CONSUMPTION NETWORK EFFECTS*

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November 23, 2015

Abstract

In this paper we study consumption network effects. Does the consumption of our peers affect our own consumption? How large is such effect? What is the economic mechanism that is behind it? We use long panel data on the entire Danish population to construct a measure of consumption based on administrative tax records on income and assets. We combine tax record data with matched employer-employee data so that we can construct peer groups based on workplace, which gives us a much tighter, precise, and credible definition of networks than used in previous literature. We use the available data to construct peer groups that do not perfectly overlap, and as such provide valid instruments derived from the network structure of one's peers group. The longitudinal nature of our data also allow us to estimate fixed effects models, which help us tackle reflection, self-selection, and common-shocks issues all at once. We estimate non-negligible and statistically significant endogenous and exogenous effects. Estimated effects are quite relevant for policies as they generate non-negligible multiplier effect. We also investigate what mechanisms generate such effects, distinguishing between "keeping up with the Joneses", a status model, and a more traditional risk sharing view.

JEL Classification: E21, D12, D85
Keywords: Consumption, Networks

*We thank Nicola Fuchs-Schuendeln, Soren Leth-Petersen, Dan Silverman, Adam Szeidl, Chris Carroll, Orazio Attanasio, Nick Souleles, Nick Roussanov, Magne Mogstad, Petra Persson and seminar participants at several seminars and conferences in Europe and the US for comments. Financial support from the Spanish Ministry of Economy and Competitiveness through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2011-0075) and ECO2011-28822, the EU through the Marie Curie CIG grant FP7-631510 (De Giorgi) and the ERC starting grant 284024 (Pistaferri) is gratefully acknowledged. All views expressed in this paper are those of the authors only and do not necessarily reflect those of the Federal Reserve Bank of New York, the Federal Reserve System in general, the U.S. government.

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1 Introduction

Does the consumption of our peers affect our own consumption? How large is such effect? What is the economic mechanism that is behind it? What are the aggregate implications of consumption network effects? These are the questions that we investigate in this paper.[1] To this purpose, we use administrative data for the entire population of Denmark for the period 1980-1996. The data set includes information on income and assets, so we can construct a measure of consumption from budget accounting. The data set also includes information on the individual's employer ID and other observable worker characteristics, which we use to construct reference groups made of co-workers sharing similar characteristics (such as occupation or education). Finally, we can match our administrative data set with a small consumption survey where we observe household expenditure on various goods. As we shall see, this allows us to distinguish between competing hypotheses regarding the economic interpretation of consumption network effects.

The study of social influences on consumption behavior has a long history in economics, dating back at least to Veblen (1899), who wrote that "in any community where goods are held in severalty it is necessary, in order to ensure his own peace of mind, that an individual should possess as large a portion of goods as others with whom he is accostumed to class himself; and it is extremely gratifying to possess something more than others (p. 38)." Veblen also stressed that social effects on consumption would be stronger for so-called conspicuous consumption: "the competitor with whom [an individual] wishes to institute a comparison is [...] made to serve as a means to the end. He consumes vicariously for his host at the same time that he is a *witness* of that excess of good things which his host is unable to dispose of singlehanded (p. 65)" (italics added). Duesenberry (1948) also emphasized the role of social influences on consumption in his relative income hypothesis: "The strength of any individual's desire to increase his consumption expenditure is a function of the ratio of his expenditure to some weighted average of the expenditures of others with whom he comes into contact".

In recent years, the study of social influences on consumption, and more generally on individual behavior, has grown substantially. In education, the importance of peer effects on students' outcome has spurred a large literature (see Calvo-Armengol et al. (2006), Carrell et al. (2007, 2009), De Giorgi et al. (2010), Hanushek et al. (2003), Sacerdote (2001) for recent contributions). There is also a small literature that looks at the importance of peer effects in welfare use and take-up of social insurance programs (Borjas and Hilton (1996), Bertrand et al. (2000)), as well as one

[1] We will use the terms "peer effect" and "network effect" interchangeably, although the latter is better used in a context in which the utility from consuming a certain good is a function of the number of consumers (either because of congestion or economies of scale).

that considers the role that peers play in the selection of (and participation in) employer-provided pension plans (Duflo and Saez (2003), Beshears et al. (2011), Dahl et al. (2014)). Finally, on the labor supply side, papers by Montgomery (1991), Bandiera et al. (2009), Mas and Moretti (2009), and Grodner and Kniesner (2006) explore the importance of peer effects in explaining job search, work effort, and workers' productivity among other things.

The study of social influences on consumption behavior has evolved along two different lines. First, the definition of the relevant reference group used to estimate consumption peer or network effects. Here, empirical work has been mostly constrained by the type of consumption data available (typically, small consumption surveys with little or no longitudinal component). Hence peers have been defined generically as individuals sharing similar socio-demographic characteristics (as in Maurer and Meier, 2008), or somewhat more precisely as a racial group within a U.S. state (Charles et al., 2011), neighbors within a zip code (Kuhn et al., 2011) or city (Ravina, 2007). Second, the literature has proposed several economic explanations for the underlying estimated peer effects. There are at least three models that have enjoyed favor among researchers. The first is the "keeping up with the Joneses" model, in which individual utility depends on current average peers' consumption.[2] The second model revisits Veblen's idea of conspicuous consumption and suggests that the allocation of consumption among goods may be tilted towards goods that are more "conspicuous" than others, such as jewelry, luxury cars, restaurants, and so forth. The third model is one where risks are shared among members of a reference group, which creates correlation among their consumptions.[3]

Our paper contributes to both lines of research. First, we assume that co-workers are the relevant reference group of individuals and reconstruct the social network of a given household using information about the husband's and the wife's workplace. In the empirical analysis we define as co-worker someone who works in the same plant and is "similar" in terms of occupation and education. Co-workers represent a naturally occuring peer group. We believe it to be a reasonable and more credible definition of a social network than those used in the existing literature. Indeed, co-workers tend to spend a substantial fraction of their time together. Moreover, friendship often causes co-workership due to job search strategies adopted by job seekers (Montgomery, 1985).

Our second contribution is to propose and implement empirical tests that allow us to distinguish between a "keeping up with the Joneses" story, a "conspicuous consumption" explanation, and a risk sharing view of consumption peer effects.

[2] This model becomes "catching up with the Joneses" when utility depends on *lagged* average peers' consumption, as in Ljungqvist and Uhlig (2000).

[3] A similar intuition is given in De Giorgi and Pellizzari (2011) in the education context.

Why is the study of consumption network effects important? There are at least two reasons. First, from a welfare point of view one may be interested in measuring and understanding the type of distortions (if any) induced by the presence of peer effects. Depending on the mechanism underlying peer effects, distortions may be intratemporal (as in conspicuous consumption case) and/or intertemporal (as in the "keeping up with the Joneses" case). In the first case, budget shares would be distorted, i.e. status-seeking behavior might inflate the share of "visible" or conspicuous goods over the consumption bundle. Since "visible" goods are typically luxuries (cars or jewelry being the most notable examples), consumption peer effects might have noticeable welfare consequences (in the form of excess "wasteful" consumption).[4] In the intertemporal case, the saving profile would be different from the optimal one we would observe when agents act atomistically. This may induce undersaving (or over-borrowing) in the attempt to *keeping up with the Joneses*.[5] The second reason why studying consumption network effects is important is because of their potential aggregate effects. Uninsured idiosyncratic shocks (such as a tax change targeting rich taxpayers) might have aggregate consequences that go beyond the group directly affected by the shock. This depends on the size of the social multiplier as well as the degree of connectedness between groups that are affected and unaffected by the shock. In our empirical analysis, we find non-negligible endogenous peer effects, which may translate into a non-negligible social multiplier. If risk sharing is the main reason for correlated consumption profiles we would actually record important welfare gains. We then analyze the effect of policy counterfactuals based on consumption stimulus programs targeting different groups in the population.

While the *economic* issues regarding the presence and importance of consumption peer effects are not trivial (as they may be consistent with different theoretical mechanisms), the *econometric* issues surrounding identification of such effects are no less trivial, as is well know at least since Manski (1993). In particular, identification of consumption peer effects in a linear-in-means model is difficult because peers may have similar levels of consumption due to: (a) contextual effects, (b) endogenous effects, and (c) correlated effects. In our specific application these three effects could be described as follows: (a) workers with highly educated peers may have different wealth accumulation attitudes than those with mostly low-educated peers; (b) there may be genuine peer

[4] This is not the case if peers provide "information" about, say, better pricing opportunities, etc.. If the information story is an important one we should see it emerging mostly among goods with larger informational asymmetries (as reflected in pricing).

[5] In a number of recent papers (Rajan, 2011; Kumhof and Rancière, 2011;Bertrand and Morse, 2015) consumption peer effects play a key role in linking the rise of income inequality with financial crises. In these contributions, people in lower quintiles of the wage distribution over-borrow in the attempt to keeping-up-with-the-(*richer*)-Joneses (or status-maintaining effects). High levels of debt held by individuals with declining or stagnating wages may then precipitate a financial crisis.

influences, i.e., consumption behavior changes (causally) in response to the consumption behavior of co-workers; finally (c) consumption of all workers within the firm may be affected by some common (firm-level) unobserved shock, such as a productivity shock or a health campaign within the firm. In principle one can tackle (a) using random assignment as in Sacerdote (2001) or De Giorgi et al. (2010). However, random assignment does not alone solve (b) or (c).

We tackle these econometric issues by extending the network approach idea of Bramoullé et al. (2009) and De Giorgi et al. (2010), which rests on the existence of intransitive triads, i.e., "friends of friends who are not friends themselves". In our specific context, the key fact is that working relationships are individual, but consumption is shared. Hence, spouses add nodes to otherwise unconnected networks (firms). It follows that exogenous variation affecting the consumption of the co-workers of the spouses of husband's and wife's co-workers represent valid exclusion restrictions.

Our IV strategy delivers an estimate of the elasticity of own consumption with respect to peers' consumption of 0.3, which is statistically undistiguishable between husband's and wife's.[6] Such an estimated effect translates into a non-trivial aggregate effect which depends upon the degree of connecteness of the households, as we will discuss later in the paper. When we explore the thoeretical mechanism behind our results, we find support for a simple model of keeping-up-with-the-Joneses, while we can rule out sharp versions of models of conspicuous consumption as well as full and partial risk sharing. These results point towards an intertemporal distortion of the spending profile rather than a tilting of consumption towards luxury and conspicuous goods.

The rest of the paper is organized as follows. In section 2 we provide information on the data we have available. In section 3 we consider three different economic mechanisms that may potentially generate a relationship between individual consumption and the consumption of peers, and discuss testing strategies that allow us to distinguish between them. Section 4 is devoted to a discussion of the identification strategy and section 5 to the results. Section 6 discusses the results of a simple simulation of the aggregate implications of our findings, while section 7 concludes.

2 Data

2.1 Tax records data matched with employee records

We use administrative longitudinal tax records for the Danish population for the 1980-1996 period. Chetty et al. (2013) provide an informed discussion of the Danish tax system. The dataset includes information on income and assets for each taxpayer. While income data are typically available in all tax record datasets, the availability of asset data is due to the fact that, until 1996, households were

[6] The response to a random peer's consumption is much smaller due to large network size.

subject to a wealth tax.[7] We match these data with the IDA, an employer-employee data set, which includes, among other things, demographics and firm ID, from which we can identify co-workers. We define as co-workers those employees who work in the same plant (for public employees, this is the physical address of their workplace).

Our sample includes households whose head is aged 18-65, where both spouses work and are employees rather then self-employed. We no longer use these households if there is a divorce/separation, if one or both members stop working or become self-employed. This selection is driven by the research objective - we can only identify the reference network if people are employed; and we can only form instruments if spouses also work. However, we stress that in the computation of peers' consumption we use *all* workers, including singles and household with only one spouse working.

Consumption is not directly measured in administrative tax data. We use the dynamic budget constraint to calculate total consumption. In particular, consumption is calculated as the difference between after-tax annual income and asset changes:

$$C_{it} = Y_{it} - T_{it} - \Delta A_{it}$$

where $Y_{it} = (GY_{it} + HS_{it} + CS_{it} - TH_{it})$, with GY gross income (the sum of income from all sources), HS the value of housing support, CS the value of child support, TH is the implicit tax on the consumption value of owned housing, T are total tax payments, and ΔA the change in asset values (defined as the sum of cash, deposits on bank accounts, stocks and shares, the value of property, and the value of cars and other types of vehicles minus liabilities). This is similar to Browning and Leth-Petersen (2005) and Leth-Petersen (2010). Browning and Leth-Petersen (2005) conclude that this simple measure tends to behave even better than other more sophisticated measures which attempt to account for capital gains, return heterogeneity, etc. (see below for a formal comparison with survey data).

