CONSUMPTION NETWORK EFFECTS*

Giacomo De Giorgi† Anders Frederiksen‡ Luigi Pistaferri§

May 1, 2017

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 are the economic mechanisms 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 peer 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, Social Multiplier, Risk sharing.

*We thank Orazio Attanasio, Chris Carroll, Nicola Fuchs-Schuendeln, Soren Leth-Petersen, Magne Mogstad, Petra Persson, Nick Roussanov, Dan Silverman, Nick Souleles, Adam Szeidl, 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), the ERC starting grant 284024 and the NSF grant 1458536 (Pistaferri) is gratefully acknowledged.

†GSEM, University of Geneva, BREAD, CEPR, and IPA.
‡Aarhus University, CCP, ICOA and IZA
§Stanford University, NBER, CEPR, SIEPR and IZA.

1 Introduction

Does the consumption of our peers affect our own consumption? How large is such effect? What are the economic mechanisms 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 administrative information on income and assets, so we can construct a measure of consumer spending 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 expenditures on various goods. 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 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., 2009, Carrell et al., 2008, 2009, De Giorgi et al., 2010, Hanushek et al., 2003, Sacerdote, 2001, for recent contributions). A branch of the literature looks at the importance of peer effects in welfare use and take-up of social insurance programs (Borjas and Hilton, 1995, Bertrand et al., 2000, Dahl et al., 2014); another considers the role that peers play in the selection

[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).

of (and participation in) employer-provided pension plans (Duflo and Saez, 2003, Beshears et al., 2011). 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. 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., 2009), neighbors within a city (Ravina, 2007), zip code (Kuhn et al., 2011), or even within the same apartment building (Agarwal et al., 2017). 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 "conspicuous", such as jewelry, luxury cars, restaurants, and so forth.[3] The third model is one where risks are shared among members of a reference group, which creates correlation among their consumptions.[4]

Our paper advances and 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 occurring peer group. 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, 1991).

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] Sometimes "keeping up with the Joneses" and "conspicuous consumption" are used interchangeably. We use them separately simply to distinguish between a case in which network effects induce *intertemporal* distortions, and a case in which they induce *intratemporal* distortions.

[4] A similar intuition is given in De Giorgi and Pellizzari (2014) 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 the 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).[5] 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*. Finally, if risk sharing is the main reason for correlated consumption profiles we would actually record important welfare gains.

The second reason why studying consumption network effects is important is because of their potential aggregate effects. Uninsured idiosyncratic shocks (such as unanticipated tax changes targeting rich taxpayers) might have aggregate consequences that go beyond the group directly affected by the shock. This depends on the size of the estimated effect as well as the degree of connectedness between groups that are directly affected and unaffected by the shock. In our empirical analysis, we find non-negligible endogenous peer effects, which translate into a non-negligible social multiplier. We then analyze the effect of policy counterfactuals based on hypothetical 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 known 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, or (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 influences, i.e., consumption behavior changes (causally) in response to the consumption behavior of co-workers; and finally, (c) consumption of all workers within the firm may be affected by some common (firm-

[5] 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).

level) unobserved shock, such as a firm-level productivity change 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) with the use of exogenous shocks to distance-3 nodes. This requires the existence of intransitive triads, i.e., "friends of friends who are not friends themselves". However, since this idea is often opaque in its practical implementation, we justify it economically with the use of firm-level idiosyncratic shocks. To give a simple example, our identification strategy rests on the idea that an event like a firm downsizing experienced by the co-worker of the spouse of my co-worker (controlling for industry-specific shocks) has no direct effect on my consumption but only an indirect one (through peer effects).

In our specific context, the key (and novel) fact that we exploit empirically is that working relationships are individual, but consumption is shared among spouses. Hence, spouses add nodes to otherwise unconnected networks (i.e., groups of workers sharing similar characteristics within a firm). 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 about 0.3, which is statistically indistinguishable between husband's and wife's.[6] Such an estimated effect translates into a non-trivial aggregate effect which depends upon the degree of connectedness of the households, as we shall discuss later in the paper. When we explore the theoretical mechanism behind our results, we find support for a keeping-up-with-the-Joneses model, 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.

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

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. (2011) provide an informed discussion of the Danish tax system. The dataset includes information on income and assets for each taxpayer. During this period information on income and assets (with the exception of durables such as cars, jewelry, etc.) come from third-party reports (e.g., from employers, banks, stockbrokers, etc.), thus minimizing measurement error. While income data are typically available in all tax record datasets, asset data is available because, until 1996, households were subject to a wealth tax.[7] We match the administrative data with the Integrated Database for Labor Market Research (IDA), an employer-employee data set, which includes, among other things, demographics and firm and plant ID's, from which we can identify co-workers. We define co-workers as individuals who work in the same plant (for public employees, this is the physical address of their workplace) - see below for more precise definition.

Our estimation 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 one or both members stop working or become self-employed.[8] 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 households with only one spouse working.

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

$$C_{it} = Y_{it} - T_{it} - \Delta A_{it} \tag{1}$$

where $Y_{it} = (GY_{it} + HS_{it} + CS_{it} - TH_{it})$, GY is gross income (the sum of income from all sources, labor and capital), HS the value of housing support, CS the value of child support, TH the implicit tax on the consumption value of owned housing, T the 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

[7] Tax record data are actually available until 2012, but the wealth tax was abolished in 1996. Collection of detailed asset data was thus discontinued after 1996. In particular, after 1996 only third-party reports remain available to researchers.

[8] Given the applied selection criteria, less than 5 percent of the households ever change spousal composition in our sample period. Hence, we abstract from divorce and separation in the analysis.

is similar to Browning and Leth-Petersen (2003) and Leth-Petersen (2010). Browning and Leth-Petersen (2003) conclude that this simple measure tends to behave as well as more sophisticated measures which attempt to account for capital gains, etc. (see below for a formal comparison with survey data). Note that this measure is robust to cases in which consumers enjoy different returns on their financial investments, as Y_{it} includes capital income, which incorporates directly such return heterogeneity (see Fagereng et al., 2016). In some of the robustness exercises below, we investigate the sensitivity of the results to dropping households for whom capital gains or losses may be important, such as stockholders or homeowners.

Table 1 provides some descriptive statistics about our sample. All monetary values are in 2000 prices. Annual household consumption is about \$49,000, while annual (before-tax) household 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 deviation of just over \$100,000). In terms of socio-demographic characteristics, husbands are slightly older than wives (42.5 vs. 40 years old), and slightly more educated. There is a large concentration of women in "white collar" jobs, and a larger concentration of males in "managerial" and "blue-collar" positions relative to females. As for sectorial concentration, there is a higher proportion of men in manufacturing and construction, and a higher proportion of women in services and "other sectors" (mostly, public employment). We also compute tenure (years with current employer within our observational period 1980-1996). We do not find large differences across genders (5 years on average). This tells us that co-workers tend to be in the same firm/location for a non-negligible number of years. Finally, the households in our sample have on average 0.4 young children (0-6 years of age), and 0.7 older children (7-18 years old).

At the bottom of Table 1 we also report firm level characteristics that we use as controls and instruments. Average firm size is 260 and 330 for husbands and wives, respectively. The annual growth rate of employment is centered at zero, but there are quite a few firms changing employment levels, as the standard deviation is about 0.4%. As mentioned above, a larger fraction of women work in the public sector (60%) relative to males (32%). Men tend to be more represented in publicly traded company than women (46 vs. 24 percent). A similar pattern emerges for limited liability companies with a larger share of men (8 vs. 4 percent), while the pattern is reversed in "other companies" (mostly located in the public sector), where the fraction of women and men working are 72% and 46%, respectively.

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 (2003) 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 (note that the spending data are not longitudinal). 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 distributions overlap significantly and differ appreciably 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 removing the tails of the consumption distribution or focus on samples where capital gains and losses are unlikely to be important.

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. While for most goods the separation is unambiguous (i.e., jewelry or home insurance), we use an index of visibility proposed by Heffetz (2011) as an anchor. To construct the index, Heffetz (2011) 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 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 (2011), with the exception of charity contributions that are not observed in the DES. See the Appendix for more details.

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 be responsible for 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 in Section 3.2 we discuss the second type of effects.

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 (1994) in considering a general form for the conditional indirect utility function $U_t(.)$:

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

In this setting $V_t(.)$ governs the within-period allocation of total spending C_{it} to goods q_{it}^k, while U_t determines the 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 characteristic. In other contexts, z_{it} includes labor supply or demographics (see, e.g., Blundell, Browning and Meghir (1994)) or "rationed" goods (as in the classic Pollak (1969)).

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 $F_t(.)$ 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: $U_t\left(\mathbf{p}_t, C_{it}, \{C_{nt}\}_{n=1,n\neq i}^N\right) = F_t\left(V_t\left(\mathbf{p}_t, C_{it}\right)\right) + G\left(\{C_{nt}\}_{n=1,n\neq i}^N\right)$, where $\{C_{nt}\}_{n=1,n\neq i}^N$ is the vector of consumptions of all i's peers.

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. Therefore, in this case, there are no network effects on 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[9]

[9] 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. See Deaton and Muellbauer (1980).

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

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

$$\Delta \ln \frac{C_{it+1}}{a\left(\mathbf{p}_{t+1}\right)} \cong \gamma^{-1}\left((r-\delta)-\Delta \ln b\left(\mathbf{p}_{t+1}\right)+\theta \Delta \overline{\frac{\ln C_{t+1}}{a\left(\mathbf{p}_{t+1}\right)}}\right) \tag{3}$$

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 $\theta = 0$.

One important remark is that, as explained above, what we observe in the empirical application is total spending (on both non-durables and durables). Under suitable restrictions, detailed in Appendix A, we show that equation (3) can be re-interpreted as describing the dynamics of total household spending as a function of the peers' total spending. In the rest of the paper, we use consumption and spending interchangeably.

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:

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

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

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

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:

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

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, the budget share for good j is:

$$
\omega_{it}^j = \alpha_{0j} + \alpha_{1j}\overline{\ln C}_t + \sum_k \eta_{jk} \ln p_t^k + \left(\beta_{0j} + \beta_{1j}\overline{\ln C}_t\right) \frac{1 - (C_t/a_t(.))^{-(1-\gamma)}}{1-\gamma} \tag{4}
$$

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

$$
\Delta \ln \frac{C_{t+1}}{a_{t+1}(.)} \cong \gamma^{-1}\left((r-\delta) - \Delta \ln b_{t+1}(.) + \theta \Delta \frac{\overline{\ln C_{t+1}}}{a(\mathbf{p}_{t+1})}\right) \tag{5}
$$

In models with "conspicuousness" 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 $a_t(.)$ and $b_t(.)$:

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

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

$$
\omega_{Vt} = \alpha_{0V} + \alpha_{1V}\overline{\ln C}_t + \sum_{k=\{V,N,X\}} \eta_{Vk} \ln p_t^k + \left(\beta_{0V} + \beta_{1V}\overline{\ln C}_t\right) \ln\left(C_t/a_t(.)\right) \tag{6}
$$

$$
\omega_{jt} = \alpha_{0j} + \sum_{k=\{V,N,X\}} \eta_{jk} \ln p_t^k + \beta_{0j} \ln\left(C_t/a_t(.)\right) \tag{7}
$$

for $j = \{N, X\}$.[10]

[10] It is possible that the price indexes depend on peers' *visible* (rather than *aggregate*) consumption, i.e., $\ln a_t(.) = \alpha_0 + \sum_{j=\{V,N,X\}} \alpha_{0j} \ln p_j + \alpha_{1V}\overline{q}_{Vt} \ln p_V + \frac{1}{2}\sum_{k=\{V,N,X\}} \sum_{j=\{V,N,X\}} \eta_{kj} \ln p_k \ln p_j$, with $\overline{c}_t = \overline{q}_{Vt} + \overline{q}_{Nt} + \overline{q}_{Xt}$. In

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 is 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 (3) or (5). 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 (Keeping-up-with-the-Joneses), or the case in which distortions are both inter- and intra-temporal (Conspicuous consumption).

