compared.

3.1 Simulation Setting

I illustrate the outcomes of the trading problem outlined in the previous section using the following simulation setting. At $t = 0$, an investor is endowed with an asset following a geometric Brownian motion with initial price $P_0 = 100$, as well as an initial belief about the true value of the asset S_0. For consistency with the simulations of Barberis and Xiong (2009) and the model calibration of Ingersoll and Jin (2013), I assume the asset has an annual $\mu = 0.09$ and $\sigma = 0.30$. We can thus think of the asset as being comparable to an individual stock.

The time increment in the simulations is one day. On each day, the investor first updates his belief according to Equation 1, and then decides whether or not to sell the asset based on the decision rule in Equations 3 and 4. I assume there are 252 trading days per year, and I impose a maximum investment horizon of ten years, after which any remaining positions are automatically sold.[8] For each model specification in each

[8]In most specifications—including the baseline specification—this limit is inconsequential, as all

analysis, the results are based on 100 000 independent iterations of the same simulation procedure.

In the baseline simulation specification I set $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, and $\tau = 0.25$. The choice of λ is informed by Coibion and Gorodnichenko (2015), who estimate a quarterly $\lambda = 0.54$ from inflation forecasts, and by Bouchaud, Krüger, Landier, and Thesmar (2019), who estimate an annual $\lambda = 0.14$ from corporate earnings forecasts. At the daily level, both of these estimates imply $\lambda = 0.54^{\frac{1}{63}} \approx 0.99$ and $\lambda = 0.14^{\frac{1}{252}} \approx 0.99$.

For the choice of the initial belief S_0 I refer to the literature on equity analysts' target price forecasts. By comparing analysts' target prices—the typical horizon of which is 12 months ahead—to the current stock price, Brav and Lehavy (2003) find that the expected return implied by the target price for stocks with a *buy* or *strong buy* recommendation is 36%, while Asquith, Mikhail, and Au (2005) find a corresponding value of 34%. More recent papers have found similar values: 40% in Da and Schaumburg (2011), and 37% in Engelberg, McLean, and Pontiff (2020). For an initial price $P_0 = 100$, these values imply an S_0 between 134 and 140.

Finally, I set $\phi = 0.50$ to establish the case where the investor places equal weight on the speculative trading motive and the tax trading motive as the baseline to which other specifications can be compared, while $\tau = 0.25$ is close to the maximum U.S. long-term capital gains tax rate of 23.8%.

3.2 Disposition Effect Measures

Several ways of measuring the disposition effect have been proposed in the prior literature, each with their own advantages and disadvantages. Following the standard approach adopted in earlier theories of the disposition effect, throughout this paper I use the Odean (1998) Proportion of Gains Realized/Proportion of Losses Realized ratio as my primary measure of the disposition effect.

trades are closed voluntarily before the limit. In some specifications with very high values of ϕ a capital gains lock-in effect can occur, with some unrealized gains being held until the limit. However, for more moderate values such as $\phi = 0.67$ this occurs for less than 2.5% of all trades.

I calculate the measure as follows. On each day that a stock is sold, each stock sold is categorized as a realized gain or a realized loss, and each stock not sold is categorized as a paper gain or a paper loss.[9] Once each stock has been appropriately categorized, the Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR) are calculated as

$$\text{Proportion of Gains Realized} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}} \tag{5}$$

and

$$\text{Proportion of Losses Realized} = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}}. \tag{6}$$

Both PGR and PLR thus compare the number of gains or losses realized by an investor to the number of gains or losses that could have been realized by the investor. The measure of the disposition effect is then given by the ratio PGR/PLR, which has a simple interpretation: a PGR/PLR ratio greater than one is evidence of a disposition effect, a PGR/PLR ratio less than one is evidence of a reversed disposition effect, and a PGR/PLR ratio equal to one is evidence of there being neither a disposition effect, nor a reversed disposition effect.

The main disadvantage of this measure is that it depends on the number of stocks an investor holds in their portfolio.[10] I thus need to make an assumption about how to allocate the simulated trades into different portfolios. One option would be to include all 100 000 trades in a single portfolio, but this would not be a very accurate representation of real-world portfolios. Instead, to make my results more directly comparable with the earlier literature, I again follow Barberis and Xiong (2009) and Ingersoll and Jin (2013) and allocate the trades into 25 000 portfolios of exactly four trades each, with the portfolio size of four being based on the empirical estimates of average portfolio size from Barber and Odean (2000) and Dhar and Zhu (2006).

[9] Following most of the disposition effect literature, I assume that the reference point used to evaluate the gain or loss status of a position is the initial purchase price P_0. However, see Meng and Weng (2018) and Quispe-Torreblanca, Gathergood, Loewenstein, and Stewart (2022) for recent papers that consider the potential role of dynamic reference points and multiple reference points in the context of the disposition effect.

[10] See Appendix D of Feng and Seasholes (2005) for an extensive discussion.

For robustness checks, and in some additional analyses where it is informative to do so, as a secondary measure of the disposition effect I also make use of the Ben-David and Hirshleifer (2012) Probability of Selling Winners/Probability of Selling Losers (PSW/PSL) ratio. This measure is simply the probability of selling a stock conditional on it trading at a gain divided by the probability of selling a stock conditional on it trading at a loss.

3.3 Empirical and Theoretical Benchmarks

To establish empirical benchmarks to which the simulation results can be compared, in Panel A of Table 1 I present empirical estimates of the disposition effect and other trading statistics, collected from Table 1, Table 3, and Footnote 11 of Odean (1998); Tables 1 and 3 of Dhar and Zhu (2006); Table 1 of Brown, Chappel, da Silva Rosa, and Walter (2006); Tables 4 and 5 of Boolell-Gunesh, Broihanne, and Merli (2009); Table 1 of Ben-David and Hirshleifer (2012); and Table 1 of An, Engelberg, Henriksson, Wang, and Williams (2022). In addition to the PGR/PLR and the PSW/PSL measures of the disposition effect, the other trading statistics I collect are the percentage of trades sold at a gain, the average holding period return conditional on selling at a gain, the average holding period return conditional on selling at a loss, the average holding period length in days, the daily unconditional probability of selling, the probability of selling conditional on trading at a gain, and the probability of selling conditional on trading at a loss.

In Panel B of Table 1 I perform a similar exercise by presenting theoretical estimates of the disposition effect and other trading statistics from Table 2 of Barberis and Xiong (2009); Section 5 of Barberis and Xiong (2012); Section 3 of Henderson (2012); Table 4 of Li and Yang (2013); Tables 1 and 2 of Ingersoll and Jin (2013); Figure 4 of Henderson, Hobson, and Tse (2018); and Tables 5 and 12 of Dai, Jiang, Liu, and Xu (in press). In cases where a paper reports different estimates for different parameter combinations, I prioritize the specifications that seem to be most representative of the overall results, and the specifications in which the model parameters are chosen based on specific empirical and experimental estimates, such as the prospect theory parameters from Tversky and Kahneman (1992). I also afford particular attention to the model calibration of Ingersoll and Jin (2013), because it is one of the few papers where the authors report other trading statistics in addition to the disposition effect measure.

