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Tax evasion on a social network

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ABSTRACT

We relate tax evasion behavior to a substantial literature on social comparison in judgements. Taxpayers engage in tax evasion as a means to boost their expected consumption relative to others in their social network. The unique Nash equilibrium of the model relates optimal evasion to a (Bonacich) measure of network centrality: more central taxpayers evade more. Given that tax authorities are now investing heavily in big-data tools that aim to construct social networks, we investigate the value of acquiring network information. We do this using networks that allow for celebrity taxpayers, whose consumption is seen widely, and who are systematically of higher wealth. We show that there are pronounced returns to the initial acquisition of network information, especially in the presence of celebrity taxpayers.

1. Introduction

Tax evasion is a significant economic phenomenon. Estimates provided by the UK tax authority put the value of the tax gap – the difference between the theoretical tax liability and the amount of tax paid – at 6.5% (H.M. Revenue and Customs, 2016). Academic studies for the US and Europe put the gap substantially higher, at around 18–20% (Cebula and Feige, 2012; Buehn and Schneider, 2016).

In this paper we link evasion behavior to a mass of evidence that people engage in comparisons with others (social comparison). Utility, evidence for developed economies suggests, is in large part derived from consumption relative to social comparators, rather than from its absolute level (e.g., Ferrer-i Carbonell, 2005; Luttmer, 2005; Clark and Senik, 2010; Mujcic and Frijters, 2013). The evolutionary processes that might explain this phenomenon are explored in Postlewaite (1998), Rayo and Becker (2007) and Samuelson (2004), among others. Researchers have proposed that social comparison can explain economic phenomena including the Easterlin paradox (Clark et al., 2008; Rablen, 2008), stable labor supply in the face of rising incomes (Neumark and Postlewaite, 1998); the feeling of poverty (Sen, 1983) the demand for risky activities (Becker et al., 2005) and migration choices (Stark and Taylor, 1991). There are important consequences for consumption and saving

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behavior (Harbaugh, 1996; Hopkins and Kornienko, 2004) the desirability of economic growth (Layard, 1980; 2005), and for tax policy (Boskin and Sheshinski, 1978; Ljungqvist and Uhlig, 2000).

We provide a network model in which taxpayers are assumed to have an intrinsic concern for consumption relative to that of other "local" taxpayers with whom they are linked on a social network.[1] In this context, taxpayers may seek to evade tax so as to improve their standing relative to those they compare against. The model exhibits strategic complementaries in evasion choices, so that more evasion by one taxpayer reinforces other taxpayers' decisions to evade also. Following the lead of Ballester et al. (2006), we utilize linear-quadratic utility functions to provide a characterization of Nash equilibrium. We show that there is a unique Nash equilibrium in which evasion is a weighted network centrality measure of the form proposed by Bonacich (1987). Network centrality is a concept developed in sociology to quantify the influence or power of actors in a network. Bonacich's measure counts the number of all paths (not just shortest paths) that emanate from a given node, weighted by a decay factor that decreases with the length of these paths. In this sense, our contribution combines sociological and economic insights in seeking to understand tax evasion behavior.

Although the model is simple enough to admit an analytic solution, it is also sufficiently rich that it may be used to address a range of questions of interest to academics and practitioners in tax authorities. Here we focus on two such questions: first, we investigate – for an arbitrary network structure – how changes in the information carried in the social network affect the private optimal evasion decision. Second, in the light of growing investment by tax authorities into "big data" tools that seek to construct social networks, we investigate the value to a tax authority – in terms of additional revenue raised through audits – of knowing the structure of social networks. The analysis is performed on a class of generative networks that possess many of the empirically observed features of social networks – in particular allowing for highly-visible celebrity taxpayers. We show that there are strong initial returns to a tax authority when moving from not observing the social network at all to observing around 10 percent of the links. The more concentrated are the links within a social network the greater the value of possessing at least some network information. These findings are robust to imperfect preference observability.

An important feature of our model is that it addresses explicitly the role of *local* comparisons on a social network. By contrast, the existing analytical literature on tax evasion allows only *global* (aggregate) social information to enter preferences: the global statistic that taxpayers are assumed to both have a concern for, and to be able to observe, is either (i) the proportion of taxpayers who report honestly (Davis et al., 2003; Gordon, 1989; Kim, 2003; Myles and Naylor, 1996; Ratto et al., 2013; Traxler, 2010) (ii) the average post-tax consumption level (Goerke, 2013) (iii) the level of evasion as a share of GDP (Dell'Anno, 2009) or (iv) the average tax payment (Mittone and Patelli, 2000; Panadés, 2004).

While reducing social information to a single global statistic known to all taxpayers promotes analytical tractability, it is problematic in other respects. Assuming that taxpayer's observe aggregate (global) information is, in our setting, implicitly the assumption that the social network is the complete network (in which every taxpayer is directly linked to all other taxpayers). But there are reasons to think that relative consumption externalities are, in fact, heterogeneous across individuals. In particular, we know that comparators are frequently neighbors, colleagues, and friends (Clark and Senik, 2010; Luttmer, 2005), and therefore "local" in nature.[2]

Consistent with this point, recent empirical literature finds evidence of enforcement spillover effects in networks, whereby intervening against one individual affects the subsequent behavior of other individuals (e.g., Boning et al., 2018; Drago et al., 2019; Lediga et al., 2019; Pomeranz, 2015; Rincke and Traxler, 2011). These spillover effects are found to be highly local in nature, making them qualitatively different in nature to the spillovers predicted by models with global social information. A further difficulty is that implicitly assuming a complete network implies that all taxpayers are equally connected socially, thereby ruling out, in particular, the existence of "stars" or "celebrities" whose consumption is very widely observed in the network. Yet, this feature of social networks may matter for the targeting of tax audits (Andrei et al., 2014).

The only literature that has enriched the analysis of social information to allow for local comparisons is that which uses agent-based simulation techniques as an alternative to analytical methods. Models in this tradition nonetheless employ representations of social networks that appear to differ markedly from real world examples. A common property of the network structures employed (e.g., Bloomquist, 2011; Hokamp, 2014; Hokamp and Pickhardt, 2010; Korobow et al., 2007) is that the number of taxpayers who observe a given taxpayer is fixed, thereby ruling out the existence of highly-observed celebrity taxpayers. Other authors (e.g., Davis et al., 2003; Hashimzade et al., 2014, 2016) utilize an *undirected* network, meaning that, if i is linked to j, then necessarily j is linked to i. Yet social networks display strong asymmetry in the direction of links (Foster et al., 2010; Szell and Thurner, 2010).[3] We offer a model that is both analytically tractable and that allows for local comparisons on an arbitrary social network. In this sense, our approach lies in the cleavage between existing analytical and

[1] The economics of networks is a growing field. For recent overviews, see Jackson and Zenou (2015) and Jackson et al. (2017). Our analysis connects to broader literatures that apply network theory to the analysis of crime (e.g., Ballester et al., 2006; Glaeser et al., 1996) and to other types of risky game (e.g., Bramoullé and Kranton, 2007a).