We can distinguish between these two cases by estimating demand functions and testing 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 (4) 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

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 $B^2 \geq 0$).

conspicuousness (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-up-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 peer effects literature. We discuss how the structure of networks (at the co-worker level), as well as the use of exogenous firm level shocks, helps us achieve 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 co-workers. Workers' repeated interactions 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 (5). 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 ($\Delta \ln Y_{it} < 0$) and co-worker j has been lucky ($\Delta \ln Y_{jt} \geq 0$), 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 understates 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 $\Delta \ln Y_{it}$ (controlling for $\Delta \ln Y_{jt}$ or, in line with our application, for $\Delta\overline{\ln Y_t}$) if risk sharing considerations are at play. Similarly, $(\ln C_i^S - \ln C_i^T)$ will be systematically *positively* correlated with $\Delta \ln Y_{jt}$ ($\Delta\overline{\ln Y_t}$ in the empirical test) once we control for individual income growth $\Delta \ln Y_{it}$. 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 tackled. 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., 2013), 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. There are two reasons why co-workers may be a more credible reference group than the definitions adopted in the consumption literature. First, if social effects increase with the time spent with members of the reference group, "co-workers" are obvious candidates for the ideal reference group, as they are the individuals people spend most of their 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 (Holzer, 1988). 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. Hence, our networks can be measured with error. The IV strategy we define below is designed to correct for this problem, as well as for the measurement error in our consumption measure, on top of the standard endogeneity problems. The variation we use comes from exogenous shocks at the firm level. The implicit assumption is that network mis-measurement and the exogenous sources of firm variation we use are uncorrelated, i.e., the fact that certain co-workers do not interact socially is independent of the fact that coworkers of the spouse's coworkers are affected by their firm performance.

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 the households in our sample. 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 (5) above (to allow for multiplexity, i.e., the fact that -at least in principle- husband and wife can have distinct networks):

$$\Delta \ln C_{it} = \alpha + \theta_1 \Delta\overline{\ln C_{it}^w} + \theta_2 \Delta\overline{\ln C_{it}^h} + \gamma_1 \overline{X_{it}^w} + \gamma_2 \overline{X_{it}^h} + \delta_1 X_{it}^w + \delta_2 X_{it}^h + \xi_{it} \tag{8}$$

Here i and t indicate household and time, while the superscripts w and h indicate wife and husband, respectively. Hence, $\overline{\ln C_{it}^w}$ 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 which can also include firm-level shocks, such as a sudden increase in size or transition to publicly traded company; 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 strength 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, and therefore we only measure total expenditure at the household level (see equation 1). Moreover, we lack information on labor supply.[11]

The main parameters of interest in (8) are the θ's (endogenous effects) 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. We discuss below how we deal with network or firm fixed effects, if present.

Equation (8) represents our main estimating equation. Note that first differencing log consumption has already eliminated household and individual fixed effects for the members of household i. These fixed effects may arise from sorting on firms based on similar unobserved characteristics. For example, suppose that workers sort into firms on the basis of their permanent income (an unobserved characteristic), i.e., higher permanent income workers sort into better firms (Abowd, Kramarz and Margolis, 1999). But since higher permanent income workers also consume more, it is not surprising that their consumptions may be correlated even in the 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 co-workers. 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.

[11] 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.

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 (8), 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.:

$$\Delta \ln C_i = \theta \sum_{n=1, n\neq i}^{3} \frac{\Delta \ln C_n}{2} + \gamma \sum_{n=1, n\neq i}^{3} \frac{X_n}{2} + \delta X_i + \varepsilon_i \tag{9}$$

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. Assume also that agent 3 is subject to an exogenous shock T_3 (to mimic the exogenous firm level shocks we use in the empirical analysis). This produces additional overidentifying restrictions in a partial population framework as in Moffit (2001).[12] Hence, we can rewrite the restricted form of (9) as:

$$\Delta \ln C_1 = \theta \Delta \ln C_2 + \gamma X_2 + \delta X_1 + \varepsilon_1 \tag{10}$$

$$\Delta \ln C_2 = \theta \Delta \ln C_3 + \gamma X_3 + \delta X_2 + \varepsilon_2 \tag{11}$$

$$\Delta \ln C_3 = \delta X_3 + \rho T_3 + \varepsilon_3 \tag{12}$$

The reduced form of this system is:

$$\begin{aligned} \Delta \ln C_1 &= \theta \left(\gamma + \theta\delta\right) X_3 + \theta^2 \rho T_3 + \left(\gamma + \theta\delta\right) X_2 + \delta X_1 + v_1 \\ \Delta \ln C_2 &= \left(\gamma + \theta\delta\right) X_3 + \theta \rho T_3 + \delta X_2 + v_2 \\ \Delta \ln C_3 &= \delta X_3 + \rho T_3 + v_3 \end{aligned}$$

The system above is triangular, and therefore it is easy to see that as long as $(\gamma + \theta\delta) \neq 0$ and $\rho \neq 0$, one can recover all the structural parameters from the reduced form ones. Identification comes from two sources. First, the exogenous shock to agent 3 (T_3), and, second, the characteristics

[12] All agents can be affected by a "firm-specific" shock. We assume in this example that only agent 3 is affected by a firm-level shock T_3 to make the argument as sharp as possible.

of agent 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* shocks and characteristics are valid instruments). This is because T_3, or alternatively X_3, affect $\Delta \ln C_2$ due to contextual effects in household 2's consumption growth equation (2 and 3 are *directly connected*, as is visible from inspection of (11)), but it has no direct effect on household 1's consumption growth (1 and 3 are *not directly connected*), as visible from (10).

The use of an exogenous source of variation like T_3 makes our identification approach stronger than the usual strategy based on the presence of an intransitive triad structure. In practice, it is similar to using experimental variation in distant nodes that percolate through the entire network (as long as networks effects are indeed present). To illustrate this idea even more clearly, consider Figure 2. Couples (A, B, D, E, J) are in circles, while co-workers are in dashed squares. For example, the husband in couple A and the husband in couple B work in firm f_1; the wife in couple J and the husband in couple D work in firm f_4, etc.

Assume that consumption growth is affected by firm-specific variables T_{f_j}. Previous evidence (Guiso et al., 2004; Fagereng et al., 2016) shows that firm pass onto wages some of their permanent value added shocks. For this reason, it is likely that some of the uninsurable shocks that shift household consumption originate from such firm-related shocks. A specification that captures this idea is (for couple A):

$$\Delta \ln C_A = \gamma \frac{(X_B + X_D)}{2} + \delta X_A + \theta \frac{(\Delta \ln C_B + \Delta \ln C_D)}{2} + (T_{f_1} + T_{f_2} + \varepsilon_A)$$

Note that the endogeneity of peers' consumption comes from sharing common firm shocks:

$$\begin{aligned} \Delta \ln C_B &= \gamma \frac{(X_A + X_E)}{2} + \delta X_B + \theta \frac{(\Delta \ln C_A + \Delta \ln C_E)}{2} + (T_{f_1} + T_{f_3} + \varepsilon_B) \\ \Delta \ln C_D &= \gamma \frac{(X_A + X_J)}{2} + \delta X_D + \theta \frac{(\Delta \ln C_A + \Delta \ln C_J)}{2} + (T_{f_2} + T_{f_4} + \varepsilon_D) \end{aligned}$$

However, this also shows that one can use T_{f_3} and T_{f_4} as possible valid instruments. A shock faced by firm f_3 affects the wage of the wife in couple B, and hence the consumption of couple B. This changes the consumption of couple A through the network effect, but (importantly) not through the common firm effect shared by A and B (firm f_1).

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's characteristics. For simplicity of notation, we focus on the $k = 1$ case. Just out of convention, we order the husband characteristics in each couple in the first N rows, followed by the wives' characteristics in each couple in the remaining N rows, i.e. $\mathbf{X} = \begin{pmatrix} \mathbf{X}_h & \mathbf{X}_w \end{pmatrix}'$. However we note that the $\mathbf{X}$ can contain the firm level exogenous shock.
  - Let also $\mathbf{S}_h$ $(\mathbf{S}_w)$ be a transformation $(2N \times N)$ matrix that maps households into husbands (wives). 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:

$$d_{i^l j^m} = \{ \; 1 \quad \text{if } i^l \text{ connected to } j^m \text{ (for } l, m = \{h, w\})$$

    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 $n_{i^l} = \sum_{m=\{h,w\}} \sum_{j=1}^{N} d_{i^l j^m}$.[13]
  - 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 $g_{i^l j^m} = n_{i^l}^{-1} d_{i^l j^m}$.
  - Given this notation, $\mathbf{S}_h'\mathbf{G}\left(\mathbf{S}_h + \mathbf{S}_w\right) = \mathbf{G}_h$ 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 (wives) of the N households in our sample (symmetrically,

[13] 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.

$\mathbf{S}'_w\mathbf{G}\left(\mathbf{S}_h+\mathbf{S}_w\right) = \mathbf{G}_w$ 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 $\mathbf{S}_h\mathbf{GX}$ ($\mathbf{S}_w\mathbf{GX}$) is the vector of the husband's (wife's) peers' exogenous characteristics.

Given this notation, the matrix equivalent of (8) can be written (omitting the constant terms for simplicity) as:

$$\Delta\mathbf{c} = \left(\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w\right)\Delta\mathbf{c} + (\mathbf{S}'_h\mathbf{G}\gamma_1 + \mathbf{S}'_w\mathbf{G}\gamma_2 + \mathbf{S}'_h\delta_1 + \mathbf{S}'_w\delta_2)\mathbf{X} + \boldsymbol{\xi} \tag{13}$$

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:

$$\begin{aligned}(\mathbf{I} - (\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w))^{-1} &= \sum_{k=0}^{\infty}\left(\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w\right)^k \\ &= \mathbf{I} + \left(\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w\right) + \left(\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w\right)^2 + \ldots \end{aligned} \tag{14}$$

which is satisfied as long as $|\theta_1| + |\theta_2| < 1$.[14]

The reduced form of (13) is obtained replacing (14) (for $k = 1$, which results in a first-order "approximate" inverse) into (13):

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

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 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 the exogenous characteristics of peers of distance-3 being valid instruments.

[14] 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, the condition $\|\theta_1\mathbf{G}_h + \theta_2\mathbf{G}_w\| < 1$ is clearly satisfied if $|\theta_1| + |\theta_2| < 1$.