When comparing the disposition effects generated by the theories to the empirical estimates in Panel A, we see that the existing theories of the disposition effect have found it difficult to generate disposition effects comparable in magnitude to the empirical estimates. While the empirical estimates lie within a fairly narrow range from 1.51 to 2.06, the theoretical estimates range from a reversed disposition effect of 0.75 in the prospect theory model of Barberis and Xiong (2009), to an infinitely strong disposition effect in the realization utility models of Barberis and Xiong (2012) and Ingersoll and Jin (2013). One exception is the recent model by Dai, Jiang, Liu, and Xu (in press), which combines investor learning and portfolio rebalancing with transaction costs, and which is able to generate a reasonable disposition effect for some parameter values. However, the average holding period implied by the same parameter values is considerably larger than the holding periods documented in empirical studies, so it remains unclear whether the chosen parameter values can simultaneously match the other dimensions of investor selling behavior. The other exception is the prospect theory model by Henderson, Hobson, and Tse (2018), which can exactly match the empirical estimates of the disposition effect if the parameter values are chosen appropriately. Unfortunately, the paper does not report any of the other trading statistics, so it again remains unclear whether the parameter values generate reasonable estimates for the other dimensions of investor selling behavior.

4 Simulation Results

In this section, I present the main results from the simulations. I structure the discussion around the four key facts about the disposition effect highlighted by Kaustia (2010a) and Ben-David and Hirshleifer (2012): the existence of the disposition effect, its relation to taxes, its relation to investor sophistication, and the shape of the propensity to sell function.

4.1 The Disposition Effect

Panel A of Table 2 reports the disposition effect estimates and other trading statistics from the baseline simulation specification, with the model parameters set to $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, and $\tau = 0.25$. From the last two columns of the table, we can see that the PSW/PSL measure of the disposition effect is equal to 2.82, which is within the range of the empirical estimates presented in Table 1, and the PGR/PLR measure of the disposition effect is equal to 2.11, which is very close to the value of 2.06 estimated by Dhar and Zhu (2006). The model in its baseline specification thus generates a disposition effect that is comparable in magnitude to the disposition effects estimated in empirical studies.

The other trading statistics for the baseline simulation specification are presented in the remaining columns. From left to right, the percentage of trades sold at a gain is 63.3%, the average holding period returns conditional on selling at a gain or loss are 19.7% and -18.5%, the average holding period length is 171 trading days, the daily unconditional probability of selling is 0.58%, and the daily probabilities of selling conditional on trading at a gain or loss are 0.98% and 0.35%. All of these values again fall within the ranges of the empirical estimates presented in Table 1. Despite the simplicity of the modeling approach, and despite making no effort to optimize for the best-fit parameter values, the model in its baseline specification is thus simultaneously able to generate a disposition effect, and other trading statistics, that are all in line with the corresponding empirical estimates.

Panel B of Table 2 reports the same estimates from alternative simulation specifications where the value of one parameter is varied while keeping the other parameters at their baseline values. Consistent with the results from the baseline specification, the model in these alternative specifications is again simultaneously able to generate a disposition effect, and other trading statistics, that are all comparable to the corresponding empirical estimates.

To examine how the disposition effect generated by the model is related to each of the model parameters, in Tables 3 and 4 I report the PGR/PLR and PSW/PSL measures of the disposition effect for different values of the model parameters. While there is more dispersion in the disposition effect estimates when using the PSW/PSL measure, the qualitative conclusions are identical for both measures: the model predicts that the magnitude of the disposition effect is increasing in the belief updating parameter λ and the asset parameters μ and σ, but decreasing in the initial belief S_0, the tax importance parameter ϕ, and the capital gains tax rate τ.

The positive relation between λ and the disposition effect implies that investors who stick to their previous beliefs more stubbornly exhibit a stronger disposition effect than investors who defer more to the market price. The intuition behind this relation is perhaps best illustrated by considering what would happen if λ were equal to zero. With $\lambda = 0$, the investor would defer fully to the market price at $t = 1$, and thus immediately sell the asset regardless of whether the price had increased or decreased from the initial price. The investor's probability of selling the asset would thus be equal to one for both gains and losses, meaning that the investor would not exhibit a disposition effect. While this is obviously an extreme case, it highlights the basic mechanism: with a lower value of λ, the investor defers more to the market price, and his belief converges to the market price more quickly for both gains and losses, thus leading to a weaker disposition effect.

The relation between λ and the disposition effect represents a novel empirical prediction of the model. Coibion and Gorodnichenko (2015) develop a methodology for estimating λ from survey data on respondents' expectations, which involves comparing respondents' forecast errors to their earlier forecast revisions. This prediction of the model could thus be tested by surveying investors about their expectations of the future, using their responses to estimate their λ parameters, and then linking the estimated values of λ with the magnitudes of their disposition effects using data on their trading behavior, to determine whether the positive relation implied by the model is confirmed in the data.

The disposition effect is also positively related to the asset parameters μ and σ. To the best of my knowledge, the relation between μ and the disposition effect has not been studied empirically, so the positive relation implied by the model represents another novel empirical prediction. By contrast, the relation between σ and the disposition effect has been studied by Kumar (2009), who uses brokerage data from the U.S. to construct stock-level measures of the disposition effect, and to show that investors exhibit a stronger disposition effect in more volatile stocks.[11] The positive relation between σ and the disposition effect implied by the model is thus consistent with the empirical evidence.

The intuition behind the negative relation between S_0 and the disposition effect can again be illustrated by considering what happens in an extreme case. Suppose an investor had an implausibly high initial belief, such as $S_0 = 10\,000$ for an initial price $P_0 = 100$. Then the price difference between an asset trading at a gain and an asset trading at a loss would be negligible relative to the very large difference between the initial belief and the asset's overall price level. The probability of selling the asset would thus primarily depend on the time it takes for the belief to converge to the overall price level—which would be similar for both gains and losses—and not on the comparatively much smaller additional amount of time it takes for the belief to converge to a loss rather than a gain. A higher S_0 thus has the effect of minimizing the differences between gains and losses, and therefore results in a weaker disposition effect.

