The Impact of In-person Communication on Resolving Tax Uncertainty with the IRS:

Evidence from Social Shutdowns during the COVID-19 Pandemic

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Abstract

We investigate whether in-person communication affects firms' ability to resolve tax uncertainty with the IRS. Using publicly available data, we construct a novel measure that approximates the driving traffic between the firm's headquarters and its closest IRS office to capture in-person communication between the firm and the IRS. We test our prediction by exploiting an exogenous social restriction shock—issuances of stay-at-home orders by different states during the COVID-19 pandemic. Firms with high in-person communication with the IRS before the issuance of stay-at-home orders experience a significant decline in their traffic to and from the closest IRS office, which supports our driving measure plausibly capturing the extent of in-person communication. Further, we find these firms are less effective at resolving tax uncertainty following the implementation of stay-at-home orders. This effect is particularly pronounced for firms having more interaction with the IRS prior to the pandemic, such as through participating in the Compliance Assurance Process (CAP) program and through auditors who provide more tax services. Our study informs both regulators and businesses on the relative effectiveness of in-person versus virtual communication during tax audits.

1. Introduction

Firms are well known for engaging in tax avoidance activities that increase after-tax cash flows (Hanlon and Heitzman 2010; Wilde and Wilson 2018). But tax authorities can challenge tax avoidance, resulting in increased uncertainty related to the loss of tax savings (Dyreng et al. 2019). As firms save cash to buffer against these future audit outcomes, they bear real costs that reduce operational efficiency, such as delaying investments and cutting R&D (e.g., Hanlon et al. 2017; Jacob et al. 2022; Williams and Williams 2021). Based on field interviews, tax professionals and executives suggest communication with tax authorities is crucial for firms to resolve uncertain tax positions (Bruhne and Schanz 2022; Seidman et al. 2022). However, how firms communicate with tax authorities, and effectively use that communication to resolve tax uncertainty, are not well understood. Using publicly available data, we estimate and examine the extent to which in-person communication between firms and the IRS helps resolve tax uncertainty.[1] Answering this question has timely implications as governments and businesses have gradually moved away from face-to-face interaction to online communication following the COVID-19 pandemic (Parker et al. 2022; Maurer 2021), meanwhile Congress is calling for rules requiring federal workers to return to their physical offices (Kasperowicz 2023).

In-person communication has unique information benefits that go beyond remote communication methods such as phone calls, emails, and video conferences. First, face-to-face communication involves simultaneous information transmission at multiple levels. In particular, nonverbal cues such as facial expressions, postures, and gestures flow naturally with the conversation to convey complex information signals (Mehrabian 1971). Second, in-person

[1] Throughout the paper, we use the terms "in-person communication" and "social interaction" interchangeably to describe face-to-face meetings between firms and tax authorities. This is in contrast to remote means of communication, such as phone calls, emails, and video conferencing.

communication requires participants to share the same physical space, which promotes involvement and a mutual connection (Bushee et al. 2011). This, in turn, reduces the psychological distance between participants (Guo et al. 2009).

Research in accounting and finance has documented the information benefits of in-person communication. For example, using novel approaches in measuring in-person communication, analysts issue more accurate forecasts following site visits to portfolio companies in China (Cheng et al. 2016) and following an increase in taxi rides from brokerage houses to company sites in New York City (Choy and Hope 2022). In addition, the introduction of direct airline routes facilitates in-person communication through reduced travel time. Following the introduction of new air routes, venture capital funds help increase portfolio companies' innovation, and mutual funds increase investments in portfolio companies (e.g., Bernstein et al. 2016; Ellis et al. 2020).

Similarly, in a tax setting, we expect in-person communication to help tax authorities and firms to resolve tax uncertainty. Field studies provide evidence of two key factors that enable firms to effectively resolve tax uncertainty with the Internal Revenue Service (IRS) (Bruhne and Schanz 2022; Seidman et al. 2022). First, when firms develop a cooperative relationship with the IRS, they can more strategically influence how the IRS perceives the firm and approaches future tax audits. Second, firms can negotiate with the IRS, such as conceding some tax issues in exchange for more favorable outcomes on other tax issues. Through in-person communication, the IRS and the firm are more likely to develop a mutual understanding to resolve tax uncertainty.

However, it is not clear whether the evidence based on a limited number of tax practitioner interviews can be generalized to a broader set of firms.[2] Meanwhile, in recent years, the IRS has been extensively rolling out online tools that allow its agents to communicate with corporate

[2] For example, Bruhne and Schanz (2022) interview 33 tax practitioners and Seidman et al. (2022) interview tax executives and directors from 26 companies. Nevertheless, these interviews provide strong motivation for our study.

taxpayers and exchange supporting documents virtually (IRS 2022; Harris 2021). Both firms and the IRS might have adjusted to conducting auditing through remote means. Thus, the open empirical questions we seek to answer are whether and the extent to which in-person communication helps firms resolve tax uncertainty with the IRS.

To answer these questions, we first develop a proxy for the likelihood of face-to-face communication between the IRS and the firm. In particular, we construct a novel measure that estimates the driving traffic between the firm's headquarters and its closest IRS office.[3] Our measure extends prior research showing when a firm's headquarters is located close to a regulatory office, more information transfer likely occurs between the firm and regulators (Kedia and Rajgopal 2011; Kubick et al. 2017). Therefore, although we cannot publicly observe how often IRS agents drive to company headquarters and vice versa,, our measure reflects that a face-to-face meeting is more likely to occur when there is more driving traffic between two locations, holding geographic distance constant. To estimate driving traffic, we obtain monthly driving trip data from the Bureau of Transportation Statistics (BTS), which reports the number of driving trips for each county within the U.S. by different distance bandwidths (e.g., as short as less than 1 mile and as long as more than 500 miles). Based on the distance between the company headquarters and its closest IRS office, we identify the corresponding distance bandwidth from the BTS data and obtain the number of trips for the county where the company headquarters (IRS office) is located within that bandwidth. The focal county can be where either the company headquarters or the closest IRS office is located, allowing us to calculate the driving traffic to and from the IRS office and infer the likely level of in-person communication between these two parties. Importantly, our driving traffic measure is calculated as the ratio of the number of trips in the focal county over the

[3] Our assumption that tax planning activities occur at the corporate headquarters is consistent with Kubick et al. (2017), and is supported by the evidence from Hossain and Mitra (2023).

population size in that county. In Appendix A, we use an example to illustrate how we construct the two-way driving traffic measure between the company headquarters and its closest IRS office. Based on the company headquarters matched with the closest IRS office, our driving traffic measure varies with time and the direction of traffic, which is useful to examine how in-person communication can change in response to different events affecting social interactions.

To support that our driving traffic measure is a reasonable proxy for in-person communication, we rely on the unprecedented COVID-19 pandemic that provides an exogenous shock to social interaction. Following the pandemic outbreak, many states enacted stay-at-home orders to reduce face-to-face interaction and virus transmission, which were later lifted at different time points at the discretion of each state (Kong and Prinz 2020).[4] The cross-state and cross-time variations in the implementation of stay-at-home orders provide exogenous shocks that significantly reduce in-person communication, which helps validate our driving traffic measure. We expect that firms with high in-person communication with the IRS (e.g., high driving traffic to and from the closest IRS office) before stay-at-home orders are issued will experience a greater decrease in driving traffic following the social restriction.

Next, we expect that firms more reliant on in-person communication with the IRS will be more adversely affected by stay-at-home orders to resolve tax uncertainty. Specifically, we predict that firms with high in-person communication with the IRS before stay-at-home orders are issued are less able to resolve tax uncertainty after the social restriction order takes effect. To capture the amount of tax uncertainty resolved, we rely on the tabular FIN 48 roll-forward disclosure of unrecognized tax benefits (UTB) in 10-Ks. Beck and Lisowsky (2014) and Dyreng et al. (2019)

[4] In addition to stay-at-home orders, various states issued other social restriction orders, such as restaurant and bar limitations, non-essential business closures, and school closures (Kong and Prinz 2020). We focus on stay-at-home orders because they are the most widespread social restriction intervention that affects the majority of the population in the state, which offers a powerful setting to capture the change in social interactions between firms and the IRS.

suggest that the UTB reflects uncertain tax positions that firms expect to be challenged by the tax authority. Robinson et al. (2016) focus on three components that collectively contribute to the process of unwinding the UTB and resolving tax uncertainty—the firm's statute of limitations lapses, tax settlements, and reductions related to prior-year positions.[5] We thus use the combination of these three components to capture the amount of tax uncertainty that firms can resolve with the IRS.

Our sample consists of 1,328 firm-year observations (15,936 firm-month observations) for which we require necessary data for tax uncertainty and driving traffic from 2019 to 2021.[6] To exploit the monthly driving data from BTS, we examine the change of driving patterns based on the 15,936 firm-month observations. We define high in-person communication firms as those with an average monthly driving traffic between its headquarters and the closest IRS office at the top tercile in the period preceding stay-at-home orders. Henceforth, we use high in-person communication to describe this treatment group. We validate that following stay-at-home orders, treatment firms experience a significantly greater decline in driving traffic than control firms. In terms of economic magnitude, the treatment firms, on average, have 13.8 (16.8) percentage points higher driving traffic from (to) their closest IRS offices before stay-at-home orders compared to the control group, but these firms' driving traffic decreases by 6.8 (7.3) percentage points following the social restriction order. The evidence supports that our driving traffic measure approximates in-person communication between the firm and the closest IRS office.

We next investigate whether the high in-person communication treatment firms are less able to resolve tax uncertainty following stay-at-home orders. Because the UTB data is only available at the annual level, we test the prediction based on the 1,328 firm-year observations.

[5] We offer a detailed discussion of the differences and similarities of these components in Section 2.2.
[6] We begin the sample period in 2019 as this is the first year when the BTS provides driving data at the county-level.

Consistent with our expectation, we find that firms with high in-person communication *from* their closest IRS offices (i.e., the flow of in-person interaction is from the IRS office to the firm, likely due to field audits that are conducted on-site at the firm) are less able to resolve tax uncertainty following stay-at-home orders. Economically, for an average size firm with high in-person communication *from* its closest IRS office, it resolves about $1.93 million less tax uncertainty as the period of stay-at-home increases by one month. Nevertheless, we only find marginal evidence that firms with high in-person communication *to* the closest IRS office experience a decrease in resolving tax uncertainty post stay-at-home orders (i.e., the flow of in-person interaction is from the firm to the IRS office, likely due to office audits that are conducted at the IRS office and are less intensive as a field audit).[7]

Following our main test, we explore cross-sectional settings where high in-person communication firms are likely more affected by stay-at-home orders to resolve tax uncertainty with the IRS. Specifically, we focus on three settings where firms need more intensive interaction with the IRS. First, when a firm is assigned to the Coordinated Industry Case program (CIC), the IRS dedicates a team of agents and experts to spend a substantial amount of time in the taxpayer's primary place of business, i.e., a field audit (Ayers et al. 2019). The CIC program offers a structured opportunity for the firm to directly interact with the IRS. Similarly, the Compliance Assurance Process (CAP) program provides firms with an opportunity to cooperate with the IRS to timely resolve tax audit issues (Beck and Lisowsky 2014).[8] By participating in the CAP program, the firm collaborates with a dedicated IRS account coordinator to review and resolve tax issues.

[7] In an office audit, taxpayers provide the IRS agents with requested documents at the IRS office, and the audit's scope is confined to these records. In contrast, field audits have a broader and more intensive scope. By conducting on-site visits to taxpayers, IRS agents can access a wide range of records (e.g., inventory and invoice) and engage with people across different positions.

[8] These two programs enable a more direct interaction between taxpayers and the IRS, but they have subtle differences. Different from the CIC program where firms are assigned by the IRS, the CAP program is based on firms' voluntary participation (Ayers et al. 2019; Beck and Lisowsky 2014).

