

Quantifying Loss-Averse Tax Manipulation

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First version received December 2014; Editorial decision April 2017; Accepted June 2017 (Eds.)

This article presents evidence that loss aversion affects taxpayers as they file their annual tax returns, and presents a framework for estimating the policy impact of this psychological phenomenon. In my theoretical framework, taxpayers manipulate the money paid to the tax authority through avoidance and evasion activities. When taxpayers face the prospect of owing the tax authority money on tax day, loss aversion generates the perception of a greater marginal utility of tax reduction and therefore motivates greater pursuit of tax reduction activities. Applying a bunching-based identification strategy to U.S. tax return data, I estimate that taxpayers facing a payment on tax day reduce their tax liability by \$34 more than taxpayers owed a refund.

Key words: Loss aversion, Income taxation, Tax sheltering, Tax avoidance, Tax evasion.

JEL Codes: D03, H24

When rewards or payments depend on a reported outcome, economic agents face incentives to manipulate the outcome that they report. Car mechanics face incentives to report that more repairs are necessary.¹ CEOs face incentives to report higher earnings.² Taxpayers face incentives to report behaviours that minimize their tax bill.³ In environments such as these, understanding the decision-making process underlying these manipulations can be of substantial importance, since knowledge of manipulation's determinants can critically inform the study and design of economic policy. However, empirical examination of this decision-making process is often challenging, since the participating agents are actively concealing their behaviour.⁴

In this article, I present a framework for detecting and measuring the influence of a prominently studied psychological phenomenon—loss aversion—on manipulation decisions like those discussed above. I develop this model in the specific context of the avoidance and evasion of tax liability. As in many environments with manipulation, precisely measuring the amount of avoidance and evasion pursued by a tax filer can be prohibitively difficult, even when audited data are available. However, I show that, even in contexts where the manipulation itself cannot be directly observed, the presence of loss aversion can be readily detected from the distribution of reported outcomes. Furthermore, I show that the quantitative impact of loss aversion on

1. For a recent demonstration in the context of an audit study, see Schneider (2012).

2. For a theoretical examination of managerial manipulation incentives and references to related empirical results, see Crocker and Slemrod (2007).

3. For a review of the magnitude and determinants of U.S. tax evasion, see Slemrod (2007).

4. For a recent summary of attempts to detect and study manipulation, see Zitzewitz (2012).

manipulation behaviour may be inferred from this distribution with relatively minimal parametric assumptions.

The context of taxation is amenable to the study of loss-averse manipulation due to an especially salient gain/loss framing and due to the presence of a rich menu of manipulation opportunities. To illustrate, consider the tax filing process typically experienced in the U.S. Throughout the year, a taxpayer earns taxable income, takes actions that might be tax advantaged, and makes tax payments based on a forecast of the tax liability that will ultimately be owed. In preparation for tax day, these activities must be precisely documented and reported to the Internal Revenue Service (IRS), and the “balance due”—the difference between the total taxes owed and the tax payments already made—must be settled. If the balance due is positive, the tax filer must pay that amount to the IRS, and thus incurs a literal loss. If the balance due is negative, the tax filer collects a refund, and thus incurs a literal gain. If taxpayers view gains and losses in this way, models of loss aversion predict that taxpayers owing a payment will be significantly more likely to take advantage of any opportunity to manipulate the taxes owed. For example, to reduce the loss that must be paid, the taxpayer might choose to pursue tax-incentivized behaviours, might devote more time and effort to making sure any incentives due are claimed, or might be more aggressive in attempts to evade taxes.

In the theoretical component of this article, I present a model of taxpayers facing a sequence of costly manipulation opportunities and deciding which opportunities to take. Consistent with models of prospect theory (Kahneman and Tversky, 1979), I assume that the perceived value of a marginal dollar drops discontinuously when losses turn to gains. This generates a distinctive pattern in the distribution of manipulated balance due that is reported to the IRS. Individuals in the loss domain pursue a greater amount of tax manipulation activities relative to individuals in the gain domain, shifting this region of the distribution to lower reported values. Moreover, a disproportionate fraction of taxpayers choose to manipulate their balance due to the immediate vicinity of the gain/loss threshold then discontinue pursuit of additional manipulations in response to the sudden drop in marginal returns. These predictions permit a reduced-form test of the existence of loss aversion in administrative tax records. Turning to structural analysis, I demonstrate that the strength of loss aversion in preferences (summarized in the parameter of loss aversion commonly denoted as λ) cannot be separately identified from features of the costs of manipulation. However, despite the inability to identify this preference parameter without significant structural restrictions, it is possible to both identify and estimate the resulting difference in tax reduction pursued across gains and losses. That difference may be used as a sufficient statistic to measure the individual and aggregate consequences of loss-averse behaviour.

In the empirical component of this article, I deploy this framework in the 1979–90 IRS Statistics of Income Panel of Individual Returns. As predicted by the model, the distribution of balance due is shifted in a manner consistent with higher manipulation in the loss domain, and significant excess mass is seen in the near vicinity of zero balance due. This pattern is shown to be associated with pursuit of common tax manipulation opportunities, is more pronounced among higher-income tax filers, and is not driven by withholding behaviour. My estimates suggest that individuals facing a loss pursue an additional \$34 of tax reductions above and beyond what would be pursued if they faced a gain.

Reference-dependent response to income taxation has been the topic of a considerable amount of prior research. This literature has demonstrated theoretically that loss aversion can help rationalize a variety of features of our tax system, such as the high rate of voluntary compliance.⁵ Furthermore, the presence of gain/loss framing effects has been demonstrated empirically in a

5. See, for example, Elffers and Hessing (1997), Yaniv (1999), Bernasconi and Zanardi (2004), Kanbur *et al.* (2008), or Dhami and al Nowaihi (2007, 2010).

number of surveys and lab experiments, supporting the possibility that taxpayers consider their position relative to a zero-balance-due reference point.⁶ Despite encouraging results from this line of research, direct study of this phenomenon in the field has been limited, presumably due to data constraints and the difficulty of compelling identification. In an admirable attempt to overcome the challenges of identifying loss aversion in field data, Engström *et al.* (2015) present evidence that Swedish taxpayers claim a deduction for “other expenses for earning employment income” more often when they face a loss. The authors document that—under the assumption that this manipulation decision is the marginal decision for all studied tax filers and under a specific assumed structure on the costs of pursuing these manipulation opportunities—their results can be rationalized by a loss averse model with a loss-aversion parameter approximately in line with existing experimental evidence.

My results contribute to this literature in three ways. First, I leverage the intuitions of the tax-bunching literature⁷ to illustrate robust and observable features of tax records that identify the presence of loss aversion with minimal structural assumptions. This approach does not require the researcher to observe manipulation directly, it does not require the researcher to know which of the myriad manipulation opportunities are marginal, and it does not require the researcher to specify a distribution of manipulation costs. Second, and more importantly, the approach taken here allows for the estimation of the impact of loss aversion on aggregate manipulation, measured in dollars. If tax filers who face gains were as motivated to manipulate as those facing losses, annual tax revenue would decrease by 3.7 billion dollars. If tax filers who face losses were as motivated to manipulate as those facing gains, annual tax revenue would increase by 1.4 billion dollars. As I demonstrate in Section 4, effects of the magnitude I document are large enough to play a significant role in assessing changes to withholding policy. Third, and finally, the approach developed for this task is broadly portable to other settings where a loss-averse individual is able to manipulate an observable outcome. In that respect, this article contributes to the exercise of building tools for exporting behavioural economic models into field settings.

The article proceeds as follows. Section 1 presents the theoretical framework for quantifying the impact of loss aversion in manipulation decisions. Section 2 describes the tax return data used to employ this framework. Section 3 presents the primary empirical analysis. Section 4 concludes by discussing the implications of these results for tax policy and behavioural economics.

1. THEORETICAL FRAMEWORK

In this section, I model the manipulation decisions of taxpayers who are preparing to file their annual tax returns. This model formally characterizes the distinguishing observable implications of loss aversion, setting the foundation for the empirical approach pursued in the remainder of the article.

1.1. *Discussion of decision-making environment*

Every April, U.S. taxpayers go through the process of filing their annual tax return. In this process, taxpayers formally document all of their tax-relevant information for the previous calendar year.

6. See, for example, Carroll (1992), Chang *et al.* (1987), Kirchler and Maciejovsky (2001), Robben *et al.* (1990), Robben *et al.* (1990), or Schepanski and Shearer (1995). In contrast, Schadewald (1989) presents experimental results where manipulations of reference points did not have significant effects. While this literature generally supports analyzing loss aversion relative to a zero-balance-due reference point, it is conceivable that other reference points are active for some tax filers. I return to discussion of this issue in Section 4.

7. Especially Saez (2010) and Chetty *et al.* (2011).

The resulting tax liability is compared to the taxes already collected through employer withholding and earlier estimated tax payments. These earlier payments are based on coarse withholding rules or imperfect forecasts: as a result, a remaining difference nearly always exists, and must be settled. Most taxpayers—77% in the sample studied in this paper—are *overwithheld*, meaning that the taxes already paid were in excess of the total taxes due. At the time of filing, these taxpayers document their overpayment and submit for a refund in that amount. The remaining taxpayers are *underwithheld*, meaning their taxes paid throughout the year were less than the total amount due. These taxpayers must make a payment to the IRS.

Completing the annual tax return involves several steps of documentation and calculations. Taxpayers first identify themselves and the members of their household. Next, taxpayers report their taxable income, documenting items such as wages, salaries, tips, business income, investment income, and income from rents or partnerships. Taxpayers may then report “adjustments” to that taxable income—claimed for things such as donations to tax-preferred retirement savings accounts and payments of alimony—resulting in the calculation of “Adjusted Gross Income” (AGI), an amount commonly used to summarize taxpayers’ income subject to tax. The taxpayer next has the opportunity to accept a standard deduction from AGI or to complete an additional form to “itemize” deductions.⁸ Through itemization, the taxpayer can reduce income subject to tax by reporting deductible activities such as charitable contributions, medical and dental expenses, or home mortgage interest payments. To finish the return, the taxpayer then calculates the tax due, claims credits for pursuing tax incentivized behaviour, reports other taxes paid and payments already made to the IRS, and finally computes the balance due.

Taxpayers commonly devote significant time and effort to completing this task. For example, in a survey administered shortly after tax day, Blumenthal and Slemrod (1992) found that taxpayers spent on average 27 hours documenting and reporting their taxable behaviour. Furthermore, time devoted to doing taxes has been shown to be especially aversive. Benzarti (2015) finds that taxpayers often forgo tax savings to avoid the hassle cost of itemizing their tax returns. His estimates imply that taxpayers dislike working on their taxes 4.2 times as much as they dislike working at their jobs, and that taxpayers leave substantial amounts of deductions “on the table” to avoid the aversive work necessary to claim them. In short, the process of filing taxes is often long and arduous, and evidence suggests that taxpayers make decisions on what tax reductions to claim by balancing their benefits of tax reduction against the costs needed for that reduction to be realized.

To make the process I seek to model concrete, imagine a taxpayer in the process of considering his tax burden. This taxpayer has a sense of the balance that will be due, and is considering a variety of options available to manipulate the final balance he will have to report. This taxpayer remembers that he made a charitable contribution and knows that if he spends time looking through his records he can find that documentation and request a deduction. This taxpayer has a tax-preferred retirement savings plan and knows that if he takes the time to add money to this plan he might claim an adjustment to income. This taxpayer also has income from a small business and believes that he might get away with illegally evading taxes by claiming less business income than he actually earned. In the section that follows, I model the behaviour of taxpayers facing a sequence of decisions like these and deciding which costly manipulations to pursue.

