A Model of Addiction and Social Interactions*

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Abstract

Many consumer behaviors are both addictive and social. Understanding how these two phenomena interact informs basic models of human behavior, and matters for policymakers when the behavior is regulated. I develop a new model of demand that incorporates both addiction and social interactions and show that, under certain conditions, social interactions reinforce the effects of addiction. I also show how the dynamics introduced by addiction can solve the pernicious problem of identifying the causal effects of social interactions. I then use the model to illustrate a new and important identification problem for studies of social interactions: existing estimates cannot be used to draw welfare conclusions or even to deduce whether social interactions increase aggregate demand. Finally, I develop a method that allows researchers to distinguish between two common forms of social interactions and draw welfare conclusions. (JEL codes: D11, H20)

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I Introduction

Many behaviors such as smoking, drinking, and exercising are widely considered to be both addictive and social in the sense that consumer utility depends both on one's own past consumption and on the current consumption of other people. Despite the fact that these two phenomena often coexist–particularly among "sin goods"–they are usually examined in isolation.[1] This paper fills this gap by developing the first model of demand that accounts for both addiction and social interactions.

Combining these features into one unified model reveals that social interactions sometimes, but not always, reinforce the effects of addiction. The model also helps to solve a pernicious econometric identification problem that makes research on social interactions challenging: the difficulty of distinguishing an individual reacting to her group's actions from other alternative explanations. This phenomenon is known as the "reflection problem" (Manski, 1993).

I show how the dynamics that arise from addiction allow the researcher to circumvent the reflection problem. The intuition follows from two simple observations. First, addiction causes group consumption to be related to past determinants of demand. Second, although demand shocks are almost certainly correlated across different individuals, resulting in the classical reflection problem, it is often plausible to assume that they are uncorrelated with past determinants of demand (e.g., Fujiwara et al., 2016) Thus, when addiction is present past determinants of demand may be used as instruments to identify social interactions. By a similar argument, if individuals are forward looking then future determinants of demand may also be valid instruments.

The unified model also reveals a second, deeper identification problem: different types of social interactions can have very different effects on demand and welfare and yet generate the same demand equation. Thus, a researcher who identifies the presence of social interactions cannot conduct welfare analysis or even determine

[1]Prominent studies of addiction include Becker et al. (1994), Chaloupka (1991), Crawford (2010), Demuynck and Verriest (2013), and Gruber and Koszegi (2001). A less than comprehensive list of social interactions studies includes the following. For theory, see Bernheim (1994), Bisin et al. (2006), Brock and Durlauf (2010), and Zanella (2007). Empirical analyses of social interactions have examined their effect on alcohol (Kremer and Levy, 2008); crime (Glaeser et al., 1996); disadvantaged youth (Case and Katz, 1991), grades (Sacerdote, 2001), obesity (Blanchflower et al., 2009; Christakis and Fowler, 2007; Fortin and Yazbeck, 2015); and smoking (Fletcher, 2010; Krauth, 2007; Powell et al., 2005). Becker (1992) notes that addiction and social interactions can reinforce each other. Alessie and Kapteyn (1991) and Woittiez and Kapteyn (1998) estimate consumer demand and female labor supply, respectively, as a function of habit formation and preference interdependence.

whether those interactions cause an increase in total consumption. I derive a set of assumptions under which one can distinguish between two common forms of social interactions, "conformity" and "spillovers", and draw welfare conclusions.[2] This is important for public policy because many of the goods that exhibit addiction and social interactions are heavily regulated (e.g., by "sin taxes"). Accurately assessing the welfare implications of these regulations requires properly modeling consumer demand for these goods.

Both conformity and spillovers generate the same "linear-in-means" model of demand estimated by many studies of social interactions, but their effects are quite different. Conformity, a desire to consume at the same level as others, reduces the dispersion of consumption within a group by discouraging individual heterogeneity. Thus, it increases the consumption of some individuals and reduces the consumption of others. The net effect on demand is zero, so conformity does not reinforce the effects of addiction. By contrast, spillovers, where consumption by others increases the marginal value of one's own consumption, increases everyone's consumption and exacerbates the effects of addiction. Moreover, spillovers generates positive externalities; conformity does not. Thus, it is beneficial to subsidize behaviors that exhibit spillovers but not ones that exhibit conformity. Despite these differences, I show that researchers can still calculate elasticities without having to make assumptions about the form of social interactions.

This paper makes two primary contributions to the literature. First, it proposes a novel solution to the reflection problem by exploiting the dynamic properties of addiction. There is a large literature concerned with solving this problem (Brock and Durlauf, 2001; Graham, 2008; Manski, 1993, 2000). It is usually difficult to justify a proposed instrument in static settings because variables that affect group consumption generally also affect individual consumption and thus do not satisfy the exclusion restriction. My proposed method, by contrast, is based on the dynamic properties of addiction and has sound theoretical justification. Although I focus on addictive goods, this method could be generalized to other settings where consumption is dynamic.

Second, this paper is among the first to investigate the *form* of social interactions. Most of the existing literature is concerned with merely identifying their presence,[3]

[2]See Brock and Durlauf (2001) and the many cites therein for more on these two forms of interactions.

[3]One notable exception is De Giorgi and Pellizzari (2014).

which is unfortunate because the form of social interactions has important implications for empirical research in a variety of contexts. For example, suppose a researcher estimates that a student's study habits are positively related to her classmates' study habits.[4] Unless she has data on a control group where social interactions are absent, the researcher cannot infer whether these interactions cause everyone to study more or whether they cause bad students to study more and good students to study less. She thus cannot recommend whether students should in general study alone or together. However, if she is willing to assume some degree of preference homogeneity–for example, that distance from a study center has the same negative effects on studying for all students–then my model shows that she can distinguish between these two scenarios because the effect of distance on studying is different under conformity than under spillovers. This method, which consists of a simple comparison of estimates across different groups, is quite general and does not require that the good in question be addictive.

The rest of this paper is organized as follows. Section II presents the model and main theoretical results. Section III discusses identification. Section IV concludes.

II Model

A consumer's instantaneous utility is represented by the function

$$V\left(a_{it}, S_{it}, x_{it}, c_{it}, E_t\left[\overline{a}_t\right]\right)$$

where a_{it} is consumer i's consumption of an addictive good in period t, S_{it} is the consumer's stock of past consumption of good a, and x_{it} represents other factors that affect utility (e.g., education or advertising). The composite good c_{it} is taken as numeraire. The consumer's time-t expectation of the mean consumption of the addictive good by other consumers in her reference group is $E_t\left[\overline{a}_t\right]$.[5] I assume throughout that the reference group is "large"in the sense that an individual's contribution to the mean is negligible. I impose the standard equilibrium condition that consumer beliefs and behaviors are self-consistent, and assume that consumers take other consumers'

[4]There is a large literature on peer effects and education. See Carrell et al. (2009), Carrell et al. (2013), Lavy et al. (2012), and Zimmerman (2003) for examples.