Table 1 provides some descriptive statistics about our sample. All monetary values are in 2000 prices. Annual consumption is about \$49,000, while annual (before-tax) income (Y_{it} above) is about \$70,000. The value of assets (about \$31,000) is smaller than what would typically be recorded in the US, although we note that there is quite a large dispersion in asset values (a standard deviaton of just over \$100,000). In terms of socio-demographic characteristics, husbands are slightly older than wives (42.5 vs. 40 years old), but they have about the same years of education (12). There

[7] Tax record data are actually available until 2008, but the wealth tax was abolished in 1996. Collection of detailed asset data were thus discontinued after 1996. Up until 1996 the base for the asset tax (which is our measure of A below) is obtained as a combination of self-reports (e.g., cars, jewelry, etc.) and third-party reports (e.g., checking accounts, etc.). After 1996 third-party reports are still available, but the self-reports are not.

is a large concentration of women in "white collar" jobs (typically, secretarial and teaching jobs), and a larger concentration of males in "managerial" positions relative to females. As far as sectoral concentration is concerned, there is a higher proportion of men in manufacturing and constructions, and a higher proportion of women in services and "other sectors" (typically, public employment). Finally, we compute tenure (years with current employer within our observational period 1980-1996). We do not find larger differences across genders (5 years on average). This tells us that co-workers tend to be in the same firm/location for a substantial number of years.

2.2 Danish Expenditure Survey

The Danish Expenditure Survey (DES) is, in (relative) size and scope, very similar to the US Consumer Expenditure Survey (CEX) or the UK Family Expenditure Survey (FES). See Browning and Leth-Petersen (2005) for more details about the survey. The survey is available from 1994, but given that our administrative data end in 1996, we use only the three waves spanning 1994 to 1996. Figure 1 plots the consumption distribution in the Tax Registry and the corresponding measure (for the same households) in the survey data (in 100,000 DKr). The two distribution overlap significantly and differ significantly only in the tails (due to issues related to capital gains and losses that are hard to account for in the Tax Registry data). In one of the robustness exercises below, we investigate the sensitivity of the results to remove the tails of the consumption distribution.

To conduct the tests we describe in the next section, we divide spending in the DES into spending on visible, neutral, and not-visible goods (with precise definitions given in the Appendix). While for most goods the separation is arbitrary, we use the Heffetz' index of visibility as an anchor (Heffetz, 2007). In particular, Heffetz (2007) conducts an original survey where each respondent is asked to rank 31 categories of expenditure according to their external "visibility". The higher the visibility, the higher is the assumed conspicuousness. We define visible goods to include Tobacco and Alcohol, Food away from home, Clothing, Furniture and Home goods, Electrics/Appliances, Vehicles, Entertainment, Books, Education, Personal care. Neutral is limited to food at home. Everything else is classified as non-visible (insurance, rent, etc.). In an extension of the testing idea, we construct spending categories that reproduce exactly the separation proposed by Heffetz (2007), with the exception of charity contributions that are not observed in the DES.

We use the DES for two main purposes: to validate our main results, and to investigate the economic mechanisms behind our findings.

3 General Theoretical Framework

In this section we explore the theoretical mechanisms that may justify the presence of consumption network effects. In general, one can think of network effects inducing either shifts in individual preferences or shifts in individual resources. In this section we discuss the first type of effects, and defer discussion of the second type of effects to Section 3.2.

3.1 Intratemporal vs. Intertemporal Distortions

The literature has focused on two broad classes of preference shifters: (a) "keeping up with the Joneses", and (b) "conspicuous consumption". To formally analyze network effects in a traditional life cycle consumption framework, we assume that the problem of the consumer can be written as:

$$\max \sum_{t=0}^{T} U_t\left(\mathbf{p}_t, C_{it}, z_{it}\right)$$

subject to the intertemporal budget constraint:

$$A_{it+1} = (1+r)\left(A_{it} + Y_{it} - C_{it}\right)$$

where $C_{it} = \sum_{k=1}^{K} p_t^k q_{it}^k$ is total spending on goods q_{it}^k with prices p_t^k $(k = 1...K)$, A_{it} is assets, Y_{it} income, and r the interest rate.

We follow Blundell, Browning and Meghir (1995) in considering a general form for the conditional indirect utility function $U_t(.)$:

$$U_t\left(\mathbf{p}_t, C_{it}, z_{it}\right) = F_t\left(V_t\left(\mathbf{p}_t, C_{it}, z_{it}^1\right), z_{it}^2\right) + G\left(z_{it}^3\right) \tag{1}$$

In this setting $V_t(.)$ governs within-period allocation of total spending C_{it} to goods q_{it}^k, while U_t determines intertemporal (or between-periods) allocation (i.e., the choice between consumption and savings). $F_t(.)$ is a strictly increasing monotonic transformation. Finally, $z_{it} = (z_{1it}, z_{2it}, z_{3it})$ is a vector of conditioning goods or characteristics (with z_{1it}, z_{2it} and z_{3it} possibly having overlapping terms). We can think of peers' consumption $\overline{C}_t$ (or the composition thereof) as being one such conditioning characteristics. In other contexts, z_{it} includes labor supply or demographics (see, e.g., Blundell, Browning and Meghir, 2000) or "rationed" goods (as in the classic Pollak, 1966).

In principle, peers' consumption $\overline{C}$ can enter any aspect of the consumption problem. To look at cases of interest, we start by noting that the demand functions (representing *intratemporal* or within-period allocation) are independent of the normalization $F_t(.)$ and are hence determined by the usual Roy's identity:

$$q_{it}^k = -\frac{\frac{\partial V_t(.)}{\partial p_t^k}}{\frac{\partial V_t(.)}{\partial C_{it}}}$$

In contrast, the Euler equation (representing *intertemporal* or between-period allocation) is given by:

$$\frac{\partial U_{t+1}(.)}{\partial C_{it+1}} = (1+r)^{-1} \frac{\partial U_t(.)}{\partial C_{it}}$$

or $\frac{\partial F_{t+1}}{\partial V_{t+1}} \frac{\partial V_{t+1}}{\partial C_{it+1}} = (1+r)^{-1} \frac{\partial F_t}{\partial V_t} \frac{\partial V_t}{\partial C_{it}}$. We can now consider three cases of interest.

CASE 1: Additive separability, or: $U_t\left(\mathbf{p}_t, C_{it}, \{C_{nt}\}_{n=1,n\neq i}^N\right) = F_t\left(V_t\left(\mathbf{p}_t, C_{it}\right)\right) + G\left(\{C_{nt}\}_{n=1,n\neq i}^N\right)$. In this case

$$\begin{aligned}
\frac{\partial q_{it}^k}{\partial C_{nt}} &= -\frac{\frac{\partial^2 V_t(.)}{\partial p_t^k \partial C_{nt}} \frac{\partial V_t(.)}{\partial C_{it}} - \frac{\partial V_t(.)}{\partial p_t^k} \frac{\partial^2 V_t(.)}{\partial C_{it} \partial C_{nt}}}{\left(\frac{\partial V_t(.)}{\partial C_{it}}\right)^2} \\
&= \frac{\frac{\partial(\partial V_t(.)/\partial C_{nt})}{\partial p_t^k} \frac{\partial V_t(.)}{\partial C_{it}} - \frac{\partial V_t(.)}{\partial p_t^k} \frac{\partial(\partial V_t(.)/\partial C_{nt})}{\partial C_{it}}}{\left(\frac{\partial V_t(.)}{\partial C_{it}}\right)^2} \\
&= 0
\end{aligned}$$

because $V_t(.)$ does not depend on C_{nt} for all $n \neq i$ and all $k = \{1, 2, ..., K\}$. Hence the intratemporal allocation is independent of peers' consumption. Since $\frac{\partial V_s}{\partial C_{ns}} = 0$ for all s, the intertemporal allocation decision is also independent of peers consumption.

CASE 2: Weak intratemporal separability, or:

$$U_t\left(\mathbf{p}_t, C_{it}, \{C_{nt}\}_{n=1,n\neq i}^N\right) = F_t\left(V_t\left(\mathbf{p}_t, C_{it}\right), \{C_{nt}\}_{n=1,n\neq i}^N\right)$$

As before, $\frac{\partial q_{it}^k}{\partial C_{nt}} = 0$ because $V_t(.)$ does not include C_{nt}. Hence intratemporal allocation is again independent of peer consumption when C_{nt} enters preferences as weakly separable, *as long as* one conditions on within-period spending C_{it}. This is a powerful testable restriction, similar in spirit to the one proposed by Browning and Meghir (1991) in a different context.

In contrast, the marginal utility of total consumption changes with peers consumption, inducing *intertemporal* distortions. To see this with a concrete example, consider a simple functional form (similar to the one proposed by Blundell et al., 1994):

$$U_t(.) = F_t\left(V_t\left(\mathbf{p}_t, C_{it}\right), \{C_{nt}\}_{n=1,n\neq i}^N\right) = (1+\delta)^{-t} \frac{\left(C_{it}/a\left(\mathbf{p}_t\right)\right)^{1-\gamma} - 1}{1-\gamma} \frac{1}{b\left(\mathbf{p}_t\right)} \prod_{n=1,n\neq i}^N C_{nt}^\theta$$

where[8]

$$\begin{aligned}\ln a\left(\mathbf{p}_t\right) &= \alpha_0+\sum_k \alpha_k \ln p_t^k+\frac{1}{2}\sum_k\sum_j \eta_{kj}\ln p_t^k \ln p_t^j \\ \ln b\left(\mathbf{p}_t\right) &= \sum_k \beta_k \ln p_t^k\end{aligned}$$

The (log-linearized) Euler equation is (approximately):

$$\Delta \ln \frac{C_{it+1}}{a\left(\mathbf{p}_{t+1}\right)} \cong \gamma^{-1}\left((r-\delta)-\Delta \ln b\left(\mathbf{p}_{t+1}\right)+\theta\Delta \frac{\overline{\ln C_{t+1}}}{a\left(\mathbf{p}_{t+1}\right)}\right) \tag{2}$$

where $\frac{C_{it+1}}{a(\mathbf{p}_{t+1})}$ is real consumption expenditure. Hence consumption allocation across periods depends on peers' consumption (as long as $\theta \neq 0$). If $\theta > 0$, peer consumption increases individual consumption ("keeping-up-with-the-Joneses), and *vice versa* if $\theta < 0$. Hence, an increase in peer consumption may change the allocation between consumption and savings (induce under- or over-saving) relative to the case $\theta = 0$.

