The Intergenerational Causal Effect of Tax Evasion: Evidence from the Commuter Tax Allowance in Austria[†]

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Abstract

Does tax evasion run in the family? To answer this question, we study the case of the commuter tax allowance in Austria. This allowance is designed as a step function of the distance between the residence and the workplace, creating sharp discontinuities at each bracket threshold. It turns out that the distance to the next higher bracket is a strong determinant of compliance. The match of different administrative data sources allows us to observe actual compliance behavior with little error at the individual level across two generations. To identify the intergenerational causal effect in tax evasion behavior, we use the paternal distance to next higher bracket as an instrumental variable for paternal compliance. We find that paternal non-compliance increases children's non-compliance by about 23 percent.

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1 Introduction

The neo-classical model of tax evasion — an application of the economics of crime approach presented by Becker (1968) — predicts that citizens simply compare the expected benefits of evasion with the expected costs (Allingham and Sandmo, 1972; Yitzhaki, 1974). In essence, the tax evasion decision is similar to a portfolio decision, where citizens can choose between a risk-free asset (compliance, in this case) and a risky-asset (non-compliance). This model is straight-forward and provides intuitively appealing comparative static effects, where compliance increases in line with the probability of detection and the penalty. Unfortunately, such a model is unable to capture the full range of factors relevant to tax evasion in reality, as it consistently underpredicts real-world compliance (Alm et al., 1992). Many scholars presume that individuals are motivated not only by the rate of return on tax evasion, but also by other (i. e., social) motivations to pay taxes (usually called *tax morale*). While this appears to be a reasonable claim, it is notoriously hard to provide empirical evidence (Luttmer and Singhal, 2014).[1]

Whether tax morale drives compliance behavior is not only of interest to scholars, but also has strong implications for tax policy. If tax morale is indeed a quantitatively important determinant of compliance, policymakers could employ measurements beyond the usual deterrence policies. Ideally, we want to be able to assess which type of policy is more cost-effective to achieve a certain level of compliance. To do so, identification of the various determinants of tax morale is a prerequisite.

In this study, we argue that the family seems to be the natural environment in which tax morale is shaped. We examine the intergenerational dimension and suggest interpreting the link between parents' and their children's behavior as "inherited tax morale". Therefore, we follow Luttmer and Singhal (2014) by understanding tax morale broadly as an umbrella term capturing all non-pecuniary motivations for tax compliance.[2] Our approach is also motivated by the key finding in the economic literature on crime that parental criminality is among the strongest predictors of the next generation's criminal activity (see, for e. g., Williams and Sickles, 2002; Hjalmarsson and Lindquist, 2012). This relationship holds for severe offences (such as violent crime), as well as for more minor offences and non-law abiding behavior such as drunk driving (Hjalmarsson and Lindquist, 2010). To our knowledge, no study has thus far examined such an intergenerational link in tax evasion behavior.[3]

[1] Complementary attempts to bridge the gap between theory and evidence focus on the role of the misperception of enforcement parameters (Chetty, 2009) and third-party reporting of income (Kleven et al., 2011, 2015).

[2] This comprises the intrinsic motivations to comply, peer effects, other social influences, information imperfections about deterrence parameters, and other factors that fall outside the standard expected utility framework.

[3] Notably, Halla (2012) shows that a survey-based measure of tax morale (*not* tax evasion) of second-generation Americans is mainly and significantly influenced by the country of origin of their ancestors. This provides evidence that tax morale is inherited to some degree.

In contrast to the above-mentioned studies of the intergenerational crime link, we do not only provide an *intergenerational association* in tax compliance, but also aim to identify an *intergenerational causal effect*.[4] Thus, we do not only want to answer the question of whether children are more likely to evade taxes if their parents were tax evaders; more importantly, we are interested in whether parental tax evasion *causes* children's non-compliance with the tax code. An association may simply reflect that parents and children share genetic and environmental factors that promote tax evasion. For instance, there is some evidence that certain genes are associated with deviant behavior (Veroude et al., 2016). If this holds for tax evasion behavior, we would observe a correlation between parents' and children's compliance behavior; however, it would be misleading to argue that parents' behavior is causing children's behavior. The distinction between these explanations for an observed correlation is important, since they require different policy responses. If tax evasion behavior across generations is causally linked, then policies that lower parental non-compliance will have spillover effects on the next generation. If, however, the intergenerational transmission only operates through genetic or environmental factors that are correlated with tax evasion, the same policy will be prone to fail.

The requirements for the identification of a causal effect are particularly high in the context of tax evasion. We tackle this problem by exploring a specific setting in which we can observe tax compliance behavior for two generations at the individual level. This is possible in the case of the commuter tax allowance in Austria, the largest standard deduction available for Austrian wage earners (Paetzold and Winner, 2016). This commuter allowance is designed as a step function of the distance between the residence and the workplace, creating sharp discontinuities at each bracket threshold. According to the Austrian tax code, employees report their eligibility for a certain commuting distance bracket to the employer that, as the third party, has to validate these claims and adjust taxable income before withholding. In practice, however, employers do not sufficiently double-check these claims, turning the allowance into a (quasi-)self-reported item. Since the tax authorities have not systematically checked whether the self-reported information is accurate (until 2014), the scheme offered employees an opportunity to overreport their travel distance to work and hence receive a tax allowance higher than they were actually entitled to. Our linked administrative data sources allow us to observe not only the claimed allowance, but also to construct a very good proxy for the true driving distance to work. This is an improvement over most tax evasion studies, which rarely observe the outcome of interest (Slemrod, 2007). We can thus observe the compliance behavior of Austrian commuters at the individual level with relatively little error. We see a robust pattern in the data showing that the closer commuters live to a respective bracket thresh-

[4] Even in the literature on intergenerational mobility — the most heavily studied intergenerational link — only recently have empirical studies begun to focus on establishing a causal relationship between the education of parents and their children (Holmlund et al., 2011). These studies typically exploit changes in compulsory schooling laws.

old, the more prone they are to misreport their distance. This pattern may be explained by different perceptions about the detection risk, or by having lower psychic or social norm costs of overreporting when residing closer to the next higher bracket threshold.

Information on family networks for a subsample of commuters allows us to compare compliance behavior across two generations. For our estimation analysis we have a sample of more than $15,000$ father-child pairs available. To establish an intergenerational causal effect in tax evasion, we use the father's distance to the next higher commuting distance bracket (henceforth distance-to-next-higher-bracket) to obtain exogenous variation in the father's compliance decision. Based on an instrumental variable (IV) approach we obtain a *local average treatment effect* that provides us with the effect of increased paternal tax evasion on the child's compliance. Thus, this estimate informs us about the spillover effects of a change in compliance for one generation on the evasion behavior of the next generation. The identifying assumption is that the father's distance-to-next-higher-bracket affects his child's compliance decision only through the channel of actual parental tax evasion behavior and is not correlated with any unobserved determinants of the child's tax evasion behavior. This implies that we need to exclude parental sorting across the distance-to-next-higher-bracket, particularly with respect to characteristics that potentially affect children's compliance behavior, i. e. earnings. We also need to assume that children do not systematically sort into home or firm location depending on father's distance-to-next-higher-bracket. We demonstrate below that the distance-to-next-higher-bracket is a highly idiosyncratic variable. For instance, we find no systematic relationship between any of the father's observable socioeconomic characteristics and his distance-to-next-higher-bracket. We also find that the children of fathers with very different distances-to-next-higher-bracket are observationally identical. Furthermore, we observe no evidence of individuals sorting or bunching around bracket thresholds.

This study contributes to the established literature on tax evasion (Andreoni et al., 1998; Slemrod and Yitzhaki, 2002; Slemrod, 2007). Most recently, the empirical branch of this literature was enhanced by a number of valuable field experiments, which brought the credibility revolution to the study of tax compliance (Slemrod and Weber, 2012). However, most designs relying on experimental methods do not allow researchers to observe the development of tax compliance over longer periods. By contrast, our setting enables us to track the compliance behavior of Austrian taxpayers who commute to work over time. This setting provides a rare opportunity to gain novel insights into how compliance behavior is transmitted through the most important social network, namely the family. To the best of our knowledge, our study is the first to examine the intergenerational link in tax evasion behavior.[5] Based on palatable assumptions, we are able to identify

[5]There is sound empirical evidence available on the distinct (but somewhat related) issue of welfare participation. Dahl et al. (2014) identify a causal link in the intergenerational correlation in welfare participation. By exploiting the random assignment of judges to Norwegian disability pension applicants as an instrument, they also establish a causal effect. This shows that when a parent is allowed a disability

an *intergenerational causal effect*: for our sample of commuters, which has an average share of tax cheaters of about 20 percent, we find that a cheating father increases the likelihood of the child's non-compliance by about 5 percentage points. The underlying transmission mechanisms behind this intergenerational link in evasion behavior can be manifold. Our results are consistent with explanations based on the transmission of social norms, the transmission of information, or any other type of intergenerational peer effect (see footnote 2). In the first case, fathers with a higher tolerance for tax evasion transmit this social norm to their children. In the second case, cheating fathers inform their children for instance about a low detection probability. In the third case, children may simply wish to conform to the behavior of their fathers. Determining the relative importance of potential causal pathways is generally very challenging. Our empirical setup and the available data do not allow us to test the one hypothesis against the other in a compelling way. Fortunately, the knowledge of the precise mechanism is not critical for our identification strategy. However, without knowing the precise mechanism it is not possible to derive clear-cut policy implications. Only if the exact transmission mechanism was known, one could target parental tax evasion exactly through this specific channel and achieve not only a reduction in evasion today, but also generate a reduction in evasion among future generations.

This finding also speaks to two further important, but difficult to study, aspects of the literature on tax compliance: spillovers and non-pecuniary motivations to comply. There exists some empirical evidence of enforcement spillovers on the compliance of non-audited taxpayers in one's network in the case of TV license fees (Rincke and Traxler, 2011; Drago et al., 2015) and of non-audited firms' suppliers along the VAT chain (Pomeranz, 2015). By contrast, evidence of complementary evasion spillovers regarding opportunities to cheat is extremely scarce. Paetzold and Winner (2016) use variation in job changes to uncover spillover effects from the work environment on the individual compliance decision. Beyond that, we are only aware of related evidence from laboratory experiments, showing that taxpayers' reporting is sensitive to the evasion decision taken by other taxpayers (Fortin et al., 2007; Alm et al., 2009).[6] The best empirical evidence of the importance of intrinsic motivation comes from two field experiments at the border between taxation and charitable giving, which use different treatments to analyze the determinants of compliance among members of the German Protestant and Catholic Church, respectively. Dwenger et al. (2016) show that starting from a zero deterrence situation, a sizeable proportion of existing intrinsic motivation to comply is driven by duty-to-comply preferences and that there is no crowding out between extrinsic and intrinsic motivations. By contrast, Boyer

pension, their adult child's participation over the next five years increases by 6 percentage points. See also Bratberg et al. (2014).

[6]Relatedly, Galbiati and Zanella (2012) present evidence of (aggregated) social externalities/multipliers in the context of evasion behavior, and Alstadsæter, Kopczuk and Telle (2014) highlight the importance of family networks in the adoption of a tax avoidance strategy.

et al. (2015), who exploit a comparable set-up for the German Catholic Church, find a significant crowding out of intrinsic motivation among weakly intrinsically motivated taxpayers.

More broadly, our study also contributes to the large empirical literature studying the extent to which socioeconomic status is transmitted from parents to children (Bowles and Gintis, 2002). Traditionally, this literature has focused on educational attainment and earnings.[7] More recently, it has also analyzed further dimensions and potential causal pathways — such as consumption (Charles et al., 2014; Bruze, 2015), health behavior (Thompson, 2014), and the willingness to compete (Ålmas et al., 2014) — to fully understand the intergenerational link. Tax evasion is a criminal activity that directly affects available income and potentially social status. As such it constitutes one of many causal pathways that underlie the intergenerational transmission of socioeconomic status.

The remainder of the paper is organized as follows: In Section 2, we present our research design. In Section 3, we present our estimation results of the intergenerational causal effect in tax evasion behavior, along with a placebo test, and a number of robustness checks. Section 4, examines the link between siblings and provides estimates of the *intra*-generational causal effect in tax evasion behavior. Section 5 concludes the paper.

2 Research design

In this section, we first discuss the institutional background with a focus on the commuter allowance in the Austrian income tax system. Second, we present our data, describe how we compile our estimation sample, and provide descriptive statistics. Third, we explain our identification strategy and spell out under which assumptions we can identify an intergenerational causal effect in tax compliance.

2.1 Institutional background

2.1.1 Commuter allowance in the Austrian income tax system

In Austria, wage earners are not required to file a tax return since employers are legally obliged to do exact and cumulative withholding via the employees' payslip. On such a payslip, taxpayers can claim standard deductions and allowances, reducing their tax liability and hence the tax withholding. The commuter tax allowance is the largest of these standard allowances, enabling employees to reduce taxable income by as much as Euros $3,672$ per year (for 2012).[8] Its intention is to compensate employees for their traffic expenses to work. The allowance comes as a step function of the commuting distance and

[7] See, for instance, Björklund and Jäntti (1997); Aaronson and Mazumder (2008); Chetty et al. (2014)

[8] Given a top tax rate of 50 percent (for incomes above Euros $60,000$), the maximum amount of tax reduction is equal to Euros $1,836$.

offers higher rates if public transport is not available or unreasonably long. More precisely, the deductible amount increases with commuting distance brackets of (2-20] km, (20-40] km, (40-60] km, and more than 60 km of commuting (see Table 1). For each of these brackets (except for the first bracket), there exists a scheme when public transport is in place, and another scheme if not. The tax code refers to these as the *minor* and *major scheme*. Eligible employees have to apply the shortest commuting distance by means of public transportation (for the minor scheme) or by using a private vehicle (for the major scheme). Since the introduction of the commuter tax allowance in 1988, the commuting distance brackets and basic structure of the allowance have remained unchanged.