[5]This formulation implicitly assumes that individuals are affected equally and symmetrically by all other individuals in the group.

consumption decisions as given (Blume et al. 2010). The stock of past consumption evolves according to the equation

$$S_{it+1} = (1-d)\left(S_{it} + a_{it}\right) \tag{1}$$

where $d \in (0,1)$ is the rate of depreciation.

The consumer's problem is

$$\max_{a_{it},c_{it}} \sum_{t=1}^{\infty} \beta^{t-1} V\left(a_{it}, S_{it}, x_{it}, c_{it}, E_t\left[\overline{a}_t\right]\right) \tag{2}$$

where S_{i1} is given and $\beta < 1$ is the consumer's discount rate. The consumer's budget constraint is

$$A_{i0} = \sum_{t=1}^{\infty} (1+r)^{-(t-1)} \left(c_{it} + p_t a_{it}\right) \tag{3}$$

where A_{i0} is the present value of wealth, r is the interest rate, and p_t denotes the price of the addictive good. I assume the consumer's discount rate is equal to $1/(1+r)$. All variables in this problem vary at the individual level except for price, mean consumption, and the discount and interest rates. I drop the i subscript for the remainder of this section for notational ease.

As in Brock and Durlauf (2001), I assume instantaneous utility can be decomposed into a private and a social component:

$$V\left(a_t, S_t, x_t, c_t, E_t\left[\overline{a}_t\right]\right) = U\left(a_t, S_t, x_t, c_t\right) + G\left(a_t, E_t\left[\overline{a}_t\right]\right) \tag{4}$$

I assume that private utility is concave and quadratic:

$$\begin{aligned} U\left(a_t, S_t, x_t, c_t\right) = &-\frac{1}{2}\left(u_{aa}a_t^2 + u_{ss}S_t^2 + u_{xx}x_t^2 + u_{cc}c_t^2\right) + u_{as}a_tS_t \\ &+ u_{ax}a_tx_t + u_{ac}a_tc_t + u_{sx}S_tx_t + u_{sc}S_tc_t + u_{xc}x_tc_t \\ &+ u_a a_t + u_s S_t + u_x x_t + u_c c_t \end{aligned} \tag{5}$$

This is a standard assumption made in the addiction literature.[6] The quadratic form captures the dynamic aspects of the model and delivers linear first-order conditions

[6] See Becker and Murphy (1988), Becker et al. (1994), Chaloupka (1991), and Gruber and Koszegi (2001).

that aid analysis and allow for empirical estimation.[7] Addictive behavior is driven by the positive coefficient u_{as}, which captures the strength of intertemporal complementarity.

I consider two different parametric representations of social utility, "conformity" and "spillovers," which have been employed in prior studies (Binder and Pesaran, 2001; Blanchflower et al., 2009; Brock and Durlauf, 2001; Glaeser and Scheinkman, 2002). Conformity penalizes consumers for deviating from the mean consumption in their group:

$$G\left(a_t, E_t\left[\overline{a}_t\right]\right) = -\frac{1}{2} b_g \left(a_t - E_t\left[\overline{a}_t\right]\right)^2 \tag{6}$$

Spillovers is defined as a linear interaction between individual consumption and expected average consumption:

$$G\left(a_t, E_t\left[\overline{a}_t\right]\right) = b_g a_t E_t\left[\overline{a}_t\right] \tag{7}$$

The parameter b_g captures the strength of social interactions in both specifications and is assumed to be positive:[8]

$$\frac{\partial^2 G\left(a_t, E_t\left[\overline{a}_t\right]\right)}{\partial a_t \partial E_t\left[\overline{a}_t\right]} = b_g > 0$$

Brock and Durlauf (2001) show that (6) and (7) result in the same choice problem for the individual when a_t is binary. This is not so in this model because a_t is continuous.[9] As we shall see, this causes conformity and spillovers to have very different effects on consumption.

The forward-looking addiction model studied in Becker and Murphy (1988) corresponds to the special case where $G\left(a_t, E_t\left[\overline{a}_t\right]\right) = 0$ and thus is embedded within the more general framework presented in this paper. I will focus my discussion on the most novel parts of the model, namely the relationship between social interactions and addiction and the effects of social interactions on aggregate consumption.

[7] Alternatively, one can allow utility to be general and take a linear approximation to the first-order conditions to analyze dynamics near a steady state. This would yield the same equations I present here, although note that non-quadratic utility may result in multiple equilibria.

[8] A negative b_g would indicate a preference for nonconformity in (6). It would signify interpersonal substitution rather than complementarity in the case of (7).

[9] Another difference is that the discrete choice model of Brock and Durlauf (2001) can exhibit multiple equilibria. Blume et al. (2010) provide a game-theoretic derivation of the existence and uniqueness of equilibria in a linear-in-means model with quadratic utility preferences.

Intuitively, an increase in conformity causes individuals to place more weight on the average consumption in their group and less weight on their own idiosyncratic preferences. This compresses the distribution of consumption within the group by causing individuals with preferences for a high level of consumption to consume less and individuals with preferences for a low level of consumption to consume more. There is no effect on aggregate consumption because these two opposing effects cancel each other out. Spillovers, by contrast, increases everyone's consumption.

Section II.A will demonstrate formally how social interactions alter consumption patterns and potentially reinforce addiction. Section II.B will show that social interactions can generate externalities that cause equilibrium to be inefficient, even when addiction is rational.

II.A Solving the model

Solving the first-order condition for c_t and substituting the result into (5) allows one to rewrite the consumer's problem (2) as a maximization problem in a_t only:

$$\max_{a_t} \sum_{t=1}^{\infty} \beta^{t-1} V^* \left(a_t, S_t, x_t, E_t\left[\overline{a}_t\right]\right) \tag{8}$$

where

$$\begin{aligned} V^* \left(a_t, S_t, x_t, E_t\left[\overline{a}_t\right]\right) = &-\frac{1}{2}\left(b_{aa}a_t^2 + b_{ss}S_t^2 + b_{xx}x_t^2\right) \\ &+ b_{as}a_tS_t + b_{ax}a_tx_t + b_{sx}S_tx_t \\ &b_a a_t + b_s S_t + b_x x_t + b_k + G\left(a_t, E_t\left[\overline{a}_t\right]\right) \end{aligned} \tag{9}$$

The coefficients in (9) capture the effect of the input variables on the consumer's utility assuming optimal consumption of the numeraire good c_t. The coefficients b_{aa}, b_{ss}, and b_{xx} are necessarily positive due to the assumed concavity of private utility. The coefficient b_{as} measures the effect of the stock of past consumption on the marginal utility of current consumption. The appendix derives the precise condition required for b_{as} to be positive. A sufficient condition is that consumer utility be additively separable in a_t and c_t. I follow the addiction literature and assume that $b_{as} > 0$.