CASE 3: Intratemporal non-separability: $U_t\left(\mathbf{p}_t, C_t, \{C_{nt}\}_{n=1,n\neq i}^N\right) = F_t\left(V_t\left(\mathbf{p}_t, C_t, \{C_{nt}\}_{n=1,n\neq i}^N\right)\right)$
Assume for example that:

$$\begin{aligned}V_t\left(\mathbf{p}_t, C_t, \overline{C}_t\right) &= \frac{\left(C_t/a\left(\mathbf{p}_t, \{C_{nt}\}_{n=1,n\neq i}^N\right)\right)^{1-\gamma}-1}{1-\gamma}\frac{1}{b\left(\mathbf{p}_t, \{C_{nt}\}_{n=1,n\neq i}^N\right)}\prod_{n=1,n\neq i}^N C_{nt}^{\theta} \\ U_t\left(.\right) &= F_t\left(V_t\left(.\right)\right)=\left(1+\delta\right)^{-t}V_t\left(.\right)\end{aligned}$$

From now on, we denote: $a_t\left(.\right)=a\left(\mathbf{p}_t, \{C_{nt}\}_{n=1,n\neq i}^N\right)$ and $b_t\left(.\right)=b\left(\mathbf{p}_t, \{C_{nt}\}_{n=1,n\neq i}^N\right)$ to avoid cluttering. In this third case, application of Roy's identity gives the budget share on good j:

$$\omega_{it}^j=\frac{p_t^j q_{it}^j}{C_{it}}=\frac{\partial \ln b_t\left(.\right)}{\partial \ln p_t^j}\frac{1-\left(C_{it}/a_t\left(.\right)\right)^{-(1-\gamma)}}{1-\gamma}+\frac{\partial \ln a_t\left(.\right)}{\partial \ln p_t^j}.$$

Intratemporal allocations will now be distorted by peers consumption if the latter shifts the price elasticity of goods. For example, if we adopt a simple linear shifter specification:

$$\begin{aligned}\ln a_t\left(.\right) &= \alpha_0+\sum_k\left(\alpha_{0k}+\alpha_{1k}\overline{\ln C}_t\right)\ln p_t^k+\frac{1}{2}\sum_k\sum_j \eta_{kj}\ln p_t^k \ln p_t^j \\ \ln b_t\left(.\right) &= \sum_k\left(\beta_{0k}+\beta_{1k}\overline{\ln C}_t\right)\ln p_t^k\end{aligned}$$

[8] The functions $a(\mathbf{p})$ and $b(\mathbf{p})$ are linear, positive and homogeneous. They can be interpreted as the costs of subsistence and bliss, respectively.

then spending on good j will depend on peers consumption according to the sign and magnitude of the coefficients α_{1j} and β_{1j}. For example, with the functional form above, budget shares for good j are:

$$\omega_{it}^{j}=\alpha_{0j}+\alpha_{1j}\overline{\ln C}_t+\sum_k\eta_{jk}\ln p_t^k+\left(\beta_{0j}+\beta_{1j}\overline{\ln C}_t\right)\frac{1-\left(C_t/a_t\left(.\right)\right)^{-(1-\gamma)}}{1-\gamma} \tag{3}$$

As for intertemporal allocation, they are also distorted, as the Euler equation is now:

$$\Delta\ln\frac{C_{t+1}}{a_{t+1}\left(.\right)}\cong\gamma^{-1}\left(\left(r-\delta\right)-\Delta\ln b_{t+1}\left(.\right)+\theta\Delta\frac{\overline{\ln C_{t+1}}}{a\left(\mathbf{p}_{t+1}\right)}\right) \tag{4}$$

In models with "conspicousness" researchers draw a difference between "visible" and "non-visible" goods. This induces reshuffling behavior. Suppose that there are three types of goods, V ("visible"), N ("not visible"), and X ("neutral"). To see reshuffling with a simple example, assume the following simplified functional forms for $a_t\left(.\right)$ and $b_t\left(.\right)$:

$$\begin{aligned}\ln a_t\left(.\right) &= \alpha_0+\sum_{k=\{V,N,X\}}\alpha_{0k}\ln p_t^k+\alpha_{1V}\overline{\ln C}_t\ln p_t^V+\frac{1}{2}\sum_{k=\{V,N,X\}}\sum_{j=\{V,N,X\}}\eta_{kj}\ln p_t^k\ln p_t^j\\ \ln b_t\left(.\right) &= \sum_{k=\{V,N,X\}}\beta_{0k}\ln p_t^k+\beta_{1V}\overline{\ln C}_t\ln p_t^V\end{aligned}$$

in which peers consumption shifts only the visible consumption component of the price indexes. Moreover, assume for simplicity quasi-homotheticity ($\gamma=1$). Then budget shares are:

$$\omega_{Vt} = \alpha_{0V}+\alpha_{1V}\overline{\ln C}_t+\sum_{k=\{V,N,X\}}\eta_{Vk}\ln p_t^k+\left(\beta_{0V}+\beta_{1V}\overline{\ln C}_t\right)\ln\left(C_t/a_t\left(.\right)\right) \tag{5}$$

$$\omega_{jt} = \alpha_{0j}+\sum_{k=\{V,N,X\}}\eta_{jk}\ln p_t^k+\beta_{0j}\ln\left(C_t/a_t\left(.\right)\right) \tag{6}$$

for $j=\{N,X\}$.[9]

[9] It is possible that the price indexes depend on peers' *visible* (rather than *aggregate*) consumption, i.e., $\ln a_t\left(.\right)=\alpha_0+\sum_{j=\{V,N,X\}}\alpha_{0j}\ln p_j+\alpha_{1V}\overline{q}_{Vt}\ln p_V+\frac{1}{2}\sum_{k=\{V,N,X\}}\sum_{j=\{V,N,X\}}\eta_{kj}\ln p_k\ln p_j$, with $\overline{c}_t=\overline{q}_{Vt}+\overline{q}_{Nt}+\overline{q}_{Xt}$. In this case, using $\overline{c}_t$ in place of $\overline{q}_{Vt}$ induces a downward bias in the estimation of α_{1V}. Unfortunately, we observe $\overline{c}_t$, not $\overline{q}_{Vt}$ (at least not a very precise one). In the Appendix we show that (under the simplifying assumption $\beta_{1V}=0$) the bias is:

$$p\lim\widehat{\alpha}_{1V}=\alpha_{1V}B$$

where $B=\left(\frac{var(\ln c)cov(\bar{q}_V,\bar{c})-cov(\ln c,\bar{c})cov(\ln c,\bar{q}_V)}{var(\ln c)var(\bar{c})-cov(\ln c,\bar{c})^2}\right)$. The term B can be estimated (with some noise whenever there are moments involving $\bar{q}_V$), which gives some information about the extent of the bias. Moreover, one can prove that $p\lim\widehat{\alpha}_{1N}=\alpha_{1N}B$, so a test of reshuffling can be based on $\widehat{\alpha}_{1V}\widehat{\alpha}_{1N}$, which converges to $\alpha_{1V}\alpha_{1N}B^2$. Under reshuffling, this product should be negative (as α_{1V} and α_{1N} move in opposite directions and $B^2\geq 0$).

To see why there is reshuffling, assume that peers' effects are positive ($\alpha_{1V} > 0$). It is straightforward to show that $\frac{\partial \omega_{jt}}{\partial \ln C_t} = -\beta_{0j}\alpha_{1V} \ln p_t^V$ for all $j = \{N, X\}$. If goods are normal, $\beta_{0j} > 0$, and hence the demand for goods that are not visible declines as peers' consumption increases. But since budget shares sum to one (and hence $\sum_{k=\{V,N,X\}} \frac{\partial \omega_{kt}}{\partial \ln C_t} = 0$), the demand for the visible goods must increase. Hence, there is a form of "reshuffling" as peers' consumption increases: the demand for visible goods increases and that for goods that are not visible declines.

From the general form $U_t(\mathbf{p}_t, C_t, z_t) = F_t\left(V_t\left(\mathbf{p}_t, C_t, z_t^1\right), z_t^2\right) + G\left(z_t^3\right)$, Table 2 summarizes the possible cases we can confront. It's easy to show that in the first case discussed above (additive separability), both the demand functions and the Euler equation for total spending are independent of peers' consumption. In the intertemporal weak separability case, the demand functions are independent of peers' consumption, but the Euler equation is not. Finally, in the intratemporal non-separable case, both demand functions and the Euler equation depend on peers' consumption.

Our strategy for distinguishing between these various cases is sequential. First, we estimate Euler equations for individual consumption growth that control for peers' consumption growth. This is meant to provide an estimate of the parameter θ in equations (2) or (4). Given that we do not observe good-specific prices, we will proxy the indexes $a_{t+1}(.)$ and $b_{t+1}(.)$ with a full set of year dummies and region dummies. If we find no peer effects ($\theta = 0$), we can conclude that preferences are intratemporally additive separable. If we find that peer effects are present (which as we shall see is the relevant empirical case), we need to distinguish between the case in which distortions are only intertemporal, or the case in which distortions are both inter- and intra-temporal.

We can distinguish between these two cases by estimating demand functions and test whether peers' consumption can be excluded from the demand for the various goods considered (controlling, crucially, for private total spending). In other words, we can estimate (3) and test whether $\alpha_{1j} = 0$ and $\beta_{1j} = 0$. Since the most prominent theory for justifying the presence of intratemporal distortions is the "conspicuous consumption" hypothesis, we divide goods according to their degree of conspicousness (i.e., "visible" vs. "less visible" goods). An additional implication of the conspicuous consumption hypothesis (discussed above) is that we should observe "reshuffling". If we reject both the presence of peers' consumption and reshuffling, then we can conclude that distortions are only intertemporal, as in the "keeping with the Joneses" case.

The estimation strategy assumes that we can obtain consistent estimates of consumption peer effects. This is notoriously difficult due to a host of identification problems remarked in the peers effects literature. We discuss how the structure of networks (at the co-worker level) helps us achieving identification in the next section. Once we have established what the main theoretical mechanism is (if any), we investigate its magnitude, heterogeneity, and robustness. Finally, we discuss welfare and macroeconomic implications.

3.2 Risk Sharing

A final theory for why consumptions can be correlated across agents is because of risk sharing among coworkers. Workers' repeated interaction in the workplace may indeed favor risk pooling.In full insurance versions of the theory, the growth rates of consumption of people belonging to the same risk sharing pool are perfectly correlated (Cochrane, 1991). Hence, full insurance implies $\gamma^{-1}\theta = 1$ when estimating an equation like (4). Note that in this case there is no meaningful "causal" relationship running from consumption of peers to individual consumption. The levels of consumption of individuals sharing risks optimally grow at the same rate because the effect of idiosyncratic shocks has been neutralized.

However, full insurance is an extreme view of risk sharing, especially in a setting like ours in which there is substantial social insurance provided by the Danish welfare system. It is more likely that, if risk sharing among co-workers exists, it provides only partial insurance. One way to test whether partial risk sharing is at play is to use the differences between consumption in the DES survey C^S (which may reflect side payments used to implement risk sharing agreements) and consumption in the tax record C^T (which should not). To see the gist of the argument, suppose that risk sharing is implemented *via* side transfers, i.e., workers receive transfer payments in bad times while the flow is reversed in good times. If worker i has been unlucky ($\Delta \ln Y_i < 0$) and coworker j has been lucky ($\Delta \ln Y_j > 0$), worker j would transfer to i some payments that go unrecorded in the tax record definition of consumption. This means that consumption in the tax records systematically underestates true consumption for the unlucky workers and systematically overestates it for the lucky workers. However, the consumption definition coming from the consumer survey ($\ln C^S$) will fully reflect transfers because it is based on actual spending on goods (which is partly financed by transfers received or paid). It follows that the difference ($\ln C_i^S - \ln C_i^T$) will be systematically *negatively* correlated with $\Delta \ln Y_i$ if risk sharing considerations are at play. Similarly, ($\ln C_i^S - \ln C_i^T$) will be systematically *positively* correlated with $\Delta \ln Y_j$. Hence, we can run a regression:

$$\ln C_{it}^S - \ln C_{it}^T = \pi_0 + \pi_1 \Delta \ln Y_{it} + \pi_2 \Delta \overline{\ln Y_t} + \upsilon_{it}$$

and test whether $\pi_1 < 0$ and $\pi_2 > 0$.

Note that the test that $\pi_2 > 0$ may be more robust than the test that $\pi_1 < 0$. The reason is that there may be a spuriously negative correlation between $\left(\ln C_{it}^{S} - \ln C_{it}^{T}\right)$ and $\Delta \ln Y_{it}$. Suppose that $\ln C_{it}^{T}$ includes spending on durables or capital gain and $\ln C_{it}^{S}$ does not. When $\Delta \ln Y_{it}$ grows, people may buy more durables, which may induce a negative correlation between $\left(\ln C_{it}^{S} - \ln C_{it}^{T}\right)$ and $\Delta \ln Y_{it}$ that is unrelated to risk sharing considerations.

4 Identification

Identifying consumption network or social interaction effects is not trivial. Two problems in particular need to be confronted. First, the definition of the relevant network or reference group. Second, the endogeneity of the peers' consumption variable.

The definition of networks or reference groups in economics is difficult and severely limited by data availability. Ideally, one would survey individuals, reconstruct the web of interactions they span (family, friends, co-workers, etc.), and then collect socio-economic information on both ends of each node. In practice, this is a rarely accomplished task (exceptions are the Add Health data in the US; and the Indian microfinance clients network of Banerjee et al., 2011), and identification of networks proceeds instead with identifying characteristics that are common to all network members (such as race, neighborhood, classroom, cohort, and interactions thereof). In this paper, we assume that individuals who work together form a social network. In our view, co-workers represent a more credible reference group than the definitions adopted in the consumption literature. There are two reasons why this may be the case. First, if social effects increase with the time spent with members of the reference group, "co-workers" are an obvious candidates for the ideal reference group, as they are the individuals we spend most of our day with. Second, in principle the ideal peer is a "friend". Evidence from sociology and labor economics shows that finding jobs through friends is one of the most frequent job search mechanisms utilized by job-seeker workers . Hence, not only do co-workers become friends; in some cases it is actually friendship that causes co-workership. Nonetheless, our definition of network may identify the true network of an individual only imperfectly: some co-workers do not exert any social influence, and other non-coworkers may play an important social role. For this reason, we assume that networks are measured with error. The IV strategy is also designed to correct for this problem.

