The Costs of Corporate Tax Complexity[†]

By Eric Zwick*

Does tax code complexity alter corporate behavior? We investigate this question by studying the decision to claim refunds for tax losses. In a sample of 1.2 million observations from the population of corporate tax returns, only 37 percent of eligible firms claim their refund. A simple cost-benefit analysis of the tax loss choice cannot explain low take-up, motivating an exploration of how complexity alters this calculation. Research designs exploiting tax preparer switches, deaths, and relocations show that sophisticated preparers increase claim rates for small firms. Imperfect take-up has implications for measuring marginal tax rates and for the design of fiscal policy. (JEL D22, D61, E62, H25, K34)

In recent decades, corporate tax provisions, subsidies, credits, and loopholes have proliferated in the United States, prompting calls for reform to simplify the tax code.¹ Economists, policymakers, taxpayers, and even the tax authority have voiced concern that tax code complexity distorts behavior and undermines efficiency, yet there have been few attempts to evalute these concerns empirically. In addition, fiscal stimulus often operates through the tax code, but policy design rarely considers whether complexity affects policy transmission. Does tax code complexity alter corporate behavior?

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¹Recent reports from both the Bush and Obama administrations made recommendations to reduce taxpayer burdens and improve tax administration by simplifying the tax code. See the "Comprehensive Strategy for Reducing the Tax Gap" (US Treasury 2006) and "The Report on Tax Reform Options: Simplification, Compliance, and Corporate Taxation" (President's Economic Recovery Advisory Board 2010). Both Congressman Paul Ryan's "A Better Way" and Senator Elizabeth Warren's "Leveling the Playing Field" policy platforms advocate reducing tax code complexity. While the 2017 US tax reform did simplify the individual tax code by expanding the standard deduction, most observers argue the reform did not reduce the complexity of the corporate code.

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To investigate this question, this paper focuses on the decision by corporate taxpayers to claim refunds for net operating losses. The treatment of losses is a permanent feature of the tax code that affects most firms, enabling a representative analysis in a setting where policy awareness is stable over time. Tax refunds for losses serve as an important automatic fiscal stabilizer: more firms report losses during recessions and aggregate eligible refunds thereby increase (Altshuler et al. 2009). Policymakers often expand refund generosity in bad times with the goal of injecting cash into firms to promote economic activity. Between 1998 and 2011, the loss offset provision made \$357 billion in refunds available, of which \$124 billion was available during the Great Recession.² Thus, whether firms claim eligible refunds is a question of policy and macroeconomic relevance.³

The refund decision offers an attractive setting for studying the role of complexity in corporate behavior: a binary choice for which we can measure the payoffs of each option. Under corporate tax rules, a firm reporting a loss can choose between a *carryback*, in which the firm applies its loss against past taxable income and claims an immediate refund, and a *carryforward*, in which the firm reserves its loss to deduct against future income. The carryback is usually more valuable both because of discounting and because the firm risks losing its stock of carryforwards if it fails. Prior research has studied the impact of these rules on marginal tax rates, typically assuming that firms elect the carryback when available.⁴ This assumption delivers a strong null hypothesis that permits a test of costless optimizing behavior.

We explore the take-up of carryback refunds using new data drawn from the population of US corporate tax returns filed between 1998 and 2011. Our data consist of more than 1.2 million firm-year observations that are eligible for tax refunds. In addition to coverage, the dataset improves on past samples by enabling us to measure both eligible and actual refunds to link firms to the tax preparers they hire to help them file their returns and to explore interactions between the claiming decision and other provisions of the tax code.

The first part of the paper documents a key fact about claiming behavior: take-up is surprisingly low. Only 37 percent of eligible firms claim their refund. Low take-up holds even when we restrict our attention to potential refunds that are large relative to a firm's operating cash flows. Just half of the potential aggregate refund amount was claimed and distributed to eligible firms. Thus, the low take-up rate substantially limits the impact of this policy as fiscal stimulus.

We conduct a net present value (NPV) analysis of the carryback-carryforward trade-off to show that traditional costs and benefits, such as the direct cost of filing or the value of waiting, cannot explain the low take-up rate. For early years in our sample, we compute the ex post NPV of each option using a firm's realized path of

²This figure includes eligible refunds for all C corporations. We restrict our analysis to this corporate form because the treatment of losses takes place at the entity level. Losses for pass-through business entities, such as S corporations and partnerships, are reported on the returns of their owners.

³The 2017 US tax reform affected carryback and carryforward incentives in several ways, including by eliminating the carryback option, imposing an 80 percent-of-income limitation on carryforwards, and repealing the corporate AMT. We note that this reform does not preclude the possibility that policymakers will consider carrybacks as a potential stimulus during recessions, and that many countries still allow carrybacks.

⁴See, for example, Auerbach and Poterba (1987), Altshuler and Auerbach (1990), and Graham (1996a, b).

taxable income over time. Most firms that fail to claim do not benefit from waiting, and many nonclaimers forgo more than 30 percent of the refund's value. Our calculations assume conservative discount rates ranging from 3 to 9 percent. If firms face financial frictions that generate higher discount rates, the net present value difference in favor of the carryback over the carryforward would be even greater.⁵

Our sampling frame is broad and representative of the full firm size distribution, which allows us to study the role of heterogeneous forces affecting small versus large firms. The median firm in our sample is small, with revenues of \$1.5 million and with payrolls less than \$500,000. The largest firms in our sample are multinational companies with billions of dollars of sales and thousands of employees. We find that small firms fail to claim refunds at higher rates than large firms and are more likely to forgo refunds with positive NPVs. However, many large firms leave substantial refunds unclaimed, and the propensity to claim is nonmonotonic in firm size, with the largest firms claiming less often than firms in the ninetieth percentile. These facts contradict a simple, fixed transaction cost explanation, which would predict claim rates increasing in firm size.

Motivated by these facts, the second part of the paper investigates the costs of complexity in driving average take-up behavior and patterns of take-up across the firm size distribution. We define "complexity" broadly to reflect two forces that arise from a long and complicated tax code. First, because claiming a refund requires significant familiarity with the tax code, taxpayers (or their paid preparers) may be either confused about or unaware of the refund choice. Second, because the tax code includes many independently legislated provisions, overlapping and offsetting incentives in the code may undermine policy goals by altering the cost-benefit calculation for taxpayers.

Our data permit a rich analysis of small and medium-sized firms, which have received less attention in past work relative to public companies. It is likely that complexity distorts behavior in different ways for small firms than for large firms. Small firms may not know how to file for the carryback refund, or even that this option is available. Most small firms rely on paid preparers to help evaluate tax code decisions. When monitoring is imperfect, agency problems between managers and preparers can promulgate poor decisions, especially if there is dispersion in preparer quality. We evaluate this hypothesis by asking whether preparer characteristics can account for the variation in corporate claiming behavior. Our research design uses firms that switch tax preparers to identify the effect of preparers on client behavior, while controlling for time-invariant, firm-level unobservable factors.⁶

The main finding is that markers for preparer sophistication consistently predict take-up of the carryback refund. Preparers are more likely to claim the carryback refund when they are certified public accountants or attorneys, have higher earnings, do not work for themselves, are older, and have bigger client bases. These effects

⁵Zwick and Mahon (2017) find that firms only respond to investment tax incentives when they have an immediate impact on cash flows, suggesting that firms face financial frictions and evaluate tax benefits using high effective discount rates.

⁶The approach is analogous to that used to explore whether managerial "style" affects corporate decisions (Bertrand and Schoar 2003; Kaplan, Klebanov, and Sorensen 2012), whether teachers affect student test scores (Jackson and Bruegmann 2009), and whether firm effects contribute to wage inequality (Abowd, Kramarz, and Margolis 1999; Card, Heining, and Kline 2013).

are quantitatively significant when compared to the mean take-up rate of 37 percent. Relative to preparers without a professional license, certified public accountants are 6.8 percentage points more likely to claim the carryback refund for their clients. Moving from the tenth to the ninetieth percentile in the size of a preparer's other clients increases take-up by 6.4 percentage points. Consistent with an interpretation that emphasizes preparer sophistication, preparer effects do not matter for the largest firms, who typically hire the most sophisticated preparers or build in-house tax departments.

The research design relies on the identifying assumption that changes in preparers are uncorrelated with unobservable changes in client determinants of take-up. Our estimates will be biased if hiring a more sophisticated manager leads to hiring a more sophisticated preparer and more sophisticated managers are more likely to claim refunds. We address this threat in two ways. First, we confirm the absence of differential trends in claiming rates prior to a preparer switch. Second, we validate our estimates in a sample of events when the prior preparer either dies or relocates, in which case it is more plausible that, around the event, client unobservables do not change. We find similar estimates as in our original design, indicating that selection bias does not confound our results.

Large firms are likely to face other costs arising from the complexity of the tax code and how it is administered. We present suggestive evidence that interactions between the carryback and other tax code provisions—such as the corporate alternative minimum tax (AMT) and other tax credits—alter the cost-benefit calculation in favor of the carryforward. We find that AMT payers are considerably less likely to claim a refund (20 percentage points among the largest firms). In contrast, among firms that claim other tax credits, we see consistently *higher* rates of carryback claims. We interpret this result as suggesting some complementarity in claiming complicated credits and claiming the carryback refund. Last, anecdotes from public company financial statements suggest the audit compliance costs of claiming a refund may outweigh the benefits of immediate refunds for many firms.⁷

I. Related Literature

This paper contributes to the literature on optimization frictions and behavioral responses to tax and public policy, which has mostly focused on settings where imperfect information or search costs weaken individual policy responses.⁸ These papers show that individuals under-respond to nonsalient taxes and often fail to take up social welfare programs. Our results show that the tax code's complexity translates into suboptimal behavior and potentially significant costs for firms as well.

⁷Online Appendix C presents the analysis of large firm take-up, summarized in Section VD. We leave a full treatment of this behavior to future work.

⁸Key empirical studies on tax salience include Chetty, Looney, and Kroft (2009); Finkelstein (2009); Chetty, Friedman, and Saez (2013); Goldin and Homonoff (2013); Bhargava and Manoli (2015); and Benzarti (2017). Abeler and Jäger (2015) use a lab experiment to show payoff schedule complexity directly interferes with optimal effort choices. The literature on public program take-up surveyed by Moffit (2003) and Currie (2006) emphasizes that low participation rates are due to filing requirements and poor information. See also Daponte, Sanders, and Taylor (1999); Currie et al. (2001); Bitler, Currie, and Scholz (2003); Heckman and Smith (2004); Aizer (2007); Hoopes, Reck, and Slemrod (2015); and the references therein.