8. Prior to 1987, the standard deduction was implemented as a “zero bracket amount”, but functioned in a similar manner.

1.2. *A model of sequential manipulation decisions*

Consider a taxpayer who seeks to manipulate his tax liability. His position is currently summarized by the balance due to the IRS. Based on his previous withholding behaviour and his current plans for tax reporting, this individual’s balance due takes the value b_{PM} , denoting the “balance due prior to manipulation”.

This taxpayer faces a sequence of manipulation opportunities. Each opportunity is characterized by the parameters (m_i, c_i) . The parameter m_i denotes the tax reduction granted by this manipulation opportunity, whereas c_i denotes the taxpayer’s forecast of the costs associated with taking that opportunity. In principle, the costs measured by c_i could derive from hassle, accounting effort, expectation of future penalties for detected evasion, or indeed any other deterrent to the pursuit of this tax manipulation opportunity. This discrete formulation of the costs and benefits of tax reductions naturally accommodates pursuing credits and deductions of fixed sizes. Furthermore, this framework can accommodate continuous decisions by including a subsequence of manipulation opportunities where each m_i is arbitrarily small—for example, considering the pursuit of an evasion opportunity one dollar at a time.⁹

To incorporate loss aversion into this decision process, let individuals evaluate their money exchanged with the IRS according to a piecewise-linear version of the prospect-theory value function:

$$\phi(x|r) = \begin{cases} x - r & \text{if } x \geq r \\ \lambda(x - r) & \text{if } x < r \end{cases} \quad (1)$$

In this framework, x denotes the money under evaluation, r denotes the reference point, and λ determines the degree of loss aversion. The assumption that $\lambda > 1$ captures the notion that decision makers value a marginal dollar more when it makes a loss smaller than when it makes a gain larger.¹⁰

Applying this underlying utility structure, a loss-averse taxpayer will evaluate the benefit from each manipulation opportunity as:

$$V(m_i|b, r) = \phi(-b + m_i|r) - \phi(-b|r) = \begin{cases} m_i & \text{if } -b \geq r \\ \lambda(r + b) + (m_i - b - r) & \text{if } -b \in [r - m_i, r] \\ \lambda m_i & \text{if } -b \leq r - m_i \end{cases} \quad (2)$$

In words, if the manipulation opportunity makes an existing gain larger, it generates 1 util per dollar of tax reduction. If it makes a loss smaller, it generates λ utils per dollar of tax reduction.

9. In a previous version of this article, I presented an alternative theoretical framework assuming that the taxpayer could continuously manipulate the total amount of tax reduction, in contrast to the sequence of discrete decisions considered here. The continuous model makes broadly similar predictions, although it is not as well suited to analysing diffuse bunching arising from imperfect targeting of manipulation amounts. For this analysis and additional discussion, see Rees-Jones (2014).

10. For the purposes of this exercise, the crucial feature of this utility function is its piecewise linearity. By assuming piecewise linearity, I am explicitly excluding two components of prospect-theoretic models that are at times applied. First, this formulation does not include “diminishing sensitivity”, a feature which induces risk-loving behaviour over losses and risk-averse behaviour over gains. In Section 3.2, I present evidence that the key observable prediction of diminishing sensitivity is not seen in my data, lending support to this modelling decision. Second, this formulation influences the manner in which a direct consumption-utility term may be incorporated into this model. A utility model in the style of Köszegi and Rabin (2006) takes the form $u(b, r) = m(w + b) + \phi(b|r)$, where $\phi(b|r)$ represents the gain/loss evaluation and where $m(w + b)$ represents a more standard consumption-utility over final wealth. If $m(w + b)$ is linear, overall utility again admits a piecewise linear representation, and the core results of this section hold without modification. However, the approach taken here would fail under the assumption of significant curvature of direct consumption-utility, of the type that is typically ruled out by, for example, Rabin’s calibration theorem (Rabin, 2000).

If this opportunity changes a loss to a gain, the portion reducing the loss is valued at λ per dollar, and the remaining amount generating gains is valued at 1 util per dollar.

1.3. Implications for total manipulation

We will now consider the implications of this valuation for the taxpayer's sequential decision problem. Assume that the tax filer directs his attention so that he considers the most efficient manipulation opportunities first: that is, if $i < j$, then $\frac{m_i}{c_i} \geq \frac{m_j}{c_j}$. Further assume that $\frac{m_1}{c_1} > 1$ —ensuring that there exists at least one desirable manipulation opportunity—and that $\frac{m_n}{c_n} \rightarrow 0$ as $n \rightarrow \infty$ —ensuring that only a finite number of these manipulation opportunities can be desirable. While considering these options, if $V(m_i|b, r) > c_i$, the taxpayer takes the manipulation opportunity and continues his search. If $V(m_i|b, r) \leq c_i$, the taxpayer does not accept the manipulation opportunity and ends his search.¹¹

This sequence can be divided into three regions of differing behaviour. Define two thresholds: $L = \max \left\{ i : \frac{m_i}{c_i} > 1 \right\}$ and $H = \max \left\{ i : \frac{m_i}{c_i} > \frac{1}{\lambda} \right\}$. By the technical assumptions above, these thresholds are guaranteed to exist. And furthermore, $L \leq H$ by construction, with the inequality strict whenever there exists a manipulation opportunity satisfying $\frac{m_i}{c_i} \in \left(\frac{1}{\lambda}, 1 \right]$. Notice that for manipulation opportunities indexed 1 through L , the tax filer would take the option regardless of gain/loss status. Even if the manipulation opportunity is making a gain bigger—the situation where the perceived value of the opportunity is minimized—the option is guaranteed to be sufficiently appealing since $\frac{m_i}{c_i} > 1$ ensures that $V(m_i|b, r) \geq m_i > c_i$. By similar logic, notice that for manipulation opportunities indexed higher than H , the tax filer would never choose to take the manipulation opportunity. Even if the manipulation is making a loss smaller—the situation where the perceived value of the opportunity is maximized—the option is guaranteed to be unappealing since $\frac{m_i}{c_i} < \frac{1}{\lambda}$ ensures that $V(m_i|b, r) \leq \lambda m_i < c_i$. In cases where $L < H$, manipulation opportunities indexed by $i \in [L + 1, H]$ will be referred to as the *marginal set*. These opportunities will not be taken if the individual has already “made it” to the gain domain, but they will be taken if the balance due is a sufficiently large loss at the moment they are considered. I will index the specific elements of this set by $j \in \{1, \dots, J\}$.

To illustrate this partitioning, we will now consider a simplified numeric example. As I proceed with the development of theoretical results, I will return to this example to build intuitions before proceeding to present the general case.

Table 1 presents an example sequence of six manipulation opportunities. Each of these opportunities reduces taxes owed by \$10 if taken. However, each requires a different amount of hassle and accounting effort to claim, resulting in different costs (listed in column 3). The taxpayer considering this sequence is loss averse, with a loss aversion parameter (λ) of 2.

11. For linear utility, considering manipulation opportunities in this manner is optimal. For the piecewise-linear utility function I study, considering manipulation opportunities in this order is *approximately* optimal in the following sense. If a taxpayer following this decision rule either accepts all, or rejects all, manipulation opportunities in the marginal set (defined below), this order of consideration results in all utility-improving manipulations being considered and taken and all utility-reducing opportunities being rejected. This describes the behaviour of all taxpayers except for those reporting balance due in a narrow window surrounding the reference point, and thus ensures that this decision rule leads to optimal decisions for nearly all taxpayers. For taxpayers ending their search on a manipulation opportunity inside the marginal set—taxpayers contributing to bunching—this decision rule could result in failure to consider a utility-improving opportunity. A manipulation opportunity that leads the taxpayer to cross the reference point can have lesser utility benefit than a smaller, less efficient manipulation opportunity that is entirely evaluated in the loss domain. Note, however, that any order of consideration of the elements of the marginal set (including the fully optimal one) would generate similar features as those discussed below. I therefore view the imposition of an exogenous order of consideration as a benign assumption that dramatically simplifies notation and exposition relative to that in a model with endogenous search order.

TABLE 1
An example sequential manipulation problem

(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>i</i>	m_i	c_i	Takes opportunity if	Terminal opportunity if	Manipulated balance due range	Alt. cost sequence
1	10	5	Always	Never	—	5
2	10	8	Always	$b_{PM} \leq 22$	$(-\infty, 2]$	8
3	10	12	$b_{PM} > 22$	$b_{PM} \in (22, 35]$	$(-8, 5]$	16
4	10	15	$b_{PM} > 35$	$b_{PM} \in (35, 48]$	$(-5, 8]$	25
5	10	18	$b_{PM} > 48$	$b_{PM} > 48$	$(-2, \infty)$	34
6	10	22	Never	Never	—	44

Notes: This table presents an example sequence of manipulation opportunities and characterizes their pursuit by a taxpayer with a loss-aversion parameter (λ) of 2. A graphical representation of this example appears in Figure 1. Columns 1–3 present the index of each opportunity (i), the tax reduction it grants (m_i), and the cost of its pursuit (c_i). Column 4 presents the conditions on pre-manipulation balance due (b_{PM}) for which manipulation opportunity i is pursued. Column 5 presents the conditions on pre-manipulation balance due for which manipulation opportunity i is the final opportunity pursued. Column 6 presents the range of manipulated balance due values that could be reported by a taxpayer who stopped manipulation at opportunity i . Column 7 presents an alternative sequence of costs which would generate the same pattern of behaviour documented in columns 4–6 under the assumption that $\lambda = 4$. Section 1.5 discusses this alternative example as an illustration of the challenge inherent in separately identifying the cost sequence and λ .

As above, we may partition this sequence into three regions of behaviour. For opportunities 1 and 2, the costs are less than \$10, and thus these opportunities will be taken regardless of gain/loss status. Applying the notation above: $L = 2$. For opportunity 6, the cost is greater than $\$20 = \$10 * \lambda$, and thus this opportunity will not be taken regardless of gain/loss status. Applying the notation above, $H = 5$. Manipulation opportunities 3, 4, and 5 form the marginal set, and each will be taken only if pre-manipulation balance due is sufficiently large, with the relevant threshold indicated in column 4.

The top panel of Figure 1 illustrates the relationship between pre-manipulation balance due and total tax reduction from manipulation that arises in this example. If the pre-manipulation balance due position is less than \$22, the tax filer pursues only manipulation opportunities 1 and 2, resulting in the minimal manipulation amount of \$20. If the pre-manipulation balance due position is larger than \$48, the tax filer pursues manipulation opportunities 1–5, resulting in the maximal manipulation amount of \$50. Between these two thresholds, optimal manipulation is a step function reflecting the progression through marginal manipulation opportunities.