Identification of peer effects (or social interactions) is plagued by a number of econometric issues (Manski 1993, Brock and Durlauf 2001, Moffit 2001) which for the popular linear-in-means model can be summarized into three categories: (a) contextual effects, (b) endogeneous effects, and (c) correlated effects. Contextual effects may emerge if co-workers share traits that make them more likely to select a given firm and these traits are important determinants of the dependent variable under study. Endogenous effects are the genuine network effects we are interested in. Finally, correlated effects may emerge if workers share unobserved shocks (say, a cut in their wages due to a firm productivity shock) that make their consumption move simultaneously *independently* of any genuine network effects. In general, when all effects are present it is very hard to distinguish one's behavior as cause or effect of someone else's behavior. In the same vein if similar individuals or households have common behavior it is very hard to say whether this is because they are very similar to start with or because they are influencing each other.

Our identification strategy relies on exploiting the social network structure of individuals. The main idea is that individuals are part of social networks that overlap only imperfectly (as in Bramoullé et al., 2009; Calvó-Armengol et al., 2009; and De Giorgi et al. 2010). In our specific context, we use the fact that social relationships are established along two lines: at the family level (e.g., husband and wife) and at the firm level (co-workers). If husband and wife work in different firms, it is possible to construct intransitive triads, i.e., "friends of friends who are not friends themselves". As we shall illustrate in what follows, this allows identification of all parameters of interest of the model.

More formally, we consider the following linear-in-mean specification for consumption growth, which is a simple generalization of the Euler equation (4) above (to allow for multiplexity, i.e., the fact that husband and wife can have distinct networks):

$$\Delta \ln C_{it} = \alpha + \theta_1 \Delta \overline{\ln C_{it}^w} + \theta_2 \Delta \overline{\ln C_{it}^h} + \gamma_1 \overline{X_{it}^w} + \gamma_2 \overline{X_{it}^h} + \delta_1 X_{it}^w + \delta_2 X_{it}^h + \xi_{it} \tag{7}$$

Here i and t indicate household and time, while the superscripts w and h indicate wife and husband, respectively. $\overline{\ln C_{it}^w}$ and $\overline{\ln C_{it}^h}$ are the (average) log consumption levels of the wife's and husband's co-workers; $\overline{X_{it}^w}, \overline{X_{it}^h}$ are the (average) characteristics of the wife's and husband's co-workers; X_{it}^w, X_{it}^h are the wife's and husband observable characteristics. There are a series of good reasons why one might want to consider the two spouses' networks separately, e.g., differential preferences, differential strenght of social influence by gender, as well as different bargaining power within the household. We will not make any attempt to micro-found our analysis as the bulk of our data comes from the administrative tax records.

The main parameters of interest in (7) are the θ's (endogenous effect) and the γ's (contextual effects). The δ's are, in this analysis, ancillary parameters of interest. Correlated effects may emerge if ξ_{it} contains firm- or network-specific effects.[10] We discuss below how we deal with network or

[10] We ignore the complications related to non-unitary household consumption behavior, although we acknowledge that in principle differences between θ_1 and θ_2 (or γ_1 and γ_2) could reflect the different bargaining weights of the spouses in the intra-family consumption allocations.

firm fixed effects, if present.

Equation (7) represents our main estimating equation. Note that first differencing log consumption has already eliminated individual fixed effects for the members of household i. These fixed effect may arise from sorting on firms based on similar unobserved characteristics. For example, suppose that workers sort into firms on the basis of risk aversion (an unobserved household characteristic), i.e., more risk averse workers will sort into firms that offer more stable employment patterns or implicit contracts. But since more risk averse workers also consume less or save more, it's not surprising that their consumptions may be correlated even in this absence of any social influence. First differencing eliminates this type of correlated effects.

While using consumption data (a household, rather than an individual variable) creates additional complications, it also makes identification possible using network structure. This is because husbands and wives who work in different firms have their own distinct network of coworkers. This means that instead of dealing with a series of isolated networks (firms), we can generate links (or "edges/bridges") across networks precisely through spouses working at different firms. In other words, if our definition of peer was a co-worker and we were dealing with single households, identification would be impossible to achieve.

4.1 Technical Discussion

4.1.1 An Introductory Example: The Simplest Intransitive Triad

To illustrate how we solve the identification problem, let's start from a simplified version of (7), in which our sample consists of three single households 1, 2, and 3. The most general model is one in which the consumption growth of a generic household i ($i = 1, 2, 3$) depends on her own exogenous characteristics X_i, and on the exogenous characteristics and the consumption growth of the other two households, i.e.:

$$\Delta \ln C_i = \theta \sum_{n=1, n \neq i}^{3} \frac{1}{2} \Delta \ln C_n + \gamma \sum_{n=1, n \neq i}^{3} \frac{1}{2} X_n + \delta X_i + \varepsilon_i \tag{8}$$

As in Manski (1993), this model is not identified. To see the type of identification strategy we follow, assume now that the households in our example represent the simplest form of an intransitive triad, i.e., agent 1's behavior is influenced by agent 2, who in turn is influenced by agent 3, who in turn behaves atomistically. Hence, we can rewrite the restricted form of (8) as:

$$\begin{aligned}
\Delta \ln C_1 &= \theta \Delta \ln C_2 + \gamma X_2 + \delta X_1 + \varepsilon_1 &(9)\\
\Delta \ln C_2 &= \theta \Delta \ln C_3 + \gamma X_3 + \delta X_2 + \varepsilon_2 &(10)\\
\Delta \ln C_3 &= \delta X_3 + \varepsilon_3 &(11)
\end{aligned}$$

The reduced form of this system is:

$$\begin{aligned}
\Delta \ln C_1 &= \theta \left(\gamma + \theta\delta\right) X_3 + \left(\gamma + \theta\delta\right) X_2 + \delta X_1 + v_1\\
\Delta \ln C_2 &= \left(\gamma + \theta\delta\right) X_3 + \delta X_2 + v_2\\
\Delta \ln C_3 &= \delta X_3 + v_3
\end{aligned}$$

The system above is triangular, and therefore it is easy to see that as long as $(\gamma + \theta\delta) \neq 0$ we can recover all the structural parameters from the reduced form ones. Identification comes from assuming that X_1 and X_2 can be excluded from individual 3's equation, while X_1 can be excluded from individual 2's equation. In other words, the exogenous characteristics of household 3 (X_3) can be used as an instrument for $\Delta \ln C_2$ in household 1's consumption growth equation (in network language, distance-3 peers' *exogenous* characteristics are valid instruments). This is because X_3 affects $\Delta \ln C_2$ due to contextual effects in household 2's consumption growth equation (2 and 3 are *directly connected*, as is visible from inspection of (10)), but it has no direct effect on household 1's consumption growth (1 and 3 are *not directly connected*, but becomes so, indirectly, through household 2), as visible from (9).

To provide a simple intuitive discussion to accompany the algebraic one, consider three childless couples, the Smiths, the Joneses, and the Rosses. The Smiths and the Joneses are close friends (from his workplace); and the Smiths are also friends with the Rosses (though her work). Assume that the Joneses and the Rosses have no connections. Suppose that the Rosses face a demographic shock (arrival of a child). Their consumption changes in response to different needs - for example, they consume more because their family is larger, or they stop eating out, etc.. This may affect the Smith's consumption in a number of ways. For example, the Smith realize that it is a good idea to start saving for college (even if they do not have kids); or perhaps the Rosses move to a better school district and this reduces their influence on what the Smiths consume (i.e., they do not go out as often). Whatever the mechanism, the events set in motion by the Rosses' change in their X's (family size), may in turn influence the Joneses' consumption behavior because of the Smith's change in consumption behavior.

4.1.2 A More General Model

The more general case requires matrix notation but the intuition given in the example above carries through identically. We generalize Bramoullè et al. (2009)'s identification argument (which applies to the individual level case) to our household level case. The multiple network case is also discussed elsewhere (i.e., Goldsmith-Pinkham and Imbens, 2013).

We allow the spouses' coworkers to have separate endogenous and exogenous effects on household consumption growth. This describes well our data, which are a combination of household level variables, i.e., income and wealth (and therefore consumption), as well as individual level variables such as occupation, education, etc.

The model primitives are as follows:

- *Household Level Variables:* $\mathbf{c}$ is the $(N \times 1)$ vector of household (log) consumption.
- *Individual Level Variables:*
  - $\mathbf{X}$ is a $(2N \times k)$ matrix of an individual characteristics. For simplicity of notation, we focus on the $k = 1$ case. Just out of convention, we order the husband characteristics in each couples in the first N rows, followed by the wifes' characteristics in each couple in the remaining N rows, i.e. $\mathbf{X} = \begin{pmatrix} \mathbf{X}_h & \mathbf{X}_w \end{pmatrix}'$.
  - Let also $\mathbf{S}_h$ ($\mathbf{S}_w$) be a transformation $(2N \times N)$ matrix that maps households into husbands (wifes). Given our conventional ordering, $\mathbf{S}_h = \begin{pmatrix} \mathbf{I} & \mathbf{0} \end{pmatrix}'$ and $\mathbf{S}_w = \begin{pmatrix} \mathbf{0} & \mathbf{I} \end{pmatrix}'$. Hence $\mathbf{S}_h\mathbf{X}$ (respectively, $\mathbf{S}_w\mathbf{X}$) will be the vector of husband's (wife's) exogenous characteristics.
  - Let $\mathbf{D}$ be the $(2N \times 2N)$ social network at the person level. The generic element of $\mathbf{D}$ is:

    $$d_{i^l j^m} = \{ \begin{array}{ll} 1 & \text{if } i^l \text{ connected to } j^m \text{ (for } l,m = \{h,w\}) \end{array}$$

    where as before i^h and i^w denote husband and wife in household i, respectively, and $d_{i^l i^m} = 0$ for $l, m = \{h, w\}$. The number of connections for a generic individual i^l is given by $n_{i^l} = \sum_{m=\{h,w\}} \sum_{j=1}^{N} d_{i^l j^m}$.[11]
  - Call $\mathbf{n}$ the $(2N \times 1)$ vector with generic element n_{i^l}. The row-normalized adjacency matrix is: $\mathbf{G} = diag\,(\mathbf{n})^{-1}\,\mathbf{D}$ with generic element $g_{i^l j^m} = n_{i^l}^{-1} d_{i^l j^m}$.

[11] A generalization of this is weighting the influence of different connections differently, i.e., $\widetilde{n}_{i^l} = \sum_{m=\{h,w\}} \sum_{j=1}^{N} d_{i^l j^m} \omega_{i^l j^m}$. This is what we do in the empirical analysis.

– Given this notation, $\mathbf{S}_h'\mathbf{G}(\mathbf{S}_h+\mathbf{S}_w)=\mathbf{G}_h$ is the husband-induced household network, with typical entry given by $\sum_{m=\{h,w\}} g_{i^h j^m}$, and identifies the households who are connected to the husbands (wifes) of the N households in our sample (symmetrically, $\mathbf{S}_w'\mathbf{G}(\mathbf{S}_h+\mathbf{S}_w)=\mathbf{G}_w$ is the wife-induced household network). Hence $\mathbf{G}_h\mathbf{c}$ ($\mathbf{G}_w\mathbf{c}$) is the vector of husband's (wife's) peers' log consumption.

– Similarly $\mathbf{S}_h\mathbf{G}\mathbf{X}$ ($\mathbf{S}_w\mathbf{G}\mathbf{X}$) is the vector of the husband's (wife's) peers' exogenous characteristics.