To receive the commuter allowance via the payslip, employees report their eligibility for one of the four commuting distance brackets as well as the availability of public transport to their employer, which, according to the tax code, should validate their claims before applying the respective commuter allowance to the tax withholding.[9] In practice, however, it turns out to be a rather self-reported feature, with employers often not meeting their responsibility to double-check the allowances claimed. To understand why non-compliance with the commuter allowance is possible, it is important to mention the main (mostly institutional) deficiencies regarding the enforcement of this tax allowance scheme. To begin with, employers do not have large incentives to sufficiently validate the allowance claims since they do not carry/pay the deductible amount but simply adjust the withholding of their employees' income tax liability. Second, there has been a significant lack of deterrence for employers to thoroughly double-check the claims of their employees, keeping the risk of detection low. Only since 2014 have the tax authorities required claimants to use computer-assisted software to prove eligibility for a certain commuting distance bracket. Third, since employees are not required to file a tax return at the end of the year, false reporting on the payslip can only be detected when the employer is audited. However, the tax authorities rarely focus on employees' deductions when conducting firm inspections. Finally, in the case of detection, the fine is typically levied on the employee but not on the third party, which is the employer. In sum, this lenient enforcement offered commuters an opportunity to overstate their commuting distances and hence receive higher commuter allowances than actually entitled to.

2.1.2 Detecting non-compliance with commuter tax allowances in administrative data

A procedure for uncovering tax evasion in the case of Austrian commuter tax allowances based on linked administrative data sources was first suggested by Paetzold and Winner

[9]Taxpayers can also claim the commuter allowance through the tax return at the end of the year. However, around 80 percent of commuter allowance recipients file for the allowance on their payslip (Statistik Austria, 2009). Analyzing claims from payslips ensures that the compliance decision was taken by the taxpayer and not by a professional tax preparer.

(2016). We build on their approach and use an equivalent procedure to detect non-compliance with commuter tax allowances in our dataset. The starting point is the individual payslip files from the *Austrian Ministry of Finance*. These payslip files are similar to the W-2 forms in the United States and provide information on the wages and standard deductions of Austrian wage earners. From these forms, we extract information regarding the commuter allowance taxpayers received. For our analysis, we exclude claimants of the minor scheme (i. e., those using public transport). This subset of claimants makes up around 30 percent of all commuter allowance recipients. The tax law requires commuters to state their eligibility based on the shortest commuting distance to work. Since public transport usually makes detours when going from location A to B, we are not in a position to measure the true commuting distance for recipients of the minor allowance precisely.

While the payslip files comprise information on the taxpayer's place of residence and the commuter allowance he/she received, they do not provide information on the location of the workplace. To obtain this information, we combine these data with information from the *Austrian Social Security Database* (henceforth ASSD). This administrative record is used to verify pension claims for the universe of Austrian workers in the private sector (Zweimüller et al., 2009). It is structured as a matched firm–worker dataset and includes detailed information on workers' employment and earnings histories. It also provides employer information, such as its location. Thus, the link between the two data sources enables us to observe both the residence and the workplace location of the taxpayer at the zip-code level.[10] To identify unjustified (high) commuter allowances, we use a route planner to calculate the driving distances between the centroids of these two zip-codes (as is commonly used in navigation devices) and use this as an approximation of the true driving distance. Based on this approximate true driving distance, we determine the eligible commuting distance bracket. A comparison between the eligible commuting distance bracket and claimed bracket reveals who evaded taxes.[11] We classify individuals as overreporters (i. e., cheaters) when they claimed a higher commuting distance bracket than they were entitled to, and as underreporters when they claimed a smaller (i. e. shorter) commuting distance bracket than what they actually could have received. More precisely, our cheating variable takes a value of one for overreporters, and zero for everyone else. In turn, the variable capturing underreporting takes a value of one for underreporters, and zero for everyone else.

Since we are especially interested in the compliance behavior of the second generation, we start by documenting the compliance behavior of cohorts born between 1974 and

[10]Notably, Austrian zip-code areas are fairly small. Their median surface area is 27 km^2 and the median circumradius is about 3 km. For comparison, the average surface area of a U.S. zip-code is around 300 km^2. Important commuting areas have several zip-codes (i. e., Vienna alone is grouped into 23 zip-codes, hence commuters to those areas do not have the exact same commuting distance.

[11]It is important to note that taxpayers claiming the commuter tax allowance do *not* report their driving distance in numbers, but declare a commuting distance bracket they supposedly belong to.

1994.[12] In total, 222,456 individuals from these cohorts received a major commuter tax allowance at least once during the period of our study. Table 2 summarizes the share of over- and underreporters of these cohorts, broken down by the reported commuting distance bracket. The table displays the misreporting of the first reporting decision (i. e., when individuals received the commuter tax allowance for the first time). The overreporting shares for the single brackets add up to 22 percent, 38 percent, and 31 percent, respectively. The underreporting shares vary by bracket between 5 and 12 percent.[13] These skewed shares of under- and overreporting give a first indication that taxpayers cheat on their commuting distance bracket in order to receive a higher allowance than they were entitled to. Since we also know the exact commuter allowances in Euros (see Table 1), we can also calculate the overclaimed amount of the commuter allowance by individuals (i. e., the difference between the justified allowance amount and the claimed allowance amount).

To further uncover systematic cheating by commuters, we study discontinuities in misreporting around the commuting distance bracket thresholds. For this purpose, we pool data across all brackets and display the share of over- and underreporters by bins of the true commuting distance. In the case that individuals systematically cheat on their bracket eligibility, we should observe a discontinuity in the proportion of over- and underreporters at the thresholds. By contrast, if people would just report a noisy estimate of their true eligibility without any cheating, we should observe very similar shares of over- and underreporting around the thresholds and no discontinuity.

The bars of Figure 1 display the fraction of misreporters by commuting distance. Each bar is broken down into misreporters who overreport (dark area) and misreporters who underreport (light area). The dashed lines indicate the thresholds where the allowance discretely increases to a higher amount. We find a sharp reaction of taxpayers to these thresholds. The closer commuters live to a respective bracket the more prone they are to misreport their allowance claim. Overall, more than 60 percent (sum of over- and underreporters) of the individuals immediately below a bracket threshold misreport their actual driving distance to the workplace. Most importantly, we observe that the sharp discontinuity in the fraction of misreporters at the thresholds is mainly driven by overreporters. To be more precise, we find commuters to be much more prone to cheat than commuters underreporting their eligibility. For instance, in the bin immediately *below* the first 20 km threshold we find that 64 percent of all commuters overreport their allowance claim compared with only 29 percent of underreporters in the bin immediately *above* it. This discontinuity in misreporting at each threshold rejects explanations based on sole

[12]For a documentation of the compliance behavior of older cohorts, see (Paetzold and Winner, 2016). In addition, we replicate Figure 1 for the father cohort (born before 1974) in the Web Appendix B.1.

[13]It is not uncommon to observe taxpayers reporting to their own disadvantage. Kleven et al. (2011) find significant overpayment of taxes (about 5 percent of self-reported income), and point at honest mistakes resulting from a complex tax code and misinformation as potential explanations for such behavior.

noise in our distance measure.[14] In fact, the discontinuity in misreporting exactly at the bracket thresholds strongly suggests that taxpayers take advantage of the self-reporting nature of the commuter allowance to overclaim their eligibility. This result is confirmed when using a smaller data set, which provides us with exact residence and workplace addresses (including house numbers), allowing us to calculate true driving distances without measurement error.[15]

As shown in Figure 1, some underreporting occurs across the entire range of distance bins. The reason for this lies in the administrative nature of our data. Specifically, the ASSD provides no clear provision on whether the employer identifier is used for a firm or for single establishments of a (larger) firm. If only the headquarter of a company with several establishments across Austria is recorded in the ASSD, our estimate for the commuting distance between the firm's location and residence of its employees is upward biased for some workers. This inflates our share of underreporters, since we assign such workers a much greater distance (i. e., to the headquarters) than where they actually work (the local establishment). This is much less of an issue when measuring overreporting, since living close to a recorded headquarters in the ASSD, but commuting to a much more distant subsidiary is rare. This is also supported by the data, where we observe only a very small share of cheaters immediately *above* the bracket thresholds compared with a much higher share of underreporters immediately *below* the thresholds.

In sum, the pattern of misreporting we observe indicates that the compliance decision of commuters is affected by the threshold structure of the allowance scheme. Consistent with deliberate tax evasion, we observe misreporting to be much more widespread on the 'tax-favourable' side of each commuting distance bracket threshold. This pattern suggests that taxpayers take advantage of the (quasi) self-reporting nature of the commuter allowance.

While the pervasiveness of non-compliance with the commuter tax allowance might be striking, it is also interesting to note that a substantial number of individuals still report their commuting distance honestly. We use the richness of our data to address this variation in cheating, allowing for a compliance study over long periods of time to explore the transmission of non-compliance behavior over two generations.

[14] For instance, false classification of commuters as misreporters caused by the use of zip-code centroids instead of actual addresses would predict symmetric increases and decreases in misreporting around the thresholds but no discontinuity.

[15] This dataset is from a large Austrian retailer chain (around $40,000$ employees) with around $4,500$ commuting employees, working at one of 546 stores scattered all across Austria. In the Web Appendix A, we provide an detailed analysis of this data. Most importantly, if we replicate Figure 1 based on these data without measurement error, we find even clearer discontinuities with a higher prevalence of overreporting and a negligible share of underreporters (see Figure A.2 in Web Appendix A.1). The latter fact suggests that underreporting in our main data is mainly due to measurement error and not driven by mistakes on part of the commuter. Further results provide evidence that the type of measurement error prevalent in our main data set is not correlated with any observed socio-economic characteristics (see Web Appendix A.2), and attenuates somewhat our first stage estimates (see Web Appendix A.3).

2.2 Linking tax reporting behavior across two generations

The individual is the taxing unit in the Austrian income tax code and thus there is no joint filing of married couples or households. Starting from 1994, we have access to individual-level tax information, and examine children who are born between 1974 and 1994 (1,336,819 individuals). We focus on commuting children who claim the major commuter allowance (222,456 individuals).[16] We have to restrict our analysis to children, who can be linked to parents within the administrative records (153,382 individuals).[17] Furthermore, we focus on the intergenerational link between fathers and their children.[18] Those father–child pairs are further required to be both active in the labor market and to have received the major commuter tax allowance at least once (34,319 individuals). The latter restriction causes the number of observations to drop substantially. The unit of observation is then a father–child pair in the year in which the child is applying for the major commuter tax allowance for the first time. To avoid any reversed causality, we only use those father–child pairs where the father received the commuter allowance in the past, namely *before* the child claimed the allowance for the first time (28,630 individuals). We further exclude father–child pairs that work in the same firm or have the same commute (i. e., possess an overlap in residential and firm postal codes; 24,675 individuals). This guarantees that fathers and children do not have a perfect overlap in commuting distance, or in their distance-to-next-higher-bracket (multicollinearity problem). Furthermore, we restrict our analysis to observations where both father and child commute less than 60 km. Taxpayers commuting more than 60 km are *above* the highest bracket threshold and are thus not at risk of cheating.[19] Finally, we end up with 15,306 unique father–child pairs.

2.2.1 Descriptive statistics on the main variables

Table 3 provides the average socioeconomic characteristics, tax evasion indicators, commuting distances and distances-to-next-higher-bracket for the studied fathers and chil-

[16]Please note that we find no any evidence of a correlation between children's probability of claiming the major commuter allowance and our IV for parental non-compliance (i. e., the father's distance-to-next-higher-bracket). Further details are provided in our discussion below and in the Web Appendix B.2.

[17]We cannot reliably link parents to children if children were born outside of Austria or due to missing information about family links or existing ambiguities in administrative data.

[18]We are aware that an intergenerational transmission of tax evasion behavior may also work through mothers. However, labor force participation rates for mothers are much lower than those for fathers and may be rather selective. For instance, micro-census data reveal that the labor force participation rate of mothers with children younger than 15 was 66.3 compared with 92.1 percent of fathers in our last observation year of 2012. Furthermore, mothers had a part-time employment rate of 70.4 percent in 2012 (5.2 percent for fathers). However, the eligibility rules of the commuter tax allowance require (almost) full-time employment in practice. To avoid any potential problems of unobserved selection into labor supply, we therefore conduct our analysis only for fathers.

[19]The latter restriction turns out to be innocuous. Indeed, using the entire population of father–child pairs and assigning those with more than 60 km an extra indicator for their distance-to-next-higher-bracket provides very comparable results (see Section 3.3 for details).

dren. To avoid potential problems of reverse causality i. e., children's cheating behavior affecting their fathers' behavior, we measure fathers' characteristics one year before children's characteristics (i. e., before the child claimed the commuter allowance for the first time).

Fathers are born between 1933 and 1976 and are on average 47 years of age when we measure their tax evasion behavior. Children are born between 1974 and 1994 and observed at about 24 years of age. The comparison of socioeconomic characteristics suggests that children experienced on average a social advancement. They are more often employed as white-collar workers, are less likely to have foreign citizenship (i. e., they have been partly naturalized), and are much more likely to hold an academic degree. Their log of annual taxable income (measured on average at age 24) is 0.34 units lower than the log of fathers' taxable income (measured on average at age 47), which corresponds to a difference of approximately Euros 6,300 per year.[20]

The variables of primary interest are the tax evasion indicators regarding the commuter tax allowance. The binary cheating indicator shows that about 16 percent of fathers apply for a higher tax allowance than they are eligible. Among children the equivalent share is about 20 percent. Hence, children tend to cheat more often than their fathers. The other two tax evasion indicators reveal differences in the actual evaded amount. While fathers on average overclaim their commuter allowance by Euros 183, children do so by Euros 236.[21] When relating the amount overclaimed to taxable income, we find that fathers on average evade 1.0 percent of their taxable income and children 1.7 percent. It is important to note that the size of the two intensive margin indicators are limited by the fact that the commuter allowance is capped (with a maximum amount of Euros 3,672, see Table 1).

Finally, Table 3 lists the average true commuting distance and average distance-to-next-higher-bracket. On average, fathers commute somewhat shorter distances compared with the average child (about 21 compared with 25 km). By contrast, we find no difference in terms of the distance-to-next-higher-bracket across generations. We see that the average father and average child have identical distances-to-next-higher-bracket (9.5 km compared with 9.6 km).

2.3 Intergenerational correlations

Table 4 summarizes several aspects of the intergenerational (father–child) and sibling correlations. In the former case, we distinguish all father–child pairs, father–son pairs, and father–daughter pairs. In the latter case, we consider all sibling pairs, brother-

[20] In Austria, wages increase substantially with age and work experience (see, e. g., Frimmel et al., 2015).