In the general case, we may similarly express the total manipulation pursued as a function of the taxpayer’s pre-manipulation balance due b_{PM} as

$$m^*(b_{PM}|r) = \begin{cases} \sum_{i=1}^L m_i & \text{if } b_{PM} \leq T_1 \\ \sum_{i=1}^{L+1} m_i & \text{if } b_{PM} \in (T_1, T_2] \\ \dots & \dots \\ \sum_{i=1}^{L+j} m_i & \text{if } b_{PM} \in (T_j, T_{j+1}] \\ \dots & \dots \\ \sum_{i=1}^{L+J-1} m_i & \text{if } b_{PM} \in (T_{J-1}, T_J] \\ \sum_{i=1}^H m_i & \text{if } b_{PM} > T_J \end{cases} \quad (3)$$

As in the example, optimal total manipulation is a step function governed by an ordered sequence of thresholds. Each threshold is determined by $T_j = \max \left\{ b_{PM} : V \left(m_{L+j} | b_{PM} + \sum_{i=1}^{L+j-1} m_i, r \right) \leq c_{L+j} \right\}$, determining the largest pre-manipulation balance due for which opportunity j will be pursued. Each interval $(T_j, T_{j+1}]$ defines the set of

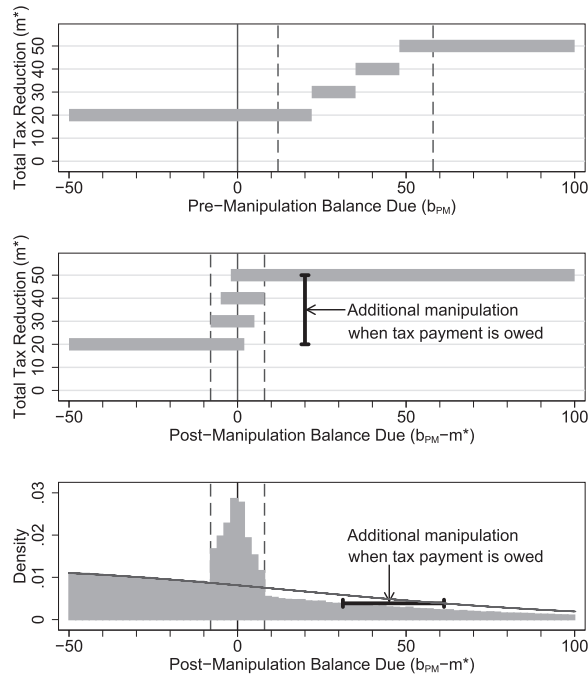


FIGURE 1

Predictions of loss-averse tax manipulation.

Notes: In the context of the example presented in Table 1, this figure illustrates the predicted relationship between total tax reduction and unmanipulated balance due (top panel), total tax reduction and manipulated balance due (middle panel), and the shape of the distribution of balance due that would result from loss-averse manipulation (bottom panel).

pre-manipulation balance due values such that, once the individual reaches marginal decision j , the individual (1) faces a sufficient loss that he will take that opportunity, but (2) will not take the next manipulation opportunity in the sequence, since opportunity m_j resulted in a balance due that was a gain (or sufficiently close to one).

If total manipulation is observed, testing for this structure would provide a very direct test of loss aversion. Unfortunately, forming an adequate measure of total manipulation in tax records is extremely challenging due to heterogeneous manipulation strategies and issues of measurement. Picking a specific, observable manipulation opportunity provides an imperfect test since it is difficult to assess *ex ante* if that opportunity will be in the marginal set for all, or even some, tax filers. Forming a measurement of the aggregate of all manipulation behaviour is also difficult since the manipulation behaviour I study includes both legal tax avoidance and illegal tax evasion, and quantifying the precise amount of illegal tax evasion is notoriously difficult even in audited tax returns. These considerations suggest that attempts to directly measure manipulation will provide noisy proxies for the behaviour we wish to study. While the presence of noise is not inherently prohibitive for some identification strategies, it is a significant hindrance to detecting sharp discontinuities—the defining feature of optimal behaviour under loss aversion.¹² To circumvent these difficulties, I adopt a latent-variable approach that embraces our imperfect ability to precisely

12. In their related work, Engström *et al.* (2015) consider a model similar to my own, but restricted to analysing a single manipulation opportunity in isolation. Their approach is effectively nested within the sequential problem presented, and is equivalent to assuming that the specific manipulation opportunity they consider—a deduction for “other expenses for earning employment income”—is the unique potentially marginal manipulation opportunity for all studied taxpayers.

measure tax manipulation. I instead identify the presence and size of manipulation based on its effects on a variable that is perfectly observed in standard administrative records: the final balance due reported to the tax authority after all manipulation has occurred.

1.4. *Implications for reported balance due*

To build intuitions for the translations of these results to reported balance due, we again return to the example presented in Table 1 and Figure 1.

To calculate the range of post-manipulation balance due amounts reported when pursuing any given level of total manipulation, we may simply subtract the total manipulation pursued from the range of pre-manipulation balance due amounts mapping to that manipulation strategy. Column 6 of Table 1 presents these ranges, and the middle panel of Figure 1 plots the resulting correspondence between post-manipulation balance due and the total manipulation pursued. As in panel 1, this relationship is characterized by pursuit of the minimal manipulation amount of \$20 for sufficiently low balance due amounts: that is, post-manipulation balance due values less than $-\$8$ —a small refund. Similarly, the maximal manipulation amount of \$50 is pursued for sufficiently high balance due amounts: that is, post-manipulation balance due values greater than $\$8$ —a small payment. For the range between $-\$8$ and $\$8$, the discontinuities in $m^*(b_{PM}|r)$ generate overlap in the region of post-manipulation balance due values that result from different amounts of manipulation.

When this pattern of optimal manipulation behaviour is applied, it generates observable and distinctive features in the distribution of reported post-manipulation balance due. These features are illustrated in the bottom panel of Figure 1, in which I plot a histogram of the manipulated balance due that the example taxpayer would report ($b_{PM} - m^*(b_{PM}|r)$). This histogram exhibits the two key observable features generated by loss-averse manipulation.

First, note that loss-averse manipulation generates excess mass, or “bunching”, around the reference point. This is generated by the fact that a comparatively wide range of pre-manipulation values—ranging from \$12 to \$58, and indicated by the vertical dashed lines in the top panel of Figure 1—result in the pursuit of manipulation opportunities from the marginal set until post-manipulation balance due falls in a comparatively narrow region around the reference point—ranging from $-\$8$ and $\$8$, and indicated by the vertical dashed lines in the lower two panels of Figure 1. Since this prediction only affects a narrow region of this distribution, it would be directly observed only among an extreme minority of taxpayers. Despite this limitation, an observation of bunching among the minority near a reference point provides a means to identify features of the decision-making process applied by the population more broadly.

Second, note that when considering balance due outside of the narrow bunching region, the distribution over the loss domain is shifted relative to the distribution over the gain domain. Across the gain domain, the observed post-manipulation distribution is simply the distribution of $b_{PM} - 20$, corresponding to the pursuit of \$20 of tax reduction. This distribution is plotted with the solid black line in the bottom panel of Figure 1. Across the loss domain, the observed post-manipulation distribution is simply the distribution of $b_{PM} - 50$, corresponding to the pursuit of \$50 of tax reduction. As a result, when comparing the distribution in the loss domain to the forecast

Under that assumption, they predict an analogous pattern of take-up as documented here, predicting a propensity of take-up for this deduction that features kinks at the boundaries of the balance due region for which this deduction is marginal. They find evidence for only one of these two kinks. The sequential model I present here illustrates that heterogeneity in manipulation opportunities across individuals would obfuscate the kinks they predicted, rationalizes their difficulty in finding some of the predictions of their model, and illustrates why I adopted a different identification strategy when seeking to test for loss aversion.

of that generated by the gain domain, it appears shifted to the left by \$30, corresponding to the \$30 of additional manipulation pursued by those who face a loss. In contrast to the prediction of bunching, the prediction of shifting directly affects taxpayers for a large range of potential reported values, and thus constitutes the primary policy-relevant outcome of loss-averse manipulation.

We will now translate these features to the general case, which will form the basis of the structural estimation exercise pursued in the remainder of this article. Assume that the taxpayer draws his pre-manipulation balance due from the distribution $f^{PM}(b)$. It will be notationally convenient to additionally define $g(b) = f^{PM}(b + \sum_{i=1}^L m_i)$, the distribution of balance due that would be observed if the minimal manipulation amount were always pursued, and $\tilde{m} = \sum_{i=L+1}^H m_i$, the difference between the minimal and maximal manipulation amounts. I will also denote the indicator function by $I(x)$; this function takes the value of 1 if statement x is true, and otherwise takes the value of 0.

Applying the optimal manipulation formula and the notation above, we may characterize the distribution of post-manipulation balance due, $f(b)$, as:

$$f(b) = f^{PM}(b + m^*) = \begin{cases} g(b) & \text{if } b \leq r - B_1 \\ g(b) + E_1(b) & \text{if } b \in (r - B_1, r] \\ g(b + \tilde{m}) + E_2(b) & \text{if } b \in (r, r + B_2] \\ g(b + \tilde{m}) & \text{if } b \geq r + B_2. \end{cases} \quad (4)$$

As in the numeric example, for values sufficiently into the gain domain, the observed post-manipulation distribution is simply the pre-manipulated distribution, shifted by the minimal amount of tax reduction, $\sum_{i=1}^L m_i$. For values sufficiently into the loss domain, the observed post-manipulation distribution is simply the pre-manipulated distribution, shifted by the maximal amount of tax reduction, $\sum_{i=1}^H m_i - \tilde{m}$ more than the minimal shift assumed in the definition of $g(b)$. For values in a narrow region near the reference point, the distribution exhibits excess mass, determined by the terms:

$$E_1(b) = g(b + \tilde{m}) * I\left(b + \sum_{i=1}^H m_i > T_J\right) + \sum_{j=1}^{J-1} g\left(b + \sum_{i=L+1}^{L+j} m_i\right) * I\left((b + \sum_{i=1}^{L+j} m_i) \in (T_j, T_{j+1}]\right) \quad (5)$$

$$E_2(b) = g(b) * I\left(b + \sum_{i=1}^L m_i \leq T_1\right) + \sum_{j=1}^{J-1} g\left(b + \sum_{i=L+1}^{L+j} m_i\right) * I\left((b + \sum_{i=1}^{L+j} m_i) \in (T_j, T_{j+1}]\right). \quad (6)$$

1.5. Detecting and measuring the policy impact of loss aversion

To summarize, loss-averse manipulation generates two qualitative predictions about the shape of the distribution of the balance due reported to the IRS.

Bunching prediction: Loss-averse manipulation generates excess mass, or “bunching”, near the reference point.

Shifting prediction: Loss-averse manipulation generates a uniform shift of the loss domain of the balance due distribution relative to the gain domain of this distribution.

Looking for evidence of these two predictions provides a sharp reduced-form test for the presence of loss aversion.

Additionally, and perhaps more importantly, equation (4) makes clear how the policy impact of loss aversion might be estimated and quantified. The quantitative impact of facing a loss is succinctly summarized in parameter \tilde{m} . This parameter governs the increase in manipulation pursued by those facing a loss compared to those facing a gain, measured in dollar units. By fitting a distribution of the form implied by equation (4) to the observed balance due distribution—simultaneously estimating parameters \tilde{m} , B_1 , B_2 , and the structure of distribution g —this impact of facing a loss might be estimated. This is the task we will turn to in Section 3.

As an alternative means of quantifying loss aversion in this model, one could instead attempt to estimate the coefficient of loss aversion (λ). While knowledge of this parameter is neither necessary nor sufficient to infer the impact of loss aversion on tax revenue, an estimate would be useful for comparison to existing experimental evidence. Unfortunately, this parameter cannot be identified from either the final balance due or from observed manipulation without knowledge of the distribution of costs of manipulations. Intuitively, one cannot distinguish between the possibility that the marginal manipulation opportunities are pursued due to strong loss aversion combined with comparatively high costs versus weak loss aversion combined with comparatively low costs. To quickly verify the identification problem, notice that column 7 of Table 1 presents a modification to the sequence of costs in the numerical example that would generate the same pattern of optimal behaviour under the alternative assumption that $\lambda = 4$. In the Appendix, I prove that any pattern of manipulation behaviour that may be rationalized by a given $\lambda > 1$ and sequence of manipulation opportunities can also be rationalized by any other value of $\lambda > 1$ with appropriate modifications to the assumed sequence of costs. Any credible estimation of λ must therefore rely on credible external knowledge of the nature of manipulation costs. Since the costs of manipulation incorporate many intangible and unmeasured components (including idiosyncratic evaluation of hassle, forecasts of necessary accounting effort, and subjective assessments of audit probabilities), little empirical evidence exists to precisely inform such modelling decisions. By focusing attention on parameter \tilde{m} , I sidestep the need to make strong assumptions regarding costs while still recovering a policy-relevant measure of loss-averse behavioural response.