Given this notation, the matrix equivalent of (7) can be written (omitting the constant terms for simplicity) as:

$$\Delta\mathbf{c}=(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w)\,\Delta\mathbf{c}+(\mathbf{S}_h'\mathbf{G}\gamma_1+\mathbf{S}_w'\mathbf{G}\gamma_2+\mathbf{S}_h'\delta_1+\mathbf{S}_w'\delta_2)\mathbf{X}+\boldsymbol{\xi} \tag{12}$$

If $(\mathbf{I}-(\boldsymbol{\theta_1}\mathbf{G_h}+\boldsymbol{\theta_2}\mathbf{G_w}))$ is invertible, we can use the Neumann series expansion of a matrix (Meyer 2000, p. 527) to write:

$$\begin{aligned}(\mathbf{I}-(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w))^{-1} &= \sum_{k=0}^{\infty}(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w)^k \\ &= \mathbf{I}+(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w)+(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w)^2+... \end{aligned}\tag{13}$$

which is satisfied as long as $|\theta_1|+|\theta_2|<1$.[12]

The reduced form of (12) is obtained replacing (13) (for $k=1$, which results in a first-order "approximate" inverse) into (12):

$$\begin{aligned}\Delta\mathbf{c} \approx\ & (\mathbf{S}_h'\mathbf{G}\gamma_1+\mathbf{S}_w'\mathbf{G}\gamma_2+\mathbf{S}_h'\delta_1+\mathbf{S}_w'\delta_2)\mathbf{X} \\ & +(\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w)(\mathbf{S}_h'\mathbf{G}\gamma_1+\mathbf{S}_w'\mathbf{G}\gamma_2+\mathbf{S}_h'\delta_1+\mathbf{S}_w'\delta_2)\mathbf{X}+\mathbf{v}\end{aligned}$$

The interesting part of the identification argument is that one derives identification power from the cross-products between the different $\mathbf{G}$ matrices (in the case considered by Bramoullè et al., 2009, the population is made of single individuals, hence identification comes only from powers of

[12] To see this, assume that α is a scalar, and $\mathbf{A}$ and $\mathbf{B}$ are two square matrices. The sufficient condition for ensuring $(\mathbf{I}-\alpha\mathbf{A})^{-1}=\sum_{k=0}^{\infty}(\alpha\mathbf{A})^k$ is that $\|\alpha\mathbf{A}\|<1$ (see Meyer, 2000). The condition in the text uses the properties that: $\|\alpha\mathbf{A}\|=|\alpha|\,\|\mathbf{A}\|$ and $\|\mathbf{A}+\mathbf{B}\|\leq\|\mathbf{A}\|+\|\mathbf{B}\|$. Moreover, we use the fact that $\|\mathbf{G}_h\|_\infty=\|\mathbf{G}_w\|_\infty=1$ because of row-normalization of the adjacency matrix. Hence, $1>|\theta_1|+|\theta_2|=|\theta_1|\,\|\mathbf{G}_h\|+|\theta_2|\,\|\mathbf{G}_w\|=\|\theta_1\mathbf{G}_h\|+\|\theta_2\mathbf{G}_w\|\geq\|\theta_1\mathbf{G}_h+\theta_2\mathbf{G}_w\|$.

the adjacency matrix). In the equation above all the parameters of interest are separately identified as long as $\mathbf{S}'_h\mathbf{G}$, $\mathbf{S}'_w\mathbf{G}$, $\mathbf{S}'_h$, $\mathbf{S}'_w$, $\mathbf{G}_h\mathbf{S}'_h\mathbf{G}$, $\mathbf{G}_w\mathbf{S}'_w\mathbf{G}$, $\mathbf{G}_h\mathbf{S}'_h$ and $\mathbf{G}_w\mathbf{S}'_w$ are linearly independent. This essentially translates into peers of distance-3 being valid instruments.

As mentioned above, the advantage of the Euler equation specification (7) is that fist-differencing removes all fixed effects for the members of household i. One may be worried that while first differencing remove household fixed effects, it does not necessarily remove network effects. For example, all workers in a given plant face a common shocks due to poor firm performance. Call $f_{i^h(t)}$ and $f_{i^w(t)}$ the plant-specific effects for husband and wife in period t, and assume:

$$\xi_{it} = \Delta f\left(i^w\right)_t + \Delta f\left(i^h\right)_t + \upsilon_{it} \tag{14}$$

We consider two approaches. In the first, we restrict our analysis to a sample of firm stayers. If the network effect is constant over time ($f_{i^j(t)} = f_{i^j(t-1)}$ for $j = \{h, w\}$), first differencing eliminates the firm-related effects for those who do not change employer.[13] Our second approach uses the whole sample and add fixed effects for the "transitions" $\Delta f\left(i^w\right)_t$ and $\Delta f\left(i^h\right)_t$.[14] [15]

5 Results

5.1 Data Example: A Danish Network

Identification requires availability of co-workers of co-workers' spouses (or distance-3 nodes, as we consider husband and wife to be distance-1 peers). To see graphically what this entails, consider Figure 1, where we plot an actual network from our data. The red symbols are individuals working in a small firm which we call XYZ (10 employees). The blue symbols next to (some of) the red symbols represent spouses, some of whom are employed at other firms. For example, 5 and 6 are a family unit (person 5 works at XYZ while the spouse works at firm A, where (s)he has 134 co-workers). Note also that XYZ employs some single workers (persons 15, 17 and 19), as well as individuals with non-employed spouses (persons 3, 7 and 11).

Who are distance-3 co-workers? Consider the family unit composed of 5 and 6. In our specification (7), the consumption growth of this family unit depends on the average consumption growth

[13] Of course, mobility across firms may be endogenous, and for this reason one may need to control for selection into staying with the same employer. Unfortunately, we do not have powerful exclusion restrictions to perform this exercise credibly.

[14] Hence we assume stationarity, or $\Delta f\left(i^j\right)_t = \Delta f\left(i^j\right)_s$ for $j = \{h, w\}$ and all s, t.

[15] This strategy will not remove time-varying plant-specific shocks that make their way onto consumption decisions. The question is hence if plant related shocks are reflected onto consumption. If the shocks are transitory, the usual consumption smoothing argument would suggest that they are unlikely to shift consumption. If shocks are permanent, however, they may potentially affect consumption. Guiso et al. (2005) show that wages are fully insured against transitory firm-specific shocks, and partially insured against permanent shocks. However, the pass-through coefficient is small (0.07), which suggests any bias from neglecting such shocks is likely to be small.

of person 5's co-workers (i.e., the consumption of 11+12, 7+8, 15, etc.) and on the average consumption growth of person 6's co-workers (i.e., the consumption of the 134 family units in firm A). Moreover, it will depend on contextual effects, etc..

In the network jargon, a distance-x peer is an individual who is at least x-nodes away from the reference point. Since consumption is a household activity, our reference point is going to be a household rather than an individual. Hence, the distance-1 peers of family 5+6 are the co-workers of 5 in firm XYZ and the co-workers of 6 in firm A. These are the ones who contribute to the construction of $\overline{\ln C^h}$ and $\overline{\ln C^w}$, respectively. Distance-2 peers are the spouses of person 5's co-workers in firm XYZ, as well as spouses of person 6's co-workers in firm A. Finally, distance-3 peers are individuals working in firm B, C and D, as well as co-workers of the spouses of person 6's co-workers. The endogeneity problem is solved by using as instruments the average X's of the distance-3 peers of the household.

In the empirical analysis we focus on couples where both spouses work. This is not a strong restriction given the high female participation rate in Denmark. However, we do face a series of difficulties when it comes to data construction. First, we need to exclude couples that work in the same firm. Second, when we deal with multi-worker firms (which is the norm), we have to choose whether to construct average peers consumption using simple or weighted averages, where the weights might depend on job title, education, etc.. Third, a potential concern is that of assortative matching within the household and the firm. We can think of this problem as generating unobserved household heterogeneity, which we deal with by differencing the data as in (7). Finally, we need to avoid "feedback network effects". Suppose that persons 1 and 3 work at firm j and their spouses 2 and 4 work at another firm k (this is not an unlikely case given the important role of job search networks, see Montgomery, 1982, Pistaferri, 1999, Pellizzari, 2010). In our scheme the consumption of 1+2 depends on the consumption of 3+4. The way we construct the instrument would imply using the exogenous characteristics of 1+2 as instrument for the consumption of 3+4, which will violate the exclusion restriction condition.

5.2 Network Statistics

Before presenting the estimation results, we provide some descriptive statistics on the network data. It is useful to recall the structure of the network we create. We start from selecting households where both husband and wife work ("household network line"). Their distance-1 peers are their co-workers ("firm network line"). Their distance-2 peers are the spouses of their co-workers (distance 1), if they are married and if the spouses work ("household network line" again). Their distance-3 peers are the co-workers of the spouses of their co-workers ("firm network line" again). Note that when we move along the household network line we are bound to get fewer nodes than when we move along the firm network line, simply because people can only have one spouse, but they can have multiple co-workers.

We consider several definitions of a co-worker. Our baseline definition takes individuals working in the same plant and weights more those with a similar occupation and level of education. We allocate individuals to five education groups (compulsory schooling, high school dropout, high school degree, college dropout, college degree) and three occupation groups (blue collar, white collar, manager). We order education from the lowest to the highest level ($E = e$ for the e-th education group, $e = \{1...5\}$) and occupation from the lowest (blue collar) to the highest level (manager) ($O = o$, $o = \{1, 2, 3\}$). Next, we define a variable called "degree of separations" between any two individuals i^s and j^m as $d_{i^s j^m} = (|E_{i^s} - E_{j^m}| + |O_{i^s} - O_{j^m}|)$. Hence if i^s is a blue collar high school dropout ($E_{i^s} = 2, O_{i^s} = 1$) and j a college graduate manager ($E_{j^m} = 5, O_{j^m} = 3$), $d_{i^s j^m} = 5$. For individuals with the same education and occupation, $d_{i^s j^m} = 0$. We then create a quadratic weight variable

$$\omega_{i^s j^m} = (d_{i^s j^m} + 1)^{-2} \tag{15}$$

and use it to generate weighted sums and averages. For example, household i wife's average consumption peers is given by:

$$\overline{\ln C_{it}^{w}} = \left(\sum_{j^m, j^m \neq i^w} \omega_{i^w j^m} \right)^{-1} \sum_{j^m, j^m \neq i^w} \omega_{i^w j^m} \ln C_{jt}$$

where j^m is the m-th member of family j ($m = \{h, w\}$). We adopt a similar weighting procedure for the creation of the contextual variables.

Using a weighted adjacency matrix has two purposes: (a) some nodes might be more "important" in affecting behavior; (b) they add variation to our right hand side variable. The use of a similarity index is also consistently with the homophily literature (Currarini et al. 2011). Since weight assignment is arbitrary, in the Appendix we present results under three different weighting procedures: (a) equal weighting for all plant peers sharing the same occupation; (b) equal weighting for all plant peers sharing the same education and occupation; and (c) using a linear similarity weight $\omega_{i^s j^m} = (d_{i^s j^m} + 1)^{-1}$, where $d_{i^s j^m}$ has been defined above.

Our networks span the entire Danish economy (or, more precisely, the part of the Danish economy that is observed working in firms). Looking at Table 3, we note that husbands have on average about 110 distance-1 peers (or co-workers), while wives tend to work in larger firms (or in the public sector), with an average distance-1 peer network size of 135 co-workers. Given our sample selection and the fact we now move along the household network line, it is not surprising that average peer group size declines when we move to distance-2 peers (where the sample selection requirement is not enforced). Hence, only 43 of the male distance-1 peers and 54 of the female distance-1 peers have spouses who themselves work (and who represent distance-2 peers). This is a combination of both being unmarried or being married with a non-working spouse. To find distance-3 peers we again move along the firm network line. Wives have on average 135 co-workers; 54 of them have valid nodes (spouses who work); the expected number of distance-3 peers is therefore around 7,300. In practice, there are more (around 10,000) due to a long right tail effect induced by skewness in firm size. In principle, the farther we move from the center, the larger the network size. In practice, this is bounded by the size of the economy.

In the last two columns of Table 3 we present network statistics using the weighting scheme (15). As one would expect, we have smaller weighted networks. In Table 4 we report descriptive statistics for distance-1 peers (co-workers). Gender differences are quite stark - most likely due to job segregation by gender (nurses, teachers, shop assistants, white collar workers in the public sectors are jobs that are traditionally disproportionally taken by women).

In Table 5 we report some statistics about our instruments (average characteristics of distance-3 peers, i.e., co-workers of spouses of co-workers). The occupation averages are more balanced, and the gender imbalance is now turned around. This is not very surprising - as for husbands, given the clustering of workplace by gender, distance-2 peers are mostly females who work disproportionately with other females. The same logic applies to all the occupation variables.

We note that the identification of the parameters of interest relies up overtime variation in two main blocks: i. change in the composition of the workforce identified as distance 3 peers, in terms of their average education, gender and so on; and ii. economic shocks to distance 3 peers' workplace, i.e. growth in size, becoming publicly traded, etc.