[2] Relative consumption externalities may be viewed more generally as a form of *peer effect*. In other contexts, generative models of peer effects predict heterogeneous exposure. For instance, when job information flows through friendship links, employment outcomes vary across otherwise identical agents with their location in the network of such links (Calvó-Armengol and Jackson, 2004).

[3] Andrei et al. (2014) and Zaklan et al. (2008) are among exceptions that do explore more general network structures.

agent-based approaches, and is complementary to each.[4] We perform simulation analysis on a class of generative networks that are not subject to the restrictions discussed above, and which are utilized widely to model network structures in the natural sciences. Our methodology in this regard, therefore, has applicability beyond the current context of tax evasion.

In related research, Goerke (2013) assumes an intrinsic concern for relative consumption by taxpayers. The primary focus of his contribution is, however, the derived impact on tax evasion from endogenous changes in labor supply, whereas we treat earned income as an exogenous parameter. In the remaining literature that considers a social dimension to the tax evasion decision, taxpayers are assumed to derive utility solely from absolute consumption, but react nonetheless to social information because, if caught evading, they experience social stigma. The extent of such stigma depends on the level of evasion of other taxpayers. The focus of much of this literature is on the potential for multiple equilibria, whereas our model yields a unique equilibrium. While a concern for relative consumption is compatible with the simultaneous existence of social stigma towards evaders, the two approaches differ in emphasis. Underlying the idea of social stigma is the concept of *social conformity*, in which individuals seek to belong to the crowd, whereas the presumption of relative consumption theories is that individuals seek to stand out from the crowd. A literature relating to this point in the context of tax evasion offers strong evidence that social information impacts compliance behavior (Alm et al., 2017; Alm and Yunus, 2009; de Juan et al., 1994; Webley et al., 1988), but rejects social conformity as the underlying mechanism (Fortin et al., 2007).

The paper proceeds as follows: Section 2 develops a formal model of tax evasion on a social network. Section 3 analyzes the comparative statics of optimal evasion with respect to information transmitted through the social network. Section 4 considers the value of network information to a tax authority, and section 5 concludes. Proofs omitted from the text are collected in the Appendix.

2. Model

Let $\mathcal{N}$ be a set of taxpayers of size $N > 1$. A taxpayer $i \in \mathcal{N}$ has an (exogenously earned) income on the finite interval $W_i \in (0, \overline{W}]$. By law taxpayers should declare W_i to the tax authority and pay tax $\theta(W_i)$, where $\theta : \mathbb{R}_+ \mapsto \mathbb{R}_+$ is a continuously differentiable and increasing function bounded above such that $\theta(z) < z$ for all $z > 0$. If a taxpayer declares their true gross income, W_i, they receive a (legal) net disposable income $X_i \equiv X_i(W_i) = W_i - \theta(W_i)$. Taxpayers can, however, choose to declare less than their true income, thereby evading an amount of tax $E_i \in [0, \theta(W_i)]$. Taxpayer i is audited with probability $p_i \in (0, 1)$. Heterogeneity in the p_i can arise, for example, if the tax authority conditions audit selection upon observable features of taxpayers. Audited taxpayers face a fine at rate $f > 1$ on all undeclared tax, à la Yitzhaki (1974). Consumption in the audited state (C_i^a) and not-audited state (C_i^n) is therefore given by:

$$C_i^n = X_i + E_i; \qquad C_i^a = C_i^n - fE_i. \tag{1}$$

Taxpayers behave as if they maximize expected utility, where the utility of taxpayer i, $U_i : \mathbb{R} \mapsto \mathbb{R}$, is taken to be linear-quadratic in form:

$$U_i(z) = \left[b_i - \frac{a_i z}{2}\right] z \qquad a_i \in \left(0, \frac{b_i}{W_i}\right),\ b_i > 0.$$

The restrictions on the parameters $\{a_i, b_i\}$ are sufficient to ensure that $U_i(z)$ is increasing on the interval $z \in (-\infty, W_i]$ and strictly concave.[5] Utility is derived from a taxpayer's level of consumption relative to a reference level of consumption R_i (the determination of which we shall discuss later). The expected utility of taxpayer i is therefore given by

$$\mathbb{E}(U_i) = [1 - p_i]\left[b_i - \frac{a_i\left[C_i^n - R_i\right]}{2}\right]\left[C_i^n - R_i\right] + p_i\left[b_i - \frac{a_i\left[C_i^a - R_i\right]}{2}\right]\left[C_i^a - R_i\right]. \tag{2}$$

An optimal strategy, E_i, for taxpayer i, taking reference consumption, R_i, as given, is described by the first order condition

$$[1 - p_i]\left[b_i - a_i\left[C_i^n - R_i\right]\right] - p_i f\left[b_i - a_i\left[C_i^a - R_i\right]\right] = 0. \tag{3}$$

2.1. Reference consumption

We assume that each taxpayer observes the consumption of a set of taxpayers $\mathcal{R}_i \subset \mathcal{N}$. The observability of consumption is represented in the form of a directed network (graph), where a link (edge) from taxpayer (node) i to taxpayer j indicates that i observes j's consumption. Links are permitted to be subjectively weighted, thereby allowing some comparators to be more focal than others. The network is represented as an $N \times N$ (adjacency) matrix, $\mathbf{G}$, of subjective comparison intensity weights $g_{ij} \in [0, 1]$, where $g_{ii} = 0$. Taxpayers i and j with $g_{ij} > 0$ are said to be *linked*. For later reference, a network in which there is a path (though not necessarily a direct link) between every pair of taxpayers is said to be *connected*. The set of all taxpayers to whom i is linked, $\mathcal{R}_i$, is termed the *reference set* of taxpayer i: $\mathcal{R}_i = \left\{j \in \mathcal{N} : g_{ij} > 0\right\}$.

[4] By extending analytical understanding of network effects upon tax evasion – in particular being able to prove formal comparative statics properties of the model – we assist the interpretation of simulation output from related agent-based models.

[5] Owing to strict concavity, $U'(W_i) > 0$ is a sufficient condition for $U'\left(C_i^n\right) > 0$ and $U'\left(C_i^a\right) > 0$, as $W_i \geq C_i^n \geq C_i^a$.