As mentioned above, the advantage of the Euler equation specification (8) is that first-differencing removes all fixed effects for the members of household i. One may be worried that while first differencing removes household fixed effects, it does not necessarily remove network effects. For example, all workers in a given plant face a common shock 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:

$$\xi_{it} = \Delta f\left(i^w\right)_t + \Delta f\left(i^h\right)_t + \upsilon_{it} \tag{15}$$

Our firm-specific instruments are designed to capture precisely these kind of shocks. However, it may still be possible to have unobserved network effects correlated with our instruments. 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.[15] Our second approach uses the whole sample and adds fixed effects for the "transitions" $\Delta f\left(i^w\right)_t$ and $\Delta f\left(i^h\right)_t$.[16]

4.1.3 Relationship to the literature

Our identification strategy combines two strands of the empirical literature on the identification of peer/network effects. The first uses random shocks to a part of the network; the second uses fixed effects and rich controls to deal with the endogeneity concerns. Similarly to Kuhn et al. (2011), we employ a partial population experiment (Moffitt, 2001). However, while Kuhn et al. (2011) use a random lottery win to neighbors, we use random firm-level shocks to distance-3 peers. Bertrand et al. (2000) employ a rich set of controls and fixed effects to estimate the network effect of welfare take-up. In particular, the authors use local area and language group fixed effects, as well as a rich set of individual controls. In a similar spirit, we control in our analysis for individual, area, and year fixed effects, adding then a rich set of controls at the individual level.

5 Results

5.1 Data Example: A Danish Network

Identification requires availability of co-workers of co-workers' spouses (or distance-3 nodes). To see graphically what this entails, consider Figure 3, where we plot a stylized network resembling what we see in our data. The red symbols are individuals working in a small firm, which we call

[15] 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.

[16] 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.

S (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, indicated by the cross marker, person 5 works at S while the spouse works at firm A, where (s)he has 134 co-workers. Note also that S 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 again the family unit composed of 5 and 6. In our specification (8), the consumption growth of this family unit depends on the average consumption growth 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 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 node. Since consumption is a household activity, our reference node 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 S 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 S, as well as spouses of person 6's co-workers in firm A. Finally, distance-3 peers are individuals working in firms B, C, and D, as well as the co-workers of the spouses of person 6's co-workers. The endogeneity problem is solved by using as instruments the firm-level shocks and 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 (above 80% in our sample period). 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 plant. 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 occupation and education. Third, a potential concern is that of assortative mating 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 (8). 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 (1991), 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, or firm level shocks of 1+2 as instrument for the consumption of 3+4, which will violate the exclusion restriction condition. We make sure to discard those cases when constructing our instruments.

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 by 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. The weights are constructed as follows. We first allocate individuals to five education groups (compulsory schooling, high school degree, vocational training, college degree, Master's degree or PhD) 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

$$\omega_{i^s j^m} = (d_{i^s j^m} + 1)^{-2} \tag{16}$$

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

Using a weighted adjacency matrix serves two purposes: (a) some nodes might be more "influential" in affecting behavior; (b) they add variation to our right hand side variable. The use of a similarity index is also consistent with the homophyly literature (Currarini et al. (2011)). Since weight assignment is inherently arbitrary, in the Robustness section we present results under three alternative weighting procedures: (a) using a quadratic similarity weight based not only on education and occupation, but also tenure, (b) using a linear, instead of a quadratic, similarity weight $\omega_{i^s j^m} = (d_{i^s j^m} + 1)^{-1}$, where $d_{i^s j^m}$ has been defined above, and (c) using a much sharper weighting scheme where only co-workers in the same occupation and educational category are (equally) weighted while all other co-workers are given zero weight.

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 73 distance-1 (weighted) 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 95 (weighted) co-workers. When looking at distance 2 peers, the numbers are only slightly larger (average sizes are 90 and 119 for husbands and wives, respectively). Finally, to find distance-3 peers we again move along the firm network line and reapply the appropriate weighting scheme. Since wives have on average 119 co-workers and 95 of them have valid nodes (spouses who work), the expected number of distance-3 peers is therefore around 11,500. In practice, there are slightly more (around 14,870) 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 remaining part of Table 3 we present the average characteristics of co-workers and of distance 3-peers. As one would expect these characteristics are in line with the characteristics of the population in Table 1, as there is nothing specific about being a distance-2 or 3 node.

Identification of the parameters of interest relies upon variation in two main blocks: (i) changes in the composition of the workforce identified as distance-3 peers, in terms of their average age, education, gender and so on; and (ii) economic shocks to distance 3 peers' workplace, i.e., growth in the number of employees, changes in the growth rate (to focus on shocks, instead of random growth rates), and a change in the firm type (such as transition from a private equity to a publicly traded company, or a process of privatization of a government-owned firm). Since we run first difference regressions and control for time, industry, and region effects in our first stage, these variables can be interpreted as "idiosyncratic shocks" to the firm's characteristics (in particular, its growth rate).[17]

It is worth pointing out that while individual characteristics are quite similar in the general population and at the various distance nodes (indicating lack of significant sorting of "different"

[17] Take a simple example in which firm size (in logs) evolve according to: $\Delta \log n_{jt} = \alpha d_t + \xi_{jt}$, where d_t is an aggregate component and ξ_{jt} is an idiosyncratic (permanent) shock to firm size. Our first stage regresses the endogenous variable $\Delta \overline{\log C_{ijt}} = \beta d_t + \gamma \log n_{jt} = (\beta + \gamma\alpha) d_t + \gamma \xi_{jt}$. The exclusion restriction is, effectively, the "idiosyncratic shock variable" ξ_{jt}.

people in larger firms), for the way we identify distance 3 nodes, there is a higher likelihood of observing them in larger firms, potentially including the public sector (which employs during our sample period almost 50% of our population, as can be seen from the bottom right part of Table 3). We can also notice that our firm-level IV's identify firms that have faster growth than the whole population, are more likely to be located in the public sector, and are less likely to be limited liability companies.

5.3 Euler Equation Estimates

The main specification we adopt follows from the Euler equation (8):

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

where C is household real consumption per-adult equivalent and ξ_{it} takes the form described in (15). We use the LIS equivalence scale, i.e., $\sqrt{n_{it}}$ where n_{it} is family size. The set of exogenous characteristics (X) include: household controls (dummies for region of residence,[18] 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, industry dummies,[19] a public sector dummy, firm size, firm-specific size growth, and firm legal type[20]), separately for husband and wife. We use the following 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. All specifications also include year dummies. We consider two sets of instruments. The first set consists of weighted averages of demographic characteristics of distance-3 peers: 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. The second set of instruments includes firm-specific variables of distance-3 peers: firm size, firm-specific size growth, firm type dummies, and a dummy for whether the firm is part of the public sector. All these variables are expressed in first differences.

The first three columns of Table 4 present estimates from three different specifications in which we control separately for the husband's and wife's networks. The other three columns re-estimate the same specifications imposing the assumption of a joint household network. Throughout the

[18] The regions are: Copenhagen, Broader Copenhagen, Frederiksborg, Roskilde, Vestsjælland, Storstrøm, Bornholm, Fyn, Sønderjylland, Ribe, Vejle, Viborg, Aarhus, Ringkøbing, and Nordjylland.

[19] The industries are: Agriculture, fishing and mining; manufacturing; utilities; construction; retail trade, hotels and resturants; transportation, storage and communication; financial intermediation and business; public and personnal services; Other.

[20] Firm type are: Limited liability ApS (Ltd.), Publicly traded limited liability A/S (Inc.), and other.

analysis standard errors are double clustered, with clusters defined by plant/occupation/education for both husband and wife.

In column (1) we present a standard OLS analysis on the first differenced consumption data. There are significant consumption network effects, which are similar for both husband and wife. However, these estimates are subject to some of the usual endogeneity (and reflection) problems. In column (2) we thus present IV regression estimates using both demographics and firm-specific instruments, while in column (3) we use only firm-level instruments. We also present first-stage statistics, which are generally much larger than conventionally acceptable thresholds (even discounting for the unusually large sample sizes).[21]

Our preferred specification is the one in column (3), where we only rely on more economically meaningful firm-level instruments. In the IV case we continue to find non-negligible consumption network effects. In column (3), the husband's network effect is 0.37 and statistically significant at the 5% level, while the wife's network effect is slightly smaller, 0.3 and significant at the 10% level. It is important to quantify these effects. A 10% increase in the average consumption of the wife's (husband's) peers would increase household consumption by 3% (3.7%). However, given network size, this is a fairly aggregate shock - it is equivalent to a 10% simultaneous increase in the consumption of *all* peers (95 and 73 weighted peers, respectively for wife and husband - see Table 3). 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.[22]

In monetary terms and evaluated at the average level of consumption, a 10% increase in the consumption of a random peer on the husband's side (corresponding to about $5,000) would increase household consumption by about $25 (and $1,825 in the aggregate). On the wife's 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 by simulating a number of policy scenarios.

Two things are worth noting. First, in columns (1)-(3), the effects of the husband's and wife's network on household consumption are economically very similar. In fact, when we test for the

[21] Note that, as remarked by Sanderson and Windmeijer (2016), in a setting with multiple endogenous variables significant first-stage F-statistics are necessary, but not sufficient, for identification of the parameters of interest. They propose the use of a conditional first-stage F-test statistic. Since we fail to reject the null hypothesis of a single endogenous variable, we do not consider this adjustment here.

[22] This calculation is obtained by multiplying the estimated network effect by the probability of a member of the network experiencing the consumption increase (i.e., for the wife the effect is computed as $0.0032 = \frac{0.3}{95.1}$, while for the husband is $0.0050 = \frac{0.37}{73.3}$).

equality of the coefficients between husband and wife ($H_0 : \theta_1 = \theta_2$) we cannot reject the null hypothesis of equality (with large p-values) in the more relevant IV models. Given this evidence, in the rest of Table 4 we re-estimate all models imposing that husband and wife belong to a single joint network (columns (4)-(6)). The second aspect of the analysis that is worth highlighting is that OLS estimates are smaller than IV estimates. This is surprising given that a pure endogeneity bias would bias OLS estimates upwards. However, measurement error in peers' consumption may induce a bias that goes in the opposite direction, and it may be larger (in absolute value) than the endogeneity bias. Recall that our OLS specification has already eliminated a lot of the bias coming from observed and unobservable heterogeneity by first differencing and by the inclusion of a large set of socio-demographic controls. Hence, OLS estimates are more likely to reflect the downward bias of measurement error than the endogeneity upward bias. As an informal check, we re-estimated the OLS model without controlling for covariates and find much larger estimates of $\widehat{\theta}_1 = 0.5$ and $\widehat{\theta}_2 = 0.45$. Moreover, any measurement error in levels is exacerbated by first differencing the data (Hausman and Griliches, 1986). Furthermore, it is possible that OLS is downward bias due to the exclusion bias highlighted by Caeyers and Fafchamps (2015).[23]

Imposing a joint household network (as in columns (4)-(6)) results in expectedly more precise IV estimates. The joint network effect is estimated to be around 0.33 and is statistically significant at the 1% level. The first-stage F-statistic in our preferred specification (column (6)) is 112, which shows that our instruments have strong identifying power. The economic interpretation of the joint network effect 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 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 effects may depend on observables such as (weighted) network size, education, share of women, the business cycle, etc.. The effect of tenure is particularly important, as one may test whether social pressure increases with the time spent with

[23] Our IV procedure is also robust to the possibility of type I and type II errors in the definition of the peer group. To see why, take Figure 2. We assume that the consumption of household A depends on the consumption of peer households B and D, and hence use as instruments the shocks of the firms employing the spouses of A^h and A^w's coworkers, i.e., f_3 and f_4. But suppose that the "true" peers of household A are households B and K (a household totally outside the picture, whose members work at firms f_5 and f_6, say). Our instrument idea remains valid: we use f_3 and f_4 as instruments, but should rather use f_3, f_5 and f_6. As long as some co-workers are at least genuine peers, we may have a problem of low power of instruments (which is testable), but not a problem of violation of the exclusion restriction.

a co-worker (effects may be small at low levels of tenure and larger at high levels of tenure).