[21] The overclaimed amount is the difference between the eligible commuter allowance and the actually claimed allowance. For underreporters and those who report correctly, this amount takes a value of zero.

pairs, and sister-pairs. For these pairs, we examine the associations among individual earnings, tax evasion, and commuting behavior. The first dimension is the most commonly used indicator in the well-established literature on intergenerational income persistence, the second dimension is the focus of our study, and the third dimension is related to our identification strategy. All variables are measured at the same point in time (i. e., when fathers are on average 47 years of age and children 24). The comparison of the intergenerational income persistence in our sample with (i) the respective benchmark estimates from this literature and (ii) with the intergenerational correlation in tax evasion allows us to put our novel results into perspective.

As expected, in our sample of matched fathers and children, we find clear evidence of intergenerational persistence in individual earnings. This persistence varies little with the sex of the child. We report the two most common measures of intergenerational income persistence, namely *intergenerational elasticity* and the *rank–rank correlation.* The *intergenerational elasticity* is the canonical measure and is obtained from a simple linear regression of children's logarithmic earnings on fathers' logarithmic earnings. Our slope coefficient of about 0.14 indicates that on average a high-earning father's child would have 14 percent more earnings than the child of a low-earning father. The *rank–rank correlation* is an alternative measure based on a regression of children's rank in the income distribution on their father's respective rank.[22] We obtain a rank–rank correlation of about 0.18. As such, intergenerational income persistence in Austria is comparable to that in Canada, Germany, and the Nordic countries (Blanden, 2015, see Figure 1). The respective correlations between siblings are considerably smaller, but highly statistically significant throughout.

The intergenerational correlations in tax evasion are listed for our three tax evasion indicators (binary, overclaimed amount relative to income, overclaimed amount). In each case, we find a statistically significant positive correlation of around 0.05. Thus, the intergenerational correlation in tax evasion behavior is roughly one-third of the intergenerational correlation in earnings. There is some evidence that the intergenerational correlations in tax evasion are somewhat higher for daughters compared with sons. In contrast to individual earnings, we observe for tax evasion that siblings and intergenerational correlations are comparable in magnitude.[23]

Regarding commuting behavior, we see a significant correlation in commuting distance of about 0.11. Thus, children of fathers with a long commute tend to also have a higher commuting distance. Notably, we find no intergenerational (or siblings) correlation in

[22] We rank each father relative to the others based on his individual earnings. Similarly, we rank children relative to other children based on their individual earnings. We then compute the relationship between the child and parent ranks. The rank–rank correlation then identifies the correlation between children's and fathers' positions in the income distribution (Chetty et al., 2014).

[23] Eriksson et al. (2016), report for Sweden sibling correlations for different types of crimes, that are considerably higher. They do not provide correlations specific to tax evasion.

terms of the distance-to-next-higher-bracket. The latter result highlights the idiosyncratic nature of this variable, which forms the basis of our identification strategy.

2.4 Estimation strategy

To examine the intergenerational link in tax evasion behavior in a more systematic way, we relate in family i the child's non-compliance, NC_i^c, to the father's past non-compliance, NC_i^f:

$$NC^c_{i,t=s} = \alpha + \tau \cdot NC^f_{i,t<s} + \beta \cdot \rho^c_{i,t=s}(dtnhb) + A \cdot X^c_{i,t=s} + B \cdot X^f_{i,t<s} + \epsilon^c_{i,t}, \qquad (1)$$

where the superscripts c and f denote the child and father variables and coefficients. The child's compliance decision is measured when he/she claims the commuter tax allowance for the first time ($t = s$). To rule out reverse causality, we measure the corresponding father's compliance behavior and all his characteristics in some period *before* the child claimed the commuter tax allowance for the first time ($t < s$).[24] The child's compliance behavior also depends on his/her distance-to-next-higher-bracket, $\rho^c_{i,t=s}(\cdot)$, and a variety of the observable child ($X^c_{i,t=s}$) and father ($X^f_{i,t<s}$) characteristics. The unobserved error term is captured by $\epsilon^c_{i,t}$.

We control for the child's distance-to-next-higher-bracket (*dtnhb*) by including binary indicators capturing the following intervals: $[0-5)$ km, $[5-10)$ km, and $>= 10$ km. The other control variables (X^c, X^f) comprise the father's and child's true commuting distance (measured in km). These enter linearly, squared, and with a binary indicator for short commuting distances (<10 km). Further, there are a variety of socioeconomic characteristics comprising sex, year of birth (binary indicators), citizenship (Austrian vs. non-Austrian), educational attainment (academic degree), occupation (blue- vs. white-collar worker), sector of employment (17 binary indicators), firm size (binary indicator for employment in a firm with more than 10 employees), individual earnings, and region of residence (9 binary indicators).

Sources of endogeneity An obvious problem in the estimation of Equation (1) is the potential endogeneity of $NC^f_{i,t<s}$. In particular, we are concerned that the father's tax evasion behavior is correlated with any unobserved determinant of children's compliance behavior included in $\epsilon^c_{i,t}$. Potential candidates for confounding factors can be either genetic or environmental. Researchers have identified genes that are associated with criminal behavior (Veroude et al., 2016). If these genetic factors are also relevant for tax compliance,

[24] When the father did not claim the commuter allowance in the year before the child started claiming, but rather claimed in an other year in the past, we take the closest year before the child's first time of claiming. This results in an average time difference between these two measurements of 3.5 years, with a median of 2 years.

and if these are inherited from father to children, Equation (1) would suffer from endogeneity. Alternatively, father and child could share unobserved environmental factors such as a subjective evaluation of the deterrence parameters. These two sources of endogeneity would lead to an upward biased τ. Thus, to obtain an unbiased τ that can be interpreted causally, we need exogenous variation in the father's compliance behavior.

2.5 Instrumental variable strategy

We suggest using the variation in the father's distance-to-next-higher-bracket as an IV for his compliance. Following the pattern observed in the data (see Figure 1) we associate a greater distance-to-next-higher-bracket with a higher compliance rate for these fathers.[25] The identifying assumption of this IV strategy is that the father's distance-to-next-higher-bracket is randomly assigned conditional on our covariates, and this affects the child's compliance behavior only through the channel of parental non-compliance. This implies, i. e. absence of parental sorting across distance-to-next-higher-bracket or systematic sorting of children into home or firm location depending on father's distance-to-next-higher-bracket. While in general this assumption is fundamentally untestable, we provide a number of falsification and plausibility checks confirming the idiosyncratic and exogenous nature of the bracket thresholds created by the tax law.

Firstly, we check whether we observe any sorting or bunching of commuters around the bracket thresholds. Therefore, we examine the distribution of the father's true commuting distance to work. We report a Kernel density plot to visually detect potential excess clustering around the bracket thresholds. Figure 2 displays the fathers' distance distribution, with the dashed lines representing the thresholds at which the allowance discontinuously jumps. We find no evidence of sorting or bunching of commuters around these bracket thresholds defined by the tax law. There is no observable spike or hump in the distance distribution around any of the three bracket thresholds. To further substantiate this finding, Figure 3 zooms in on each bracket threshold and provides McCrary tests to detect signs of discontinuity (McCrary, 2008). The estimate of the log change in height and its bootstrapped standard error are displayed directly on each graph and these confirm that we cannot detect a lack of continuity at any of the thresholds. We obtain an equivalent result when using bunching estimations in the spirit of Saez (2010); in other words, we find no evidence of excess clustering at any threshold (see Figure B.3 in the Web Appendix B.3.) All these findings strongly suggest that the bracket thresholds we used to construct our IV are exogenous to commuting distance. Put differently, there is no evidence that the bracket thresholds influence the location or commuting decisions of our population.

[25] The observation that taxpayers close to a bracket threshold are more prone to cheat may be explained by different perceptions of the detection risk, or by having lower psychic or social norm costs of overreporting.

Secondly, we check whether there is any correlation between the father's and child's distance-to-next-higher-bracket. We split the data into 20 equal-sized bins based on the distance-to-next-higher-bracket of the father and plot the mean distance-to-next-higher-bracket of the child within each bin. The resulting binned scatter plot in Figure 4 shows that there is no relationship between the distance-to-next-higher-bracket of the father (our IV) and that of the child. This finding indicates that there is no systematic sorting of children into home or firm location depending on their father's distance-to-next-higher-bracket.

Thirdly, we perform balancing tests to check whether children's observable characteristics vary with their father's distance-to-next-higher-bracket. Therefore, we distinguish between three groups with a low, medium, and high distance-to-next-higher-bracket, which are defined by the following intervals: $[0-5)$ km, $[5-10)$ km, and $>= 10$ km. Panel A of Table 5 compares the average child characteristics across these three groups defined by the father's distance-to-next-higher-bracket. It turns out that the children, despite having fathers with different distances to the next threshold, are observationally identical. Panel B of Table 5 compares the average father characteristics. Again, we observe that the groups are essentially identical.

Overall, we do not find a systematic relationship between individual characteristics and the distance-to-next-higher-bracket, which forms the basis for our IV. In line with the graphical evidence presented above, our balancing tests confirm the premise that assignment to a distance-to-next-higher-bracket is as good as random and not affected by any systematic sorting of individuals. Importantly, this also holds for the selection of children into claiming the major commuter allowance (see the Web Appendix B.2 for details).

Functional form of the first stage It is *a priori* unclear which functional form should be used to describe the relationship between the father's distance-to-next-higher-bracket and his tax compliance. We explore several alternative specifications of the first-stage relationship in Table 6. The dependent variable is in each case a binary variable equal to one if the father evades taxes, and zero otherwise. In columns (1) to (4), we use semi-parametric specifications based on varying binary indicators for the different distance-to-next-higher-bracket intervals. In column (5), we use a linear specification of the distance-to-next-higher-bracket. Across all specifications we see that a higher distance-to-next-higher-bracket significantly reduces the likelihood of cheating. For instance, the specification in column (1) shows that fathers with a distance-to-next-higher-bracket between 5 and 20 km are about 31 percentage points less likely to cheat compared with fathers with a distance-to-next-higher-bracket of 5 km or less. While the predictive power varies across the specifications, the F-statistics are all above 460. We replicate the analysis for the two alternative measurements of tax evasion. In Table 7, the dependent variable is the overclaimed amount relative to the father's income, and in Table 8 the overclaimed amount in Euros is used. In both cases, we observe a significant negative effect of the distance-to-next-higher-bracket on the extent of tax evasion, with sufficiently high F-statistics.

This set of estimations shows that the choice of the specific functional form of the first stage should not be decisive. As a baseline specification, we pick the semi-parametric specification from column (2) and provide the second-stage results for the other specifications in the sensitivity analysis section.

3 Estimation results

3.1 Intergenerational causal effect in tax evasion behavior

Table 9 summarizes our main estimation results. For each of our three tax evasion indicators, we list the results from a simple OLS estimation and the second-stage estimates from a 2SLS estimation using the IV strategy described above. Both estimation methods provide evidence of a significant positive effect of the father's tax compliance behavior on child's compliance. Across all indicators, the 2SLS estimates are larger than the OLS estimates; however, the 95 percent confidence intervals overlap in each case. Our *a priori* belief about the source of endogeneity would imply a comparably smaller 2SLS estimate. The pattern of the larger 2SLS estimates is not uncommon in the well-established literature on intergenerational income persistence (Havari and Savegnago, 2016) for two reasons: First, the 2SLS estimates correct both for classical measurement errors (which lead to a downward-biased OLS estimate) and for the endogeneity of the dependent variable. The former effect may dominate the latter one. Second, the 2SLS estimate is a *local average treatment effect* that refers to the specific sub-population whose behavior is affected by the IV being used (Imbens, 2010). By contrast, the OLS estimate provides an *average effect treatment*. The local average treatment effect may simply be larger than the (true) average treatment effect.

The 2SLS estimates suggest a substantial intergenerational causal effect in tax evasion behavior. The non-compliance of a father increases the likelihood of cheating for his child by 4.6 percentage points (see column (2)). Given an average non-compliance rate of 20 percent for children, the estimated effect amounts to a 23 percent increase in non-compliance among children. We interpret this result as evidence of an intergenerational transmission of tax morale that is non-negligible. While the underlying transmission mechanism (see footnote 2) cannot be disentangled within our research design, we consider the transmission of social norms and/or of information as plausible causal pathways. The estimations using the other two indicators also provide information on the intensive margin: an increase in the overclaimed amount by the father of 1 percent of his income leads to an increase in the overclaimed amount by the child of 0.1 percent (see column (4)). In absolute terms, we observe that an increase by one Euro leads to an increase of about 6 cents (see column (6)). The respective beta coefficients are comparable (0.056 compared with 0.051). All these estimates are significant at least at the 5 percent level and based on sufficiently strong IVs. The intergenerational causal effect is thus smaller along the intensive margin (compared with the extensive one). This results from the cap on the deductible amount defined by the commuter allowance (see Table 1).

When looking at the covariates included in the model, we consistently find that only the child characteristics are decisive. Notably, all the estimated effects of the covariates (child and father characteristics) are almost identical in the 2SLS and OLS models. Thus, there seem to be no large correlations between the IVs and covariates. The most important determinant is the child's own distance-to-next-higher-bracket. As expected, a shorter distance-to-next-higher-bracket increases non-compliance considerably. The size of the estimated coefficients is comparable to those of the father in the respective first stage estimations. The effect of income on tax evasion is complex. We find that the probability of cheating and the overclaimed amount in Euros rises with income, while the overclaimed amount relative to income decreases with income. Remarkably, this finding is fully consistent with neo-classical model of income tax evasion. Allingham and Sandmo (1972) suggest that evasion increases with gross income, while the effect on the fraction of income evaded depends on relative risk aversion.[26] Our finding implies that individuals exhibit a decreasing relative risk aversion. Moreover, we find that non-compliance is more wide-spread among white-collar workers. There are no significant differences in compliance behavior between men and women, Austrians and foreigners, and individuals with and without university degrees.

3.2 Placebo test

One relevant threat to the identification of a causal effect are environmental factors shared by fathers and children, such as subjective evaluations of deterrence parameters. In Section 2.5 we provide evidence for the idiosyncratic nature of our IV (i. e., the distance-to-next-higher-bracket), which should resolve this endogeneity problem. As an additional test for the validity of our identification strategy, we conduct a test based on *placebo* father–child pairs. In particular, we assign each father to a child in our dataset, who is closest in terms of observable characteristics to his own child. The idea of this test is that this placebo father–child pair should be exposed to comparable environmental factors, despite having no intergenerational link. If we would find a link in the tax evasion behavior of this placebo father–child pair, this could only be explained by confounding environmental factors. If we would not find an intergenerational link, this would suggest

[26] In the Web Appendix B.4, we use survey data to replicate our estimation for the widely used self-reported tax morale. We observe that tax morale is higher among females, married individuals, older people, and those residing in more rural areas. It deteriorates with rising income, higher educational attainment and it is lower among self-employed individuals.

that no confounding environmental factors are present.