2. DATA

The data considered in this study come from the 1979 to 1990 IRS Statistics of Income (SOI) Panel of Individual Returns, which I obtained from the Office of Tax Policy Research at the University of Michigan. The SOI Panel of Individual Returns is an unbalanced panel that follows a random sample of tax filers. Randomization occurred over Social Security Numbers (SSNs): five 4-digit numbers were drawn, and tax filers whose last four SSN digits matched one of these codes were included in the sample. These data contain many line items reported on the tax return, allowing the direct observation of balance due and many steps of its calculation.

In the process of preparing the dataset, I exclude data according to several criteria. First, I restrict my sample to taxpayers in the fifty states or the District of Columbia. Second, I remove a small number of observations that were drawn from a different sampling frame.¹³ Finally, I drop any data for filing years before 1979.¹⁴ These exclusions remove 3,051 observations from the raw data, and yield a sample size of 291,275 person-years for 64,027 tax filers.

13. Not all five groups of SSN numbers were sampled in all years of the panel. Three groups were sampled in 1979–81. One group was sampled in 1979–81, 1983, 1985, and 1987–90. The remaining group was sampled from 1979 to 90. In years where a given SSN group was excluded from this panel, it was not excluded from other IRS sampling frames. As a result, a small number of those taxpayers were randomly sampled to be part of that year's IRS tax model file. These observations were subsequently included in this dataset, but flagged. I exclude them to preserve a consistent sampling structure.

14. The small number of such observations available are tardy returns filed during the sampling period.

TABLE 2
Summary statistics

	Mean	Std. Dev.	Percentiles			Fraction claiming
			25 th	50 th	75 th	
<i>Summary tax information:</i>						
Balance due	-951	5,983	-2,129	-948	-101	
Adjusted gross income	59,388	47,524	27,481	47,545	77,718	
Tax before credits	8,363	12,499	1,972	4,890	10,253	
<i>Common components of tax reduction</i>						
Itemized deductions	21,059	15,366	12,436	17,045	24,604	38%
Adjustments to income	5,449	8,446	1,334	3,779	6,430	21%
Credits	626	2,253	13	213	639	33%

Notes: This table reports the mean, standard deviation, and quartiles of key components of tax calculations. All statistics reported for the tax reduction variables are conditional on that tax reduction being claimed. The fraction claiming each tax reduction is reported in the right-most column. All monetary amounts are expressed in 2016 dollars.

In addition to these basic data-integrity sample exclusions, I will further restrict the data to only individuals with non-zero total tax liability as well as non-zero tax prepayments. This restriction excludes 62,159 observations from the data, and is conducted to avoid a potentially important confound. Note that individuals without taxable income will often face a balance due of zero for reasons unrelated to loss aversion, potentially confounding the bunching prediction. Additionally note that for individuals with zero tax prepayments, zero balance due aligns with zero total tax. Excess mass at zero total tax has previously been documented, and can be attributed to non-preference-based discontinuities in the tax environment (Saez, 2010).¹⁵

After these data exclusions, my final sample consists of 229,116 tax returns filed by 53,177 taxpayers. Basic summary statistics are presented in Table 2. To facilitate the interpretation of monetary values across years, all monetary amounts are expressed in 2016 dollars. This conversion is made using the Consumer Price Index, as reported by the U.S. Bureau of Labor Statistics.

3. TESTING AND QUANTIFYING LOSS AVERSION

In this section, I test the predictions of the loss-averse manipulation model presented in Section 1 and directly estimate the model expressed in equation (4).

To do so, I fit a distribution with the predicted structure of equation (4) to the frequency histogram of observed balance due. I partition balance due values into \$20 bins, denoting the count of observations within the bin centered on point k by C_k . I estimate the parameters of the fitted distribution by minimizing the squared distance between actual and fitted counts, yielding the formal estimation equations:

$$\min_{(\tilde{m}, B_1, B_2, \theta_g, \theta_e)} \sum_k \left(C_k - \hat{C}(k|\tilde{m}, -B_1, B_2, \theta_g, \theta_e) \right)^2. \quad (7)$$

$$\hat{C}(k|\tilde{m}, -B_1, B_2, \theta_g, \theta_e) = v_g \cdot g(k + \tilde{m} \cdot I(k > 0) | \theta_g) + v_E \cdot E(k | \theta_e, -B_1, B_2). \quad (8)$$

15. In particular, bunching at zero total tax might reasonably be expected due to (1) the discontinuity in marginal tax, and (2) the nature of non-refundable credits and deductions. Non-refundable credits cannot be used to generate a net refund for the year relative to total tax payment (the sum of tax prepayments and payments on tax day). Assuming non-zero tax prepayments, the total tax and balance due are distinct, and thus non-refundable credits *can* be used to generate a refund on tax day.

As in the theory section, \tilde{m} denotes the excess manipulation pursued in the loss domain relative to the gain domain. $g(k|\theta_g)$ represents the distribution of balance due that would be observed if all filers pursued the low manipulation amount. I model $g(k|\theta_g)$ as a mixture of three normal distributions, with θ_g denoting its vector of parameters.¹⁶ This distribution is augmented by the excess mass function $E(k|\theta_e, -B_1, B_2)$, with θ_e denoting its vector of parameters and $(-B_1, B_2)$ denoting the range of its support. I implement this component as a triangular distribution with a free parameter to allow for extra mass in the zero balance due bin.¹⁷ To ensure the distribution resulting from these two components integrates to 1, and to translate that distribution to frequency counts, these two components of the model are multiplied by endogenous scaling parameters $v_E = \frac{N}{\sum_k E(k|\theta_e, -B_1, B_2)} \cdot \int_0^{\tilde{m}} g(x|\theta_g) dx$ and $v_g = \frac{N}{\sum_k g(k+\tilde{m}\cdot I(k>0)|\theta_g)} \cdot \left(1 - \int_0^{\tilde{m}} g(x|\theta_g) dx\right)$.

In this formulation, note that our key parameter of interest—the extra manipulation pursued in the loss domain (\tilde{m})—is jointly identified by the two predicted features of the data emphasized in Section 1. First, and most obviously, it is partially determined by the uniform shift of the loss domain, represented by the term $\tilde{m} \cdot I(k > 0)$ in equation (8). Additionally, the size of this shift determines the amount of mass “bunched” near the reference point, since \tilde{m} sets the region of integration seen in the formalization of v_E . Estimating parameter \tilde{m} thus provides a means of jointly measuring these two features of the data while maintaining their interdependency that is imposed by the model.

Since this parameterization of the model becomes ill-defined if B_1 , B_2 or \tilde{m} take on negative values, I estimate each of these components as the exponent of an index variable, reconstruct their implied value from the estimated index, and estimate the standard error via a bootstrap procedure. To account for the clustered structure of my data (with multiple observations across years from each tax filer), I use a block bootstrap with 5,000 simulations resampled by taxpayer ID. Calculating standard errors in this way has the additional desirable feature of accounting for the two-stage structure of the estimation procedure above (first estimating the empirical frequency counts, and then fitting a model to them).

Figure 2 presents the estimated model from the full-sample application of this procedure. The top panel presents a plot of the estimated distribution, while the lower panel presents an examination of this fitted distribution in the near vicinity of the gain/loss threshold. First assessing the bunching prediction, note that there is a clearly apparent region of excess mass near zero, with a sharp spike of mass in the zero-balance-due bin and with diffuse excess mass in the nearby vicinity. In the estimated model, the region of excess mass ranges from $-\$159.7$ (S.E. = 27.00) to $\$103.2$ (S.E. = 36.20); this region is represented by the vertical grey lines included in the plot. Assessing the shifting prediction next, notice that there appears to be less mass in the loss domain than might reasonably be forecasted from the gain domain. The model parameter that jointly determines the excess mass near zero and the shift of the loss domain, \tilde{m} , is estimated to be 33.8 (S.E. = 4.68). This estimate indicates that the qualitative features of the distribution discussed above are strongly statistically significant, as assessed by traditional p -value thresholds. Furthermore, this estimate quantifies the economic significance of this behaviour, implying that approximately \$34 of additional tax reduction is pursued when facing losses as opposed to gains.

16. While mixture distributions like these are often used to estimate the proportions of different “types”, that interpretation is not meant here. Rather, this is a simple but flexible way to approximate a large class of distributions. For its application here, it may best be thought of as an eight parameter distribution that can accommodate substantial skew, kurtosis, and multi-modal structure. As will be seen in the models to come, it results in a good fit of the empirical histograms studied. In many cases, these distributions would not be well fit by more common but less flexible parametrizations.

17. Formally, $E(k|\theta_e, -B_1, B_2) = \max\left\{0, \frac{1}{\bar{B}} - \frac{|k|\cdot I(k<0)}{B_1\cdot\bar{B}} - \frac{|k|\cdot I(k>0)}{B_2\cdot\bar{B}} + \theta_{e,1} \cdot I(k=0)\right\}$ where $\bar{B} = \frac{B_1+B_2}{2}$.

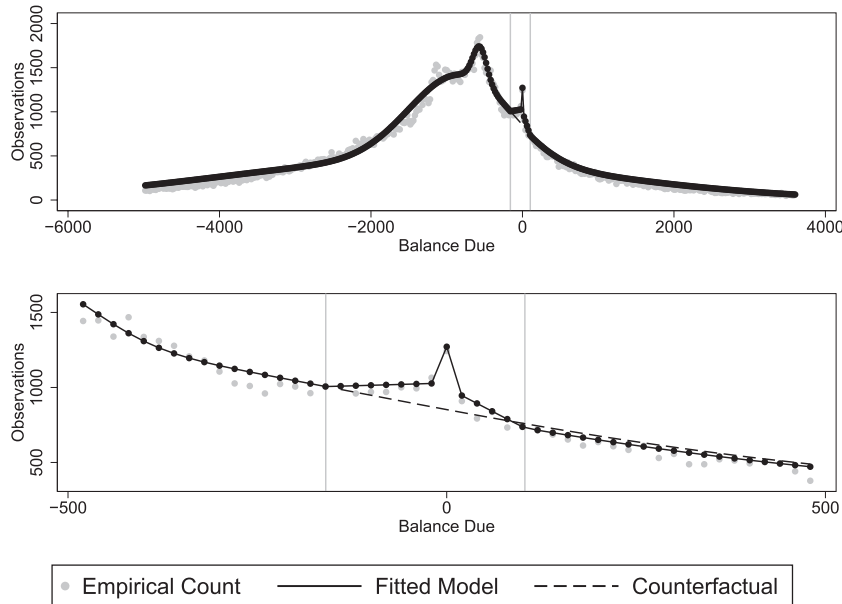


FIGURE 2

Distribution of balance due.

Notes: This figure presents the fitted distribution arising from the estimation strategy described in Section 3. Estimation sample restricted to balance due values between the 5th and 95th percentile. The grey dots illustrate the empirical count of observations in each \$20 balance due bin. The solid black line illustrates the fitted model, and the dashed black line illustrates the counterfactual model if extra manipulation were not pursued in the loss domain. The vertical grey lines denote the estimated region of excess mass. All monetary amounts are expressed in 2016 dollars.

