

A Service of



Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre

Müller, Jens; Weinrich, Arndt

Working Paper

Tax knowledge diffusion via strategic alliances

arqus Discussion Paper, No. 253

Provided in Cooperation with:

arqus - Working Group in Quantitative Tax Research

Suggested Citation: Müller, Jens; Weinrich, Arndt (2020): Tax knowledge diffusion via strategic alliances, argus Discussion Paper, No. 253, Arbeitskreis Quantitative Steuerlehre (argus), Berlin

This Version is available at: https://hdl.handle.net/10419/214656

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.





Arbeitskreis Quantitative Steuerlehre Quantitative Research in Taxation – Discussion Papers

Jens Müller, Arndt Weinrich

Tax Knowledge Diffusion via Strategic Alliances

arqus Discussion Paper No. 253 February 2020

Tax Knowledge Diffusion via Strategic Alliances

Jens Müller

Arndt Weinrich

Paderborn University

Paderborn University

jens.mueller@upb.de

arndt.weinrich@upb.de*

Acknowledgements: We thank Alissa Brühne (discussant), Paul Demeré, Alex Edwards, Beatriz Garcia-Osma, Martin Jacob, Alastair Lawrence and Harun Rashid (discussant) for their helpful comments. We also thank the participants at the 2019 annual meeting of the foundation Stiftung Prof. Dr. oec. Westerfelhaus, the 2019 arqus Conference, the 5th Berlin-Vallendar Conference on Tax Research, the 6th Annual MaTax Conference and the 2020 Hawaii Accounting Research Conference. We further acknowledge the helpful discussions with our colleagues at the Department Taxation, Accounting and Finance at Paderborn University. Funding by the foundations Stiftung Prof. Dr. oec. Westerfelhaus (Bielefeld, Germany) and the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project-ID 403041268 – TRR 266 Accounting for Transparency is gratefully acknowledged.

*Send correspondence to Arndt Weinrich, Paderborn University, Faculty of Business Administration and Economics, Warburger Str. 100, DE 33098 Paderborn.

Tax Knowledge Diffusion via Strategic Alliances

Working Paper, February 2020

Abstract

This study examines strategic alliances as channels for tax knowledge diffusion between firms. Although

strategic alliances are primarily expected to foster their main business purposes, we focus on whether tax

knowledge potentially diffuses as a second order effect of peer-to-peer cooperation. To tease out diffusion

of tax knowledge, we investigate changes in the tax planning behavior of high-tax firms in strategic

alliances with low-tax firms in comparison to high-tax firms in strategic alliances with other high-tax firms.

Our results suggest an economically meaningful decrease of high-tax firms' cash effective tax rates when

cooperating with low-tax firms. Additionally, we find that this adjustment occurs within two years of a

strategic alliance's initiation. We apply textual analysis to control for the strategic alliances' main business

purposes in our analyses. Because these activities do not appear to drive our findings, we argue to identify

tax knowledge diffusion as a second order effect and conjecture that strategic alliances are not intended to

be tax planning investments. Finally, we test whether partner characteristics intensify or mitigate the

identified effects. Overall, our results provide robust evidence for tax knowledge diffusion via strategic

alliances.

Keywords: Corporate Tax Planning/Avoidance, Knowledge Diffusion, Network, Strategic Alliance.

JEL Qualification: C31, G34, H26.

Data: Data are available from public and/or subscription-based sources identified in the paper.

Declarations of Interest: None.

1

1. Introduction

Do strategic alliances serve as channels for tax knowledge diffusion? In the form of contractual-based cooperation between firms, strategic alliances are one means of striving for optimal corporate institutionalization. Their relevance is emphasized by the observation that firms currently plan to disrupt other industries by entering via cooperation (PwC, 2018). Although strategic alliances are expected to foster their main business purposes, they also facilitate knowledge diffusion in other areas (e.g., Li, Qiu, and Wang (2019)). As a second order effect of peer-to-peer cooperation, our study analyzes the diffusion of tax knowledge. Previous studies, which investigate cross-firm connections and tax knowledge, focus on either intentional transfers (Cen et al., 2018) or the effect of intermediaries (e.g., Brown and Drake (2014)). Our analysis, however, neither requires the existence of an intermediary nor imperatively assumes intentional transfers.

Conceptually, diffusion of tax knowledge comprises gaining access to and being willing and capable of employing relevant information and know-how. An exemplary driver within this process could be a shift in a firm's management preferences and confidence towards implementing a specific tax planning activity when observing unchallenged or successfully defended strategies by other participants in a strategic alliance. As a result of tax knowledge diffusion, one may observe changes in the actual tax planning behavior of a firm. Strategic alliances, which we also refer to as "networks", are, in contrast to equity joint ventures, not subject to corporate taxation. They are regarded as "lying somewhere in between single-firm activity and spot contracting" (Lindsey, 2008), involving mutual commitment not typically found in arm's-length market transactions but having less impact on the partnering firms' operations than equity joint ventures (Chan et al., 1997). This is useful for us since we are not interested in whether firms potentially use joint ventures as vehicles in tax planning activities but in whether peer-to-peer cooperation may serve as a channel through which tax knowledge diffuses between firms. Observing tax consequences at the level of the investing firms allows us to identify tax knowledge diffusion via strategic alliances. This is the key innovation of our study.

We empirically exploit information on strategic alliances that were established between publicly traded US firms from 1994 to 2016. Given that accounting data are available for a network's participants, we reshape the data from the alliance to the participant level (network-firm observations). We measure tax knowledge by observing a firm's nonconforming tax planning behavior (cash ETR3) and classify the participants and the network as low-tax and high-tax. To tease out tax knowledge diffusion after network initiation, we analyze changes in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms in comparison to high-tax firms in strategic alliances with high-tax firms. We gain insights into the business purpose of a network by applying textual analysis of the networks' deal descriptions. For our inferences, we apply a multivariate regression design and a difference-in-differences (DiD) model, which both complement a descriptive analysis. We find a substantial increase in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms relative to high-tax firms in high-tax strategic alliances. Our results are also economically meaningful because they lead to expected cash effective tax rate levels for high-tax firms in low-tax networks of approximately 5 percentage points below the cash effective tax rate levels for high-tax firms in high-tax networks. Furthermore, we assess firms to be able to adjust their tax planning behavior on average within two years of network initiation. Finally, we test whether partner characteristics intensify or mitigate the identified effects but find that tax knowledge diffusion via strategic alliances is rather unaffected by such heterogeneity.

Our study refers to the emerging literature that identifies cross-firm connections to determine increases in the tax planning behavior of linked firms. By examining a potential determinant of cross-sectional variation in the tax planning practices among firms, we follow calls for contributions to the understanding of this matter (Cen et al., 2018; Dyreng and Maydew, 2017; Wilson, 2009). By focusing on cross-firm connections via intermediaries and intentional transfers of tax knowledge, recent research has analyzed board ties (Brown, 2011; Brown and Drake, 2014), banks (Gallemore, Gipper, and Maydew, 2018), human capital turnover (Barrios and Gallemore, 2019), auditors (Frey, 2018; Lim et al., 2018) and the supply chain (Cen et al., 2017, 2018). Strategic alliances, which are established on a peer-to-peer basis without an

intermediary, aim to foster a specific business purpose and constitute, per se, no tax planning investment. Budget meetings, monitoring and within-firm reporting, however, could establish opportunities to gain insights into the partnering firms' tax positions. If we observed the actual exploitation of these opportunities, we could shed light on diffusion of tax knowledge during peer-to-peer contracting and contribute to this yet underexplored literature.

Additionally, we contribute to the management literature on identifying knowledge flows via strategic alliances. Empirical inferences in such studies are usually based on the contracting parties' stock price performance (Boone and Ivanov, 2012; Mohanram and Nanda, 1996; Chen, King, and Wen, 2015; Anand and Khanna, 2000), return on equity, (cash flow) return on assets (Chan et al., 1997; Porrini, 2004), post-reorganization performance (Cai and Sevilir, 2012; Higgins and Rodriguez, 2006; Ishii and Xuan, 2014; Porrini, 2004) and patent citations (Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Li, Qiu, and Wang, 2019). Although firms are often found to benefit from what they learn in alliances in other contexts, not all corporate practices diffuse in the same way (Cai et al., 2014). Since tax knowledge characteristics are considered to lie somewhere between being excessively complex (Hoppe et al., 2019) and serving as massmarket ideas (Lisowsky, 2010), ambiguity arises when analyzing the diffusion of tax knowledge. To the best of our knowledge, we are the first to measure knowledge diffusion via strategic alliances based on a firm's tax planning behavior. Our study therefore combines accounting and management research.

In the next section, we review the related literature to discuss whether tax knowledge could diffuse between firms via strategic alliances. Subsequently, we explain our data exploitation and identification strategy. We discuss an appropriate research design and then present and discuss the results of our study. Before this paper closes with a brief conclusion, we provide several sensitivity analyses.

2. Conceptual Framework & Prior Literature

2.1. Cross-Firm Connections and Tax Knowledge

The extensive research that considers within-firm determinants of tax planning by firms underlines the perceived importance of corporate taxes in economic theory, politics and society (for comprehensive reviews, see Hanlon and Heitzman (2010) and Wilde and Wilson (2018)). Given the substantial economic impact of tax planning activities (Clausing, 2016; Tørsløv, Wier, and Zucman, 2018; Blouin and Robinson, 2019), tax advisors are intuitively linked to observations of tax planning. However, by investigating "tax planning ecosystem[s]" (Dyreng and Maydew, 2017) between firms, recent research suggests the existence of further channels. The findings indicate that cross-firm connections impact tax planning behavior of linked firms. Brown (2011) pioneered this strand of literature by examining the spread of a specific tax planning tool, the corporate-owned life insurance shelter. Although she finds that board interlocks and (to some extent) geographical proximity increase the probability that a firm adopts the shelter from a prior user, she does not find significant shelter adoption via shared audit firms. This result, although it is theoretically convincing due to independence regulations on audit services, is somewhat surprising given the literature on auditors who transgress their limited scope of function (Aobdia, 2015; Cai et al., 2016; Dhaliwal et al., 2016; McGuire, Omer, and Wang, 2012). By calibrating from the audit firm level to the individual audit engagement partner, Frey (2018) suggests that the engagement of a German tax certified auditor, who signals high competency in taxes, is associated with higher effective tax rates at client firms. In contrast, Lim et al. (2018) find that Chinese firms with stronger connections to low-tax firms through individual audit partners show lower effective tax rates. Further disentangling the role of intermediaries, Barrios and Gallemore (2019) document that firms exhibit increasing tax planning when they hire tax staff from sophisticated tax planners. This finding is consistent with the inferences from analyzing board ties to lowtax firms (Brown and Drake, 2014). Gallemore, Gipper, and Maydew (2018) show that firms experience meaningful tax reductions when they start a relationship with a bank whose existing clients engage in tax planning.

[Figure 1]

These studies are conceptually aligned by the presence of intermediaries who implement tax planning expertise in their set of contracts and intentionally transfer the tax knowledge gained to other parties that they are contracting with. Consistently, intermediaries are found to play a key role in the acquisition and dissemination of information in many research fields (e.g., see Di Maggio et al. (2019)). Figure 1 aligns institutional settings with identified channels of prior research on transfers and diffusion of tax knowledge. The research focuses on the role of intermediaries, whereas Cen et al. (2017) and Cen et al. (2018) analyze peer-to-peer contracting between firms. Specifically, they focus on transfers of tax knowledge via the supply chain and document that both customers and suppliers increase their tax planning activities once their relationship is considered to be dependent. Cen et al. (2018) suggest that customers and suppliers share tax planning benefits through lower product prices. Although evidence for the intended sharing of tax benefits is scarce (for instance, see Erickson (1998) and Erickson and Wang (1999)), an intentional transfer of tax knowledge aligns the "supply chain channel" with research on intermediaries.

2.2. Strategic Alliances and Tax Knowledge Diffusion

In contrast to previous research, we ease the studies' assumptions of existing intermediaries and intentional transfers of tax knowledge and focus on tax knowledge diffusion between firms when peer-to-peer contracting. For this purpose, we not only need to identify tax knowledge characteristics but also must resolve whether strategic alliances conceptually allow for (tax) knowledge diffusion.

2.2.1.Tax Knowledge

Generally, repeated business transactions are found to enable knowledge spillovers (Isaksson, Simeth, and Seifert, 2016). However, not all corporate practices diffuse in the same way (Cai et al., 2014), as major barriers to knowledge spillovers are shown to be knowledge-related factors (Szulanski, 1996). Explicit knowledge can easily be codified and is systematically transferable, whereas tacit knowledge is difficult to formulate and communicate because it "is deeply rooted in action, commitment, and involvement in a

specific context" (Nonaka, 1994). Consequently, when (tax) knowledge qualifies as more explicit, it should be more easily transferable (Meier, 2011). One might reflexively refer to tax knowledge as tacit given the substantial complexity of corporate taxes (Hoppe et al., 2019) and the increased uncertainty (Dyreng, Hanlon, and Maydew, 2019; Guenther, Matsunaga, and Williams, 2017) and costs (Hundsdoerfer and Jacob, 2018) of tax planning. One also has to consider that know-how is somewhat sticky, difficult to codify and, therefore, more tacit than pure information (Kale, Singh, and Perlmutter, 2000). However, anecdotal evidence suggests that tax shelters, such as the German family office shelter for limited partnerships, are repetitive among firms and not limited to a particular industry. Recent findings suggest tax knowledge to be of an explicit nature, given the inferences on corporate-owned life insurance shelters (Brown, 2011) or lease-in, lease-out transactions (Wilson, 2009). Lisowsky (2010) further argues that a significant portion of tax shelters serve as mass-market tax-saving ideas for advisors.