To implement the match of placebo father–child, we use nearest neighbor matching based on the following list of observable characteristics: total commuting distance, distance-to-next-higher-bracket, sex, year of birth, citizenship, educational attainment, occupation, earnings, firm size, sector of employment, and zip-code of residence. To increase the quality of our matches, we allow for replacement when applying the nearest neighbor match. Table 10 reproduces the estimations presented in Table 9 based on these placebo father–child pairs. Across all tax evasion indicators and methods, we find no significant effect of the matched placebo father's tax compliance behavior on the child's compliance. Thus, the result suggests that our main results are not driven by shared environmental factors, but solely relate to the intergenerational transmission from fathers to children.

3.3 Sensitivity analysis

We conducted several additional analyses to verify the robustness of our findings. Table 11 summarizes the estimation results from selected alternative specifications of our estimation model. The estimates of the intergenerational causal effect in tax evasion turn out to be robust.

Alternative first-stage specifications In the first two columns, we employ different functional form specifications of our first stage. In column (1), we use a semi-parametric specification based on four distance-to-next-higher-bracket intervals (see column (3) of Table 6). The resulting second-stage estimates are identical to our baseline estimates. In column (2), we use a linear specification of distance-to-next-higher-bracket intervals (see column (5) of Table 6). The resulting second-stage estimates are somewhat smaller, but still statistically significant. These tests corroborate that the identification of the causal effect is not driven by the specific functional form in the first stage.

Alternative estimation samples In the next two columns, we modify our estimation sample. In column (3), we also include fathers with a true commuting distance of more than 60 km. We originally excluded these observations, since these fathers are not at risk of cheating owing to the construction of the commuter tax allowance. The inclusion of these additional observations changes our estimates only marginally. In column (4), we exclude all observations with fathers and/or children with comparably short commuting distances (less than 8 km). The measurement error of the true commuting distance may be larger for this group. The estimated effects, however, hardly change in this reduced sample.

Controlling for the behavior of other peers In the remaining three columns, we control for the impact of other potential peer groups. Children's tax compliance behavior might also be influenced by their friends or co-workers. We approximate their circle of friends by referring to residents from the child's zip-code area born in the same year. We start by calculating the mean distance-to-next-higher-bracket among this group, to which we refer below for simplicity as 'friends'. A potential concern might be that the father's distance-to-next-higher-bracket is correlated with those of the child's friends. To test for this possibility, column (5) controls for the mean distance-to-next-higher-bracket of the child's friends. Our estimates change only marginally. In column (6), we additionally control directly for the cheater share among the child's friends. While this additional control variable turns out to be statistically significant positive, our estimates of the intergenerational causal effect in tax evasion hardly change following the inclusion of this additional variable. Finally, in column (7), we control for the cheater share among the child's co-workers. In line with Paetzold and Winner (2016), we find a positive and strong relationship between the share of cheating co-workers and individual propensity to cheat. Again, the estimates of the intergenerational causal effect remain stable.

4 Evidence on siblings

Is the causal link in tax evasion behavior unique to parents and their children, or do links exist in other networks as well? The siblings correlations presented in Section 2.3, and the final two sensitivity checks discussed in the previous section, which accounted for cheating among friends and co-workers, provide suggestive evidence for spillovers across other groups. In fact, the siblings and the intergenerational correlations are quite comparable in magnitude. In particular, the link between two brothers is quite strong (see Table 4). For friends and co-workers we also find substantial correlations. Based on the estimations presented in columns (6) and (7) of Panel A of Table 11, we find that an increase in the cheating share among the child's friends and co-workers by one standard deviation is associated with an increased likelihood of the child cheating of about 7 and 5 percentage points, respectively. Evidently, it is unclear to which degree these correlations capture a causal effect.

In this final section, we aim to identify the *intra*-generational causal effect in tax evasion behavior. We assume that the sibling who claimed the major commuter tax allowance first, may causally affect the compliance decision of the other sibling.[27] Our empirical specification using $9,650$ pairs of siblings is equivalent to that summarized by eq. (1). Thus, we relate the tax compliance decision of the younger sibling to the past compliance of the older sibling. We use the distance-to-next-higher-bracket of the

[27] We use the same sample selection criteria as for our main analysis (of father–child pairs), but focus now on all siblings, who claim the major commuter tax allowance, are born after 1973, are born to married mothers, and are active on the labor market. The unit of observation is a pair of first–claiming sibling—later–claiming sibling, in the year in which the later–claiming sibling is applying for the major commuter tax allowance for the first time. For the sake of simplicity, we refer below to the former as the 'older sibling', and to the latter as the 'younger sibling'. All covariates of the older sibling are measured before the younger sibling's year of observation.

older sibling as an IV for his/her tax evasion decision, and we assume that this variable affects the younger sibling's compliance behavior only through the older sibling's behavior. Under the validity of this assumption, the IV strategy solves the reflection problem of simultaneity.

Our findings summarized in Table 12 point to an *intra*-generational causal effect in tax evasion behavior that is very comparable to the intergenerational causal effect. For instance, according to column (2), the non-compliance of the older sibling increases the likelihood of cheating of her/his younger sibling by 4.4 percentage points. Or, in absolute terms, we observe that an increase by one Euro leads to an increase of 6 cents (see column (6)). However, the estimated effects for siblings, have to be interpreted with some caution. Despite a very strong first stage, we obtain less precise second-stage estimates here.

5 Conclusions

Tax evasion is a widespread phenomenon that redistributes income from honest to dishonest citizens. The fight against tax evasion is a typical aspect of political agendas in order to increase tax revenues and raise the efficiency of government. Tax evasion has also attracted the attention of scholars from various academic disciplines. There seems to be interdisciplinary agreement that individuals are motivated not only by the rate of return on tax evasion, but also by other motivations (usually called *tax morale*). Unfortunately, it is notoriously hard to test this supposition empirically. The key limitation is that tax evasion and tax morale are usually not observable to the researcher.

In this study, we resolve these key limitations. We focus on the case of the commuter tax allowance in Austria and combine various administrative data sources to observe actual tax evasion behavior with relatively little error at the individual level. We test the hypothesis that the family is important in shaping individual tax morale and is thus an important determinant of tax evasion. In a first step, we show the significant *intergenerational association* in tax compliance. In a second step, we utilize exogenous variation in the father's tax evasion behavior to identify an *intergenerational causal effect* in tax evasion behavior. By exploiting the strong idiosyncratic variation in the father's distance-to-next-higher-bracket (our IV), we are able to show that paternal non-compliance increases children's non-compliance by about 23 percent. We also find evidence for spillovers across siblings.

To highlight the economic significance of the estimated intergenerational causal effect of tax evasion, we suggest a thought experiment, where we eliminate non-compliance among one generation of cheating fathers and approximate the changing behaviour of their children. In our sample, 20 percent of the children and 16 percent of the fathers are cheating. Among the 20 percent of cheating children, 19.2 percent have also a cheating father. We assume that only this sub-set of 3.84 percent of all children is affected by our thought experiment. Referring to our IV-estimate an elimination of the intergenerational transmission of *non*-compliance would reduce cheating in the children's generation from 20 to 18.97 percent. In the year 2012 approximately 1.1 million Austrians received a commuter allowance (both schemes). Thus, our thought experiment would reduce the number of cheaters in the Austrian population of commuters from about 220.000 to 208.670. In each calendar year, these newly compliant taxpayers would pay around 3.39 Mio in additional taxes. This additional tax revenue would accrue every year and result in a present value of about 204,76 Mio for an annual interest rate of 2 percent and a working life of 40 years. This amount is equal to 1.14 percent of the total income tax revenue collected in the year 2012. This simple calculation abstracts from further tax revenue gains, which arise due to the effect on future generations. Hence, a policy intervention which helps reducing tax evasion today has not only an immediate present effect but also generates a positive future externality.

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6 Tables and figures (to be placed in the article)

Table 1: Commuter allowances in the Austrian tax code in Euro

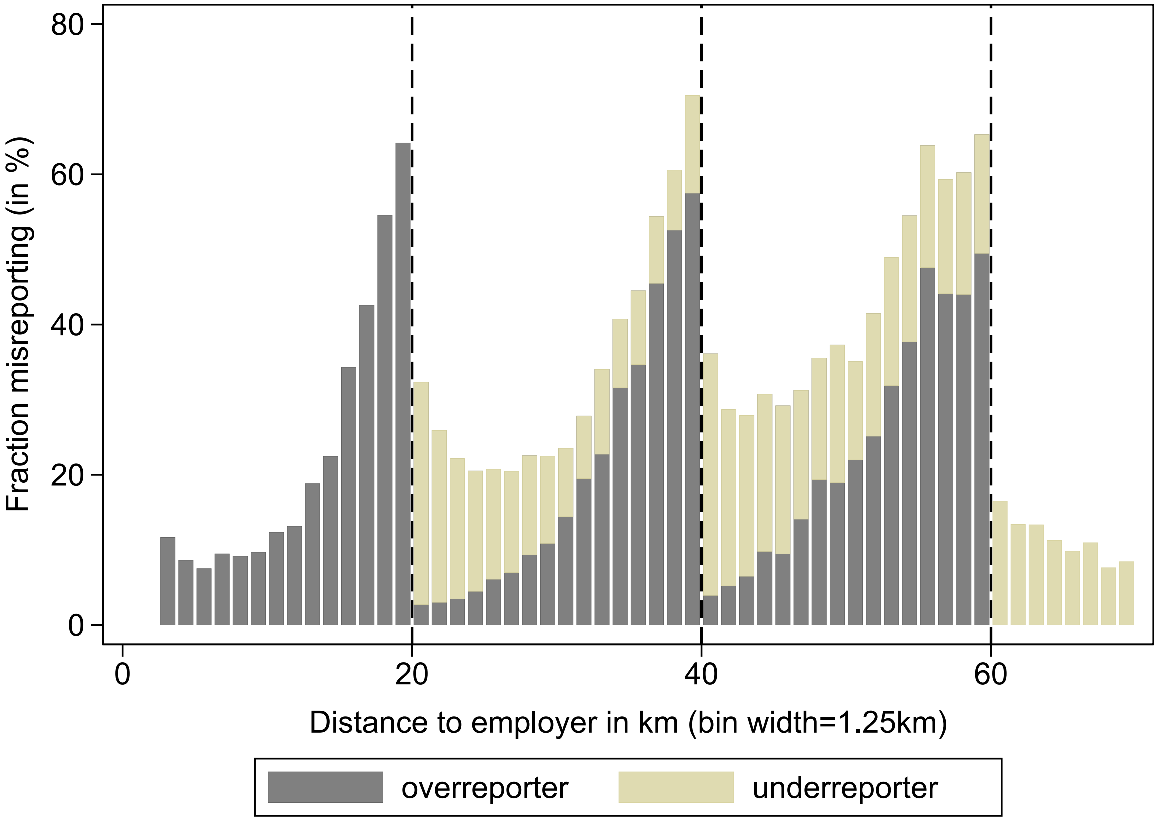
Commuting distance bracket	**Public transport** available ('minor scheme')	**Public transport** not available ('major scheme')
(2–20] km	–	372
(20–40] km	696	1,476
(40–60] km	1,356	2,568
>60 km	2,016	3,672

Table 2: Misreporting by commuting distance brackets (cohorts born 1974-1994)

Commuting distance bracket	**Number of commuters**	**Misreporters (in percent):** Under-reporters	**Misreporters (in percent):** Over-reporters = Tax cheaters
(2–20] km	83,538	12.7	–
(20–40] km	86,510	5.6	21.3
(40–60] km	29,877	6.2	38.3
>60 km	22,531	–	31.2
All intervalls	222,456	7.8	16.6

Notes: This table summarizes misreporting of cohorts born between 1974-1994 (who have received the commuter allowance at least once) by commuting distance brackets intervals. Misreporting is measured when commuters receive the allowance for the first time (which was on average in the year 2006). Two types of misreporting are distinguished: underreporting and overreporting. The latter is equivalent to tax evasion.

Figure 1: Share of misreporters by commuting distance



Notes: This figure displays the percent share of misreporters by commuting distance. Each bar is broken down between misreporters who overreport (dark area) and misreporters who underreport (light area). To give an example, the total fraction of misreporters in the 38.75-40km bin is 69 percent, with 58 percent over- and 11 percent underreporter. The dashed lines represent the thresholds, where the allowance discontinuously increases to a higher amount (at 20, 40, and 60 km, respectively).

Table 3: Average characteristics of father and child

	Father	**Child**
Socioeconomic characteristics:		
Age	47.2	23.6
	(6.1)	(3.7)
Female		0.43
White collar worker	0.31	0.48
Foreigner	0.177	0.125
Academic degree	0.004	0.046
Log of annual taxable income	10.40	10.06
	(0.394)	(0.383)
Tax evasion indicators:		
Cheater (1/0)	0.158	0.200
Overclaimed amount/income	0.010	0.017
	(0.025)	(0.041)
Overclaimed amount in Euro	183.3	235.7
	(435.4)	(493.3)
True commuting distance:		
Distance in km	21.3	24.7
	(13.2)	(13.7)
Distance-to-next-higher-bracket:		
Distance-to-next-higher-bracket in km	9.54	9.57
	(5.26)	(5.49)
Number of observations	15,308	

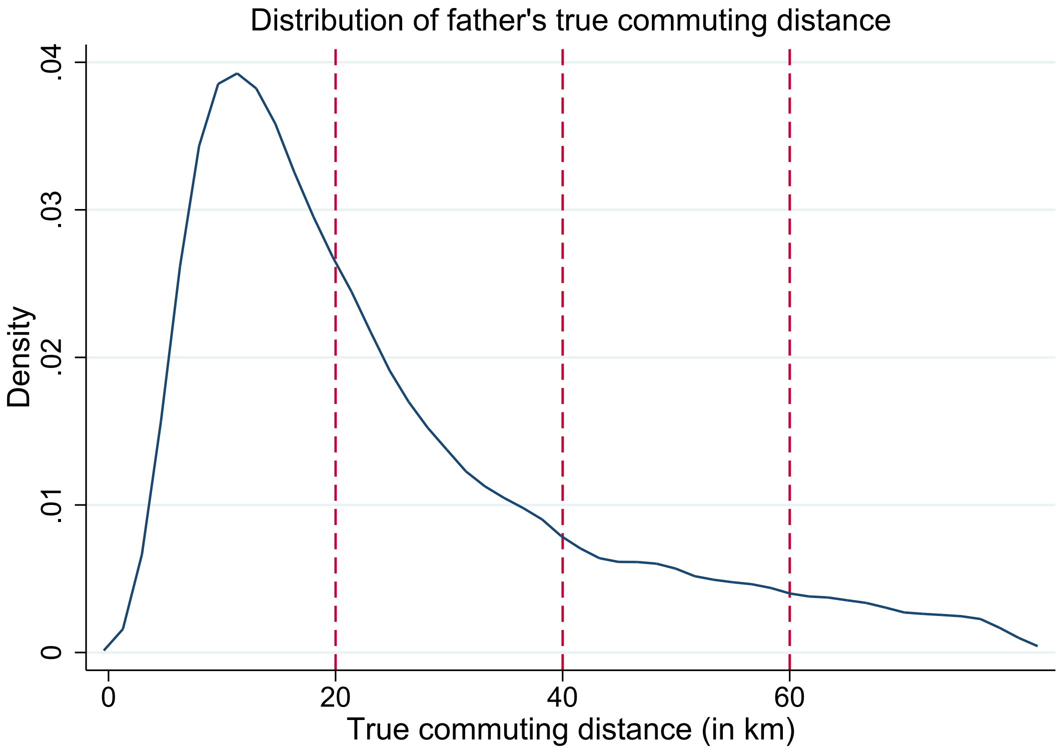
Notes: Standard deviations in parenthesis.