3.1. Correlates of loss-averse behaviour

In this section, I replicate the above estimation exercise while restricting the sample to various groups of interest. Since the goal of this exercise is to determine which groups contribute to the generation of excess mass observed in Figure 2, I fix the bunching range to be the region estimated in that analysis. I then re-estimate the shape of the distribution and the parameter \tilde{m} for each relevant subgroup.¹⁸ As seen in the first panel of Table 3, imposing this restriction preserves the same point estimate of the shifting parameter in the full sample analysis but reduces the standard error from 4.68 to 2.89.

To better understand which types of taxpayers are driving this documented behaviour, I begin by examining differences by income levels. I split the dataset into four subsamples corresponding to the four AGI quartiles and perform the estimation exercise described above.¹⁹ The predicted models are plotted in Figure 3, and the point estimates of \tilde{m} are reported in the first panel of Table 3. While evidence of the loss-averse pattern is seen and estimated in all four quartiles, it becomes noticeably more pronounced among higher income filers. Estimated additional manipulation under losses is \$20.8 for the poorest income quartile, but increases to \$45.0 for the richest

18. While imposing this restriction is important for attributing explanations for the excess mass in Figure 2, it also is important for technical considerations. As the amount of loss-averse manipulation tends towards zero, our ability to distinguish the boundaries of the bunching region are diminished, and the estimates of these parameters become unstable. This restriction sidesteps these problems in cases where little loss-averse manipulation would be detected.

19. Since the income distribution changes over time, observations are assigned into quartiles based on year-specific income distributions.

TABLE 3
Estimates of additional manipulation when facing a loss

Panel A: full sample estimate and heterogeneity by income						
	Full sample		Income quartiles			
			1	2	3	4
Extra manip. for loss (\tilde{m})	33.8 (2.89)		20.8 (5.59)	20.5 (4.76)	33.4 (10.11)	45.0 (9.18)
<i>N</i>	206,188		57,126	55,986	52,354	40,722
Panel B: restricting sample by presence of tax reductions						
	Itemized deductions		Adjustments to income		Credits	
	claimed	not claimed	claimed	not claimed	claimed	not claimed
Extra manip. for loss (\tilde{m})	45.6 (6.96)	26.0 (3.59)	47.3 (7.06)	29.9 (3.71)	19.6 (5.72)	33.9 (3.32)
<i>z</i> -test <i>p</i> -value		0.012		0.029		0.031
<i>N</i>	70,278	135,910	39,611	166,577	65,433	140,755

Notes: This table presents parameter estimates of the extra manipulation pursued when facing a loss (\tilde{m}) based on the estimation strategy described in Section 3. Estimation sample restricted to balance due values between the 5th and 95th percentile. Block-bootstrapped standard errors, resampling by taxpayer ID and based on 5,000 simulations, are presented in parentheses. Plots of the fitted distributions are presented in Figures 3 and 4. All monetary amounts are expressed in 2016 dollars. Assignment to income quartiles is evaluated according to filing-year-specific AGI distributions.

quartile (z of difference = 2.25, $p < 0.03$). This is consistent with the notion that higher-income tax filers have more complex tax behaviour and thus more options for tax manipulation that might fall in the marginal set. Furthermore, this demonstrates that this behaviour is not corrected by the variation in financial sophistication that occurs across the income distribution.

Next, I directly assess the association of these patterns with observable categories of tax reduction. In Figure 4, I plot estimated distributions while conditioning on the presence or absence of itemized deductions, adjustments to income, or credits. Point estimates of \tilde{m} are reported in the second panel of Table 3. As seen in these figures and estimates, the patterns predicted by loss aversion are more pronounced when itemized deductions are present ($\tilde{m} = \$45.6$ versus $\tilde{m} = \$26.0$, $z = 2.50$, $p < 0.02$) and when adjustments to income are present ($\tilde{m} = \$47.3$ versus $\tilde{m} = \$29.9$, $z = 2.18$, $p < 0.03$). These results are consistent with the notion that these behaviours are candidate manipulation opportunities in the marginal set. In contrast, however, the patterns predicted by loss aversion are more pronounced among those not claiming credits as opposed to those claiming credits ($\tilde{m} = \$33.9$ versus $\tilde{m} = \$19.6$, $z = 2.16$, $p < 0.04$). While this particular result is unexpected, it can be rationalized by noting that the claiming of credits is a comparatively small component of overall tax reductions (Table 2). Furthermore, while AGI, itemization, and claiming adjustments are all strongly positively correlated (correlations ranging from 0.19 to 0.54), the claiming of credits is only weakly correlated with these other features (correlations ranging from 0.05 to 0.10). This suggests that the claiming of credits is likely a less suitable proxy for total manipulation than the other two tax reductions considered.²⁰

20. Instead of comparing, for example, those with and without itemized returns, one may instead wish to compare those who itemized returns but did not claim credits or adjustments to those who did not use any of these three manipulation channels. Partitioning filers in this manner results in comparatively small bin sizes, and thus results in comparatively low-power analysis. However, this analysis reveals a similar pattern of point-estimates to the results of Table 3. Compared to respondents without itemized deductions, adjustments to income, or credits, respondents with only itemized deductions

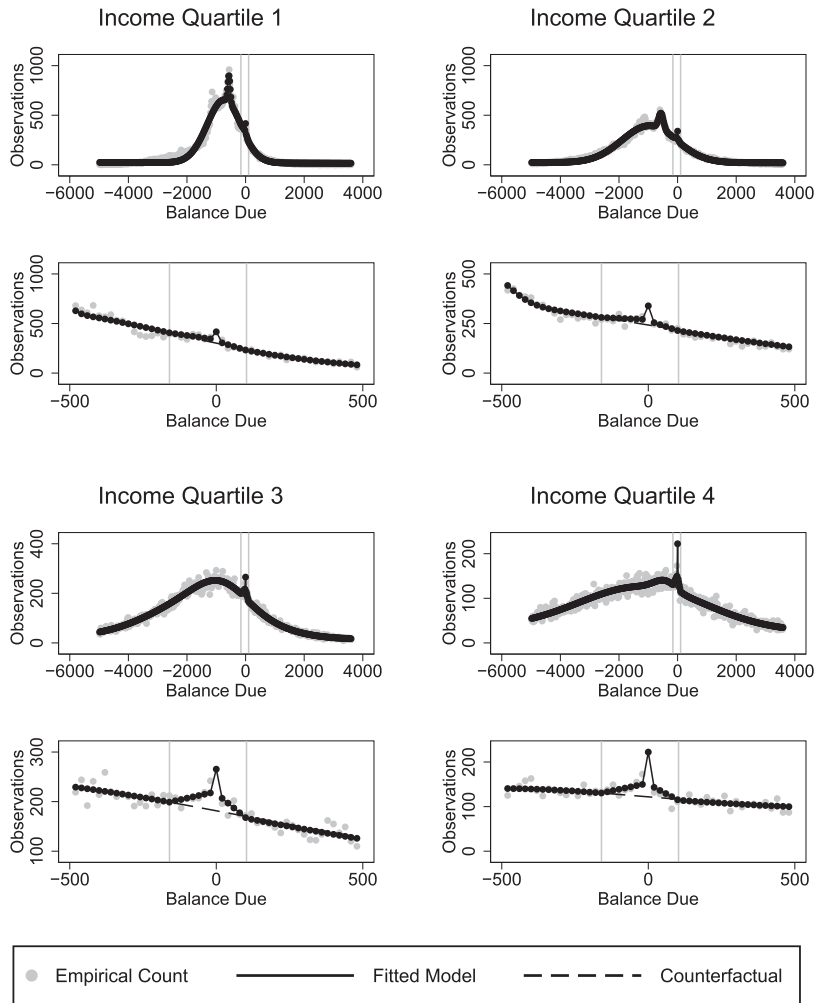


FIGURE 3

Distribution of balance due by income quartile.

Notes: This figure presents the fitted distribution arising from the estimation strategy described in Section 3. Corresponding parameter estimates are reported in Table 3. Estimation samples restricted to balance due values between the 5th and 95th percentile. The grey dots illustrate the empirical count of observations in each \$20 balance due bin. The solid black line illustrates the fitted model, and the dashed black line illustrates the counterfactual model if extra manipulation were not pursued in the loss domain. The vertical grey lines denote the estimated region of excess mass. All monetary amounts are expressed in 2016 dollars.

To better approximate total tax reduction activities while simultaneously controlling for taxpayer characteristics, I construct an approximate measure of an individual's "residual" tax reductions occurring through these three channels. To construct my measure, I build the variable

or only adjustments to income demonstrate a larger degree of loss-averse manipulation (itemized deductions: $\tilde{m} = \$47.3$ versus $\bar{m} = \$20.8$, $z = 0.74$, $p = 0.46$; adjustments to income: $\tilde{m} = \$41.8$ versus $\bar{m} = \$20.8$, $z = 0.33$, $p = 0.74$). Respondents with only credits again demonstrate a lesser degree of loss-averse manipulation ($\tilde{m} \approx \$0$ versus $\bar{m} = \$20.8$, $z = 3.07$, $p < 0.01$).

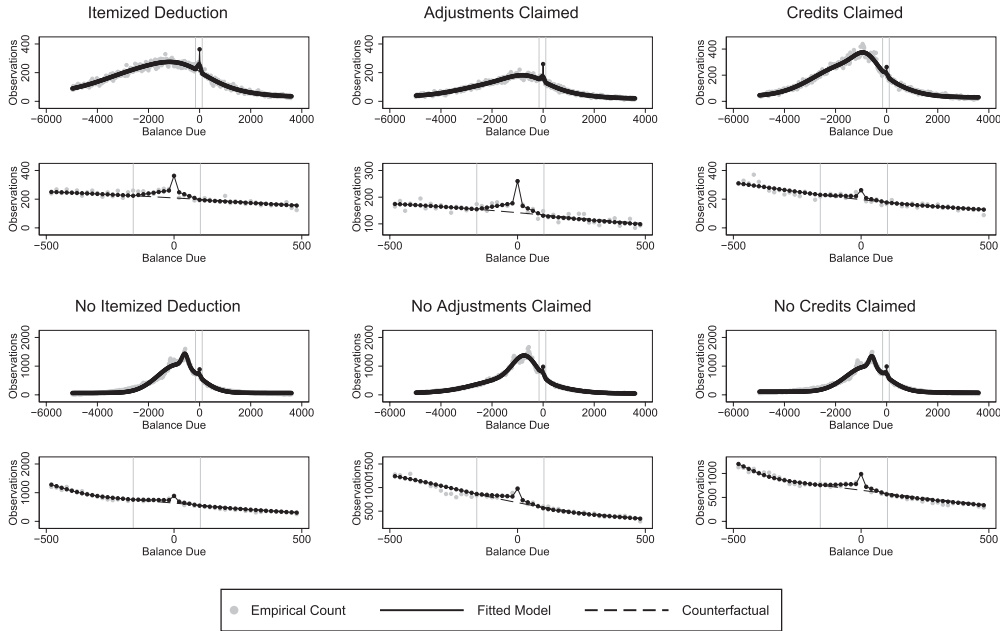


FIGURE 4

Distribution of balance due by tax reduction activity.

Notes: This figure presents fitted distributions arising from the estimation strategy described in Section 3. Corresponding parameter estimates are reported in Table 3. Estimation samples restricted to balance due values between the 5th and 95th percentile. Grey dots illustrate the empirical count of observations in each \$20 balance due bin. Solid black lines illustrates the fitted model, and dashed black lines illustrates the counterfactual model if extra manipulation were not pursued in the loss domain. The vertical grey lines denote the region of excess mass estimated in Figure 2. All monetary amounts are expressed in 2016 dollars.