An implication is that the classic focus on marginal tax rates may neglect important factors that mediate how firms respond to taxes.

Cooper and Knittel (2006) use similar data to ours to show that a significant portion of net operating losses are not used for carrybacks or claimed in the future as carryforwards. However, they do not explore whether firms maximize the value of net operating losses, implicitly assuming that firms claim refunds as soon as possible. Moreover, a large body of work uses simulated marginal tax rates, following Shevlin (1990) and Graham (1996b), to understand how firms make decisions in light of taxes. A key assumption in calculating these marginal tax rates is that firms use carrybacks before carryforwards whenever possible. Much of the variation in simulated marginal tax rates at the firm level depends on this neoclassical assumption, which we test and reject. Our findings on take-up apply both to large firms and especially to small and medium-sized firms.

From the perspective of fiscal policy, along with Kitchen and Knittel (2011) who document imperfect take-up of accelerated depreciation incentives, our results suggest that complexity can undermine the design of tax-based fiscal stimulus. These forces operate even though the policy setting is familiar and those targeted are relatively sophisticated. That many large firms also fail to claim tax refunds suggests this concern likely has aggregate implications. We show complexity alters corporate tax decisions in different ways for large versus small firms, which complements findings in Zwick and Mahon (2017) that heterogeneity within the population of firms matters for understanding tax policy responses.

The paper also adds to a growing literature on the role of human capital in firm decision-making. These studies have documented that firm investment, leverage, and effective tax rates depend on managerial style.⁹ We apply a novel research design using quasi-experimental tax preparer switches to show that, in addition to internal managers, external consultants significantly affect corporate behavior. Our results support the idea in Romer (2006) that competition may not rid the market of suboptimal decision-making among firms and the experts they hire.

II. Policy Background

Consider a firm that reports a tax loss. The corporate tax code allows the firm to apply losses in one year to offset profits in other years and thus reduce its average tax burden. The firm can choose either to carry the loss back against past taxable income or to carry the loss forward into the future. In tax code terminology, the option is between a *carryback* and a *carryforward*.

A statutory window limits the application of loss deductions to past and future tax years. Online Appendix Table A1 summarizes the statutory window for carrybacks

⁹Bertrand and Schoar (2003) study the role of managers in corporate decision making. Bloom and Van Reenen (2007) and Kaplan, Klebanov, and Sorensen (2012) document strong correlations between management practices and firm performance measures. Dyreng, Hanlon, and Maydew (2010) and Armstrong, Blouin, and Larcker (2012) show that managers influence corporate effective tax rates. Klassen, Lisowsky, and Mescall (2016) find a cross-sectional relationship between the aggressiveness of corporate tax positions and whether a firm's financial auditor prepares the tax return. Graham et al. (2017) find that many CFOs use theoretically incorrect tax rates when making decisions and that this behavior is correlated with behavioral biases and managers' education.

		Event time relative to loss year				
	-2	-1	0	1	2	3
Taxable income before loss deduction	50	100	-100	0	100	100
Panel A. Carryback election Loss deduction Taxable income after loss deduction NPV of carryback election	$-50 \\ 0$	$-50 \\ 50$	$^{+100}_{0}_{35}$	0 0	0 100	0 100
Panel B. Carryforward election Loss deduction Taxable income after loss deduction NPV of carryforward election	0 50	0 100	$^{+100}_{0}$	0 0	-100 0 30.6	0 100

TABLE 1—ILLUSTRATIVE COMPARISON OF CARRYBACK AND CARRYFORWARD DECISIONS

Notes: This table illustrates the application of carryback and carryforward deductions for a firm that reports a tax loss of \$100 at time t = 0. Panel A assumes that the firm makes the carryback election and panel B assumes that the firm makes the carryforward election. The illustration also assumes that the firm pays a tax rate of $\tau = 0.35$ and has a discount rate of r = 0.07. Under the carryback election in panel A, the hypothetical firm applies its loss deduction against its past taxable income. It starts with the earliest eligible tax year (t = -2) and then proceeds to the next tax year (t = -1). Under the carryforward election in panel B, the hypothetical firm applies its loss deduction against its post taxable income. It starts with the earliest eligible tax year (t = 2). Even though this hypothetical firm always pays the same tax rate, the net present value of these two elections differ because they realize the tax benefits at different times. The carryback election realizes the tax benefits until time t = 0 as a tax refund. In contrast, the carryforward election has a higher net present value than the carryforward election. In this example, the carryback election has a higher net present value than the carryforward election.

Source: Author's calculations

and carryforwards in the United States tax code between 1998 and 2011. The carryforward window was twenty years throughout this time. The carryback window was mostly two years, except when Congress twice lengthened it to five years in response to recessions. These policy changes enhance the automatic stabilizer feature of the carryback provision, which generates more refunds in bad times when corporate losses are common.

The size of the refund generated by the carryback election depends on how much the firm has paid in past taxes. When a firm claims a carryback, it must fully apply the loss to all eligible past income. When the current loss exceeds eligible past income, a carryback generates both a refund for past taxes paid and a potential carryforward deduction equal to the losses in excess of past income. Loss firms without past income in the statutory window are ineligible for a carryback.

Table 1 uses a simple, numerical example to clarify the difference between the carryback and carryforward choices for a firm with a loss of \$100 at t = 0. In each case, the loss generates deductions that the firm applies to offset taxable income in other years. If choosing the carryback, the firm first deducts its loss against taxable income at t = -2 and then deducts the remaining loss against taxable income at t = -1. Assuming a tax rate of 35 percent, the net present value of the carryback election equals $$100 \times \tau$, or \$35.

If choosing the carryforward, the firm adds the loss to its stock of carryforwards and waits to deduct the loss. In the example, the firm does not have taxable income to offset at t = 1 but can deduct all of its loss at t = 2. The undiscounted value of this choice is the same as for the carryback. However, the deduction comes two years later. Continuing to assume a tax rate of 35 percent and applying a 7 percent discount rate, the net present value of the carryforward election equals $100 \times \tau/(1+r)^2$, or \$30.6. In this example, the carryback has a higher value because the tax rate is constant and the firm discounts future tax savings.

In theory, the economic consequences for the firm derive from differences in the tax benefit's timing. Under the carryback, firms immediately receive a refund for the taxes they paid in the past. Under the carryforward, firms defer the tax benefit until the future. The carryforward can be better if the firm expects to face a higher marginal tax rate in the future. For example, the corporate tax rate schedule is progressive for very low levels of income, so claiming a refund against this small amount might generate less savings than carrying the loss forward. Below, we show that this consideration is second order. Thus, in the traditional view of the tax loss choice, the carryback is typically more valuable for the simple reason that the firm values money now more than money later.

The traditional view, however, neglects the administrative differences involved in the tax loss choice. Claiming a carryforward is relatively straightforward. The firm must keep a record of its carryforward stock from past losses and then take a net operating loss deduction on its future tax return. The deduction is taken on the front page of the tax return after deductions for current business expenses.

To claim a carryback, the firm must file a special form documenting how it computed its refund. The form details how the loss deduction is applied to past tax returns to generate a tax refund.¹⁰ This calculation essentially requires the firm to redo its past tax returns. The more complicated a firm's tax return is, the more likely this process is to trigger additional computations or offset past tax credits. Below, we estimate that the additional cost for claiming a carryback ranges from roughly \$40 to \$3,000 for most small and medium-sized firms.

Upon approving the firm's claim, the tax authority issues a refund equal to the amount of past overpaid taxes after accounting for the loss deduction. While the authority is not permitted to use the carryback claim to reopen a past tax return for other reasons, the authority may challenge the claim or seek adjustments. Thus, beyond the additional work required to file the carryback, the carryback is a more complex choice, as it entails interactions with prior tax planning decisions and possibly more scrutiny from the tax authority. This complexity may interfere with the firm's ability and desire to claim a refund.

Several studies consider how dynamic loss offsets alter effective tax rates and corporate behavior. Beginning with Cordes and Sheffrin (1983) and Auerbach and Poterba (1987), studies have attempted to quantify the effect of tax asymmetries

¹⁰ A firm claims the carryback by filing either Form 1139 or Form 1120X. To remain eligible for the carryback, the firm must file within three years of the due date (plus extensions) of the tax return where it reports the loss. Alternatively, when filing its income tax return, the firm can elect to irrevocably forgo the carryback and fully carry forward the loss. This election is made by checking a box on the income tax return. All loss deductions against past and future taxable income are computed in nominal terms.

on marginal tax rates, taking into account both carryforwards and carrybacks.¹¹ Cummins, Hassett, and Hubbard (1995) and Edgerton (2010) study the role of net operating loss carrybacks in mediating how investment responds to tax incentives. Dobridge (2016) and Bethmann, Jacob, and Müller (2018) use policy variation to study the effect of net operating loss carrybacks on corporate investment, employment, and financial decisions. Data limitations have prevented these studies from testing the assumption that firms claim carrybacks when eligible.

III. Data and Measurement

A. Business Tax Data

We use deidentified, administrative IRS databases to study the tax loss choice and what factors influence a firm's decision to claim a carryback refund when eligible.¹² These databases collect information for the population of corporations in the United States, approximately 5.9 million firms per year between 1998 and 2011. We rely on two main files: (i) a tax return file that records line items from corporate income tax returns, and (ii) a transactions file that records debits and credits to individual tax accounts. We draw corporate characteristics from the tax return file and claimed refunds and tax adjustments from the transactions file. Characteristics for individual tax preparers come from a combination of individual tax returns and information returns for labor income reported on Forms W-2 and 1099-MISC. The IRS uses these databases to administer the corporate tax and to produce aggregate statistics used by other government agencies in policy analysis, revenue estimation, and economic measurement.

We limit our study to C corporations because they are taxed at the firm level and retain the decision over claiming the tax refund for losses. We exclude firms with mean sales and mean payroll over all active years between 1996 and 2011 of below \$100,000 because they may not represent operating firms (Kitchen and Knittel 2011). To focus on firms with a meaningful carryback option, our main analysis sample includes firm-year observations that are eligible for a carryback refund of at least \$1,000 (see the next section for details on carryback calculation). Our sampling frame is broader than in other recent papers working with administrative firm data in the United States, which allows us to consider the role of heterogeneous forces affecting small versus large firms.¹³ We carefully partition the data to account for the skewness of the firm size distribution present in our sample.