Table 4: Intergenerational correlations in earnings, tax evasion, and in commuting behavior

	Father–child correlations			**Sibling correlations**[a]		
	All	Sons	Daughters	All	Brothers	Sisters
Individual earnings:						
Intergenerational elasticity	0.151***	0.149***	0.159***	0.129***	0.123***	0.132***
	(0.008)	(0.010)	(0.011)	(0.010)	(0.012)	(0.014)
Rank–rank correlation	0.180***	0.184***	0.172***	0.146***	0.074***	0.170***
	(0.008)	(0.010)	(0.012)	(0.010)	(0.014)	(0.016)
Tax evasion indicators:[b]						
Cheating	0.048***	0.045***	0.052***	0.052***	0.069***	0.032**
	(0.009)	(0.012)	(0.014)	(0.010)	(0.014)	(0.015)
Overclaimed amount/income	0.055***	0.038**	0.084***	0.037***	0.036***	0.036**
	(0.013)	(0.016)	(0.023)	(0.009)	(0.011)	(0.016)
Overclaimed amount in Euro	0.049***	0.045***	0.056***	0.054***	0.065***	0.039**
	(0.009)	(0.012)	(0.014)	(0.010)	(0.014)	(0.016)
Commuting distance and distance-to-next-higher-brackets:[b]						
Commuting distance (in km)	0.112***	0.123***	0.097***	0.105***	0.119***	0.088***
	(0.008)	(0.011)	(0.013)	(0.011)	(0.014)	(0.016)
Distance-to-next-higher-bracket (in km)	-0.003	0.002	-0.010	0.009	0.009	0.009
	(0.008)	(0.011)	(0.013)	(0.010)	(0.013)	(0.016)
Number of observations	15,308	8,663	6,645	9,650	5,465	4,185

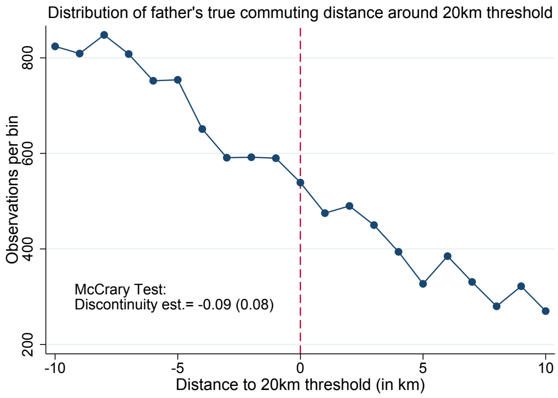
Notes: Stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The sibling correlations are computed between the first-claiming sibling and his/her later-claiming siblings. Hence, the sample consists of all sibling pairs, where both receive the major commuter allowance. The construction of the sibling sample follows exactly the sample selection criteria for our main estimation sample of father–child pairs (see section 2.2).
[b] Statistics shown in this category are simple pairwise correlations with standard deviations in brackets below.

Figure 2: Distribution of father's true commuting distance

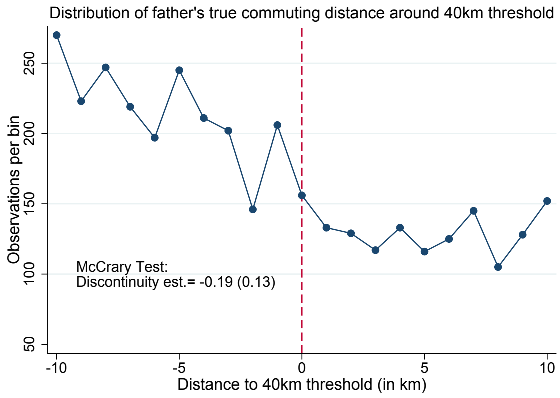


Notes: This figure plots the kernel density of the father's true commuting distance with a bandwidth of 1.25 km. The dashed lines represent the thresholds, where the allowance discontinuously increases to a higher amount (at 20, 40, and 60 km, respectively).

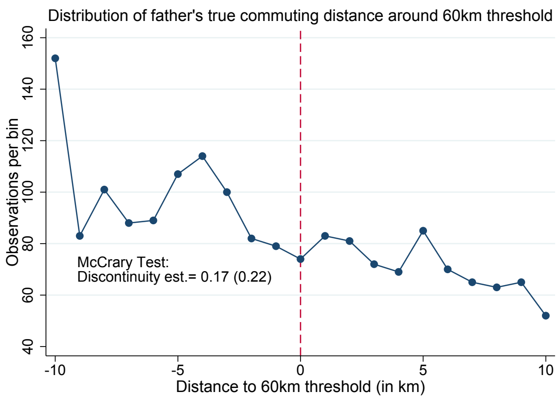
Figure 3: Distribution of father's true commuting distance around bracket thresholds



(a) Panel A



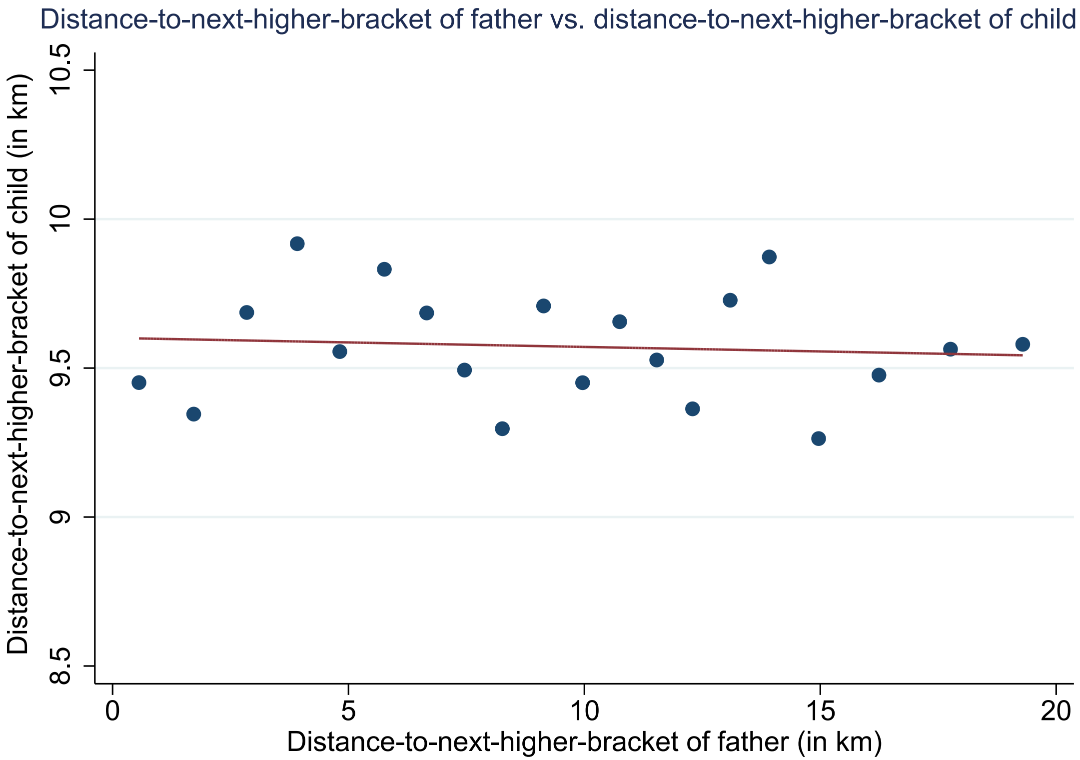
(b) Panel B



(c) Panel C

Notes: The figure assesses the smoothness of the distribution of fathers' true commuting distance around the bracket thresholds. In each panel, we put taxpayers in 1km wide bins of distance-to-next-higher-bracket and plot the number of individuals within these bins. The dashed lines represent the bracket thresholds where the allowance discontinuously increases (i. e. zero represents the 20, 40, and 60 km threshold, respectively). Each graph also displays a McCrary test of the discontinuity of the probability density function at the respective bracket threshold.

Figure 4: Distance-to-next-higher-bracket of father vs. distance-to-next-higher-bracket of child



Notes: The figure displays the relationship between the distance-to-next-higher-bracket of the father (our IV) and the distance-to-next-higher-bracket of the child. To construct the figure, we split the data into 20 equal-sized bins based on the distance-to-next-higher-bracket of the father, and plot the mean distance-to-next-higher-bracket of the child within each bin. The figure shows no systematic relationship between the distance-to-next-higher-bracket of the father and the distance-to-next-higher-bracket of the child.

Table 5: Average child and father characteristics by father's distance-to-next-higher-bracket

	Father's distance-to-next-higher-bracket			
	$0-5$km	$5-10$km	$10-20$km	All
Panel A: Child characteristics				
Female	0.43	0.45	0.43	0.43
Log of annual taxable income	10.07	10.06	10.06	10.06
Academic degree	0.05	0.05	0.04	0.05
Age	23.63	23.68	23.55	23.61
White collar worker	0.48	0.49	0.48	0.48
Foreigner	0.11	0.12	0.13	0.12
Employed in large firm[a]	0.41	0.42	0.41	0.42
Size of ZIP-code area	40.90	41.10	40.19	40.63
Commuting distance (in km)	24.95	24.87	24.38	24.66
Distance-to-next-higher-bracket (in km)	9.59	9.60	9.55	9.57
Panel B: Father characteristics				
Log of annual taxable income	10.42	10.39	10.39	10.40
Academic degree	0.01	0.00	0.00	0.00
Age	47.14	47.27	47.26	47.24
White collar worker	0.32	0.30	0.31	0.31
Foreigner	0.17	0.18	0.18	0.18
Employed in large firm[a]	0.49	0.47	0.47	0.47
Size of ZIP-code area	40.94	41.59	37.92	39.71
Commuting distance (in km)	25.58	20.09	20.01	21.34
Number of observations	3,604	4,501	7,203	15,308

[a] Binary indicator for employment in a firm with more than 10 employees.

Table 6: Alternative specifications of the first stage — binary cheating variable

	(1) **2 IV categories**	(2) **3 IV categories**	(3) **4 IV categories**	(4) **5 IV categories**	(5) **Linear IV**
Father's distance-to-next-higher-bracket:					
0-2 km				Base group	
0-5 km	Base group	Base group	Base group		
5-20 km	-0.314***				
	(0.010)				
2-5 km				-0.227***	
				(0.018)	
5-10 km		-0.241***	-0.242***	-0.388***	
		(0.011)	(0.011)	(0.016)	
10-20 km		-0.397***			
		(0.010)			
10-15 km			-0.382***	-0.519***	
			(0.012)	(0.017)	
15-20 km			-0.406***	-0.546***	
			(0.010)	(0.015)	
linear in km					-0.028***
					(0.001)
Father and child covariates[a]	Yes	Yes	Yes	Yes	Yes
Number of observations	15,308	15,308	15,308	15,308	15,308
Mean of dep. variable	0.16	0.16	0.16	0.16	0.16
F-test of weak instrument	1089.92	745.87	555.53	461.23	1770.20
Shea's R-squared	0.13	0.15	0.15	0.17	0.14

Notes: Standard errors clustered on families in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] We control for the following characteristics of father and child: year of birth (binary indicators), citizenship (Austrian vs. non-Austrian), educational attainment (academic degree), occupation (blue- vs. white-collar worker), sector of employment (17 binary indicators), firm size (binary indicator for employment in a firm with more than 10 employees), individual earnings, region of residence (9 binary indicators), commuting distance in km (linearly, squared, and with a binary indicator for short commuting distances <10 km), size of ZIP-code area of residence (linear and squared). Further we control for the child's sex and distance-to-next-higher-bracket, where we include binary indicators capturing the following intervals: $[0-5)$ km, $[5-10)$ km, and >= 10 km.

Table 7: Alternative specifications of the first stage — overclaimed amount/income

	(1) **2 IV categories**	(2) **3 IV categories**	(3) **4 IV categories**	(4) **5 IV categories**	(5) **Linear IV**
Father's distance-to-next-higher-bracket between:					
0-2 km				Base group	
0-5 km	Base group	Base group	Base group		
5-20 km	-0.018***				
	(0.001)				
2-5 km				-0.013***	
				(0.001)	
5-10 km		-0.014***	-0.014***	-0.022***	
		(0.001)	(0.001)	(0.001)	
10-20 km		-0.022***			
		(0.001)			
10-15 km			-0.021***	-0.029***	
			(0.001)	(0.001)	
15-20 km			-0.023***	-0.031***	
			(0.001)	(0.001)	
linear in km					-0.002***
					(0.000)
Father and child covariates[a]	Yes	Yes	Yes	Yes	Yes
Number of observations	15,299	15,299	15,299	15,299	15,299
Mean of dep. variable	0.01	0.01	0.01	0.01	0.01
F-test of weak instrument	781.09	504.67	376.93	300.11	1168.37
Shea's R-squared	0.09	0.10	0.10	0.12	0.10

Notes: Standard errors clustered on families in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] See respective note to Table 6.