Consumption is dynamic in this framework because utility depends on both current and past consumption. Moreover, forward-looking (or "rational") individuals will behave differently from myopic ones. Becker et al. (1994) provide evidence in favor of rationality in the context of cigarette addiction, but Gruber and Koszegi (2001) argue that it is difficult for empirical studies to distinguish rationality from alternative models such as hyperbolic discounting. The main contribution of this paper–showing how to identify social interactions using addiction and how to distinguish conformity from spillovers–does not rely on how consumers discount the future. Indeed, the results hold even if consumers are myopic. Thus, for ease of exposition I first derive the model under a myopia assumption and then later generalize to a forward-looking framework. Detailed derivations are available in Appendix A.

II.A.1 Myopic consumers

Conformity

Analytically, the myopia assumption corresponds to ignoring any forward-looking terms in the first-order condition when solving the consumer's problem. Assuming the conformity specification (6) and solving the consumer's problem (8) subject to the law of motion for the stock of past consumption (1) and the budget constraint (3) yields the following demand equation:

$$a_t = \alpha_m S_t + \gamma_m \overline{a}_t + \pi_m p_t + \delta_m x_t + k_m \tag{10}$$

where

$$\alpha_m = \frac{b_{as}}{b_g + b_{aa}} > 0$$
$$\gamma_m = \frac{b_g}{b_g + b_{aa}} > 0$$
$$\pi_m = \frac{-\lambda}{b_g + b_{aa}} < 0$$
$$\delta_m = \frac{b_{ax}}{b_g + b_{aa}} \lesseqgtr 0$$
$$k_m = \frac{b_a}{b_g + b_{aa}} > 0$$

and λ is the marginal utility of wealth. The positive coefficient α_m indicates that, all else equal, an increase in the stock of past consumption increases current consumption, i.e., the good is addictive. Individual consumption is positively related to group consumption ($\gamma_m > 0$) and negatively related to price ($\pi_m < 0$). Each coefficient in equation (10) is affected by the parameter governing the strength of conformity, b_g.

Define an individual's expected steady-state level of consumption as

$$a^* = S^* d / (1 - d)$$

Plugging this into (10) and using that $E[a^*] = \overline{a}^*$ yields

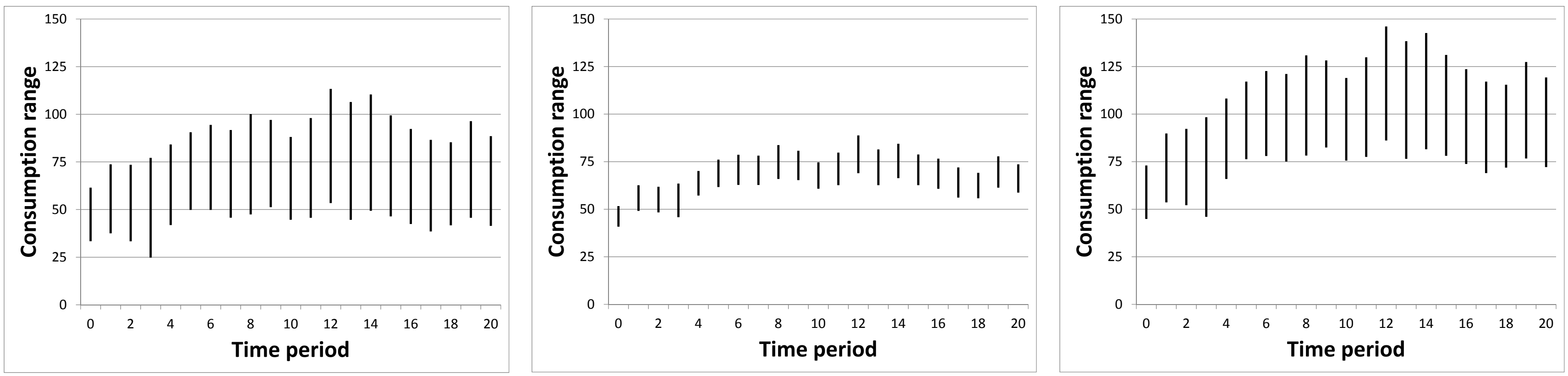
$$\begin{aligned} a^* &= \frac{E[\pi_m p_t + \delta_m x_t] + k_m}{1 - \alpha_m(1-d)/d - \gamma_m} \\ &= \frac{E[-\lambda p_t + b_{ax} x_t] + b_a}{b_{aa} - b_{as}(1-d)/d} \end{aligned}$$

where the expectation is taken with respect to the random variables p_t and x_t. Stable demand requires that $b_{aa} - b_{as}(1-d)/d > 0$. Violating this condition leads to unstable behavior where demand increases uncontrollably. We see here the familiar result from the literature on addiction that these unstable states are mostly likely to occur with highly addictive goods (i.e., goods with large values for b_{as}). Conformity, however, plays no role in determining the level or stability of demand.

What effect does conformity have, then? It reduces dispersion, as illustrated in Figure 1. Comparing Figure 1a to Figure 1b shows that conformity compresses the distribution of consumption relative to a setting with no social interactions.

Figure 1: The effect of conformity and spillovers on consumption

(a) No social interactions **(b)** Conformity **(c)** Spillovers



Notes: These graphs display the results of three simulations. The vertical lines display the range (minimum to maximum) of consumption for a group of consumers for each time period t. Panel (a) displays consumption for an addictive good that exhibits no social interactions. Panel (b) adds conformity to the simulation. Panel (c) adds spillovers instead of conformity to the simulation. All other factors are held constant. See Appendix B for details.