Finally, firms interact with the IRS through service intermediaries such as auditors who provide tax services to the firm (Klassen et al. 2016). When the firm purchases more tax services from its auditors, the firm will interact more with the IRS through the auditors to resolve tax uncertainty.

For firms with high in-person communication from (to) their closest IRS offices, we find stay-at-home orders have a greater adverse impact on their ability to resolve tax uncertainty, especially those that had a higher likelihood of participating in the CAP program and had purchased more tax services from their auditors prior to COVID-19. We find some evidence that the adverse impact of stay-at-home orders is concentrated in firms that had a higher likelihood of being assigned into the CIC program before the pandemic. Overall, our evidence is consistent with firms relying more on in-person meetings to resolve tax uncertainty when they have more intensive interaction with the IRS, including through their auditors. The results further support our driving measure in capturing in-person communication between the firm and the IRS.

Our study provides timely evidence to assess the impact of COVID-19 on the communication between firms and the IRS to resolve tax uncertainty. The COVID-19 pandemic is having a profound long-term impact on how people work. According to a Pew research survey (Parker et al. 2022), 59 percent of workers with jobs that can be done from home are teleworking in 2022, an increase from only 23 percent in 2019. Similarly, many federal government employees that have transitioned to remote work plan to continue this flexible arrangement going forward (Maurer 2021). Along with the trend of an increasingly virtual working environment, we seek to understand whether in-person communication has unique information benefits for regulators and businesses. We show that in-person communication is important for firms to resolve tax uncertainty with the IRS. Our findings thus have timely implications for both regulators and businesses to consider the effect of remote work on enforcement actions and business planning.

Furthermore, our findings seek to inform the IRS on how to effectively communicate with corporate taxpayers as the agency prioritizes budget spending. Over the past decade, the amount of funding and staff for IRS enforcement has decreased by approximately 30 percent since 2010 (Congress Budget Office 2020; Taxpayer Advocate Service 2012), and it is currently assessing how to spend $80 billion in newly appropriated funds from the Inflation Reduction Act of 2022 (IRS 2023). The IRS must therefore carefully balance its budget priorities with the need to travel to corporate taxpayers' sites for effective tax enforcement. Meanwhile, the IRS has been rolling out online (virtual) tools to communicate with corporate taxpayers during tax audits (IRS 2022; Harris 2021). Our findings show that firms intensively interacting with the IRS benefit from continued in-person communication to resolve tax uncertainty. Therefore, our results inform the tax agency's decision on the trade-offs between in-person and virtual audits for corporate taxpayers.

Finally, our findings extend prior research examining the information environment between regulators and firms. Previous research shows regulators have a better understanding of the firm that they monitor when the firm's headquarters is located in close geographic proximity (Kedia and Rajgopal 2011; Kubick et al. 2017). We provide additional insight into this stream of research by constructing a novel measure of driving traffic between the IRS office and firms' headquarters, capturing the variation in potential in-person communication over time. We empirically corroborate our measure using the exogenous shock of stay-at-home orders during the COVID-19 pandemic. For future research, our measure provides a unique opportunity to examine how changes in face-to-face communication might influence enforcement outcomes of financial, auditing, and tax regulators.

2. Literature Review and Hypothesis Development

2.1. In-person communication

Face-to-face communication has unique information benefits that go beyond what is contained in verbal content. Specifically, face-to-face communication involves the integration of multimodal sensory information (Jiang et al. 2012). Non-verbal cues such as facial expressions, postures, and gestures flow naturally and simultaneously with the conversation to convey complex information signals (Mehrabian 1971). In a face-to-face meeting, participants share the same physical location and can see and hear all non-verbal cues, which prompt their interactions in sequence (Guo et al. 2009). For example, to better understand the firm they are covering, financial analysts are regularly trained by ex-CIA or ex-FBI agents to watch for non-verbal cues that tell whether the management is truthful (Brown et al. 2015).

However, it is difficult to achieve these in-person communication benefits through remote means such as phone calls, emails, and even video conferences (e.g., Zoom). Foremost, it is impossible to observe non-verbal cues from phone calls and emails. Though video conferences provide visual interactions, what meeting participants observe is socially distorted and limited. For example, in an in-person meeting, it is common for people to naturally make head and eye movements to signal the turn of conversation, agreement, and other cues (Kleinke 1986). But on Zoom, the most popular video conference platform in recent years, listeners and speakers often forego natural head and eye movements and make direct and unwavering eye gaze perpetually, which is not socially realistic (Bailenson 2021).[9] Even when Zoom users make eye movements, it often has different meanings from a typical social setting (Bailenson 2021). For example, in a face-

[9] According to a social experiment, when meeting participants make prolonged eye gaze for 8 minutes, they have the lowest level of social presence. In other words, they do not feel "in tune" with the speaker (Bailenson et al. 2006).

to-face meeting, a quick sidelong glance has a social meaning. But in Zoom, this could be due to different grid layouts on the user's computer. Finally, most people focus their cameras towards their heads in Zoom. As a result, other physical cues such as body size, leg movements, and postures are missing. Because video conferences provide distorted and limited evidence of non-verbal cues, in-person meetings are often the most effective mode of communication.

Additionally, compared to remote meetings, in-person meetings require the same physical space for participants to communicate. The sharing of physical space increases environmental cues to build a sense of connection (Bushee et al. 2011). Research shows that physical proximity promotes a higher degree of involvement and a mutual connection from participants (Guo et al. 2009). Similarly, face-to-face interaction increases personalization and reduces psychological distance compared to remote communication such as video conferences (Sellen 2009).

Research in accounting and finance has documented the benefits of in-person communication in business. The first stream of research uses publicly observable in-person meetings. Specifically, firms listed on the Shenzhen Stock Exchange in China are required to provide detailed disclosures of meetings with investors. Researchers find that corporate site visits in particular are associated with more accurate analysts' forecasts (Cheng et al. 2016), more mutual fund trading activities (Chen et al. 2022), and higher expected returns (So et al. 2021). But such disclosures do not exist in the U.S. setting, making it a challenge to identify in-person interactions.[10]

To address this challenge, the second stream of research uses reduction in travel time such as new airline routes to proxy for more in-person communication. For example, following the introduction of new airline routes, headquarters-based managers more efficiently monitor and

[10] Due to data constraints, U.S. studies are limited to small sample data from specific firms (e.g., Soltes 2014).

invest in subsidiary-level plants (Giroud 2013). Venture capital funds improve portfolio companies' innovations following new airline routes as well (Bernstein et al. 2016). Other research finds similar evidence in capital markets, as the introduction of new air routes is associated with more mutual fund investments in the firm and a lower cost of equity (Ellis et al. 2020; Da et al. 2022). Different from the airline data, Choy and Hope (2022) innovatively use taxi trip data from New York City to infer in-person communication between analysts and firms. They find increases in taxi rides are associated with more accurate analysts' forecasts.

Building on these prior approaches, to infer in-person communication between the IRS and firms, we rely on a novel source of data that detail driving traffic at the county-level nationwide. These data best suit our research question because caseloads are assigned to IRS agents based on their geographic proximity to firms (Kubick et al. 2017) and, according to our conversations with practitioners, agents rarely fly to firms' office sites. Additionally, it is challenging to extrapolate taxi rides in one city to IRS offices and corporate headquarters located throughout the country.

2.2. Resolving tax uncertainty

Corporate tax avoidance has received much attention in recent decades. To curb the surge of corporate tax avoidance activities, policymakers and regulators have strengthened their scrutiny (U.S. Senate 2012, 2013) and stepped up their enforcement efforts (OECD 2015). Based on the classic theoretical framework of tax planning (Scholes and Wolfson 1992), firms engage in tax avoidance when their expected cash savings outweigh the tax planning costs. In practice, firms face a continuum of tax avoidance strategies ranging from municipal bond investments at one end to aggressive activities such as tax sheltering at the other end (Lisowsky et al. 2013). Following the tax authority's challenge to these aggressive activities, the firm's underlying tax avoidance position might not prevail, resulting in the loss of tax savings. Dyreng et al. (2019) define tax uncertainty as the potential loss of tax savings upon the tax authority's challenge to the firm's tax positions. To buffer against losses resulting from tax uncertainty, firms increase cash holdings (Hanlon et al. 2017), delay investments and reduce the sensitivity of investments to growth (Jacob et al. 2022; Goldman 2019), and curb R&D spending (Williams and Williams 2021). Tax uncertainty imposes real opportunity costs on firms by diverting internal funds away from investments in growth opportunities. Thus, efficiently resolving tax uncertainty is crucial for firms.

To resolve tax uncertainty, both the firm and the IRS need to agree on the underlying tax position and resolve their differences, resulting in the firm's updated belief about the sustainability of tax benefits. Following the implementation of Financial Interpretation No. 48 (FIN 48), later codified as Accounting Standards Codification (ASC) 740-10, firms are required to disclose the amount of tax reserves for uncertain tax positions in their 10-Ks. Specifically, FIN 48 requires firms to accrue unrecognized tax benefits (UTB) for positions that are unlikely to be sustained upon the IRS audit. Based on a tabular roll-forward disclosure approach, UTBs increase with uncertain tax positions that the firm claims in the current or a prior year.

The UTB can decrease due to three reasons—the firm's statute of limitations lapses, a settlement is made with the tax authority, and/or adjustments are made to prior-year positions. Statute of limitation lapses result from uncertain positions that ultimately go unaudited by the IRS (Holt et al. 2022). Tax settlements could result from cash tax payments to the tax authority (PWC 2013) and/or non-cash adjustment such as the reversal of over-accruals related to prior year uncertain tax positions (Bauer and Klassen 2019).[11] Finally, the reductions related to prior-year positions mostly refer to decreases in reserves. These reductions are a result of new information

[11] There are likely variations in the accounting practice for tax settlements (Dyreng et al. 2019). While PWC (2013) recommends that firms should include cash tax payments to the tax authority as tax settlement, Bauer and Klassen (2019) find examples of firms including the reduction of over-accruals related to prior-year tax positions in the tax settlement. Thus, we consider tax settlements in conjunction with other accounts to identify the unwinding of UTBs.

obtained from the IRS, other taxpayers, or the courts, which would require adjustments to the UTB balance. Robinson et al. (2016) suggest that these three components account for different angles in the unwinding process of UTBs, resulting in the firm's updated beliefs about whether it will keep or lose its tax benefits. These components therefore offer a helpful measure for identifying a firm's resolution of tax uncertainty with the IRS. However, it does not provide an insight into *how* this occurs. We examine the extent to which the communication process between the firm and the IRS facilitates the unwinding of UTBs.

2.3. Prediction

Based on field interviews with tax executives and tax advisers, firms widely acknowledge the importance of cooperatively communicating with the IRS to resolve tax uncertainty (Seidman et al. 2022; Brühne and Schanz 2022). Through cooperative communication, firms can strategically present their views of tax laws and how they comply with the law, which will shape the tax (IRS) agent's perception of the firm and influence the direction of the tax audit. For example, one tax director explained, "When they [IRS agents] are just asking the question, you try to spend a little bit of time educating them. And in some ways that ignites opportunity because it's your opportunity to present your view of the law and the requirements and how you're complying with it […]" (Seidman et al. 2022, 32). Further, some tax executives suggest the cooperative communication process with IRS can lead to "horse trading." By conceding on smaller gray area issues, firms can gain more favorable tax outcomes on larger issues (Seidman et al. 2022). Therefore, the communication between the firm and the IRS is highly dynamic, requiring extensive back-and-forth negotiation and trust building.