5.3 Euler Equation Estimates

The main specification we adopt follows from the Euler equation (7):

$$\Delta \ln C_{it} = \alpha + \theta_1 \Delta\overline{\ln C_{it}^w} + \theta_2 \Delta\overline{\ln C_{it}^h} + \gamma_1 \overline{X_{it}^w} + \gamma_2 \overline{X_{it}^w} + \delta_1 X_{it}^w + \delta_2 X_{it}^h + \xi_{it}$$

where C is household real consumption per-adult equivalent and ξ_{it} takes the form described in (14). We use the LIS equivalence scale, i.e., $\sqrt{n_{it}}$ where n_{it} is family size. The set of exogenous characteristics include: household controls (dummies for municipality of residence, number of children aged 0 to 6, and number of children aged 7 to 18), individual controls (age, age squared, years of schooling, dummies for blue collar, white collar, manager), contextual controls (age, age squared, years of schooling, number of children aged 0 to 6, number of children aged 7 to 18, share of female peers, share of blue collars, white collars, managers), and controls that are both individual and contextual (year dummies, sector dummies, the interaction of sector and year dummies, firm size, firm employment changes, whether firm is part of the public sector, and dummies for the firm legal status). We consider two sets of instruments: demographic-based (age, age squared, years of schooling, share of women, share of blue collars, share of white collars, share of managers, kids aged 0-6, kids aged 7-13) and firm-based (firm size, firm employment changes, whether firm is part of the public sector, and dummies for firm legal status - distinguishing between publicly traded, limited liability, or other type).

The first three columns of Table 6 presents estimates from three different specifications. In column (1) we present a traditional OLS specification applied to the first differenced consumption data. This is subject to the usual reflection problem. In column (2) and (3) we estimate our baseline IV regressions with different sets of instruments (demographic and firm IVs, and firm IVs only, respectively). Throughout the analysis standard errors are double clustered with clusters defined by plant/occupation/education for both husband and wife. We also present first-stage statistics, which are generally fairly large and in our most preferred specification (column (3)) much larger than conventional acceptability thresholds (even discounting for the unusually large sample sizes). Our preferred specification is the one in column (3), where we restrict attention to instruments reflecting economic shocks induced by firm performance (as captured by variation in size) and changes thereof.

The table shows non-negligible consumption network effects. In our preferred specification (column 3) the husband's network effect is 0.37 and statistically significant at the 5%, while the wife's network effect is slightly smaller, 0.3 and significant at 10% level. It is important to quantify these effects. A 10% increase in the average consumption of the wife's peers would increase household consumption by 3%. However, given network size, this is a fairly aggregate shock - it is equivalent to a 10% simultaneous increase in the consumption of *all* peers. A different (and perhaps more meaningful) way of assessing these effects economically is to ask by how much household consumption would increase in response to a 10% increase in the consumption of a *random* peer in his/her network. We estimate this to be 0.03% in the wife's case and 0.05% in the case of the husband's. In monetary terms and evaluated at the average level of consumption, a 10% increase in the consumption of a random peer on the husband side (corresponding to about $5,000) would increase household consumption by about $25 (and $1,825 in the aggregate). On the wife side, the effect would be \$15 (and \$1,425 in the aggregate). Since individual and aggregate effects may be very different, in Section 6 we attempt to quantify the macroeconomic implications of the network effects we estimate.

In column 3, the effect of the husband's and wife's network consumption are very similar. In fact, the last diagnostic statistic we present in Table 5 is a test for the equality of the husband and wife's networks effects. In all the IV specifications we cannot reject the null hypothesis of equality of the coefficients (with large p-values).

Given this evidence, in the rest of Table 6 we re-estimate all models imposing that husband's and wife's effects are the same (columns 4 to 6). Estimates are close to those presented in columns 1-3, but expectedly more precise. We estimate a network effect of around 0.33, statistically significant at the 1%. The first-stage F-statistics in our preferred specification (column (6)) is high, about 110. Note that there are very similar results independently of the set of instruments used. From now on, we present results assuming that the husband's and wife's network are actually just a single larger network. The economic interpretation is similar to the one presented above. A random peer's 10% increase in consumption would increase household consumption by 0.04%.

5.3.1 Other Concerns

Table 7 contains the results of a number of specifications designed to address a variety of specific concerns. Column (1) reproduces, for comparison, the results of our preferred specification (Table 6, column 6). The first concern is the possibility that the error term contains network (correlated) effects which may generate spurious evidence of endogenous effects (despite our controls for sector shocks and local labor market shocks). To address this issue, we follow two strategies. In column (2) we focus on a sample of firm stayers, for whom firm fixed effects are differenced out. In column (3) we use the whole sample but include fixed effects for all possible cross-firm transitions (and assume stationarity). The results remain very similar to the baseline.

Our measure of consumption, based on a budget accounting, may miss capital gains and capital losses, i.e., may fail to be accurate at the top and bottom of the consumption distribution. In column (4) of Table 7 we present results obtained using a measure of consumption that drops the top and bottom 1% of the consumption values. The estimate declines in value and is more precise, but overall remains in the same ballpark.

In column (5) we use a different weighting scheme, in which all workers in the same plant and occupation are treated equally (regardless of their education). The estimate of endogenous effect increases in size but again the change is not dramatic.

Bias from correlated effects may come from co-workers suffering similar aggregate shocks.

Columns 6 and 7 are designed to address these concerns. In column (6) we control for neighborhood specific shocks (measured by chages in local unemployment rates), while in column 7 we control for sector specific shocks (measured by sector*year dummies). The results remain unchanged.

Finally, can our results be spurious? There could be some unobserved factors running through the economy which might produce correlation in consumption that have nothing to do with network effects. To assuage these fears, we construct a placebo sample, i.e., randomly assign workers to given firms and occupations and then re-run our regressions. We keep firm size constant and we only reshuffle workers across firms. The results, reported in the last column of Table 6, show that the effects are not spurious. When individuals are randomly allocated peers, their consumption is independent of that of their randomly allocated peers.

5.3.2 Heterogeneity of network effects

Are network effects heterogeneous? For example, one may believe that effects vary with network size: peer effects may be much more important in a small firm than in a large firm where personal and social contacts can be more diluted. Moreover, peer effect may depend on observable demographics: education, tenure, firm turnover, business cycle, etc.. The effect of tenure is particularly important, as one may test whether social pressure increases with the time spent with a co-worker (effects may be small at low levels of tenure and larger at high levels of tenure). Unfortunately, our measure of tenure is limited and subject to left-censoring. We use age as a proxy for tenure.

In lieu of presenting regression results, Figure 3 show how the consumption network effect vary with observable characteristics (age, network size, years of schooling, gender, and a measure of the business cycle). The graph also plots the upper and lower bounds of a 95% confidence interval.

As one might expect, peer effects are smaller when the network is larger, but the effect is noisy. Peer effects increase with the age of the household head, but again effects are imprecise. The effect of schooling is positive, but only among college-educated peers. Finally, network effects are larger when economy is booming, smaller during recessions - but estimates are significant only for growth rate above 2% or so. The only effect that is precisely measured throughout the range of variation of the running variable is the share of women peers - networks in which co-workers are predominantly women exert a larger impact on household consumption.

5.4 Demand Estimation

The results presented in the previous section point to the presence of considerable intertemporal distortions on consumer behavior. Table 2 suggests that intertemporal distortions may also be compatible with the presence of intratemporal distortions, which may have very different policy implications, as well as suggesting different theoretical mechanisms.

In this section we follow the structure developed in Section 3.1 and estimate demand equations for "visible" and "non-visible" goods. In particular, we run the following regressions:

$$\omega_{it}^{j} = X_{it}'\alpha_{0j} + \alpha_{1j}\overline{\ln C}_t + \beta_{0j}\ln C_{it} + \beta_{1j}\left(\ln C_{it} \times \overline{\ln C}_t\right) + \upsilon_{it}^{j} \tag{16}$$

for $j = \{V, N\}$ (neutral goods represent the excluded category). We test whether - controlling for total spending $\ln C_{it}$ - the average consumption peer variables are insignificant determinants of the demand for goods (i.e., $\alpha_{1j} = \beta_{1j} = 0$ for all j). We also report the results of a simpler specification in which we omit the interaction (and hence assume $\beta_{1j} = 0$ for all j). This is useful because it allows us to perform a simple test of reshuffling, i.e., testing that $\alpha_{1V}\alpha_{1N} < 0$.

We report results for two samples. The first sample is all households that can be matched with the tax registry (independently of marital and work status). This results in 2,438 households. For these households we do not have distance-3 instruments (as this depends on both the work and marital status) and hence run simple OLS regressions. Our second sample is a perfect match with our tax registry baseline sample, and is hence much smaller (454 households). For these households we can run IV regressions..

The results are reported in columns (1)-(6) of Table 8. In columns (1)-(2) we report estimates of (16). There is no evidence that conspicuous consumption changes intratemporal allocations. Controlling for total consumption, the marginal effect of peers consumption, $\frac{\partial \omega_{jt}}{\partial \overline{\ln C}_t}$, is small and statistically insignificant for both visible and non-visible goods. To avoid collinearity problems, in columns (3)-(4) we impose $\beta_{1j} = 0$. We now estimate significant main effects for total log consumption (suggesting that visible goods are luxuries and non-visibipe goods are necessities), but again find no statistically significant effects of peers consumption. At face value, there is no evidence of reshuffling (the sign of the variable is positive in both equations). Note that the results do not depend on the richness of controls used, and are confirmed even when we have no controls in the regression besides total consumption, peers consumption, and their interaction. Finally, the results do not depend on assuming that peers consumption is exogenous. In columns (5)-(6) we replicate estimation on our baseline sample, where we can instrument peer consumption with distance-3 exogenous characteristics. The results are qualitatively unchanged.

There is some inherent arbitrariness in how we classify goods into visible, neutral, and non-visible categories. To counter this criticism, we disaggregate spending into the 30 categories considered by Heffetz (2011), and run the budget share regression (16) separately for each category (imposing again $\beta_{1j} = 0$ for all j). Figure 4 plots the estimated coefficients (and corresponding 90% confidence intervals) against the degree of visibility as estimated in Heffetz (2011). We also plot a local linear regression line. We do this for the two samples described above (so that α_{1j} is estimated by OLS in the first sample and by IV in the second sample). In principle, the regression coefficient should rise with the degree of visibility. However, the disaggregated evidence is similar to the one commented above. The effect of peer consumption and budget share on good j appears independent of the degree of conspicousness of the good. The relationship is increasing only for high conpiscuous goods, but the estimates are very noisy. In the baseline sample where we control for the endogeneity of peer consumption the effect goes in the opposite direction of what models with conspicuous consumption would suggest.

5.5 Risk Sharing

As discussed in Section 3.2, another reason for observing a correlation between individual and peer consumption is because of risk sharing within the firm. The theory of risk sharing states that when risks are shared optimally, consumption growth of two individuals who are part of a risk sharing agreement will move in locksteps even if the two individuals do not interact socially. The extreme case is where co-workers only observe income but do not observe consumption (i.e., all relevant consumption is domestic). However, this is enough to generate risk sharing as long as we believe problems of private information or limited enforcement are more easily solved within the strict confines of the workplace.

Results reported in Table 6 already reject the strongest form of full insurance (i.e., that individual consumption should move at the same rate as aggregate peer consumption). The way we test for partial risk sharing is explained in Section 3.2. We consider the regressions:

$$\ln C_{it}^{S} - \ln C_{it}^{T} = X_{it}'\pi_0 + \pi_1 \Delta \ln Y_{it} + \pi_2 \Delta \overline{\ln Y_t} + \upsilon_{it}$$

and test whether $\pi_1 < 0$ and $\pi_2 > 0$.

The results are reported in Table 9. As in Table 8, we focus on the "All household" sample (column 1) and the "Baseline" sample (columns 2 and 3). Risk sharing would suggest a negative association between earnings growth and the survey-tax record consumption log-differential. This is because individuals who suffer a negative income loss should receive a transfer from peers, which would increase the survey-based measure of consumption (which includes the transfer) relative to the tax records measure (which does not). In the data (irrespective of sample used) there is actually a positive, significant association. Similary, there is no evidence of a positive association between average earnings growth of peers and the survey-tax record consumption log differential. We conclude that it is unlikely that our results of significant peer effects are spuriously coming from risk sharing within the firm.