Spillovers

Solving the model assuming the spillovers specification (7) yields

$$a_t = \alpha'_m S_t + \gamma'_m \bar{a}_t + \pi'_m p_t + \delta'_m x_t + k'_m \tag{11}$$

where

$$\begin{aligned}
\alpha'_m &= \frac{b_{as}}{b_{aa}} > 0 \\
\gamma'_m &= \frac{b_g}{b_{aa}} > 0 \\
\pi'_m &= \frac{-\lambda}{b_{aa}} < 0 \\
\delta'_m &= \frac{b_{ax}}{b_{aa}} \lesseqgtr 0 \\
k'_m &= \frac{b_a}{b_{aa}} > 0
\end{aligned}$$

As in the case of conformity, consumption is positively related to the stock of past consumption and to group consumption, and negatively related to price.

Expected consumption is equal to

$$\begin{aligned}
a^* &= \frac{E\left[\pi'_m p_t + \delta'_m x_t\right] + k'_m}{1 - \alpha'_m(1-d)/d - \gamma'_m} \\
&= \frac{E\left[-\lambda p_t + b_{ax} x_t\right] + b_a}{b_{aa} - b_{as}(1-d)/d - b_g}
\end{aligned}$$

Unlike conformity, the parameter governing the strength of spillovers, b_g, enters explicitly into the formula for expected consumption by affecting the condition required for stable demand: $b_{aa} - b_{as}(1-d)/d - b_g > 0$.[10] In other words, demand stability imposes a limit on the combined strength of addiction and social interactions. Strong spillovers can cause an otherwise stable addiction to become unstable.

Spillovers act as a multiplier on demand. This effect is illustrated in Figure 1c. This differs significantly from the case of conformity, which has no effect on average consumption.

[10]If addiction is absent, then this condition reduces to the "moderate social influence" condition of Glaeser and Scheinkman (2002).

II.A.2 Forward-looking consumers

For simplicity, I assume that consumers have perfect foresight, which will generate clean analytical expressions. Some critics argue that perfect foresight implies that addicts should never express regret and that there is no scope for public policy (Akerlof, 1991; Winston, 1980). Gruber and Koszegi (2001) show, however, that perfect foresight is compatible with time inconsistency and thus also compatible with beneficial public policies that alter consumer behavior. Furthermore, Orphanides and Zervos (1995) relax the assumption of perfect foresight and show that the main empirical predictions of the Becker and Murphy (1988) addiction model remain unchanged.

Conformity

Relaxing the assumption that consumers are myopic yields the forward-looking demand equation:

$$a_t = \alpha_1 S_t + \alpha_2 a_{t+1} + \gamma_1 \overline{a}_t + \gamma_2 \overline{a}_{t+1} + \pi_1 p_t + \pi_2 p_{t+1} + \delta_1 x_t + \delta_2 x_{t+1} + k \qquad (12)$$

This demand model retains the main results from the literature on forward-looking addiction. For example, current consumption is positively related to future consumption and future prices. See the appendix for a complete derivation and additional discussion of how this model compares to the standard addiction model.

As in the myopic case, conformity (which operates through the parameter b_g) has no effect on the expected steady-state level of consumption, a^*:

$$\begin{aligned} a^* &= \frac{E\left[(\pi_1 + \pi_2)p_t + (\delta_1 + \delta_2)x_t\right] + k}{1 - \alpha_1(1-d)/d - \alpha_2 - \gamma_1 - \gamma_2} \\ &= E\left[\pi_p p_t + \delta_x x_t\right] + k_k \qquad (13) \end{aligned}$$

where

$$\pi_p = -\frac{d\,(1-\beta+d\beta)\,\lambda}{\xi}$$

$$\delta_x = \frac{db_{ax} + d\,(1-d)\,\beta\,(b_{sx} - b_{ax})}{\xi}$$

$$k_k = \frac{d\,(1-(1-d)\,\beta)\,b_a + d\,(1-d)\,\beta b_s}{\xi}$$

$$\xi = d\,(1-(1-d)\,\beta)\,b_{aa} + (1-d)^2\,\beta b_{ss} - (1-d)\,(1-(1-2d)\,\beta)\,b_{as}$$

Demand stability requires that $\xi > 0$. Because consumers are forward-looking, stability now depends on the negative effect that current consumption has on future utility, as captured by the parameter b_{ss}. But, just as in the myopic case, conformity plays no role in determining the level or stability of demand.

Spillovers

Under the spillovers specification (7), the forward-looking demand equation becomes:

$$a_t = \alpha_1' S_t + \alpha_2' a_{t+1} + \gamma_1' \overline{a}_t + \gamma_2' \overline{a}_{t+1} + \pi_1' p_t + \pi_2' p_{t+1} + \delta_1' x_t + \delta_2' x_{t+1} + k' \qquad (14)$$

The appendix shows that only the coefficients on mean consumption, γ_1' and γ_2', are affected by the strength of social interactions, b_g. It is easily shown that $\partial a_t / \partial b_g > 0$, i.e., an increase in the strength of spillovers increases aggregate consumption, just like the myopic case.

The condition required for dynamic stability is $\xi - d\,(1-(1-d)\,\beta)\,b_g > 0$, which is identical to the condition presented above for conformity except for the addition of a second term involving the parameter b_g. This mirrors the results presented for myopic consumers: social interactions affect the level of demand, and demand stability, only when they take the form of spillovers.

II.B Welfare

Consumption can be suboptimal if consumers are not fully rational or if they fail to internalize externalities attributable to their own consumption. For example, I show in the appendix that the first-order condition for the forward-looking consumer's problem is

$$0 = V_a^*(t) - \lambda p_t + \Sigma_{j=1}^{\infty} \beta^j V_s^*(t+j) \frac{\partial S_{t+j}}{\partial a_t} \tag{15}$$

where $V_a^*(t)$ and $V_s^*(t+j)$ represent the partial derivative of the optimized utility function V^* with respect to a_t and S_{t+j}, respectively. Myopic consumers fail to account for the effect of their current consumption on their future discounted utility, which is represented by the last term on the right-hand side of (15). The sign of this term is ambiguous and depends on coefficients in the utility function (9).[11] Thus, the myopic consumer's suboptimal consumption can in general be higher or lower than the forward-looking consumer's optimal consumption.[12]

Both myopic and forward-looking consumers fail to internalize how their consumption affects other individuals in their reference group. Let equilibrium average consumption be $\overline{a}_t^*$. Direct examination of equations (6) and (7) reveals that, in equilibrium, conformity generates no net externality while spillovers generate a positive externality:

$$E\left[\frac{\partial G(a_t, \overline{a}_t^*)}{\partial \overline{a}_t^*}\right] = E\left[b_g(a_t - \overline{a}_t^*)\right] = 0 \quad \text{(Conformity)}$$
$$E\left[\frac{\partial G(a_t, \overline{a}_t^*)}{\partial \overline{a}_t^*}\right] = E\left[b_g \overline{a}_t^*\right] > 0 \quad \text{(Spillovers)}$$

These results mirror those derived for the discrete choice model in Brock and Durlauf (2001). They imply that if social utility takes a spillovers form then a social planner should subsidize consumption, even if individuals are forward looking. If social utility instead takes a conformity form then social interactions do not generate any externalities.