Expected consumption writes as $q_i = [1 - p_i]C_i^n + p_i C_i^a = X_i + [1 - p_i f]E_i$. We define reference consumption, R_i, as a weighted sum of expected consumption among taxpayers in the reference set. Hence

$$R_i \equiv R_i(\mathbf{q}) = \mathbf{g}_i\mathbf{q}, \tag{4}$$

where $\mathbf{g}_i$ is the ith row of $\mathbf{G}$ and $\mathbf{q}$ is a $N \times 1$ vector of the expected consumptions.

2.2. Nash equilibrium

Using (4) in the first order condition (3), we now solve for the unique Nash equilibrium of the model. To do this, we first define a notion of network centrality due to Bonacich (1987), which computes the (weighted) discounted sum of paths originating from a taxpayer in the network:

Definition 1. Consider a network with (potentially weighted) adjacency matrix $\mathbf{G}$. For a scalar β and weight vector $\boldsymbol{\alpha}$, the weighted Bonacich centrality vector is given by $\mathbf{B}(\mathbf{G}, \beta, \boldsymbol{\alpha}) = [\mathbf{I} - \beta\mathbf{G}]^{-1}\boldsymbol{\alpha}$ provided that $[\mathbf{I} - \beta\mathbf{G}]^{-1}$ is well-defined and non-negative.

In Definition 1, the scalar β specifies the discount factor that scales down (geometrically) the relative weight of longer paths, while the vector $\boldsymbol{\alpha}$ is a set of weights. In the present context the matrix $[\mathbf{I} - \beta\mathbf{G}]^{-1}$ is a form of social comparison multiplier. It measures the way in which actions by one taxpayer feed through into other taxpayers' actions. Ballester et al., 2006 show that $[\mathbf{I} - \beta\mathbf{G}]^{-1}$ will be well-defined, as required in Definition 1, when $1 > \beta\rho(\mathbf{G})$, where $\rho(\mathbf{G})$ is the spectral radius of $\mathbf{G}$.[6] In our context, this condition is that the local externality that a taxpayer's evasion imparts upon other taxpayers cannot be too strong. If local externality effects are too strong then the set of equations that define an interior Nash equilibrium have no solution. In this case, multiple corner equilibria can instead arise (see, e.g., Bramoullé and Kranton, 2007b; Bramoullé et al., 2014). Focusing on the case when local externality effects are not too strong, we have the following Proposition:

Proposition 1. *Consider a network with adjacency matrix* $\mathbf{M}$ *and weight vector* $\boldsymbol{\alpha}$ *with elements given by*

$$m_{ij} = \frac{[1 - p_i f][1 - p_j f]}{\zeta_i} g_{ij}; \qquad \zeta_i = [1 - p_i f]^2 + p_i[1 - p_i]f^2 > 0;$$

$$\alpha_{i1} = \frac{1 - p_i f}{a_i \zeta_i}\{b_i - a_i[X_i - R_i(\mathbf{X})]\}.$$

If

$$1 > \rho(\mathbf{M}); \qquad [\mathbf{I} - \mathbf{M}]\boldsymbol{\theta}(\mathbf{W}) - \boldsymbol{\alpha} > \mathbf{0};$$

then there is a unique interior Nash equilibrium for evaded tax, given by

$$\mathbf{E} = [\mathbf{I} - \mathbf{M}]^{-1}\boldsymbol{\alpha}.$$

Proof. Eq. (3) solves to give optimal evasion at an interior solution as

$$E_i = \frac{1 - p_i f}{a_i \zeta_i}\{b_i - a_i[X_i - R_i]\}, \tag{5}$$

where $\zeta_i > 0$ is defined in the Proposition. Using (4), optimal evasion in (5) is written in full as

$$E_i = \frac{1 - p_i f}{a_i \zeta_i}\{b_i - a_i[X_i - R_i(\mathbf{X}) + [1 - p_i f]R_i(\mathbf{E})]\}, \tag{6}$$

The set of N equations defined by (6) for taxpayers $i \in \mathcal{N}$ can be stacked in matrix form as $\mathbf{E} = \boldsymbol{\alpha} + \mathbf{M}\mathbf{E}$ where the elements of the matrices $\{\boldsymbol{\alpha}, \mathbf{M}\}$ are as in Proposition 1. It follows that $[\mathbf{I} - \mathbf{M}]\mathbf{E} = \boldsymbol{\alpha}$, so $\mathbf{E} = [\mathbf{I} - \mathbf{M}]^{-1}\boldsymbol{\alpha} \equiv \mathbf{B}(\mathbf{M}, 1, \boldsymbol{\alpha})$. □

Proposition 1 characterizes the unique interior Nash equilibrium of the model, and the conditions under which it arises. The first condition ensures $E_i > 0$, while the second ensures $E_i < \theta(W_i)$, so that the amount a taxpayer evades does not exceed the tax owed. The uniqueness of equilibrium evasion follows intuitively from the observation that, under linear-quadratic utility, each taxpayer's best-response function is linear in the evasion of other taxpayers.

According to Proposition 1 a taxpayer's optimal evasion corresponds to a Bonacich centrality on the social network $\mathbf{M}$. By this measure, *taxpayers that are more central in the social network evade more*. The social network $\mathbf{M}$ transforms the underlying comparison intensity weights, g_{ij}, by a factor $[1 - p_i f][1 - p_j f]\zeta_i^{-1} \in (0, 1)$ that captures heterogeneity in audit probabilities across taxpayers. It follows that in the special case in which all taxpayers face a common audit probability, as occurs if a tax authority chooses a policy of random auditing, no adjustment to the underlying comparison intensity weights

[6] Given the formal similarity between network adjacency matrices and Leontief input-output matrices, this condition plays an equivalent role to the Hawkins-Simon condition (Hawkins and Simon, 1949) in that literature.

is warranted. In this case, therefore, optimal evasion is a weighted Bonacich centrality measure on the untransformed network **G**:

Corollary 1. *Under the conditions of Proposition 1 and setting $p_i = p$ for all $i \in \mathcal{N}$, the unique interior Nash equilibrium for evasion is given by*

$$\mathbf{E} = [\mathbf{I} - \omega\mathbf{G}]^{-1}\boldsymbol{\alpha},$$

where

$$\omega = \frac{[1 - pf]^2}{[1 - pf]^2 + p[1 - p]f^2} < 1.$$

We illustrate Corollary 1 in the simple context of an unweighted "hub-and-spoke" (or "star") network with $n > 1$ spoke-taxpayers. Thus, if the hub-taxpayer is indexed $i = 1$, **G** writes as

$$\mathbf{G} = \begin{pmatrix} 0 & 1 & \cdots & 1 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}.$$