2.2.2. Diffusion of (Tax) Knowledge

Knowledge diffusion requires communication through channels over time among members of a social system (Rogers, 2003). In accomplishing a common goal, the contracting parties of a strategic alliance are engaged in joint problem solving via a social system. Consistent with this, cooperation is found to mitigate problems that ensue from cultural differences (Kogut and Singh, 1988). Spillovers are also more likely to occur in cases of a high frequency of interactions between firms (Isaksson, Simeth, and Seifert, 2016) and with increasing partner trustworthiness (Jiang et al., 2016). Regarded as "lying somewhere in between single-firm activity and spot contracting" (Lindsey, 2008) and presenting increased mutual commitment compared to arm's-length market transactions (Chan et al., 1997), strategic alliances further comply with the diffusion requirements proposed by Rogers. Empirical inferences about knowledge diffusion via strategic alliances are usually based on the contracting parties' stock price performance (Boone and Ivanov, 2012; Mohanram and Nanda, 1996; Chen, King, and Wen, 2015; Anand and Khanna, 2000), return on equity, (cash flow) return on assets (Chan et al., 1997; Porrini, 2004), post-reorganization performance (Cai and Sevilir, 2012; Higgins and Rodriguez, 2006; Ishii and Xuan, 2014; Porrini, 2004) and patent citations

(Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Li, Qiu, and Wang, 2019). Other scholars apply exploratory approaches by conducting surveys (Dyer and Hatch, 2006) or interviews (Inkpen, 2008). Firms are often found to benefit from what they learn in alliances in other contexts (Porrini, 2004).

Based on these findings and combining them with the characteristics of tax knowledge, one could expect strategic alliances to serve as channels for tax knowledge diffusion between firms. Tension, however, arises from various aspects. Basically, the business purpose of a strategic alliance itself does not aim at immediate tax consequences. Furthermore, limits to a recipient's absorptive capacity create a barrier to knowledge diffusion (Dyer and Hatch, 2006; Szulanski, 1996), and joint operations could induce complexity in the contracting parties' organizations that reduces the ability to fine-tune the tax sheltering of their affiliates (Desai, Foley, and Hines, 2004). Additionally, both cooperation (Chen, King, and Wen, 2015) and tax planning are found to increase a firm's uncertainty (Dyreng, Hanlon, and Maydew, 2019). Even prudent managers could expect the marginal disutility of uncertainty to exceed the benefits of received tax knowledge. Furthermore, firms need to trade off deriving know-how from their alliance partners with protecting themselves from losing their own core capabilities (Kale, Singh, and Perlmutter, 2000). Khanna, Gulati, and Nohria (1998) frame this in the context of earning private benefits in an alliance. Earning private benefits permit a firm to apply what it learns to its business outside the scope of the alliance but harm the network by inducing underinvestment in shared learning.

2.2.3.Mechanisms

Inkpen (2000) describes learning through networks as a multi-stage process that consists of forming a network, gaining access to knowledge and adopting the knowledge. However, there is little evidence on the mechanisms behind knowledge diffusion. Chan et al. (1997) identify optimal decision making authority, organizational flexibility and control of opportunistic behavior as major drivers. Khanna, Gulati, and Nohria (1998) argue that although contracting parties must invest in learning, both parties need not earn private

benefits. They argue that a firm [with poor tax knowledge] would not have an incentive to continue the alliance once it had earned private benefits [tax knowledge] if its private benefits exceeded the common benefits. The other party [with sophisticated tax knowledge] would then "race" to earn benefits itself before termination of the alliance. As such racing behaviors appear to be mutually reinforcing, common benefits would still be attainable (Khanna, Gulati, and Nohria, 1998). Furthermore, strategic alliances enhance managerial flexibility because the contracting parties are not fully committed to the investment (Chen, King, and Wen, 2015). Fiol and Lyles (1985) contemplate that the probability of learning increases with an organizational structure that allows innovativeness and new insights.

Seconded employees to a strategic alliance not only are involved in the alliance's business as such but also monitor the network and the partner. Within-firm reporting thus creates opportunities for experience-sharing. Additionally, observing effectively implemented tax planning strategies by participants in a network could increase a firm's management confidence in also implementing the respective tax planning activity. This would be consistent with knowledge diffusion being a gradual process of dissemination (Szulanski, 1996) and with increasing probability of uniformity of actions in networks over time (Gale and Kariv, 2003) while also aligning with anecdotal evidence on tax advisors who heavily pitch tax planning ideas across the population of firms with only partial success from the spot. Gained confidence could also overcome the fear of reputational costs from engaging in tax planning (Gallemore, Maydew, and Thornock, 2014; Hanlon and Slemrod, 2009).

Regarding supply chains, Cen et al. (2018) suggest that intentional tax knowledge transfers enhance and maintain a supply chain's stability. Strategic alliances are also exposed to instability that is inherent in their institutionalization and specific to cooperation. Cultural differences, product market competition, availability of new technology, cost differences, market entry barriers, deadlocks, or an imitation of a partner cause this instability. However, whether the participants in a strategic alliance follow the intuition

¹ The content in square brackets is added by the authors.

of Cen et al. (2018) and share tax knowledge to establish bonding mechanisms is not decisive for our study since we do not have to imperatively assume intentional transfers of tax knowledge.

Given the variety of potential mechanisms, we do not expect that tax knowledge diffusion via strategic alliances is exposed in (one) specific accounting measure(s). Instead, the experiences of other firms and the communication structure between parties explain information flows (Acemoglu et al., 2011; Blonski, 1999). Consequently, tax knowledge diffusion via strategic alliances should be driven by complex elements such as trust, confidence and skills. If we observed actual exploitation of opportunities for tax knowledge diffusion, we could shed light on diffusion of knowledge when peer-to-peer contracting. Overall, it thus remains an empirical question whether strategic alliances actually serve as channels for tax knowledge diffusion between firms.

3. Data

[Table 1]

3.1. Sample Construction

We exploit data on strategic alliances from the Securities Data Company (SDC) Platinum database on strategic alliances over the 1994–2016 period.² SDC is widely used in relevant research on corporate cooperation (Anand and Khanna, 2000; Boone and Ivanov, 2012; Cai and Sevilir, 2012; Chen, King, and Wen, 2015; Ishii and Xuan, 2014), and its accuracy is generally perceived to be very high for most items (Anand and Khanna, 2000). SDC issues data at the strategic alliance level. We reshape data from the alliance to the participant level because accounting data are available for the (publicly traded) contracting parties. For instance, a strategic alliance between two participants translates to a network-firm observation for each of the two firms. Compustat provides us with firm-year-level accounting information, and we merge SDC and Compustat data by using a firm's six-digit CUSIP number (at the level of the ultimate

² A list of the requested data items is available from the authors upon request.

parent of the participant) as an identifier. Although SDC provides reliable network observations from the beginning of 1990 onwards, we start our sample in 1994 due to changes in reporting requirements on cash taxes paid (Cen et al., 2017). We end our sample in 2016 to exclude any inferences from the 2017 US tax reform. Furthermore, we respectively consider strategic alliances between publicly traded firms incorporated and headquartered in the US and in which all contracting parties are identified in Compustat (Table 1 Panel A). Our base sample contains 4,159 network-firm observations, which translate to 2,064 strategic alliances by 1,603 unique firms and 19,447 overall firm-year observations.

3.2. Identification Strategy

3.2.1. Measuring Tax Knowledge

We measure tax knowledge by observing a firm's nonconforming tax planning behavior. The lingua franca in determining the degree to which a firm succeeds in this attempt is the effective tax rate, which puts tax expenses and pre-tax book income into perspective. The interpretation of effective tax rates is fairly straightforward, and an advantage is that although it is conceptually incorrect, effective tax rates are widely used as input for corporate decisions on new investment (Graham et al., 2017). We base our inferences on the cash effective tax rate (*cash ETR*) because *cash ETR* also captures tax deferral strategies (Hanlon and Heitzman, 2010). Furthermore, we apply a multi-period (3-year) form of *cash ETR* (Brown and Drake, 2014; Barrios and Gallemore, 2019; Gallemore, Gipper, and Maydew, 2018) because we expect the likelihood of tax knowledge diffusion to increase over time.

$$cash \ ETR3_{i,t=1} = \frac{\sum_{t=1}^{3} (txpd_{i,t})}{\sum_{t=1}^{3} (pi_{i,t} - spi_{i,t})}$$
(1)

The terms txpd, pi and spi correspond to their Compustat data item equivalents of cash taxes paid, pretax income and special items. Missing spi are reset to 0, while any $cash\ ETR3$ with a negative denominator is reset to missing. Non-missing $cash\ ETR3$ are winsorized at 0 and 1. By nature of this approach, $cash\ ETR3$ would always be missing for the final (penultimate) firm-year of a firm in our panel. For the final

(penultimate) firm-year, we therefore substitute *cash ETR*3 with *cash ETR*(2).³ Applying a forward-looking *cash ETR*3 has the advantage that potential tax knowledge diffusion via strategic alliances can be directly linked to the year of network initiation.

3.2.2. Networks between Low-Tax and High-Tax Firms

[Figure 2]

For tax knowledge diffusion to occur, at least one network participant must possess sophisticated tax knowledge. Therefore, we classify the strategic alliances' participants into low-tax and high-tax firms. Applying a forward-looking *cash ETR3* for our output analysis has the advantage of aligning any influence on the *cash ETR3* directly with the year of network initiation. However, identifying low-tax firms based on a forward-looking measurement would come with the disadvantage of concluding the type of input based on the output. For the identification of sophisticated tax planners, we therefore consider the *pre cash ETR3*, which is constructed over a three-year preceding period:

$$pre\ cash\ ETR3_{i,t=0} = \frac{\sum_{t=-2}^{0} (txpd_{i,t})}{\sum_{t=-2}^{0} (pi_{i,t} - spi_{i,t})}$$
(2)

For every t = 1 in which a new network is initiated, we consider the participants' initial $pre\ cash\ ETR3$, which is constructed from t = -2 to t = 0. For the first (second) firm-year of a firm in our panel, we substitute $pre\ cash\ ETR3$ with $pre\ cash\ ETR(2)$. To increase the accuracy of our analysis, we require to observe $cash\ ETR3$ and $pre\ cash\ ETR3$ of all participants for a network to be considered in our analysis (Table 1 Panel B). Figure 2 provides additional information regarding how we identify low-tax and high-tax observations. We classify low-tax firms based on their industry-adjusted $pre\ cash\ ETR3$ and allocate firm-year observations into 4 bins ($pre\ taxrank$) according to the quartiles of the distribution of the industry-adjusted $pre\ cash\ ETR3$. Industry adjustment (Brown and Drake, 2014) and a multi-period

12

³ For example, given our overall sample period, *cash ETR*3 would always be missing for fiscal year 2015. In this case, we construct the numerator and denominator over two years, respectively.

measure (Dyreng, Hanlon, and Maydew, 2008) help us to validate identification of sophisticated tax planners. A network participant that is aligned with the first *pre taxrank* is treated as a low-tax firm in a network. Consequently, a strategic alliance in which at least one participant qualifies as a low-tax firm is treated as a low-tax network. Firms that do not qualify as low-tax firms are treated as high-tax firms, and networks in which none of the participants is a low-tax firm qualify as high-tax networks. We focus on high-tax firms in our analyses and thereby distinguish between high-tax firms that invest in low-tax networks and high-tax firms that invest in high-tax networks (Table 1 Panel C). Tax knowledge diffusion can occur for high-tax firms in low-tax networks (*hightolow*). However, high-tax firms in high-tax networks are in a very similar situation except for potentially experiencing tax knowledge diffusion. Finally, we exclude multiple network initiations of one firm in a single year to rule out the overweighing of a firm in the sample. Our identification strategy leads us to 197 observations of high-tax firms in networks with low-tax firms and 540 network-firm observations solely among high-tax firms.

3.3. Information on Networks and Firms

[Table 2]

Panel A of Table 2 contains information on the distribution of *pre cash ETR3* by *pre taxrank*, which is used to identify low-tax networks. Although the mean *pre cash ETR3* in the first bin of *pre taxrank* equals 7.08%, the average rises to 63.91% in the top *pre taxrank*. The overall mean of 30.66% for *pre cash ETR3* is relatively close to but below the federal corporate income tax rate of 35%, which is consistent with prior research on multi-period cash effective tax rates (e.g., Dyreng, Hanlon, and Maydew (2008)). Furthermore, Panel B of Table 2 contains descriptive statistics for firm-level characteristics separated by the classification of firms as low-tax or high-tax and by the network type for high-tax firms. Panel B includes measures of firm-level accounting information (*firm controls*), which are included in our regression analyses. Following Dyreng, Hanlon, and Maydew (2010), we show information on

⁴ The variable definitions in the Appendix contain detailed descriptions of the steps taken.