In lieu of presenting a Table with regression estimates, Figure 4 shows how the consumption network effect varies with observable characteristics (network size, age, years of schooling, share of women peers, a measure of the business cycle, and tenure). These effects come from IV regressions similar to those in column (6) of Table 4, but with the inclusion of an interaction of the peers' average log consumption with the relevant source of heterogeneity. The graph also plots the upper and lower bounds of a 95% confidence interval. All demographic characteristics refer to the husband (due to his primary earner role).

The first interesting result is that consumption peer effects do not vary significantly with the network size. The effect increases slightly with age, but the effect is very noisy at older ages. Consumption network effects seems also stronger for the low educated and in male-dominated professions. Interestingly, network effects are larger when the economy is booming and smaller during recessions - but estimates are significant only for a growth rate above 2% or so. Finally, we look at the effect of tenure. Unfortunately, our measure of tenure is limited and subject to left-censoring. We hence use a simple dummy for new employee. As expected network effects are present among those who have been in the firm for at least some time, but are statistically and economically absent for newly hired employee, perhaps because these individuals have yet to "learn" about co-workers' consumption choices and habits.

5.3.2 Other Concerns

In this section we investigate a variety of concerns and present some robustness analyses.

Correlated effects A first concern with our estimates is the possibility that the error term may still contain network (correlated) effects which may generate spurious evidence of endogenous effects. To address this issue, we follow two strategies. In Table 5A, column (2) we focus on a sample of firm stayers, for whom firm fixed effects are differenced out so that they are no longer a concern (column (1) reproduces, for comparison, the results of our preferred specification, that of Table 4, column 6). In column (3) we use the whole sample but include fixed effects for all possible cross-firm transitions (and assume stationarity).[24] Reassuringly, looking at stayers or including transition fixed effects leaves the results very similar to the baseline.

Bias from correlated effects may also come from co-workers suffering similar aggregate shocks. Columns (4) and (5) are designed to further address these concerns. In column (4) we control for

[24] In other words, we include dummies for each possible transition between any two firms in our data. While we do not impose the restriction that transitions from firm A to B are the same as transitions from B to A, we have to impose that the transition effects are constant over time (stationarity).

neighborhood specific shocks (measured by changes in local unemployment rates), while in column (5) we control for sector specific shocks (measured by a full set of sector-year dummies). The results remain unchanged.

Measurement error Our measure of consumption, based on a budget accounting, may miss capital gains and capital losses, i.e., it may fail to be accurate at the top and bottom of the consumption distribution. In column (2) of Table 5B we present results obtained using a measure of consumption that drops the top and bottom 1% of the consumption distribution. The estimate is essentially unchanged both in magnitude and statistical precision. Another way to address this issue is to focus on samples for whom capital gains and losses are unlikely to be important. Hence in column (3) we exclude stockholders, while in column (4) we focus on renters. In both cases, the estimate remains in the ballpark of the estimate obtained in the whole sample, which is comforting.

Weighting scheme As emphasized above, the way we weight co-workers within the firm to form peer groups is inherently arbitrary. In Table 5C we assess whether the results are robust to adopting different weighting schemes. Column (1) reproduces our baseline results, obtained using the quadratic weighting scheme (16), which gives more weight to peers with similar education and occupation within the plant. In column (2) to (4) we use alternative weighting schemes (and report the main features of the networks in Tables A2-A4). In column (2) we experiment with a linear scheme, while in column (3) we consider a richer quadratic weighting scheme based on education and occupation (as before) but also age (to capture tenure effects). To keep the number of groups within the feasible range, we consider just two age ranges, 40 and less, and more than 40. Finally, in column (4) we use a sharper weighting scheme in which all workers in the same plant and occupation are treated equally (regardless of their education). The estimates of the endogenous effects vary in size across adopted schemes. However, once these estimates are appropriately rescaled for the larger or smaller peer group, the elasticities we obtain are in the same ballpark as those in column (1), and discussed above. For example, a 10% increase in the consumption of a random peer produces a 0.05% effect for the linear scheme in column (2), a 0.053% for the scheme of column (3), and finally a 0.036% effect for the same occupation scheme in column (4) (as opposed to 0.04% in the baseline specification).

In column (6) we consider a "placebo" weighting scheme. This exercise is motivated by the consideration that our results could still be spurious if there are some unobserved factors running through the economy which produce correlation in consumption patterns that have nothing to do with network effects. To assuage these fears, we construct placebo samples where we randomly reassign workers to firms, keeping firm sizes constant. The results, based on 50 replications, are reported in the last column of Table 5C. They show that the main estimated effects are not spurious. When individuals are randomly allocated peers, their consumption is independent of that of their randomly allocated peers, with an estimated small network effect of 0.01 and a large standard error.

Responding to labor supply or saving changes? Our definition of consumption from the administrative data is the difference between income and saving. Since

$$\ln C = \ln\left((Y - T) - \Delta A\right) \cong \ln\left(Y - T\right) - s,$$

(where $s = \Delta A / \left(Y - T\right)$ is the household's saving rate), one can decompose the consumption response to peers' consumption into two parts: a response to a change in peers' disposable income (or, broadly, labor supply) (θ^Y), and a response to a change in peers' saving rate (θ^s). This decomposition is informative about what kind of peer behavior influences household consumption decisions most.

We implement this idea by running the following regression:

$$\Delta \ln C_{it} = \alpha + \theta^Y \Delta\overline{\ln Y_{it}} + \theta^s\left(-\Delta\overline{s_{it}}\right) + \gamma_1\overline{X_{it}^w} + \gamma_2\overline{X_{it}^w} + \delta_1 X_{it}^w + \delta_2 X_{it}^h + \xi_{it}$$

If peers' labor supply and saving rates decisions contribute in the same way to the overall response, we should find $\theta^Y = \theta^s$. In Table 5D, we find $\theta^Y = 0.094$ (s.e. 0.17) and $\theta^S = 0.334$ (s.e. 0.08). It thus appears that both types of responses matter (although the income component is noisy), but that consumption is more likely to be affected by changes in peers' saving/borrowing than changes in peers' effort or labor supply. As we shall see, this result can be read as consistent with the main finding from the demand analysis below - namely, that consumers do not seem to over-react to "visible" or conspicuous consumption patterns of peers. In the context examined here, the response to labor supply/effort activities (which are presumably more visible than saving or borrowing decisions, at least in a workplace context) is actually smaller than the response to saving/borrowing choices of peers.

Overall, we take the series of results presented in Tables 5A-5C as reassuring. The estimated effects appear robust to several potential sources of bias and change in predictable ways when we change the way we weight co-workers within a plant. The robustness of results is perhaps not surprising, given that our identification strategy uses admittedly exogenous firm shocks, the network structure of households in our sample (which can only be finely reconstructed with the type of data we have available), and a rich set of controls, including household fixed effects and controls for local shocks.

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:

$$\omega_{it}^{j} = X_{it}'\alpha_{0j} + \alpha_{1j}\overline{\ln C}_t + \beta_{0j}\ln C_{it} + \beta_{1j}\left(\ln C_{it} \times \overline{\ln C}_t\right) + \upsilon_{it}^{j} \tag{17}$$

for $j = \{V, N\}$. Neutral goods (which we assume include only food at home) represent the excluded category. The detailed categorization of what we include in the three types of goods is presented in Table A1. As discussed in Section 3, we test whether the average consumption peer variables are insignificant determinants of the demand for goods (i.e., $\alpha_{1j} = \beta_{1j} = 0$ for all $j = \{V, N\}$), *controlling for* total spending $\ln C_{it}$. 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), comprised of 2,438 households (the "ALL" sample). For these households we do not have distance-3 instruments (as this depends on both the work and marital status) and hence we run simple OLS regressions. Our second sample is a perfect match with our tax registry baseline sample, and is hence much smaller given the restrictions we apply for estimation (454 households, or the "MATCH" sample). For these households we can run IV regressions instrumenting peer consumption with distance-3 instruments as in the Euler equation case discussed above.

The results are reported in Table 6. In columns (1)-(2) we report estimates of (17) for the "ALL" sample. 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-visible 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 estimated coefficients, α_{1j}, 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 the estimation on the "MATCH" sample, where we can instrument peer consumption with distance-3 exogenous firm-level shocks and characteristics. The results are qualitatively unchanged (but expectedly less precise in this smaller sample).

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 all the 30 categories considered by Heffetz (2011), and run the budget share regression (17) separately for each good category (imposing again $\beta_{1j} = 0$ for all j). Figure 5 plots the estimated coefficients (and corresponding 90% confidence intervals) against the degree of visibility as estimated in Heffetz (2011).[25] We also plot a local linear regression line to detect any possible relationship between the visibility index and the estimated coefficients. 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 if there were any intratemporal effects. However, the disaggregated evidence is similar to the one noted above. The effect of peer consumption on the budget share on good j appears independent of the degree of conspicuousness of the good. The relationship is increasing only for highly conspicuous goods in the OLS case, 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 lockstep 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

[25] The consumption categories used by Heffetz (ordered according to his visibility index, high to low) are: Cigarettes, cars, clothing, furniture, jewelry, recreation type 1, food out, alcohol home, barbers etc., alcohol out, recreation type 2, books etc. education, food home, rent/home, cell phone, air travel, hotels etc. public transportation, car repair, gasoline, health care, charities, laundry, home utilities, home phone, legal fees, car insurance, home insurance, life insurance, underwear. We use the same categories except charities for which we have no survey information.

problems of private information or limited enforcement are more easily solved within the strict confines of the workplace.

Results reported in Table 4 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 7. As in Table 6, we focus on the "ALL" sample (column 1) and the "MATCH" sample. However, we perform in both cases simple OLS regressions as we are only interested in the sign of the relationship between the coefficient on income growth and the consumption differences between survey and tax registry data. 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 "shared" transfer) relative to the tax records measure (which does not). In the data (irrespective of sample used) there is actually a positive, and statistically significant association. Similarly, 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 effects 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, and so forth, to highlight the role of network effects in the sharpest possible way.