4.2 The Disposition Effect and Taxes

Tables 3 and 4 also show that the magnitude of the disposition effect is decreasing in both the tax importance parameter ϕ and the capital gains tax rate τ. In other words, when an investor places more emphasis on the tax consequences of his trading actions, or when a higher capital gains tax rate makes those consequences more significant,

[11] Vasudevan (2019) finds the same result using administrative data from Finland.

the investor exhibits a weaker disposition effect. Taxes thus act as a constraint that disciplines the investor's disposition behavior.[12]

These results are consistent with the empirical and experimental evidence on the relation between taxes and the disposition effect. For example, Bazley, Moore, and Vosse (2021) present causal evidence from an experimental setting showing that reminding participants about the tax consequences of selling an asset reduces the disposition effect. In the context of the model, reminding participants about taxes would be equivalent to increasing ϕ, which reduces the disposition effect. Similarly, Birru, Chague, De-Losso, and Giovannetti (2021) exploit a unique feature of the Brazilian stock market to show that investors who are inattentive to taxes exhibit a stronger disposition effect. In the context of the model, being inattentive to taxes would be equivalent to having a low ϕ, which implies a stronger disposition effect.

These results are also consistent with the popular intuition in the disposition effect literature linking the reversed disposition effect that occurs at the end of the tax year to investors' tax-related trading. For example, Barber and Odean (2004) use brokerage data from the U.S. to show that investors in taxable trading accounts exhibit a disposition effect in each month from January to November, but in December they exhibit a reversed disposition effect between 0.6 and 0.8, when measured using the PGR/PLR measure. By contrast, investors in tax-exempt trading accounts exhibit similar behavior from January to November, but do not exhibit a reversed disposition effect in December. This strongly suggests that the reversed disposition effect in taxable accounts is specifically related to investors' tax-related trading.[13]

More broadly, the simulation results show that for all specifications with $\phi \leq 0.50$, and even for some with $\phi = 0.67$, the disposition effect measure is greater than one. In other words, all investors for whom speculative trading is at least as important as

[12] See also Heimer and Imas (2022) for evidence on how leverage constraints can discipline behavioral biases, improve trading performance, and reduce the disposition effect.

[13] Additional evidence on the relation between taxes and the reversed disposition effect is presented by Grinblatt and Keloharju (2004), Brown, Chappel, da Silva Rosa, and Walter (2006), and Firth (2015), using data from Finland, Australia, and Singapore, respectively. The paper by Brown, Chappel, da Silva Rosa, and Walter (2006) is particularly important, because it exploits the fact that the tax year in Australia ends in June to show that the reversed disposition effect is specifically related to the end of the tax year, and not the calendar year.

tax-related trading, and even some investors for whom tax-related trading is more important than speculative trading, exhibit a disposition effect. By contrast, for most specifications with $\phi = 0.67$ or $\phi = 0.75$ the disposition effect measure is less than one.[14] In other words, most investors for whom tax-related trading is more important than speculative trading will exhibit a reversed disposition effect.

The fact that the model can generate a reversed disposition effect for high values of ϕ can potentially help to explain the empirical finding that not all investors exhibit a disposition effect in their regular trading. For example, Dhar and Zhu (2006) use brokerage data from the U.S. to show that 19.7% of the investors in their sample exhibit a reversed disposition effect in their regular trading, while Barber, Lee, Liu, and Odean (2007) and Boolell-Gunesh, Broihanne, and Merli (2012) find corresponding figures of 15.8% and 13.7% using data from Taiwan and France, respectively. In the context of the model, these would be investors that have a consistently high ϕ, which could reflect fixed investor characteristics related to wealth, investment experience, or other factors that determine the extent to which an investor considers the tax consequences of their actions when making their trading decisions.

4.3 The Disposition Effect and Investor Sophistication

The results on the relation between taxes and the disposition effect are also relevant for the relation between the disposition effect and investor sophistication. In particular, it seems reasonable to assume that more sophisticated investors are more likely to consider the tax consequences of their actions when making their investment decisions, while also being less likely to engage in speculative trading. In the context of the model, this would be equivalent to assuming that more sophisticated investors have higher values of ϕ than less sophisticated investors. Because of the negative relation between ϕ and the disposition effect, this implies that more sophisticated investors should exhibit

[14] For specifications with $\phi > 0.75$, the disposition effect measures approach zero. As mentioned earlier, with $\phi = 1$ the investor trades like the optimal tax trader in Constantinides (1983)—he holds winners indefinitely while selling losers immediately—and thus has an infinitely strong reversed disposition effect.

a weaker disposition effect than less sophisticated investors, which is indeed the case empirically (Dhar and Zhu, 2006). In addition, if more sophisticated investors on average have more taxable income than less sophisticated investors, then in tax regimes such as the U.S. where capital gains tax rates are progressive, the negative relation between τ and the disposition effect would also contribute to more sophisticated investors exhibiting a weaker disposition effect.

Investor sophistication is also related to the other parameters of the model. In particular, it again seems reasonable to assume that more sophisticated investors are more likely to defer to the market price as being correct, and less likely to stubbornly hold on to their previous beliefs. On average, more sophisticated investors should thus have lower values of λ than less sophisticated investors. Because of the positive relation between λ and the disposition effect, this implies that more sophisticated investors should again exhibit a weaker disposition effect than less sophisticated investors.

4.4 The Shape of the Propensity to Sell Function

The propensity to sell function describes an investor's probability of selling an asset as a function of its holding period return. A consistent finding among papers that have estimated the propensity to sell function empirically is that the function is increasing in the gain domain, with larger gains having a higher probability of being sold than smaller gains. By contrast, the research on the shape of the function in the loss domain is less conclusive. In different countries, and during different sample periods, the function can be either clearly decreasing (Ben-David and Hirshleifer, 2012; Barber and Odean, 2013); slightly decreasing (Seru, Shumway, and Stoffman, 2010; Lehtinen, 2016); roughly constant (Kaustia, 2010b; Bernard, Loos, and Weber, 2022); or roughly constant for small losses, but lower—or even increasing—for large losses (Grinblatt and Keloharju, 1998; Quispe-Torreblanca, Gathergood, Loewenstein, and Stewart, 2022). Any successful theory of investor selling behavior should thus be able to generate different shapes for the propensity to sell function in different situations.

To study the implications that the model has for the shape of the propensity to sell function, I follow Ben-David and Hirshleifer (2012) and estimate propensity to sell functions from the simulated trades using probit regressions. For model specifications with ϕ equal to 0.00, 0.25, 0.33, 0.50, 0.67, or 0.75, and with the other parameters at their baseline values, I regress a sell indicator variable on a set of dummy variables corresponding to holding period returns grouped into 1% bins from -10% to 10%, and extract the selling probabilities implied by the coefficients for each of the bins. The results are plotted in Figure 3. To allow for a direct comparison of the different model specifications, I normalize the selling probabilities in such a way that the value on the holding period return bin from -1% to 0% is equal to one. The normalized values thus tell us how many times more likely the investor is to sell at a given holding period return, compared to selling at a return between -1% and 0%.