EBITDA3, RnDExp3, AdExp3, SGA3, CapEx3, ChangeSale3, Leverage3, Cash3, MNE3, NOL3, Intangibles3, PPE3, and Size3.⁵ Consistently with cash ETR3, these measures are constructed over rolling three-year periods. In Panel C of Table 2, we present information regarding the industry affiliation of networks and firms. Industry affiliation is determined on a two-digit SIC-code basis. It can be observed that the majority of networks operate in business services, while the investing firms are predominantly manufacturers and business service providers. Additionally, Panel D of Table 2 contains a correlation matrix of all independent variables included in our analyses.

4. Methodology

4.1. Regression Analysis

If engaging in low-tax strategic alliances is associated with tax knowledge diffusion, one should be able to identify increasing levels of tax planning at high-tax firms. Nevertheless, if the influence of a network on a firm's tax planning behavior as such were omitted, no inferences could be drawn. Consequently, our main variable of interest hightolow is constructed as an indicator variable to distinguish between high-tax firms that enter into high-tax networks (hightolow = 0) and high-tax firms that engage in low-tax networks (hightolow = 1). By running our regression among high-tax firms, hightolow isolates the incremental effect a low-tax network exerts on the high-tax firm's Tax Knowledge:

 $Tax\ Knowledge_{i,t=1}$

$$= \beta_{0} + \beta_{1} hightolow_{i,t=1} + \sum_{n} \beta_{n} partner controls_{i,t=1}^{n}$$

$$+ \sum_{l} \beta_{l} network controls_{i,t=1}^{l} + \sum_{k} \beta_{k} firm controls_{i,t=1}^{k}$$

$$+ \delta_{ind} + \tau_{t} + \varepsilon_{i,t}.$$
(3)

_

⁵ All variables are defined in detail in the Appendix. There is a large variety of control variables in the tax planning research. For instance, Kubick et al. (2015) suggest considering a firm's price cost margin to control for market power. In untabulated robustness checks, we include several vectors of firm controls but do not find our results to be driven by them. Therefore, we apply the basic approach by Dyreng, Hanlon, and Maydew (2010).

By using indicator notation (hightolow), the coefficient estimate describes the effect from moving from one condition to another condition. As we use a three-year rolling specification of a firm's cash effective tax rate ($pre\ cash\ ETR3$) for identification purposes, we primarily measure $Tax\ Knowledge$ by $cash\ ETR3$. Consistently, Kim et al. (2019) suggest that firms are generally able to adjust their tax planning behavior within three years. Consequently, the coefficient estimate for hightolow would load negatively if strategic alliances served as channels for tax knowledge diffusion. To alleviate concerns about interpreting a level-based dependent variable, we also construct the change-indicating variable $delta\ cash\ ETR3$, which is $cash\ ETR3\ [t_1;t_3]$ scaled by $pre\ cash\ ETR3\ [t_{-2};t_0]$. Given a suggested average lifespan for strategic alliances of five years (Chan et al., 1997), we also measure $Tax\ Knowledge$ as $cash\ ETR5$ and $delta\ cash\ ETR5$.

Because strategic alliances go beyond bringing together high-tax and low-tax firms, we include vectors of variables on $partner \& network \ controls$ in our main regression model. From Compustat data, we can infer whether network participants share an audit firm in the year of network initiation (SameAuditor). Furthermore, we manually collect the geographical distance (as the crow flies) between the zip codes of the network participants' headquarters to control for the potential impact of geographical proximity in tax knowledge diffusion (Proximity). We normalize Proximity between 1 for the closest and 0 for the farthest distance, which allows us to interpret the sign of the coefficient in agreement with the sign of a potential indicator variable for a geographical linkage (as, for instance, in Brown (2011)). In our main regression, we do not include an indicator for firms belonging to the same industry (SameInd), as we include industry fixed effects (δ_{ind}) .

[Figure 3]

Generally, business activities in a strategic alliance are in no way limited and could thus exert an influence on the options of tax planning that are available for a network participant. Therefore, we are interested in the main business purposes of the strategic alliances (*network controls*). To derive these, we apply textual

analysis. For illustration purposes, the word cloud depicted in Figure 3 shows the 50 most common words used in SDC's deal descriptions of the networks in our regression sample. By systematically searching through the deal descriptions, we identify PurposeWholesale, PurposeRnD, PurposeLicensing, PurposeService, PurposeMarketing, PurposeSupply, and PurposeManufacturing as network activities, create respective indicator variables at the individual network level, and include these $network\ controls$ in equation (3). Furthermore, we control for within-firm determinants of tax planning by including a vector of $firm\ controls$. We follow Dyreng, Hanlon, and Maydew (2010) and include EBITDA3, RnDExp3, AdExp3, SGA3, CapEx3, ChangeSale3, Leverage3, Cash3, MNE3, NOL3, Intangibles3, PPE3, and Size3. Consistent with $cash\ ETR3$, these measures are constructed over rolling three-year periods. The Appendix includes a complete list of the variable definitions. In addition to industry fixed effects (δ_{ind}), we include year fixed effects (τ_t) and cluster standard errors at the firm level (Petersen, 2009).

4.2. Difference-in-Differences (DiD)

The regression model in equation (3) allows us to observe actual tax knowledge diffusion, which should occur over time, in the year of network initiation. This approach allows us to account for $partner\ \&\ network\ controls$, although it condenses our panel to a cross-section. An alternative approach for measuring tax knowledge diffusion is to maintain the panel structure of our data and apply a DiD methodology. In this model, treatment is in alignment with hightolow. We create an embargo period of eight years around a hightolow observation during which no further network may occur, which reduces the number of observations in the sample. The embargo period contains the three years preceding and five years subsequent to network initiation. Our sample allows firms to enter into a network at any point in time of their discretion. We therefore compose a matched panel by matching control observations (hightolow = 0) to treatment observations (hightolow = 1) based on year and industry affiliation. As we no longer

-

⁶ The sign and overall significance of our main variable of interest are not sensitive to the design choices regarding fixed effects or the clustering of standard errors.

exploit cross-sectional but panel data, we adjust dependent and control variables from multi-period measures to their single-year versions:

$$cash \ ETR_{i,t} = \beta_0 + \beta_1 treated_i + \beta_2 post_t + \beta_3 treated * post_{i,t}$$

$$+ \sum_{k} \beta_k \ firm \ controls_{i,t}^k + \delta_{ind} + \varepsilon_{i,t}.$$

$$(4)$$

In this model, *treated* measures the baseline difference in *cash ETR* that is not due to the presence of the treatment. The parameter *post* captures changes in *cash ETR* from before to after treatment. The parameter of interest is the interaction *treated* * *post*. It measures the effect on *cash ETR* that is due to the treatment (i.e., low-tax network of high-tax firm). We include industry fixed effects and the annual measures of *firm controls* as defined in the Appendix. We base our inferences on standard errors clustered at the firm level (Petersen, 2009).

4.3. Endogeneity

A firm's decision to engage in a network is intentional and not random, which could lead to biased sample selection. Nevertheless, it is important to note that our study does not compare network firms to nonnetwork firms but instead focuses on a within-comparison of network firms. Nevertheless, once a firm experiences knowledge diffusion via a low-tax network, engaging in subsequent networks could, to some extent, also depend on an expected learning effect. Our sample could thus be nonrandomly selected, which leads to concerns about endogenous treatment assignment (regarding scholars on strategic alliances, see Carpenter, Li, and Jiang (2012)). One may account for this empirically by constructing a two-stage estimator (Heckman, 1979). However, identifying valid covariates that predict treatment assignment while having no direct impact on the dependent variable is difficult (Bodnaruk, Massa, and Simonov, 2013; Chan et al., 1997; McGuire, Omer, and Wang, 2012). Following the recommendation by Lennox, Francis, and Wang (2012), we emphasize that our study potentially has an endogeneity problem that could affect the inferences from OLS regressions. However, if tax planning was an endogenous choice based on having high effective tax rates prior to engaging in tax planning (Dyreng, Hanlon, and Maydew, 2008), tax planning

research would generally face endogeneity concerns. Additionally, research indicates that firms could accept expected high taxation when establishing an [international] network (Owen and Yawson, 2013). If a network's primary aim was facilitating tax planning, we would further expect firms to cover their tracks by not disclosing the partner. These cases, however, are excluded from our sample since we require the identification of all participants in a network.

For further mitigation purposes, we conduct a thorough descriptive analysis. We analyze changes in the tax planning behavior of high-tax firms in strategic alliances with low-tax firms in comparison to high-tax firms in strategic alliances with high-tax firms. First, we compare $pre\ cash\ ETR3\ [t_{-2};t_0]$ between the two groups. Subsequently, we focus on our primary measure of $Tax\ Knowledge$ after network initiation, $cash\ ETR3\ [t_1;t_3]$, and test the significance of the differences between the groups and within-group change by applying a z test following Paternoster et al. (1998):

$$z = \frac{b_1 - b_2}{\sqrt{SEb_1^2 + SEb_2^2}} \tag{5}$$

5. Results & Discussion

5.1. Descriptive Insights

[Table 3]

The results of our descriptive analysis are depicted in Table 3. In Panel A, we compare changes in $Tax\ Knowledge$ between and within groups. Interestingly, the mean of $pre\ cash\ ETR3$ is very similar for high-tax firms in the period before investing in low-tax or high-tax networks, with 38.96% and 39.35%, respectively (p-value of difference 0.8613). This alleviates concerns about analyzing level measures of $Tax\ Knowledge$ in equation (3). It also indicates that low-tax firms do not tend to stay among themselves by engaging in strategic alliances with sophisticated tax planners. For periods subsequent to the initiation of a network by high-tax firms, the distribution of $cash\ ETR3$ points towards a completely different direction. While observations of hightolow = 1 are accompanied with a mean $cash\ ETR3$ of 27.55%,

networks solely among high-tax firms (hightolow = 0) are aligned to an average $cash\ ETR3$ of 32.82%. The respective difference of 5.27% is also highly significant (p-value 0.0065). Generally, we observe substantial reductions in cash effective tax rates for both groups (within-group change), each being highly significant (p-values < 0.0000). These decreases could comprise reversion to the mean. However, this would not explain differences in the development between the groups. We therefore test whether the difference in the within-group change of 4.88 percentage points is significant and find it to be so (z-statistic -1.6994). In Panel B, we compare the development of $cash\ ETR3$ for high-tax firms' involvement in low-tax and high-tax networks with a growing number of networks. In this test, we again observe lower levels of $cash\ ETR3$ for high-tax firms in low-tax networks, with differences increasing in intensified networking. Although our descriptive analysis does not allow us to include further covariates, we interpret our findings to be consistent with strategic alliances serving as channels for tax knowledge diffusion. Therefore, we are interested in whether the multivariate regression results further support this notion.

5.2. Regression Results

[Table 4]

5.2.1. Multivariate Regression

The main variable of interest in our regression analysis is *hightolow* because it isolates the incremental effect a low-tax network exerts on a high-tax firm's *Tax Knowledge*. In Panel A of Table 4, we show multi-period specifications of *Tax Knowledge* for equation (3) with *cash ETR3*, *delta cash ETR3*, *cash ETR5* and *delta cash ETR5*. By observing multi-period measures, we can link our inferences to the period of network initiation. For brevity, we report only the coefficient estimates for *hightolow* and *partner controls*. Throughout all specifications, the estimate for *hightolow* is negative and highly significant. In the specification with *cash ETR3* as the dependent variable, the estimate for *hightolow* has a magnitude of -0.0480 (p-value 0.0103), which is consistent with our descriptive inferences in terms of direction and magnitude. Because an overall network effect is absorbed by including high-tax firms in our

regression and because the covariates of *partner*, *network* & *firm controls* account for a broad range of alternative explanations, we find it plausible to associate the (relative) increase in tax planning practices for high-tax firms in low-tax networks to be induced by the presence of a low-tax firm in the network. Extending equation (3) to a change-indicating variable, *delta cash ETR3*, yields the same implications (p-value 0.0061). Furthermore, we extend our model to *cash ETR5* and *delta cash ETR5*, which are constructed identically to *cash ETR3* and *delta cash ETR3*, respectively, but over five years subsequent to and including the year of network initiation as the dependent variables. The results for these specifications imply a slightly smaller magnitude (coefficient estimate for (*delta*) *cash ETR5* is -0.0376 (-0.1229)) in effects but are both negative and highly significant. Interestingly, the estimates for the *partner controls*, namely, *Proximity* and *SameAuditor*, do not surpass the usual levels of significance. In several additional analyses (see Section 6), we focus on the interactions of *hightolow* and *partner controls* to align our findings with prior research. Furthermore, we do not observe that the business purposes of the strategic alliances (*network controls*) drive our findings, which supports the notion that strategic alliances are not intended to be tax planning investments. Overall, our findings in Panel A convey that decreases in cash taxes paid are driven by the partner firm's tax planning behavior.