Panel A of Table 2 reports summary statistics for the sample of carryback eligible corporations, which consists of 1,244,729 firm-year observations for 612,070 distinct firms. Throughout the paper, we report figures in 2013 dollar values. The

¹¹ Altshuler and Auerbach (1990) extend Auerbach and Poterba (1987) to model tax credit interactions. Graham (1996a) develops a simulation methodology to derive the appropriate effective tax rates from financial accounting data. Plesko (2003) and Graham and Mills (2008) compare book-simulated tax rates to tax rates derived from tax returns.

 $^{^{12}}$ Zwick (2020) contains disclosable code and instructions for replication for researchers with access to these data.

¹³ Yagan (2015) focuses on corporations with between \$1 million and \$1 billion in assets, and Zwick and Mahon (2017) focus on corporations with greater than \$100,000 in average investment during years of positive investment.

	Mean	P10	P50	P90
Panel A. Carryback eligible corporations Firm variables				
Revenue (\$1M) Assets (\$1M)	42.189 91.631	0.307 0.048	1.485 0.489	12.442 6.394
Payroll (\$1M) EBITDA (\$1M) EBITDA/revenue	5.336 2.020 -0.101	$0.103 \\ -0.118 \\ -0.092$	0.469 0.079 0.046	3.356 0.603 0.296
Refund variables Take-up of carryback refund Eligible refund (\$1K)	0.3742 286.490	1.463	5.696	70.670
Eligible refund/revenue	0.0415	0.0008	0.0042	0.0281
Has matching tax return Labor income (\$1K) Mean client revenue (\$1M) Number of corporate clients	0.7107 127.824 9.676 51.55	5.080 0.463 8.00	99.450 1.339 37.99	269.583 7.323 103.26
Tax firm variables				
Has matching tax return Revenue (\$1M) Firm is sole proprietorship	0.7673 132.119 0.1637	0.136	0.785	10.741
Mean client revenue (\$1M) Number of corporate clients	7.738 498.35	0.538 21.51	1.577 98.49	7.031 539.88
Panel B. Sample with preparer switches Firm variables				
Revenue (\$1M) Assets (\$1M) Payroll (\$1M) EBITDA (\$1M) EBITDA/revenue	24.877 38.817 5.027 0.525 -0.149	$\begin{array}{c} 0.338 \\ 0.063 \\ 0.103 \\ -0.228 \\ -0.109 \end{array}$	1.873 0.650 0.572 0.075 0.037	23.370 15.285 5.801 0.796 0.264
Refund variables Take-up of carryback refund Eligible refund (\$1K) Eligible refund/revenue	0.3572 233.866 0.0506	1.566 0.0007	7.045 0.0042	125.411 0.0298
Preparer variables 1(certified public accountant) 1(attorney) 1(other professional license) log(labor income)	0.8314 0.0214 0.0556 11.36	0.08	11 57	12 51
1(self-employment) Age log(mean client revenue)	0.1794 49.89 14.59	35.52 13.06	50.00 14.27	63.48 16.62

TABLE 2—SUMMARY STATISTICS: POPULATION AND SWITCHER SAMPLE, 1998–2011

Notes: During our sample period, there were 12.1 million firm-year observations, of which 4.42 million had a net operating loss. Of those, 1.24 million were eligible for a carryback, and 0.47 million claimed the carryback. Number of observations: 1,244,729 in panel A and 124,862 in panel B. Number of firms: 612,070 in panel A and 62,431 in panel B. Panel A reports summary statistics for all C corporations with tax losses between 1998 and 2011 that were eligible for a carryback refund of at least \$1,000. The sample is derived from the US population of corporate tax returns. All dollar values are normalized to 2013 price levels. The firm variables are based on the corporate tax return. EBITDA refers to earnings before interest, taxes, depreciation, and amortization. See online Appendix A for details about how we construct these measures from the individual line items on the corporate income tax return. We directly observe take-up of the carryback refund, but we impute the eligible refund based on the policy rules and each firm's historical tax liability. The preparer and tax firm variables are based on their matching tax returns. Their statistics exclude observations that do not have a matching tax return. Labor income equals the sum of W-2 wages and self-employment income. Mean client revenue refers to the corporate clients of each preparer and each tax firm. Percentiles are computed as percentile means.

Source: Author's calculations

median firm is small, with \$1.5 million in revenue, \$489,000 in assets, and \$469,000 in payroll. The eligible carryback refunds are also modest in size, with a median of approximately \$5,700. Among eligible firms, the median ratio of refund to revenue is 0.4 percent. For these firms, the median ratio of earnings before interest, tax, and depreciation (EBITDA) to revenue is 4.6 percent. Thus, the median refund is modest but not negligible relative to a firm's earnings. We show below that focusing our analysis on a subsample with larger refunds does not affect the qualitative results.

Table 2 also includes variables for the tax preparer and tax firm matched to each corporate tax return. Most corporations hire small tax firms. The median corporation hires a tax firm with \$785,000 in revenue and 98 corporate clients. The median tax preparer earns \$99,000 in labor income and signs for 38 corporate clients. Roughly 16 percent of tax firms are unincorporated businesses, or sole proprietorships.

Panel B of Table 2 reports summary statistics for a subset of firms that switch tax preparers between 1998 and 2011. All observations in this subsample match to a preparer. This subsample only includes two observations per firm: the last observation before switching preparers and the first observation after switching preparers. It consists of 124,862 firm-year observations for 62,431 individual firms. The firms in this sample look very similar on average to the full sample. The table also includes the preparer characteristics used to test whether client claiming behavior depends on which preparer is employed. Most tax preparers are certified public accountants (83 percent), but a nonnegligible share report some other professional license (6 percent), a law degree (2 percent), or no license (9 percent). Approximately 18 percent of tax preparers are self-employed, as opposed to working at a tax firm.

Table 3 presents statistics for a size-based partition of the carryback sample. We divide the sample into deciles based on mean firm sales over all active years. We then divide the top decile into five equal-sized bins and isolate the top 0.1 percent to provide detail on the tail of the distribution. Ninety percent of observations feature firm-years for relatively small firms, having mean sales between \$340,000 and \$8.7 million. In contrast, mean sales among the top 2 percent of firms are \$1.96 billion. Considerable heterogeneity in the population implies that first-order factors affecting the tax loss choice for some firms may be irrelevant for others, a possibility that motivates our analysis of various subpopulations.

B. Measuring Carryback Eligibility

The IRS databases do not explicitly record whether firms are eligible for a carryback, which requires us to simulate eligible refunds. Our algorithm proceeds as follows. First, we collect tax loss observations and for each observation the history of taxes paid in the years prior to the loss. We then adjust these past tax payments for various adjustments made in intervening years due to previously claimed carrybacks, the resolution of audits, and other amendments. We use the adjusted tax payments to impute past taxable income potentially eligible to be offset by the current loss. We apply the policy rules for the relevant year to determine the eligible carryback window. Starting with the earliest eligible year, we apply the current tax

		Firm characteristics					
		Unique					
Percentile	Sales	observations	Payroll	EBITDA	External?		
Panel A. Firm chard	acteristics by a	size group					
1–10	340K	72.934	220K	46K	0.928		
11-20	570K	67,547	240K	66K	0.945		
21-30	800K	64,874	320K	83K	0.950		
31-40	1.1M	62,756	400K	94K	0.952		
41-50	1.5M	60,875	510K	110K	0.956		
51-60	2.0M	59,641	670K	130K	0.958		
61-70	2.9M	58,205	930K	170K	0.959		
71-80	4.5M	57,724	1.4M	200K	0.960		
81-90	8.7M	55,837	2.4M	280K	0.960		
91–92	15.3M	10,819	3.9M	300K	0.962		
93–94	20.8M	10,692	5.4M	300K	0.960		
95–96	31.7M	10,457	10.2M	370K	0.955		
97–98	62.8M	10,078	13.9M	200K	0.946		
99–99.9	505M	9,149	99.7M	19.5M	0.812		
Top 0.1 percent	29.6B	480	2.0B	1.6B	0.293		
			Refund facts			Aggre	gates
			Eligible				
Percentile	Refund	Claim?	observations	Always?	Never?	Eligible \$	Claim \$
Panel B. Refund cha	aracteristics b	y size group					
1-10	4.9K	0.313	1.7	0.148	0.525	610M	270M
11-20	5.8K	0.316	1.8	0.146	0.510	720M	320M
21-30	7.2K	0.329	1.9	0.150	0.489	890M	420M
31-40	8.8K	0.341	2.0	0.154	0.467	1.1B	530M
41-50	11K	0.356	2.0	0.159	0.441	1.4B	700M
51-60	14K	0.375	2.1	0.169	0.416	1.8B	950M
61–70	20K	0.392	2.1	0.177	0.388	2.5B	1.4B
71-80	32K	0.419	2.2	0.189	0.353	3.9B	2.3B
81-90	65K	0.442	2.2	0.200	0.320	8.1B	5.1B
91–92	130K	0.460	2.3	0.207	0.289	3.1B	1.9B
93–94	180K	0.458	2.3	0.199	0.287	4.4B	2.7B
95–96	260K	0.460	2.4	0.193	0.282	6.4B	4.0B
97–98	580K	0.459	2.5	0.182	0.261	14.5B	8.8B
99–99.9	5.2M	0.457	2.6	0.164	0.221	123B	72.7B
Top 0.1 percent	143M	0.522	2.6	0.212	0.199	177B	82.5B

TABLE 3—FIRM AND REFUND CHARACTERISTICS BY SIZE (POPULATION, 1998–2011)

Notes: This table presents statistics for firm and refund characteristics with firms grouped and ordered by size bin based on mean firm-level sales over all years between 1996 and 2011 for which a firm files a tax return. The underlying data are all carryback eligible firm-year observations in the main analysis sample. Except where otherwise noted, the reported statistics are means. "Sales" and "Payroll" are firm-level means of sales and total W-2 plus 1099-MISC labor payments over all years between 1996 and 2011 for which a firm files a tax return. Unique observations is the count of distinct firms (EINs). "EBITDA" is EBITDA as defined in online Appendix A in the year of the loss event. "External?" is an indicator for whether the tax return indicates presence of an external tax preparer. Refund is the simulated eligible refund. "Claim?" is an indicator for whether the refund was claimed. "Eligible observations" is the number of potential refunds for a firm between 1998 and 2011. "Always?" is an indicator for whether a firm between 1998 and 2011. "Always?" is an indicator for whether a firm between 1998 and 2011. "Always?" is an indicator for whether a firm always claims a refund when eligible, defined only for firms where Eligible observations exceeds 1. "Never?" is an indicator for whether a firm never claims a refund when eligible, defined only for firms where Eligible observations. "Claim \$" are total claimed refunds across firm-year observations. All dollar values are normalized to 2013 price levels.