Figure 3 shows that the model generates different shapes for the propensity to sell function depending on the value of the ϕ parameter. For $\phi \leq 0.50$, the propensity to sell is increasing in the gain domain, and either constant or slightly decreasing in the loss domain, consistent with Kaustia (2010b) and Seru, Shumway, and Stoffman (2010). By contrast, for $\phi = 0.67$ the propensity to sell is decreasing in the loss domain and slightly increasing in the gain domain, which is more in line with Ben-David and Hirshleifer (2012), while for $\phi = 0.75$ the propensity to sell is decreasing in both the gain and loss domains, thus reflecting a reversed disposition effect.

Each of the propensity to sell functions presented in Figure 3 are based on simulations where the parameters values are fixed at their given levels. They can thus each be thought of as representing the individual-level propensity to sell function of an investor with fixed parameter values, who trades the same asset 100 000 times. In empirical studies, however, the propensity to sell functions are estimated at the aggregate level, by combining the trades of a large number of investors who vary based on their personal characteristics and asset holdings. This has led Peng (2017) to argue that the aggregate propensity to sell functions estimated in empirical studies may not accurately reflect the propensity to sell function of any particular investor, but may instead be the result of different types of investors combining to form the aggregate shape of the propensity to sell function that we observe.

To study the effect that investor heterogeneity has on the aggregate-level propensity to sell function, in Figure 4 I present propensity to sell functions from four simulation specifications where ϕ is randomly distributed. Specifically, for each of the 100 000 simulated trades for each specification, I randomly draw a value of ϕ from a beta distribution with shape parameters α and β, and expectation $\mathrm{E}[\phi] = \alpha/(\alpha + \beta)$. Each of the simulations can thus be thought of as representing an economy where 100 000 investors with different values of ϕ each trade the same asset once. The results thus allow us to see how investors that are heterogeneous in ϕ contribute to the shape of the aggregate-level propensity to sell function.

The top-left and top-right panels of Figure 4 show that when $\mathrm{E}[\phi] = 0.33$ or $\mathrm{E}[\phi] = 0.50$ the aggregate propensity to sell is increasing in the gain domain and either constant or slightly decreasing in the loss domain. By contrast, the bottom-left and bottom-right panels show that when $\mathrm{E}[\phi] = 0.60$ or $\mathrm{E}[\phi] = 0.67$ the aggregate propensity to sell is still increasing in the gain domain, but now more clearly decreasing in the loss domain. The model is thus able generate aggregate-level propensity to sell functions consistent with Ben-David and Hirshleifer (2012) and Barber and Odean (2013) for higher values of $\mathrm{E}[\phi]$, while for lower values of $\mathrm{E}[\phi]$ the functions are consistent with Seru, Shumway, and Stoffman (2010), Kaustia (2010b), Lehtinen (2016), and Bernard, Loos, and Weber (2022). This relation between ϕ and the shape of the propensity to sell function represents another novel empirical prediction of the model.

4.5 Summary

In summary, the simulation results presented in this section show that the theory of investor selling behavior I present can (1) generate a disposition effect that is comparable in magnitude to the disposition effects estimated in prior empirical studies, while simultaneously generating other trading statistics that match the empirical estimates; (2) generate a reversed disposition effect when taxes are particularly salient, or otherwise important to investors, such as in the last month of the tax year; (3) provide an explanation for why more sophisticated investors exhibit a weaker disposition effect than less sophisticated investors; and (4) generate both individual- and aggregate-level propensity to sell functions that are consistent with the propensity to sell functions estimated in prior empirical studies. The theory can thus address each of the key facts about the disposition effect highlighted by Kaustia (2010a) and Ben-David and Hirshleifer (2012).

5 Additional Results and Applications

In this section, I present additional results from the simulations, and discuss how the theory can be applied to other important features of the disposition effect.

5.1 The Disposition Effect and Volatility Shocks

Vasudevan (2019) uses administrative data from Finland to show that an unexpected increase in volatility during the holding period of a stock increases the magnitude of the disposition effect.[15] The author attributes this result to loss-averse investors revising their beliefs about the riskiness of the stock, and thus being more likely to sell the stock at a gain because its increased volatility increases the probability that the stock ends up in the loss domain.

To see whether my theory can generate this same result, I modify the baseline simulation setting by adding a shock to the asset's volatility parameter σ equal to 10%, 30%, or 50% of its baseline value. I assume that the shock occurs on day $t = 21$, and that the increase in volatility persists until the end of the simulation. I then calculate the probability of selling the asset conditional on the asset trading at a gain, the probability of selling the asset conditional on the asset trading at a loss, and the PSW/PSL measure of the disposition effect, which is just the ratio of the two conditional probabilities.

Consistent with the empirical results of Vasudevan (2019), Table 5 shows that an increase in volatility during the holding period increases the magnitude of the

[15]Vasudevan (2019) shows that this effect is distinct from the general relation between volatility and the disposition effect documented by Kumar (2009).

disposition effect, with a larger shock leading to a larger increase. The table also shows that the increase in the disposition effect is driven by the increased probability of selling assets trading at a gain, while the effect on selling assets trading at a loss is more muted. For example, a 30% shock to volatility—that is, an increase from $\sigma = 0.30$ to $\sigma = 0.39$—increases the probability of selling at a gain from 0.98% to 1.21%, while the probability of selling at a loss increases only marginally from 0.35% to 0.37%. This is in line with Vasudevan (2019), who shows that the effect of unexpected volatility changes on the propensity to sell assets trading at a gain is positive and statistically significant, while the effect on the propensity to sell assets trading at a loss is close to zero and statistically insignificant. My theory thus provides an alternative explanation for this empirical pattern.

5.2 The Disposition Effect and Stock Splits

Using brokerage data from the U.S., Birru (2015) shows that the disposition effect is substantially weakened following a stock split. The author argues that this is because investors fail to correctly update their reference prices after the nominal decrease in the share price caused by a stock split, and thus incorrectly classify some of their gains as losses.[16] As a result, an investor will hold on to winning positions for longer than they would have in the absence of a stock split, which decreases their probability of selling assets trading at a gain, and thus decreases the magnitude of their disposition effect. Birru (2015) refers to this argument as the "nominal reference price hypothesis."

To see whether my theory can generate this same result, I modify the baseline simulation setting by adding a stock split with ratio 1.33-for-1, 1.50-for-1, 2.00-for-1, or 2.50-for-1, that occurs on day $t = 21$. In line with the nominal reference price hypothesis, I assume that the investor does not update their reference price following the stock split, but instead continues to evaluate the gain or loss status of their position with respect to the initial purchase price $P_0 = 100$. As in the previous section, I then calculate the

[16]See also Frydman and Rangel (2014) for evidence on how reducing the salience of an asset's purchase price causally reduces the disposition effect in an experimental setting.

probability of selling the asset conditional on the asset trading at a gain, the probability of selling the asset conditional on the asset trading at a loss, and the PSW/PSL measure of the disposition effect.