Due to the dynamic nature of communication between firms and the IRS, we expect in-person communication to facilitate the resolution of tax uncertainty. As we previously discussed, in-person meetings facilitate the simultaneous transmission of non-verbal cues to convey complex information and meaning among participants. Additionally, the sharing of physical space builds a sense of connection and fosters mutual trust for participants. These benefits of in-person communication likely help firms and the IRS build a cooperative relationship to resolve their different views. Additionally, through in-person meetings, firms and the IRS are more likely to gain a broad assessment of various tax issues, allowing firms to concede some tax issues in exchange for more favorable outcomes on other tax positions. Therefore, if in-person communication is reduced, the resolution of tax uncertainty should also be reduced. We formalize this predication as follows:

> **Hypothesis**: The reduction of in-person communication between firms and the IRS will reduce the resolution of firms' tax uncertainty.

However, while field interviews offer a helpful glimpse into the communication process between firms and the IRS, it is not clear how well the findings generalize to a broad sample of firms. Additionally, the IRS has been transitioning to remote communication with taxpayers in recent years, a trend that has accelerated in the wake of the COVID-19 pandemic (IRS 2022; Harris 2021). It is possible that both firms and the IRS have adapted to communicating without in-person meetings. Therefore, whether in-person communication helps the firm and the IRS resolve tax uncertainty is an empirical question.

3. Empirical Design

3.1. IRS offices and company headquarters

Since we focus on U.S. firms, we obtain the firm's headquarters zip code from Compustat NA. If Compustat NA does not provide the firm's headquarters zip code, we use the zip code data extracted from 10-K filings on SEC EDGAR. To obtain IRS office locations, we identify regional offices from the IRS Large Business & International (LB&I) Division organizational chart.[12] This chart lists three main regional divisions and 39 offices under these divisions: Eastern Compliance (13 offices), Northeastern Compliance (14 offices), and Western Compliance (12 offices). We use the IRS Internal Revenue Manuals to identify the specific states that each IRS regional office monitors. [13] This approach enables us to match states where firms' headquarters are located to their corresponding IRS regional offices. Figure 1 provides a map of IRS offices marked by black dots and company headquarters marked by grey circles. Larger grey circles indicate more company headquarters located within a county. Overlapping grey circles represent adjacent counties with clusters of company headquarters.

We next calculate the distance between matched IRS offices and company headquarters using the central node of the zip code. Based on the shortest distance between the firm's headquarters and the IRS office, we identify the firm's closest IRS office. To eliminate outliers in distance calculation, we keep company headquarters located in the continental U.S. and remove observations in Alaska and Hawaii.

3.2. Driving traffic measure

We exploit a novel dataset provided by the Bureau of Transportation Statistics (BTS) to measure the driving traffic between the company headquarters and its closest IRS office. This dataset is constructed by tracking the trips of individuals each day within a county.[14] We offer a detailed discussion in Appendix A of how we use the data to capture driving traffic *from* the closest

[12] We obtained the organizational chart from the IRS Large Business and International Division website on December 8, 2021.
[13] We download the IRS internal revenue manuals from https://www.irs.gov/irm.
[14] BTS constructs driving data by passively collecting mobile device location data. In general, a mobile application generates a location sighting when the device updates its location based on any of the location sensors, such as Wi-Fi, Bluetooth, cellular tower, or GPS. These location sightings can reflect the exact location of mobile devices and describe individual-level mobility patterns. The data from location sighting is anonymized to remove any potential identification information and is used by the BTS to capture trips across the nation. BTS then uses the location sighting data to identify trips. See Bureau of Transportation Statistics (2022) for additional details.

IRS office *to* the firm's headquarters (our "from" condition, likely capturing on-site field audits), and driving traffic *from* the firm's headquarters *to* the closest IRS office (our "to" condition, likely capturing audits that are conducted at an IRS office). Using the IRS office in Chicago as an example, we report the distance distribution between company headquarters and the IRS office in Panel A, and illustrate that the driving traffic measure varies with distance bandwidth, time, and the direction of traffic in Panel B. For example, the level of driving traffic in the shortest distance bandwidth (<1 mile) is higher than that in longer bandwidths, suggesting that short-distance trips are more prevalent than long-distance ones. Based on the distance bandwidth of less than one mile, the average driving traffic from the IRS Chicago office to the firm's headquarters is 1.038. This implies that within the county of the IRS Chicago office, an individual on average makes more than one driving trip within a mile per month.

Based on aggregated driving traffic measures, Figure 2 shows an overview of monthly driving trends over time, especially during the COVID-19 pandemic. Specifically, we construct *Aggregate Driving Traffic by County* as the ratio of the aggregate number of trips in a county over the population size in that county. Using data from all counties across the continental U.S. (denoted as the "population"), we plot the time trend for the median value of *Aggregate Driving Traffic by County* with a dark gray line and use thick vertical lines to highlight key events during the COVID-19 pandemic. We find that the aggregate driving trend reaches its lowest point following issuances of stay-at-home orders, remains relatively low throughout the COVID-19 pandemic, and starts to recover after the roll out of vaccines. We also plot the median value for *Aggregate Driving Traffic by County* based on the counties where firms in our sample are headquartered (denoted as the "sample"). We observe a similar time trend in our sample as in the overall population, which supports the validity and generalizability of our inferences.

3.3. Stay-at-home orders

The COVID-19 pandemic provides an unprecedented social restriction shock that significantly reduces in-person communication. In Figure 3 Panel A, we report the issuance day of stay-at-home orders by state from Kong and Prinz (2020), most of which cluster towards the end of March and the beginning of April 2020. We note that 8 states (e.g., Arkansas and Iowa) did not issue any stay-at-home orders. We obtain the lifting date of stay-at-home orders from the timeline compiled by USA Today (USA Today 2022) and supplement with data from state-level public health orders and business reopening timelines.[15] States vary in the time length of stay-at-home orders. For example, Alabama, Florida, Georgia, Idaho, Montana, Tennessee, and Texas lifted their stay-at-home orders by the end of April 2020. In contrast, California did not officially lift its stay-at-home orders until the end of January 2021.The variation in stay-at-home order implementation across states and over time helps strengthen our empirical identification of in-person interaction.

Figure 2 Panel B shows the graph depicting the trend of driving traffic around the time when stay-at-home orders were issued (4 months prior and post). Based on the driving traffic measure defined in Appendix A, we separately plot the average driving traffic for two treatment groups (e.g., *from* IRS to the firm's headquarters, and from the firm's headquarters *to* IRS), which consist of firms headquartered in states issuing stay-at-home orders. We also plot the data for two control groups consisting of firms headquartered in states without stay-at-home orders. Overall, while the driving traffic for the control group remains relatively stable across the eight-month window, the treatment group experiences a sharp decline leading to the stay-at-home orders (event

[15] Four states, including California, Kentucky, New Jersey, and Oregon, do not have a clear ending date for their stay-at-home orders according to the USA Today (2022). To determine the conclusion of these orders, we searched for state-level public health orders and business reopening timelines.

window=0) and slowly recovers afterwards. The difference between the treatment and control group supports using our driving traffic measure to capture in-person communication.

3.4. Regression

We use a difference-in-differences (DiD) approach to examine the impact of stay-at-home orders during the COVID-19 pandemic on monthly driving traffic between firms' headquarters and IRS offices. The various enactments of stay-at-home orders by different states over time plausibly provide exogenous shocks that reduces in-person communication, which we anticipate will lead to a decrease in monthly driving traffic. We outline the DiD model below:

$$DriveTraffic_{i,y,m} = \alpha_0 + \alpha_1 HighDriveTreat_i + \alpha_2 PostSHOMonth_{s,y,m} + \alpha_3 HighDriveTreat_i * PostSHOMonth_{s,y,m} + e_{i,y,m} \quad (1)$$

where *i*, *y*, *m*, and *s* denote firm, year, month, and state, respectively. Based on the definition from Appendix A, *DriveTraffic* is the monthly adjusted driving traffic between the firm's headquarters and its closest IRS office Specifically, based on the distance bandwidth between the firm's headquarters and its closest IRS office, we use the monthly driving traffic ratio as defined in Section 3.2 and subtract it by the average driving traffic within that bandwidth for the same year. Appendix A Panel B shows a highly skewed distribution of the raw driving traffic measure. For example, there is significantly less driving traffic as the distance bandwidth increases above 50 miles. To compare driving traffic across different bandwidths, it is important to account for the driving data skewness. Otherwise, our empirical inference would be heavily influenced by firm headquarters in the short distance bandwidth (e.g., below 50 miles) with its closest IRS office. After adjusting the raw driving traffic by the yearly average within each bandwidth, the adjusted driving traffic (*DriveTraffic*) becomes more comparable across different bandwidths. In untabulated analysis, the average adjusted driving traffic, *DriveTraffic*, is 0.000 across different bandwidths.

To capture the two-way traffic, we separately measure the traffic from the closest IRS office to the firm's headquarters (*IRS to HQ*) and the traffic from the headquarters to its closest IRS office (*HQ to IRS*). *HighDriveTreat* is a binary variable for firms with high in-person communication before any stay-at-home order is issued. Specifically, this variable is set to one if the firm's average driving traffic in the pre-stay-at-home period (from January 2019 to February 2020) is in the top tercile of our sample, zero otherwise. We expect the coefficient on *HighDriveTreat* (α_1) to be positive by definition. *PostSHOMonth* is a binary variable equal to one if the state where the company's headquarters is located has implemented a stay-at-home order during the month and year, zero otherwise. We expect the coefficient on *PostSHOMonth* (α_2) to be negative as stay-at-home orders should reduce the number of driving trips for all types of firms. Our main variable of interest is the interaction between *HighDriveTreat* and *PostSHOMonth.*[16] To the extent that high in-person communication firms experience a greater decline in driving traffic following stay-at-home orders, we expect the coefficient α_3 to be negative. We include industry (Fama-French 30 industries)-, year-, month-, and county- fixed effects to control for industry-, time-, and county- invariant factors. We cluster standard errors by state.[17]

[16] Different from the classic difference-in-differences model where the treatment observation stays treated throughout the sample period (Baker et al. 2023), our stay-at-home treatment group ends as early as one month following the enactment of social restriction. It is thus challenging to use traditional approaches, such as the Callaway and Sant'Anna (2021) estimator, to address comparison issues related to earlier-treated and never-treated groups in our setting. Nevertheless, we employ a battery of tests to assess the robustness of our results with different comparison groups. We find consistent evidence of Equation (1) after we remove states that never issue stay-at-home orders and exclude observations after stay-at-home orders are lifted.

[17] We do not cluster standard errors by firm for several reasons. deHaan (2021) suggests that the level of fixed effects should be nested within error clusters. Because we have county fixed effects, counties should be nested within states. On the other hand, the firm-level error cluster would be nested within the county fixed effects, which violates the econometric assumption. Second, Bertrand et al. (2004) suggest that economic variables typically have high correlations within a state over time and clustering by the headquarters state is more appropriate to control for within state variation. Additionally, we have a short time series with three years of data and there is not sufficient time variation within the firm for error clustering.

Next, we adapt the DiD model to examine the impact of stay-at-home orders on the resolution of uncertain tax positions. Since UTB data is only available on an annual basis, we estimate our DiD model at the yearly level below.

$$\begin{aligned} ResolveUTB_{i,y} = \beta_0 + \beta_1 HighDriveTreat_i + \beta_2 PostSHOYear_{s,y} + \\ \beta_3 HighDriveTreat_i * PostSHOYear_{s,y} + \\ \sum Controls_{i,y} + e_{i,y} \end{aligned} \quad (2)$$

where *i* and *y* denote firm and year respectively. *ResolveUTB* represents the resolution of uncertain tax positions, measured as the sum of UTB tax settlements, UTB net prior year adjustments, and UTB statute of limitation lapses, scaled by lagged total assets and multiplied by 1,000 for the ease of interpretation.[18] Following our discussion in Section 2.2, we consider *ResolveUTB* as a comprehensive measure for the unwinding of uncertain tax positions. *HighDriveTreat* is defined the same as in Equation (1) and we will separately examine the traffic from (to) the closest IRS office.[19] To estimate the yearly regression, we construct an annual variable for stay-at-home orders. Specifically, *PostSHOYear* represents the number of months (i.e., ranges from zero to 12) in which the firm is subject to stay-at-home orders during its fiscal year. *PostSHOYear* increases as the state where the firm's headquarters is located extends the duration of stay-at-home orders.[20] Our primary variable of interest is the interaction between *HighDriveTreat* and *PostSHOYear*, which captures the impact of stay-at-home orders on the resolution of uncertain tax positions for firms heavily reliant on in-person communication with the closest IRS office. Consistent with our

[18] Compustat NA reports these items as positive values, even though they represent a reduction in the UTB balance. Therefore, negative coefficients on our primary variable of interest would indicate reduced resolution of tax uncertainty.