6 Implications

6.1 Aggregate Effects

The effect of macroeconomic stabilization policies may depend on the presence of peer effects. Small stabilization policies may have larger or smaller effects than in a world where peer effects are absent because of social multiplier effects. Here we discuss a simple macro experiment based on our empirical estimates. In this experiment we neglect General Equilibrium effects on asset prices, labor supply, etc.

We start from the consideration that a tax/transfer imposed on a group may reverberate through the entire distribution, depending on the degree of connectedness of individuals. A "benchmark" multiplier, which abstract from the degree of connectedness, is about 1.4 (from the regression of Table 6, obtained as $1/(1-\widehat{\theta})$ with $\widehat{\theta} \cong 0.3$), so aggregate effects may potentially be important.

Our first two experiments consist of transferring the equivalent of a 1% of aggregate consumption equally among: (a) households in the top 10% of the consumption distribution, and (b) a 10% random sample of households. These two policies are financed by issuing debt and running a government deficit. As an alternative to a debt-financed policy, we consider (c) a purely redistributive policy in which the receivers of the transfers are households in the bottom 10%,and the policy is financed by a "tax" on the top 10% of households. Note that we abstract from the possibility that MPCs are heterogeneous. Alternatively, the government transfer is a consumption coupon, so it is entirely consumed (and MPC heterogeneity plays no role).[16]

The results are in Table 10. We distinguish between two cases, with and without network effects. We also notice that while the size of the transfer is 1% in the population, it may be smaller or higher in our sample due to sample selection.

Consider the first experiment, which consist of distributing resources to the top 10% of the consumpitn distribution. The aggregate effect on our sample is slightly smaller than 1% because rich households are less likely than an average family in the population to have both spouses at work, below age 65, etc. (which is how we have selected our sample in the empirical analysis). The policy in the no network effect case gives money to the rich and they spend it all by definition, resulting in a 0.94% increase in aggregate consumption. In the network effects case, they also

[16]See Jappelli and Pistaferri (2014) about the importance of MPC heterogeneity.

induce an increase in consumption of their peers who have not received any transfer. Through connectedness of the rich (which we estimate from the data recreating all the firm and household networks in the population), this generates a 1.15% increase in aggregate consumption growth despite a transfer equivalent to 0.94%. The implied multiplier is hence 1.22 (0.0115/0.0094).

In the second experiment, we select 10% random households as being the recipients of the government transfer. In the no network case they receive the equivalent of 0.92% of aggregate consumption and spend it all by assumption. Aggregate consumption goes up by the same amount (the multiplier is 1). But in our data a random household is more connected than a rich household, and this induces a larger response once network effects are factored in. Indeed, the multiplier is now 1.63.

Finally, in the last row we consider moving resources from rich to poor in a balanced-budget manner. In the population this redistributive policy is neutral (as MPCs are homogenous), but in our sample there are more rich households that are hurt by the policy than poor who benefit (due again to sample selection), hence the 0.57% decline in aggregate consumption of the no-network-effect case. The effect on aggregate consumption in the network case is to *increase* it by 0.73%, implying quite large connectedness among the poor households and a large impact of balanced-budget policies.

7 Conclusions

We build a consistent framework of consumption choices that is able to capture social effects and allows us to distinguish between different mechanisms of interaction. We then take those testable predictions to the data and test for the prevailing mechanism using a very rich set of data where we observe the entire Danish population for almost two decades. We find that peers' consumption enters the intertemporal decision, i.e. in a Keeping up with the Joneses fashion, rather then the demand system or in a form of risk sharing.

We estimate such social effect to be quite substantial, and interestingly indistinguishable between husbands and wives, on average this produces a substantial social multiplier effect which depends on the degre of connectdeness between households. Ultimately we provide a series of policy experiments where we are able to estimate policy effects of the order of 1.3-1.6. As such we show that policies which are addressed at the top or bottom of the distribution might actually affect the entire population.

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Table 1: Descriptive Statistics

	Mean	Std.Dev.		Mean	Std.Dev.
		Outcomes:			
ln *Consumption* (AE)	12.07	0.66	*Income*	515,877	186,305
($)	10.08	0.66	($)	70,388	25,420
Consumption	358,893	324,117	*Assets*	226,567	758,139
($)	48,969	44,224	($)	30,914	103,443
		Socio-Demographics:			
Age			*Sector: Manufacturing*		
Husband	42.53	9.42	Husband	25.14	
Wife	40.06	9.10	Wife	12.75	
Years of schooling			*Sector: Service*		
Husband	12.06	2.33	Husband	15.63	
Wife	11.70	2.33	Wife	12.22	
Occupation: Blue			*Sector: Construction*		
Husband	43.04		Husband	10.30	
Wife	31.63		Wife	0.99	
Occupation: White			*Sector: Other*		
Husband	15.83		Husband	48.93	
Wife	45.20		Wife	74.05	
Occupation: Manager			*Tenure (in 1996):*		
Husband	41.14		Husband	4.79	4.92
Wife	23.18		Wife	4.68	4.94
# Kids 0-6	0.38	0.66	# Kids 7-18	0.72	0.86
		Workplace characteristics:			
Size (in 1,000)			*Type: Publicly traded*		
Husband	0.26	0.65	Husband	0.46	
Wife	0.33	0.82	Wife	0.24	
Growth			*Type: Limited liability*		
Husband	-0.000	(0.003)	Husband	0.08	
Wife	-0.000	(0.004)	Wife	0.04	
Public sector			*Type:Other*		
Husband	0.32		Husband	0.46	
Wife	0.61		Wife	0.72	

Number of households: 757,439

Table 2: **Does $\overline{\ln C}$ enters the demand functions or the Euler equation?**

	$\overline{\ln C} \in z^3, \overline{\ln C} \notin \{z^1, z^2\}$	$\overline{\ln C} \in z^2, \overline{\ln C} \notin z^1$	$\overline{\ln C} \in z^1, \overline{\ln C} \notin z^2$
Demand functions	No	No	Yes
Euler equation	No	Yes	Yes

Table 3: Network Statistics

	Workplace-occupation (Matched)		Workplace-occup.-educ. (Weighted)	
	Peers	Std.dev.	Peers	Std.dev
Distance 1				
Husband	113.09	266.89	73.30	179.77
Wife	134.94	324.75	95.07	233.34
Distance 2				
Husband	43.01	97.00	40.19	95.94
Wife	53.81	125.69	52.35	124.45
Distance 3				
Husband	8,830	23,478	12,535	33,285
Wife	10,089	28,869	14,871	40,534

Table 4: Co-workers' averages

Variable	Workplace-occupation (Matched) Wife	Workplace-occupation (Matched) Husband	Workplace-occup.-educ. (Weighted) Wife	Workplace-occup.-educ. (Weighted) Husband
Age	38.49	39.32	38.24	38.59
	(5.68)	(6.04)	(5.61)	(5.62)
Years of schooling	11.73	11.86	11.69	11.81
	(1.80)	(1.75)	(1.86)	(1.82)
Share of females	0.73	0.24	0.71	0.27
	(0.26)	(0.27)	(0.26)	(0.26)
Share of blue collars	0.32	0.44	0.36	0.47
	(0.47)	(0.50)	(0.37)	(0.41)
Share of white collars	0.45	0.15	0.39	0.22
	(0.50)	(0.36)	(0.35)	(0.28)
Share of managers	0.24	0.40	0.25	0.31
	(0.43)	(0.49)	(0.34)	(0.36)
# Kids 0-6	0.28	0.27	0.28	0.27
	(0.22)	(0.21)	(0.21)	(0.21)
# Kids 7-18	0.51	0.48	0.50	0.47
	(0.31)	(0.30)	(0.30)	(0.29)

Table 5: Distance-3 Peers' averages

	Workplace-occupation (Matched)		Workplace-occup.-educ. (Weighted)	
Variable	Wife's peers	Husband's peers	Wife's peers	Husband's peers
Age	38.88	38.53	38.62	38.46
	(3.29)	(3.15)	(2.48)	(2.51)
Years of schooling	11.85	11.80	11.89	11.67
	(1.33)	(1.37)	(1.26)	(1.29)
Share of females	0.39	0.64	0.45	0.62
	(0.24)	(0.22)	(0.21)	(0.20)
Share of blue collars	0.43	0.36	0.42	0.40
	(0.36)	(0.35)	(0.27)	(0.27)
Share of white collars	0.25	0.38	0.30	0.35
	(0.28)	(0.32)	(0.19)	(0.21)
Share of managers	0.32	0.26	0.29	0.25
	(0.33)	(0.32)	(0.23)	(0.22)
# Kids 0-6	0.27	0.28	0.28	0.28
	(0.11)	(0.11)	(0.09)	(0.09)
# Kids 7-18	0.46	0.48	0.46	0.47
	(0.16)	(0.17)	(0.13)	(0.14)
Size (in 1,000)	1.27	1.47	1.45	1.56
	(1.30)	(1.45)	(1.13)	(1.39)
Growth	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Public sector	0.49	0.65	0.53	0.63
	(0.34)	(0.33)	(0.30)	(0.30)
Publicly traded	0.40	0.27	0.36	0.29
	(0.33)	(0.30)	(0.29)	(0.27)
Limited liability	0.02	0.01	0.02	0.01
	(0.11)	(0.09)	(0.08)	(0.08)
Other	0.58	0.72	0.62	0.70
	(0.33)	(0.30)	(0.29)	(0.27)

Table 6: Baseline results

Model	(1) OLS FD	(2) IV FD	(3) IV FD	(4) OLS FD	(5) IV FD	(6) IV FD
Wife's peers ln C	0.11***	0.26**	0.30*	-.-	-.-	-.-
	(0.002)	(0.113)	(0.163)	-.-	-.-	-.-
Husband's peers ln C	0.13***	0.39***	0.37**	-.-	-.-	-.-
	(0.003)	(0.111)	(0.182)	-.-	-.-	-.-
Avg. peer's ln C	-.-	-.-	-.-	0.12***	0.32***	0.33***
	-.-	-.-	-.-	(0.002)	(0.061)	(0.078)
Demographic IV's	-.-	YES	-.-	-.-	YES	-.-
Firm IV's	-.-	YES	YES	-.-	YES	YES
Test for equality ($\theta_1 = \theta_2$)						
p-value	0.000	0.504	0.819	-.-	-.-	-.-
F-stat first stages						
Wife	-.-	44.16	78.34	-.-	-.-	-.-
Husband	-.-	43.14	59.88	-.-	-.-	-.-
All	-.-	-.-	-.-	-.-	62.87	111.50
Number of obs.	2,671,889	2,671,889	2,671,889	2,671,889	2,671,889	2,671,889

Note: *,**,***= significant at 10%, 5%, 1%. Dependent variable: Log of adult equivalent consumption. Individual controls (for husband and wife): Age, Age sq., Years of schooling, Occupation dummies, Industry dummies, Public sector dummy, Firm size, Firm growth, Firm type dummies. Household controls: Year dummies, Region dummies, # kids 0-6, # kids 7-18. Contextual controls (peer variables for husband and wife): Age, Age sq., Years of schooling, # kids0-6, # kids 7-18, share of female peers, shares of peers by occupation. Demographic IV's: Age, Age sq., Years of schooling, # kids0-6, # kids 7-18, share of female peers, shares of peers by occupation. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy.

Table 7: Robustness

Model	(1) Baseline	(2) Stayers	(3) Transition FE	(4)* 1% Trim	(5)** Unweighted	(6) Local shocks	(7) Sector shocks	(8) Placebo
Avr. peer's ln C	0.33***	0.36***	0.29***	0.30***	0.44***	0.33***	0.34***	0.01
	(0.078)	(0.09)	(0.063)	(0.072)	(0.083)	(0.78)	(0.73)	(0.196)
Firm IV's	YES	YES	YES	YES	YES	YES	YES	YES
F-stat first stage	111.5	59.03	58.83	101.9	88.22	109.5	127.8	-.-
Number of obs.	2,671,889	2,045,787	2,671,889	2,628,110	2,171,426	2,671,889	2,671,889	2,671,889

Note: *,**,***= significant at 10%, 5%, 1%. Dependent variable: Log of adult equivalent consumption. Individual controls (for husband and wife): Age, Age sq., Years of schooling, Occupation dummies, Industry dummies, Public sector dummy, Firm size, Firm growth, Firm type dummies. Household controls: Year dummies, Region dummies, # kids 0-6, # kids 7-18. Contextual controls (peer variables for husband and wife): Age, Age sq., Years of schooling, # kids0-6, # kids 7-18, share of female peers, shares of peers by occupation. Demographic IV's: Age, Age sq., Years of schooling, # kids0-6, # kids 7-18, share of female peers, shares of peers by occupation. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy.