Consistent with the empirical results of Birru (2015), Table 6 shows that stock splits significantly decrease the magnitude of the disposition effect. For example, with a split ratio of 2.00-for-1—which is close to the average split ratio of 1.90-for-1 in the Birru (2015) data set—the PSW/PSL measure of the disposition effect falls from 2.82 to 1.12. In other words, the disposition effect almost completely disappears following a stock split. Consistent with the intuition from Birru (2015), this decrease is primarily driven by a decrease in the propensity to sell assets trading at a gain, which falls from 0.98% to 0.55%.

While the intuition laid out above makes no specific prediction about the probability of selling assets trading at a loss, the increase reported in Table 6 can be explained by the fact that the tax benefit of selling an asset trading at a loss increases as the nominal price of the asset decreases. For an investor who does not update their reference price after a stock split, a larger split ratio—and thus a lower nominal price—makes harvesting tax losses seem more attractive than it actually is. This will increase the probability of selling assets trading at a loss, and thus also contribute to decreasing the magnitude of the disposition effect.

5.3 The Disposition Effect in Short Sales

In all of the analyses presented so far in this paper, I have maintained the implicit assumption that the investor's initial belief S_0 is greater than the initial price P_0, so that the investor starts by taking a long position in the asset. However, there is nothing in the theory that requires this to be the case, and it could instead be that the investor's initial belief is below the initial price, so that the investor starts by taking a short position in the asset. To the extent that short sellers also trade for speculative reasons, the same belief-updating mechanism presented in Figure 1 would also apply to short sellers, and the theory would thus predict that short sellers also exhibit a disposition effect.

The intuition behind this prediction is presented in Figure 5. Suppose a short seller takes a short position in an asset at price P_0 because he incorrectly believes the true value of the asset is $S_0 < P_0$. If the market price of the asset decreases (solid blue line) then the short seller's belief about the asset's value (dashed blue line) will converge to the market price relatively quickly, at which point he no longer believes the asset is overvalued, and closes his position. By contrast, if the market price of the asset increases (solid red line) then the short seller's belief (dashed red line) will converge to the market price much more slowly. The short seller thus holds his losing positions for much longer than he holds his winning positions, and therefore exhibits a disposition effect.

The theory is thus consistent with the empirical findings of Barber, Lee, Liu, and Odean (2007), who use data from Taiwan to study the short selling behavior of individual investors and corporations, and who show that for both investor types the probability of closing a position trading at a gain is greater than the probability of closing a position trading at a loss. The theory is also consistent with the findings of von Beschwitz and Massa (2020), who use data from the U.S. to show that short sellers' probability of closing a position is positively and significantly related to the size of the capital gain on the position. In other words, in both Taiwan and the U.S., short sellers are more likely to close their winning positions than their losing positions, and thus exhibit a disposition effect.

6 Conclusion

In this paper, I present a theory of investor selling behavior in which the disposition effect arises because investors are slow to update their beliefs about the values of the assets they hold. I show numerically that the theory generates a disposition effect, propensity to sell functions, and other trading statistics that are in line with empirical estimates. I also show that the theory generates a reversed disposition effect at the end of the tax year, a weaker effect for more sophisticated investors and after stock splits, a stronger effect in more volatile stocks and after shocks to volatility, and a disposition effect in short sales. The theory can thus address each of the key facts about the disposition effect highlighted by Kaustia (2010a) and Ben-David and Hirshleifer (2012).

The theory also makes several novel empirical predictions, such as the relation between λ and the disposition effect, the relation between μ and the disposition effect, and the relation between ϕ and the shape of the propensity to sell function. I leave the testing of these predictions open as a promising avenue for future research.

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Table 1: Empirical and Theoretical Benchmarks.

Reported are empirical estimates and theoretical values of (1) the percentage of trades sold at a gain, (2) the average holding period return conditional on selling at a gain, (3) the average holding period return conditional on selling at a loss, (4) the average holding period in trading days, (5) the daily unconditional probability of selling, (6) the daily probability of selling conditional on trading at a gain, (7) the daily probability of selling conditional on trading at a loss, (8) the Ben-David and Hirshleifer (2012) PSW/PSL measure of the disposition effect, and (9) the Odean (1998) PGR/PLR measure of the disposition effect. Panel A reproduces the available empirical estimates from Table 1, Table 3, and Footnote 11 of Odean (1998); Tables 1 and 3 of Dhar and Zhu (2006); Table 1 of Brown, Chappel, da Silva Rosa, and Walter (2006); Tables 4 and 5 of Boolell-Gunesh, Broihanne, and Merli (2009); Table 1 of Ben-David and Hirshleifer (2012); and Table 1 of An, Engelberg, Henriksson, Wang, and Williams (2022). Panel B reproduces the available theoretical values from Table 2 of Barberis and Xiong (2009); Section 5 of Barberis and Xiong (2012); Section 3 of Henderson (2012); Table 4 of Li and Yang (2013); Tables 1 and 2 of Ingersoll and Jin (2013); Figure 4 of Henderson, Hobson, and Tse (2018); and Tables 5 and 12 of Dai, Jiang, Liu, and Xu (in press).

Panel A: Empirical Benchmarks									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
O	53.8 %	27.7 %	-22.8 %	315	–	–	–	–	1.51
DZ	65.8 %	–	–	122	–	–	–	–	2.06
BCRW	70.5 %	–	–	–	–	–	–	–	1.99
BBM	60.0 %	11.2 %	-6.8 %	–	–	–	–	–	1.68
BH	–	–	–	–	0.24 %	0.29 %	0.18 %	1.61	–
AEHWW	–	–	–	72	3.62 %	7.88 %	2.11 %	3.73	–
Panel B: Theoretical Benchmarks									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BX09	–	–	–	–	–	–	–	–	0.75
BX12	–	–	–	–	–	–	–	–	∞
H	–	–	–	–	–	–	–	–	100
LY	–	–	–	–	–	–	–	–	1.07
IJ-1	100.0 %	96.2 %	N/A	3743	–	–	–	–	∞
IJ-2	95.9 %	4.0 %	-47.3 %	63	–	–	–	–	108
IJ-3	80.6 %	3.9 %	-13.5 %	15	–	–	–	–	10.2
IJ-4	96.3 %	60.4 %	-90.7 %	2037	–	–	–	–	50.2
IJ-5	85.3 %	44.6 %	-64.1 %	909	–	–	–	–	9.36
HHT	–	–	–	–	–	–	–	–	1.51
DJLX-1	–	–	–	528	–	–	–	–	1.97
DJLX-2	–	–	–	–	–	–	–	–	1.26

Table 2: Trading Statistics from Simulated Trades.