Suppose taxpayers are identical in all respects and face identical enforcement (so we may drop i subscripts), the only difference being that the hub-taxpayer is more central in the social network than is a spoke-taxpayer. Using Corollary 1, equilibrium evasion is given by

$$E_{spoke} = \frac{\omega}{a[1 - pf][1 - n\omega^2]}\{[1 + \omega][b - aX] + [1 + n\omega]aX\} > 0; \tag{7}$$

$$E_{hub} = E_{spoke} + \frac{[n - 1]\omega}{a[1 - pf][1 - n\omega^2]}\{\omega[b - aX] + aX\} > E_{spoke}. \tag{8}$$

From (8) we see that, due solely to their more central position in the social network, the hub-taxpayer evades more than does each spoke-taxpayer. Furthermore, a careful inspection of the comparative statics of $E_{hub} - E_{spoke}$ shows that the additional evasion of the hub-taxpayer increases in (legal post-tax) wealth (X), the number of spoke-taxpayers (n), risk aversion $\{a, b\}$; and decreases in tax authority enforcement $\{p, f\}$.[7]

What if utility is not linear-quadratic? For an arbitrary twice-differentiable utility function we may generalize the model by considering the first order linear approximation around a Nash equilibrium to a set of (potentially non-linear) first order conditions of the form in (3). The resulting set of equations are given by

$$\mathbf{E} = \mathbf{J}\mathbf{E} + \hat{\boldsymbol{\alpha}} = [\mathbf{I} - \mathbf{J}]^{-1}\hat{\boldsymbol{\alpha}} = \left[\sum_{k=0}^{\infty} \mathbf{J}^k\right]\hat{\boldsymbol{\alpha}}, \tag{9}$$

where $\hat{\boldsymbol{\alpha}}$ is again a vector of weights for the different taxpayers, and **J** is a matrix of coefficients measuring how actions interact. By appropriate decomposition of **J**, therefore, a solution to the equation system in (9) is a Bonacich centrality measure of the form given in Definition 1.[8]

Proposition 1 survives multiple extensions to the (intentionally) simple model we present. For instance, whereas we represent utility as purely relative, absolute utility may also play a role.[9] If, accordingly, utility is instead specified as $U(C - R, C)$, such that consumption matters absolutely, not only relative to R, then a Bonacich representation of Nash equilibrium pertains so long as $U(\cdot)$ is specified to preserve linearity in the best-response functions. Other extensions compatible with the Bonacich centrality interpretation of equilibrium include (i) distinguishing between observable (or "conspicuous") consumption and unobservable consumption (Frank, 1985; Veblen, 1899); and (ii) allowing reference consumption to reflect additional features to social comparison, such as habit effects (see, e.g., Bernasconi et al., 2019), or moral/stigma costs.

We now show examples of how our basic framework may be used to analyze a range of questions of interest to academics and practitioners in tax authorities. In particular, subsequent sections will consider how information carried by the social network affects optimal evasion, and the value of knowing the network to a tax authority. These analyses by no means exhaust the range of questions that can be analyzed within the framework, however.

[7] Noting that absolute risk aversion is given by $A(z) = a[b - az]^{-1} > 0$, increases in a associate with decreased risk aversion, while increases in b associate with increased risk aversion.

[8] See also Allouch (2015) for results relating Nash equilibrium and Bonacich centrality under Gorman polar form preferences.

[9] We note that measures of subjective wellbeing typically become uncorrelated with absolute income above a threshold of average national income estimated at $5,000 (in 1995, PPP) by Frey and Stutzer (2002). As most citizens of developed countries lie above this threshold, a model with purely relative utility may plausibly be a reasonable approximation in such cases.

3. Comparative statics of network interaction

We now seek to understand the way in which social information affects the evasion decision. We do this for an arbitrary social network satisfying the conditions in Proposition 1.

A basic property of the model is strategic complementarity in evasion choices: an increase in evasion by one taxpayer induces others to do likewise.[10] This is equivalent to the expected utility of taxpayer i being supermodular in the cross evasion choice of another taxpayer j belonging to i's reference set:

$$\frac{\partial^2 \mathbb{E}(U_i)}{\partial E_i \partial E_j} = a_i g_{ij}[1-p_i f][1-p_j f] > 0 \qquad j \in \mathcal{R}_i.$$

We now analyze how the evasion decision of a taxpayer i, E_i, is affected by a permanent marginal increase in a parameter z_j belonging to a different taxpayer $j \neq i$. Differentiating the expression for evasion in Proposition 1 we obtain:

Proposition 2. *Under the conditions of Proposition 1 it holds at an interior Nash equilibrium that:*

$$\frac{\partial E_i}{\partial W_j} = B_{1i}\left(\mathbf{M}, 1, \frac{\partial \boldsymbol{\alpha}}{\partial X_j}\right) \geq 0;$$
$$\frac{\partial E_i}{\partial p_j} = B_{1i}\left(\mathbf{M}, 1, \frac{\partial \mathbf{M}}{\partial p_j}\mathbf{E} + \frac{\partial \boldsymbol{\alpha}}{\partial p_j}\right) \leq 0.$$

The results in Proposition 2 underscore that the attributes of other taxpayers, and the treatment of other taxpayers by the tax authority, both affect own compliance. Moreover, the effects are heterogeneous across taxpayers, depending upon how "close" taxpayers are in the social network. In respect of sign, these results are in line with those of models of tax evasion that assume a social norm for compliance, albeit there are important differences in economic interpretation.

The first result is that an increase in the income of taxpayer j induces taxpayer i to evade more. When j gets richer this pushes up their expected consumption, causing those taxpayers who observe j's consumption to feel poorer in relative terms. This, in turn, induces these taxpayers to increase their evasion in an attempt to boost their consumption. This behavior, in turn, induces a further set of taxpayers to also feel poorer, and also increase their evasion, and so on. If the network **G** is connected then this ripple effect ultimately reaches every taxpayer in the network, so the result in Proposition 2 may be strengthened to a strict inequality. If **G** is not connected, however, then there exists at least one taxpayer pair $\{i, j\}$ between whom social information does not flow. For such pairs it will hold that $\partial E_i / \partial W_j = 0$.

The second result in Proposition 2 is an enforcement spillover effect: the evasion of taxpayer i responds negatively to the level of tax authority enforcement of other taxpayers in the social network. When a taxpayer j experiences an increase in audit probability they decrease their evasion. This decreases the evasion required of taxpayer i to maintain a given level of expected relative consumption, leading i to evade less. The result can be strengthened to a strict inequality if the network **M** is connected. This finding is consistent with the empirical literature documenting local enforcement spillover effects in networks discussed in the introduction.