Source: Author's calculations

loss against imputed past taxable income.¹⁴ We continue with these deductions until either the current loss or past taxable income is exhausted. We then recompute the historical tax liability based on the post-deduction taxable income. The difference between the pre-deduction and post-deduction tax liability provides our estimate for the eligible carryback refund.

We verify our algorithm for eligible refunds using firms that claim the carryback (see online Appendix B for detail). For those firms that choose a carryback, we compare our simulated amount to the claimed amount. We impute the eligible refunds with a high degree of accuracy. Regressing log(claimed amount) on log(eligible amount) yields a coefficient of 0.96 and an R^2 of 0.93.

In computing eligible carrybacks, we do not adjust for the alternative minimum tax, nor do we track the foreign tax credit or various general business credits and their respective statutory windows. This simplification affects the size of the estimated refund, but usually not whether a firm is eligible. Our results focus on the binary decision to claim the refund, which we measure well in cases where these features are relevant. The analysis summarized in Section VD considers these additional tax code features, which apply to a small but important set of companies and interact with the carryback in influencing claiming behavior.

IV. Evidence on Tax Loss Choices

A. Low Take-Up of Tax Refunds for Losses

Taxable corporate losses are very common. Our sampling frame includes 12.1 million firm-year observations between 1998 and 2011, of which 4.42 million experience a net operating loss. Eighty percent of firms experience a taxable loss at some point in time. Among these loss events, we identify 1.24 million, or 28 percent, as being eligible for a carryback refund of at least \$1,000. The reason all loss firms are not eligible for a refund is that a firm must have paid taxes in the past years within the statutory window. Still, firms frequently face the choice between applying a tax loss as a carryback or a carryforward.

Our first finding is that only 37 percent of eligible firms claim the refund. Because of low take-up, claimed refund amounts significantly understate the potential size of the policy. During the 1998–2011 period, C corporations were eligible for \$357 billion in carryback refunds yet claimed only \$187 billion (Figure 1). In 2008 and 2009 alone, they were eligible for \$124 billion yet claimed only \$68 billion.¹⁵ As a benchmark for the significant potential size of this program, total payments for unemployment insurance were \$209 billion in 2008 and 2009 (US Department of Labor 2014). Thus, if policymakers intend for all eligible firms to claim a refund,

¹⁴Tax losses are defined from the front page of the income tax return for C corporations. We use the statutory definition of tax losses for ordinary income, which equals net income (Line 28) plus special deductions (Line 29b). This definition excludes capital income losses. It also excludes losses obtained from mergers and acquisitions, which are reported with the stock of losses from prior periods (Schedule K, Line 12).

¹⁵Using financial accounting data for public companies, Graham and Kim (2009) estimate potential refunds of approximately \$131 billion for tax years 2008 and 2009 (see table 4, 419). Possible differences between our estimates and theirs include our use of tax accounts, our exclusion of capital losses, and our inclusion of small and medium-sized firms.

low take-up may substantially undermine the potential effect of the carryback policy as either a macroeconomically relevant fiscal stimulus or a loss offset mechanism to reduce marginal tax rates on investment.

Table 3 explores low take-up across the firm size distribution. Moving from the bottom decile to the ninth decile, the average eligible refund ranges from \$4,900 to \$65,000. In the tenth decile, eligible refunds range from \$130,000 to \$12.1 million on average for the top 2 percent of firms and \$143 million for the top 0.1 percent of firms. These refunds are nontrivial as a share of firm cash flows for all groups and typically exceed estimates of the direct cost of preparing the carryback claim. At the same time, the refunds are not so large as to render implausible the notion that complexity might lead firms to ignore the carryback.

Claim rates increase with firm size, rising from 31 percent in the lowest decile to 46 percent among the top 2 percent and 52 percent among the top 0.1 percent. On average, firms in our sample appear more than once, with this frequency increasing with firm size. Among firms appearing multiple times, fewer than one in five always claim a refund. This share varies little with firm size. In contrast, approximately half of the smallest firms never claim a refund, while just one in four of the largest firms never claim. Taken together, these patterns are consistent with a story where sophistication increases in firm size. Yet, since the largest firms are not perfect claimers, limited know-how is unlikely to explain low take-up among all firms. Table 3 highlights the importance of understanding the factors that drive the largest firms' behavior, as eligible refunds among the top 2 percent and top 0.1 percent of firms respectively amount to 84 percent and 50 percent of aggregate eligible refunds.

On average, the carryback stimulus policies increase eligible carrybacks by 40 to 50 percent, implying much more generous potential refunds in 2001–2002 and 2008–2009. Despite these policies, overall take-up is 2 percent lower in stimulus periods than in nonstimulus periods. Conditional on refund and firm size, take-up is 4 percent lower than in nonstimulus periods. Online Appendix Table A2 presents regressions exploring whether firms are more likely to claim carrybacks that are specifically larger due to stimulus policy. Unconditionally, firms are 6 percent more likely to claim these refunds. Conditioning on refund size reduces this difference to 4 percent, and further conditioning on firm size reduces this difference to 3 percent. We interpret these results as reflecting that carryback extensions increase take-up to the extent they increase the size of potential refunds (which raises take-up) and target larger firms (which have higher baseline take-up).¹⁶

B. A Net Present Value Analysis of Tax Loss Choices

We begin our exploration of the factors driving low refund take-up with a simple net present value (NPV) analysis of the tax loss choice. This analysis compares the NPV of the carryback and carryforward options under various assumptions about

¹⁶We consider two specifications in comparing eligible refunds to what they would have been under a two-year carryback rule. The first specification focuses on all refunds that are larger, and the second considers only refunds that are at least 20 percent larger because of the stimulus policy. The differences are similar but smaller in the latter specification.

the firm's path of future taxable income. This setting provides a rare opportunity to ask whether firms make the value-maximizing choice from a binary set of options, in which the costs and benefits are relatively easy to measure.

Loss firms deciding between the carryback and the carryforward elections must consider whether it is better to use the loss as a deduction against past taxable income or against future taxable income. The carryback's value depends on the tax rates that the firm paid in the past. In contrast, the carryforward's value depends on the tax rates that it will pay in the future, the length of time that it will take the firm to return to a profitable state, and the firm's discount rate.

Computing the value of the carryback and carryforward elections involves an NPV calculation because either option can generate carryforward deductions to be applied against future taxable income. The key difference between their formulas is that the carryback election deducts the loss against past taxable income and the carryforward election does not. Carryback deductions against past taxable income are not discounted because they generate an immediate tax refund.

We formalize the NPV formulas for the carryback and carryforward assuming the firm has perfect foresight over the timing of future taxable income:

(1)
$$NPV^{b} = \sum_{t=T_{\min}}^{-1} \tau_{t} D_{t}^{b} + \sum_{t=1}^{T_{\max}} \frac{\tau_{t} D_{t}^{b}}{(1+r)^{t}}, \quad NPV^{f} = \sum_{t=1}^{T_{\max}} \frac{\tau_{t} D_{t}^{f}}{(1+r)^{t}},$$

where τ_t is the tax rate at time t, D_t^b is the deduction taken at time t under the carryback election, D_t^f is the deduction taken at time t under the carryforward election, T_{\min} is the earliest tax year against which a carryback can be applied, T_{\max} is the latest tax year against which a carryforward can be applied, and r is the firm's discount rate for future tax savings. Deductions applied to past taxable income are not discounted because the refund is immediate. In either case, the nominal sum of the deductions cannot exceed the loss reported at t = 0. The nominal sum of the deductions can be less than the current loss in cases where the firm does not have sufficient past and future taxable income to offset the loss.

We empirically evaluate the NPV formulas in equation (1) for firms with losses between 1998 and 2002. We restrict our sample to this period because we want to use a future ten-year period of realized taxable income to value each firm's carryforwards. We assume that all firms in this period do not have any carryforwards from prior tax years. We make this assumption because the administrative tax data do not collect this information until 2003.¹⁷

We simulate the claiming of future carryforward deductions over a ten-year period based on firms' realized taxable income. We perform this simulation under both the carryback and carryforward elections. We assume firms claim future carryforward deductions as soon as possible, and surviving firms with unused losses after ten years claim all unused losses in the eleventh year. This assumption raises the value of carryforwards relative to actual claiming behavior if some losses go unclaimed. We then compute the NPV of the carryback and carryforward elections

¹⁷We find identical results when we replicate our analysis on firms with losses in 2003 where we do not need to make assumptions about their preexisting stock of carryforwards.







FIGURE 1. AGGREGATE CARRYBACK TAKE-UP STATISTICS BY YEAR (POPULATION, 1998-2011)

Notes: This figure plots the incidence of carryback refund eligibility and claiming behavior over time. Panel A plots the share of total dollars claimed and the share of eligible refunds claimed each year. Panel B plots aggregate dollar amounts of eligible and claimed refunds. We limit eligibility to firms that have the option to claim a carryback refund of at least \$1,000. We exclude firms with mean revenue and mean payroll less than \$100,000. All dollar amounts are indexed to 2013 price levels.

Source: Author's calculations

using a discount rate of 7 percent.¹⁸ If firms use higher discount rates when evaluating this decision (Summers 1987, Zwick and Mahon 2017), this assumption will also raise the value of carryforwards relative to their perceived value.

Panel A of Figure 2 plots the NPV difference between the carryback and carryforward elections, $NPV^b - NPV^f$, in dollars and as a percent of NPV^b . For 79 percent of

¹⁸ If there was no correlation between tax status and aggregate risk, then the appropriate discount rate would be the riskless rate. If tax status was perfectly correlated with the firm's exposure to aggregate risk, the discount rate should reflect the risk in the firm's cost of capital. The 7 percent rate is a compromise between these views, reflecting the idea that future deductions are less risky than cash flows but not riskless. See Summers (1987) for an analogous discussion in the context of depreciation deductions. Our results do not change qualitatively and are very similar quantitatively under discount rates between 3 and 9 percent (online Appendix Table A3).