Table 8: Alternative specifications of the first stage — overclaimed amount in Euro

	(1) **2 IV categories**	(2) **3 IV categories**	(3) **4 IV categories**	(4) **5 IV categories**	(5) **Linear IV**
Father's distance-to-next-higher-bracket between:					
0-2 km				Base group	
0-5 km	Base group	Base group	Base group		
5-20 km	-356.050***				
	(11.113)				
2-5 km				-266.323***	
				(21.234)	
5-10 km		-270.151***	-271.369***	-442.628***	
		(12.911)	(12.944)	(19.353)	
10-20 km		-452.882***			
		(12.122)			
10-15 km			-434.923***	-595.279***	
			(14.361)	(19.831)	
15-20 km			-463.881***	-627.573***	
			(11.867)	(18.214)	
linear in km					-31.457***
					(0.778)
Father and child covariates[a]	Yes	Yes	Yes	Yes	Yes
Number of observations	15,300	15,300	15,300	15,300	15,300
Mean of dep. variable	183.71	183.71	183.71	183.71	183.71
F-test of weak instrument	1026.54	698.13	510.87	420.30	1636.72
Shea's R-squared	0.12	0.13	0.13	0.16	0.13

Notes: Standard errors clustered on families in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] See respective note to Table 6.

Table 9: Estimation of the intergenerational causal effect in tax evasion behavior

	(1)	(2)	(3)	(4)	(5)	(6)
	Cheating (0/1)		**Overclaimed amount/income**		**Overclaimed Euros**	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Father is cheating (0/1)	0.039***	0.046**				
	(0.009)	(0.022)				
Father's overclaimed amount/income			0.043***	0.091**		
			(0.014)	(0.040)		
			[0.025]	[0.056]		
Father's overclaimed amount in Euro					0.038***	0.056**
					(0.010)	(0.024)
					[0.033]	[0.051]
Child characteristics						
Distance-to-next-higher-bracket betw. 5-10 km	−0.295***	−0.295***	−0.023***	−0.023***	−326.688***	−326.757***
	(0.010)	(0.010)	(0.001)	(0.001)	(12.236)	(12.187)
Distance-to-next-higher-bracket above 10-20 km	−0.400***	−0.400***	−0.032***	−0.032***	−451.745***	−451.646***
	(0.009)	(0.009)	(0.001)	(0.001)	(10.490)	(10.449)
Female	0.002	0.002	−0.000	−0.000	−4.073	−3.894
	(0.007)	(0.007)	(0.001)	(0.001)	(9.195)	(9.160)
Log income	0.056***	0.056***	−0.014***	−0.014***	75.447***	75.186***
	(0.008)	(0.008)	(0.002)	(0.002)	(10.707)	(10.679)
Academic degree	−0.029	−0.028	−0.001	−0.001	−23.693	−22.870
	(0.020)	(0.019)	(0.002)	(0.002)	(25.564)	(25.441)
White-collar	0.027***	0.027***	0.002***	0.002***	41.260***	41.222***
	(0.007)	(0.007)	(0.001)	(0.001)	(9.052)	(9.022)
Foreigner	0.006	0.006	0.000	0.000	11.246	11.536
	(0.009)	(0.009)	(0.001)	(0.001)	(11.500)	(11.466)
Commuting distance in km	0.002**	0.002**	0.000***	0.000***	1.688	1.684
	(0.001)	(0.001)	(0.000)	(0.000)	(1.136)	(1.133)
Size of ZIP-code area	−0.000	−0.000	−0.000	−0.000	−0.352	−0.356
	(0.000)	(0.000)	(0.000)	(0.000)	(0.284)	(0.283)
Squared size of ZIP-code area	−0.000*	−0.000*	−0.000	−0.000	−0.002	−0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
Father characteristics						
Log income	0.008	0.007	0.000	0.001	−4.631	−5.198
	(0.010)	(0.010)	(0.001)	(0.001)	(12.347)	(12.357)
Academic degree	−0.001	−0.001	0.003	0.003	−0.213	−0.464
	(0.048)	(0.048)	(0.005)	(0.005)	(59.960)	(59.543)
White-collar	0.006	0.005	0.001	0.001	9.626	8.955
	(0.008)	(0.008)	(0.001)	(0.001)	(10.069)	(10.033)
Foreigner	0.003	0.003	−0.001	−0.001	6.233	6.457
	(0.008)	(0.008)	(0.001)	(0.001)	(10.089)	(10.065)
Commuting distance in km	−0.001	−0.001	−0.000	−0.000	−1.578	−1.579
	(0.001)	(0.001)	(0.000)	(0.000)	(1.607)	(1.601)
Commuting distance in km squared	0.000	0.000	0.000	0.000	0.023	0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.026)
Size of ZIP-code area	0.000	0.000	0.000	0.000	0.135	0.149
	(0.000)	(0.000)	(0.000)	(0.000)	(0.311)	(0.309)
Squared size of ZIP-code area	−0.000	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
Further father and child covariates[a]	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	15,308	15,308	15,299	15,299	15,300	15,300
Mean of dep. var.	0.20	0.20	0.02	0.02	235.67	235.67
S.d. of dep. var	0.40	0.40	0.04	0.04	493.86	493.86
R-squared	0.20	–	0.14	–	0.17	–

Notes: This table summarizes 2SLS estimation results of the effect of paternal tax evasion behavior on children's tax evasion behavior. Father's distance-to-next-higher-bracket serves as an IV for the fathers tax evasion decision. Reported estimates are second-stage coefficients with standard errors clustered on families in parentheses below. Values in brackets are beta coefficients. All estimations include child and father birthyear, industry, and regional fixed effects. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level respectively. [a] We further control for the following non-tabulated characteristics of father and child: year of birth (binary indicators), sector of employment (17 binary indicators), firm size (binary indicator for employment in a firm with more than 10 employees), and region of residence (9 binary indicators).

Table 10: Placebo test using statistically matched father–child pairs

	(1)	(2)	(3)	(4)	(5)	(6)
	Cheating (0/1)		**Overclaimed amount/income**		**Overclaimed Euros**	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Father is cheating (0/1)	−0.006	−0.014				
	(0.008)	(0.021)				
Father's overclaimed amount/income			0.001	0.009		
			(0.014)	(0.041)		
Father's overclaimed amount in Euro					−0.004	−0.003
					(0.009)	(0.023)
Father and child covariates[a]	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,308	15,308	15,300	15,300	15,301	15,301
R-squared	0.20	–	0.14	–	0.17	–

Notes: This table summarizes estimation results equivalent to those presented in Table 9, but based on *placebo* father–child pairs. These placebo pairs are created by assigning each father to another child that is closest in terms of observable characteristics to his own child. Closeness is defined via nearest neighbor matching, using the following list of observable characteristics: total commuting distance, distance-to-next-higher-bracket, sex, year of birth, nationality, educational attainment, occupation, earnings, firm size, sector of employment, and zip-code of residence. Standard errors clustered on families in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] All models include the same set of covariates as in Table 9. The father's distance-to-next-higher-bracket serves again as an IV.

Table 11: Sensitivity analysis of the estimation of the intergenerational causal effect in tax evasion behavior

	(1) Alternative first stage: 4 IV categories[a]	(2) Alternative first stage: linear IV[b]	(3) Include very long commuting distances (>60km)[c]	(4) Exclude very short commuting distances (<8km)[d]	(5) Control for av. dist.to-next-higher-bracket among friends[e]	(6) Control for cheater share among friends[f]	(7) Control for cheater share among co-workers[g]
Panel A: Binary cheating variable							
Father is cheating	0.046**	0.036*	0.035**	0.049**	0.046**	0.043**	0.045**
	(0.022)	(0.022)	(0.016)	(0.024)	(0.022)	(0.022)	(0.021)
Av. dist.-to-next-higher-bracket among friends					Yes	Yes	Yes
Cheater share among friends					No	Yes	Yes
Cheater share among co-workers					No	No	Yes
Observations	15,306	15,306	24,292	10,665	14,977	14,977	14,977
Mean of dep. var.	0.20	0.20	0.16	0.22	0.20	0.20	0.20
F-test of weak instrument	555.90	1770.97	763.38	679.65	728.29	729.95	731.37
Panel B: Overclaimed amount/income							
Father's overclaimed amount/income ratio	0.088**	0.075*	0.061*	0.088**	0.088**	0.085**	0.087**
	(0.039)	(0.039)	(0.032)	(0.042)	(0.040)	(0.040)	(0.039)
Av. dis.-to-next-higher-bracket among friends					Yes	Yes	Yes
Cheater share among friends					No	Yes	Yes
Cheater share among co-workers					No	No	Yes
Observations	15,298	15,298	24,280	10,665	14,969	14,969	14,969
Mean of dep. var.	0.02	0.02	0.01	0.02	0.02	0.02	0.02
F-test of weak instrument	383.39	1193.09	538.62	469.01	505.02	505.57	506.47
Panel C: Absolute overclaimed amount							
Father's overclaimed amount in Euro	0.056**	0.044*	0.048***	0.055**	0.057**	0.054**	0.056**
(0.024)	(0.024)	(0.018)	(0.026)	(0.024)	(0.024)	(0.024)	
Av. dist.-to-next-higher-bracket among friends					Yes	Yes	Yes
Cheater share among friends					No	Yes	Yes
Cheater share among co-workers					No	No	Yes
Number of observations	15,298	15,298	24,280	10,665	14,969	14,969	14,969
Mean of dep. var.	235.90	235.90	183.51	254.90	235.90	234.50	234.50
F-test of weak instrument	511.29	1638.06	732.30	635.15	681.84	682.88	684.31

Notes: This table summarizes sensitivity checks of the 2SLS estimation results of the effect of paternal tax evasion behavior on children's tax evasion behavior presented in Table 9. All models include the same set of covariates as in Table 9, and the father's distance-to-next-higher-bracket serves again as an IV. Across panels different measurements of tax evasion behavior are used. Reported estimates are second-stage coefficients with standard errors clustered on families in parentheses below. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level respectively. [a] Estimation results are based on an alternative specification of the first stage, which includes in addition a binary indicator for a father's distance-to-next-higher-bracket between 15-20 km (see column (3) of Table 7). [b] Estimation results are based on an alternative specification of the first stage, which uses father's linear distance-to-next-higher-bracket measure as an IV (see column (5) of Table 7). [c] This estimation sample includes all observations commuting 60 kilometers or more (i. e. those above the highest commuting distance bracket). We include a binary indicator for these commuters as an additional instrument. [d] This estimation sample excludes all observations with fathers and/or children commuting 8 kilometers or less. [e] This specification controls for the mean distance-to-next-higher-bracket among residents from the child's zip-code area, who belong to the same birth cohort (proxy for his/her group of friends). [f] Controls for the share of children's friends who cheat. [g] Controls for the share of children's co-workers who cheat (see, Paetzold and Winner, 2016).

Table 12: Siblings: Estimation of the intra-generational causal effect in tax evasion behavior

	(1)	(2)	(3)	(4)	(5)	(6)
	Cheating (0/1)		**Overclaimed amount/income**		**Overclaimed Euros**	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Older sibling is cheating (0/1)	0.034***	0.044*				
	(0.010)	(0.023)				
Older sibling's overclaimed amount/income			0.026***	0.045*		
			(0.009)	(0.026)		
Older sibling's overclaimed amount (EUR)					0.034***	0.061**
					(0.011)	(0.026)
Siblings' covariates[a]	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	9,650	9,650	9,648	9,648	9,648	9,648
F-test of weak instrument		654.82		429.45		580.51

Notes: This table summarizes 2SLS estimation results of the effect of tax evasion behavior of the older sibling on the younger siblings's tax evasion behavior. The older sibling's distance-to-next-higher-bracket serves as an IV for the older sibling's tax evasion decision. Reported estimates are second-stage coefficients with standard errors clustered on families in parentheses below. Stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] We control for the following characteristics of both siblings: year of birth (binary indicators), citizenship (Austrian vs. non-Austrian), sex, educational attainment (academic degree), occupation (blue- vs. white-collar worker), sector of employment (17 binary indicators), firm size (binary indicator for employment in a firm with more than 10 employees), individual earnings, region of residence (9 binary indicators), commuting distance in km (linearly, squared, and with a binary indicator for short commuting distances <10 km), size of ZIP-code area of residence (linear and squared). Further, we control for the older sibling's distance-to-next-higher-bracket, where we include binary indicators capturing the following intervals: $[0-5)$ km, $[5-10)$ km, and $>= 10$ km.

Web Appendix

This Web Appendix provides additional material discussed in the paper 'The Intergenerational Causal Effect of Tax Evasion: Evidence from the Commuter Tax Allowance in Austria' by Wolfgang Frimmel, Martin Halla, and Jörg Paetzold, which is forthcoming in the *Journal of the European Economic Association.*

A Using exact Addresses from a large Austrian retailer chain

In this section, we present evidence against the concern that the compliance pattern we observe may be driven by measurement error in our commuting distance measure. For this purpose, we rely on an additional dataset from a large Austrian retailer chain (with around 40,000 employees), which provides us with exact residence and workplace addresses (including house numbers) of around 4,500 of its commuting employees, working at one of 546 stores scattered all across Austria. This data also comprises information on the commuter allowance employees received.

A.1 The extent of the measurement error in detecting non-compliance

In a first step, we use this data to illustrate the consequences of the measurement error in our commuting distance measure for the classification of taxpayers into the categories of overreporters, underreporters (and correct-reporters). Therefore, we use the *retailer-data* and first ignore that we have the exact door-to-door distance between the employees' residence and the workplace, and replicate Figure 1 from the paper. Figure A.1 is constructed in exactly the same way as Figure 1 in the main text. Thus, we apply our distance measure based on zip-code level information (i. e., centroid-based measure).[1] Figure A.1 shows a very similar pattern as Figure 1 in the main text: We see a pattern of misreporting which displays a discontinuity in over-and underreporting at each bracket threshold. In a second step, we exploit the availability of exact addresses in the *retailer-data* and calculate exact driving distances between the employees' residence and the workplace (door-to-door). The resulting Figure A.2 is free of any measurement error. In contrast to the equivalent Figure A.1 with measurement error, it displays even clearer discontinuities, with overreporting being much more prevalent than underreporting. The reason why the discontinuity becomes more pronounced using exact addresses is that the zip-code centroid-based distance measure allocates some commuters to the wrong distance-bin, which blurs the actual pattern of misreporting. Hence, the distribution of misreporting found in the tax data as well as in Table A.1 may be seen as a lower bound of the actual level of tax evasion.