Reported are simulated values of (1) the percentage of trades sold at a gain, (2) the average holding period return conditional on selling at a gain, (3) the average holding period return conditional on selling at a loss, (4) the average holding period in trading days, (5) the daily unconditional probability of selling, (6) the daily probability of selling conditional on trading at a gain, (7) the daily probability of selling conditional on trading at a loss, (8) the Ben-David and Hirshleifer (2012) PSW/PSL measure of the disposition effect, and (9) the Odean (1998) PGR/PLR measure of the disposition effect. Panel A reports the results from the baseline simulation specification, with $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, and $\tau = 0.25$. Panel B reports the values from alternative simulation specifications that vary the value of the indicated parameter while keeping the others at their baseline values. The simulation results are from 100 000 simulated trades for each specification.

Panel A: Baseline Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Baseline	63.3 %	19.7 %	-18.5 %	171	0.58 %	0.98 %	0.35 %	2.82	2.11

Panel B: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\lambda = 0.97$	58.1 %	13.9 %	-12.9 %	79	1.26 %	1.71 %	0.93 %	1.85	1.73
$\lambda = 0.98$	59.8 %	15.9 %	-14.8 %	106	0.94 %	1.37 %	0.64 %	2.14	1.87
$S_0 = 145$	62.3 %	22.0 %	-19.1 %	194	0.52 %	0.80 %	0.33 %	2.45	2.00
$S_0 = 155$	61.7 %	23.8 %	-19.6 %	213	0.47 %	0.69 %	0.31 %	2.23	1.91
$\phi = 0.40$	64.9 %	18.3 %	-18.4 %	166	0.60 %	1.12 %	0.33 %	3.43	2.27
$\phi = 0.60$	60.2 %	22.9 %	-18.7 %	187	0.53 %	0.74 %	0.38 %	1.95	1.72
$\tau = 0.20$	64.3 %	18.8 %	-18.5 %	168	0.60 %	1.06 %	0.33 %	3.19	2.21
$\tau = 0.30$	62.2 %	20.7 %	-18.6 %	176	0.57 %	0.88 %	0.36 %	2.47	1.98

Table 3: The Disposition Effect – PGR/PLR.

Reported are the Odean (1998) PGR/PLR measures of the disposition effect for different simulation specifications. In the baseline specification $\mu = 0.09$, $\sigma = 0.30$, $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, and $\tau = 0.25$. Panels A through E report the results from varying the value of the indicated parameter while keeping the others at their baseline values.

Panel A: Belief Updating Speed λ							
λ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.985		2.40	2.28	2.23	1.97	0.86	0.39
0.990		2.51	2.40	2.34	2.11	1.04	0.43
0.995		2.76	2.64	2.59	2.37	1.46	0.51
Panel B: Initial Belief S_0							
S_0	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
130		2.58	2.47	2.42	2.19	1.13	0.43
135		2.51	2.40	2.34	2.11	1.04	0.43
140		2.45	2.34	2.29	2.05	0.97	0.42
Panel C: Asset Drift μ							
μ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.06		2.45	2.34	2.29	2.08	1.01	0.39
0.09		2.51	2.40	2.34	2.11	1.04	0.43
0.12		2.57	2.46	2.40	2.15	1.06	0.47
Panel D: Asset Volatility σ							
σ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.25		2.46	2.34	2.28	2.03	0.92	0.45
0.30		2.51	2.40	2.34	2.11	1.04	0.43
0.35		2.55	2.45	2.40	2.18	1.17	0.41
Panel E: Capital Gains Tax Rate τ							
τ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.20		2.51	2.42	2.38	2.21	1.58	0.66
0.25		2.51	2.40	2.34	2.11	1.04	0.43
0.30		2.51	2.38	2.31	1.98	0.64	0.33

Table 4: The Disposition Effect – PSW/PSL.

Reported are the Ben-David and Hirshleifer (2012) PSW/PSL measures of the disposition effect for different simulation specifications. In the baseline specification $\mu = 0.09$, $\sigma = 0.30$, $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, and $\tau = 0.25$. Panels A through E report the results from varying the value of the indicated parameter while keeping the others at their baseline values.

Panel A: Belief Updating Speed λ							
λ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.985		4.11	3.47	3.19	2.39	0.38	0.07
0.990		4.87	4.10	3.77	2.82	0.67	0.10
0.995		6.77	5.67	5.21	3.89	1.51	0.18
Panel B: Initial Belief S_0							
S_0	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
130		5.38	4.52	4.16	3.10	0.79	0.10
135		4.87	4.10	3.77	2.82	0.67	0.10
140		4.47	3.78	3.49	2.62	0.59	0.10
Panel C: Asset Drift μ							
μ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.06		4.74	3.95	3.62	2.69	0.66	0.09
0.09		4.87	4.10	3.77	2.82	0.67	0.10
0.12		5.00	4.26	3.93	2.97	0.67	0.10
Panel D: Asset Volatility σ							
σ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.25		4.35	3.71	3.42	2.58	0.49	0.10
0.30		4.87	4.10	3.77	2.82	0.67	0.10
0.35		5.44	4.53	4.15	3.09	0.90	0.10
Panel E: Capital Gains Tax Rate τ							
τ	$\phi =$	0.00	0.25	0.33	0.50	0.67	0.75
0.20		4.87	4.24	3.98	3.19	1.72	0.23
0.25		4.87	4.10	3.77	2.82	0.67	0.10
0.30		4.87	3.96	3.58	2.47	0.21	0.06

Table 5: Volatility Changes and the Disposition Effect.

Reported are the daily probability of selling conditional on trading at a gain, the daily probability of selling conditional on trading at a loss, and the Ben-David and Hirshleifer (2012) PSW/PSL measure of the disposition effect, from simulation specifications where on day $t = 21$ the volatility parameter of the asset increases from its initial value $\sigma = 0.30$ by 10%, 30%, or 50%, and then remains at the new level until the end of the simulation. The other model parameters are fixed at their baseline values: $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, $\tau = 0.25$, and $\mu = 0.09$. The results are from 100 000 simulated trades for each specification.

$\Delta(\sigma)$	P(Sell ∣ Gain)	P(Sell ∣ Loss)	Disposition Effect
Baseline	0.98 %	0.35 %	2.82
10 %	1.05 %	0.35 %	2.98
30 %	1.21 %	0.37 %	3.31
50 %	1.37 %	0.38 %	3.64

Table 6: Stock Splits and the Disposition Effect.