[19] Our estimation results of Equations (1) and (2) remain consistent when we define *HighDriveTreat* based on the top quartile (rather than tercile) of driving traffic in the pre-stay-at-home orders period.

[20] To account for variation in the timing of stay-at-home orders, which may not always align with the beginning or ending of a month, we utilize the following empirical scheme: if a state initiates its stay-at-home order after the 20th day of the month, we consider the state starting its order in the following month. For example, Connecticut enacted its stay-at-home order on March 23rd (after 20th) and we use April as its starting month. Similarly, if a state ends its stay-at-home order earlier than the 10th day of the month, we consider the state ending its order in the prior month. For example, Pennsylvania ended its stay-at-home order on May 8th (before 10th) and we use April as its ending month.

Hypothesis, a negative and significant β_3 is consistent with stay-at-home orders having a negative impact on the resolution of UTBs for high in-person communication firms.

Following Robinson et al. (2016), we use a set of control variables that are related to the unwinding of UTB, including book effective tax rate (*ETR*), UTB ending balance from the prior three years (*UTB_End3*), R&D expenses (*R&D*), advertising expenditure (*Advertise*), sales and administration expenses (*SG&A*), capital expenditures (*Capx*), *Leverage*, an indicator of foreign income (*Foreign income*), and indicator for net operation loss carry forwards (*NOL*), intangible assets (*Intangible*), *PP&E*, and pretax return on sales (*PT_ROS*).[21] Notably, we also control for geographic distance between the firm's headquarters and the closest IRS office (*Distance*) to account for the level of communications due to geographic proximity, which notably, is static over time (Kubick et al. 2017). Similar to Equation (1), we include industry (Fama-French 30 industries), year, and county fixed effects and cluster standard errors by state.

Following our main tests, we next conduct three sets of cross-sectional tests to examine whether in-person communication is more important in resolving tax uncertainty for firms that engage in more interaction with the IRS. First, we use the likelihood of being assigned into the Coordinated Industry Case (CIC) program as a proxy for firms' interaction with the IRS. Because CIC assignment is not publicly observable, we use the prediction model in Ayers et al. (2019) to estimate the likelihood of a firm's CIC assignment (*CIC*).[22] We bifurcate the sample based on the median value of *CIC* before the COVID-19 pandemic (e.g., 2019). A firm-year is in the high (low) CIC subsample if its *CIC* is above (below) the median. Second, we follow Beck and Lisowsky (2014) to estimate the likelihood of firms participating in the CAP program to resolve tax

[21] Robinson et al. (2016) use the changes in control variables as their dependent variable is the change in ETR. Since our dependent variable is the resolution of tax uncertainty, we use the levels of control variables instead.
[22] Specifically, we follow their model reported in Table 3 Panel B Column (1) on Pages 339-340.

uncertainty with the IRS (*CAP*). Similar to the *CIC* cross-sectional test, we partition the sample based on the median value of *CAP* in 2019. Finally, to capture firms' interaction with the IRS through auditors, we use auditor-provided tax services. Specifically, based on tax fees scaled by total fees (*Tax Fees*), we assign firms into high (low) tax fee groups if its *Tax Fees* in 2019 are above (below) the median. We expect our main results to be more pronounced in the subsample with high tax fees. Throughout the cross-sectional tests, we expect our main results to be greater when firms had a higher likelihood of *CIC* assignment, a greater probability of participating in the *CAP* program, and higher auditor-provided tax service fees.

Following prior research (e.g., Shroff et al. 2014; Huang 2018), we examine the statistical significance of the coefficient difference between high and low groups using nonparametric bootstrap tests. By randomly assigning observations into pseudo-high and -low groups 500 times, we form a null distribution of the difference in coefficients across high and low groups, providing a basis on which we can test the significance of our coefficient difference.

4. Empirical Results

4.1. Sample construction

Our sample starts from firms in the Compustat NA database from 2019 to 2021. We begin the sample period from 2019 as this is the first year when the driving trip data became available from BTS. To estimate tax uncertainty, we require firms to have non-missing UTB-related variables, including UTB tax settlements, UTB net prior year adjustments, and UTB statute of limitation lapses. Consistent with prior research examining tax uncertainty (Dyreng et al. 2019), we eliminate firm-years with negative pretax income, total income tax expense, or cash tax paid, as well as firms with ETRs greater than 1 or less than 0. To estimate Equation (2), we require non-missing value for the control variables. We also follow prior research and remove firms in the financial industry because their tax incentives might be significantly different from non-financial firms. Finally, we require firms to have available and reasonable driving trip data by eliminating observations with missing zip codes and those headquartered in non-contiguous or island states such as Alaska and Hawaii, respectively. Our steps result in 1,328 firm-year observations. To estimate the monthly driving traffic in Equation (1), we expand the firm-year sample by multiplying it by 12 (i.e., months) to create the firm-month panel, resulting in 15,396 firm-month observations.

Based on the 1,328 firm-year sample, Panels B-D report the sample distribution by year, industry, and state. The number of observations is similar across years. The top three most populated industries are Personal and Business Services (15.51%), Business Equipment (10.32%), and Healthcare, Medical Equipment, Pharmaceutical Products (7.68%). The top three states where firms locate their headquarters are California (11.14%), Illinois (7.38%), and Texas (6.55%). This pattern closely aligns with the distribution of corporate headquarters documented by Armstrong et al. (2019).

4.2. Univariate results

Table 2 Panel A reports summary statistics for the variables used in Equation (1) based on the firm-month sample defined in Table 1. The average value of the yearly adjusted driving traffic from the closest IRS office to the firm's headquarters is -0.054 (*DriveTraffic(IRS to HQ)*), which means the average traffic is 5.4 percentage points lower than the yearly average. Similarly, the average driving traffic from the firm's headquarters to its closest IRS office is -0.035 (*DriveTraffic(HQ to IRS)*). The average value for the indicator variable of firms with high in-person communication from the closest IRS office is 0.289 (*HighDriveTreat(IRS to HQ)*), which is consistent with our definition of high in-person communication firms based on the top tercile of the sample.

Table 2 Panel B reports summary statistics for the variables used in Equation (2) based on the firm-year sample defined in Table 1. We previously constructed the ratio *ResolveUTB*, equal to the sum of tax settlement, net prior year reductions, and lapses, over lagged total assets, which is then multiplied by 1,000 for presentation purposes. The mean value of annual *ResolveUTB* is 0.455, suggesting that an average firm in our sample can resolve unrecognized tax benefits for about $5.49 million.[23] Similar to the distribution of UTB increases documented by Dyreng et al (2019), *ResolveUTB* has a highly skewed distribution as its standard deviation (1.901) is higher than its median (0.131), which creates variations for us to examine how firms differ in their ability to resolve tax uncertainty with the IRS. For other controls, the mean value of leverage (*Leverage*) is 0.306 and the percentage of firms with a net operating loss (NOL) carryforward (*NOL*) is 0.619, which are similar to these reported by Dyreng et al. (2019). For the *Distance* variable, the mean (median) distance between the firm's headquarters and its closest IRS office is 26.5 (24.3) miles.[24]

Table 2 Panel C reports the correlations of key variables used in Equation (2) based on the firm-year sample. *ResolveUTB* has a 21.9% correlation with the prior three-year average balance of UTB (*UTB_End3*), suggesting that firms with a higher prior UTB balance have more tax uncertainty to resolve. *HighDriveTreat(IRS to HQ)* has a 68.6% correlation with *HighDriveTreat(HQ to IRS)*, indicating that these two directions of driving traffic measures are highly correlated, but are also distinct from each other.

[23] The mean lagged asset size in our sample is $12,074 million. Multiplying this by the *ResolveUTB* ratio of 0.05%, we estimate the mean magnitude of UTB resolved to be $5.49 million.

[24] Because we log-transform the distance variable, we report the exponential value of the mean (3.279) and median (3.190) to interpret the untransformed distance variable.

4.3. Regression results

We begin our analysis by examining the baseline impact of stay-at-home orders during the COVID-19 pandemic on monthly driving traffic between firms' headquarters and IRS offices; we examine the effects on UTB resolution later. Table 3 reports the estimation results of Equation (1) based on the firm-month sample. In Column (1), the dependent variable is the driving traffic from the closest IRS office to the firm's headquarters (*DriveTraffic(IRS to HQ)*). The coefficient on *HighDriveTreat(IRS to HQ)* is positive and significant (0.138, p<0.01). This result is consistent with our definition for the high in-person communication treatment firms having more driving traffic before the issuance of stay-at-home orders. The coefficient on *PostSHOMonth* is negative and significant (-0.032, p<0.01), indicating that on average, the driving traffic decreases following stay-at-home orders. This result is in line with the intended effect of the social restriction measure. Our primary variable of interest in Equation (1) is the interaction term *HighDriveTreat(IRS to HQ)*PostSHOMonth*, and the coefficient is negative and significant (-0.068, p<0.01). The evidence supports our expectation that high in-person communication treatment firms experience a greater decline in driving traffic after the issuance of COVID-19 social restriction orders. To put the evidence into economic perspective, the high in-person treatment firms, on average, have 13.8 percentage points higher driving traffic from their closest IRS offices before stay-at-home orders compared to the control group. After stay-at-home orders were implemented, the treatment group's driving traffic decreases by 6.8 percentage points, or approximately 49 percent (0.068/0.138), indicating a significant impact of social restrictions on in-person communication.

Table 3, Column (2) reports results from examining traffic from the firm's headquarters to its closest IRS office. The dependent variable is *DriveTraffic(HQ to IRS)*. The results on the key independent variables are similar to these in Column (1). For example, the coefficient on

HighDriveTreat(HQ to IRS) is 0.168 ($p<0.01$), and that on *HighDriveTreat(HQ to IRS)*PostSHOMonth* is -0.073 ($p<0.01$). By comparing these two coefficients, we show that the treatment group's average driving traffic to the closest IRS office decreases by 7.3 percentage points, or approximately 43 percent (0.073/0.168), following the issuance of COVID-19 stay-at-home orders. Overall, the evidence validates using the driving traffic measure to capture in-person communication.

Our next analysis uses the driving traffic measure to examine the impact on firms' UTB resolutions related to restrictions on in-person communication between firms and the IRS. Table 4 reports the estimation results of Equation (2) based on the firm-year sample. The dependent variable is UTBs resolved by the firm (*ResolveUTB*). In Column (1), we focus on the driving traffic *from* the closest IRS office to the firm's headquarters (*HighDriveTreat(IRS to HQ)*) (i.e., field audits). The coefficient on *HighDriveTreat(IRS to HQ)* is positive but not statistically significant. The results indicate that firms with varying degrees of in-person communication with the IRS exhibit similar capabilities in resolving tax uncertainty before stay-at-home orders. The lack of significant difference underscores the importance of examining the ability of high in-person communication firms to resolve tax uncertainty under stay-at-home restrictions.