Panel A. Distribution of NPV difference between carryback and carryforward

Panel B. Undiscounted carryforwards by carryback-eligible nonclaimers



FIGURE 2. COMPARING THE VALUE OF CARRYBACKS AND CARRYFORWARDS (NPV SAMPLE, 1998–2002)

Notes: This figure provides information about the relative value of carrybacks and carryforwards for a sample of eligible firms for which we have ten years of data following the loss event. Panel A plots two histograms of the net present value difference between the carryback and carryforward elections. On the left, we plot the distribution in dollars. On the right, we plot the distribution as a percent of the estimated carryback. We calculate the net present value based on each firm's realized taxable income over a ten-year period. We use realized taxable income to simulate the claiming of future carryforward deductions and to compute the net present value of future tax benefits. The sample includes firms with tax losses between 1998 and 2002 that were eligible for a carryback refund of at least \$1,000. Panel B plots mean cumulative carryforward deductions taken relative to the initial loss over the ten years following the loss event. The sample is restricted from the sample in panel A to those firms that do not claim a carryback refund. The solid line measures observed deductions and the dashed line measures simulated deductions based on realized taxable income.

Source: Author's calculations

the sample, the carryback has a larger NPV than the carryforward. The modal premium is 10 percent relative to the carryback, but many firms face carryback premia above 25 percent. Thus, in the absence of other costs, most firms should value the carryback more than the carryforward. This finding would be even stronger and the NPV differences even larger under less conservative but realistic assumptions about unused losses or firm discount rates.

This calculation may indeed understate the extent to which the carryback looks more appealing than the carryforward (Figure 2, panel B). We ask whether firms that do not elect the carryback immediately use most of the loss in future deductions. We restrict the sample to those firms that do not claim a carryback. Over the ten years following the loss event, we plot mean cumulative carryforward deductions taken relative to the initial net operating loss. On average, firms capture just \$0.50 of carryforward per dollar of loss by t = 2. The level tapers off at approximately \$0.75 per dollar at t = 6. That some of the loss is never deducted reflects the possibility that firms often fail or do not return to positive tax position for many years. This finding is consistent with the facts in Cooper and Knittel (2006, 2010), who use corporate tax data to document incomplete utilization of net operating loss deductions. This fact significantly strengthens the appeal of the carryback option when it is available.¹⁹

Do some firms show higher propensity to claim positive NPV refunds than others? Panel A of Figure 3 shows how failure to claim positive NPV carrybacks varies across the firm size distribution within the NPV sample and compares this to the share of refunds unclaimed for all eligible refunds in the full sample. Moving from the bottom decile to the ninth decile, the rate at which firms fail to claim positive NPV carrybacks falls with firm size, from 65 percent for the bottom decile to 25 percent around the ninetieth percentile. At this point, the pattern reverses, reaching 43 percent of positive NPV refunds unclaimed for the largest firms. The nonmonotonic relationship between firm size and take-up propensity highlights the possible role of different barriers to take-up across the firm size distribution.

Because claiming a carryback entails more paperwork, it is possible the direct filing cost exceeds the value of claiming. Conversations with preparers that serve small and mid-market firms suggest that filing for the carryback involves approximately two hours of additional work. The IRS estimates the average time to complete Form 1139 and claim a carryback is 16.5 hours, of which five hours entails learning about the form and presumably need not be paid for every claim. We use the preparers in our full sample to impute an hourly wage by dividing each individual preparer's annual labor income (including W-2 earnings and self-employment income) by 2,000. The imputed wage at the twenty-fifth, fiftieth, and seventy-fifth percentiles is approximately \$20, \$45, and \$80, respectively. This number is well below the average CPA billing rate of \$180 from the AICPA National MAP Survey, which likely reflects differences between the sample of surveyed CPAs and the full population of tax preparers. Combining these figures yields a range of potential cost

¹⁹Panel B of Figure 2 also presents a series that simulates carryforward claims based on observed taxable income trajectories over time. This series tracks observed deductions closely, implying that incomplete utilization of carryforwards is mostly due to firms' slow and incomplete recovery to profitability.

Panel A. Unclaimed refunds versus firm size and refund NPV (NPV sample, 1998–2002)







FIGURE 3. CHARACTERISTICS OF UNCLAIMED REFUNDS

Notes: This figure documents carryback claiming behavior by firm size, refund NPV, and refund size. Panel A plots the share of refunds unclaimed for all eligible refunds and for a restricted sample of refunds where the net present value difference between the carryback and carryforward elections favors claiming the refund. The sample includes firms with tax losses between 1998 and 2002 that were eligible for a carryback refund of at least \$1,000. Panel B plots the share of refunds unclaimed for all eligible refunds, for those refunds worth at least \$10,000, and for those refunds worth at least \$100,000. There is an insufficient number in the latter category for size bins 1 through 4. The sample includes firms that have the option to claim a carryback refund between 1998 and 2011. We exclude firms with mean revenue and mean payroll less than \$100,000. All dollar amounts are indexed to 2013 price levels. Size bins 1 through 9 demarcate the first nine deciles of the main analysis sample firm size distribution in mean sales. Size bins 10 through 14 divide the tenth decile into 2 percent bins.

Source: Author's calculations

estimates from roughly \$40 to \$3,000 for most firms. Even allowing for a markup for overhead expenses and profit, the value of the carryback exceeds these costs for most refunds in our sample.²⁰

Panel B of Figure 3 provides an alternative examination of whether a simple cost-benefit approach can explain claiming behavior. We plot the share of refunds unclaimed for all eligible refunds, for those refunds worth at least \$10,000, and for those refunds worth at least \$100,000. There is an insufficient number in the latter category for size bins below the fiftieth percentile. Refund size is strongly correlated with propensity to claim. However, many large refunds remain unclaimed. For the small and mid-market firms, approximately half of refunds with value greater than \$10,000 are unclaimed. Among larger firms, approximately one in four refunds exceeding \$100,000 is unclaimed. Among the largest firms, refund size is only weakly correlated with the take-up rate, partly because most refunds for these firms exceed \$100,000.

For a subsample of firms, we can ask whether a firm's choice not to claim a carryback reflects a conscious choice to forego the carryback or instead reflects unawareness of the option. We focus on firm years that appear both in our main analysis sample and the Statistics of Income (SOI) Corporate Study sample. The latter sample is a size-stratified sample of tax returns that over-samples larger firms and contains additional variables not available for the population data. The matched dataset contains 99,804 observations, which represent approximately 1.2 million observations using sampling weights.

First, we ask whether firms confirm unclaimed refunds in Schedule K, Item 11, which is a checkbox indicating if the firm is electing to forgo the carryback. Only 30 percent of firms that do not claim refunds actively check the box to forgo a carryback. This fact is not obviously due to measurement error, as just 3 percent of firms that claim refunds check the box. Thus, most firms that fail to claim a carryback also fail to indicate this decision explicitly. As a second test, we explore whether firms adequately account for net operating losses (NOL) when they forgo a refund by incrementing their NOL stock in Schedule K, Item 12 in the next year. Among firms with observations in both t and t + 1, 62 percent increase their NOL stock in the next year when they do not claim a refund, compared to 31 percent when they do claim a refund. Thus, a significant share (38 percent) of firms both fail to claim refunds and fail to account for them in subsequent years. These findings point toward the idea that many firms are either unaware of the carryback option or unprepared to account properly for NOLs.²¹

Taken together, the results suggest that while the value of waiting clearly plays a role in the take-up decision, the choice to forgo the carryback appears to fail a simple cost-benefit analysis. First, most firms appear to value the carryback more than the carryforward. Second, the money left on the table typically exceeds the estimated cost of claiming the refund. Third, small firms fail to claim refunds at higher rates than large firms and are more likely to forgo refunds with positive

²⁰We thank Erin Towery for providing data on hours from the IRS and CPA billing rates.

²¹ This interpretation complements Gallemore and Labro (2015), who find that public firms with weaker internal information environments engage in less tax planning.

NPVs. Fourth, many firms that do not claim refunds also fail to indicate they have made this choice or fail to account for unelected refunds in subsequent years. Last, many large firms leave substantial refunds unclaimed, and the propensity to claim is nonmonotonic in firm size, with the largest firms claiming less often than firms in the ninetieth percentile. These facts motivate an investigation of the costs of complexity in driving take-up behavior.

V. Can Tax Code Complexity Explain Low Take-up?

In 2006, the US Department of the Treasury's Office of Tax Policy conducted a study to develop a "comprehensive strategy" for reducing the gap between taxes owed and taxes paid. The report offers an assessment of the current system and a call to simplify it, stating bluntly, "[the] current tax code is too complicated." The deleterious effects of this complexity include making the law "too difficult for taxpayers to understand and for the IRS to administer," leading to "unintentional errors," providing new "opportunities for those who are willing to exploit the system," while making it "difficult for the IRS to detect noncompliance." The report presages some of our findings with regard to fiscal policy (US Department of the Treasury, Office of Tax Policy 2006, 15):

[L]imited IRS resources are increasingly committed to administering a wide array of targeted tax provisions created to meet social policy goals. These targeted provisions, which themselves are growing increasingly complicated, divert IRS resources from basic compliance efforts.

In this section, we present direct evidence of the role of tax code complexity in driving the low take-up of carryback refunds. Based on a simple cost-benefit analysis, most firms should claim the carryback. Our goal is to explore several channels where our data permit an evaluation of how complexity can alter this calculation. We focus on the relationship between small and medium-sized firms and the experts they hire to prepare their taxes. Tax code complexity may amplify agency problems if principals cannot perfectly monitor their agents because they do not understand the code. We also briefly explore for large firms the compliance costs associated with the interaction between carryback claims and other tax code provisions or existing audits of past tax returns.

A. The Market for Corporate Tax Preparation Services

Most small firms rely on paid preparers to help evaluate tax code decisions. Tax preparers inform their clients about the tax code, file tax returns on their clients' behalf, and warn clients about the audit risk of different tax reporting choices. Preparers may differ in whether they encourage their clients to claim the tax refund based on their own beliefs about its merits for their clients, its filings costs, and its audit risks. When monitoring is imperfect, agency problems between managers and preparers can promulgate poor decisions, especially if there is dispersion in preparer quality.