Reported are the daily probability of selling conditional on trading at a gain, the daily probability of selling conditional on trading at a loss, and the Ben-David and Hirshleifer (2012) PSW/PSL measure of the disposition effect, from simulation specifications where on day $t = 21$ a stock split with ratio 1.33-for-1, 1.50-for-1, 2.00-for-1, or 2.50-for-1 occurs. The model parameters are fixed at their baseline values: $\lambda = 0.99$, $S_0 = 135$, $\phi = 0.50$, $\tau = 0.25$, $\mu = 0.09$, and $\sigma = 0.30$. The results are from 100 000 simulated trades for each specification.

Split Ratio	P(Sell ∣ Gain)	P(Sell ∣ Loss)	Disposition Effect
Baseline	0.98 %	0.35 %	2.82
1.33-for-1	0.62 %	0.43 %	1.46
1.50-for-1	0.59 %	0.45 %	1.32
2.00-for-1	0.55 %	0.49 %	1.12
2.50-for-1	0.53 %	0.51 %	1.04

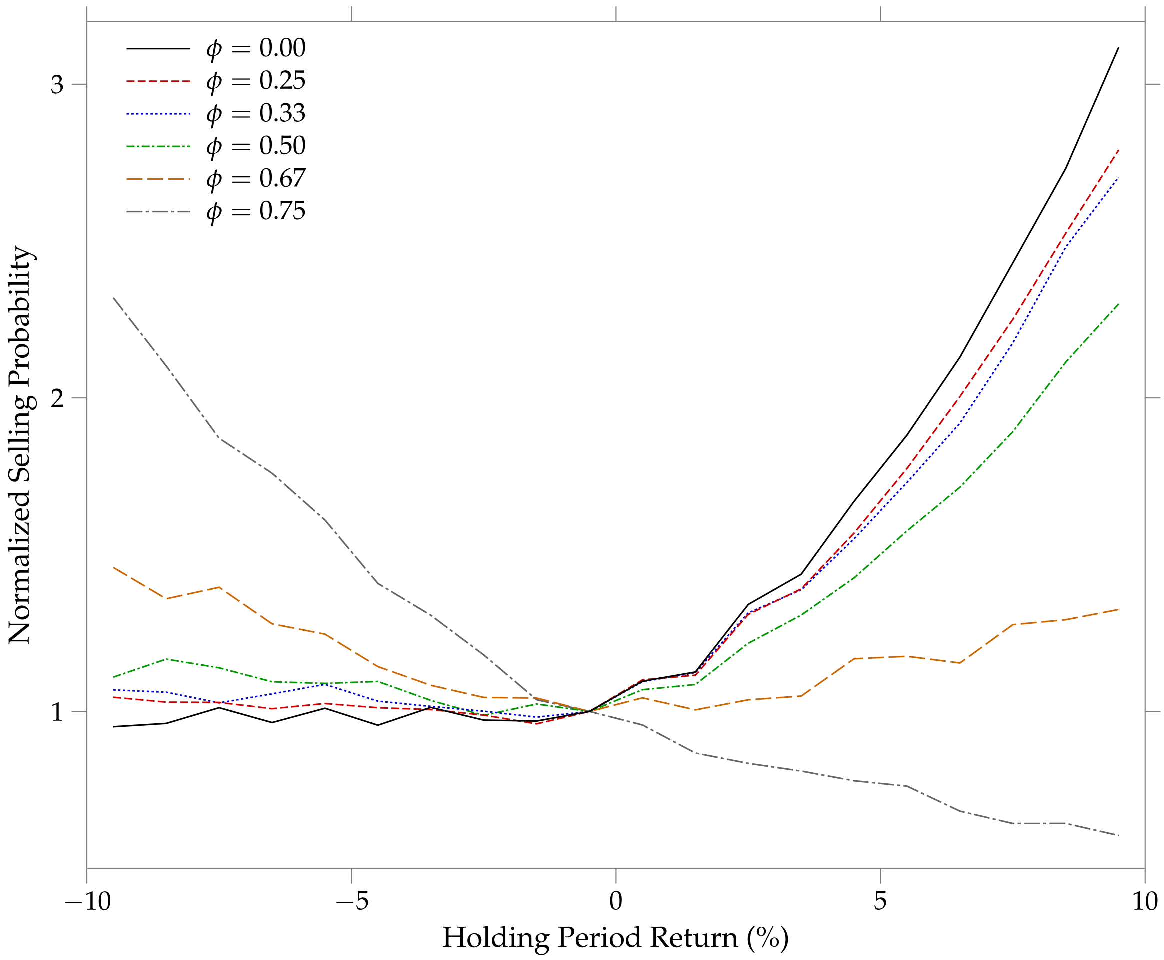

Figure 3: Propensity to Sell Functions.

Presented are propensity to sell functions estimated from probit regressions of a sell indicator variable on a set of dummy variables corresponding to holding period returns grouped into 1% bins from -10% to 10%, for model specifications with ϕ equal to 0.00, 0.25, 0.33, 0.50, 0.67, or 0.75. The other model parameters are fixed at their baseline values: $\lambda = 0.99$, $S_0 = 135$, $\tau = 0.25$, $\mu = 0.09$, and $\sigma = 0.30$. The selling probabilities are normalized in such a way that the value on the holding period return bin $(-1\%, 0\%]$ is equal to one for each specification. The results are from 100 000 simulated trades for each specification.