The coefficient on our primary variable of interest, *HighDriveTreat(IRS to HQ)*PostSHOYear*, is negative and significant (-0.160, $p<0.01$). This result suggests that following COVID-19 social restriction orders, high in-person communication firms are less effective in resolving tax uncertainty relative to the control group. In terms of economic magnitude, for an average size firm with high in-person communication from its closest IRS office, it resolves about \$1.93 million less tax uncertainty as the period of stay-at-home increases by one month.[25]

[25] The average scalar (lagged total assets, untabulated) for *ResolveUTB* is \$12,075 million. Since the *ResolveUTB* measure is multiplied by 1,000, a 0.160 coefficient converts to 0.160/1,000*12,075=\$1.93 million in tax uncertainty.

Overall, our evidence shows firms that heavily relied on in-person communication pre-COVID are adversely affected by the stay-at-home orders to resolve tax uncertainty. At a high level, the results support our hypothesis that a reduction of in-person communication between firms and the IRS reduces the resolution of firms' tax uncertainty, suggesting in-person communication is vital for effectively negotiating with the tax administration.

In Table 4, Column (2), we focus on the driving traffic *to* the closest IRS office from the firm's headquarters (i.e., office audits). The coefficient on our interaction term *HighDriveTreat(HQ to IRS)*PostSHOYear* is negative, but just misses statistical significance at the conventional level (-0.114, $p<0.11$). Compared to Column (1), the results are likely weaker in Column (2) to the extent that office audits (consistent with the driving traffic *to* the closest IRS office from headquarters) are easier to conduct remotely than field audits (consistent with the driving traffic *from* the closest IRS office to headquarters) that require intensive in-person inspection and interviews. For the control variables, firms with higher prior UTB balance (*UTB_End3*) are associated with more UTB resolved. On the other hand, firms with more *R&D* and *NOL* are associated with less UTB resolved, suggesting that tax complexity makes it difficult for firms to resolve tax uncertainty with the IRS. Consistent with prior literature that information transmission improves when firms are located closer to the IRS office (e.g., Kubick et al. 2017), the coefficients on *Distance* are negative and significant at the 10 percent level in Column (2).

4.4. Cross-sectional results

We next explore cross-sectional settings where firms and the IRS likely have more intensive interaction before COVID-19 and examine how these firms' capability of resolving UTBs is affected by social restriction orders. Table 5, Panel A focuses on the driving traffic *from* the closest IRS office to the firm's headquarters. The dependent variable is UTB resolved by the firm (*ResolveUTB*). In Columns (1) and (2) we partition the sample based on high vs. low CIC likelihood (*CIC*), where the high CIC subsample contains firms that are likely under continual audit by the IRS (Ayers et al. 2019). The coefficient on *HighDriveTreat(IRS to HQ)*PostSHOYear* is negative and significant (-0.147, $p<0.05$) in the high CIC subsample reported in Column (2), and is negative and insignificant in the low CIC subsample reported in Column (1). However, using a nonparametric test to compare these two coefficients, the difference is not statistically significant.

In Columns (3) and (4) we partition the sample based on *CAP* probability, where the high CAP subsample contains firms that are part of the IRS's voluntary real-time tax audit (Beck and Lisowsky 2014). The coefficient on *HighDriveTreat(IRS to HQ)*PostSHOYear* is negative and significant (-0.199, $p<0.01$) in the high *CAP* subsample in Column (4), and is positive and insignificant in the low *CAP* subsample in Column (3). Unlike in the CIC subsamples, the difference between these two coefficients across the CAP subsamples is statistically significant at the 10 percent level.

Taking the evidence together, we show that following the stay-at-home orders, firms with high in-person communication from the closest IRS office struggle to resolve tax uncertainty, particularly if they had a higher likelihood of participating in the *CAP* program prior to the pandemic. The evidence is weaker for firms more likely to be assigned into the *CIC* program. Nevertheless, the results support our hypothesis that a reduction of in-person communication with the IRS has a detrimental effect on resolving tax uncertainty, especially for firms that already intensively engage with the IRS.

In Columns (5) and (6), we partition the sample based on fees paid by firms to their financial statement auditors for tax work (i.e., auditor-provided tax services) (Klassen et al. 2016).

The coefficient on *HighDriveTreat(IRS to HQ)*PostSHOYear* is negative and significant in the high tax fees subsample reported in Column (6) (-0.262, $p<0.01$), but is negative and insignificant in the low tax fees subsample reported in Column (5). As in the CAP subsample analysis, the difference between the two coefficients across the high vs. low tax fee subsamples is statistically significant at the 10 percent level ($p=0.08$). Again, the evidence suggests that stay-at-home orders have a greater negative impact with respect to the resolution of tax uncertainty on high in-person communication firms when they have more interaction with the IRS, including through their auditors who provide tax services.[26]

Table 5, Panel B focuses on the driving traffic *to* the closest IRS office from a firm's headquarters. Consistent with the results in Panel A, when comparing Columns (1) and (2) of Panel B, we find high in-person communication firms struggle to resolve tax uncertainty under stay-at-home orders when their likelihood of CIC assignment is higher. Similarly, when comparing Columns (3) and (4), we find high in-person communication firms are less effective in solving tax uncertainty under stay-at-home orders when their probability of *CAP* participation is higher. We find similar evidence for firms with higher auditor-provided tax service fees by comparing Columns (5) and (6).

Overall, the evidence is consistent across Tables 4 and 5 that in-person communication is vital in resolving tax uncertainty, especially when firms intensively interact with the IRS either directly or through their auditors.

[26] In addition to financial statement auditors who work directly with the firm to provide tax services, we also assess the firm's access to the local population of Certified Public Accountants (CPAs). In untabulated tests, we partition the sample based on the concentration of CPAs in the county where a firm's headquarters is located, and find that the adverse effect of stay-at-home orders is stronger when firms are located in counties with a higher CPA concentration.

5. Conclusion

This paper examines the extent to which in-person communication between firms and the IRS helps to resolve firms' tax uncertainty. Though tax communication is proprietary and a challenge to identify empirically, we construct a novel measure to capture the likelihood of in-person meetings between the firm and the IRS by estimating the two-way driving traffic between the firm's headquarters and its closest IRS office. By exploiting exogenous stay-at-home orders issued during the COVID-19 pandemic, we first validate that firms with high in-person communication with the IRS before stay-at-home orders experience a greater decline in driving traffic following social restriction orders. This finding supports our driving measure of capturing the likelihood of in-person communication.

Our primary results show that firms with high in-person communication with the IRS are less effective at resolving tax uncertainty following COVID-19 stay-at-home orders, compared to firms with low in-person communication with the IRS. The results manifest more strongly in the condition of traffic *to* the firm's headquarters *from* the IRS office, likely representing a reduction in on-site field audits, compared to the condition of traffic *to* the IRS office *from* the firm's headquarters, likely representing a reduction of office audits that may be more amenable to virtual communication. In cross-sectional tests, we find this effect is more pronounced for firms having more interaction with the IRS before the COVID-19 pandemic. Specifically, firms more likely to participate in the CAP program or purchase more tax services from their auditors are more adversely affected by the reduction of in-person communication with the IRS, compared to firms less likely to participate in the CAP program or purchase less tax services from their auditors. The results on CIC participation are slightly weaker, but directionally consistent with the results using the CAP and auditor-provided tax services subsamples.

Overall, our evidence supports the importance of in-person communication in resolving tax uncertainty between firms and the tax regulator. Importantly, we document a tax clientele effect whereby firms with more interaction with the IRS are more likely to rely on in-person communication to resolve tax uncertainty, and are thus more adversely affected when the opportunity to interact with the IRS in person is significantly reduced. Our findings offer timely implications for the IRS as it evaluates whether to conduct in-person or virtual audits for businesses, especially in light of the tax agency’s growing adoption of online tools for tax audits.

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Figure 1. Locations of IRS Offices and Company Headquarters

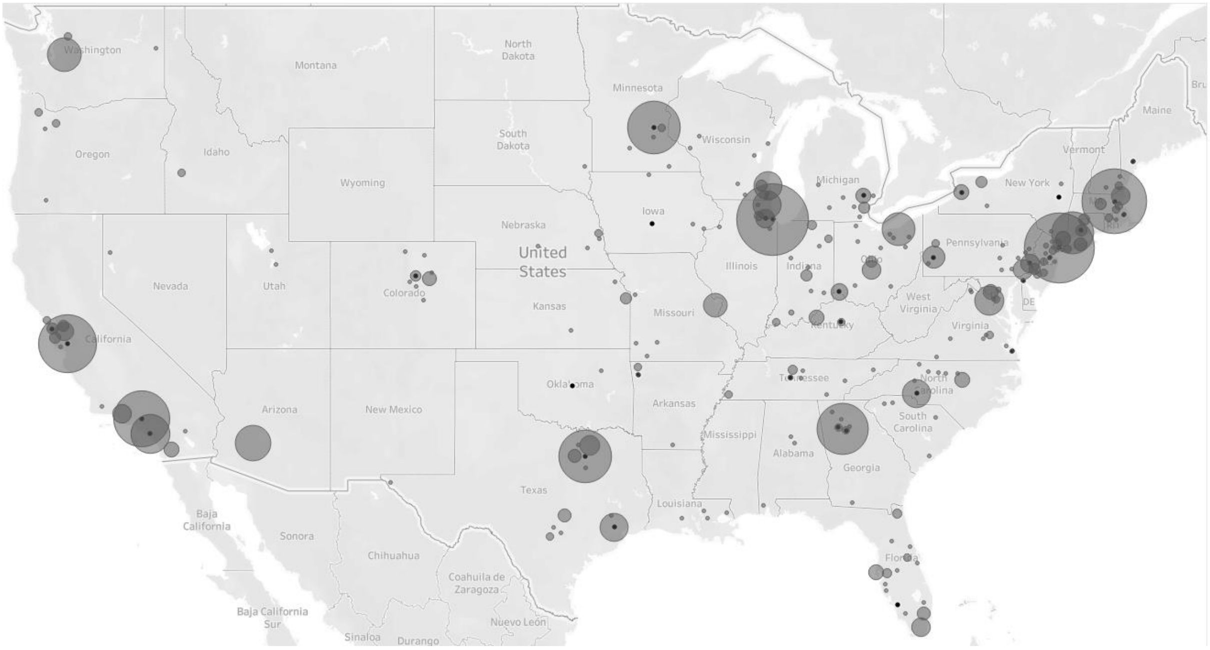
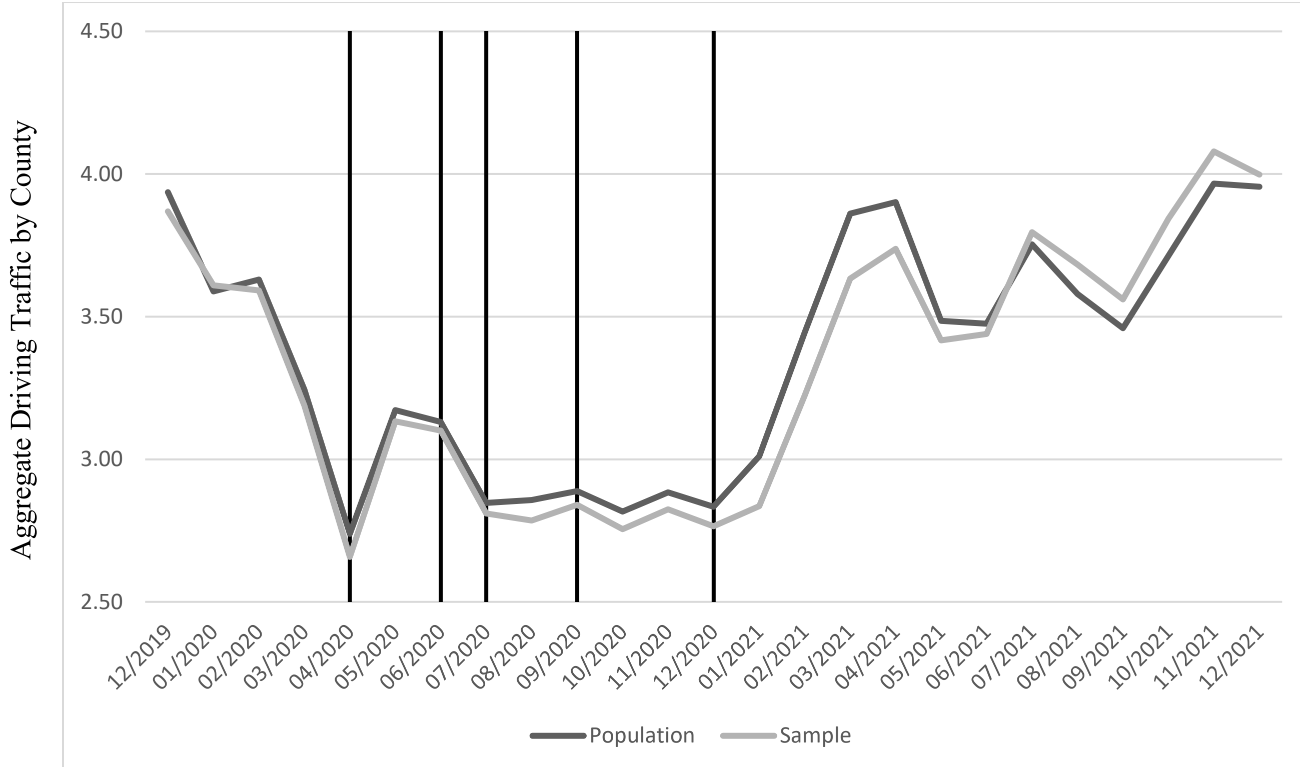