$R = (\text{credits}) + (\text{marginal tax rate}) \times (\text{adjustments} + \text{deductions})$.²¹ I then regress this measure on filing-year dummies and individual fixed effects, and estimate the remaining residual. High values of this residual suggest that an individual is pursuing an unusually high amount of tax reduction activity, conditional on the year and their usual behaviour. While this is still an imperfect proxy for total manipulation activities—as it misses any manipulation occurring through evaded income or through selective claiming of items relevant for income calculations²²—it provides a more complete measure of the totality of tax reductions occurring through the three channels just examined in isolation. I divide this variable into quartiles, estimate quartile-specific values of \tilde{m} , and plot these estimates in Figure 5. As is immediately visually apparent, the estimate of loss-averse tax reduction is strongly associated with this measure of unusual tax reduction activity. While \tilde{m} is estimated to be \$30.9 in the first quartile, it rises to \$85.7 in the top quartile (z of difference = 5.45, $p < 0.01$).

Analysis of this variety is additionally useful for assessing a possible alternative means of manipulating balance due: earlier tax payments. If a taxpayer anticipates that he will evaluate his balance due in a loss-averse manner on tax day, he might choose to raise his withholding levels during the year to offset this effect. This change in withholding and the hassle costs associated

21. While credits apply directly to the taxes due—and thus one dollar of credits leads to one dollar of tax reduction—itemized deductions and adjustments reduce the individual's taxable income, and thus reduce taxes by their amount multiplied by the individual's marginal tax rate.

22. For example, deductible business expenses.

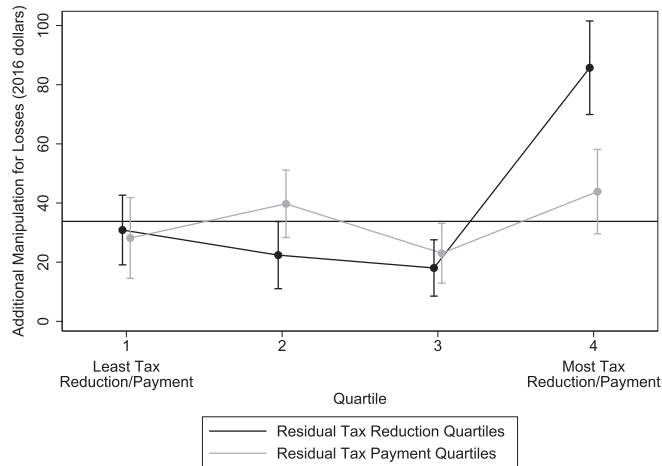


FIGURE 5

Association of manipulation measure with tax reduction and tax payment.

Notes: This figure graphically presents the estimated values of the extra manipulation pursued when facing a loss (\bar{m}), conditional on measures capturing deviations from normal manipulation and withholding activities. The 95% confidence intervals presented are inferred from block-bootstrapped standard errors, resampling by taxpayer ID and based on 5,000 simulations. For reference, the horizontal line represents the full-sample estimate of \bar{m} . All estimation samples are restricted to balance due values between the 5th and 95th percentile.

with this action can be interpreted as another type of manipulation opportunity appearing in the sequence modeled in Section 1. While behaviour of this sort could still be used to identify loss-averse evaluation of taxes, this type of manipulation is arguably of significantly less policy importance since it would affect only the timing of payment rather than the final amount paid. To test if this type of manipulation is present, I construct an analogous residualized measure to that created above. I regress the total of tax prepayments on filing-year dummies and individual fixed effects and recover the estimated residual. This provides a measure of the degree to which withholdings deviated from the taxpayer's typical behaviour. As can be seen by the grey line in Figure 5, this measure shows no association with our estimates of loss-averse manipulation. As a supplemental analysis, I directly regress residualized withholding on a dummy variable for gain/loss status. In contrast to the prediction of the loss-averse model, I find that withholding is lower for those facing a loss than for those facing a gain (loss dummy coefficient = -531.53 , clustered S.E. = 32.80 , $p < 0.01$).²³ In short, I find no evidence that supports the worry that these patterns are driven by withholding behaviour, and indeed find withholding patterns that are directly inconsistent with the use of tax prepayment as a loss-averse manipulation opportunity. In contrast, I find substantial evidence that the patterns I document are associated with the pursuit of common tax reduction activities.

23. In contrast, similar analysis on the residualized manipulation measure suggests that manipulation is higher in the loss domain, although standard errors are comparatively large (loss dummy coefficient = 22.34 , clustered S.E. = 14.55 , $p < 0.13$). This is consistent with the prediction of the loss-averse model, and aligns with previously published results suggesting positive associations between owing a tax payment and tax evasion (Clotfelter, 1983), 401k claiming (Feenberg and Skinner, 1989), and the Swedish deduction for "other expenses for earning employment income" (Engström *et al.*, 2015).

3.2. *Assessing alternative explanations for observed results*

In this section, I evaluate several robustness considerations and alternative theories of the observed behaviour, and present evidence in favour of the loss-averse account.

3.2.1. Alternative forms of reference dependence. The theory presented in Section 1 introduces reference dependence in a piecewise-linear manner, capturing the perception of a higher marginal return to manipulation when facing losses. This theory did not include two additional forms of reference dependence that could conceivably be relevant. The first alternative form is a “notch”—that is, a direct discontinuity in utility levels (as opposed to slopes) when losses turn to gains. Such a discontinuity could arise if taxpayers face a fixed psychological cost when making any positive tax payment, if taxpayers are significantly annoyed by having to write a check in the course of tax filing, or if taxpayers believe audit rates change significantly near the reference point. The second alternative form is a change in utility curvature occurring at the reference point; models of prospect theory often include the assumption of “diminishing sensitivity”, which implies that utility is concave over gains and convex over losses. As illustrated in Figure 6, both of these forms of reference dependence make predictions contrasting with the loss-averse theory and with the empirical results. These forms generate bunching in a different manner than loss aversion: rather than inducing extra motivation for manipulation across the entire loss domain, these forms operate by motivating individuals facing small losses to take steps to move just past the reference point. Thus, while loss aversion generates excess mass surrounding the reference point, a notch or diminishing sensitivity would predict excess mass on the gain side and *missing* mass on the loss side. The observed distributions in figures 2, 3, and 4 do not support these predictions. For a detailed investigation of alternative forms of reference dependence in the context of marathon running, with accompanying simulation studies supporting the intuitions discussed above, see Allen *et al.* (2017).

3.2.2. Financial constraints. As explored in Andreoni (1992), financial constraints can incentivize tax non-compliance. Tax evasion can serve as a risky substitute for a loan, implicitly trading income now for expected penalties in the future. Financial constraints generate a discontinuity in marginal incentives to take such a loan at the precise point where the borrowing constraint binds. However, a theory of financial constraints would naturally predict effects driven by low-income filers with comparatively low access to savings or credit. In contrast, the patterns attributed to loss aversion are most prevalent among high-income filers. As a more direct test of this logic, I identify tax filers in my panel whose tax returns reveal the presence of savings to draw on. A total of 41% of the taxpayers in my sample report positive taxable interest income—the reporting category for interest from checking accounts, savings accounts, and other savings instruments—on every observed return. Restricting the sample to just these filers, the estimate of loss-averse manipulation is \$30.4 (S.E. = 4.05): similar to the full-sample estimate and within its relatively narrow confidence intervals. While financial constraints do undoubtedly influence tax manipulation decisions, these results suggest that their presence has little influence on the patterns documented in this article.

3.2.3. Interaction with tax preparers. A substantial fraction of tax returns are filed by a paid tax preparer on the taxpayer’s behalf. In principle this could complicate the manner in which manipulation decisions are made. In six years of my panel, I am able to observe if the use of a paid preparer was reported. I may therefore estimate loss-averse manipulation

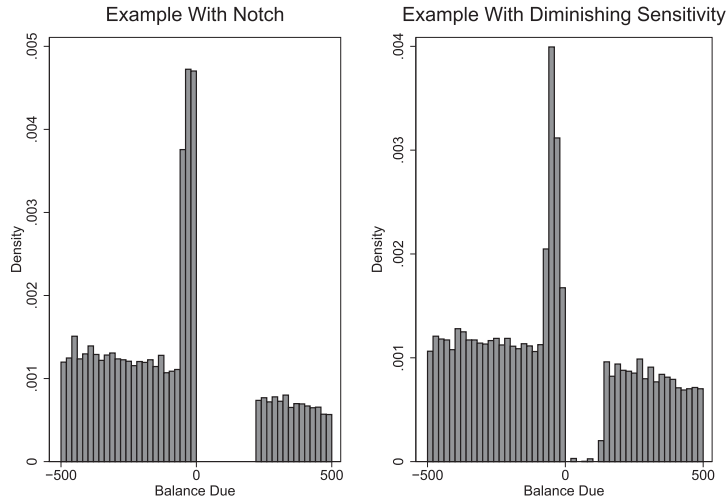


FIGURE 6

Implications of alternative forms of reference dependence.

Notes: This figure illustrates the qualitative features of distributions manipulated by individuals with alternative forms of reference dependence. I present two simulated distributions, each over 50,000 tax manipulation sequences. Pre-manipulation balance due was randomly drawn from a $N(-500, 1000)$ distribution. Each sequence contained twenty manipulation opportunities, indexed by i . Each manipulation opportunity reduces taxes by \$55 at a cost of $10 \cdot i$. In the example illustrating the implications of a notch, the taxpayer values balance due according to the utility function $U(b) = -b + 100 \cdot I(b \leq 0)$. In the example illustrating the implications of diminishing sensitivity, the taxpayer values balance due according to the utility function $\phi(x|r) = \begin{cases} 60 \cdot (x-r)^{\frac{1}{10}} & \text{if } x \geq r \\ -120 \cdot (r-x)^{\frac{1}{10}} & \text{if } x < r \end{cases}$.

conditional on this variable. These fitted distributions are plotted in Figure 7. I find that loss-averse manipulation is present in both groups but more pronounced among self-prepared returns ($\tilde{m} = 43.7$, S.E. = 9.94) than professionally prepared returns ($\tilde{m} = 22.6$, S.E. = 6.56; z of difference = 1.77, $p < 0.08$). The continued presence of loss-averse manipulation among professionally prepared returns can be rationalized by assuming that either (1) paid tax preparers are themselves loss averse, or (2) paid tax preparers believe their customers are loss averse, and incorporate their customers' utility into the avoidance and evasion strategies they pursue. Furthermore, the finding in Figure 7 that the excess mass is more tightly distributed at zero for paid preparers is consistent with the notion that paid tax preparers have greater access to continuous manipulation opportunities.²⁴ While these patterns suggest interesting interactions between loss-aversion and professional assistance, the persistence of bunching and shifting among those not utilizing a paid tax preparer alleviates the concern that these patterns are somehow unique to that principal-agent relationship.

3.2.4. Misunderstanding of the underwithholding penalty. The underwithholding penalty and the discontinuity in the tax schedule it induces can drive bunching behaviour in tax manipulation activity. However, this penalty is not imposed until substantial underwithholding

24. For example, using audited returns from 1979, Erard (1993) demonstrated that tax non-compliance is dramatically higher among individuals with CPA or lawyer-prepared returns, in contrast to self-prepared returns. Weighted results from his subsample suggest that 39.2% of self-prepared returns understate their income, with a mean level of non-compliance of \$244. In contrast, 63% of CPA or lawyer-prepared returns understate their income, with a mean level of non-compliance of \$1,786. To the extent the misrepresentation of one's income can be targeted to-the-dollar, pursuit of this type of manipulation would generate precise bunching in the manner observed.