4. Audit targeting and network structure

Can tax authorities observe links in social networks? Although surely the full gamut of links cannot be observed, importantly, there exist some individuals – celebrities – whose widespread visibility is common knowledge. Also, even for non-celebrities, the idea that tax authorities know at least something about people's associations is becoming more credible with the advent of "big data". The UK tax authority, for instance, uses a system known as "Connect", operational details of which are in the public domain (see, e.g., Baldwin and McKenna, 2014; Rigney, 2016; Suter, 2017). Connect cross-checks public sector and third-party information, seeking to detect relationships among actors. According to Baldwin and McKenna (2014), the system produces "spider diagrams" linking individuals to other individuals and to legal entities such as "property addresses, companies, partnerships and trusts". The IRS is known to have also invested in big data heavily, but has so far been much more reticent in revealing its capabilities.

Accordingly, in this section we consider the business case for investing in the means to acquire information about social networks. Can such knowledge be used to systematically improve audit yields through improved targeting? We also address the related questions of how the value of network information varies with the topological properties of the network. We begin by developing a theoretical framework for analyzing rigorously these questions, and then perform simulations of this framework to obtain numerical estimates.

[10] The version of the model we present here is simple enough to admit computation of exact comparative statics. An advantage of the strategic complementarity property, however, is that, if one only seeks the signs of the comparative statics (as might be appropriate in more complex versions of the model), these can be elucidated straightforwardly using the theory of monotone comparative statics (e.g., Edlin and Shannon, 1998; Tremblay and Tremblay, 2010).

4.1. Theoretical framework

We consider the problem of a tax authority seeking to target audits towards the taxpayers who have evaded most, conditional on observing (i) an income declaration $d_i \in [0, W_i]$; and (ii) partial information regarding the social network. For now, suppose that taxpayer preferences are known to the tax authority: imperfect information exists only with respect to the network. We may write evasion as $E(W_i) = \theta(W_i) - \theta(d_i; \mathbf{G})$. Inverting this relationship we may obtain a function $W_i(d_i; \mathbf{G})$, which, for a given network $\mathbf{G}$, gives the true income W_i of a taxpayer who will optimally declare income d_i. On receipt of a taxpayer's declaration d_i, the tax authority uses $W(d_i; \cdot)$ to compute a prediction, $\hat{W}_i$, of i's true income. If the tax authority perfectly observes the network, it predicts true income correctly, i.e., $\hat{W}_i = W(d_i; \mathbf{G}) = W_i$. When, however, the tax authority does not perfectly observe the social network – instead observing some other (related) network $\mathbf{G}' \neq \mathbf{G}$ – it obtains an imperfect prediction of W_i, given by $\hat{W}_i = W\left(d_i; \mathbf{G}'\right) \neq W_i$.

The estimate $\hat{W}_i$ is used to compute predicted evasion as $\hat{E}_i = \theta(\hat{W}_i) - \theta(d_i)$. Audit targeting is then towards the proportion p of taxpayers with the highest $\hat{E}_i$. To the extent that the ordering of the $\hat{W}_i$ does not match the ordering of the true W_i an imperfect knowledge of the social network leads to a suboptimal choice of audit targets. Accordingly, if $\mathfrak{R}(\mathbf{G})$ denotes the audit revenue (in recovered taxes and fines) from targeting audits using social network $\mathbf{G}$, then $\mathfrak{R}\left(\mathbf{G}'\right) \leq \mathfrak{R}(\mathbf{G})$ when $\mathbf{G}' \neq \mathbf{G}$.

To formalize this idea, consider the set $\mathcal{G}$ of all possible subsets of links, ranging from the full network when all taxpayer links are observed to the empty (i.e., zero) network when no links are observed. Let $\left\{\underline{\mathbf{G}}, \overline{\mathbf{G}}\right\} \in \mathcal{G}$ denote, respectively, the social networks that achieve, respectively, the lowest and highest revenues among the networks in $\mathcal{G}$:

$$\underline{\mathbf{G}} = \arg\min_{\mathbf{G}\in\mathcal{G}} \mathfrak{R}(\mathbf{G}); \qquad \overline{\mathbf{G}} = \arg\max_{\mathbf{G}\in\mathcal{G}} \mathfrak{R}(\mathbf{G}).$$

Analogously, the revenues attained when targeting according to these social networks are given by

$$\underline{\mathfrak{R}} = \mathfrak{R}(\underline{\mathbf{G}}); \qquad \overline{\mathfrak{R}} = \mathfrak{R}\left(\overline{\mathbf{G}}\right).$$

To quantify the value of network information in improving audit targeting, we examine the evolution of audit revenue when incrementally improving the quality of the tax authority information regarding the social network. We suppose that the tax authority observes the social network $\mathbf{G}_\kappa$ formed as a convex combination of $\underline{\mathbf{G}}$ and $\overline{\mathbf{G}}$:

$$\mathbf{G}_\kappa = \kappa\underline{\mathbf{G}} + [1-\kappa]\overline{\mathbf{G}}; \qquad \kappa \in [0, 1].$$

When $\kappa = 0$ the tax authority observes the network poorly and attains revenue $\mathfrak{R}(\underline{\mathbf{G}})$; when $\kappa = 1$ the tax authority observes the network perfectly and attains the maximum revenue $\mathfrak{R}\left(\overline{\mathbf{G}}\right)$. Thus κ measures the ability of the tax authority to observe the social network. Our analysis centers on the statistic

$$\Psi(\kappa) \equiv \frac{\mathfrak{R}(\mathbf{G}_\kappa) - \underline{\mathfrak{R}}}{\overline{\mathfrak{R}} - \underline{\mathfrak{R}}} \times 100. \tag{10}$$

$\Psi(\kappa) = 100$ signifies that revenue attains its upper bound $\overline{\mathfrak{R}}$, whereas $\Psi(\kappa) = 0$ signifies that revenue attains its lower bound $\underline{\mathfrak{R}}$. $\Psi(\kappa) = 50$ indicates that revenue lies half-way between the upper and lower bounds, with other intermediate values being interpreted similarly.

4.2. Simulation methodology

We now discuss how we simulate the model to obtain numerical estimates of the function $\Psi(\kappa)$.[11]

4.2.1. The social network

We generate the social network $\mathbf{G}$ following the approach of network scientists, who utilize a class of network models, known as *generative models*, to investigate complex network formation (see, e.g., Pham et al., 2016). In this modelling paradigm, complex networks are generated by means of the incremental addition of nodes and edges to a seed network over a sequence of time-steps. Two processes governing the node/edge dynamics in generative models have been shown to generate features consistent with a multitude of social, biological, and technological networks (see, e.g., Adamic and Huberman, 2000; Capocci et al., 2006; Jeong et al., 2000; Ormerod and Roach, 2004; Redner, 1998). The first – the *node-degree* (or *preferential attachment*) process – makes the probability that each new taxpayer added to the network observes an existing taxpayer, i, a positive function of i's degree (the number of taxpayers who already observe i). The second – the *node-fitness* process – makes the probability that a new taxpayer added to the network observes an existing taxpayer, i, a positive function of i's *fitness* (an exogenous and time-invariant characteristic of node i).