Figure 1 plots the distribution of IRS office and company headquarters within the continental U.S. IRS offices are represented by black dots. Company headquarters are represented by gray circles. Larger circles indicate more companies in our sample within a county. Overlapping circles represent adjacent counties with clusters of company headquarters.

Figure 2. Time Trends of Aggregate Driving Traffic around the COVID-19 Pandemic



Date	Key Events during COVID-19
3/13/2020-4/3/2020	Stay-at-home orders implemented in 40 out of 51 states and the District of Columbia (Kong and Prinz 2020)
6/10/2020	U.S. total COVID-19 cases surpass 2 million
9/22/2020	Global death toll reaches over 1 million
12/11/2020	Pfizer-BionNTech receive "Emergency Use Authorization (EUA)" for vaccine from FDA
12/18/2020	Moderna receives EUA for vaccine from FDA
Source:	https://www.cdc.gov/museum/timeline/covid19.html

Figure 2 plots the time trend of aggregate monthly driving traffic pattern throughout our sample period with the key events around COVID-19 highlighted. On the left vertical axis, *Aggregate Driving Traffic by County* is the ratio of the aggregate number of trips in a county over the population size in that county. The dark gray line plots the median *Aggregate Driving Traffic by County* for all counties across the continental U.S. – "Population." The light gray line plots the median *Aggregate Driving Traffic by County* for the subset of counties in our sample where corporate headquarters are paired up with the closest IRS offices – "Sample". We report key events during the COVID-19 pandemic in the table above. We use the thin black vertical line to mark these key events by month throughout the sample period.

Figure 3. Stay-at-home orders (SHOs) and Drive Traffic Changes

Panel A: Stay-at-home orders by state

SHOs									No SHOs
State	***Enacted***	***Lifted***	***State***	***Enacted***	***Lifted***	***State***	***Enacted***	***Lifted***	***State***
Alabama	4/4/20	4/30/20	Kentucky	3/26/20	5/30/20	New York	3/22/20	5/15/20	Arkansas
Alaska	3/11/20	4/21/20	Louisiana	3/23/20	5/14/20	Ohio	3/23/20	5/30/20	Iowa
Arizona	3/30/20	5/15/20	Massachusetts	4/24/20	5/18/20	Oregon	3/23/20	5/26/20	Nebraska
California	3/19/20	1/25/21	Maine	4/2/20	5/31/20	Pennsylvania	4/1/20	5/8/20	North Dakota
Colorado	3/26/20	5/8/20	Maryland	3/30/20	5/15/20	Rhode Island	3/28/20	5/8/20	Oklahoma
Connecticut	3/23/20	5/20/20	Michigan	3/24/20	6/5/20	South Carolina	4/7/20	5/12/20	South Dakota
District of Columbia	4/1/20	5/29/20	Minnesota	3/27/20	5/4/20	Tennessee	4/2/20	4/30/20	Utah
Delaware	3/24/20	5/15/20	Missouri	4/6/20	5/3/20	Texas	4/2/20	4/30/20	Wyoming
Florida	3/20/20	4/30/20	Mississippi	4/3/20	5/11/20	Virginia	3/30/20	6/10/20	
Georgia	4/3/20	4/30/20	Montana	3/26/20	4/24/20	Vermont	3/24/20	5/15/20	
Hawaii	3/25/20	5/31/20	North Carolina	3/30/20	5/8/20	Washington	3/23/20	5/4/20	
Idaho	3/25/20	4/30/20	New Hampshire	3/27/20	6/15/20	Wisconsin	3/25/20	5/26/20	
Illinois	3/21/20	5/30/20	New Jersey	3/21/20	6/9/20	West Virginia	3/24/20	5/4/20	
Indiana	3/25/20	5/1/20	New Mexico	3/24/20	5/15/20				
Kansas	3/30/20	5/3/20	Nevada	3/31/20	5/15/20				

Figure 3 Panel A provides a timeline for state governments enacting and lifting stay-at-home order (SHO) as well as states that did not implement SHOs. California lifted SHO in 2021. All other states lifted SHOs in 2020. We obtain the lifting dates of SHOs from USA Today (2022). For states not covered by USA Today, we use their public health orders and business reopening timelines to determine the ending date. Note that Alaska and Hawaii are excluded from our final sample to focus on the continental U.S. states. If a state initiates its stay-at-home order after the 20th day of the month, we consider the state starting its order in the following month. Similarly, if a state ends its stay-at-home order earlier than the 10th day of the month, we consider the state ending its order in the prior month.

Figure 3. Stay-at-home orders (SHOs) and Drive Traffic Changes (*Continued*)

Panel B: Driving traffic surrounding the issuance of SHOs

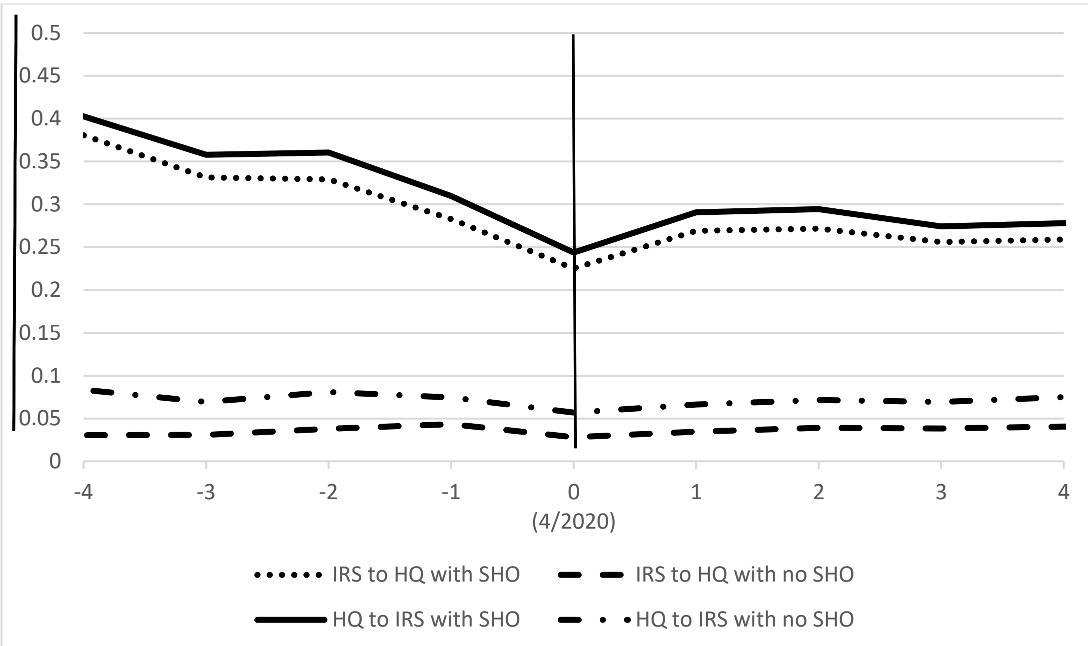


Figure 3 Panel B plots the average value of our measures for two-way driving traffic for firms headquartered in states issuing SHOs and firms headquartered in states not issuing SHOs over the window of eight months surrounding the issuance of SHOs. We use the vertical line to indicate the event month when a SHO is first enacted. Note that the majority of SHOs, specifically 39 states, were attributed to April 2020 (i.e., after March 20 and before April 10, 2020), as shown in Panel A.

Appendix A. An Illustration of the Driving Traffic Measure

Appendix A illustrates how we construct the driving traffic measure from the company headquarters to its closest IRS office and vice versa. We use the IRS office in Chicago as our example. Based on the algorithm the calculates the shortest distance between IRS offices and company headquarters, we identify the IRS office in Chicago (Cook County) as the closest office for 30 company headquarters. We summarize the distance distribution between the IRS Chicago office and company headquarters in Panel A below:

Pane A: The distribution of distance between the IRS Chicago office and company headquarters (in miles)

	N	Mean	Min	Median	Max
Firms in the Same County as the Chicago IRS office	6	4.66	0	4.28	12.03
Firms in a Different County from the Chicago IRS office	24	128.37	7.67	124.67	254.88

Next, we collected the number of daily driving trips for the county where the IRS Chicago office is located from the Bureau of Transportation Statistics (BTS). Trips are summarized by bandwidths of distance: less than 1 mile, 1 to 3 miles, 3 to 5 miles, 5 to 10 miles, 10 to 25 miles, 25 to 50 miles, 50 to 100 miles, 100 to 250 miles, 250 to 500 miles, and greater than 500 miles. We identify 8 bandwidths where company headquarters are paired with the IRS Chicago office. Next, we aggregate the daily trips at the monthly level and scale it by the total population of the county where the IRS Chicago office is located to control for size, which generates the ratio of driving traffic from the IRS office to the firm's headquarters. Within each bandwidth of distance, the driving traffic measure varies over time. To illustrate the time variation, we identify 8 companies from 8 different distance bandwidths and report the distribution of driving traffic for these firms in Panel B below.

Similarly, to capture the driving to the IRS Chicago office from a company's headquarters, we collect the number of trips from BTS for the county where the company headquarters is located. These trips are reported in the same bandwidths as above. We aggregate the daily trips at the monthly level and scale it by the total population of the county where the company headquarters is located to control for size, which generates the ratio of driving traffic to the IRS office from the firm's headquarters. We also report the distribution of driving traffic for these 8 firms in Panel B below.