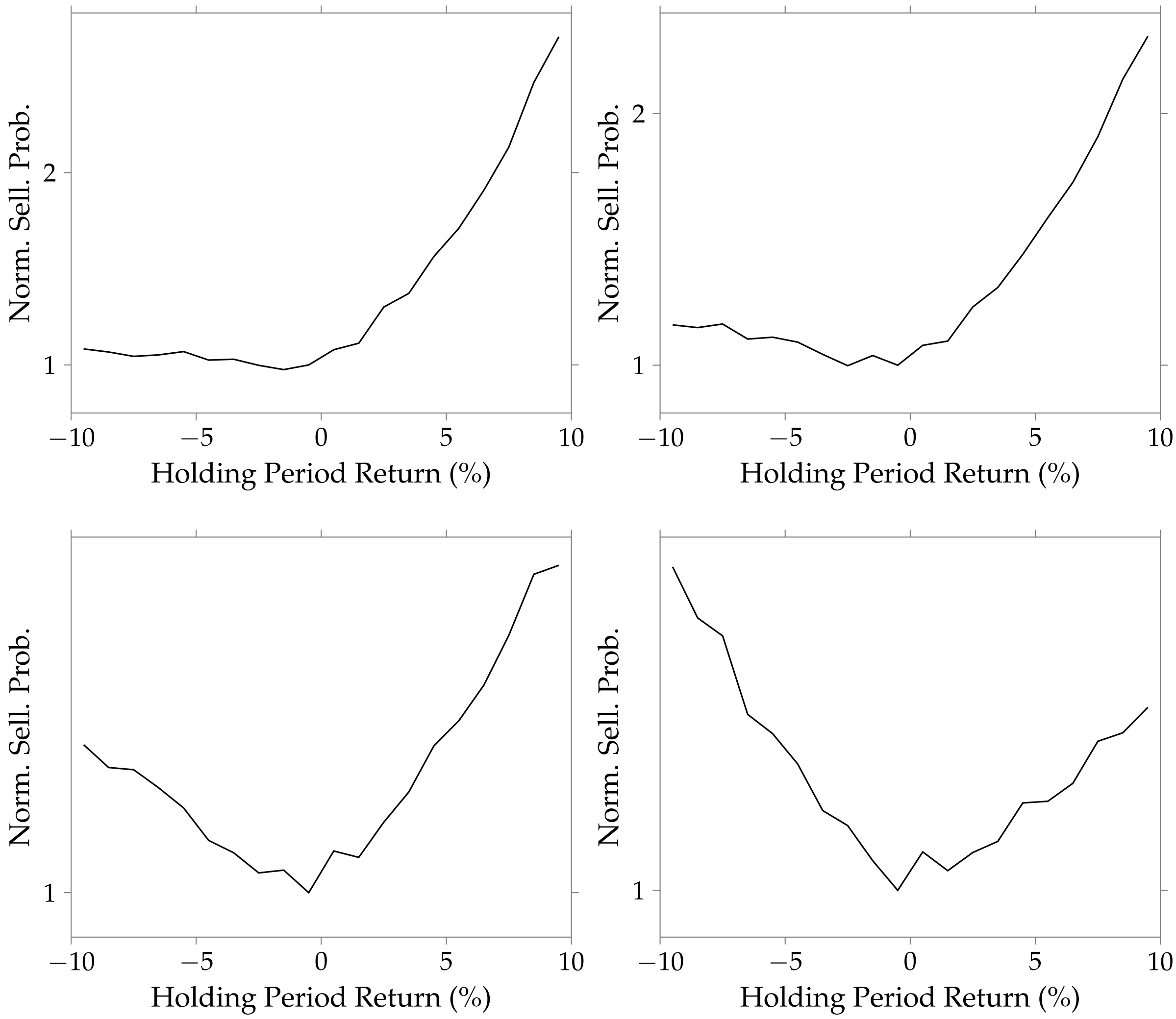

Figure 4: Aggregate-Level Propensity to Sell Functions.

Presented are aggregate-level propensity to sell functions estimated from probit regressions of a sell indicator variable on a set of dummy variables corresponding to holding period returns grouped into 1% bins from -10% to 10%, for model specifications where ϕ follows a beta distribution with shape parameters α and $\beta = 40$. In the top-left panel $\alpha = 20$ and $\mathrm{E}[\phi] = 0.33$. In the top-right panel $\alpha = 40$ and $\mathrm{E}[\phi] = 0.50$. In the bottom-left panel $\alpha = 60$ and $\mathrm{E}[\phi] = 0.60$. In the bottom-right panel $\alpha = 80$ and $\mathrm{E}[\phi] = 0.67$. The other model parameters are fixed at their baseline values: $\lambda = 0.99$, $S_0 = 135$, $\tau = 0.25$, $\mu = 0.09$, and $\sigma = 0.30$. The selling probabilities are normalized in such a way that the value on the holding period return bin $(-1\%, 0\%]$ is equal to one for each specification. The results are from 100 000 simulated trades for each specification.

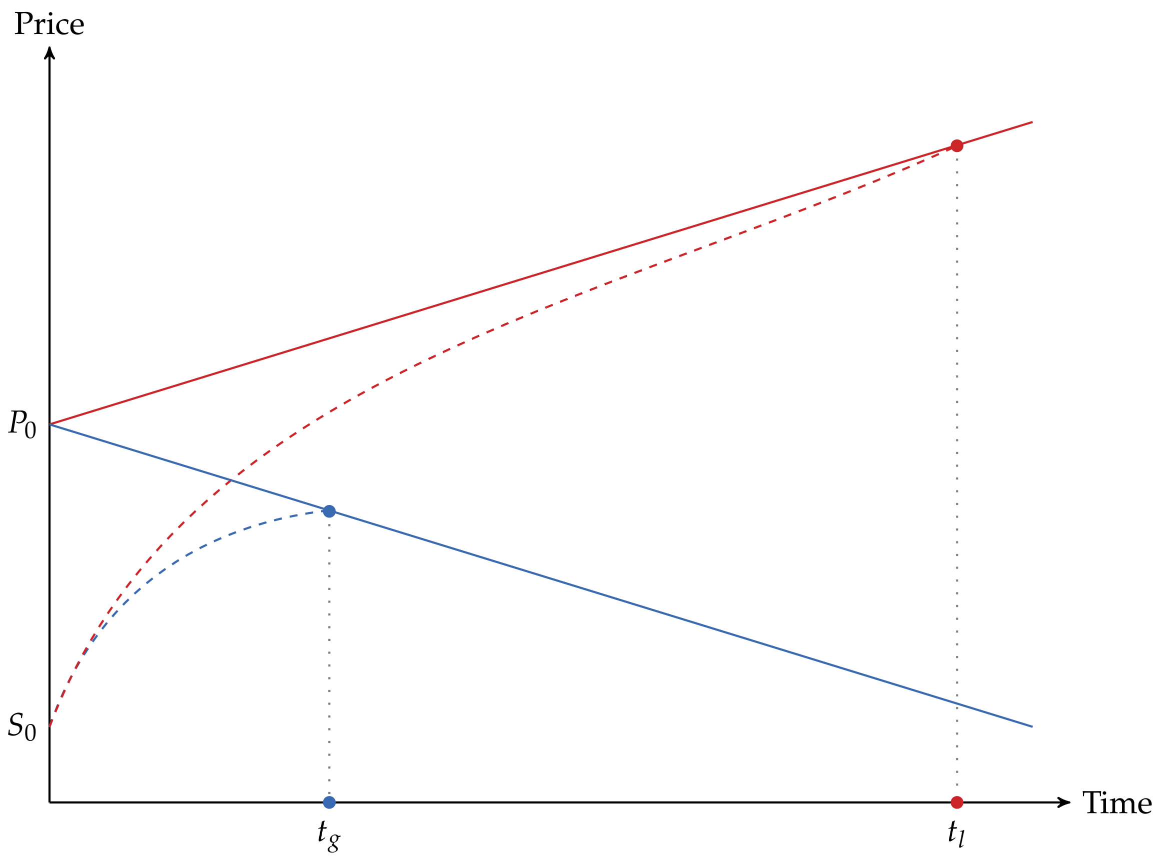

Figure 5: Graphical Intuition for Short Sales