5.2.2.Difference-in-Differences

[Figure 4]

Panel B of Table 4 shows the results for our DiD analysis from equation (4). Any DiD specification relies on the parallel trend assumption. Otherwise, one could not empirically identify the posttreatment outcome absent the treatment. Usually, the parallel trend assumption is graphically examined by observing pretreatment trends of the dependent variable among the treatment and control groups. Accordingly, Panel A of Figure 4 provides visual evidence that the trends of $cash\ ETR$ are parallel for treatment and control firms prior to the treatment (hightolow = 1). Consistent with our analysis on the full sample, it can also be observed that the pretreatment levels of $cash\ ETR$ are very similar for the treated and untreated

firms in the matched panel. Although a direct empirical test for the parallel trend assumption is not possible, Patel and Seegert (2015) developed an approach to alleviate concerns about potential confounding factors. They suggest regressing the treatment indicator, time fixed effects and the interaction of the treatment indicator and time fixed effects on the dependent variable:

$$cash \ ETR_{i,t} = \alpha + treated_i + \tau_t + \tau_t * treated_i + \varepsilon_{i,t}. \tag{6}$$

They argue that failure to reject that the coefficient estimates for the interaction terms for $\tau_t * treated_i$ are jointly zero in the pretreatment period supports the parallel trend assumption. In Panel B of Figure 4, we therefore present the coefficient and the 95% confidence interval of the interaction of the treatment indicator and time fixed effects from equation (6) for the pretreatment years. First, none of the individual coefficients are significantly different from zero. More importantly, however, the p-value of the parallel trend test (the coefficients of $\tau_t * treated_i$ are jointly zero during pretreatment) is far beyond the usual levels of significance (p = 0.7427). Consequently, we are able to provide visual and statistical evidence for the parallel trend assumption.

In Panel B of Table 4, we depict several specifications of equation (4) with varying levels of including $firm\ controls$ and industry fixed effects (δ_{ind}). The estimate for the interaction of treated*post is negative and significant throughout all these specifications. Consequently, we find a negative $cash\ ETR$ response to low-tax networks in comparison to high-tax networks for high-tax firms. Taken together, the results from our descriptive and regression analyses are consistent with strategic alliances serving as channels through which tax knowledge diffuses between firms. For the purpose of interpreting the economic significance of our findings, we computed the margins of response of $cash\ ETR$ for all specifications of equation (4). High-tax firms show an approximately 5-percentage point lower $cash\ ETR$ when in networks with low-tax firms than when high-tax firms are in high-tax networks. Although this difference is economically meaningful (and statistically significant), the predicted levels of $cash\ ETR$ are also reasonable with approximately 26.5%.

5.2.3.Adjustment Speed

We are further interested in how fast high-tax firms can adjust their tax planning behavior when cooperating with low-tax firms. Therefore, we estimate five specifications of equation (4). We extend the posttreatment period by one year with each specification. Thus, we notate post = 1 only for the year of network initiation $[t_1]$ first and finish with post equaling one for the entire posttreatment embargo period $[t_1; t_5]$. The coefficient estimates of treatment * post thus present the cumulative adjustment of a high-tax firm's tax planning behavior with progressing time $(t_1 \text{ to } t_5)$ when cooperating with low-tax firms (i.e., adjustment speed). The results of this analysis are presented in Panel C of Table 4. In accordance with the theory that suggests that diffusion of (tax) knowledge increases in probability over time, the coefficient estimate of treatment * post is not significant when the posttreatment period is limited to the year of network initiation. This finding is consistent with our notion that strategic alliances, per se, do not aim at facilitating tax planning. Otherwise, one would expect to find an immediate adjustment. The coefficient estimate of the interaction, however, turns significant when post equals one for t_1 and t_2 . Furthermore, the estimated effect continues to be significant when extending the posttreatment period to t_3 , t_4 and t_5 . Consequently, we assess high-tax firms on average to be able to adjust their tax planning behavior within two years of network initiation. These findings are consistent with recent research by Kim et al. (2019) who suggest that firms generally are able to adjust their tax planning behavior within three years and that high-tax firms may increase their tax planning behavior even faster. Additionally, our results suggest that a firm's adjustment of its tax planning behavior, once implemented, stays constant over subsequent years.

6. Additional Analyses

[Table 5]

Thus far, we have considered the overall implications of low-tax networks for high-tax firms. We are also interested in partnering firms' characteristics, which could intensify or mitigate the identified effects. Thereby, we focus on geographical proximity, identical industry affiliation and shared audit firms.

In Panel A of Table 5, we compare two subsamples of networks by following the identification strategy of Brown (2011). One group consists of firms with their headquarters located in the same region as defined by the Bureau of Economic Analysis (BEA; SameBEARegion = 1).⁷ The other group consists of firms with headquarters located in different BEA regions in the year of network initiation (SameBEARegion = 0).⁸ The intuition behind this approach is that shared membership in a geographical region could allow higher levels of interfirm interaction. We run specifications of equation (3) with (delta) cash ETR3 as the dependent variable and are interested in the interaction of hightolow * SameBEARegion because the coefficient estimates comprise the incremental influence of geographical proximity on tax knowledge diffusion via low-tax networks. We observe a significant coefficient estimate of the main effect of hightolow. Neither SameBEARegion nor the interaction of the two variables are significantly different from zero. Although this finding is generally consistent with the inferences by Brown (2011) on geographical proximity, Cen et al. (2018) report that the correlation of effective tax rates is stronger for the members of a supply chain that are located within the same geographical region.

In their hypothesis development, Brown and Drake (2014) argue that firms with the same industry affiliation share the same operating environment and suggest that this should enhance the identified effect. However, the results from comparing intra- and interindustry board ties fall short of their expectation. To test the potential effect of shared industry affiliation in our setting, we construct two subsamples, which coincides with our approach in Panel A. One group consists of network participants who share industry affiliation (SameInd = 1), and the other group consists of firms with different industry affiliations (SameInd = 0). Consistent with Brown and Drake (2014) and in line with our inferences on geographical proximity, we cannot reject that the interactions of hightolow and SameInd are significantly different

_

⁷ The respective BEA regions are Far West, Great Lakes, Mideast, New England, Plains, Rocky Mountains, Southeast and Southwest

⁸ Our findings are not conditional on choosing either a state-level indicator, a region-level indicator or continuous distance.

from zero. This finding supports the notion that tax shelters are repetitive among firms, are not limited by industry barriers and serve as mass-market tax-saving ideas (Lisowsky, 2010).

Finally, we examine the role of shared audit firms and identify whether the firms in a network share an audit firm in the year of network initiation. We construct an indicator variable (SameAuditor) and interact it with hightolow. In specifications of equation (3) with cash ETR3 and delta cash ETR3 as dependent variables, the interaction terms for hightolow * SameAuditor approach common levels of statistical significance. Our inferences take their place alongside a range of mixed inferences concerning auditors' impact on firms' tax planning behavior. Brown (2011) does not find significant tax shelter adoption via shared audit firms and Klassen, Lisowsky, and Mescall (2016) show that less tax aggressiveness in the past is associated with the auditor preparing a firm's tax return. In contrast, Lim et al. (2018) and Cen et al. (2018) suggest that common auditors facilitate tax planning. Consistent with the mixed evidence from prior literature, Nesbitt, Persson, and Shaw (2019) suggest that there are limits to the relation between auditor-provided tax services and clients' tax aggressiveness.

The results presented in Table 5 might easily be subject to misinterpretation. We do not posit that industry affiliation, auditor ties or geographical proximity have no impact on firms' tax planning behavior. We are interested solely in whether partner heterogeneity accelerates or alleviates tax knowledge diffusion for high-tax firms that invest in low-tax networks. It appears that tax knowledge diffusion via strategic alliances is rather unaffected by such heterogeneity.

7. Robustness Checks

In this section, we examine the robustness of our primary findings regarding alternative explanations and potential concerns about our identification strategy. We rule out the possibility that our findings are unrelated to tax knowledge diffusion.

7.1. Alternative Explanations

[Table 6]

Applying three-year rolling measures of cash effective tax rates would systematically exclude from our sample network-firm observations that occur at the first, second, penultimate and final firm-years of a network participant. For identification purposes, we substitute [pre] cash ETR3 with [pre] cash ETR(2). However, it is possible that strategic alliances serve as preliminary ties between successive acquirers and targets (Ishii and Xuan, 2014; Porrini, 2004). Survivorship bias could thus exert an influence on our inferences. Consequently, we present a specification of equation (3) in Panel A of Table 6 in which we exclude from the analysis nonsurvivors (i.e., firms with network-firm observations within the last two years of their presence in our panel). In this model, we still find the loading of hightolow to be significant (p-value 0.0571) and the economic magnitude to be consistent with our primary findings. This result indicates that our inferences are robust to survivorship bias.

Another alternative explanation of our findings could be that the difference in the levels of *Tax Knowledge* between the two groups in our sample is not induced by tax knowledge diffusion from low-tax firms to high-tax firms but by increases in *cash ETR3* for high-tax firms in high-tax networks.

[Figure 5]

Figure 5 depicts a kernel density plot of the distribution of $delta\ cash\ ETR3$ for all high-tax firms. The dotted line at x=1 indicates the threshold between a decrease and an increase for $cash\ ETR3$ relative to $pre\ cash\ ETR3$. It can be observed that some parts of the high-tax firm population experience increases in $cash\ ETR3$, which would, to some extent, not be consistent with knowledge diffusion. In Panel B of Table 6, we provide a specification of equation (3) in which we control for increases in $cash\ ETR3$ by excluding observations of $delta\ cash\ ETR3$ that are above the threshold of one. Again, our results indicate a negative and significant coefficient estimate for hightolow. Consequently, we are confident that our

inferences are based on tax knowledge diffusion via low-tax networks rather than on increases in *cash ETR3* in the control group.

Although we identify tax knowledge diffusion for high-tax firms via low-tax networks, we have not considered the tax position of low-tax firms. Like high-tax firms, low-tax firms can be bound to either high-tax firms or low-tax firms. Intuitively, there is little reason to expect incremental, "negative" tax knowledge spillovers for low-tax firms bound to high-tax firms. To empirically control for this notion, we construct *lowtohigh*, which is an indicator that equals one for low-tax firms in networks with high-tax firms and zero for low-tax firms in low-tax networks. The results for this specification of equation (3) are presented in Panel C of Table 6. The coefficient estimate for *lowtohigh* is far beyond common levels of significance, with a p-value of 0.9961. This finding further supports our inferences of tax knowledge diffusion occurring among high-tax firms.

Since effective tax rates are mechanically influenced by taxes paid and profitability, changes in $cash\ ETR3$ could be solely income induced. This would to some extent speak against identifying tax knowledge diffusion. To account for this concern, we construct ChangeEBITDA3, which is the annual average growth rate in EBITDA from t_1 to t_3 (geometric mean). We then run equation (3) with ChangeEBITDA3 as the dependent variable and find the coefficient estimate for hightolow to be nonsignificant (p-value 0.6569) and of small economic magnitude (Panel D of Table 6). From this, it follows that the identified effects are not linked to profitability.

7.2. Alternative Identification Strategy

[Table 7]

There are some judgment calls involved in classifying strategic alliances as high-tax- and low-tax networks and including an indicator variable in the respective regression. Therefore, we provide a modified model in which we regress the industry-adjusted $pre\ cash\ ETR3\ [t_{-2};t_0]$ of a firm and of its partner on the firm's $cash\ ETR3\ [t_1;t_3]$:

$$cash\ ETR3_{i,t=1} = \beta_0 + \beta_1 Own_ind_adj_pre_cash_ETR3_{i,t=0}$$

$$+ \beta_2 Partner_ind_adj_pre_cash_ETR3_{i,t=0}$$

$$+ \sum_n \beta_n \ partner\ controls^n_{i,t=1}$$

$$+ \sum_l \beta_l \ network\ controls^l_{i,t=1}$$

$$+ \sum_k \beta_k \ firm\ controls^k_{i,t=1} + \varepsilon_{i,t}.$$

$$(7)$$

Since we use industry-adjusted measures of *cash ETR3* in this model, we do not insert industry fixed effects. However, we include the indicator *SameInd* in addition to the *partner controls* (*SameAuditor*, *Proximty*). If the partner firm's tax position is correlated with the firm's own levels of tax planning, one would find a positive coefficient estimate of *Partner_ind_adj_pre_cash_ETR3*. In a first specification of equation (7), we include network-firm observations of low-tax firms and high-tax firms. The results are depicted in Panel A of Table 7. While we observe a positive and highly significant coefficient estimate of *Own_ind_adj_pre_cash_ETR3*, *Partner_ind_adj_pre_cash_ETR3* is not significant. The latter finding is, however, little surprising given the inference that low-tax firms are rather unaffected by their partner firms' tax positions (Table 6 Panel C). Therefore, we include network-firm observations of high-tax firms in a second specification of equation (7). In this model, the coefficient estimate of *Partner_ind_adj_pre_cash_ETR3* is significant (p-value 0.0936). Consistent with the findings from our main analysis and with the notion of tax knowledge diffusion via strategic alliances, we find a positive association between partner firms' cash effective tax rates.