Appendix A. An Illustration of the Driving Traffic Measure (*Continued*)

Panel B: Two-way driving traffic between the IRS Chicago office and company headquarters

				Driving traffic *from* the IRS Chicago office to company headquarters				Driving traffic *to* the IRS Chicago office from company headquarters			
Distance Bandwidth	No. Firms	Firm Name	Same county as the IRS	Mean	25%	50%	75%	Mean	25%	50%	75%
< 1	1	DOVER	Yes	1.038	0.901	1.028	1.159	1.038	0.901	1.028	1.159
3 to 5	4	FEDERAL SIGNAL	Yes	0.465	0.393	0.448	0.526	0.465	0.393	0.448	0.526
5 to 10	2	INGREDION	No	0.573	0.474	0.557	0.683	0.577	0.486	0.546	0.679
10 to 25	6	CDK GLOBAL	No	0.573	0.478	0.540	0.698	0.537	0.468	0.511	0.621
25 to 50	2	APTARGROUP	No	0.167	0.153	0.170	0.190	0.291	0.263	0.285	0.320
50 to 100	2	REGAL REXNORD	No	0.030	0.025	0.031	0.034	0.084	0.078	0.086	0.092
100 to 250	6	EMERSON ELECTRIC	No	0.023	0.020	0.022	0.026	0.019	0.016	0.019	0.022
250 to 500	7	CASS INFORMATION SYSTEMS	No	0.008	0.006	0.008	0.009	0.005	0.004	0.005	0.006

Appendix B. Variable Definitions

Variable	Definition
ResolveUTB	The extent of UTB resolved by the firm and the IRS, equal to the ratio of the sum of tax settlement (TXTUBSETTLE), net reductions related to prior-year positions (TXTUBPOSPDEC less TXTUBPOSPINC), and statute of limitations lapses (TXTUBSOFLIMIT), over lagged total assets (AT), multiplied by 1,000.
DriveTraffic(IRS to HQ)	The yearly adjusted driving traffic from the IRS to the firm's headquarters, equal to the ratio of the number of trips in a month from the county where the closest IRS office is located (IRS county) to the county where the firm's headquarters is located (firm county) over the population of the IRS county; this measure is then adjusted by the yearly average within the distance bandwidth. See Appendix A for an illustration of the driving traffic calculation.
DriveTraffic(HQ to IRS)	The yearly adjusted driving traffic from the firm's headquarters to the IRS, equal to the ratio of the number of trips in a month from the county where the firm's headquarters is located (firm county) to the county where its closest IRS office is located (IRS county) over the population of the firm county; this measure is then adjusted by the yearly average within the distance bandwidth.. See Appendix A for an illustration of the driving traffic calculation.
HighDriveTreat(HQ to IRS)	Indicator variable for a firm with high driving traffic to the closest IRS office before the enactment of stay-at-home-orders in the firm's headquarters state, equal to 1 when the firm's average *DriveTraffic(HQ to IRS)* in the pre-stay-at-home-order period (from January 2019 to February 2020) is at the top tercile, zero otherwise.
HighDriveTreat(IRS to HQ)	Indicator variable for a firm with high driving traffic from the closest IRS office before the enactment of stay-at-home-orders in the firm's headquarters state, equal to 1 when the firm's average *DriveTraffic(IRS to HQ)* in the pre-stay-at-home-order period (from January 2019 to February 2020) is at the top tercile, zero otherwise.
PostSHOMonth	Indicator variable equal to 1 when the stay-at-home order is implemented by the firm's headquarters state in a month, 0 otherwise.
PostSHOYear	Count variable equal to the number of months in a fiscal year that are subject to the stay-at-home order implemented by the firm's headquarters state. This variable ranges from 0 to 12.
CIC	Predicted likelihood that a firm is assigned into the IRS Coordinated Industry Case (CIC) program. Parameters are obtained from Table 3, Panel B, Column (1) in Ayers, Seidman, and Towery (2019). High/low CIC likelihood is defined based on sample median value of *CIC* in 2019 (before COVID-19).
CAP	Predicted likelihood that a firm participates in the IRS Compliance Assurance Process (CAP) program. Parameters are obtained from Table 2, Column (1) in Beck and Lisowsky (2014). High/low CAP participation likelihood is defined based on sample median value of *CAP* in 2019 (before COVID-19).

Tax fee	Tax fees provided by Audit Analytics, scaled by total fees paid to the financial statement auditor. High/low tax fee is defined based on sample median value of *Tax fee* in 2019 (before COVID-19).
ETR	Total income tax expense (TXT) scaled by the sum of Income before extraordinary items (IB) and total income tax expense (TXT)
UTB_End3	Sum of UTB ending balance (TXTUBEND) from t-3 to t-1, scaled by lagged total assets (AT)
R&D	R&D expense (XRD) scaled by sales (SALE); missing value in XRD replaced as zero
Advertise	Advertising expense (XAD) scaled by sales (SALE); missing value in XAD replaced as zero
SG&A	Selling, general and administrative expenses (XSGA) scaled by sales (SALE); missing value in XSGA replaced as zero
Capx	Capital expenditure (CAPX) scaled by total property, plant and equipment (PPEGT)
Leverage	Sum of current debt (DLC) and long-term debt (DLTT) scaled by total assets (AT)
Foreign income	Indicator variable equal to 1 if foreign pretax income (PIFO) is non-zero and non-missing, 0 otherwise
NOL	Indicator variable equal to 1 if tax loss carry-forward (TLCF) is non-zero and non-missing, 0 otherwise
Intangible	Intangible assets (INTAN) scaled by total assets (AT)
PP&E	Total property, plant and equipment (PPEGT) scaled by total assets (AT)
PT_ROS	The sum of Income before extraordinary items (IB) and total income tax expense (TXT) scaled by sales (SALE)
Distance	The natural logarithm of the distance between a firm's headquarters and its closest IRS office, in miles.

Table 1. Sample Construction

Panel A: Sample selection		
All observations in CompStat NA from 2019 to 2021		36,489
Less:	Missing data on UTB-related variables	(28,980)
	Negative pretax income, negative total income tax expense, or negative cash taxes paid	(4,094)
	ETR than 1 or less than 0	(89)
	Missing control variables	(1,617)
	Financial industries	(93)
	Missing driving trips data (missing zip code) and firms located in Alaska and Hawaii	(288)
	Firm-year observations	1,328
Multiply by:		12
	Firm-month observations (Firm-year observations expanded by 12 months)	15,936

Panel B: Distribution by year based on the firm-year sample

Year	Number of Observations	Percent of Observations
2019	487	36.67%
2020	427	32.15%
2021	414	31.17%
	1,328	100.00%

Table 1. Sample Construction (*Continued*)

Panel C: Distribution by industry based on the firm-year sample		
FF30 Industry	Number of Observations	Percent of Observations
Food Products	54	4.07%
Beer & Liquor	10	0.75%
Tobacco Products	5	0.38%
Recreation	20	1.51%
Printing and Publishing	3	0.23%
Consumer Goods	40	3.01%
Apparel	25	1.88%
Healthcare, Medical Equipment, Pharmaceutical Products	102	7.68%
Chemicals	63	4.74%
Textiles	8	0.60%
Construction and Construction Materials	106	7.98%
Steel Works Etc.	22	1.66%
Fabricated Products and Machinery	80	6.02%
Electrical Equipment	39	2.94%
Automobiles and Trucks	45	3.39%
Aircraft, ships, and railroad equipment	25	1.88%
Precious Metals, Non-Metallic, and Industrial Metal Mining	6	0.45%
Petroleum and Natural Gas	5	0.38%
Utilities	12	0.90%
Communication	24	1.81%
Personal and Business Services	206	15.51%
Business Equipment	137	10.32%
Business Supplies and Shipping Container	27	2.03%
Transportation	28	2.11%
Wholesale	72	5.42%
Retail	111	8.36%
Restaurants, Hotels, Motels	21	1.58%
Everything Else	32	2.41%
Total	1,328	100.00%

Table 1. Sample Construction (*Continued*)

Panel D: Distribution by state based on the firm-year sample					
Headquarter State	Number of Observations	Percent of Observations	Headquarter State	Number of Observations	Percent of Observations
Alabama	5	0.38%	Minnesota	45	3.39%
Arkansas	5	0.38%	Missouri	29	2.18%
Arizona	24	1.81%	North Carolina	30	2.26%
California	148	11.14%	Nebraska	10	0.75%
Colorado	31	2.33%	New Hampshire	10	0.75%
Connecticut	45	3.39%	New Jersey	42	3.16%
Washington DC	6	0.45%	Nevada	1	0.08%
Delaware	3	0.23%	New York	86	6.48%
Florida	62	4.67%	Ohio	70	5.27%
Georgia	59	4.44%	Oklahoma	1	0.08%
Iowa	5	0.38%	Oregon	15	1.13%
Idaho	2	0.15%	Pennsylvania	70	5.27%
Illinois	98	7.38%	Rhode Island	3	0.23%
Indiana	38	2.86%	South Carolina	6	0.45%
Kansas	8	0.60%	South Dakota	2	0.15%
Kentucky	11	0.83%	Tennessee	28	2.11%
Louisiana	11	0.83%	Texas	87	6.55%
Massachusetts	85	6.40%	Utah	5	0.38%
Maryland	10	0.75%	Virginia	43	3.24%
Maine	3	0.23%	Washington	20	1.51%
Michigan	25	1.88%	Wisconsin	41	3.09%
			Total	1,328	100%

Table 1 reports the sample selection process in Panel A. Table 1 illustrates the sample distribution by year in Panel B, by Fama-French 30 industries in Panel C, and by firm headquarters state in Panel D. Distributions are based on the firm-year sample (1,328 observations).

Table 2. Univariate Statistics

Panel A: Firm-year-month sample						
Variable	N	Mean	SD	25^{th}	Median	75^{th}
DriveTraffic(IRS to HQ)	15,936	-0.054	0.112	-0.108	-0.051	-0.005
DriveTraffic(HQ to IRS)	15,936	-0.035	0.101	-0.084	-0.028	-0.001
HighDriveTreat(IRS to HQ)	15,936	0.289	0.453	0	0	1
HighDriveTreat(HQ to IRS)	15,936	0.281	0.449	0	0	1
PostSHOMonth	15,936	0.069	0.253	0	0	0
Panel B: Firm-year sample						
ResolveUTB	1,328	0.455	1.901	0.000	0.131	0.804
HighDriveTreat(IRS to HQ)	1,328	0.289	0.453	0	0	1
HighDriveTreat(HQ to IRS)	1,328	0.281	0.449	0	0	1
PostSHOYear	1,328	0.877	1.854	0	0	1
CIC	1,013	0.348	0.343	0.053	0.224	0.558
CAP	1,221	0.025	0.036	0.001	0.009	0.035
Tax fee	1,328	0.087	0.099	0.002	0.048	0.147
ETR	1,328	0.219	0.089	0.176	0.221	0.251
UTB_End3	1,328	7.453	9.850	1.173	4.119	9.570
R&D	1,328	0.028	0.048	0.000	0.004	0.034
Advertise	1,328	0.012	0.025	0.000	0.000	0.011
SG&A	1,328	0.215	0.132	0.114	0.197	0.286
Capx	1,328	0.081	0.045	0.049	0.068	0.099
Leverage	1,328	0.306	0.215	0.153	0.287	0.416
Foreign income	1,328	0.730	0.443	0	1	1
NOL	1,328	0.619	0.485	0	1	1
Intangible	1,328	0.272	0.203	0.089	0.244	0.425
PP&E	1,328	0.436	0.306	0.211	0.360	0.603
PT_ROS	1,328	0.129	0.088	0.064	0.106	0.174
Distance	1,328	3.279	1.504	2.233	3.190	4.595

Table 2. Univariate Statistics (*continued*)