[11] The only assumptions made so far about the coefficients in (9) are that b_{aa}, b_{ss}, and b_{xx} are negative (due to the quadratic utility assumption) and that b_{as} is positive. Note that additionally assuming $b_s < 0$ is not sufficient to determine the sign of $V_s^*(t+i)$ because $b_{as} > 0$ may be large.

[12] Gruber and Koszegi (2001) assume in their analysis of cigarette consumption that addiction reduces future discounted utility. Under this assumption, myopic consumers necessarily consume more than forward-looking consumers.

II.C Discussion

The model demonstrates that conformity and spillovers both generate the same linear-in-means demand equation commonly estimated in empirical studies.[13] This means that researchers and policymakers who identify social interactions can generally draw only limited conclusions from their analyses.

For example, take the case of cigarette consumption. Prior research has estimated an optimal tax of at least one dollar per pack if consumers are hyperbolic discounters Gruber and Koszegi (2001). Several studies have documented that social interactions matter for smoking behavior, which raises the possibility that the optimal tax estimated by Gruber and Koszegi needs to be adjusted. However, if the social interactions of smokers reflect conformity rather than spillovers, then they do not produce a net externality and therefore do not call for an adjustment to the optimal tax. It also means they do not affect the overall level of consumption and thus did not contribute to the rapid increase and subsequent decrease in cigarette consumption during the latter half of the 20th century.

In the next section I discuss under what assumptions one can separately identify conformity and spillovers. However, some statistics of interest, such as price elasticities, can be calculated without knowledge of the form of social interactions. For example, consider the long-run price elasticity of demand, which gives the percentage change in quantity demanded in response to a permanent change in price in all periods. Suppose an individual reaches an expected steady-state level of consumption $a^* = S^* d / (1 - d)$, and that she is myopic. Then the long-run price elasticity is equal to

$$\frac{\partial a^*}{\partial p} \frac{p}{a^*} = \frac{\pi}{1 - \alpha (1 - d) / d - \gamma} \frac{p}{a^*} \tag{16}$$

where p and a^* are evaluated at the mean price and consumption levels for the sample.[14] Equation (16) holds for both conformity and spillovers specifications.

One can also compare the strength of social interactions to the strength of addiction, without making any assumptions about the form of interactions, by simply

[13] Boucher and Fortin (2016) derive this same result in a static setting.

[14] If the individual is forward-looking, then the long-run price elasticity is equal to $\frac{\pi_1 + \pi_2}{1 - \alpha_1 (1-d)/d - \alpha_2 - \gamma_1 - \gamma_2} \frac{p}{a^*}$.

comparing the demand coefficients γ and α:

$$\frac{\gamma}{\alpha} = \frac{b_g}{b_{as}}$$

This ratio reveals the strength of social interactions, relative to addiction, regardless of what form those interactions take. If consumers are forward-looking, one can use the corresponding metric

$$\frac{\gamma_1}{\alpha_1} = \frac{b_g}{b_{as} - (1-d)^2 \beta (b_{as} + b_{ss})}$$

which accounts for the intertemporal effects of addiction.

III Identification

There are two identification challenges associated with estimating the two different social interactions models derived in Section II. First, the researcher must consistently estimate the demand equation, which requires addressing the "reflection problem". Second, she must find a way to distinguish conformity from spillovers, which is necessary in order to determine whether social interactions affect the overall level of consumption and to draw welfare conclusions.

III.A Estimating the demand equation

Estimating the demand equation is difficult for two reasons. First, the stock of past consumption is necessarily correlated with the error term in the presence of serial correlation. Second, mean group consumption is also correlated with the error term if unobserved demand shocks are correlated across individuals within the same group (the "reflection problem"). Prior studies have addressed the first problem by instrumenting for the stock with lags (and sometimes leads) of determinants of demand, such as prices or taxes in the case of cigarettes (Becker et al., 1994; Chaloupka, 1991; Fenn et al., 2001; Sloan et al., 2002), or rainfall in the case of voting (Fujiwara et al., 2016). The key assumption in those models–as here–is that these instruments must not affect future outcomes except through the stock. Conveniently, these instruments can also be used to obtain a consistent estimate of the coefficient on group consumption.

Consider estimating the myopic consumer's demand for an addictive good:

$$a_{igt} = \alpha S_{igt} + \gamma \overline{a}_{gt} + \pi p_{gt} + \delta x_{igt} + \epsilon_{igt} \tag{17}$$

where S_{igt} is consumer i's stock of past consumption at time t; $\overline{a}_{gt}$ is the mean consumption for reference group g at time t; and p_{gt} and x_{igt} represent price and individual-level determinants of demand, respectively. Recall that the reference group is assumed to be "large" in the sense that an individual's contribution to $\overline{a}_{gt}$ is negligible. The error term can be decomposed into two components: $\epsilon_{igt} = \eta_g + e_{igt}$. The first component, η_g, represents unobserved (to the econometrician) determinants of demand that are common to the group and constant over time. The second component, e_{igt}, captures unobserved individual-level determinants of demand and measurement error in the dependent variable. Equation (17) is a standard "linear-in-means" social interactions model with the addition of the term S_{igt} (Manski, 1993).[15]

Ordinary least squares estimates of the endogenous social effect, $\widehat{\gamma}$, are biased in the presence of group-wide demand shocks, which necessarily induce a positive correlation between $\overline{a}_{gt}$ and e_{igt}. Unfortunately, this occurs frequently in empirical analyses because it is impossible to observe all relevant determinants of demand and it is likely that at least some of those determinants are common to members of the same reference group. Employing fixed effects does not solve this problem because demand shocks may vary over time.

Fortunately, the dynamics that operate through the addiction channel offer a solution to this problem. Equation (28) in the appendix shows that individual consumption is related to past determinants of demand through the stock of past consumption. Becker et al. (1994) note that this in turn implies that lagged determinants of demand are valid instruments for the stock. This insight extends naturally to addressing the endogeneity of group consumption because it is necessarily governed by the same forces that govern individual consumption. If consumers are forward looking then future determinants of demand are also valid instruments.