8. Conclusion

The purpose of this study is to shed light on channels through which tax knowledge diffuses between firms. Despite solid insights on the within-firm determinants of corporate tax planning, research on cross-firm connections in this field is still developing. We contribute to the emerging literature by being the first to identify strategic alliances as channels of tax knowledge diffusion between firms. With our study, we also

ease prior studies' assumptions of existing intermediaries and intentional transfers of tax knowledge. By using data on strategic alliances between publicly traded US firms, we can distinguish between networks that bring together high-tax and low-tax firms and networks that are established among high-tax firms. Conditional on the level of the tax planning of their strategic alliance partner, we find a substantial and economically meaningful increase in the tax planning behavior of high-tax firms. Our results also suggest that this adjustment occurs within two years of a strategic alliance's initiation. Based on textual analysis, we find that the business purposes of the strategic alliances do not drive our results. Overall, our results are consistent with diffusion of tax knowledge via strategic alliances. We think that the results of our study are of interest to corporate executives, regulators, and researchers because the perception and valuation of this examination's inferences likely depend on the respective position taken.

Although prior research has dedicated substantial attention to corporate cooperation and firms' tax planning, there are a number of unanswered questions regarding the interplay of the two. Primarily, we encourage research on the actual mechanisms of (tax) knowledge diffusion. Furthermore, it remains unclear whether the tax position of a potential network partner influences the decision of a firm to invest in a specific strategic alliance. Our hope is that our study enhances interdisciplinary research in accounting and management.

References

- Acemoglu, D., Dahleh, M.A., Lobel, I., Ozdaglar, A., 2011. Bayesian Learning in Social Networks. The Review of Economic Studies 78 (4), 1201–1236.
- Anand, B.N., Khanna, T., 2000. Do Firms Learn to Create Value? The Case of Alliances. Strategic Management Journal 21 (3), 295–315.
- Aobdia, D., 2015. Proprietary information spillovers and supplier choice: evidence from auditors. Review of Accounting Studies 20 (4), 1504–1539.
- Barrios, J.M., Gallemore, J., 2019. Tax-Related Human Capital: Evidence from Employee Movements. SSRN Electronic Journal.
- Blonski, M., 1999. Social learning with case-based decisions. Journal of Economic Behavior & Organization 38 (1), 59–77.
- Blouin, J., Robinson, L., 2019. Double Counting Accounting: How Much Profit of Multinational Enterprises Is Really in Tax Havens? SSRN Electronic Journal.
- Bodnaruk, A., Massa, M., Simonov, A., 2013. Alliances and corporate governance. Journal of Financial Economics 107 (3), 671–693.
- Boone, A.L., Ivanov, V.I., 2012. Bankruptcy spillover effects on strategic alliance partners. Journal of Financial Economics 103 (3), 551–569.
- Brown, J.L., 2011. The Spread of Aggressive Corporate Tax Reporting: A Detailed Examination of the Corporate-Owned Life Insurance Shelter. The Accounting Review 86 (1), 23–57.
- Brown, J.L., Drake, K.D., 2014. Network Ties Among Low-Tax Firms. The Accounting Review 89 (2), 483–510.
- Cai, Y., Dhaliwal, D.S., Kim, Y., Pan, C., 2014. Board interlocks and the diffusion of disclosure policy. Review of Accounting Studies 19 (3), 1086–1119.
- Cai, Y., Kim, Y., Park, J.C., White, H.D., 2016. Common auditors in M&A transactions. Journal of Accounting and Economics 61 (1), 77–99.
- Cai, Y., Sevilir, M., 2012. Board connections and M&A transactions. Journal of Financial Economics 103 (2), 327–349.
- Carpenter, M.A., Li, M., Jiang, H., 2012. Social Network Research in Organizational Contexts. Journal of Management 38 (4), 1328–1361.
- Cen, L., Maydew, E.L., Zhang, L., Zuo, L., 2017. Customer–supplier relationships and corporate tax avoidance. Journal of Financial Economics 123 (2), 377–394.
- Cen, L., Maydew, E.L., Zhang, L., Zuo, L., 2018. Tax Planning Diffusion Along the Supply Chain. SSRN Electronic Journal.
- Chan, S.H., Kensinger, J.W., Keown, A.J., Martin, J.D., 1997. Do strategic alliances create value? Journal of Financial Economics 46 (2), 199–221.
- Chen, J., King, T.-H.D., Wen, M.-M., 2015. Do joint ventures and strategic alliances create value for bondholders? Journal of Banking & Finance 58, 247–267.
- Clausing, K.A., 2016. The Effect of Profit Shifting on the Corporate Tax Base in the United States and Beyond. National Tax Journal 69 (4), 905–934.
- Desai, M.A., Foley, C.F., Hines, J.R., 2004. The costs of shared ownership: Evidence from international joint ventures. Journal of Financial Economics 73 (2), 323–374.
- Dhaliwal, D.S., Lamoreaux, P.T., Litov, L.P., Neyland, J.B., 2016. Shared auditors in mergers and acquisitions. Journal of Accounting and Economics 61 (1), 49–76.
- Di Maggio, M., Franzoni, F., Kermani, A., Sommavilla, C., 2019. The relevance of broker networks for information diffusion in the stock market. Journal of Financial Economics 134 (2), 419–446.
- Dyer, J.H., Hatch, N.W., 2006. Relation-specific capabilities and barriers to knowledge transfers: creating advantage through network relationships. Strategic Management Journal 27 (8), 701–719.
- Dyreng, S., Maydew, E.L., 2017. Virtual Issue on Tax Research Published in the Journal of Accounting Research. SSRN Electronic Journal.

- Dyreng, S.D., Hanlon, M., Maydew, E.L., 2008. Long-Run Corporate Tax Avoidance. The Accounting Review 83 (1), 61–82.
- Dyreng, S.D., Hanlon, M., Maydew, E.L., 2010. The Effects of Executives on Corporate Tax Avoidance. Accounting Review 85 (4), 1163–1189.
- Dyreng, S.D., Hanlon, M., Maydew, E.L., 2019. When Does Tax Avoidance Result in Tax Uncertainty? The Accounting Review 94 (2), 179–203.
- Erickson, M., 1998. The Effect of Taxes on the Structure of Corporate Acquisitions. Journal of Accounting Research 36 (2), 279.
- Erickson, M.M., Wang, S.-w., 1999. Exploiting and Sharing Tax Benefits: Seagram and DuPont. The Journal of the American Taxation Association 21 (2), 35–54.
- Fiol, C.M., Lyles, M.A., 1985. Organizational Learning. Academy of Management Review 10 (4), 803–813.
- Frey, L., 2018. Tax certified individual auditors and effective tax rates. Business Research 11 (1), 77–114.
- Gale, D., Kariv, S., 2003. Bayesian learning in social networks. Games and economic behavior 45 (2), 329–346
- Gallemore, J., Gipper, B., Maydew, E.L., 2018. Banks as Tax Planning Intermediaries. Journal of Accounting Research 126, 1841.
- Gallemore, J., Maydew, E.L., Thornock, J.R., 2014. The Reputational Costs of Tax Avoidance. Contemporary Accounting Research 31 (4), 1103–1133.
- Gomes-Casseres, B., Hagedoorn, J., Jaffe, A.B., 2006. Do alliances promote knowledge flows? Journal of Financial Economics 80 (1), 5–33.
- Graham, J.R., Hanlon, M., Shevlin, T., Shroff, N., 2017. Tax Rates and Corporate Decision-making. The Review of Financial Studies 30 (9), 3128–3175.
- Guenther, D.A., Matsunaga, S.R., Williams, B.M., 2017. Is Tax Avoidance Related to Firm Risk? The Accounting Review 92 (1), 115–136.
- Hanlon, M., Heitzman, S., 2010. A review of tax research. Journal of Accounting and Economics 50 (2-3), 127–178.
- Hanlon, M., Slemrod, J., 2009. What does tax aggressiveness signal? Evidence from stock price reactions to news about tax shelter involvement. Journal of Public Economics 93 (1-2), 126–141.
- Heckman, J.J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47 (1), 153.
- Higgins, M.J., Rodriguez, D., 2006. The outsourcing of R&D through acquisitions in the pharmaceutical industry. Journal of Financial Economics 80 (2), 351–383.
- Hoppe, T., Schanz, D., Sturm, S., Sureth-Sloane, C., 2019. Measuring Tax Complexity Across Countries: A Survey Study on MNCs. Accounting for Transparency Working Papers No. 5.
- Hundsdoerfer, J., Jacob, M., 2018. Corporate Taxes and Firms' Cost Behavior: The Role of Conforming Tax Planning. Working Paper.
- Inkpen, A.C., 2000. Learning Through Joint Ventures: A Framework Of Knowledge Acquisition. Journal of Management Studies 37 (7), 1019–1044.
- Inkpen, A.C., 2008. Knowledge transfer and international joint ventures: the case of NUMMI and General Motors. Strategic Management Journal 29 (4), 447–453.
- Isaksson, O.H.D., Simeth, M., Seifert, R.W., 2016. Knowledge spillovers in the supply chain: Evidence from the high tech sectors. Research Policy 45 (3), 699–706.
- Ishii, J., Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. Journal of Financial Economics 112 (3), 344–363.
- Jiang, X., Bao, Y., Xie, Y., Gao, S., 2016. Partner trustworthiness, knowledge flow in strategic alliances, and firm competitiveness: A contingency perspective. Journal of Business Research 69 (2), 804–814.
- Kale, P., Singh, H., Perlmutter, H., 2000. Learning and Protection of Proprietary Assets in Strategic Alliances: Building Relational Capital. Strategic Management Journal 21 (3), 217–237.
- Khanna, T., Gulati, R., Nohria, N., 1998. The Dynamics of Learning Alliances: Competition, Cooperation, and Relative Scope. Strategic Management Journal 19 (3), 193–210.

- Kim, J., McGuire, S.T., Savoy, S., Wilson, R., Caskey, J., 2019. How Quickly Do Firms Adjust to Optimal Levels of Tax Avoidance? Contemporary Accounting Research 36 (3), 1824–1860.
- Klassen, K.J., Lisowsky, P., Mescall, D., 2016. The Role of Auditors, Non-Auditors, and Internal Tax Departments in Corporate Tax Aggressiveness. The Accounting Review 91 (1), 179–205.
- Kogut, B., Singh, H., 1988. The Effect of National Culture on the Choice of Entry Mode. Journal of International Business Studies 19 (3), 411–432.
- Kubick, T.R., Lynch, D.P., Mayberry, M.A., Omer, T.C., 2015. Product Market Power and Tax Avoidance: Market Leaders, Mimicking Strategies, and Stock Returns. The Accounting Review 90 (2), 675–702.
- Lennox, C.S., Francis, J.R., Wang, Z., 2012. Selection Models in Accounting Research. The Accounting Review 87 (2), 589–616.
- Li, K., Qiu, J., Wang, J., 2019. Technology Conglomeration, Strategic Alliances, and Corporate Innovation. Management Science 65 (11), 5065–5090.
- Lim, C.Y., Shevlin, T.J., Wang, K., Xu, Y., 2018. Tax Knowledge Diffusion Through Individual Auditor Network Ties: Evidence from China. SSRN Electronic Journal.
- Lindsey, L., 2008. Blurring Firm Boundaries: The Role of Venture Capital in Strategic Alliances. The Journal of Finance 63 (3), 1137–1168.
- Lisowsky, P., 2010. Seeking Shelter: Empirically Modeling Tax Shelters Using Financial Statement Information. The Accounting Review 85 (5), 1693–1720.
- McGuire, S.T., Omer, T.C., Wang, D., 2012. Tax Avoidance: Does Tax-Specific Industry Expertise Make a Difference? The Accounting Review 87 (3), 975–1003.
- Meier, M., 2011. Knowledge Management in Strategic Alliances: A Review of Empirical Evidence. International Journal of Management Reviews 13 (1), 1–23.
- Mohanram, P., Nanda, A., 1996. When do Joint Ventures create value? Academy of Management Proceedings 1996 (1), 36–40.
- Nesbitt, W.L., Persson, A., Shaw, J., 2019. Auditor-provided Tax Services and Clients' Tax Avoidance: Do Auditors Draw a Line in the Sand for Tax Advisory Services? Working Paper.
- Nonaka, I., 1994. A Dynamic Theory of Organizational Knowledge Creation. Organization Science 5 (1), 14–37.
- Owen, S., Yawson, A., 2013. Information asymmetry and international strategic alliances. Journal of Banking & Finance 37 (10), 3890–3903.
- Patel, E., Seegert, N., 2015. Using Strategic Interactions in Investment Decisions to Increase the Efficiency of Tax Policy. SSRN Electronic Journal.
- Paternoster, R., Brame, R., Mazerolle, P., Piquero, A., 1998. Using The Correct Statistical Test For The Equality Of Regression Coefficients. Criminology 36 (4), 859–866.
- Petersen, M.A., 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. The Review of Financial Studies 22 (1), 435–480.
- Porrini, P., 2004. Can a Previous Alliance Between an Acquirer and a Target Affect Acquisition Performance? Journal of Management 30 (4), 545–562.
- PwC, 2018. New Entrants New Rivals. How Germany's top companies are creating a new industry world. Rogers, E.M., 2003. Diffusion of innovations. Free Press, New York, London, Toronto, Sydney.
- Szulanski, G., 1996. Exploring Internal Stickiness: Impediments to the Transfer of Best Practice Within the Firm. Strategic Management Journal 17, 27–43.
- Tørsløv, T., Wier, L., Zucman, G., 2018. The Missing Profits of Nations. National Bureau of Economic Research, Cambridge, MA.
- Wilde, J.H., Wilson, R.J., 2018. Perspectives on Corporate Tax Planning: Observations from the Past Decade. The Journal of the American Taxation Association 40 (2), 63–81.
- Wilson, R.J., 2009. An Examination of Corporate Tax Shelter Participants. The Accounting Review 84 (3), 969–999.