Panel C: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *ResolveUTB*	1.000																
(2) *HighDriveTreat(IRS to HQ)*	0.031	1.000															
(3) *HighDriveTreat(HQ to IRS*	0.006	**0.686**	1.000														
(4) *PostSHOYear*	-0.015	-0.024	-0.022	1.000													
(5) *ETR*	**-0.096**	**-0.074**	-0.035	-0.044	1.000												
(6) *UTB_End3*	**0.219**	**0.090**	**0.055**	**0.137**	**-0.197**	1.000											
(7) *R&D*	0.065	**0.152**	**0.162**	**0.167**	**-0.281**	**0.435**	1.000										
(8) *Advertise*	0.007	-0.031	-0.079	0.062	-0.022	**0.144**	0.074	1.000									
(9) *SG&A*	0.030	0.007	0.007	**0.117**	**-0.080**	**0.179**	**0.504**	**0.429**	1.000								
(10) *Capx*	-0.002	0.023	-0.007	-0.008	**-0.079**	**0.081**	**0.142**	0.003	**0.072**	1.000							
(11) *Leverage*	0.013	-0.001	0.013	-0.068	0.037	**0.107**	**-0.178**	**0.087**	**-0.072**	**-0.065**	1.000						
(12) *Foreign income*	**0.068**	**0.145**	**0.168**	0.051	-0.041	**0.244**	**0.242**	0.040	**0.128**	**-0.079**	**0.086**	1.000					
(13) *NOL*	-0.028	0.039	0.020	0.056	0.000	**0.098**	**0.145**	0.043	**0.156**	0.041	0.018	**0.220**	1.000				
(14) *Intangible*	-0.030	0.014	0.048	**-0.082**	**-0.115**	0.056	**0.117**	-0.008	**0.124**	0.005	**0.124**	**0.228**	**0.134**	1.000			
(15) *PP&E*	0.015	-0.032	0.014	**-0.078**	**0.105**	**-0.088**	**-0.245**	-0.014	**-0.233**	**-0.185**	**0.164**	**-0.120**	-0.066	**-0.459**	1.000		
(16) *PT_ROS*	**0.067**	0.039	0.053	**0.079**	**-0.264**	**0.301**	**0.411**	**0.078**	**0.202**	**0.125**	-0.037	0.052	0.000	-0.003	-0.068	1.000	
(17) *Distance*	0.010	**-0.314**	**-0.477**	**-0.092**	0.048	**-0.104**	**-0.120**	**-0.083**	**-0.090**	0.021	-0.047	**-0.190**	-0.043	-0.048	0.049	**-0.093**	1.000

Table 2 shows the descriptive statistics for the firm-year-month sample (Panel A) and the firm-year sample (Panel B) and the correlations between variables used in the firm-year sample (Panel C). In Panel C, numbers in bold are statistically significant at the 1% level.

Table 3. The Effect of Stay-at-home Orders on Driving

DV =	*DriveTraffic(IRS to HQ)*	*DriveTraffic(HQ to IRS)*
	(1)	(2)
HighDriveTreat(IRS to HQ)	0.138***	
	(4.97)	
HighDriveTreat(HQ to IRS)		0.168***
		(5.85)
PostSHOMonth	-0.032***	-0.040***
	(-4.27)	(-3.61)
*HighDriveTreat(IRS to HQ)*PostSHOMonth*	-0.068***	
	(-3.20)	
*HighDriveTreat(HQ to IRS)*PostSHOMonth*		-0.073***
		(-4.40)
Controls	No	No
Industry FEs	Yes	Yes
Year FEs	Yes	Yes
Month FEs	Yes	Yes
County FEs	Yes	Yes
Observations	15,936	15,936
R-squared	0.608	0.543

Table 3 shows the estimations results of Equation (1) based on the firm-month sample defined in Table 1 Panel A: $DriveTraffic_{i,y,m} = \alpha_0 + \alpha_1 HighDriveTreat_i + \alpha_2 PostSHOMonth_{s,y,m} + \alpha_3 HighDriveTreat_i * PostSHOMonth_{s,y,m} + e_{i,y,m}$. The dependent variable is the yearly adjusted driving traffic from the closest IRS office to the firm's headquarters (*DriveTraffic(IRS to HQ)*) in Column (1), and is the yearly adjusted driving traffic from the firm's headquarters to the closest IRS office (*DriveTraffic(HQ to IRS)*) in Column (2). Treatment (*HighDriveTreat*) is defined as firms with average driving traffic in the top tercile in period preceding stay-at-home orders. The treatment is based on the traffic from IRS to HQ in Column (1) and the traffic to IRS from HQ in Column (2). *PostSHOMont*h is equal to 1 for months when stay-at-home order is implemented, 0 otherwise. All variables are defined in Appendix B. Industry, year, month, and county fixed effects are included. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed test).

Table 4. The Effect of Stay-at-home Orders on Resolving Tax Uncertainty

DV =	*ResolveUTB*	
	(1)	(2)
HighDriveTreat(IRS to HQ)	0.059	
	(0.31)	
HighDriveTreat(HQ to IRS)		-0.011
		(-0.07)
PostSHOYear	-0.017	-0.030
	(-0.70)	(-1.40)
*HighDriveTreat(IRS to HQ)*PostSHOYear*	-0.160***	
	(-3.68)	
*HighDriveTreat(HQ to IRS)*PostSHOYear*		-0.114
		(-1.66)
ETR	-2.153**	-2.124**
	(-2.33)	(-2.26)
UTB_End3	0.050***	0.050***
	(4.37)	(4.37)
R&D	-5.807*	-5.745*
	(-2.00)	(-1.96)
Advertise	-3.176	-3.040
	(-1.00)	(-0.95)
SG&A	0.757	0.758
	(1.21)	(1.20)
Capx	-0.483	-0.493
	(-0.46)	(-0.48)
Leverage	-0.632	-0.639
	(-1.64)	(-1.66)
Foreign income	0.229	0.235
	(1.16)	(1.19)
NOL	-0.310**	-0.310**

	(1)	(2)
	(-2.44)	(-2.40)
Intangible	-0.406	-0.410
	(-0.93)	(-0.95)
PP&E	0.124	0.130
	(0.42)	(0.45)
PT_ROS	-0.189	-0.203
	(-0.20)	(-0.22)
Distance	-0.138	-0.144*
	(-1.59)	(-2.00)
Industry FEs	Yes	Yes
Year FEs	Yes	Yes
Month FEs	No	No
County FEs	Yes	Yes
Observations	1,328	1,328
R-squared	0.203	0.202

Table 4 shows the estimations results of Equation (2) based on the firm-year sample defined in Table 1 Panel A: $ResolveUTB_{i,y} = \beta_0 + \beta_1 HighDriveTreat_i + \beta_2 PostSHOYear_{s,y} + \beta_3 HighDriveTreat_i * PostSHOYear_{s,y} + \sum Controls_{i,y} + e_{i,y}$. The dependent variable is the extent of UTB resolved by the firm (*ResolveUTB*). Treatment (*HighDriveTreat*) is defined as firms with average driving traffic in the top tercile in the period preceding stay-at-home orders. The treatment is based on the driving traffic from the closest IRS office to the firm's headquarters in Column (1) and is based on the driving traffic from the firm's headquarters to its closest IRS office in Column (2). *PostSHOYear* is equal to the number of months in a fiscal year subject to stay-at-home orders implemented by the firm's headquarters state. All variables are defined in Appendix B. Industry, year, and county fixed effects are included. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed test).

Table 5. Cross-sectional Tests

Panel A: Driving traffic from the closest IRS office to the company headquarters

	(1) Low CIC	(2) High CIC	(3) Low CAP	(4) High CAP	(5) Low tax fee	(6) High tax fee
HighDriveTreat (IRS to HQ)	0.344	0.103	0.002	0.193	-0.237	0.225
	(0.66)	(0.21)	(0.01)	(0.47)	(-0.82)	(0.47)
PostSHOYear	0.094*	-0.103**	0.064***	-0.081	0.005	-0.046
	(1.82)	(-2.19)	(2.96)	(-1.66)	(0.20)	(-0.88)
HighDriveTreat (IRS to HQ)*PostSHOYear	-0.116	-0.147**	0.025	-0.199***	-0.039	-0.262***
	(-1.02)	(-2.09)	(0.21)	(-3.37)	(-0.54)	(-3.93)
	p = 0.420		p = 0.082*		p = 0.082*	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	FF30	FF30	FF30	FF30	FF30	FF30
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	No	No	No	No	No	No
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State	State	State	State	State	State
Observations	513	500	621	600	663	665
R-squared	0.390	0.238	0.331	0.232	0.296	0.251

Table 5 Panel A presents cross-sectional results of estimating Equation (2) based on the firm-year sample defined in Table 1 Panel A: $ResolveUTB_{i,y} = \beta_0 + \beta_1 HighDriveTreat_i + \beta_2 PostSHOYear_{s,y} + \beta_3 HighDriveTreat_i * PostSHOYear_{s,y} + \sum Controls_{i,y} + e_{i,y}$. The dependent variable is the extent of UTB resolved by the firm (*ResolveUTB*). The treatment is based on the driving traffic from the closest IRS office to the firm's headquarters. In columns (1) and (2), we partition the sample based on the firm's likelihood of being assigned into the CIC program in 2019. A firm-year is in the high (low) CIC subsample if its CIC likelihood is above (below) the median per Ayers et al. (2019). In columns (3) and (4), we partition the sample based on the firm's likelihood of participating in the CAP program in 2019. A firm-year is in the high (low) CAP subsample if its CAP likelihood is above (below) the median per Beck and Lisowsky (2014). In columns (5) and (6), we partition the sample based on the firm's tax fees paid to the auditors in 2019. A firm-year is in the high (low) tax fees subsample if its tax fees is above (below) the median per Klassen et al. (2016). We compare coefficients across high and low subsamples using a non-parametric test. All variables are defined in Appendix B. Industry, year, and county fixed effects are included. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed test).

Panel B: Driving traffic to the closest IRS office from the company headquarters						
	(1)	(2)	(3)	(4)	(5)	(6)
	Low CIC	High CIC	Low CAP	High CAP	Low tax fee	High tax fee
HighDriveTreat (HQ to IRS)	0.135	0.144	-0.051	-0.018	-0.273	0.239
	(0.27)	(0.29)	(-0.15)	(-0.06)	(-0.78)	(0.49)
PostSHOYear	0.089*	-0.112**	0.059**	-0.091*	-0.011	-0.054
	(1.87)	(-2.35)	(2.52)	(-2.00)	(-0.47)	(-1.04)
HighDriveTreat (HQ to IRS)*PostSHOYear	-0.097	-0.121*	0.066	-0.169***	0.026	-0.235***
	(-0.80)	(-1.93)	(0.44)	(-3.51)	(0.23)	(-3.52)
	p = 0.434		*p* = 0.084*		*p* = 0.048**	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	FF30	FF30	FF30	FF30	FF30	FF30
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	No	No	No	No	No	No
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	State	State	State	State	State	State
Observations	513	500	621	600	663	665
R-squared	0.389	0.237	0.332	0.230	0.296	0.248

Table 5 Panel B presents cross-sectional results of estimating Equation (2) based on the firm-year sample defined in Table 1 Panel A: $ResolveUTB_{i,y} = \beta_0 + \beta_1 HighDriveTreat_i + \beta_2 PostSHOYear_{s,y} + \beta_3 HighDriveTreat_i * PostSHOYear_{s,y} + \sum Controls_{i,y} + e_{i,y}$. The dependent variable is the extent of UTB resolved by the firm and the IRS (*ResolveUTB*). The treatment is based on the driving traffic from the firm's headquarters to the closest IRS office. In columns (1) and (2), we partition the sample based on the firm's likelihood of being assigned into the CIC program in 2019. A firm-year is in the high (low) CIC subsample if its CIC likelihood is above (below) the median. In columns (3) and (4), we partition the sample based on the firm's likelihood of being assigned into the CAP program in 2019. A firm-year is in the high (low) CAP subsample if its CIC likelihood is above (below) the median. In columns (5) and (6), we partition the sample based on the firm's tax fees paid to the auditors in 2019. A firm-year is in the high (low) tax fees subsample if its tax fees is above (below) the median. We compare coefficients across high and low subsamples using a non-parametric test. All variables are defined in Appendix B. Industry, year, and county fixed effects are included. Standard errors are clustered at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively (two-tailed test).