In allowing for a role for node-fitness in social network formation, we are able to account for the observation that, empirically, celebrity taxpayers are surely not drawn at random from the distribution of income, but rather belong systematically to the upper tail. TV and sports stars, whose consumption habits are widely reported, are also some of the richest members of society. To replicate this feature, we equate node-fitness with income W_i. We specify the distribution function of W_i across taxpayers to satisfy a power law, consistent with a large body of empirical evidence (e.g., Coelho et al., 2008).

[11] The simulations are performed in R. The implementation files are openly available at https://github.com/dgdi/tax_evasion_on_a_social_network.

In our implementation we generate networks of $N = 200$ taxpayers, starting from a seed network composed of two interlinked taxpayers. Consider a taxpayer i with fitness $W_i > 0$ and degree $\eth_{is}$ at step s of the generative process. We entwine the node-degree and node-fitness processes by setting the probability that taxpayer i is observed by the taxpayer added at step s to be proportional to the product $W_i \eth_{is}^{0.43}$.[12] The coefficient of 0.43 is from Pham et al. (2016) 7), who analyze the social network constituted by a sample of 46,000 Facebook wall-posts (we also investigate the systematic effects of varying this coefficient).

The taxpayer i incrementally added to the network at step s is linked to existing taxpayers according to the outcome of five random draws under the probability distribution $W_i \eth_{is}^{0.43}$ discussed previously. Note, however, that these draws are with replacement, so a taxpayer may be linked to another multiple times. As the model of section 2 allows for only a single, albeit weighted, link between taxpayers, we construct the comparison intensity weights to be proportional to the frequency of links realized by the generative process. Specifically, let $\#_{ij} \in \mathbb{N}$ denote the number of times taxpayer i is linked with j by the generative process. The comparison intensity weight is then set as $g_{ij} = \#_{ij}/5$.

Owing to its stochastic nature, any single iteration of the generative process may realize a $\mathbf{G}$ that is unrepresentative. To mitigate this concern, the results we report are averages of multiple independent iterations of the generative process.[13]

4.2.2. Model functions and parameters

Having now described the social network, we specify the remaining model functions and parameters. To make concrete the vector of predicted income, $\hat{\mathbf{W}} = \mathbf{W}(\mathbf{d}; \mathbf{G})$, we specify the tax system as a linear income tax, $\theta(W_i) = \theta W_i$, where $\theta \in (0, 1)$, such that $E(W_i) = \theta[W_i - d_i]$ and $X(W_i) = [1 - \theta]W_i$. We then have:

Lemma 1. *Consider a network with adjacency matrix* $\mathbf{V}$ *and weight vector* $\boldsymbol{\gamma}$ *with elements given by*

$$v_{ij} = \frac{[1 - p_i f]\big[1 - \theta p_j f\big]}{\xi_i} g_{ij}; \qquad \xi_i = [1 - \theta][1 - p_i f]^2 + \theta\big[1 + p_i[1 - p_i]f^2\big] > 0;$$

$$\gamma_{i1} = \frac{\{1 + [f - 2]p_i f\}\theta a_i d_i + b_i[1 - p_i f]}{a_i \xi_i} - \frac{\theta[1 - p_i f]\sum_{j \in \mathcal{R}_i}\big[1 - p_j f\big] d_j g_{ij}}{\xi_i}.$$

Then, under the conditions of Proposition 1, and with a linear income tax, the set of incomes $\mathbf{W}$ *corresponding to a set of optimal income declarations* $\mathbf{d}$ *is given by*

$$\mathbf{W}(\mathbf{d}; \mathbf{G}) = [\mathbf{I} - \mathbf{V}]^{-1}\boldsymbol{\gamma}.$$

Taxpayers are assumed to know the true average probability of audit, p, but do not know how the tax authority will select audit targets. Consistent with this idea, tax authorities are known to shroud their audit selection rules – the so-called "DIF score" in the case of the IRS – in great secrecy (see, e.g., Alm and McKee, 2004; Hashimzade et al., 2016; Plumley and Steuerle, 2004). We set $\{p, f\}$ to be consistent with a level of evasion of 10%, as is broadly consistent with the empirical evidence for developed countries cited in the Introduction.[14]

4.3. Results

Our results for $\Psi(\kappa)$ are shown in Fig. 1.[15] As would be expected, $\Psi(\kappa)$ is monotonically increasing in κ: improved network information results in improved audit revenues. It is apparent from the initial steepness of the left-side of the figure that there are significant returns from acquiring a little network information (observing around 10% of all links). Thus, tax authorities that are in the infancy of their attempts to systematically construct social networks have an especially strong case to invest in this endeavor. The strong initial returns to network visibility are seen to diminish on an interval of intermediate values of κ, increase strongly again at around 40% network visibility, and finally diminish again in the neighborhood of full visibility. Thus, in a way we have made precise, knowledge of the structure of social networks can be of value to tax authorities.

It is of interest to understand how these results are systematically affected by network structure. We therefore vary the importance of preferential attachment in the network generative process by varying the coefficient ϕ in the probability distribution $W_i \eth_{is}^{\phi}$ around its benchmark value of 0.43. Raising ϕ increases the importance of preferential attachment in the generative process, so higher values produce networks with a greater concentration of links upon a smaller number of highly-visible "celebrity" taxpayers. Fig. 2 depicts $\Psi(\kappa)$ when $\phi \in \{0, 0.43, 1\}$. The left-side of the Figure indicates that,

[12] Our approach is a special case of the specification of the product as $W_i A(\eth_{is})$, where A is an increasing function. This specification nests the influential works of Barabási and Albert (1999), who assume fitness to be equal across taxpayers; and of Bianconi and Barabási (2001), who assume A to be the identity function. The implicit specification of A we adopt, $A(\eth) = \eth^{\phi}$, $\phi < 1$, is advocated in much of the most recent studies of social networks, however (see, e.g., Backstrom et al., 2006; Kunegis et al., 2013; Pham et al., 2016).

[13] We do not average over a prescribed number of iterations, but rather implement a stopping rule that monitors the rate of convergence of the sample mean towards the true mean.

[14] The level of evasion predicted by the model relates closely to the product pf, such that we are able to hold evasion at the ten percent level when, e.g., lowering f and raising p. The qualitative features of $\Psi(\kappa)$ that we shall report are unaffected by the chosen decomposition of pf, however.

[15] The results shown are for common preference parameters $\{a_i, b_i\} = \{2, 80\}$ for all i. Based on tests of the model predictions for a range of choices of $\{a, b\}$ consistent with an interior equilibrium, our qualitative findings are not sensitive to the particular choice of these two parameters.