In 2011, 96 percent of corporations hired an external preparer to file their income taxes. The market comprised 188,000 individual preparers who file tax returns for corporations. Although federal regulations do not mandate licensing requirements for preparers, 89 percent of firms hired a preparer with a professional license (mainly certified public accountants).²² The remaining 11 percent of firms hired preparers without any professional credentials.

Table 3 shows that dependence on an external preparer is nearly universal across the firm size distribution. In the bottom decile, 93 percent of firms rely on an external preparer. The share increases to 96 percent for firms above median size. Only among the very largest firms do we see a switch to internal preparers, with 79 percent of the top 2 percent of firms using external preparers.

The tax preparation market includes a wide variety of tax firms. They range from sole proprietorships with a single employee to national brands with thousands of locations. These firms also vary in their degree of specialization. Some focus on tax preparation (e.g., H&R Block, Inc.), whereas others offer a broad portfolio of professional services for businesses (e.g., BDO USA, LLP). At most tax firms, employees use tax preparation software to manage client returns (Internal Revenue Service 2009). Conversations with mid-market preparers suggest this software does not fully automate the process of claiming a carryback.

Contracts between external preparers and their clients offer relatively low-powered incentives for preparers to minimize their clients' tax burdens. Incentive fees are explicitly prohibited by law.²³ Preparers instead bill their clients by the hour or by the tax form. This structure does mean it may be in a preparer's advantage to "overwork" the return rather than rush through it, particularly if the preparer can show the benefits of the extra work. Nevertheless, the return to the preparer of making the right choice is not directly linked to the value of that choice to the client. Against this indirect incentive to claim a carryback, firms face the risk that a refund claim will increase the likelihood of IRS audit. When a firm applies for the carryback, the IRS reviews the recomputed tax liability for prior years. This review carries the risk that the IRS will spot something that will prompt an audit. Legally, the IRS cannot use such a review to open claims that exceed the value of the refund. However, the perceived risk of audit may be sufficient to deter claiming a carryback.

B. Claiming Decisions and Preparer Characteristics

We use firms that switch preparers to show that preparer characteristics predict claiming behavior. We restrict the sample to firms that were eligible in multiple years and that switched preparers. For each firm, we include the last observation before and the first observation after switching preparers. These observations are

²²Either a certified public accountant, attorney, enrolled agent, or state licensed preparer. Enrolled agents are licensed by the Internal Revenue Service. They must pass an examination and fulfill 72 hours of continuing education every three years.

²³ Title 31 "Regulations Governing Practice before the Internal Revenue Service" in Treasury Department Circular No. 230 states: "(a) In general. A practitioner may not charge an unconscionable fee in connection with any matter before the Internal Revenue Service. (b) Contingent fees— (1) Except [in audit, challenge, or judicial proceeding], a practitioner may not charge a contingent fee for services rendered in connection with any matter before the Internal Revenue Service."



FIGURE 4. PREPARERS AND THE PERSISTENCE OF CARRYBACK CLAIMS (SWITCHER SAMPLE, 1998–2011)

Notes: This figure reports the within-firm covariances of residual carryback take-up. Standard errors are block bootstrapped with 1,000 replications. The estimates are based on the residual $T_{ijt} = 1(carryback take-up) - W_{it}\pi$, where W_{it} are client observables. The coefficients π are estimated from a regression of take-up on client observables and a preparer fixed effect. Client observables include deciles in the eligible carryback refund, deciles in revenue, deciles in assets, deciles in payroll, state-year fixed effects, and industry-year fixed effects. We estimate covariances for pairs of observations from the same firm. We differentiate between pairs by the length of time between observations and by whether the observations share the same preparer.

Source: Author's calculations

often not consecutive because firms are usually not eligible for the carryback refund in multiple consecutive tax years. If a firm changes preparers multiple times, we only include observations associated with the last switching event.

We begin with a graphical illustration of the role of preparer effects in driving refund claims. We first regress carryback take-up on a set of client and refund observables, including indicators for deciles of eligible carryback refund, revenue, assets, and payroll; state-year and industry-year fixed effects; and firm fixed effects. Next, for each firm we group the residuals into observation pairs based on the length of time between them and whether they share the same preparer. Figure 4 plots the covariances of these residuals for each group.

Three facts emerge. First, covariances are consistently higher for pairs where the firm has the same preparer. Second, the difference in covariance is stable over time between observations, consistent with the preparer effect being a time-invariant attribute of the preparer. Third, the difference in covariances (approximately 2.5 percent) is quantitatively relevant. As a benchmark, client and refund observables account for approximately 9 percent of the variance in claiming. To gain a broader sense of preparer effects before exploring the role of preparer observables, we estimate the variance of preparer effects using an Empirical Bayes approach (Kane and Staiger 2008). This analysis yields an estimate of 5.8 percent, which is large both relative to

the residual variance of 16.2 percent and the unconditional variance of claim rates of 23.4 percent.²⁴ Online Appendix Table A4 presents additional statistics at the preparer level for preparers with at least three firm-year observations in the main analysis sample. Even in this sample where carryback eligibility is relatively common, 26 percent of preparers never claim refunds on their clients' behalf.

These results may reflect differences in preparer quality or differences in the information available to a new preparer after a firm switches, as internal information environments can affect tax planning behavior (Gallemore and Labro 2015). To further isolate potential explanations, we exploit rich data on preparer characteristics to investigate the factors driving these preparer effects. Our main specification is a panel regression given by

(2)
$$\mathbf{1}(carryback \ take-up)_{ijt} = Z_{\mathbf{J}(i,t)}\gamma + X_{it}\beta + \alpha_i + \delta_t + \epsilon_{it},$$

where the subscripts represent client *i* with preparer *j* in tax year *t*, $Z_{\mathbf{J}(i,t)}$ are preparer characteristics, X_{it} are client characteristics, α_i is the client fixed effect, and δ_t is the tax-year fixed effect. Preparer observables include indicators for professional credentials, log(labor income), **1**(self-employment), age, log(mean client revenue), and log(total client revenue). Client observables include log(revenue), log(assets), and log(EBITDA).²⁵

The research design is analogous to strategies used by Bertrand and Schoar (2003) to estimate the effects of CEO style on firm performance and by Card, Heining and Kline (2013) to estimate how dispersion in the firm component of pay contributes to wage inequality. These switching designs rely on the identifying assumption that client unobservables in the error term are uncorrelated with preparer characteristics conditional on client observables, a client fixed effect, and a tax-year fixed effect. Because the switchers design uses within-firm variation, this assumption holds if unobservable determinants of carryback take-up do not change before and after switching preparers. Because it is hard to determine what factors are driving switches, we validate this assumption using pre-trend tests and a subsample of plausibly exogenous switching events. More broadly, we view this evidence as complementary to the simpler descriptive analyses presented above.

Panel A of Table 4 reports estimates from equation (2) for the full sample of switching events. The regressions in columns 1 through 5 are univariate with respect to preparer characteristics. Column 6 presents a multivariate specification. All regressions include a firm fixed effect, a tax-year fixed effect, and firm controls.

²⁴ First, we regress claiming behavior on log(refund size), log(revenue), log(assets), log(EBITDA), tax-year fixed effects, and preparer fixed effects. Second, we construct residuals using the coefficients for refund, client characteristics, and tax-year effects. Third, we estimate preparer-year regressions of mean residual take-up on its lag, weighted by the number of clients per preparer-year, to estimate the covariance of claiming behavior across years. Finally, the estimated variance of preparer effects equals the coefficient from this regression multiplied by the weighted variance of residual from the second step. The results when we drop duplicate preparer-firm pairs prior to estimating the within-preparer regression are similar and statistically indistinguishable: 5.1 percent for the variance of preparer effects and 18.5 percent for the residual variance of claiming.

²⁵We include separate indicators for certified public accountants, attorneys, and preparers with another professional license. The last category includes enrolled agents and state licensed preparers. The omitted category are preparers without any professional credential. The self-employment indicator equals one if the preparer derives at least half of their labor income from self-employment.

	LHS variable is 1(claimed refund)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Switcher sample, 1998–2011 1(CPA)	0.0681					0.0590
1(attorney)	(0.0055) 0.0474					(0.0062) 0.0387
1(other license)	(0.0124) 0.0099 (0.0080)					(0.0130) 0.0092 (0.0087)
log(labor income)	(0.0000)	0.0074 (0.0014)				(0.0007) 0.0042 (0.0015)
1(self-employment)		· · /	-0.0205 (0.0045)			-0.0158 (0.0046)
Age				0.0003 (0.0002)		$0.0006 \\ (0.0001)$
log(mean client revenue)					$0.0179 \\ (0.0017)$	0.0091 (0.0024)
Firm FE, year FE, controls Observations	Yes 124,862	Yes 124,862	Yes 124,862	Yes 124,862	Yes 124,862	Yes 124,862
Panel B. Deaths/movers sample, 1998–201 1(CPA)	0.0857 (0.0219)					
1(attorney)	0.0728 (0.0526)					
1(other license)	0.0551 (0.0319)					
log(labor income)		0.0073 (0.0050)				
1(self-employment)			$0.0095 \\ (0.0151)$			
Age				0.0007 (0.0005)		
log(mean client revenue)					$0.0162 \\ (0.0068)$	
Predicted preparer effect						0.9372 (0.1880)
Firm FE, year FE, controls Observations	Yes 9,824	Yes 9,824	Yes 9,824	Yes 9,824	Yes 9,824	Yes 9,824

Notes: This table reports coefficients from regressions of carryback take-up on preparer characteristics. All regressions include a firm fixed effect, a tax year fixed effect, and firm controls. Firm controls include log(eligible refund), log(revenue), log(assets), and log(EBITDA), and an indicator for negative EBITDA. Panel A includes all switching events, and panel B is limited to switching events contemporaneous with either the death or relocation of the prior preparer. The sample only includes the last observation before a client changes its preparer and the first observation after a client changes its preparer. In columns 1 and 6, preparers that do not have a professional license are the omitted certification category. The predicted preparer effect in panel B, column 6 is constructed using the estimated coefficients from panel A, column 6. Standard errors are clustered at the firm level.

Source: Author's calculations

They also include dummies for missing values of the preparer characteristics and the client controls. We cluster standard errors at the firm level.