Appendix: Variable Definitions

Variable	Definition (Compustat/SDC equivalent)
	Network Characteristics
high-tax network	Equals 1 for networks with solely high-tax firms as participants.
hightolow	Indicator variable; equals 1 for high-tax firms in low-tax
	networks; equals 0 for high-tax firms in high-tax networks; if a
	firm enters into multiple networks in one year, only one
	observation of this firm enters our sample in this year. In these
	cases, network selection is primarily done on a randomized basis.
	However, if a firm entered as high-tax firm into a low-tax network
	and into (a) high-tax network(s) in one year, we keep the low-tax
	network observation.
low-tax network	Equals 1 for networks involving at least one low-tax firm.
lowtohigh	Indicator variable; equals 1 for low-tax firms in high-tax
	networks; equals 0 for low-tax firms in low-tax networks.
\sum network controls	Indicator variables for the main business purpose of a network,
	which is derived from a network's deal description (DealText) in
	SDC; comprises PurposeWholesale, PurposeRnD,
	PurposeLicense, PurposeService, PurposeMarketing,
	PurposeSupply and PurposeManufacture; information is
	systematically extracted with R: dofile available upon request.
Partner Controls	
Proximity	Distance (as the crow flies) between the participants of a network
	according to the zip code of the participants' headquarters
	(addzip); collected from freemaptools.com; normalized between
	1 and 0 for closest (same addzip) and farthest distance.
SameAuditor	Indicator variable; equals 1 when all participants of a network
	share the same auditor firm (au) in the year of network initiation;
	0 otherwise; by nature of construction missing for non-network-
	firm observations.
SameInd	Constructed as SameAuditor but for industry affiliation; industry
	is classified using two-digit SIC codes (sic); see also Table 2.
SameBEARegion	Constructed as SameAuditor; equals 1 when all network
	participants are located in the same BEA region in the year of
	network initiation; 0 otherwise; the respective regions, as defined
	by the Bureau of Economic Analysis, are Far West, Great Lakes,
	Mideast, New England, Plains, Rocky Mountains, Southeast and
	Southwest.
\sum partner controls	See Proximity and SameAuditor for main analysis (equation (3)).

Variable	Definition (Compustat/SDC equivalent)
	Firm Characteristics
cash ETR	Cash effective tax rate; defined as cash taxes paid (txpd) divided by pre-tax income (pi) before special items (spi); special items are reset to 0 when missing; cash ETR observations with negative denominator are reset to missing; winsorized at 0 and 1.
cash ETR3	Cash effective tax rate; defined as cash taxes paid (txpd) divided by pre-tax income (pi) before special items (spi); special items are reset to 0 when missing; numerator and denominator are constructed as the sum of the current and two subsequent years; observations with negative denominator are reset to missing; for the final (penultimate) firm-year of a firm substituted by cash ETR(2); winsorized at 0 and 1.
cash ETR5	Cash effective tax rate; constructed as cash ETR3, but for five years.
ChangeEBITDA3	Three-year annual average growth rate (geometric mean) of EBITDA (ebitda) ($\sqrt[3]{ebitda_{t3}/ebitda_{t1}} - 1$); reset to 0 when missing.
delta cash ETR3	Cash ETR3 [t ₁ ; t ₃] scaled by pre cash ETR3 [t ₋₂ ; t ₀]: $\frac{cash ETR3_{[t_1;t_3]}}{pre \ cash \ ETR_{[t_{-2};t_0]}}$
delta cash ETR5	Cash ETR5 $[t_1; t_5]$ scaled by pre cash ETR3 $[t_{-2}; t_0]$.
high-tax firm	Indicator variable; equals 1 when a firm's industry adjusted pre cash ETR3[t ₋₂ ; t ₀] is aligned to pre taxrank [2; 4] (if pre taxrank[t ₀] is missing, replaced by pre taxrank[t ₋₁]); 0 otherwise.
low-tax firm	Indicator variable; equals 1 when a firm's industry adjusted pre cash ETR3[t_{-2} ; t_0] is aligned to pre taxrank = 1 (if pre taxrank[t_0] is missing, replaced by pre taxrank[t_{-1}]); 0 otherwise.
post	Indicator variable; equals 0 for a period of three years before network initiation and 1 for a period of five years subsequent to initiation and includes treatment/control observations. post constitutes an embargo period during which no other hightolow observation may occur.
pre cash ETR3	Constructed as cash ETR3 but with numerator and denominator constructed as the sum of the current and two preceding periods; for first (second) firm-year of a firm substituted by pre cash ETR(2).
pre taxrank	Allocates ranks (1-4) according to the quartiles of the distribution of industry adjusted pre cash ETR3; 1 for the bottom end, 4 for the top end of the distribution.
treated	Treatment is in alignment with hightolow (see post for embargo period) and extended to pre- and post-periods.

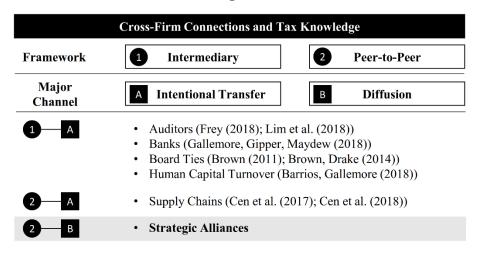
Variable	Definition (Compustat/SDC equivalent)
treated * post	Interaction of treated and post; main variable of interest in the
reacea post	difference-in-differences model.
	Firm Controls*
AdExp3	Advertising expense (xad) divided by net sales (sale); numerator
	and denominator are constructed as the sum of the current and two
	subsequent years; when missing reset to annual measure,
	thereafter reset to 0.
CapEx3	Reported capital expenditures (capx) divided by gross property,
	plant, and equipment (ppegt); numerator and denominator are
	constructed as the sum of the current and two subsequent years;
	when missing reset to annual measure, thereafter reset to 0.
Cash3	Cash and cash equivalents (che) divided by total assets (at);
	numerator and denominator are constructed as the sum of the
	current and two subsequent years; when missing reset to annual
	measure, thereafter reset to 0.
ChangeSale3	Three-year annual average growth rate (geometric mean) of net
	sales (sale) $(\sqrt[3]{sale_{t3}/sale_{t1}} - 1)$; when missing reset to annual
	change, thereafter reset to 0.
EBITDA3	Earnings before interest, taxes, depreciation and amortization
	(ebitda) scaled by total assets (at); numerator and denominator are
	constructed as the sum of the current and two subsequent years;
	when missing reset to annual measure, thereafter reset to 0.
Intangibles3	The ratio of intangible assets (intan) to total assets (at); numerator
	and denominator are constructed as the sum of the current and two
	subsequent years; when missing reset to annual measure, thereafter reset to 0.
Leverage3	The sum of long-term debt (dltt) and long-term debt in current
Leverages	liabilities (dlc) divided by total assets (at); numerator and
	denominator are constructed as the sum of the current and two
	subsequent years; when missing reset to annual measure,
	thereafter reset to 0.
MNE3	Indicator variable; equals 1 if pifo > 0 (non-missing, non-zero
	value for pre-tax income from foreign operations), 0 otherwise;
	measured as the sum over three years.
NOL3	Indicator variable equals 1 if tlcf > 0 (non-missing, non-zero value
	of tax loss carry forward), 0 otherwise; measured as the sum over
	three years.
PPE3	Gross property, plant, and equipment (ppegt) divided by total
	assets (at); numerator and denominator are constructed as the sum
	of the current and two subsequent years; when missing reset to
	annual measure, thereafter reset to 0.

Variable	Definition (Compustat/SDC equivalent)
RnDExp3	Research and development expenses (xrd) scaled by net sales
	(sale); numerator and denominator are constructed as the sum of
	the current and two subsequent years; when missing reset to
	annual measure, thereafter reset to 0.
SGA3	Selling, general, and administrative expense (xsga); divided by
	net sales (sale); numerator and denominator are constructed as the
	sum of the current and two subsequent years; when missing reset
	to annual measure, thereafter reset to 0.
Size3	The natural log of total assets (at) for the respective and two
	subsequent periods; when missing reset to annual measure,
	thereafter reset to 0.

^{*}Continuous $firm\ controls$ are winsorized at p1 and p99 and not mean-centered.

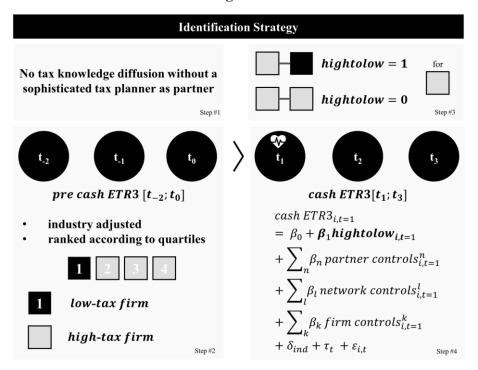
Figures

Figure 1



This figure categorizes prior research regarding transfers and diffusion of tax knowledge via cross-firm connections. It aligns the framework (i.e., institutional setting) with identified channels.

Figure 2



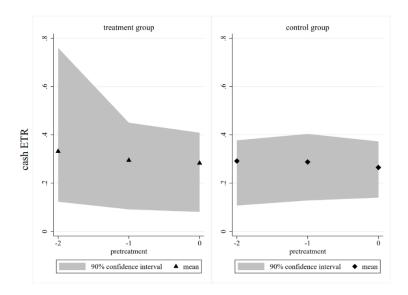
This figure summarizes our identification strategy. For simplification purposes, we show the strategic alliances of two participants in the upper right corner. The heartbeat pictogram at t_1 indicates the year of initiation of a strategic alliance. We also show a specification of equation (3), where $Tax\ Knowledge$ is measured as $cash\ ETR3$.

Figure 3



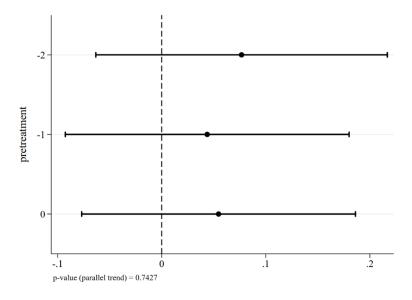
The word cloud depicted in Figure 3 shows the 50 most common words used in SDC's deal description of the networks in our regression sample. By systematically searching through the deal descriptions, we identify *wholesale*, *licensing*, *marketing* and *manufacturing* activities as well as *research and development*, providing *services* and engaging in *supply functions* as major business purposes of the networks in our sample. The respective indicator variables are included in equation (3). All variables are defined in detail in the Appendix.

Panel A

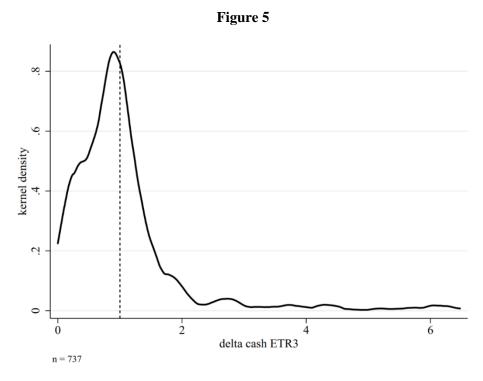


Panel A of this figure provides visual evidence that the trend of cash ETR is similar for the treatment and control firms prior to the treatment.

Panel B



In Panel B, we apply the approach of Patel and Seegert (2015) to provide statistical evidence for the parallel trend assumption. The figure reports the coefficient and 95% confidence interval of the interaction of the treatment indicator and time fixed effects for pretreatment years from the specification $cash\ ETR_{i,t} = \mathfrak{K}_0 + \mathfrak{K}_1 * treated_i + \tau_t * treated_i + \varepsilon_{i,t}$ (with the end of the embargo period as base year of τ_t). We test that the coefficients on $\tau_t * treated_i$ are jointly zero in the pretreatment period and fail to reject the null hypothesis. This supports the parallel trend assumption. The p-value for the parallel trend test is reported at the bottom of Panel B.



This figure depicts a kernel density plot of the distribution of $delta\ cash\ ETR3$ for high-tax firms. The dotted line at x=1 indicates the threshold between a decrease and an increase in $cash\ ETR3$ relative to $pre\ cash\ ETR3$. The Appendix contains detailed definitions of all variables.