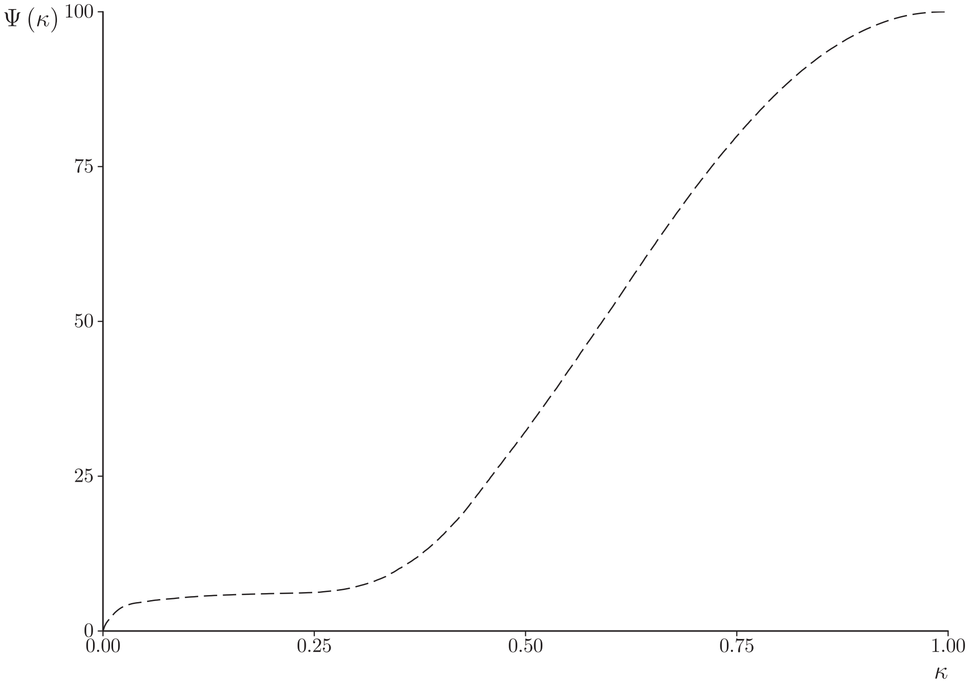

Fig. 1. Network information and audit revenues.

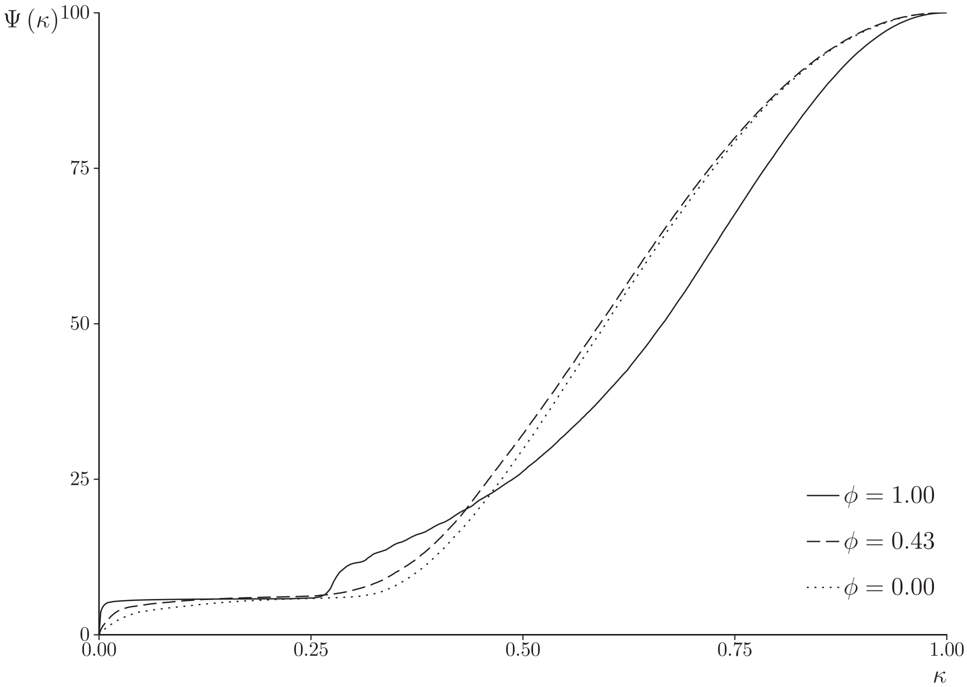

Fig. 2. The role of network structure.

the greater the role of preferential attachment, the stronger are the initial gains to acquiring a small amount of network information. Intuitively, in cases of strong preferential attachment the true distribution of links will be highly concentrated. A successful audit strategy must therefore target a small number of key taxpayers. As a high proportion of taxpayers have the same few celebrity taxpayers in their reference set it quickly becomes possible for the tax authority to identify these celebrity taxpayers, even when observing the network in a relatively limited way.

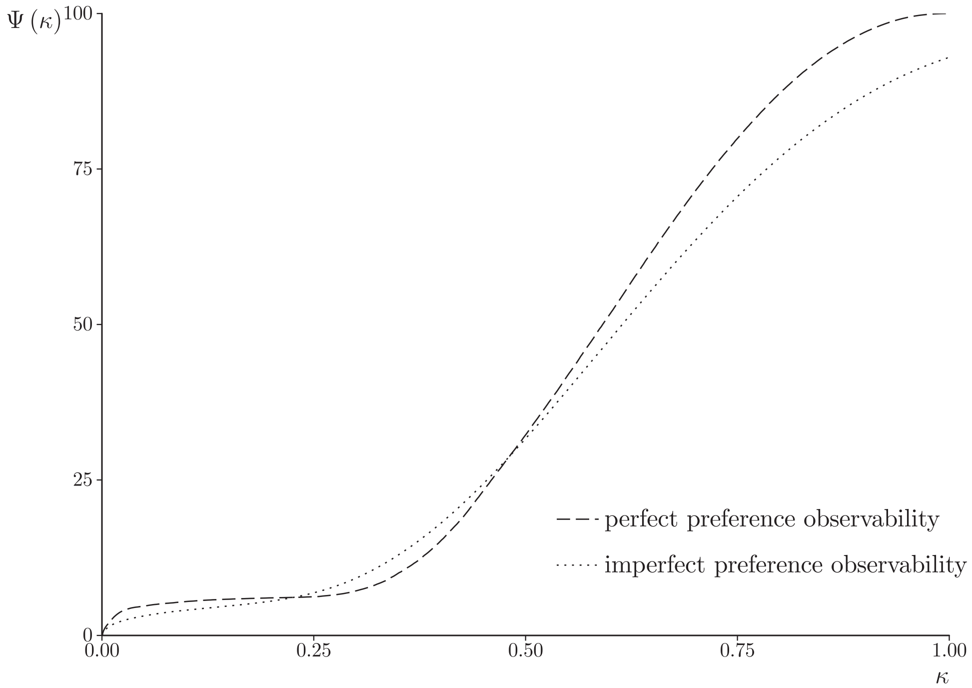

Fig. 3. The role of preference observability.