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 abstracts from the degree of connectedness, is about 1.5 (from the regression of Table 4 column 6, obtained as $1/(1-\widehat{\theta})$ with $\widehat{\theta} \cong 0.33$), so aggregate effects may potentially be important. We should note that the specific multiplier is only valid in a world where the network is full, i.e., all the nodes are directly connected, which is clearly not the case in a standard setting and in our specific application. We therefore have to account for the degree of connectedness as well as for the introductory point of the policy (i.e., which group is directly targeted) in order to understand the aggregate implications of network effects. To do so, we engineer a series of experiments, summarized in Table 8. We present not only the multiplier effects of a one-time policy (in a static framework), but also several moments of the resulting distribution of consumption. We do this in order to understand the level and distributional effects of such policy experiments. Note that in the first row of Table 8 we present the actual moments from the 1996 sample (our last sample year).

Our first three experiments consist of transferring the equivalent of 1% of aggregate consumption equally among: (a) households in the top 10% of the consumption distribution, (b) a 10% random sample of households, and (c) households in the bottom 10% of the consumption distribution. These three policies are financed by issuing debt and running a government deficit. As an alternative to a debt-financed policy, we consider: (d) 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" to 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).[26]

Consider the first experiment, which consists of distributing resources to households in the top 10% of the consumption distribution. In a world without network effects, this would increase aggregate consumption by 1%, with an implied multiplier of 1.01. With network effects, the implied multiplier effect is instead slightly larger, 1.012.[27] There is also a slight increase in the dispersion of consumption, as measured by the standard deviation of log consumption or the 90-10 percentile difference in log consumption. The reverberation effects are concentrated in the top half of the consumption distribution (as can be seen by looking at the 90/50 and 50/10 log consumption differences). What can be learned from this experiment is that consumption policies targeted at the top 10% of the consumption distribution (presumably also the wealthier households), have limited aggregate effects, and in particular do not spread along the distribution of consumption. The reason is that households at the top of the consumption distribution have fewer direct connections

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

[27] The multiplier is obtained as the ratio of the post-transfer to the pre-transfer aggregate consumption. We obtain post-transfer aggregate consumption using a simple iterative algorithm. After increasing the consumption of households targeted by the policy by the amount of the transfer, we compute peer consumption using the weighted formula explained in the text. We then compute the new level of consumption of all households in the sample using the network effect estimate. We recompute peer consumption, and so forth. We stop after 10 iterations.

and their network structures are smaller and more sparse then those of random households in the population.

The next experiment (where we target a random 10% of households) confirms this intuition. In this case the multiplier is 1.017 and consumption inequality declines. A look at the 90-50 and 50-10 differences reveals that policies that target a random sample of households (most likely located in the middle of the distribution) have larger, and more far reaching consequences than policies of identical magnitude targeted at the top 10%. This is because those households have larger and denser networks than those at the top.

Even larger aggregate effects are found when the policy targets the bottom 10% of households. In this case the multiplier effect is noticeably larger than in the previous cases (1.034), with a much larger fall in dispersion (a 13% decline in the standard deviation of log consumption). These results suggest that households at the bottom of the distribution have larger and denser networks, which tend to be concentrated among households with similarly low consumption levels. Indeed, a look at the 50/10 and 90/50 percentile differences show that the latter barely moves (relatively to the baseline), while the former declines substantially.

In the final row of Table 8 we consider a balanced budget experiments in which a transfer to poorer households is financed by a tax imposed on the richer households (who hence mechanically reduce their consumption). This case yields an intermediate multiplier effect (1.021), with the largest reduction in dispersion among all experiments. This is because there are now richer effects: households connected with those at the top (presumably near the top themselves) reduce their consumption, while households connected with those at the bottom (presumably also located in the bottom half) increase it. The result is that the post-policy consumption distribution becomes more compressed, and the larger degree of connectedness at the bottom than at the top drives aggregate consumption upwards.

In conclusion, what we learn from the experiments detailed in Table 8 is that stimulus policies can have quite differential impacts on aggregate consumption and on the distribution of household consumption depending on the groups that are directly targeted (and their overall connectedness with the different segments of the population). Another important, and obviously related lesson is that the multiplier effect generally computed as $(1-\theta)^{-1}$ can be highly misleading in the presence of fairly general network structures.[28]

[28] A related point based on social distance is given in Glaeser, Scheinkman, and Sacerdote (2003).

7 Conclusions

This paper builds a consistent theoretical framework for consumption choices within and between periods that is able to capture social effects and allows us to distinguish between different ways in which social interactions can emerge. We take the testable empirical predictions that come from the model and bring them to bear on a very rich set of data containing (derived) information on the consumption of the entire Danish population and the social networks they span (at the household and firm level). We find that peers' consumption enters the intertemporal decision, i.e. in a "Keeping-up-with-the-Joneses" fashion. We do not find evidence that network effects distort intratemporal decision (i.e., the demand for goods). As well, we find little evidence that peer effects emerge as a way of rationalizing risk sharing agreements. We have discussed the policy consequences of these results using simple stimulus policy experiments that transfer consumption resources to different groups in the population. The results highlight two important conclusions: the effects of the policies depend on the degree of connectedness of the group directly targeted, and social multipliers (typically computed as $(1-\theta)^{-1}$, where θ is the estimated network effect) can be highly misleading when network structures are far from full.

Our results could be extended in a number of directions. While we have emphasized the importance of peers defined on the basis of co-worker relationships, it could be possible to construct family networks or location networks. Family identifiers, for example, could allow us to match parents and children, or siblings. The problem with this approach is that a non-negligible number of households may be completely disconnected (i.e., older households or only children). On the location side, we observe the municipality where the household resides. Here, we may face the opposite problems (i.e., the network may be too large and composed of people who do not interact socially in any meaningful way). On the theoretical side, it could be possible to test whether peers provide primarily "information", i.e., whether peer effects manifest themselves among goods that are "experience goods". Unfortunately, our microdata on spending are too limited to implement such exercise.

References

[1] Abowd, J. M., Kramarz, F. and Margolis, D. N. (1999), "High Wage Workers and High Wage Firms." *Econometrica*, 67: 251–333.

[2] Agarwal, S., W. Qian and X. Zou (2017), "Thy neighbor's misfortune: Peer effect on consumption", mimeo.

[3] Beshears, J., J. Choi, D. Laibson, B. Madrian, and K. Milkman (2011). "The Effect of Providing Peer Informationon Retirement Savings Decisions." mimeo

[4] Bandiera, O., I. Barankay, and I. Rasul (2009a). "Social Incentives in the Workplace." *Review of Economic Studies*, 62: 777–795.

[5] Banerjee, A., A. Chandrasekhar, E. Duflo, and M. Jackson (2013). "The Diffusion of Microfinance." *Science*, 341(6144).

[6] Bertrand, M., E.F.P. Luttmer, and S. Mullainathan (2000). "Network Effects and Welfare Cultures," *Quarterly Journal of Economics*, 115(3): 1019-1055.

[7] Blundell, R., M. Browning, and C. Meghir (1994). "Consumer demand and the life-cycle allocation of household expenditures." *The Review of Economic Studies*, 61(1): 57-80.

[8] Borjas, G., and L. Hilton (1995). "Immigration and the Welfare State: Immigrant Participation in Means- Tested Entitlement Programs." NBER Working Paper No. 5372.

[9] Bramoullé, Y., H. Djebbari, and B. Fortin (2009). "Identification of Peer Effects through Social Networks." *Journal of Econometrics*, 150(1): 41-55.

[10] Brock, W., and S. Durlauf (2001). "Interaction-based Models", *Handbook of Econometrics*, vol. 5, J. Heckman and Leamer E. (Eds), Amsterdam: North-Holland.

[11] Browning, M., and S. Leth-Petersen (2003). "Imputing Consumption from Income and Wealth Information." *The Economic Journal,* 113(488): F282-F301

[12] Browning, M. and C. Meghir (1991). "The effects of male and female labor supply on commodity demands." *Econometrica: Journal of the Econometric Society,* 925-951.

[13] Calvó-Armengol, A., E. Patacchini, and Y. Zenou (2009). "Peer Effects and Social Networks in Education." *Review of Economic Studies*, forthcoming.

[14] Carrell, S., R. Fullerton, and J. West (2009). "Does Your Cohort Matter? Measuring Peer Effects in College Achievement." *Journal of Labor Economics*, 27(3): 439-464.

[15] Carrell, S., F. Malmstrom, and J. West (2008). "Peer Effects in Academic Cheating." *Journal of Human Resources*, 43(3): 173-207.

[16] Caeyrers, B. and M. Fafchamps (2015). "Exclusion Bias in the Estimation of Peer Effects." mimeo NEUDC.

[17] Charles, K., E. Hurst, and N. Roussanov (2009). "Conspicuous Consumption and Race." *Quarterly Journal of Economics*, 124(2): 425-467.

[18] Chetty, R., J. N. Friedman, T. Olsen, and L. Pistaferri (2011). "Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records." *The Quarterly Journal of Economics* 126 (2): 749-804.

[19] Cochrane, J. (1991). "A simple test of consumption insurance." *Journal of Political Economy*, 99(5): 957–976.

[20] Currarini, S., M. Jackson, and P. Pin (2009). "An Economic Model of Friendship: Homophily, Minorities, and Segregation." *Econometrica*, 77(4): 1003-1045.

[21] Dahl, G., K. Løken, and M. Mogstad (2014). "Peer Effects in Program Participation." *American Economic Review*, 104(7): 2049-2074.

[22] Deaton, A., and J. Muellbauer (1980). "An almost ideal demand system." *The American Economic Review*, 70(3): 312-326.

[23] De Giorgi, G., M. Pellizzari, and S. Redaelli (2010). "Identification of Peer Effects through Partially Overlapping Peer Groups." *The American Economic Journal: Applied Economics*, 2(2).

[24] De Giorgi, G. and M. Pellizzari (2014). "Understanding Social Interactions." *The Economic Journal*, 124(579): 917-953.

[25] Duflo, E., and E. Saez (2003). "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment." *Quarterly Journal of Economics*, 118(3): 815-842.

[26] Duesenberry, J. S. (1948). Income-consumption relations and their implications. *Lloyd Metzler et al., Income, Employment and Public Policy, New York: WW Norton & Company, Inc.*

[27] Fagereng, A., L. Guiso, D. Malacrino and L. Pistaferri (2016). "Heterogeneity and Persistence in Returns to Wealth." National Bureau of Economic Research Working Paper 22822.

[28] Gali, J. (1994). "Keeping up with the Joneses: Consumption Externalities, Portfolio Choice, and Asset Prices." *Journal of Money, Credit and Banking*, 26(1): 1-8.

[29] Glaeser, E. L., J. A. Scheinkman, and B. Sacerdote (2003). "The Social Multiplier." *Journal of the European Economic Association P&P*, 1(2/3): 345–353.

[30] Goldsmith-Pinkham, P., and G. W. Imbens (2013). "Social networks and the identification of peer effects." *Journal of Business & Economic Statistics*, 31(3): 253-264.

[31] Grodner, A., and T. J. Kniesner (2006). "Social interactions in labor supply." *Journal of the European Economic Association*, 4(6): 1226-1248.

[32] Guiso, L., L. Pistaferri, and F. Schivardi (2005). "Insurance within the firm." *Journal of Political Economy*, 113(5): 1054-1087.

[33] Hanushek, E., J. Kain, J. Markman, and S. Rivkin (2003). "Does Peer Ability Affect Student Achievement?" *Journal of Applied Econometrics*, 18(5): 527-544.

[34] Hausman, J. A., and Z. Griliches (1986). "Errors in Variables in Panel Data." *Journal of Econometrics*, 31: 93-118.