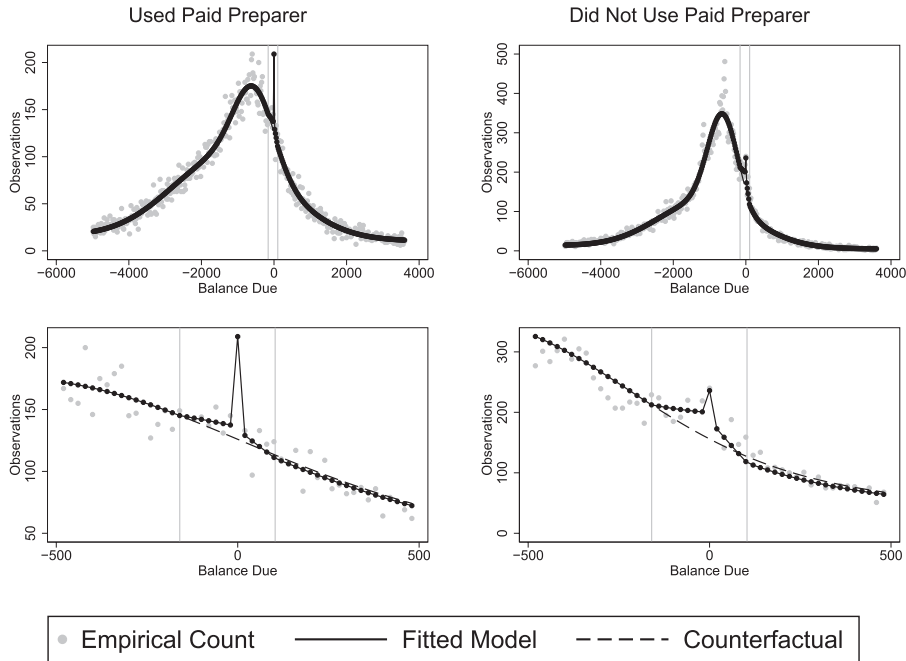


FIGURE 7

Distribution of balance due by use of tax preparer.

Notes: This figure presents fitted distributions arising from the estimation strategy described in section 3. Estimation samples restricted to balance due values between the 5th and 95th percentile. Grey dots illustrate the empirical count of observations in each \$20 balance due bin. Solid black lines illustrates the fitted model, and dashed black lines illustrates the counterfactual model if extra manipulation were not pursued in the loss domain. The vertical grey lines denote the region of excess mass estimated in Figure 2. All monetary amounts are expressed in 2016 dollars.

has occurred, exceeding a grace window bounded below by a percentage of total tax. As a result, the bunching behaviour induced by rational response to this provision would not occur at zero and cannot rationalize the observed results. Widespread misunderstandings of these withholding requirements, such as the incorrect belief that any positive balance due leads to a penalty, could potentially generate bunching and shifting patterns similar to what I have documented. Two results suggest that this is not the mechanism driving the observed results. First, the fact that these behaviours are still seen among professionally prepared returns alleviates concerns that misunderstandings of tax law are responsible. Second, due to the panel nature of this dataset, I can run this estimation exercise restricting the sample to only observations where the taxpayer has previously been observed facing a loss. In this subsample, the estimate of loss-averse manipulation remains large ($\tilde{m} = \$41.8$, S.E. = 8.74). Under the assumption that the process of reporting a loss would correct an inaccurate belief that all losses induce penalties, this result alleviates the concern that this possible misunderstanding drives my results.

4. DISCUSSION

In recent years, we have seen great interest in transporting the insights of prospect theory into mainstream empirical economics; as argued in Barberis (2013), this enterprise is bearing fruit but is still in its early stages. The results explored in this article demonstrate a setting where a key component of prospect theory—loss aversion—productively informs our understanding

of a centrally important economic field behaviour. Beyond simply highlighting a psychological mechanism in play, the nature of the observed reaction to loss framing has important implications for tax policy and behavioral economics. I discuss these implications below and suggest paths for research moving forward.

The estimates provided in this article suggest that changing the distribution of balance due can influence aggregate tax manipulation through purely psychological channels. To help assess the magnitude of this effect, note that over 150 million tax returns were filed in 2015, with 109 million claiming a refund (Internal Revenue Service, 2016). If tax filers claiming a refund were as motivated to manipulate as those facing a payment—and thus pursued \$34 of additional manipulation as my full-sample estimates suggest—3.7 billion dollars of additional tax reduction would occur. Conversely, if tax filers owing a payment were as motivated to manipulate as those facing a refund, 1.4 billion dollars of additional tax revenue would be collected. In short, since tax interactions affect orders of magnitude more individuals than exist in most demonstrations of loss aversion, loss-averse response can aggregate to amounts rarely seen in previous studies of prospect theory.

To provide a quantification of effect sizes tied to more concrete policies, we may use these estimates to consider the impact of changing withholding rules. Since early payments to the tax authority are equivalent to granting an interest-free loan, the current prevalence of overwithholding has been argued to be undesirable for taxpayers. Jones (2012) calculates that the average opportunity cost from this lost interest is \$80, and reports examples of states intentionally changing withholding policy to try to capture some portion of this interest.²⁵ Accounting for loss-averse manipulation significantly affects these comparisons. Focusing on the interpretation of my results for individuals, my full-sample estimate suggests that the excess transfer to the IRS associated with overwithholding is 42% higher than you would infer if you considered interest costs alone. Focusing on the interpretation of my results for government revenue, my full-sample estimate suggests that at least 30% of the extra revenue accrued to the government from overwithholding arises from loss-averse behavioral response.²⁶ While it has been recognized at least since Schepanski and Shearer (1995) that overwithholding is more desirable for the tax authority if tax filers are loss averse, the approach taken here provides the first estimates of the magnitude of these effects. The resulting estimates suggest that loss-averse behavioral response accounts for a significant portion of the costs or benefits to changing withholding policy.

As a more qualitative consideration for tax policy, these results suggest that gain/loss framing can assist in controlling tax morale, and can be employed to reduce evasion or improve the efficacy of tax incentives. Conceptually, it may be possible to manipulate a taxpayer's perception of what constitutes a gain or a loss—potentially through relatively cheap manipulations to phrasing or presentation.²⁷ Loss framing could be induced to increase the take-up rate of a specific tax-based incentive in targeted populations. Gain framing could be induced to reduce evasion motives among traditionally non-compliant groups, potentially in a cost-effective manner when compared to audits. These promising possibilities merit further research. For a recent review of related issues in tax morale, see Luttmer and Singhal (2014).

25. His reported estimate is \$63 measured from 2004 data. I have converted this to 2016 dollars for comparison to my own estimates.

26. I say “at least” because Jones's (2012) estimate of \$80 of interest payments is calculated using the highest of an individual's applicable credit card, CD, or savings account interest rates. The government is unlikely to achieve a rate of return equivalent to credit card interest rates, and thus they will only capture a fraction of this \$80 estimate.

27. For an attempt to influence the timely payment of UK taxes with gain/loss framing (among other behavioral interventions), see Hallsworth *et al.* (2014).

Moving beyond the implications specific to tax policy, the techniques and the results put forth in this study contribute to the recent literature utilizing bunching-based empirical strategies. Analysis of bunching is rapidly becoming a key identification strategy for understanding reference effects. Recently published papers have used such approaches to study the importance of round numbers as goals (Pope and Simonsohn, 2011), effort provision in the lab (Abeler *et al.*, 2011), price targets in mergers and acquisitions (Baker *et al.*, 2012), and the goal-setting behaviour of marathon runners (Allen *et al.*, 2017). These papers use the presence of excess mass as a qualitative test for the presence of reference-dependent thinking. My theoretical framework provides a technical contribution to this literature by illustrating how to identify policy-relevant parameters of the loss-averse model from this bunching. Approaches like this are necessary as the work of behavioral economists moves beyond demonstrating that prospect theory is qualitatively relevant to economic decision making, and towards precise statements of the quantitative impact of this psychology in the field.²⁸

In the context of the broad study of reference-dependent behaviour, results presented here inform an ongoing debate on the precise nature of the reference point. The loose specification of the gain/loss threshold has long been considered an undesirable degree of freedom in reference-dependent models. Recent research has focused on expectations-based reference dependence, which rationalizes a variety of empirical regularities and which successfully “closes the model” by endogenizing the reference point (Kőszegi and Rabin, 2006, 2007). Some empirical studies have found support for the expectations-based model (*e.g.* Crawford and Meng, 2011; Ericson and Fuster, 2011), while others have not (Heffetz and List, 2013). In the tax setting considered here, a simple model of the reference point, more in line with Kahneman and Tversky’s original presentation, provides significant insights into the observed behaviour—insights which would not be explained by a rational-expectations-based model. However, while this article has focused on evidence supporting a reference point of zero, evidence consistent with alternative reference points is also present in these data; indeed, diffuse bunching is observed around last years’ balance due (a potential status quo) and the person-specific average balance due (an expectations-based reference point in line with Crawford and Meng (2011)).²⁹ While this suggests that other reference points might be in play, cleanly interpreting bunching along these dimensions as evidence of loss aversion is difficult since similar behaviour over time is to be expected. To the extent that I have focused on one of potentially many reference points, my estimates of the aggregate impact of loss aversion are likely conservative. As we continue to export the insights of prospect theory out of the lab and into policy, approaches accommodating heterogeneous and individual-specific reference points will likely prove essential.

A. APPENDIX

A.1. Identification of the loss aversion parameter

In this section, I will demonstrate the inability to identify the loss aversion parameter λ in the theoretical framework of Section 1.

Proposition 1. *Consider an optimal manipulation strategy ($m^*(b_{PM}|r)$) resulting from an individual with loss aversion parameter $\lambda^1 > 1$ making manipulation decisions from the sequence $\{(m_i, c_i^1)\}_{i \in \mathcal{D}}$. For any alternative $\lambda^2 > 1$, we may*

28. For a recent exploration of the predictions of reference-dependent job search—with corresponding structural estimation from bunching behaviour in the context of a hazard model—see DellaVigna *et al.* (2017).

29. Furthermore, Copeland and Cuccia (2002) and Kirchler and Maciejovsky (2001) find evidence of alternative reference points in experimental settings.

define an alternative formulation of the sequence of costs, denoted $\{(m_i, c_i^2)\}_{i \in \mathcal{D}}$, that generates the same optimal manipulation strategy.

Proof. Consider a sequence of manipulation opportunities, denoted $\{(m_i, c_i^1)\}_{i \in \mathcal{D}}$. I will denote the pattern of optimal manipulation behaviour resulting from this sequence and loss aversion parameter $\lambda^1 > 1$ as $m^*(b_{PM}|r, \{(m_i, c_i^1)\}_{i \in \mathcal{D}}, \lambda^1)$. For an arbitrary alternative $\lambda^2 > 1$, I proceed by demonstrating how to construct an alternative sequence, denoted $\{(m_i, c_i^2)\}_{i \in \mathcal{D}}$ for which $m^*(b_{PM}|r, \{(m_i, c_i^1)\}_{i \in \mathcal{D}}, \lambda^1) = m^*(b_{PM}|r, \{(m_i, c_i^2)\}_{i \in \mathcal{D}}, \lambda^2)$. This new sequence contains the same number of elements as the original. Furthermore, the sequence of manipulation amounts m_i remains the same. The sole differences across these two sequences are the assumed costs of manipulation, represented by c_i^1 and c_i^2 , respectively. Define c_i^2 as follows:

$$c_i^2 = \begin{cases} c_i^1 & \text{if } i \leq L \\ \frac{\lambda^2 - 1}{\lambda^1 - 1} (c_i^1 - m_i) + m_i & \text{if } L < i \leq H \\ \frac{\lambda^2}{\lambda^1} c_i^1 & \text{if } i > H \end{cases}$$

To begin, note that this alternative sequence preserves the same ordering of consideration as the original: $\frac{m_i}{c_i^1} < \frac{m_j}{c_j^1}$ implies that $\frac{m_i}{c_i^2} < \frac{m_j}{c_j^2}$.