In contrast to the findings at low levels of network visibility, at somewhat higher levels preferential attachment actually reduces sensitivity to network visibility. This occurs as, once the celebrity taxpayers are accurately identified, further network information becomes of less value. In summary, the existence of celebrity taxpayers in social networks appears to present both threats and opportunities to tax authorities: it is gainful to tax authorities who can observe the network to a degree just sufficient to identify the celebrity taxpayers, but weakens revenue responses thereafter.

The analysis so far has been under the assumption that $\{a_i, b_i\}$ are perfectly observed by the tax authority. In practice, however, it seems certain that tax authorities imperfectly observe taxpayer preferences. As a final analysis, therefore, we consider the robustness of our findings to the case in which preferences and the network are both observed imperfectly. To do this we suppose the tax authority does not observe $\{a_i, b_i\}$ as before, but only the noisy signals $\{\tilde{a}_i, \tilde{b}_i\}$, where $\tilde{a}_i \sim U(0.95a_i, 1.05a_i)$ and $\tilde{b}_i \sim U(0.95b_i, 1.05b_i)$. In the presence of imperfect preference information we see (Fig. 3) that, even when the social network is fully observed ($\kappa = 1$), the tax authority does not achieve the maximal audit revenue. The qualitative shape of $\Psi(\kappa)$ remains as in Fig. 1, however. Accordingly, we find no evidence of important interaction effects between uncertainty over background preference parameters and uncertainty over the network.

5. Conclusion

Tax evasion is estimated to cost governments of developed countries up to 20% of income tax revenues. In this paper we apply to tax evasion recent advances in network theory and a large literature on the role in individual decision-making of social comparison. Our key theoretical advance is to demonstrate a link between network (Bonacich) centrality on a social network and tax evasion. Our modelling allows for local consumption comparisons and utilizes networks that have the properties of observed social networks. By contrast, previous studies have restricted comparisons to be at the aggregate, rather than local, level, and restricted attention to highly regular network structures.

Given that tax authorities are now investing in technology that seeks to construct social networks, we show that network information can allow a tax authority to better predict the likely revenue benefits from conducting an audit of a particular taxpayer. In particular, for a tax authority that is largely ignorant of the social network, we document strong initial revenue gains from acquiring relatively small amounts of network information.

The basic model we have presented here offers much scope for future research. Here we suggest three avenues. First, it would be of interest to introduce dynamic features to the model that relate behavior today to past reporting decisions and audit outcomes. Second, while we have focused on tax evasion, early empirical work (Alstadsaeter et al., 2018) suggests the relevance of a similar modelling approach to tax avoidance behavior, or indeed criminal activity more generally. Third, as we have assumed income to be exogenously determined, it would be of interest to introduce formally a labor-supply decision.

Declaration of Competing Interest

None.

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Appendix

Proof of Proposition 2. We have

$$
\begin{aligned}
\frac{\partial \mathbf{E}}{\partial p_j} &= \frac{\partial [\mathbf{I}-\mathbf{M}]^{-1}}{\partial p_j}\boldsymbol{\alpha} + [\mathbf{I}-\mathbf{M}]^{-1}\frac{\partial \boldsymbol{\alpha}}{\partial p_j};\\
&= [\mathbf{I}-\mathbf{M}]^{-1}\frac{\partial \mathbf{M}}{\partial p_j}[\mathbf{I}-\mathbf{M}]^{-1}\boldsymbol{\alpha} + [\mathbf{I}-\mathbf{M}]^{-1}\frac{\partial \boldsymbol{\alpha}}{\partial p_j};\\
&= [\mathbf{I}-\mathbf{M}]^{-1}\left[\frac{\partial \mathbf{M}}{\partial p_j}[\mathbf{I}-\mathbf{M}]^{-1}\boldsymbol{\alpha} + \frac{\partial \boldsymbol{\alpha}}{\partial p_j}\right];\\
&= [\mathbf{I}-\mathbf{M}]^{-1}\left[\frac{\partial \mathbf{M}}{\partial p_j}\mathbf{E} + \frac{\partial \boldsymbol{\alpha}}{\partial p_j}\right];\\
&= \mathbf{B}\left(\mathbf{M}, 1, \frac{\partial \mathbf{M}}{\partial p_j}\mathbf{E} + \frac{\partial \boldsymbol{\alpha}}{\partial p_j}\right);
\end{aligned}
$$

$$
\frac{\partial \mathbf{E}}{\partial W_j} = \frac{\partial \mathbf{E}}{\partial X_j} = [\mathbf{I}-\mathbf{M}]^{-1}\frac{\partial \boldsymbol{\alpha}}{\partial X_j} = \mathbf{B}\left(\mathbf{M}, 1, \frac{\partial \boldsymbol{\alpha}}{\partial X_j}\right);
$$

from which the Proposition follows. □

Proof of Lemma 1. Substituting $X(W_i) = [1-\theta]W_i$ and $E_i = \theta[W_i - d_i]$ into (5) and rearranging for W_i gives

$$
W_i = \frac{\{1+[f-2]p_i f\}\theta a_i d_{it} + b_i[1-p_i f] + a_i[1-p_i f]R_i}{a_i \xi_i}; \tag{A.1}
$$

$$
\xi_i = [1-\theta][1-p_i f] + \theta\{1+[f-2]p_i f\}.
$$

Noting that the second order condition for (5) to define a maximum is $-\theta^2 a_i\{1+[f-2]p_i f\} < 0$, it follows that $\xi_i > 0$. Using (4), (A.1) is written in full as

$$
W_i = \frac{\{1+[f-2]p_i f\}\theta a_i d_i + b_i[1-p_i f]}{a_i \xi_i} + \frac{a_i[1-p_i f]\{R(\mathbf{X} - \theta[1-p_i f]\mathbf{d}) + [1-p_i f][1-p_i f]\mathbf{g}_i\mathbf{W}\}}{a_i \xi_i}. \tag{A.2}
$$

Then the set of N equations defined by (A.2) for taxpayers $i \in \mathcal{N}$ can be written in matrix form as $\mathbf{W} = \boldsymbol{\gamma} + \theta\mathbf{V}\mathbf{W}$ where the elements of $\{\boldsymbol{\gamma}, \theta, \mathbf{V}\}$ are as in Lemma 1. Hence $\mathbf{W} = [\mathbf{I} - \theta\mathbf{V}]^{-1}\boldsymbol{\gamma} = \mathbf{B}(\mathbf{V}, \theta, \boldsymbol{\gamma})$. □

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