The main finding is that markers for preparer sophistication consistently predict take-up of the carryback refund. Preparers are more likely to claim the carryback refund when they are certified public accountants or attorneys, when they are better paid, when they are older, when they do not work for themselves, and when they have bigger client bases. Except for age effects, we can consistently reject the null of zero effect in the univariate regressions. These effects also retain their statistical significance in the multivariate specification, and the effect for age is stronger and statistically significant in this case. The multivariate specification reveals that these markers capture different dimensions of the underlying concept of preparer sophisti-

These effects are quantitatively significant when compared to the mean take-up rate of 37 percent. Relative to preparers without a professional license, certified public accountants are 6.8 percentage points more likely to claim the carryback refund for their clients. Similarly, attorneys are 4.7 percentage points more likely to claim. Moving from the tenth to the ninetieth percentile in log(labor income) increases take-up by 1.9 percentage points (= $(12.51 - 9.98) \times 0.0074$). Moving from the tenth to the ninetieth percentile in log(mean client revenue) increases take-up by 6.4 percentage points (= $(16.62 - 13.06) \times 0.0179$). The effects of age are smaller, with an increase of roughly 0.3 percentage points for each additional decade. Combined with data in panel B of Figure 2 on the typical value lost by nonclaimers, the results imply that moving from a tenth to ninetieth percentile preparer in terms of observables increases take-up by 13.5 percent and saves firms 3.6 percent of their expected refund relative to electing the carryforward.²⁶ Taken together, the results indicate a substantial effect of preparers on client behavior.

cation, as coefficients only modestly weaken relative to the univariate specifications.

How plausible is it that preparers differ markedly in sophistication? Further evidence comes from two Government Accountability Office (GAO) studies of paid preparers. In these studies, the GAO sent field examiners to have individual tax returns prepared and then investigate whether preparers were making consistent and legal recommendations to their clients. The GAO documented serious errors and inconsistencies across preparers, in some cases within the same tax firm. These reports prompted a broader review of paid preparers by the IRS and eventually led to the launch of a 120-question basic competency test required for noncredentialed preparers.²⁷

In a field experiment providing information to Earned Income Tax Credit (EITC) applicants, Chetty and Saez (2013) document heterogeneous treatment effects by tax preparers and argue these effects derive from differences in preparers' understanding of the code. Furthermore, in a separate study of EITC take-up among individuals, Bhargava and Manoli (2015) report conversations with practitioners who

²⁷ The studies are GAO-06-563T and GAO-14-467T, both titled "Paid Tax Return Preparers: In a Limited Study, Chain Preparers Made Serious Errors" (Brostek 2006 and McTigue 2014). IRS regulation of the paid preparer industry has been challenged in federal court and remains an area of active legal and policy concern.

 $^{^{26}}$ Using estimates from panel A of Table 4, column 6, going to a CPA preparer who is not self-employed and from the tenth to ninetieth percentiles in all observables increases take-up by $0.059 + 0.0158 + 0.0042 \times (12.51 - 9.98) + 0.0006 \times (63.48 - 35.52) + 0.0091 \times (16.62 - 13.06) = 13.46\%$. The median cost of claiming a refund is 6.75 hours of work (mean of 2 and 11.5 hours) at \$54 per hour (\$45 plus an assumed 20 percent markup), which equals 5.2 percent of the median eligible refund (\$346/\$7,045). Discounting at 7 percent the observed path of carryforwards in panel B of Figure 2 implies a typical value of 68 percent relative to the carryback. Thus, the incremental benefit of moving from a tenth to ninetieth percentile preparer is $13.46\% \times (1 - 0.68 - 0.052) = 3.6\%$, relative to the size of the carryback. Note this figure increases with the firm's discount rate, as the carryforward becomes less attractive.

suggest the "sheer size of the preparer population and the ease of application ... has led to significant variation in preparer quality," which may contribute to low take-up rates of complex credits.

While these studies focus on individual tax returns, it is plausible that similar dispersion in tax code knowledge and practice exists among preparers filing corporate tax returns, especially among small firms. An alternative but complementary interpretation is that tax preparers without professional licenses and with low incomes and few clients are lazy or even actively choosing not to act in the best interest of their clients, instead opting for the "quiet life" in the spirit of Bertrand and Mullainathan (2003). Similarly, despite limitations on how the IRS can audit carryback claims, inexperienced preparers may be less willing to risk a higher chance of audit or may believe claiming a refund significantly raises this chance.²⁸ In this interpretation, the only potential role for complexity is to prevent clients who are confused about or unaware of the refund decision from being able to monitor their preparers. We do not believe the facts permit separating these interpretations.

One prediction of the sophistication hypothesis is that preparer effects should be less important for larger firms, either because these firms are able to monitor preparers more effectively or because these firms hire from the pool of skilled experts. We test this by running separate switcher analyses within each firm size decile as defined in Table 3. Specifically, we implement the multivariate regression from column 6 of Table 4, panel A, and conduct *F*-tests for the joint significance of the preparer characteristics. Within the bottom nine deciles, average *F*-statistics vary from 1.56 to 4.67, which correspond to *p*-values between 0.15 and 0.00. In the tenth decile, the *F*-statistic is 0.89 with a *p*-value of 0.51. Thus, consistent with a preparer sophistication interpretation, for all but the largest firms we can reject the hypothesis that preparers are irrelevant for the take-up decision.

Under uncertainty, if the firm expects tax rates to increase or expects to return immediately to profitability, the expected value of the carryforward will increase. We have seen that, even with modest discount rates and generous accounting for unused carryforwards, most firms should still prefer the carryback option—indeed, the frictionless neoclassical model predicts this choice. It is possible, however, that less experienced preparers are more miscalibrated in their beliefs. Such preparers would need to be very optimistic about future profitability, given the typical path of future deductions displayed in panel B of Figure 2. Furthermore, in terms of discount rates, we might expect less experienced preparers to be more present-biased and effectively display *higher* discount rates, which would predispose them toward the carryback (see online Appendix Table A3). Thus, a beliefs-based interpretation does not fit the data as naturally as the alternatives discussed above.

A common validation for an event study design plots trends before and after the event. To implement this test, we focus on a subsample where we have at least four observations per firm.²⁹ For each firm, we order observations by tax year and define

²⁸ Slemrod, Blumenthal, and Christian (2001) present evidence from an audit notification experiment, which suggests that taxpayers that have been through audit before are less responsive to audit threats.
²⁹ Unfortunately, the data do not permit a traditional event study analysis with many pre-period placebo tests.

²⁹ Unfortunately, the data do not permit a traditional event study analysis with many pre-period placebo tests. The reason for this is that eligibility depends upon a particular sequence of tax gains followed by tax losses, which make the likelihood of consecutive events quite unlikely due to the persistence of tax status.

them relative to the first observation after the firm changes preparers. We call this order event time *e*, where $e \in \{-3, -2, -1, 0, 1, 2\}$. We then construct a measure of the treatment effect associated with each event from the multivariate estimates from column 6 of Table 4, panel A: $\Delta \hat{\mu}_{\mathbf{J}(i,0)} = Z_{\mathbf{J}(i,0)} \hat{\gamma} - Z_{\mathbf{J}(i,-1)} \hat{\gamma}$. We then estimate a variant of our baseline panel regression where we allow the coefficient θ_e on the treatment effect $\Delta \hat{\mu}_{\mathbf{J}(i,0)}$ to vary with event time:

(3)
$$\mathbf{1}(carryback \ take-up)_{iit} = \Delta \hat{\mu}_{\mathbf{J}(i,0)} \theta_e + X_{it}\beta + \alpha_i + \delta_t + \zeta_e + \nu_{it}$$

The regression equation above also includes client characteristics X_{it} , a client fixed effect α_i , a tax-year fixed effect δ_t , and an event time fixed effect ζ_e . We omit a dummy for the event time e = -2 to avoid collinearity, so coefficients θ_e are estimated relative to the coefficient at event time e = -2.

Estimating equation (3) tests for pre-trends and post-trends that are correlated with the preparer effect $\Delta \hat{\mu}_{\mathbf{J}(i,0)}$. The key test is whether predicted effects are zero in the carryback-eligible years prior to the switch (i.e., at e = -1 and e = -3). On average, the coefficient after the switch θ_0 should equal one because the client has changed preparers, and take-up reflects the change in the predicted preparer effect. We should also expect θ_1 and θ_2 to equal one because most clients are with the same preparer at event time e = 1. If the sample for this test were the same as for the full sample, then θ_0 will equal one by construction. However, no mechanical restrictions apply to θ_{-3} , θ_{-1} , θ_1 , and θ_2 because the baseline regression excludes observations from event times e = -2, e = 1, and e = 2.

Figure 5 plots estimates of the coefficients θ_e . The regression includes dummies for missing values of the preparer characteristics and client controls. We cluster standard errors at the firm level. We cannot reject the null of zero for the coefficients θ_{-3} or θ_{-1} and find point estimates close to one for both θ_0 and θ_1 . The point estimate for θ_2 is lower (0.70, standard error = 0.19) but statistically indistinguishable from one. As in Figure 4 and the Empirical Bayes analysis, preparer effects are persistent within preparer-firm matches over time. The results validate our research design, confirming the absence of both pre-trends and post-trends that are correlated with the treatment effect.

C. Preparer Deaths and Relocations

Our estimates above rely on the identifying assumption that unobservable determinants of client take-up remain unchanged when switching preparers. But clients may change preparers in response to a change in their firm. For example, a client may hire a new preparer when it hires a new manager. The change in client unobservables that cause the firm to switch preparers could also affect its claiming behavior. Here, we focus on a subsample of events where the prior preparer either dies or relocates at least 75 miles away. In these cases, it is more plausible that client unobservables remain unchanged around the switching event.

We identify deaths and relocations by linking preparers to a social security file and to their individual income tax returns. We compute the distance between personal residence addresses based on the centroids of their zip codes before and after



FIGURE 5. CARRYBACK CLAIMS AND PREDICTED PREPARER EFFECTS (SWITCHER SAMPLE, 1998–2011)

Notes: This figure plots the coefficients from a regression of carryback take-up on interactions between event time and the change in the predicted preparer effect at event time e = 0. We construct the predicted preparer effects using the estimated coefficients from column 6 of Table 4, panel A. The change in the predicted preparer effect at event time e = 0 equals $\Delta \hat{\mu}_{\mathbf{J}(i,0)} \hat{\gamma} - Z_{\mathbf{J}(i,-1)} \hat{\gamma}$. The regression includes a firm fixed effect, a tax-year fixed effect, firm controls, and an event-time fixed effect. Firm controls include log(eligible refund), log(revenue), log(assets), and log(EBITDA). The regression also includes dummies for missing values in firm controls. The plotted coefficients are estimated relative to event time e = -2. Standard errors are clustered at the firm level.