For example, consider estimating (17) using ordinary least squares. If $Cov\left(\overline{a}_{gt}, e_{igt}\right) \neq 0$ then the econometrician will likely overestimate the effect of social interactions,

[15] For simplicity, equation (17) assumes that the group-level average of the covariates, $\overline{x}_{gt}$, do not affect demand. The identification argument presented in this section still holds if one adds "contextual effects" like $\overline{x}_{gt}$ to the demand equation. Note that if contextual effects are in fact absent, then these variables could be used as instruments to achieve identification.

γ, because she will incorrectly attribute changes in individual consumption to changes in group consumption when in fact they are due to the unobserved error term, e_{igt}. By contrast, instrumenting for $\overline{a}_{gt}$ with lags of, for example, price identifies γ using only the variation in $\overline{a}_{gt}$ that is explained by past prices.

This example demonstrates the key identifying assumption relied upon by this approach: the lagged instrument must be uncorrelated with unobserved contemporaneous determinants of demand. Whether this assumption is reasonable will depend on the context. Many studies of rational addiction employ lagged prices as instruments, although Auld and Grootendorst (2004) argue that these instruments are unlikely to be valid when applied to aggregate data. In their study of voting behavior, Fujiwara et al. (2016) make a strong case that lagged rainfall likely affects contemporaneous voting only through an addiction channel.

Consistently estimating the parameters of (17) requires at least two instruments because there are two endogenous variables present ($\overline{a}_{gt}$ and S_{igt}). Moreover, although group-level observables such as lagged prices might be valid instruments for either $\overline{a}_{gt}$ or S_{igt} individually, when instrumenting for both these variables the researcher must employ at least one instrument that varies at the individual level in order to satisfy the rank condition for instrumental variables estimation.[16] This is easily seen by noting that an individual's steady-state level of consumption is equal to $a^* = S^* d/(1-d)$. In expectation, this relationship must hold at the group level as well. Thus, if the researcher includes only group-level instruments, then the projections of the first stage onto these two endogenous variables will be linearly dependent because they differ in expectation only by the factor $d/(1-d)$.[17]

I perform a simulation exercise to demonstrate the validity of my proposed instrumental variables approach. Specifically, I simulate 10 periods of data for 100 different reference groups, each containing 100 individuals, and then estimate demand equation (17) using both ordinary least squares (OLS) and instrumental variables (IV) estimators.[18] Table 1 reports the results of this exercise. Column (1) lists the true values of the demand coefficients. Column (2) shows that the OLS estimates differ

[16] Fujiwara et al. (2016) encounter this challenge in their analysis of voting behavior. They have one group-level instrument, and as a result they cannot separately identify addiction and social interactions in their setting.

[17] I am grateful to an anonymous referee for pointing this out.

[18] The corresponding code is publicly available on the author's website. The data are generated using the same parameters as Figure 1. See Appendix B for additional details.

significantly from these true values for three of the four coefficients. The OLS estimate of γ (0.713) is about 15 percent larger than the true value (0.625), illustrating its upward bias. Columns (3), (4), and (5) report results from three different IV specifications that instrument for S_{igt} and $\overline{a}_{gt}$ using lags of x_{igt} and p_{gt}. Unlike the OLS estimates, none of the IV estimates is statistically distinguishable from the true value. Table 1 also shows that the first-stage F statistic grows with the number of lagged instruments, and always exceeds 10, the typical threshold recommended for avoiding weak instrument bias (Stock et al., 2002).

In general the identification strategy proposed here does not require the good in question to be addictive; it can also apply to other settings where dynamics arise for a different reason. For example, suppose that the utility of consumption depends not on contemporaneous group consumption, but instead on group consumption in the previous period. In this case, demand determinants will have a lagged, indirect effect on current consumption in addition to the standard direct, contemporaneous effect. Lagged determinants of demand will then be valid instruments for identifying social interactions.

Finally, I pause to note that the framework presented here abstracts from important issues regarding network formation. In many settings, it is challenging even just to define the proper reference group. For example, one's decision to smoke can be influenced by friends, family, coworkers, and even television personalities, and may differ drastically across individuals. Moreover, individuals may choose their reference groups in a way that is correlated with the outcome of interest, which will often necessitate further modeling by the researcher (Badev, 2017; Boucher, 2016; Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; Hsieh and Lin, 2017).

III.B Identifying the form of social interactions

The identification strategy outlined above identifies the *presence* of social interactions but it sheds no light on the *form* of those interactions. As shown in Section II, preferences for conformity can generate the linear-in-means demand model:

$$\begin{aligned} a_{igt} &= \alpha S_{igt} + \gamma \overline{a}_{gt} + \pi p_{gt} + \delta x_{igt} + \epsilon_{igt} \\ &= \frac{b_{as}}{b_g + b_{aa}} S_{igt} + \frac{b_g}{b_g + b_{aa}} \overline{a}_{gt} + \frac{-\lambda}{b_g + b_{aa}} p_{gt} + \frac{b_{ax}}{b_g + b_{aa}} x_{igt} + \epsilon_{igt} \end{aligned} \tag{18}$$

But, preferences for spillovers can also generate this model:

$$\begin{aligned} a_{igt} &= \alpha' S_{igt} + \gamma' \overline{a}_{gt} + \pi' p_{gt} + \delta' x_{igt} + \epsilon'_{igt} \\ &= \frac{b_{as}}{b_{aa}} S_{igt} + \frac{b_g}{b_{aa}} \overline{a}_{gt} + \frac{-\lambda}{b_{aa}} p_{gt} + \frac{b_{ax}}{b_{aa}} x_{igt} + \epsilon'_{igt} \end{aligned} \tag{19}$$

Therefore, it is clear that successfully estimating the coefficient on $\overline{a}_{gt}$ is not sufficient to distinguish between conformity and spillovers. How can the researcher overcome this obstacle? Figure 1 suggests that identifying a source of variation in the strength of social interactions is one possible approach. Under conformity, consumption in groups with strong social interactions should be less dispersed than consumption in groups with weak social interactions. Under spillovers, by contrast, the consumption in groups with strong social interactions should be higher rather than less dispersed.

This line of inquiry motivates the following informal test. Notice that the parameter governing the strength of social interactions, b_g, is present in each coefficient's denominator in the case of conformity (equation 18), but only affects the coefficient on group consumption, $\overline{a}_{gt}$, in the case of spillovers (equation 19). Thus, conformity generates the testable hypothesis that, all else equal, groups with stronger social interactions should have smaller demand coefficients for all demand determinants except group consumption. Under spillovers, changes in the strength of social interactions should only affect the coefficient on group consumption.