Panel A of Table A.1 provides a summary statistic on the shares of different types of taxpayers (overreporters, underreporters, and correct-reporters), depending on whether we use the exact distance measure (column 1) or the rough centroid-based measure (column 2). It confirms what we have seen already from the comparison of Figure A.2 and Figure A.1. Echoing the differences of Figure A.2 and A.1, we find that if anything, overreporting (underreporting) is underestimated (overestimated) in the data based on the centroid-based measure. In contrast, the share of compliers is very similar irrespective of which measurement is used. Panel B of Table A.1 further shows that average commuting distances and the average distances-to-next-higher-bracket (our IV) are very similar irrespective of the measurement error.

Furthermore, we find that only 18% of all commuters assigned as overreporters by using the centroid-measure are in fact compliers (when compared with using the measure

[1]Note that we put commuters into 2km bins instead of 1.25km bins for the retailer data, since we are left with only a few observations for higher-distance bins.

based on exact addresses), and only 7% of all commuters assigned as compliers by using the centroid-measure are in fact cheaters (results not displayed). When plotting the distribution of such wrongly assigned commuters, we find the bulk of them being concentrated in a narrow corridor around each bracket threshold (see Figure A.3).[2]

This result motivates robustness checks for the population tax data where we leave out commuters being located close to a bracket threshold. Specifically, columns (1), (3), and (5) of Table A.2 replicate 2SLS results presented in Table 9 of the main text, but leave out all paternal commuters being located closer than 10% of the next higher bracket threshold (i. e., those residing between 18-20km, 36-40km, and 54-60km, respectively). In a similar vein, columns (2), (4), and (6) leave out those being located in a corridor of 4km around each bracket threshold (i. e., those residing between 18-22km, 38-42km, 58-62km, respectively). We find that the intergenerational effect persists, being still positively and statistically significant at the 5 percent level.[3]

A.2 The non-systematic nature of the measurement error

The *retailer-data* also provide some socio-economic information on the employees, such as sex, age, income and occupation. This allows us to check, whether the measurement error in our IV (the distance-to-next-higher-bracket) — introduced by using zip-code centroids instead of exact addresses — is correlated with any observable characteristics of the taxpayers. Therefore, we construct a new variable which captures the difference in the distance-to-next-higher-bracket measured by using zip-code centroids and by using exact addresses. We then provide pairwise correlations between this new variable and each available characteristic. Table A.2 shows that the measurement error in our IV is not correlated with any of the socio-economic characteristics available in the *retailer data*.

A.3 The impact of the measurement error in our first stage estimations

The *retailer-data* also allows to examine how the measurement error in our IV (the distance-to-next-higher-bracket) influences our first-stage estimation. Therefore, we compare first-stage estimations based on the *retailer-data* using exact addresses versus using zip-code centroids. Thus, we regress the binary cheating variable on the various specifications of the distance-to-next-higher-bracket (as done in Table 6 in the paper).

Table A.4 is based on the zip-code centroids and thus, can be compared with Table 6 in the paper. It is reassuring to find the estimated size of the coefficients to be very comparable, being always negative and statistically highly significant. Table A.5 reproduces Table A.4 but uses the exact addresses. This eliminates the measurement error in

[2] Please note that the shares presented in Figures A.1, A.2 and A.3 do not exactly add up because in case of Figure A.1, the vertical axis is based on the centroid measure, whereas the vertical axis in Figure A.2 as well as A.3 are based on the exact measure.

[3] The robustness check also rules out the possibility that our findings are solely driven by taxpayers, who mistakenly round up to the next higher bracket threshold. While such rounding mistakes may be the case for taxpayers in the immediate vicinity of the threshold, rounding up several kilometers is very difficult to reconcile with behavior simply caused by mistake. In this context it is also important to note that every commuter in our data travels to work by car and hence, can simply read driving distances from the odometer built into every car. Finally, using population tax data we find a significantly positive association between tax rates and evasion decision, which provides additional evidence against the notion that the observed non-compliance is simply driven by mistakes

the distance-to-next-higher-bracket measure and in the binary cheating variable. As expected, the estimated coefficients from estimations using data free of measurement error are larger in absolute terms and are more precisely estimated. This suggests that our strong first-stage results depicted in Section 2.5 of the main text are not the byproduct of the noise in our distance measure and are, if anything, somewhat attenuated when compared to using the exact measure.

Finally, we want to note that we are not in the position to identify taxpayer from the retailer in our intergenerational sample. In addition, due to the small sample size of the *retailer-data*, we are not able to use this data to correct the measurement error in our tax data. To be more precise, one may propose that by using the *retailer-data*, we could approximate the average measurement error per zip-code pair and correct observations in our tax data accordingly. However, having about 2200 $\times$ 2200 zip-code pairs but only around 4,000 observations from the retailer renders any correction on zip-code level impossible.

Tables and figures of Appendix A

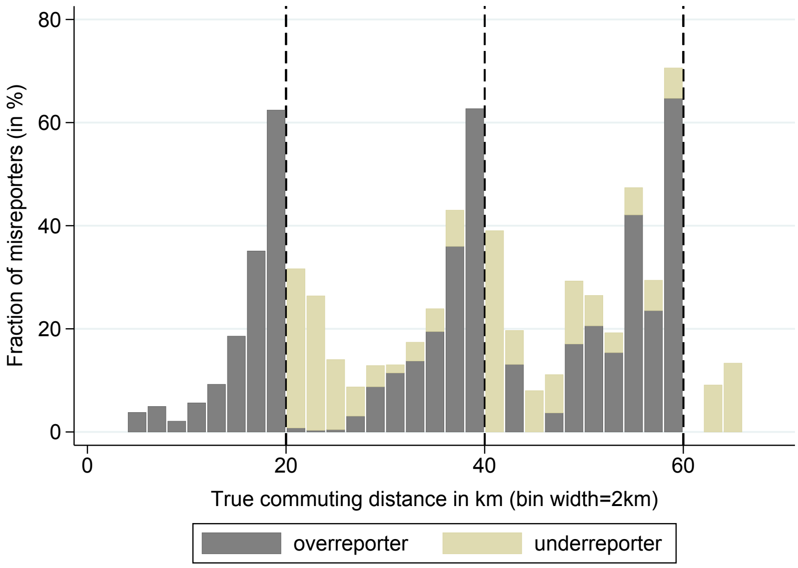


Figure A.1: Misreporting with centroid-based distance measure (using the *retailer data*)

Notes: The figure displays the reporting behavior of commuters by distance to the workplace using the *retailer data* (bin width=2 km). Distance is computed based on the zip-code level information (i. e. centroid-based measure as used for the tax data). The bars show the fraction of over- and underreporters, respectively. The dashed lines represent the thresholds, where the commuting tax allowance discontinuously increases to a higher amount.

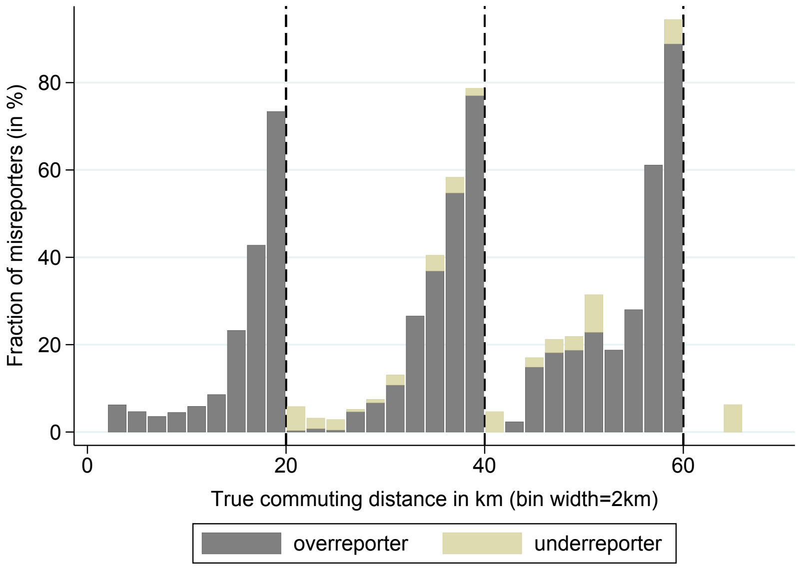


Figure A.2: Misreporting with exact door-to-door measure (using the *retailer data*)

Notes: The figure displays the reporting behavior of commuters by distance to the workplace using the *retailer data* (bin width=2 km). Distance is computed based on the exact door-to-door distance between the residence and the workplace address. The bars show the fraction of over- and underreporters, respectively. The dashed lines represent the thresholds, where the commuting tax allowance discontinuously increases to a higher amount.

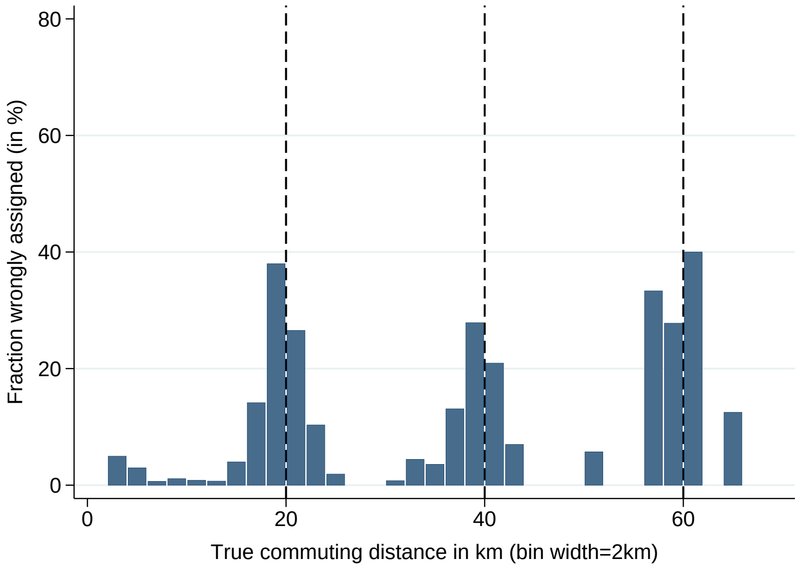


Figure A.3: Wrong assignment of commuters due to measurement error (using the *retailer data*)

Notes: The figure displays the fraction of commuters who are wrongly assigned as overreporters when using the exact versus the centroid-based measure for assignment.

Table A.1: Descriptive statistics of retailer data

	Based on exact distances (door-to-door)	**Based on approximate distances (Zip-code centroids)**
Panel A: Share of different types of taxpayers		
Overreporters (=cheaters)	0.180	0.143
Underreporters	0.011	0.059
Correct-reporters (=compliers)	0.808	0.797
Panel B: Average distances		
Distance in km	21.28	22.10
	(18.04)	(15.86)
Distance-to-next-higher-bracket in km	10.34	10.47
	(5.67)	(6.05)
Number of observations	4,563	

Notes: Standard deviations in parenthesis.

Table A.2: 2SLS when leaving out commuters close to bracket threshold

	(1)	(2)	(3)	(4)	(5)	(6)
	Cheating (0/1)		**Overclaimed amount/income**		**Overclaimed Euros**	
Exclusion criteria	10%	4km around threshold	10%	4km around threshold	10%	4km around threshold
Father is cheating (0/1)	0.077**	0.075**				
	(0.037)	(0.036)				
Father's overclaimed amount/income			0.150**	0.164**		
			(0.072)	(0.069)		
Father's overclaimed amount (EUR)					0.084**	0.089**
					(0.041)	(0.040)
Full set of father and child covariates	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	13,375	12,947	13,367	12,938	13,368	12,939
R-squared	0.20	0.20	0.14	0.14	0.18	0.17
Mean of dep. var.	0.20	0.20	0.02	0.02	231.67	235.74
S.d. of dep. var	0.40	0.40	0.04	0.04	488.60	493.29
F-test of weak instrument	273.98	300.37	199.25	207.69	256.07	281.35

Notes: This table replicates 2SLS estimation results of Table 9 in the paper, but leaves out commuters residing close to a commuting distance bracket thresholds. Columns (1), (3) and (5) leave out commuters being located closer than 10% of the next higher bracket threshold (i. e., those residing between 18-20km, 36-40km, and 54-60km, respectively). Columns (2), (4) and (6) leave out paternal commuters being located in a corridor of 4km around each bracket threshold (i. e., those residing between 18-22km, 38-42km, 58-62km, respectively). Father's distance-to-next-higher-bracket again serves as an IV for the fathers tax evasion decision. Reported estimates are second-stage coefficients with standard errors clustered on families in parentheses below. All estimations include the full set of child and father characteristics, identical to Table 9 in the paper. *, ** and *** indicate statistical significance at the 10-percent, 5-percent and 1-percent level respectively.

Table A.3: Correlation between measurement error in IV and covariates

Difference in distance-to-next-higher-bracket	**Correlation**	**p-value**
Socio-economic characteristics		
Age	−0.008	(0.604)
Female	−0.018	(0.227)
White collar worker	0.003	(0.850)
Log of income	0.007	(0.655)
Number of observations	4,563	

Notes: For this table we construct a new variable capturing the difference in the distance-to-next-higher-bracket measured by using zip-code centroids and by using exact addresses. The table depicts pairwise correlations between this new variable and each available characteristic in the *retailer-data*, with the corresponding p-values in parenthesis.

Table A.4: Replication of First-Stage using retailer data and centroid-based measure — binary cheating variable

	(1)	(2)	(3)	(4)	(5)
	2 IV categories	**3 IV categories**	**4 IV categories**	**5 IV categories**	**Linear IV**
Distance-to-next-higher-bracket:					
0-2 km				Base group	
0-5 km	Base group	Base group	Base group		
5-20 km	-0.296***				
	(0.018)				
2-5 km				-0.156***	
				(0.033)	
5-10 km		-0.242***	-0.251***	-0.334***	
		(0.020)	(0.020)	(0.025)	
10-20 km		-0.354***			
		(0.019)			
10-15 km			-0.301***	-0.372***	
			(0.021)	(0.025)	
15-20 km			-0.394***	-0.482***	
			(0.019)	(0.026)	
linear in km					-0.025***
					(0.001)
Covariates[a]	Yes	Yes	Yes	Yes	Yes
Number of observations	4,464	4,464	4,464	4,464	4,464
R-squared	0.18	0.19	0.19	0.21	0.20
Mean of dep. variable	0.15	0.15	0.15	0.15	0.15
S.d. of dep. variable	0.35	0.35	0.35	0.35	0.35

Notes: Standard errors in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] We control for the following characteristics: occupation (blue- vs. white-collar worker), individual earnings, female, commuting distance in km (linearly, squared, and with a binary indicator for short commuting distances <10 km), and birthyear.