Source: Author's calculations

a relocation. We then identify firms that change preparers contemporaneously with either the death or relocation of the prior preparer. The sample includes 4,912 death or mover events.

Panel B of Table 4 reports results from estimating equation (2) for this subset of events. We estimate regressions separately for each preparer characteristic, and we also include the predicted preparer effect based on column 6 of Table 4, panel A, as an additional covariate. We find coefficients close to our earlier point estimates, with the exception of the covariates 1(other professional license), which has a stronger effect than in the full sample, and 1(self-employment), which has a different sign but loses statistical significance. As the sample falls from 124,862 to 9,824 observations, these tests have less statistical power to detect effects, but we still find strongly significant results for 1(certified public accountant) and log(mean client revenue). We estimate a strongly significant coefficient of 0.9372 on the predicted preparer effect, which implies that the switchers design estimates an unbiased preparer effect. Together, our estimates indicate that changes in client unobservables do not confound the original results from the switchers design.

We focus on deaths and relocations because we believe it is more likely that client unobservables remain unchanged before and after the switching event. But selection could still arise in this subsample from the hiring of new preparers. Our results could be confounded if the same client unobservables that determine preparer hiring also determine take-up of the carryback refund.³⁰

We address this additional concern with a two-stage least squares estimate with the deaths and relocations subsample. Intuitively, we instrument for the change in the preparer effect with the prior preparer characteristic because we think that the change in client unobservables is unrelated to the prior preparer. We express our estimates for this design in a first-differences version of equation (2):

(4)
$$\Delta \mathbf{1}(carryback\ take-up)_{ije} = \Delta Z_{\mathbf{J}(i,e)}\gamma + \Delta X_{ie}\beta + \Delta \delta_{\mathbf{T}(i,e)} + \Delta \epsilon_{ie}$$

with observations indexed by event time e^{31} . The difference is taken between the first observation after the switch and the last observation before the switch.

To instrument for the change in the preparer effect $\Delta Z_{\mathbf{J}(i,e)}$, we use the difference between the sample mean preparer effect and the predicted effect for the preparer prior to the switch, $\Delta \tilde{Z}_{\mathbf{J}(i,e)} = \bar{Z} - Z_{\mathbf{J}(i,e-1)}$. The instrument therefore derives its relevance from mean reversion in preparer quality after a switch. The two-stage least squares estimates identify the causal treatment effect of preparer covariates under the assumption that the change in client unobservables is uncorrelated with the characteristics of the prior preparer (as represented by the instrument $\Delta \tilde{Z}_{\mathbf{J}(i,e)}$), the change in client observables, and the tax-year fixed effects. If changes in client unobservables do not correlate with preparer deaths and relocation, then this assumption is likely to hold.

Table 5 reports two-stage least squares estimates for regressions with client fixed effects and different control sets. Column 2 adds a tax-year fixed effect. Column 3 adds firm controls. As discussed above, the predicted preparer effect captures the estimated relationship between preparer characteristics and carryback take-up, which implies an expected coefficient of one. Consistent with this prediction, the regressions yield point estimates of 1.15, 0.96, and 0.73 in columns 1, 2, and 3. The confidence intervals are relatively large, but in all specifications we can reject the null of a zero coefficient at a 5 percent level and cannot reject the hypothesis that the coefficients equal one. These results further validate the predicted preparer effect estimated under the switchers design.

D. Large Firms and Tax Code Interactions

Because large firms are more sophisticated tax planners, they may be less subject to agency problems between the firm and hired experts. However, large firms are

³⁰One might also be concerned that dying preparers are a selected sample and that movers might be moving because they were fired for being low quality. Relative to the full sample of preparer switches, preparers in this sample are older (56 versus 50), less likely to be CPAs (77 percent versus 83 percent), and more likely to be self-employed (29 percent versus 18 percent). In terms of client size, they are comparable to the full sample. Thus, based on observable characteristics, it is unclear whether this sample should show higher take-up (as older preparers have higher claim rates), lower take-up (as self-employed and non-CPA preparers show lower claim rates), or no difference. Regarding potential reverse causality, if an accountant is fired for reasons that are unrelated to the outcomes of the one client of her possibly many clients included in the research design (see online Appendix Table A4 for statistics on how many clients tax preparers typically have), then the identifying assumption from a relocation is still valid.

³¹The function $\mathbf{T}(i, e)$ maps firm *i* at event time *e* to tax year *t*.

	(1)	(2)	(3)
Predicted preparer effect	1.1513 (0.3802)	0.9609 (0.3878)	0.7339 (0.3678)
First-stage coefficient	0.5463 (0.0130)	0.5387 (0.0129)	0.5355 (0.0129)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes
Firm controls	No	No	Yes
Observations	9,824	9,824	9,824

TABLE 5—REFUND CI	LAIMS AND I	V Predictei	PREPARER	Effects
(Deaths	/MOVERS S	AMPLE, 1998	-2011)	

Notes: This table reports coefficients from a two-stage least squares regression of carryback take-up on preparer characteristics. The predicted preparer effect is constructed using the estimated coefficients from panel A, column 6 of Table 4. The instrument equals the preparer covariate in the pre-event period and the sample mean for the preparer covariate in the post-event period. All regressions include a firm fixed effect. Column 2 adds a tax year fixed effect. Column 3 adds firm controls, which include log(eligible refund), log(revenue), log(assets), log(EBITDA), and an indicator for negative EBITDA. The sample is limited to switching events contemporaneous with either the death or relocation of the prior preparer. It only includes the last observation before a client changes its preparer and the first observation after a client changes its preparer. Relocations are defined based on moving personal residences to a new zip code at least 75 miles away. Standard errors are clustered at the firm level.

Source: Author's calculations

more likely to face other costs arising from the complexity of the tax code and its administration. This section summarizes evidence in online Appendix C from two factors. First, interactions between the carryback and other tax code provisions may alter the cost-benefit calculation in favor of the carryforward, either by reducing the value of the carryback or by increasing the cost of filing a claim. Second, if a prior tax return is currently under audit, a taxpayer may choose to forgo the carryback to avoid interfering with the audit.

We analyze two sets of tax provisions that generate additional complexity through interactions with carrybacks: (i) the corporate alternative minimum tax (AMT) and (ii) a basket of tax credits and offsets. Both the AMT and tax credits contribute significantly to estimated costs of tax return filing and estimated time to file, making them likely to contribute to the complexity of a large corporation's tax return. Claiming a carryback requires a firm to recompute its AMT liability and eligibility for tax credits claimed in the past, thus increasing the cost of claiming and possibly reducing the size of a refund.

AMT payers are considerably less likely to claim a refund, and this gap in claiming rates is widest for firms at the top of the firm size distribution. For the top 2 percent of firms, the gap is approximately 20 percentage points, which suggests that AMT interactions may be a pivotal determinant of refund take-up among large firms.³² When studying interactions with other tax credits, we find that firms that do claim other credits consistently show *higher* rates of carryback claims. The effects

³²One potential explanation for this fact is that net operating losses can only be used to offset 90 percent of AMT income, which can reduce the value of a refund. Unfortunately, our data do not permit us to decompose post-adjustment tax liabilities into regular and AMT liability. We thank Andrew Lyon for this suggestion.

are smaller than for the AMT but remain notable. We interpret these results as suggesting some complementarity in claiming complicated credits and claiming the carryback refund. Last, to complement our administrative data, we turn to public company filings to ask how firms talk about their burden as taxpayers when communicating with shareholders. The anecdotes collected reveal substantial heterogeneity in reported compliance costs across firms.

VI. Conclusion

The most direct finding of our work is that the assumption that firms always claim refunds for tax losses does not fit the data. This departure is quantitatively relevant and suggests that additional costs of claiming refunds mute the potential impact of carryback extensions as fiscal stimulus. Fiscal stimulus measures often rely on the introduction of new and temporary tax benefits.³³ Our results underscore the importance of careful, transparent design of fiscal policy, even when the policy setting is familiar and even when those targeted are sophisticated.

More broadly, our results show that corporate tax decisions reflect the complexity of the tax code in addition to the simple costs and benefits of individual provisions and in contrast to the classic focus on marginal tax rates. Tax code complexity factors into corporate decision-making in different ways for small firms versus large firms. For small firms, the primary focus of this study, complexity can amplify agency frictions between firms and the experts they hire to help them file their tax returns. For large firms, complexity emerges from interactions with other tax code provisions and with the compliance process. Carryback stimulus policy thus favors firms that are better prepared to claim refunds and may disfavor some large firms with complicated tax returns.

Our study highlights the mediating role that preparers play between the tax code and taxpayers by showing that preparers influence tax claiming decisions. The results suggest that investing in better take-up of tax benefits could be as important as adding new targeted provisions. Future research might consider whether targeting preparers with informational materials or training or providing taxpayers with defaults through automatic calculation of carryback eligiblity can improve the take-up of corporate tax benefits.

Our research has several limitations. First, we focus primarily on one policy and thus cannot speak directly to whether these considerations prove critical in other settings. Second, measuring the effects of complexity is inherently difficult. Our approach offers an incomplete look into how complexity can affect behavior by focusing on measurable channels. Last, we are not directly measuring the real effects of failure to claim a tax refund, so some caution is warranted in drawing conclusions about whether complexity affects other firm outcomes.

The recently passed Tax Cuts and Jobs Act of 2017 provides an opportunity to advance this research in several directions. First, exploring whether preparers or other delegated experts influence take-up of new provisions, such as the

³³For example, the American Reinvestment and Recovery Act of 2009 distributed 36 percent of its stimulus dollars through 55 different tax benefits (Recovery Accountability and Transparency Board 2014).

deduction for pass-through business income, would be fascinating. Second, studying how firms adjust to the new international tax regime would shed light on how tax reforms affect large taxpayers. Third, Congress was able to eliminate carrybacks without significant pushback from taxpayers or the tax preparation industry, perhaps because of how the policy worked in the previous regime. Although the carryback was abolished in this reform, the option to implement an improved carryback as fiscal stimulus remains available to policymakers. In addition, many other countries continue to offer the carryback to corporate taxpayers. We hope our research can help guide future policy design.

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