[35] Heffetz, O. (2011). "A test of conspicuous consumption: Visibility and income elasticities." *Review of Economics and Statistics*, 93(4): 1101-1117.

[36] Holzer, H.J. (1988). "Search method use by unemployed youth." *Journal of Labor Economics,* 6:1-20.

[37] Jackson, M (2006). "The Economics of Social Networks." Chapter 1 in Volume I of Advances in Economics and Econometrics, Theory and Applications: Ninth World Congress of the Econometric Society, edited by Richard Blundell, Whitney Newey, and Torsten Persson, Cambridge University Press.

[38] Jappelli, T. and L. Pistaferri (2014). "Fiscal policy and MPC heterogeneity." *American Economic Journal: Macroeconomics,* 6(4): 107-136.

[39] Kuhn, P., P. Kooreman, P., A. Soetevent, and A. Kapteyn (2011). "The Effects of Lottery Prizes on Winners and their Neighbors: Evidence from the Dutch Postcode Lottery." *The American Economic Review,* 101(5): 2226-2247.

[40] Ljungqvist, L. and H. Uhlig (2000). "Tax policy and aggregate demand management under catching up with the Joneses." *American Economic Review*, 356-366.

[41] Leth-Petersen, S. (2010). "Intertemporal consumption and credit constraints: Does total expenditure respond to an exogenous shock to credit?" *The American Economic Review*, 100(3): 1080-1103.

[42] Mace, B. J. (1991). "Full insurance in the presence of aggregate uncertainty." *Journal of Political Economy*, 99(5): 928–956.

[43] Manski, C. (1993). "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60: 531-542.

[44] Mas, A., and E. Moretti (2009). "Peers at Work." *American Economic Review*, 99(1): 112-145.

[45] Maurer, J., and A. Meier (2008). "Smooth It Like the 'Joneses'? Estimating Peer-Group Effects in Intertemporal Consumption Choice." *The Economic Journal*, 118(2): 454-476.

[46] Meyer, C. (2000). *Matrix Analysis and Applied Linear Algebra.*

[47] Moffitt, R. (2001). "Policy Interventions, Low-Level Equilibria, and Social Interactions." In *Social Dynamics*, S. Durlauf and H. P. Young eds., Cambridge: MIT Press.

[48] Montgomery, J. D. (1991). "Social Networks and Labor-market Outcomes: Toward an Economic Analysis". *The American Economic Review,* 81(5): 1408–1418.

[49] Pistaferri, L. (1999). "Informal networks in the Italian labor market." *Giornale degli economisti e annali di economia,* 355-375.

[50] Pellizzari, M. (2010). "Do friends and relatives really help in getting a good job?" *The Industrial and Labor Relations Review*, 63(3): 494-510.

[51] Pollak, R.A. (1969). "Conditional Demand Functions and Consumption Theory." *The Quarterly Journal of Economics*, 83 (1): 60-78.

[52] Ravina, E. (2007). "Habit Persistence and Keeping Up with the Joneses: Evidence from Micro Data." mimeo Columbia

[53] Sacerdote, B. (2001). "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics*, 116: 681-704.

[54] Sanderson, E., & Windmeijer, F. (2016). "A Weak Instrument F-Test in Linear IV Models with Multiple Endogenous Variables." *Journal of Econometrics*, 190(2): 212-221.

[55] Veblen, T. (1899). "The theory of the leisure class: An economic study in the evolution of institutions." Macmillan

Table 1: Descriptive Statistics

	Mean	Std.Dev.		Mean	Std.Dev.
		Outcomes:			
ln *Consumption* (Ad.Eq.)	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 (in 1,000)			*Type: Limited liability*		
Husband	-0.009	(0.32)	Husband	0.08	
Wife	-0.013	(0.42)	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: Weighted Network Statistics (Quadratic Weights)

	Co-workers' group			Distance-3 Peers' averages	
	Peers	Std.dev.	Variable	Wife's peers	Husband's peers
Distance 1			Age	38.62	38.46
Husband	73.30	179.77		(2.48)	(2.51)
Wife	95.07	233.34	Years of schooling	11.89	11.67
				(1.26)	(1.29)
Distance 2			Share of females	0.45	0.62
Husband	89.27	212.77		(0.21)	(0.20)
Wife	118.78	285.88	Share of blue collars	0.42	0.40
				(0.27)	(0.27)
Distance 3			Share of white collars	0.30	0.35
Husband	12,535	33,285		(0.19)	(0.21)
Wife	14,871	40,534	Share of managers	0.29	0.25
				(0.23)	(0.22)
	Co-workers' averages		# Kids 0-6	0.28	0.28
				(0.09)	(0.09)
Variable	Wife	Husband	# Kids 7-18	0.46	0.47
Age	38.24	38.59		(0.13)	(0.14)
	(5.61)	(5.62)	*Size (in 1,000)*	1.45	1.56
Years of schooling	11.69	11.81		(1.13)	(1.39)
	(1.86)	(1.82)	Growth	0.001	0.001
Share of females	0.71	0.27		(0.002)	(0.002)
	(0.26)	(0.26)	Public sector	0.53	0.63
Share of blue collars	0.36	0.47		(0.30)	(0.30)
	(0.37)	(0.41)	Publicly traded	0.36	0.29
Share of white collars	0.39	0.22		(0.29)	(0.27)
	(0.35)	(0.28)	Limited liability	0.02	0.01
Share of managers	0.25	0.31		(0.08)	(0.08)
	(0.34)	(0.36)	Other	0.62	0.70
# Kids 0-6	0.28	0.27		(0.29)	(0.27)
	(0.21)	(0.21)			
# Kids 7-18	0.50	0.47			
	(0.30)	(0.29)			

Table 4: 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%. Standard errors are double clustered for husbands and wives at the workplace, occupation, and education level. Dependent variable: Log of adult equivalent consumption. Individual controls (separately 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: 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. We also control for year fixed-effects. For details on the weighting schemes see the main text.

Table 5A: Robustness to correlated effects

Model	(1) Baseline	(2) Stayers	(3) Transitions FE	(4) Local shocks	(5) Sector shocks
Avg. peer's ln C	0.33***	0.36***	0.29***	0.33***	0.34***
	(0.078)	(0.090)	(0.063)	(0.078)	(0.073)
F-stat first stage	111.50	59.03	58.83	109.5	127.8
Number of obs.	2,671,889	2,045,787	2,671,889	2,671,889	2,671,889

Note: *,**,***= significant at 10%, 5%, 1%. Standard errors are double clustered for husbands and wives at the workplace, occupation, and education level. Dependent variable: Log of adult equivalent consumption. Individual controls (separately 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: 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. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy. We also control for year fixed-effects. The regression in column (1) is the baseline (from Table 4, column 6). For details on the other specifications, see the main text.

Table 5B: Robustness to measurement error

Model	(1) Baseline	(2) 1% trim	(3) Drop stockholders	(4) Renters
Avg. peer's ln C	0.33***	0.30***	0.36***	0.24***
	(0.078)	(0.072)	(0.088)	(0.082)
F-stat first stage	111.50	101.09	82.40	34.72
Number of obs.	2,671,889	2,628,110	2,016,137	318,317

Note: *,**,***= significant at 10%, 5%, 1%. Standard errors are double clustered for husbands and wives at the workplace, occupation, and education level. Dependent variable: Log of adult equivalent consumption. Individual controls (separately 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: 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. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy. We also control for year fixed-effects. The regression in column (1) is the baseline (from Table 4, column 6). For details on the other specifications, see the main text.

Table 5C: Robustness to weighting scheme

Model	(1) Baseline	(2) Linear	(3) Exp. quadratic	(4) Sharp	(5) Placebo
Avg. peer's ln C	0.33***	0.62***	0.30***	0.44***	0.01
	(0.078)	(0.164)	(0.082)	(0.083)	(0.028)
F-stat first stage	111.50	127.03	77.67	88.22	-.-
Number of obs.	2,671,889	2,671,889	2,671,823	2,171,426	2,671,889

Note: *,**,***= significant at 10%, 5%, 1%. Standard errors are double clustered for husbands and wives at the workplace, occupation, and education level. Dependent variable: Log of adult equivalent consumption. Individual controls (separately 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: 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. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy. We also control for year fixed-effects. The regression in column (1) is the baseline (from Table 4, column 6). For details on the other specifications, see the main text.

Table 5D: Response to effort vs. saving rate

Avg. peer's ln Y	0.09
	(0.166)
Avg. peer's saving rate	0.33***
	(0.078)
Number of obs.	2,671,889

Note: *,**,***= significant at 10%, 5%, 1%. Standard errors are double clustered for husbands and wives at the workplace, occupation, and education level. Dependent variable: Log of adult equivalent consumption. Individual controls (separately 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: 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. Firm IV's: Public sector dummy, Firm size, Firm growth, Firm type dummy. We also control for year fixed-effects.

Table 6: Demand Estimation

	ALL Sample				MATCH sample	
	Visible cons.	Not-visible cons.	Visible cons.	Not-visible cons.	Visible cons.	Not-visible cons.
	(1)	(2)	(3)	(4)	(5)	(6)
ln C	-0.025	0.092	0.015***	-0.009**	0.026*	-0.018
	(0.156)	(0.143)	(0.004)	(0.004)	(0.014)	(0.012)
Avg. peer's ln C	-0.037	0.099	0.004	0.001	0.012	-0.006
	(0.154)	(0.141)	(0.012)	(0.011)	(0.025)	(0.021)
ln C×Avg. peer's ln C	0.003	-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, Public sector dummy, Firm size, Firm growth, Firm type dummies. Household controls: Year dummies, Region dummies, # kids 0-6, # kids 7-18.

Table 7: Tests of Risk Sharing

	ALL Sample		MATCH sample
	(1)	(2)	(3)
$\Delta \ln Y$	0.226***	0.269**	0.275**
	(0.070)	(0.110)	(0.110)
$\overline{\Delta \ln Y}$			-0.094
			(0.082)
Observations	2,432	824	824

Note: *,**,***= significant at 10%, 5%, 1%. Individual controls: 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.