For example, suppose one estimates demand separately for two different groups, A and B, yielding estimates $(\widehat{\alpha}^A, \widehat{\gamma}^A)$ and $(\widehat{\alpha}^B, \widehat{\gamma}^B)$. Suppose further that the structural parameters governing addiction, b_{aa} and b_{as}, do not differ across the two groups. If $\widehat{\gamma}^A > \widehat{\gamma}^B$ then we can conclude that social interactions are stronger in group A. Furthermore, $\widehat{\alpha}^A < \widehat{\alpha}^B$ indicates conformity while $\widehat{\alpha}^A = \widehat{\alpha}^B$ indicates spillovers. (The result $\widehat{\alpha}^A > \widehat{\alpha}^B$ indicates model misspecification.)

This example highlights the key assumption required for this empirical approach to properly distinguish between conformity and spillovers: groups that differ in the strength of their social interactions must not differ with respect to at least two other structural parameters. The plausibility of this assumption depends on the application and structural parameters in question. Comparing estimates of $(\widehat{\alpha}, \widehat{\gamma})$ across groups may be quite reasonable when estimating, for example, cigarette consumption. It is plausible that addictive preferences for cigarettes do not vary systematically across these groups because many argue that they are primarily a biological phenomenon (Dackis and O'Brien, 2005; Nestler and Aghajanian, 1997). Put differently, the structural parameters b_{aa} and b_{as} in the model are unlikely to be correlated with an individual's group g.

In practice, this assumption is made frequently in studies of social interactions although it is rarely stated explicitly. Notice that the coefficient γ reflects the strength of social interactions, b_g, relative to preferences for the addictive good, b_{aa}. Thus, one cannot conclude that groups with larger γ's have stronger social interactions without making an assumption about heterogeneity in the preference parameter b_{aa}. Nevertheless, it is common practice to compare the strength of social interactions across groups (e.g., Gaviria and Raphael (2001); Nakajima (2007); Sorensen (2006)).

Boucher and Fortin (2016) propose an alternative identification strategy that compares demand estimates for "isolated" groups of size one to non-isolated groups. Because the coefficients for the isolated groups are not a function of social interactions, the comparison allows the researcher to infer the source of the interactions. This approach requires a similar identifying assumption as above: the structural parameters of demand must be sufficiently similar between isolated and non-isolated groups.

IV Conclusion

Addiction and social interactions affect the consumption of drugs like cigarettes and alcohol as well as many other common activities such as exercising and eating. The strengths of addiction and social interactions depend on the particular good in question and must be determined empirically. This can be accomplished using the general framework of demand developed in this paper. I develop a new method that harnesses the consumption dynamics generated by addiction to identify the presence of social interactions, a phenomenon that is devilishly difficult to detect. My proposed method circumvents Manski's reflection problem and provides consistent estimates in a general setting.

I also show that two common forms of social interactions, conformity and spillovers, have very different effects on demand and welfare but cannot separately be identified using standard instrumental variable techniques. This problem can be resolved if preferences are sufficiently homogenous across different reference groups. This novel solution does not require addiction to be present and thus can be applied to a variety of different social interactions models. Although it requires making additional assumptions about consumers, I have argued that these are no stronger than the assumptions frequently made in other studies of social interactions.

Finally, my model demonstrates the value of moving beyond the mere identification of social interactions to an investigation of their form. This provides a more detailed understanding of their effects and allows researchers to connect their empirical findings to important policy decisions.

Tables

Table 1: OLS and IV estimates of the myopic demand model

	(1)	(2)	(3)	(4)	(5)
α	0.250	0.196**	0.250	0.255	0.258
		(0.004)	(0.013)	(0.011)	(0.011)
γ	0.625	0.713**	0.629	0.615	0.601
		(0.006)	(0.024)	(0.021)	(0.021)
π	-1.250	-0.961**	-1.240	-1.288	-1.337
		(0.025)	(0.084)	(0.075)	(0.072)
δ	2.500	2.505	2.507	2.517	2.519
		(0.015)	(0.014)	(0.016)	(0.016)
N		110,000	100,000	90,000	80,000
Estimator		OLS	IV	IV	IV
Lags			1	2	3
First-stage F			16.7	17.5	34.1

Notes: This table reports ordinary least squares (OLS) and two-stage least squares (IV) estimates of equation (17) using simulated data. Standard errors, reported in parentheses, are clustered at the reference group level. Column (1) reports the true value of the coefficient. Column (2) reports OLS estimates. Columns (3), (4), and (5) instrument for S and $\overline{a}$ with one, two, and three lags of x and p, respectively. A */** in columns (2)-(5) indicates that the estimated coefficient differs significantly from the true value at the 5/1% level. The first-stage F statistic is robust to arbitrary heteroskedasticity and autocorrelation. See Appendix B for additional details.

A Mathematical appendix

Let private utility take the quadratic form (5). Then maximizing (2) with respect to c_t and subject to the budget constraint (3) yields

$$c_t = \frac{-\lambda + u_c + u_{ac}a_t + u_{sc}S_t + u_{xc}x_t}{u_{cc}}$$

where λ is the marginal utility of wealth. Plugging this result into (5) allows utility (4) to be expressed as

$$V^*(t) = -\frac{1}{2}\left(b_{aa}a_t^2 + b_{ss}S_t^2 + b_{xx}x_t^2\right) + b_{as}a_tS_t + b_{ax}a_tx_t + b_{sx}S_tx_t \qquad (20)$$
$$+ b_aa_t + b_sS_t + b_xx_t + b_k + G\left(a_t, E_t\left[\overline{a}_t\right]\right)$$

where

$$b_{aa} = \frac{u_{aa}u_{cc} - u_{ac}^2}{u_{cc}} > 0$$
$$b_{ss} = \frac{u_{ss}u_{cc} - u_{sc}^2}{u_{cc}} > 0$$
$$b_{xx} = \frac{u_{xx}u_{cc} - u_{xc}^2}{u_{cc}} > 0$$
$$b_{as} = \frac{u_{ac}u_{sc} + u_{as}u_{cc}}{u_{cc}} > 0 \text{ if } u_{ac}u_{sc} \geq 0$$
$$b_{ax} = \frac{u_{ac}u_{xc} + u_{ax}u_{cc}}{u_{cc}} \lesseqqgtr 0$$
$$b_{sx} = \frac{u_{sc}u_{xc} + u_{sx}u_{cc}}{u_{cc}} \lesseqqgtr 0$$
$$b_a = \frac{u_cu_{ac} + u_au_{cc}}{u_{cc}} \lesseqqgtr 0$$
$$b_s = \frac{u_cu_{sc} + u_su_{cc}}{u_{cc}} \lesseqqgtr 0$$
$$b_x = \frac{u_{ac}u_{xc} + u_{ax}u_{cc}}{u_{cc}} \lesseqqgtr 0$$
$$b_k = \frac{u_c^2 - \lambda^2}{2u_{cc}} \lesseqqgtr 0$$

(Recall that the parameters u_{aa}, u_{ss}, u_{xx} and u_{cc} are all positive due to the assumed concavity of U.)