Table A.5: Replication of First-Stage using retailer data and exact addresses — binary cheating variable

	(1) **2 IV categories**	(2) **3 IV categories**	(3) **4 IV categories**	(4) **5 IV categories**	(5) **Linear IV**
Distance-to-next-higher-bracket:					
0-2 km				Base group	
0-5 km	Base group	Base group	Base group		
5-20 km	-0.449***				
	(0.019)				
2-5 km				-0.341***	
				(0.033)	
5-10 km		-0.386***	-0.382***	-0.599***	
		(0.022)	(0.022)	(0.029)	
10-20 km		-0.514***			
		(0.020)			
10-15 km			-0.549***	-0.749***	
			(0.024)	(0.029)	
15-20 km			-0.501***	-0.707***	
			(0.020)	(0.026)	
linear in km					-0.032***
					(0.001)
Covariates[a]	Yes	Yes	Yes	Yes	Yes
Number of observations	4,461	4,461	4,461	4,461	4,461
R-squared	0.26	0.27	0.27	0.31	0.22
Mean of dep. variable	0.18	0.18	0.18	0.18	0.18
S.d. of dep. variable	0.39	0.39	0.39	0.39	0.39

Notes: Standard errors in parentheses, stars indicate statistical significance:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] We control for the following characteristics: occupation (blue- vs. white-collar worker), individual earnings, female, commuting distance in km (linearly, squared, and with a binary indicator for short commuting distances <10 km), and birthyear.

B Additional results

B.1 Misreporting of father cohort (born<1974)

Figure B.1 replicates Figure 1 of the main text for older cohorts (i. e., commuters born before 1974). As for Figure 1, we pool data across all brackets and display the fraction of over- and underreporters by bins of distance to the workplace. The dashed lines indicate the thresholds, at which the allowance discretely increases to a higher amount. Again, we observe a sharp reaction of taxpayers to these thresholds. The closer commuters live to a respective bracket the more prone they are to misreport their allowance claim. Importantly, the fraction of misreporters falls discontinuously at each bracket threshold, with commuters being much more prone to cheat than to underreport their eligibility. In sum, Figure B.1 shows that taxpayers of older cohorts are equally aware of the allowance scheme's structure and its incentive to overreport.

B.2 Take-up of major commuter allowance

In our main analysis, we have to exclude claimants of the minor commuter allowance scheme (using public transport), because we are not able to measure the actual/true travel distance for these commuters precisely enough. We test now, whether we observe a selection of children into the major allowance by father's distance-to-next-higher-bracket. Figure B.2 plots the fraction of all employed children claiming a major commuter allowance against the distance-to-next-higher-bracket of their fathers. Specifically, we put all children of the cohort 1974-1994 into 2 km wide bins of distance-to-next-higher-bracket of their fathers and plot the fraction of children claiming the major commuter allowance within these bins. We do not find children of fathers close to the bracket threshold to be more likely to claim a major allowance. Thus, we find no evidence that children are systematically selected into the major commuter allowance by their father's distance-to-next-higher-bracket.

B.3 Test for sorting of fathers around the bracket thresholds

Figure B.3 assesses the smoothness of the distribution of fathers' commuting distance around the commuting distance bracket thresholds using bunching estimations (Saez, 2010). We pool data across all bracket thresholds and put taxpayers in 1 km wide bins of distance-to-next-higher-bracket, displaying the number of commuters within such bins. The dashed line represents the bracket thresholds where the allowance discontinuously increases (i. e., zero represents the 20, 40, and 60 km threshold, respectively). The solid vertical lines indicate the bunching area, i. e. we exclude a window of 2 bins on each side of the thresholds. The solid line beneath the empirical distribution is a seventh-degree polynomial fitted to the empirical distribution excluding the bunching window. The graph is constructed using the father–child sample. We do not observe any evidence for fathers' bunching around bracket thresholds (excess mass: coeff. = -0.0034, s.e. = 0.256).

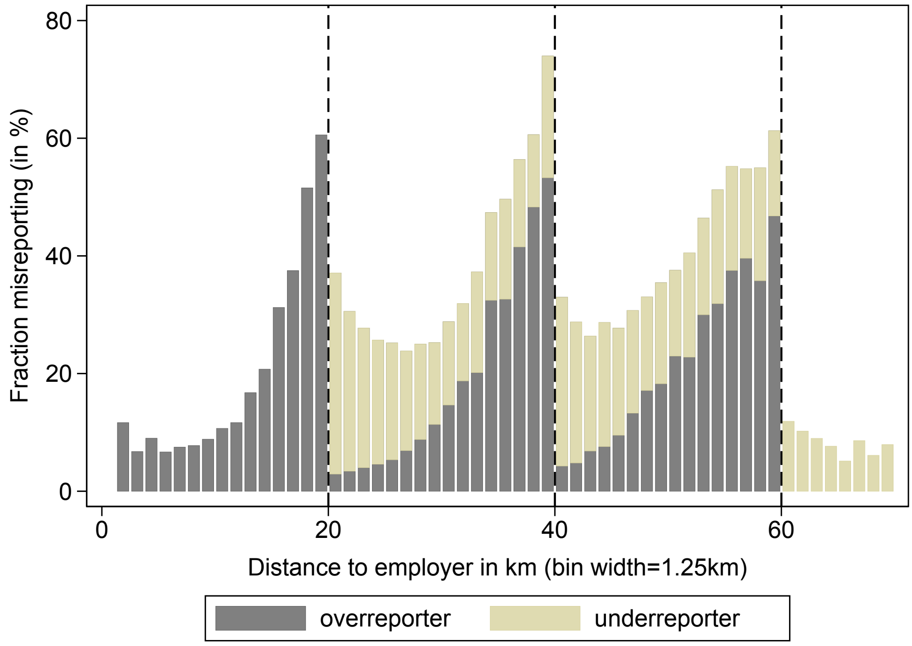
B.4 Determinants of tax morale: evidence from survey data

In this subsection, we use individual level data from the *European and World Values Survey* (E/WVS) to study the determinants of self-reported tax morale of Austrian respondents for the years 1990 and 1999. The E/WVS contains information on basic attitudes, beliefs and human values covering religion, morality, politics, work and leisure. In particular, respondents are asked to evaluate on a ten-point scale whether they think '*cheating on tax if [they] have the chance can always be justified, never be justified, or something in between*'. We use this questions to construct two alternative measures of tax morale. The first is an ordinal variable, which measures tax morale on the original 10-point scale. The second variable is a binary indicator equal to one, if respondents answered 'never be justified'; and zero otherwise.

For each tax morale variable we summarize in Table B.1 three OLS estimations. In columns (1) and (4), we restrict the estimation to employed individuals (i. e., wage earners) and explain tax morale with sex, income, educational attainment (proxies by school leaving age), occupation, size of place of residence, and age. These specification resemble our estimations of actual tax evasion behavior presented in Table 9. In columns (2) and (5), we control in addition for own children and marital status. In columns (3) and (6), we include all respondents (irrespective of their employment status) and control for their labor market status.

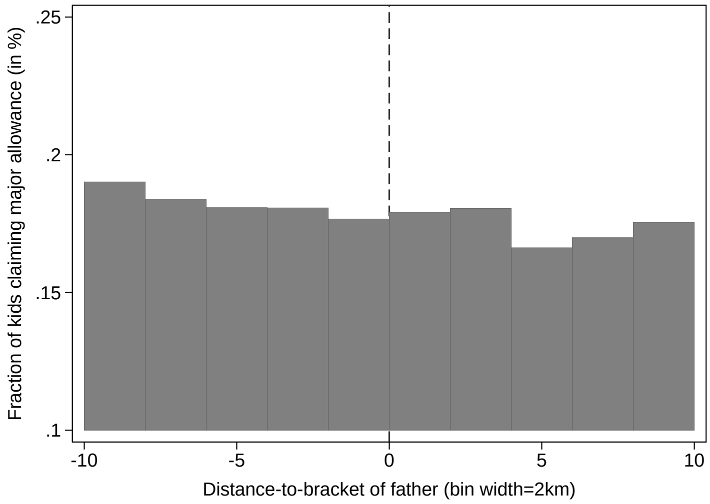
Tables and figures of Appendix B

Figure B.1: Distance-to-next-higher-bracket and misreporting (cohorts < 1974)



Notes: This figure displays the percent share of misreporters by commuting distance. Each bar is broken down between misreporters who overreport (dark area) and misreporters who underreport (light area). The dashed lines represent the thresholds, where the commuting tax allowance discontinuously increases to a higher amount (at 20, 40, and 60 km, respectively). The histogram includes allowance recipients from cohorts born before 1974.

Figure B.2: Children claiming major commuter allowance by father's distance-to-next-higher-bracket



Notes: The figure displays the fraction of all employed children claiming a major commuter allowance against the distance-to-next-higher-bracket of their fathers. To construct the figure we put all children of the cohort 1974-1994 into 2 km wide bins of distance-to-next-higher-bracket of their fathers and plot the fraction of children claiming the major commuter allowance within these bins. The bars show the fraction of claimants for each bin. The dashed line represents the bracket thresholds where the allowance discontinuously increases (i. e., zero represents the 20, 40, and 60 km threshold, respectively).

Figure B.3: No bunching of fathers around bracket thresholds

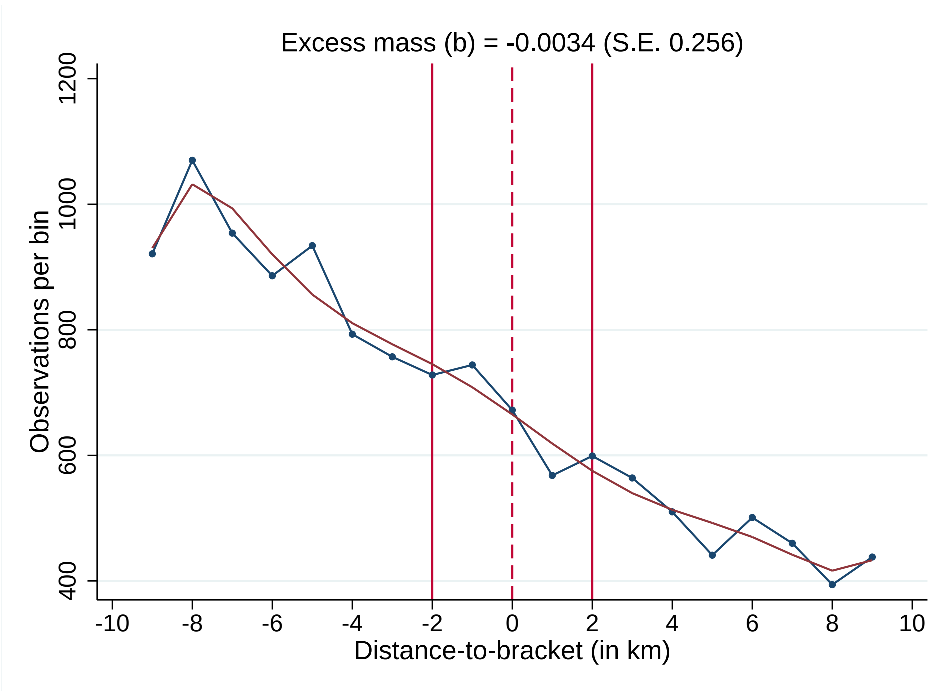


Table B.1: Determinants of tax morale in Austria using data from the World Values Survey

	(1)	(2)	(3)	(4)	(5)	(6)
	Tax morale (ordinal variable)			**Tax morale (binary indicator)**		
Female	0.204*	0.211*	0.204***	0.061**	0.061**	0.065***
	(0.112)	(0.113)	(0.075)	(0.028)	(0.029)	(0.020)
Income (10 point-scale)	−0.042*	−0.050**	−0.034**	−0.012**	−0.014**	−0.011***
	(0.024)	(0.024)	(0.016)	(0.006)	(0.006)	(0.004)
School leaving age	−0.073***	−0.070***	−0.051***	−0.022***	−0.021***	−0.015***
	(0.015)	(0.015)	(0.011)	(0.004)	(0.004)	(0.003)
White collar	0.204	0.185	0.120	0.041	0.034	0.024
	(0.126)	(0.127)	(0.080)	(0.032)	(0.032)	(0.021)
Town size (3 point-scale)	−0.395***	−0.379***	−0.352***	−0.092***	−0.088***	−0.075***
	(0.083)	(0.084)	(0.056)	(0.021)	(0.021)	(0.015)
Age	0.016***	0.008	0.012***	0.006***	0.003*	0.003***
	(0.005)	(0.006)	(0.003)	(0.001)	(0.002)	(0.001)
Married		0.313*	0.293***		0.069*	0.049**
		(0.160)	(0.091)		(0.040)	(0.025)
Children (no/yes)		0.052	−0.064		0.048	0.023
		(0.171)	(0.109)		(0.043)	(0.029)
Labor market status (base group: employed)						
Self-employed			−0.304**			−0.079*
			(0.150)			(0.040)
Unemployed			0.069			0.038
			(0.245)			(0.066)
Out of labor force			−0.080			−0.005
			(0.100)			(0.027)
Number of observations	1,179	1,174	2,500	1,179	1,174	2,500
R-squared	0.06	0.07	0.06	0.08	0.09	0.06
Mean of dep. var.	8.80	8.80	8.98	0.56	0.56	0.62
S.d. of dep. var.	1.95	1.95	1.80			

Notes: This table summarizes OLS estimation results of the determinants of tax morale. Tax morale is based on individual responses to the following question from the *European and World Values Surveys* of the years 1999/2000: '*Please tell me for each of the following statements whether you think it can always be justified, never be justified, or something in between: Cheating on taxes if you have a chance*'. Respondents are asked to evaluate this statement on an ordered scale from '*never justifiable*' (1) to '*always justifiable*' (10). In columns (1) to (3), the dependent variable is an ordinal measurement of tax morale using the original 10-point scale. In columns (4) to (6), the dependent variable is an binary indicator of high tax morale. This variable is equal to one, if respondents answered '*never be justified*'; and zero otherwise. Standard errors in parentheses, stars indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$