Tables

Table 1 Sample Selection & Identification Strategy

Panel A Compustat & SDC Platinum Data

	network-firm observations	networks	firms	firm-years
Compustat and SDC Platinum dataset of firms matched according to year of network initiation (DateEffective), US firms only (loc, fic, curcd), period 1994 - 2016 (fyear)	17798	15387	3570	52914
./. requirement to identify all contracting parties in network	4159	2064	1603	19447

Panel B Identification Strategy: Missing Information

	network-firm observations
all network-firm observations in sample	4159
./. missing pre cash ETR3 [t-2; t0]	2520
./. missing cash ETR3 [t1; t3]	2247
./. requirement to identify pre cash ETR3 and cash ETR3 of all participants in network	1301

Panel C Identification Strategy: Classification of network-firm observations

OV .			
	low-tax partner	high-tax partner	Σ
low-tax firm [including multiple new networks of a firm in one year]	58 [78]	159[225]	217 [303]
high-tax firm [including multiple new networks of a firm in one year]	197 [226]	540 [772]	737 [998]
	255 [304]	699 [997]	954 [1301]

All variables are defined in detail in the Appendix. Data items from Compustat and SDC Platinum are in parentheses.

Table 2 Information on Networks and Firms

Panel A pre cash ETR3 by pre taxrank

	N	mean	min	p5	p25	p50	p75	p95	max
pre taxrank = 1	2872	0.0708	0.0000	0.0000	0.0228	0.0699	0.1136	0.1515	0.2213
pre $taxrank = 2$	2872	0.2104	0.1055	0.1549	0.1836	0.2107	0.2367	0.2643	0.3255
pre taxran $k = 3$	2872	0.3062	0.2161	0.2577	0.2801	0.3047	0.3316	0.3602	0.4197
pre taxran $k = 4$	2872	0.6391	0.3094	0.3559	0.3973	0.4979	1.0000	1.0000	1.0000
pre cash ETR3	11488	0.3066	0.0000	0.0141	0.1527	0.2599	0.3574	1.0000	1.0000

Panel B Descriptive Statistics

	low-ta	x firm in	network		ax firm in k (hightol			x firm in l k (hightol	0
	N	mean	p50	N	mean	p50	N	mean	p50
cash ETR	294	0.1396	0.1166	193	0.2708	0.2533	520	0.2918	0.2659
cash ETR3	303	0.2017	0.1544	197	0.2755	0.2516	540	0.3282	0.2715
cash ETR5	231	0.1836	0.1618	162	0.2366	0.2313	434	0.2697	0.2586
EBITDA3	303	0.1387	0.1291	197	0.1527	0.1455	540	0.1582	0.1503
RnDExp3	303	0.1031	0.0959	197	0.0737	0.0489	540	0.0614	0.0296
AdExp3	303	0.0129	0.0000	197	0.0147	0.0000	540	0.0138	0.0000
SGA3	303	0.3471	0.3363	197	0.2702	0.2720	540	0.2599	0.2432
CapEx3	303	0.2082	0.1488	197	0.1536	0.1131	540	0.1598	0.1258
ChangeSale3	303	0.0693	0.0524	197	0.0484	0.0337	540	0.0605	0.0393
Leverage3	303	0.1681	0.1123	197	0.1815	0.1849	540	0.1942	0.1879
Cash3	303	0.2647	0.2180	197	0.1818	0.1254	540	0.1657	0.1040
MNE3	303	0.6931	1.0000	197	0.6041	1.0000	540	0.5444	1.0000
NOL3	303	0.3432	0.0000	197	0.3503	0.0000	540	0.2722	0.0000
Intangibles3	303	0.1556	0.0854	197	0.1844	0.1363	540	0.1585	0.0877
PPE3	303	0.3067	0.2204	197	0.4116	0.3313	540	0.4341	0.3286
Size3	303	9.1756	9.1257	197	9.6259	9.5942	540	9.1201	9.2695

All variables are defined in detail in the Appendix.

Table 2 Information on Networks and Firms (continued)

Panel C Industry Affiliation of Networks and Firms (two-digit SIC-code)

							i	ndustr	y of ne	tworks					Σ
		#	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
	Agriculture, Forestry, & Fishing (01-09)	I	0	0	0	1	0	1	0	0	0	0	0	0	2
	Mining (10-14)	II	0	6	0	1	2	0	2	0	0	0	1	0	12
	Construction (15-17)	III	0	0	0	0	0	3	0	0	0	0	1	0	4
rms	Manufacturing: Chemical & Allied Products (28)	IV	0	0	0	26	15	0	23	0	20	8	35	0	127
fir	Manufacturing (20-39, except 28)	V	0	4	2	11	167	17	41	4	39	131	48	7	471
of	Transportation & Public Utilities (40-49)	VI	0	3	2	0	7	32	4	0	1	30	10	0	89
ıstry	Wholesale Trade (50-51)	VII	0	1	0	0	3	2	19	1	3	8	4	0	41
indus	Retail Trade (52-59)	VII I	0	0	0	0	4	3	9	1	4	10	2	2	35
	Finance, Insurance, & Real Estate (60-67)	IX	0	0	0	1	1	1	2	1	25	17	6	2	56
	Services: Business Services (73)	X	0	0	0	1	31	10	21	3	22	273	22	3	386
	Services (70-89, except 73)	XI	0	0	0	0	0	3	2	0	4	8	16	0	33
	Nonclassifiable Establishments (99)	XII	0	0	0	3	8	6	1	0	4	15	8	0	45
	·		0	14	4	44	238	78	124	10	122	500	153	14	1301

All variables are defined in detail in the Appendix.

Table 2 Information on Networks and Firms (continued)

Panel D Pearson's correlation coefficients\Spearman's rank correlations

	hightolow	Proximity	SameAuditor	PurposeWholesale	PurposeRnD	PurposeLicense	PurposeService	PurposeMarketing	PurposeSupply	PurposeManufacture	EBITDA3	RnDExp3	AdExp3	SGA3	CapEx3	ChangeSale3	Leverage3	Cash3	MNE3	NOL3	Intangibles3	PPE3	Size3
hightolow	1.000	- 0.008	- 0.012	0.093	- 0.047	- 0.008	0.060	0.082	- 0.026	0.090	- 0.035	0.087	0.052	0.025	- 0.041	- 0.025	- 0.018	0.060	0.053	0.076	0.088	0.000	0.097
Proximity	- 0.034	1.000	0.076	- 0.030	0.034	0.060	- 0.069	0.034	0.001	0.021	0.028	- 0.021	- 0.048	- 0.068	- 0.037	- 0.011	0.057	- 0.048	- 0.050	- 0.033	- 0.009	0.061	- 0.019
SameAuditor	- 0.012	0.013	1.000	- 0.012	0.023	- 0.009	- 0.029	- 0.040	0.014	0.061	- 0.041	0.020	0.019	- 0.052	- 0.062	- 0.153	0.017	- 0.034	0.006	- 0.019	- 0.003	0.053	0.039
PurposeWholesale	0.093	- 0.049	- 0.012	1.000	- 0.143	- 0.099	- 0.079	- 0.031	0.105	0.027	- 0.036	- 0.061	0.094	0.025	- 0.094	- 0.008	0.029	- 0.024	0.109	0.005	0.119	0.010	- 0.016
PurposeRnD	- 0.047	0.086	0.023	- 0.143	1.000	- 0.092	- 0.072	- 0.093	- 0.085	- 0.013	0.084	0.267	- 0.061	0.124	0.050	- 0.041	- 0.087	0.157	0.100	0.017	- 0.041	- 0.055	- 0.003
PurposeLicense	- 0.008	0.123	- 0.009	- 0.099	- 0.092	1.000	- 0.256	- 0.071	- 0.020	0.163	0.057	0.121	- 0.043	0.100	0.153	0.074	- 0.005	0.056	- 0.088	- 0.066	- 0.155	- 0.003	- 0.181
PurposeService	0.060	- 0.080	- 0.029	- 0.079	- 0.072	- 0.256	1.000	0.222	- 0.089	- 0.149	- 0.037	- 0.184	- 0.039	- 0.150	- 0.053	0.009	0.039	- 0.030	0.003	0.054	0.094	- 0.004	0.155
PurposeMarketing	0.082	0.030	- 0.040	- 0.031	- 0.093	- 0.071	0.222	1.000	- 0.050	- 0.011	0.039	- 0.050	0.052	- 0.008	- 0.051	0.020	0.002	0.001	0.073	0.073	0.011	0.082	- 0.015
PurposeSupply	- 0.026	- 0.057	0.014	0.105	- 0.085	- 0.020	- 0.089	- 0.050	1.000	- 0.005	- 0.056	- 0.093	0.009	- 0.090	- 0.094	- 0.044	0.084	- 0.096	- 0.039	- 0.075	0.013	0.042	0.032
PurposeManufacture	0.090	- 0.043	0.061	0.027	- 0.013	0.163	- 0.149	- 0.011	- 0.005	1.000	0.039	0.065	- 0.019	0.035	0.036	0.007	- 0.026	0.035	- 0.003	- 0.035	- 0.052	0.093	- 0.074
EBITDA3	- 0.033	- 0.031	- 0.039	- 0.036	0.099	0.057	- 0.041	0.044	- 0.041	0.027	1.000	0.077	0.167	0.095	0.061	0.120	- 0.118	0.091	0.132	- 0.029	- 0.046	0.301	0.066
RnDExp3	0.071	0.091	- 0.003	- 0.070	0.254	0.102	- 0.125	- 0.033	- 0.111	0.034	0.045	1.000	0.124	0.640	0.313	0.066	- 0.409	0.617	0.269	0.093	- 0.118	- 0.183	- 0.133
AdExp3	0.013	0.018	- 0.023	0.079	- 0.056	- 0.029	- 0.058	0.042	0.031	- 0.025	0.174	0.011	1.000	0.325	0.041	- 0.075	0.006	0.131	0.168	0.036	0.138	0.023	0.173
SGA3	0.024	0.018	- 0.049	0.015	0.120	0.088	- 0.150	- 0.011	- 0.089	0.024	0.059	0.632	0.246	1.000	0.329	0.040	- 0.332	0.499	0.186	0.111	0.006	- 0.241	- 0.269
CapEx3	- 0.021	- 0.006	- 0.046	- 0.081	0.042	0.103	- 0.062	- 0.071	- 0.084	0.012	- 0.028	0.401	0.039	0.501	1.000	0.308	- 0.368	0.401	0.004	- 0.008	- 0.274	- 0.343	- 0.301
ChangeSale3	- 0.051	- 0.005	- 0.099	- 0.024	- 0.010	0.092	0.005	0.005	- 0.050	0.002	0.125	0.094	- 0.050	0.050	0.253	1.000	- 0.146	0.148	0.026	0.003	- 0.110	- 0.175	- 0.099
Leverage3	- 0.038	- 0.001	0.021	0.015	- 0.074	0.015	0.033	- 0.003	0.084	- 0.023	- 0.148	- 0.406	0.023	- 0.318	- 0.302	- 0.146	1.000	- 0.636	- 0.039	0.045	0.316	0.314	0.321
Cash3	0.044	0.019	- 0.050	- 0.063	0.129	0.084	- 0.035	- 0.022	- 0.096	0.019	0.089	0.612	0.014	0.500	0.488	0.188	- 0.563	1.000	0.172	0.095	- 0.247	- 0.365	- 0.241
MNE3	0.053	0.040	0.006	0.109	0.100	- 0.088	0.003	0.073	- 0.039	- 0.003	0.133	0.188	0.150	0.170	0.003	- 0.019	- 0.054	0.121	1.000	0.324	0.066	- 0.034	0.259
NOL3	0.076	- 0.008	- 0.019	0.005	0.017	- 0.066	0.054	0.073	- 0.075	- 0.035	- 0.032	0.086	0.008	0.118	0.047	- 0.018	0.018	0.090	0.324	1.000	0.105	- 0.079	0.024
Intangibles3	0.064	0.006	- 0.009	0.088	- 0.014	- 0.158	0.066	- 0.020	- 0.019	- 0.074	- 0.080	- 0.098	0.093	0.024	- 0.180	- 0.077	0.285	- 0.276	0.043	0.140	1.000	- 0.139	0.204
PPE3	- 0.031	0.012	0.043	- 0.002	- 0.062	- 0.027	0.060	0.083	0.028	0.039	0.246	- 0.245	- 0.029	- 0.293	- 0.277	- 0.169	0.255	- 0.357	- 0.046	- 0.078	- 0.236	1.000	0.138
Size3	0.098	0.018	0.035	- 0.017	- 0.003	- 0.182	0.163	- 0.009	0.027	- 0.079	0.068	- 0.183	0.125	- 0.301	- 0.339	- 0.118	0.311	- 0.308	0.267	0.036	0.201	0.162	1.000

The matrix shows the Pearson's correlation coefficients (Spearman's rank correlations) in the lower triangle (above the diagonal). Casewise deletion is used. All variables are defined in the Appendix.