Table 8: Counterfactual Policy Simulations

Transfer recipients	Implied multiplier	Std.Dev. log cons.	90-10 log difference	50-10 log difference	90-50 log difference
Baseline	-.-	0.729	1.5795	0.8630	0.7165
Top 10%	1.012	0.736	1.5818	0.8631	0.7187
Random 10%	1.017	0.718	1.5607	0.8504	0.7103
Bottom 10%	1.034	0.601	1.4525	0.7349	0.7176
Balanced budget	1.021	0.593	1.4216	0.7347	0.6869

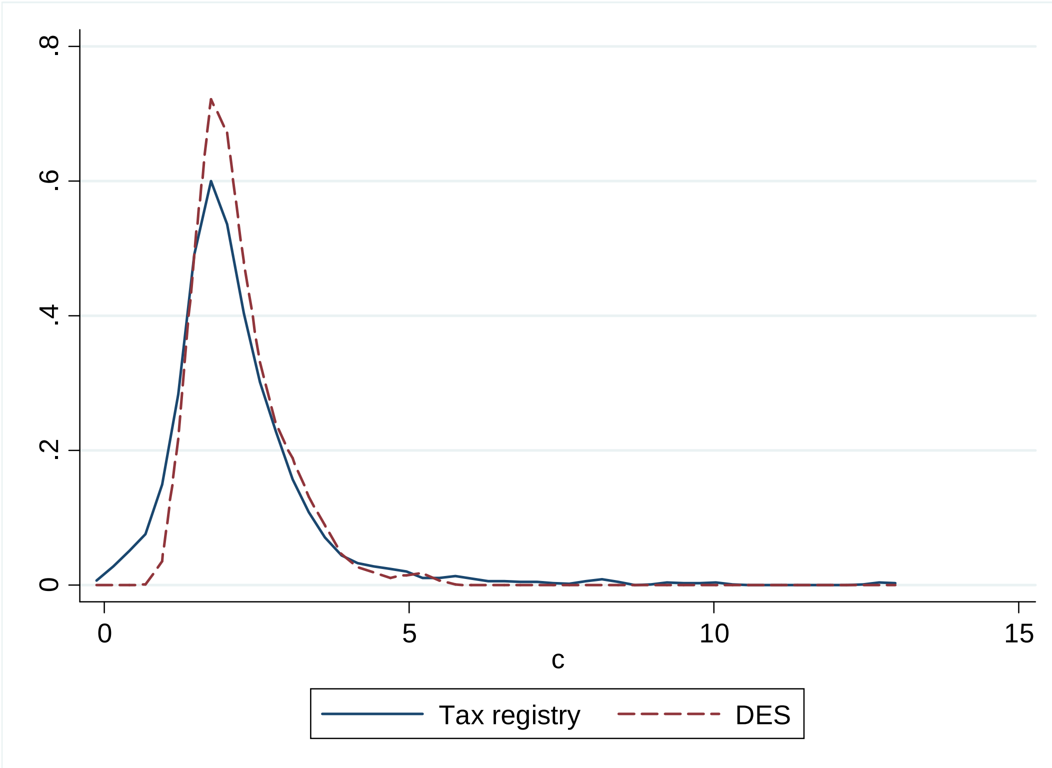

Figure 1: The distribution of consumption in the Tax Registry and in the Danish Expenditure Survey.

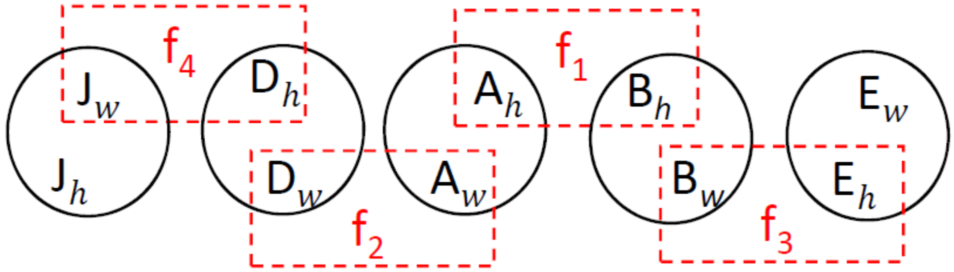

Figure 2: A simple example of network identification.

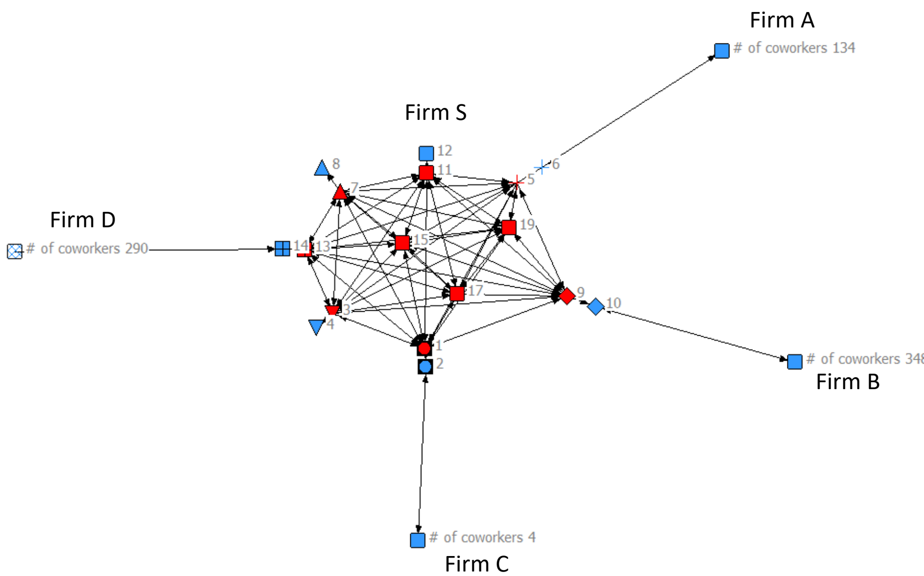

Figure 3: An actual network in our data

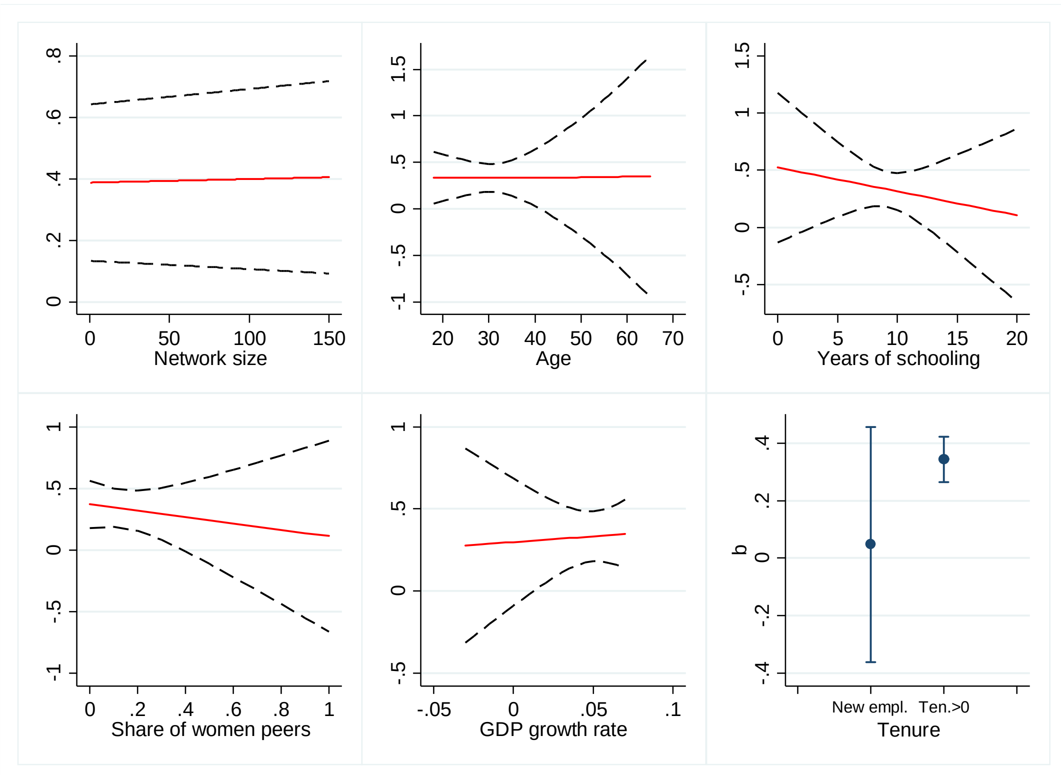

Figure 4: Heterogeneous network effects

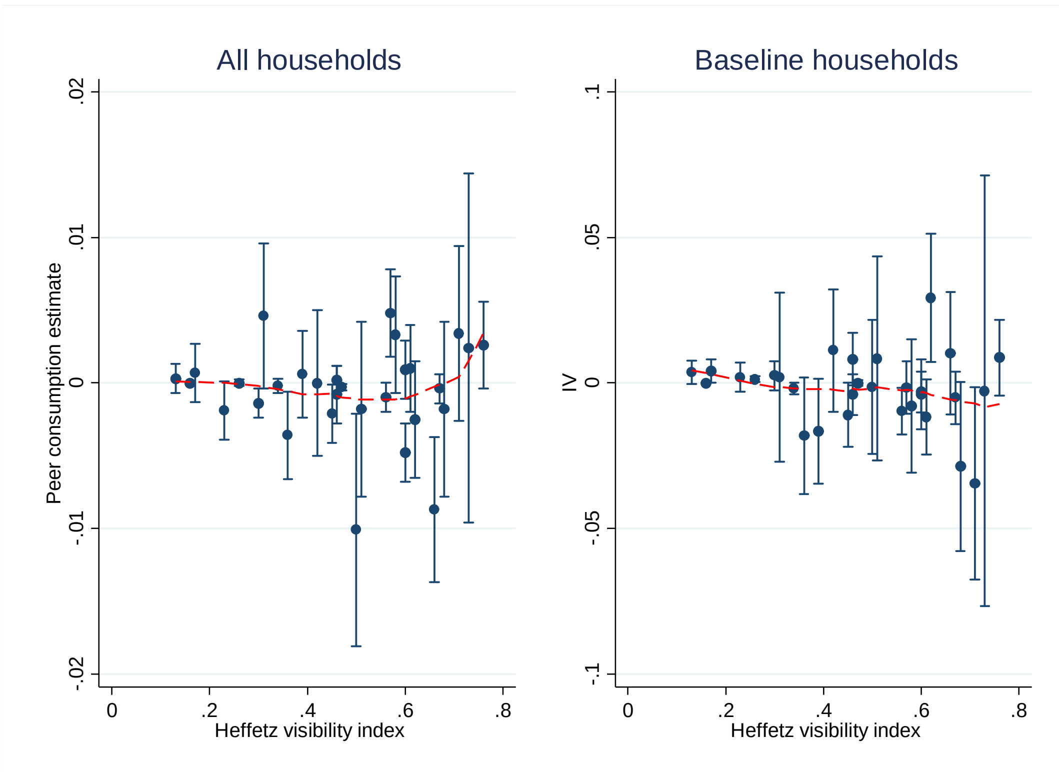

Figure 5: The relationship between the shift in budget shares due to peer consumption and the Heffetz visibility index

A Restrictions on consumption vs. restrictions on spending

As we noted in the main text, what we observe in the administrative data is total spending (on both non-durables and durables), while the theoretical restrictions discussed in Section 3 refer mostly to consumption of nondurables and services, not total spending. In this Appendix we show that, under suitable restrictions, one can re-interpret equation (3) as describing the dynamics of total household spending as a function of the peers' total spending.

Assume that consumers draw utility from non-durable consumption C_{it} and the stock of durables D_{it}. In particular, assume that preferences over the non-durable/durable bundle are restricted to be of the Cobb-Douglas variety, i.e.:

$$V_t (\mathbf{p}_t, C_{it}, D_{it}) = \frac{\left(C_{it}^{\alpha} D_{it}^{1-\alpha} / a(\mathbf{p}_t)\right)^{1-\gamma} - 1}{1-\gamma}.$$

Assume finally that the price of the durable good is p_t^D and that the price of the non-durable bundle is the numeraire ($p_t^{ND} = 1$) ($\mathbf{p}_t$ is a vector of these two prices in this simple case).