Table 8: Demand Estimation

	Visible cons. (1)	Not-visible cons. (2)	Visible cons. (3)	Not-visible cons. (4)	Visible cons. (5)	Not-visible cons. (6)
ln C	-0.046	0.102	0.015***	-0.009**	0.026*	-0.016
	(0.157)	(0.144)	(0.005)	(0.004)	(0.014)	(0.012)
Avg. peer's ln C	-0.059	0.109	0.002	0.0001	0.002	-0.021
	(0.155)	(0.142)	(0.013)	(0.011)	(0.007)	(0.060)
ln C×Avg. peer's ln C	0.005	-0.009				
	(0.013)	(0.012)				
Observations	2,436	2,438	2,436	2,438	454	452

Note: *,**,***= significant at 10%, 5%, 1%. The dependent variables are budget shares for three consumption groups: Visible, Not-visible and Neutral. The omitted category is Neutral. Individual controls: Age, Age sq., Years of schooling, Occupation dummies, Industry dummies, Industry×Year dummies, Public sector dummy, Firm size, Firm growth, Firm type dummies. Household controls: Year dummies, Region dummies, Region×Year dummies, # kids 0-6, # kids 7-18.

Table 9: Tests of Risk Sharing

	(1)	(2)	(3)
$\Delta \ln Y$	0.228***	0.269**	0.275**
	(0.071)	(0.110)	(0.110)
$\overline{\Delta \ln Y}$			-0.094
			(0.082)
Observations	2,432	824	824

Note: *,**,***= significant at 10%, 5%, 1%. The dependent variable is log household consumption. Individual controls: Age, Age sq., Years of schooling, Occupation dummies, Industry dummies, Industry×Year dummies, Public sector dummy, Firm size, Firm growth, Firm type dummies. Household controls: Year dummies, Region dummies, Region×Year dummies, # kids 0-6, # kids 7-18.

Table 10: Aggregate cons. growth

Transfer recipients	No network effects: Population	No network effects: Our sample	With network effects	Implied multiplier
Top 10%	1.00%	0.94%	1.30%	XXX
Random 10%	1.00%	0.92%	2.00%	XXX
Balanced budget	0%	-0.57%	2.02%	-.-

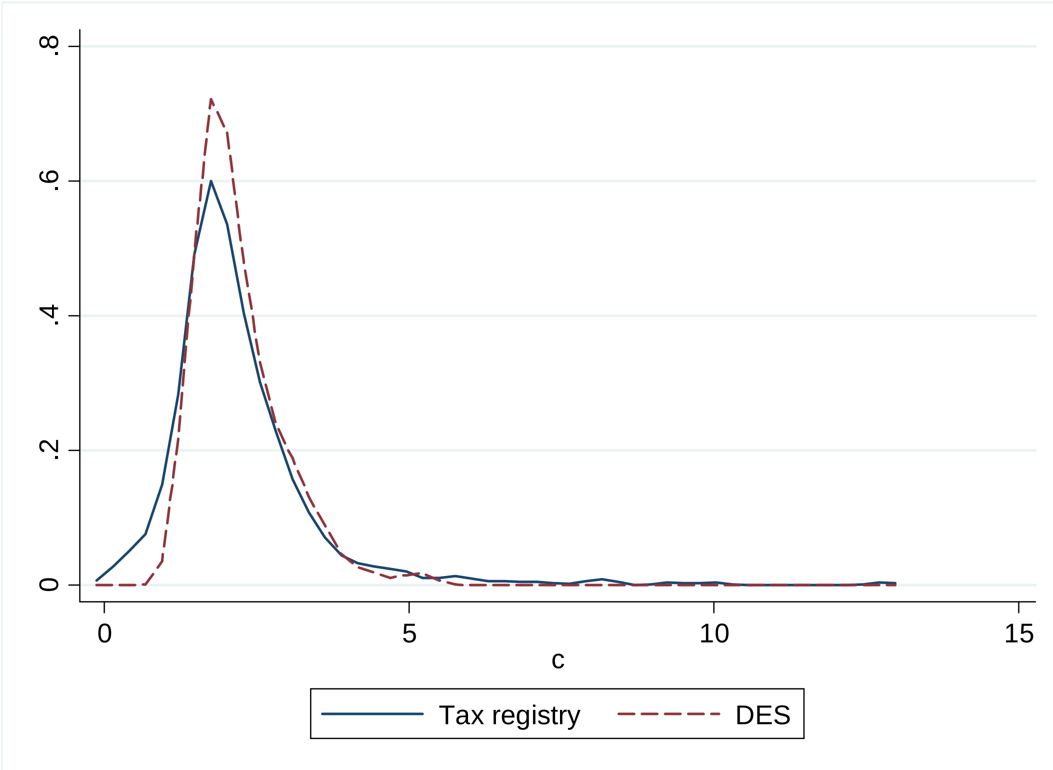

Figure 1: The distribution of consumption in the Tax Registry and in the Danish Expenditure Survey.

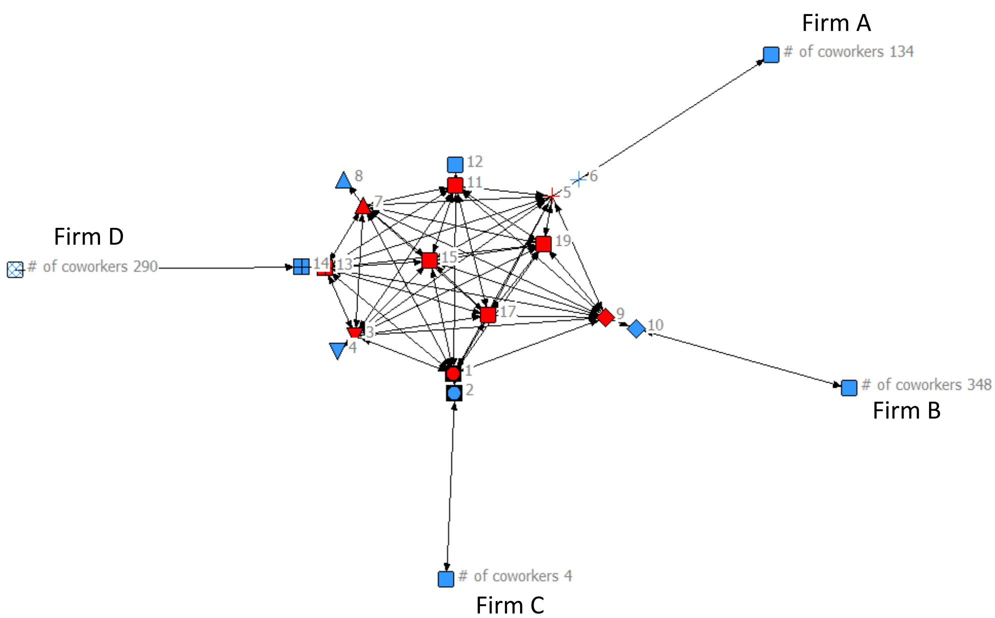

Figure 2: An actual network from our data.

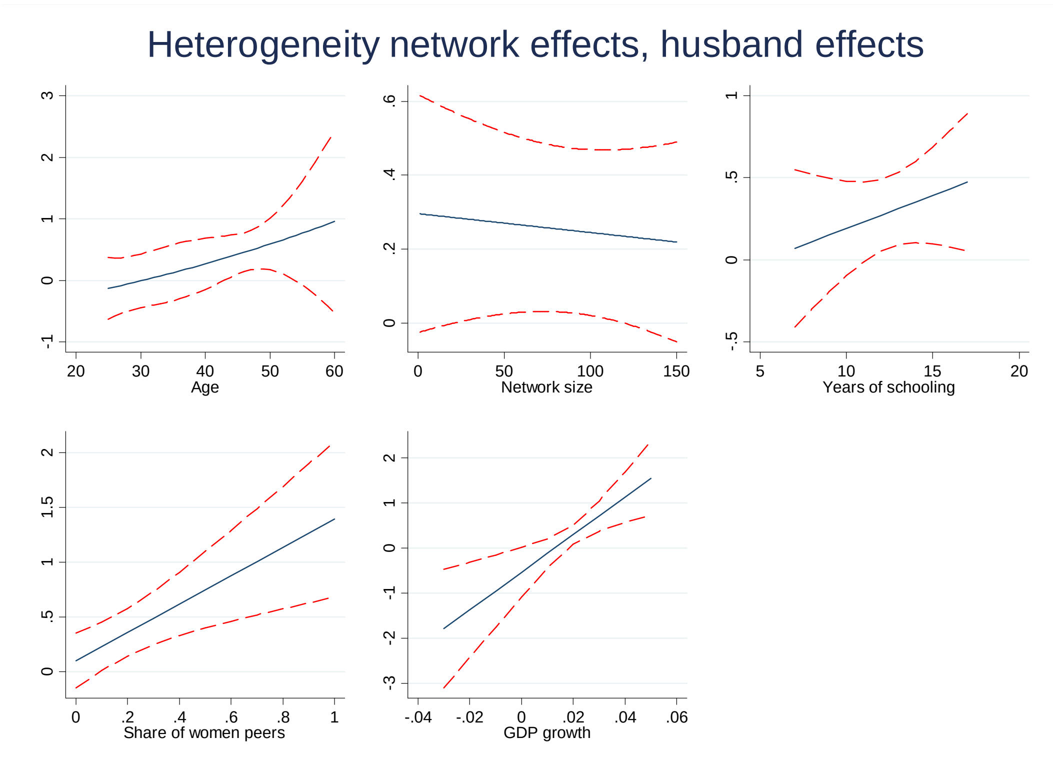

Figure 3: Heterogeneous network effects

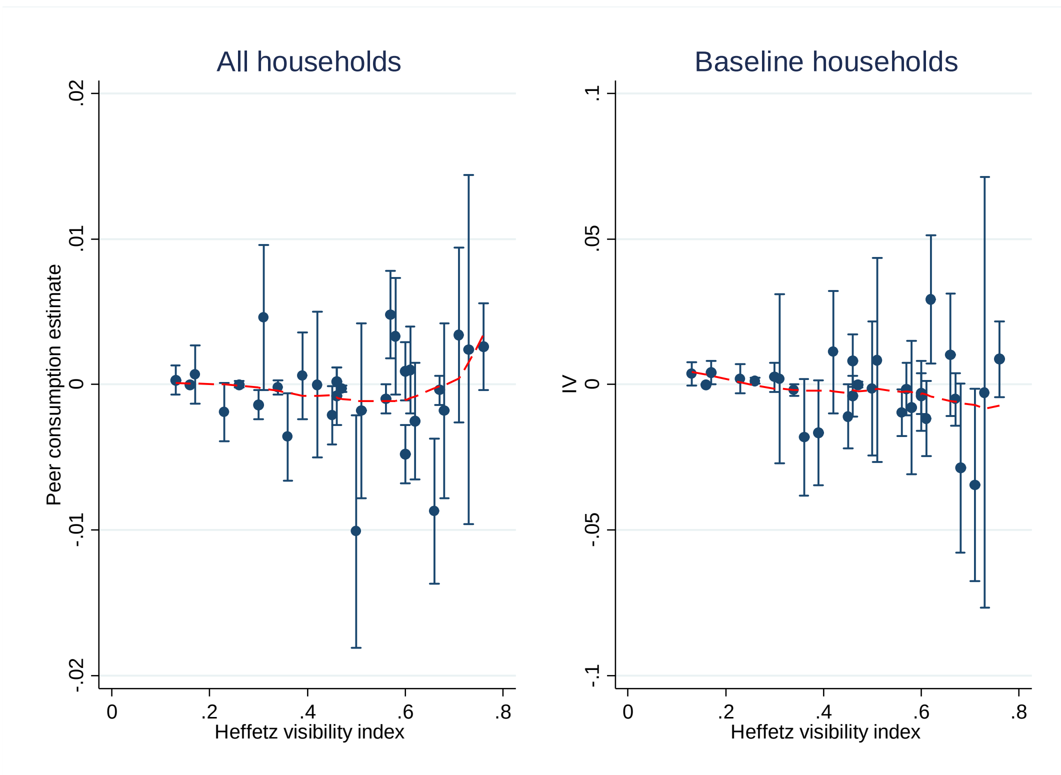

Figure 4: The relationship between the shift in budget shares due to peer consumption and the Heffetz visibility index