Table 3 Descriptive Analysis

Panel A Comparison of cash ETR3 change between and within groups

		U	rm in low-tax hightolow = 1)	U	rm in high-tax nightolow = 0)		
		N	mean	N	mean	difference	p-value
pre cash ETR3 [t-2; t0]	I	197	0.3896	540	0.3935	- 0.0039	(0.8613)
cash ETR3 [t1; t3]	II	197	0.2755	540	0.3282	- 0.0527 ***	(0.0065)
Within-group change (hightolow = 1)	I to II					- 0.1141 ***	(0.0000)
Within-group change (hightolow $= 0$)	I to II					- 0.0653 ***	(0.0000)
							z-statistic
Difference in within-group change						- 0.0488*	-1.6994

Panel B Comparison of cash ETR3-development for intensified networking

		O	rm in low-tax ightolow = 1)	U	rm in high-tax nightolow = 0)		
		N	mean	N	mean	difference	p-value
1 st and 2 nd high-/low-tax network	I	153	0.2922	418	0.3390	- 0.0468 **	(0.0376)
subsequent (≥3) high-/low-tax networks	II	44	0.2174	122	0.2915	- 0.0740 **	(0.0455)

All variables are defined in detail in the Appendix.

Table 4 Main Analysis

Panel A Regression Analysis

Dependent variable	cash E'	TR3	delta cash	ETR3	cash E	ΓR5	delta cash	ETR5
,	coefficient	p-value	coefficient	p-value	coefficient	p-value	coefficient	p-value
hightolow	- 0.0480**	(0.0103)	- 0.2062***	(0.0061)	- 0.0376***	(0.0087)	- 0.1229**	(0.0191)
Proximity	- 0.0877	(0.1171)	- 0.2488	(0.2795)	0.0269	(0.4762)	0.1089	(0.4028)
SameAuditor	- 0.0107	(0.6173)	- 0.0427	(0.6201)	0.0107	(0.5414)	0.0309	(0.6342)
Network controls	Yes	S	Yes		Yes		Yes	S
Firm controls	Yes	8	Yes		Yes		Yes	S
Fixed effects	Industry &	& Year	Industry &	z Year	Industry &	z Year	Industry &	& Year
SE cluster	Firm	n	Firm	1	Firm	1	Firm	n
Observations	735	5	735		594		594	1
Adjusted R ²	0.12	33	0.104	17	0.057	77	0.12	28

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. The results for equation (3) are presented in Panel A. Our main variable of interest is *hightolow*, which is an indicator variable set equal to 1 for observations of high-tax firms cooperating with low-tax firms and set equal to 0 for high-tax firms cooperating with high-tax firms. The number of observations is decreased from 737 to 735 (596 to 594) by two singleton observations in the fixed effects. All variables are defined in detail in the Appendix.

Table 4 Main Analysis (continued)

Panel B Matched Panel: Difference-in-Differences

Dependent variable	cash E	cash ETR		cash ETR		cash ETR	
	coefficient	p-value	coefficient	p-value	coefficient	p-value	
treated	0.0221	(0.3097)	0.0140	(0.5047)	0.0137	(0.5268)	
post	0.0364**	(0.0372)	0.0374**	(0.0291)	0.0350*	(0.0536)	
treated*post	- 0.0695**	(0.0159)	- 0.0710**	(0.0132)	- 0.0699**	(0.0131)	
Firm controls	No		No		Yes (annual r	measures)	
Fixed effects	No		Indust	ry	Indust	ry	
SE cluster	Firm	ı	Firm	1	Firm	ı	
Observations	609		609)	609		
Adjusted R ²	0.005	52	0.023	39	0.043	31	
Economic signif	icance: margins	of responses f	for cash ETR [SE	E] (p-value)			
control*post	0.3162 [0.	.0197]	0.3224 [0.	.0187]	0.3212 [0.	.0179]	
treated*post	0.2688 [0.	.0159]	0.2654 [0.0161]		0.2651 [0.	.0159]	
Difference	- 0.0474*	(0.0608)	- 0.0570**	(0.0231)	- 0.0561 **	(0.0168)	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. Panel B depicts the results for equation (4). We compose our sample by creating an embargo period of eight years (from -3 to +5 years) around an hightolow observation during which no further hightolow observations may occur. We match control observations (hightolow = 0) according to year and industry to each treatment occurrence (hightolow = 1). All variables are defined in detail in the Appendix.

Table 4 Main Analysis (continued)

Panel C Adjustment Speed

Dependent variable	cash ETR		
(#) of specification	coefficient	p-value	
(1) treated*post [t1]	- 0.0555	(0.1946)	
(2) treated*post [t1; t2]	- 0.0988**	(0.0154)	
(3) treated*post [t1; t3]	- 0.0697**	(0.0423)	
(4) treated*post [t1; t4]	- 0.0765**	(0.0118)	
(5) treated*post [t1; t5]	- 0.0699**	(0.0131)	
Controls	Firm (annual measures)	& treated & post	
Fixed effects	Industry		
SE cluster	Firm		
Observations	331; 405; 479; 545; 609		
Adjusted R ²	0.0403; 0.0505; 0.0359; 0.0420; 0.0431		

Panel C depicts the results for five specifications of equation (4). The posttreatment period is extended by one year for each specification (from post = 1 for $[t_1]$ to post = 1 for $[t_1; t_5]$). post remains 0 for t_{-2} to t_0 throughout all specifications. The coefficient estimates of treatment*post comprises the cumulative adjustment (i.e., adjustment speed) of a high-tax firm's tax planning behavior with progressing time when cooperating with low-tax firms. Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests.

Table 5 Additional Analyses

Panel A Headquarter

Dependent variable	cash ETR3		delta cash ETR3	
	coefficient	p-value	coefficient	p-value
hightolow	- 0.0579***	(0.0033)	- 0.1912**	(0.0107)
SameBEARegion	- 0.0316	(0.1938)	- 0.0474	(0.6590)
hightolow*SameBEARegion	0.0524	(0.2386)	- 0.0486	(0.7772)
Controls	Network &	Firm	Network &	k Firm
Fixed effects	Industry &	Year	Industry &	Year
SE cluster	Firm		Firm	1
Observations	735		735	
Adjusted R2	0.1233		0.104	40

Panel B Industry

Dependent variable	cash ETR3		delta cash	delta cash ETR3	
	coefficient	p-value	coefficient	p-value	
hightolow	- 0.0678***	(0.0078)	- 0.2505 **	(0.0197)	
SameInd	- 0.0403*	(0.0530)	- 0.1567*	(0.0735)	
hightolow*SameInd	0.0526	(0.1267)	0.1348	(0.3235)	
Controls	Network &	Firm	Network &	k Firm	
Fixed effects	Year		Year	r	
SE cluster	Firm		Firm		
Observations	736		736		
Adjusted R2	0.1215		0.107	79	

Table 5 Additional Analyses (continued)

Panel C Auditor

I allei C Auditoi					
Dependent variable	cash ETR3		delta cash	delta cash ETR3	
	coefficient	p-value	coefficient	p-value	
hightolow	- 0.0428**	(0.0367)	- 0.2152***	(0.0077)	
SameAuditor	- 0.0042	(0.8833)	0.0594	(0.5950)	
hightolow*SameAuditor	- 0.0237	(0.5566)	0.0642	(0.6976)	
Controls	Network &	& Firm	Network &	k Firm	
Fixed effects	Industry &	& Year	Industry &	Year	
SE cluster	Firn	n	Firm	1	
Observations	735		735		
Adjusted R2	0.1213		0.103	37	

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. In Panel A, we test for the impact of geographical distance between the headquarters of cooperating firms. Distance is measured by an indicator variable that is set equal to one if network participants are headquartered in the same region, as defined by the Bureau of Economic Analysis, at network initiation. Panel B follows the approach of Panel A for the industry affiliation of network participants. We interact *hightolow* with an indicator for changes to a shared audit firm within three years of the network initiation in Panel C. All variables are defined in detail in the Appendix.

Table 6 Robustness Checks: Alternative Explanations

Panel A Survivorship Rice

Panel A Survivorship Bias				
Dependent variable	cash ETR3			
Specification	exclude nonsurvivors			
	coefficient	p-value		
hightolow	- 0.0279*	(0.0571)		
Proximity	- 0.0663	(0.1718)		
SameAuditor	- 0.0109	(0.5264)		
Network controls	No)		
Firm controls	Yes			
Fixed effects	Industry & Year			
SE cluster	Firm			
Observations	638			
Adjusted R2	0.09	0.0966		

Panel B Increases in cash ETR3

Dependent variable	delta cash ETR3		
Specification	only if		
Specification	delta cash ETR ≤ 1		
	coefficient	p-value	
hightolow	- 0.0543*	(0.0950)	
Proximity	- 0.0398	(0.7199)	
SameAuditor	- 0.0216	(0.5289)	
Network controls	No)	
Firm controls	Yes	S	
Fixed effects	Industry & Year		
SE cluster	Firm		
Observations	455		
Adjusted R2	0.1603		

Panel C Impact on low-tax firms			
Dependent variable	cash ETR3		
Specification	only low-tax firms		
	coefficient	p-value	
lowtohigh	- 0.0002	(0.9961)	
Proximity	0.2021	(0.1885)	
SameAuditor	- 0.0140	(0.5520)	
Network controls	No)	
Firm controls	Yes		
Fixed effects	Industry & Year		
SE cluster	Firm		
Observations	301		
Adjusted R2	0.0666		

Panel D Effect on Profitability

Dependent variable	ChangeEBITDA3		
	coefficient	p-value	
hightolow	- 0.0069	(0.6569)	
Proximity	0.0287	(0.4767)	
SameAuditor	- 0.0194	(0.1936)	
Network controls	Yes	S	
Firm controls	Yes (no EBITDA3)		
Fixed effects	Industry & Year		
SE cluster	Firm		
Observations	735		
Adjusted R2	0.3577		

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. In Panel A, nonsurvivors are excluded from the sample. A firm is deemed a nonsurvivor if the year of network initiation is the final or penultimate fiscal year of coverage of this firm in our panel. Panel B excludes increases in cash ETR3 $[t_1; t_3]$ in comparison to pre cash ETR3 $[t_{-2}; t_0]$. We change our focus from high-tax to low-tax firms in Panel C and construct an indicator variable lowtohigh, which is set equal to one for low-tax firms in networks with high-tax firms and equal to zero for low-tax firms in networks with other low-tax firms. We cannot include network controls because we have the relevant information for networks of high-tax firms. In Panel D, we control for the (three-year) average annual growth rate in EBITDA (ChangeEBITDA3) subsequent to network initiation. All variables are defined in detail in the Appendix.

Table 7 Robustness Checks: Identification Strategy

Panel A Low-tax- and high-tax firms

I allei A Low-tax- allu iligii-tax ili ilis				
Dependent variable	cash ETR3 [t1; t3]			
Specification	low-tax- and			
Specification	high-tax	firms		
	coefficient	p-value		
Own industry-adjusted pre cash ETR3	0.1606***	(0.0000)		
[t-2; t0]	0.1000	(0.0000)		
Partner industry-adjusted pre cash ETR3	0.0300	(0.2828)		
[t-2; t0]	0.0300	(0.2020)		
Proximity	- 0.0579	(0.1812)		
SameAuditor	- 0.0133	(0.3777)		
SameInd	- 0.0249*	(0.0600)		
Network controls	No			
Firm controls	Yes			
Fixed effects	No			
SE cluster	Firm			
Observations	1276			
Adjusted R2	0.1487			

Panel B Only high-tax firms

Dependent variable	cash ETR3 [t1; t3]		
Specification	high-tax firms only		
	coefficient p-value		
Own industry-adjusted pre cash ETR3 [t-2; t0]	0.0616	(0.1216)	
Partner industry-adjusted pre cash ETR3 [t-2; t0]	0.0592*	(0.0936)	
Proximity	- 0.0760	(0.1004)	
SameAuditor	- 0.0134	(0.5110)	
SameInd	- 0.0337*	(0.0551)	
Network controls	Ye	S	
Firm controls	Ye	S	
Fixed effects	No		
SE cluster	Firm		
Observations	728		
Adjusted R2	0.1211		

Superscripts ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, for two-tailed tests. We examine correlations of cash effective tax rates between network participants. Panel A contains low-tax and high-tax firms in network-firm observations. Panel B is limited to only high-tax firms. Both panels are limited to networks of two participants. We cannot include *network controls* in Panel A because we collected information for networks of high-tax firms. All variables are defined in detail in the Appendix.

Impressum:

Arbeitskreis Quantitative Steuerlehre, arqus, e.V. Vorstand: Prof. Dr. Ralf Maiterth (Vorsitzender), Prof. Dr. Kay Blaufus, Prof. Dr. Dr. Andreas Löffler Sitz des Vereins: Berlin

Herausgeber: Kay Blaufus, Jochen Hundsdoerfer, Martin Jacob, Dirk Kiesewetter, Rolf J. König, Lutz Kruschwitz, Andreas Löffler, Ralf Maiterth, Heiko Müller, Jens Müller, Rainer Niemann, Deborah Schanz, Sebastian Schanz, Caren Sureth-Sloane, Corinna Treisch

Kontaktadresse:

Prof. Dr. Caren Sureth-Sloane, Universität Paderborn, Fakultät für Wirtschaftswissenschaften, Warburger Str. 100, 33098 Paderborn, www.arqus.info, Email: info@arqus.info

ISSN 1861-8944