With Cobb-Douglas preferences over the non-durable/durable bundle, the MRS between durables and non-durables is:

$$\frac{C_t}{D_t} = \xi p_t^D \tag{A1}$$

where ξ is a constant. It follows that

$$(1 + g_C) = (1 + g_D)\left(1 + g_{p^D}\right) \tag{A2}$$

where g_C, g_D and g_{p^D} are the growth rates of non-durable consumption, the growth rate of the durable stock and the growth rate of the durable's price, respectively. From the dynamic equation for the stock of durables,

$$D_{t+1} = (1 - \delta) D_t + I_t$$

it is easy to show that durable spending I_t grows at the same rate as the stock of durables (approximately, and exactly if the growth rate of the durable stock is constant over time), $g_I \cong g_D$. Hence, replacing in (A2),

$$(1 + g_C) \cong (1 + g_I)\left(1 + g_{p^D}\right)$$

Since total spending (what is observed in administrative data) is $X_t = C_t + p_t^D I_t$, it is easy to show that, dividing both sides by X_{t-1} gives

$$(1 + g_X) \cong (1 + g_C)$$

i.e., the growth rate of total spending is the same as the growth rate of non-durable spending. Since our Euler equation estimates regress the household's consumption growth rate against the average consumption growth rate of their peers, one can re-interpret equation (3) as describing the dynamics of total household spending as a function of the peers' total spending.

B Additional tables

Table A1: Goods Characterization

Good	Heffetz Restat	Good	Heffetz Restat
Tobacco	Visible	Oils and fats	Food at home
Clothing materials	Visible	Fruit	Food at home
Garments	Visible	Vegetables	Food at home
Other articles of clothing and clothing accessories	Visible	Sugar, jam, honey, chocolate and confectionery	Food at home
Cleaning, repair and hire of clothing	Visible	Food products	Food at home
Shoes and other footwear	Visible	Coffee, tea and cocoa	Food at home
Repair and hire of footwear	Visible	Mineral waters, soft drinks, fruit and vegetable juices	Food at home
Furniture and furnishings	Visible		
Carpets and other floor coverings	Visible	Spirits	Not Visible
Repair of furniture, furnishings and floor coverings	Visible	Wine	Not Visible
Household textiles	Visible	Beer	Not Visible
Major household appliances whether electric or not	Visible	Actual rentals paid by tenants	Not Visible
Small electric household appliances	Visible	Other actual rentals	Not Visible
Repair of household appliances	Visible	Imputed rentals of owner-occupiers	Not Visible
Glassware, tableware and household utensils	Visible	Other imputed rentals	Not Visible
Major tools and equipment	Visible	Materials for the maintenance and repair of the dwelling	Not Visible
Motor cars	Visible	Services for the maintenance and repair of the dwelling	Not Visible
Motor cycles	Visible	Small tools and miscellaneous accessories	Not Visible
Bicycles	Visible	Non-durable household goods	Not Visible
Equipment for the reception, recording and reproduction of sound and pictures	Visible	Domestic services and household services	Not Visible
Photographic and cinematographic equipment and optical instruments	Visible	Pharmaceutical products	Not Visible
Information processing equipment	Visible	Other medical products	Not Visible
Recording media	Visible	Therapeutic appliances and equipment	Not Visible
Repair of audio-visual, photographic and information processing equipment	Visible	Medical services	Not Visible
Major durables for outdoor recreation	Visible	Dental services	Not Visible
Musical instruments and major durables for indoor recreation	Visible	Paramedical services	Not Visible
Maintenance and repair of other major durables for recreation and culture	Visible	Hospital services	Not Visible
Games, toys and hobbies	Visible	Spare parts and accessories for personal transport equipment	Not Visible
Equipment for sport, camping and open-air recreation	Visible	Fuels and lubricants for personal transport equipment	Not Visible
Gardens, plants and flowers	Visible	Maintenance and repair of personal transport equipment	Not Visible
Pets and related products	Visible	Other services in respect of personal transport equipment	Not Visible
Veterinary and other services for pets	Visible	Fees in association with personal transports	Not Visible
Recreational and sporting services	Visible	Passenger transport by road	Not Visible
Cultural services	Visible	Passenger transport by air	Not Visible
Games of chance	Visible	Passenger transport by sea and inland waterway	Not Visible
Books	Visible	Combined passenger transport	Not Visible
Newspapers and periodicals	Visible	Other purchased transport services	Not Visible
Miscellaneous printed matter	Visible	Package holidays	Not Visible
Stationery and drawing materials	Visible	Water supply	Not Visible
Secondary education	Visible	Refuse collection	Not Visible
Tertiary education	Visible	Sewage collection	Not Visible
Education not definable by level	Visible	Other services relating to the dwelling	Not Visible
Restaurants, cafés and the like	Visible	Electricity	Not Visible
Canteens	Visible	Gas	Not Visible
Personal care	Visible	Liquid fuels	Not Visible
Personal effects	Visible	Solid fuels	Not Visible
Day care institutions	Visible	Heat energy	Not Visible
		Postal services	Not Visible
Bread and cereals	Food at home	Telephone and telefax equipment	Not Visible
Meat	Food at home	Telephone and telefax services	Not Visible
Fish and seafood	Food at home	Insurance	Not Visible
Milk, cheese and eggs	Food at home		

Note: The classification uses a discretization of the heffetz linear index (column 1 of Table 3; Heffetz, 2010). Visible goods have index above 0.51, Food at home has index 0.51s and Not Visible goods have index below 0.50

Table A2: Weighted Network Statistics (Linear Weights)

	Co-workers' group			**Distance-3 Peers' averages**	
	Peers	Std.dev.	Variable	Wife's peers	Husband's peers
Distance 1			Age	39.11	38.47
Husband	111.82	267.42		(2.30)	(2.33)
Wife	142.16	343.69	Years of schooling	11.81	11.70
				(1.00)	(1.02)
Distance 2			Share of females	0.47	0.61
Husband	89.27	212.77		(0.20)	(0.19)
Wife	118.78	285.88	Share of blue collars	0.41	0.39
				(0.23)	(0.22)
Distance 3			Share of white collars	0.31	0.35
Husband	19,079	51,148		(0.15)	(0.16)
Wife	22,994	63,558	Share of managers	0.28	0.26
				(0.17)	(0.17)
	Co-workers' averages		# Kids 0-6	0.27	0.28
				(0.08)	(0.08)
Variable	Wife	Husband	# Kids 7-18	0.46	0.47
Age	38.30	38.37		(0.12)	(0.13)
	(5.21)	(5.27)	*Size (in 1,000)*	1.49	1.60
Years of schooling	11.72	11.66		(1.32)	(1.40)
	(1.54)	(1.52)	Growth	0.001	0.001
Share of females	0.69	0.29		(0.002)	(0.002)
	(0.26)	(0.25)	Public sector	0.53	0.63
Share of blue collars	0.37	0.48		(0.30)	(0.29)
	(0.32)	(0.36)	Publicly traded	0.36	0.29
Share of white collars	0.37	0.24		(0.28)	(0.27)
	(0.29)	(0.25)	Limited liability	0.02	0.01
Share of managers	0.27	0.28		(0.08)	(0.08)
	(0.28)	(0.29)	Other	0.62	0.70
# Kids 0-6	0.27	0.27		(0.29)	(0.27)
	(0.18)	(0.18)			
# Kids 7-18	0.50	0.46			
	(0.27)	(0.26)			

Table A3: Network Statistics (Occupation-Education-Age Weighting)

	Co-workers' group			**Distance-3 Peers' averages**	
	Peers	Std.dev.	Variable	Wife's peers	Husband's peers
Distance 1			Age	39.11	38.50
Husband	50.30	122.70		(3.76)	(3.82)
Wife	65.64	162.53	Years of schooling	11.89	11.68
				(1.23)	(1.25)
Distance 2			Share of females	0.45	0.62
Husband	89.27	212.76		(0.21)	(0.20)
Wife	118.79	285.89	Share of blue collars	0.42	0.40
				(0.26)	(0.26)
Distance 3			Share of white collars	0.30	0.35
Husband	8,595	22,891		(0.19)	(0.20)
Wife	10,257	28,138	Share of managers	0.29	0.25
				(0.22)	(0.21)
	Co-workers' averages		# Kids 0-6	0.27	0.28
				(0.11)	(0.12)
Variable	Wife	Husband	# Kids 7-18	0.46	0.47
Age	38.33	39.32		(0.13)	(0.14)
	(6.85)	(6.95)	*Size (in 1,000)*	1.50	1.60
Years of schooling	11.69	11.77		(1.32)	(1.41)
	(1.81)	(1.78)	Growth	0.001	0.001
Share of females	0.71	0.27		(0.003)	(0.003)
	(0.26)	(0.26)	Public sector	0.54	0.63
Share of blue collars	0.36	0.47		(0.30)	(0.30)
	(0.36)	(0.40)	Publicly traded	0.36	0.29
Share of white collars	0.39	0.22		(0.28)	(0.27)
	(0.34)	(0.27)	Limited liability	0.02	0.01
Share of managers	0.25	0.31		(0.08)	(0.08)
	(0.33)	(0.35)	Other	0.62	0.70
# Kids 0-6	0.28	0.26		(0.29)	(0.27)
	(0.23)	(0.22)			
# Kids 7-18	0.50	0.47			
	(0.31)	(0.29)			

Table A4: Network Statistics (Sharp Weighting)

	Co-workers' group			**Distance-3 Peers' averages**	
	Peers	Std.dev.	Variable	Wife's peers	Husband's peers
Distance 1			Age	38.88	38.53
Husband	113.09	266.89		(3.29)	(3.15)
Wife	134.94	324.75	Years of schooling	11.85	11.80
				(1.33)	(1.37)
Distance 2			Share of females	0.39	0.64
Husband	43.01	97.00		(0.24)	(0.22)
Wife	53.81	125.69	Share of blue collars	0.43	0.36
				(0.36)	(0.35)
Distance 3			Share of white collars	0.25	0.38
Husband	8,830	23,478		(0.28)	(0.32)
Wife	10,089	28,869	Share of managers	0.32	0.26
				(0.33)	(0.32)
	Co-workers' averages		# Kids 0-6	0.27	0.28
				(0.11)	(0.11)
Variable	Wife	Husband	# Kids 7-18	0.46	0.48
Age	38.49	39.32		(0.16)	(0.17)
	(5.68)	(6.04)	*Size (in 1,000)*	1.27	1.47
Years of schooling	11.73	11.86		(1.30)	(1.45)
	(1.80)	(1.75)	Growth	0.001	0.001
Share of females	0.73	0.24		(0.002)	(0.002)
	(0.26)	(0.27)	Public sector	0.49	0.65
Share of blue collars	0.32	0.44		(0.34)	(0.33)
	(0.47)	(0.50)	Publicly traded	0.40	0.27
Share of white collars	0.45	0.15		(0.33)	(0.30)
	(0.50)	(0.36)	Limited liability	0.02	0.01
Share of managers	0.24	0.40		(0.11)	(0.09)
	(0.43)	(0.49)	Other	0.58	0.72
# Kids 0-6	0.28	0.27		(0.33)	(0.30)
	(0.22)	(0.21)			
# Kids 7-18	0.51	0.48			
	(0.31)	(0.30)			