Next, I demonstrate that sequence 2 preserves the same partitioning by L and H as sequence 1.

Manipulation decisions indexed with $i \leq L$ were always pursued under the first sequential manipulation problem. By the definition of L , these decisions satisfy $V^1(m_i|b, r) \geq m_i > c_i^1$. By setting $c^2 = c^1$ in this regime, we may similarly establish that $V^2(m_i|b, r) \geq m_i > c_i^2$. Thus, decisions indexed $i \leq L$ are also always pursued under the second sequential manipulation problem.

Manipulation decisions indexed with $i > H$ were never pursued under the first sequential manipulation problem. By the definition of H , these decisions satisfy $V^1(m_i|b, r) \leq \lambda^1 m_i < c_i^1$. By setting $c_i^2 = \frac{\lambda^2}{\lambda^1} c_i^1$ in this regime, we may similarly establish that $V^2(m_i|b, r) \leq \lambda^2 m_i < c_i^2$. Thus, decisions indexed $i > H$ are also never pursued under the second sequential manipulation problem.

Manipulation decisions for which $L < i \leq H$ formed the marginal set under first sequential manipulation problem. By the definitions of L and H , these decisions satisfy $\frac{1}{\lambda^1} < \frac{m_i}{c_i^1} \leq 1$. By construction, it must similarly hold that $\frac{1}{\lambda^2} < \frac{m_i}{c_i^2} \leq 1$. To establish the first inequality, notice that

$$\begin{aligned} \frac{1}{\lambda^1} &< \frac{m_i}{c_i^1} && \Leftrightarrow \\ \lambda^1 - 1 &> \frac{c_i^1}{m_i} - 1 && \Leftrightarrow \\ 1 &> \left(\frac{c_i^1}{m_i} - 1\right) \frac{1}{\lambda^1 - 1} && \Leftrightarrow \\ \lambda^2 - 1 &> \left(\frac{c_i^1}{m_i} - 1\right) \frac{\lambda^2 - 1}{\lambda^1 - 1} && \Leftrightarrow \\ \lambda^2 &> \frac{(c_i^1 - m_i) \frac{\lambda^2 - 1}{\lambda^1 - 1} + m_i}{m_i} = \frac{c_i^2}{m_i} && \Leftrightarrow \\ \frac{1}{\lambda^2} &< \frac{m_i}{c_i^2}. \end{aligned}$$

To establish the second inequality, notice that $\frac{c_i^2}{m_i} = \frac{\lambda^2 - 1}{\lambda^1 - 1} \left(\frac{c_i^1}{m_i} - 1\right) + 1 \geq 1$, and thus $\frac{m_i}{c_i^2} \leq 1$. It thus follows that the marginal set remains the same under the second sequential manipulation problem.

Having established that the set of marginal decisions are the same under the first and second sequential manipulation problems, it now suffices to show that the conditions under which each decision in the marginal set is pursued are the same. Recall that, for manipulation opportunities in the marginal set, each opportunity will only be pursued if the pre-manipulation balance due represents a sufficiently large loss. As established in Section 1, this results in an optimal manipulation function that is characterized by a sequence of thresholds, each denoted T_j^1 (see equation (3)). Each threshold

determines the minimal value of pre-manipulation balance due that would result in manipulation opportunity j of the marginal set being pursued. Opportunity j will be pursued if and only if $V(m_{L+j}|b_{pm} + \sum_{i=1}^{L+j-1} m_i, r) > c_{L+j}^1$. It can be quickly verified that this condition will be satisfied when $b_{PM} > T_j^1$, with T_j^1 is defined according to the formula

$$T_j^1 = \frac{c_{L+j}^1 - m_{L+j}}{\lambda^1 - 1} - \sum_{i=1}^{L+j-1} m_i.$$

Applying the definition of c_i^2 , it follows that, for all j ,

$$\begin{aligned} T_j^2 &= \frac{c_{L+j}^2 - m_{L+j}}{\lambda^2 - 1} - \sum_{i=1}^{L+j-1} m_i = \frac{\left(\frac{\lambda^2 - 1}{\lambda^1 - 1}(c_{L+j}^1 - m_{L+j}) + m_{L+j}\right) - m_{L+j}}{\lambda^2 - 1} - \sum_{i=1}^{L+j-1} m_i \\ &= \frac{c_{L+j}^1 - m_{L+j}}{\lambda^1 - 1} - \sum_{i=1}^{L+j-1} m_i = T_j^1. \end{aligned}$$

This establishes that the formal construction of optimal manipulation, expressed in equation (3), is identical: that is, $m^*(b_{PM}|r, \{(m_i, c_i^1)\}_{i \in \mathcal{D}}, \lambda^1) = m^*(b_{PM}|r, \{(m_i, c_i^2)\}_{i \in \mathcal{D}}, \lambda^2)$. \parallel

This result implies that the loss aversion parameter (λ) cannot be separately identified from the magnitude of costs of manipulation (embedded in the sequence c_i) under the data-generating process I study.

A.2. Additional robustness checks

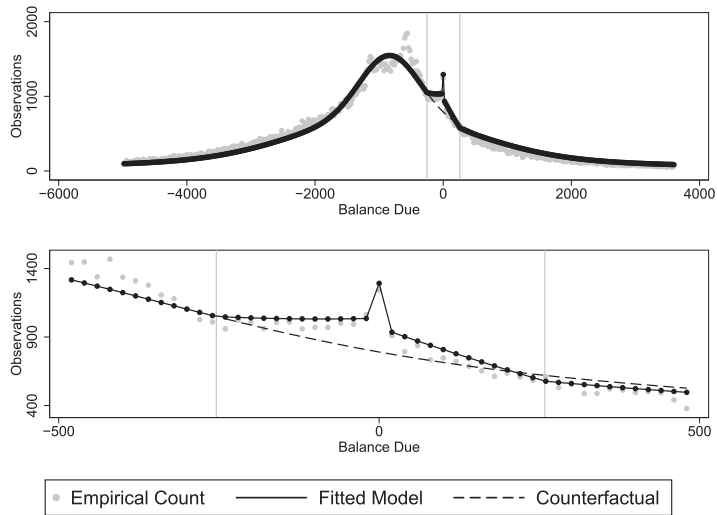


FIGURE A.1

Distribution of balance due (symmetric counterfactual).

Notes: This figure presents the fitted distribution estimated in column 3 of Table A.1, which applies the estimation strategy described in Section 3 but assumes a symmetric counterfactual distribution. Estimation sample restricted to balance due values between the 5th and 95th percentile. The grey dots illustrate the empirical count of observations in each \$20 balance due bin. The solid black line illustrates the fitted model, and the dashed black line illustrates the counterfactual model if extra manipulation were not pursued in the loss domain. The vertical grey lines denote the estimated region of excess mass. All monetary amounts are expressed in 2016 dollars.

TABLE A.1
Robustness to symmetry assumptions

	(1)	(2)	(3)
Extra manip. for loss (\bar{m})	33.8 (4.68)	37.1 (4.61)	90.7 (81.45)
Width of bunching region (gain side: B_1)	159.7 (27.00)	153.3 (24.51)	254.0 (276.35)
Width of bunching region (loss side: B_2)	103.2 (36.20)	153.3 (24.51)	258.6 (69.67)
Symmetric bunching region	No	Yes	No
Symmetry constraint on counterfactual	No	No	Yes
N	206,188	206,188	206,188

Notes: This table presents parameter estimates of the extra manipulation pursued when facing a loss (\bar{m}) based on the estimation strategy described in Section 3. The first column presents the primary estimates presented in the article. The second column reproduces these estimates, applying the assumption of a symmetric bunching region (*i.e.* $B_1 = B_2$). The third column reproduces the estimates under the assumption that the counterfactual distribution is symmetric. In the context of a three-component mixture model, symmetry is imposed by assuming a common mean across the three components. While the imposition of a symmetric bunching region has little quantitative effect on the estimates, the imposition of a symmetric counterfactual distribution leads to a substantially higher estimate of loss-averse manipulation. As can be seen in the plot of the fitted distribution from column 3 (Figure A.1), the imposition of symmetry results in a visibly worse fit, and results in skew of the underlying distribution being misattributed to loss-averse manipulation. Block-bootstrapped standard errors, resampling by taxpayer ID and based on 5,000 simulations, are presented in parentheses. All monetary amounts are expressed in 2016 dollars.

TABLE A.2
Robustness to bin size and tail trimming thresholds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Extra manip. for loss (\bar{m})	33.8 (4.68)	35.0 (4.60)	40.7 (5.34)	36.8 (5.31)	35.2 (4.30)	36.3 (4.64)	36.4 (4.23)
Width of bunching region (gain side: B_1)	159.7 (27.00)	174.0 (27.33)	180.0 (25.50)	173.2 (30.11)	180.0 (30.88)	197.5 (33.02)	200.0 (34.35)
Width of bunching region (loss side: B_2)	103.2 (36.20)	104.2 (35.64)	144.2 (36.36)	106.6 (35.65)	113.8 (28.21)	134.1 (37.64)	126.5 (31.21)
Trimming	5/95	1/99	10/90	5/95	5/95	5/95	5/95
Bin size	20	20	20	10	30	40	50
N	206,188	224,525	183,293	206,190	206,227	206,187	206,225

Notes: This table presents parameter estimates of the extra manipulation pursued when facing a loss (\bar{m}) based on the estimation strategy described in Section 3. The first column presents the primary estimates presented in the article. Columns 2 and 3 reproduce these results while varying the boundaries of the estimation sample to the 1st/99th or the 10th/90th percentiles of balance due. Columns 4–7 reproduce these results while varying the width of bins used in the frequency histogram. Block-bootstrapped standard errors, resampling by taxpayer ID and based on 5,000 simulations, are presented in parentheses. All monetary amounts are expressed in 2016 dollars.

Acknowledgments. An earlier draft of this article circulated as “Loss Aversion Motivates Tax Sheltering: Evidence from U.S. Tax Returns”. For comments and suggestions that improved the project, I am grateful to John Bakija, Dan Benjamin, Jim Berry, Greg Besharov, Aaron Bodoh-Creed, Steve Coate, Stefano DellaVigna, Ori Heffetz, Ben Ho, David Laibson, Rosella Levaggi, Francesca Molinari, Ted O’Donoghue, Daniel Reck, Charlie Sprenger, Ken Whelan, seminar audiences at Boston University SOM, Cornell University, Dartmouth College, Haas School of Business, Harvard Business School, NBER, University of Michigan, and Wharton, as well as conference participants at the AEA Annual Meetings, the NTA Annual Conference on Taxation, the Southern Economics Association Annual Meetings, the Stanford Institute for Theoretical Economics, and the CEBID Conference on Taxation, Social Norms, and Compliance. I thank the Cornell Institute for the Social Sciences, the National Bureau of Economic Research, and the National Institute on Aging (grant T32-AG00186) for generous research support, and Anthony Hawkins for research assistance. The views expressed in this article are those of the author, and do not necessarily represent the views of any other individual or organization.

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