Maximizing $\sum_{t=1}^{\infty}\beta^{t-1}V^{*}(t)$ with respect to a_t implies the following first-order condition:

$$\begin{aligned}
0 &= V_a^{*}(t) - \lambda p_t + \Sigma_{i=1}^{\infty}\beta^{i}V_s^{*}(t+i)\frac{\partial S_{t+i}}{\partial a_t} \\
&= V_a^{*}(t) - \lambda p_t + \beta(1-d)V_s^{*}(t+1) + \Sigma_{i=2}^{\infty}\beta^{i}V_s^{*}(t+i)\frac{\partial S_{t+i}}{\partial a_t}
\end{aligned}$$

where $V_a^{*}(t) = \frac{\partial V^{*}(t)}{\partial a_t}$ and $V_s^{*}(t) = \frac{\partial V^{*}(t)}{\partial S_t}$. The corresponding first-order condition for a_{t+1} is

$$\begin{aligned}
0 &= V_a^{*}(t+1) - \lambda p_{t+1} + \Sigma_{i=1}^{\infty}\beta^{i}V_s^{*}(t+1+i)\frac{\partial S_{t+1+i}}{\partial a_{t+1}} \\
&= \beta V_a^{*}(t+1) - \lambda\beta p_{t+1} + \Sigma_{i=2}^{\infty}\beta^{i}V_s^{*}(t+i)\frac{\partial S_{t+i}}{\partial a_{t+1}} \\
&= \beta V_a^{*}(t+1) - \lambda\beta p_{t+1} + \Sigma_{i=2}^{\infty}\beta^{i}V_s^{*}(t+i)\frac{\partial S_{t+i}}{\partial a_t}/(1-d) \\
&= \beta(1-d)V_a^{*}(t+1) - \lambda\beta(1-d)p_{t+1} + \Sigma_{i=2}^{\infty}\beta^{i}V_s^{*}(t+i)\frac{\partial S_{t+i}}{\partial a_t}
\end{aligned}$$

where I use that $\frac{\partial S_{t+i}}{\partial a_{t+1}} = \frac{\partial S_{t+i}}{\partial a_t}/(1-d)$. Equating the first-order conditions for a_t and a_{t+1} yields

$$V_a^{*}(t) - \lambda p_t + \beta(1-d)V_s^{*}(t+1) = \beta(1-d)V_a^{*}(t+1) - \lambda\beta(1-d)p_{t+1} \tag{21}$$

Plugging in the quadratic utility form (20) and then the social utility specification (6) or (7) yields equations (12) and (14) in the main text. The coefficients on the variables of these two equations are shown in Appendix Table A.1.

Table A.1: Demand equation coefficients

Coefficient	Conformity	Spillovers
α_1 (α_1')	$\frac{b_{as}-(1-d)^2\beta(b_{as}+b_{ss})}{\Delta} \lesseqgtr 0$	$\frac{b_{as}-(1-d)^2\beta(b_{as}+b_{ss})}{\Delta'}$
α_2 (α_2')	$(1-d)\,\beta\frac{b_g+b_{aa}+b_{as}}{\Delta} > 0$	$(1-d)\,\beta\frac{b_{aa}+b_{as}}{\Delta'} > 0$
γ_1 (γ_1')	$\frac{b_g}{\Delta} > 0$	$\frac{b_g}{\Delta'} > 0$
γ_2 (γ_2')	$-(1-d)\,\beta\frac{b_g}{\Delta} < 0$	$-(1-d)\,\beta\frac{b_g}{\Delta'} < 0$
π_1 (π_1')	$-\frac{\lambda}{\Delta} < 0$	$-\frac{\lambda}{\Delta'} < 0$
π_2 (π_2')	$(1-d)\,\beta\frac{\lambda}{\Delta} > 0$	$(1-d)\,\beta\frac{\lambda}{\Delta'} > 0$
δ_1 (δ_1')	$\frac{b_{ax}}{\Delta} \lesseqgtr 0$	$\frac{b_{ax}}{\Delta'} \lesseqgtr 0$
δ_2 (δ_2')	$(1-d)\,\beta\frac{b_{sx}-b_{ax}}{\Delta} \lesseqgtr 0$	$(1-d)\,\beta\frac{b_{sx}-b_{ax}}{\Delta'} \lesseqgtr 0$
k (k')	$\frac{b_a-(1-d)\beta(b_a-b_s)}{\Delta} \lesseqgtr 0$	$\frac{b_a-(1-d)\beta(b_a-b_s)}{\Delta'} \lesseqgtr 0$
Δ (Δ')	$b_g + b_{aa} + (1-d)^2\,\beta\,(b_{as}+b_{ss}) > 0$	$b_{aa} + (1-d)^2\,\beta\,(b_{as}+b_{ss}) > 0$

Consumption is negatively related to the current price ($\pi_1 < 0$) but positively related to future price ($\pi_2 > 0$). This positive relationship may seem surprising since past and future consumption are complementary with present consumption. However, as explained in Becker et al. (1990), the demand equation (12) holds future consumption constant, eliminating the mechanism through which past and future prices affect present consumption. For example, if the future price increases but future consumption is unchanged, then some other force must be offsetting the price effect by raising the future stock. This in turn means current consumption must be higher because the future stock is directly related to both the current stock and current consumption.

A well-known result from Becker and Murphy (1988) is that adjacent complementarity, as measured by the coefficient α_2, increases the more past consumption raises the marginal utility of current consumption and decreases the more quickly the harm from past consumption increases. In other words, forward-looking individuals temper their consumption of addictive goods because they anticipate the negative future consequences of their consumption. Social interactions affect adjacent complementarity, but only if they take the form of conformity. Even in that case, the effect is ambiguous:

$$\frac{\partial \alpha_2}{\partial b_g} = (1-d)\,\beta \frac{(1-d)^2\,\beta\,(b_{as}+b_{ss}) - b_{as}}{\Delta^2} \lesseqgtr 0$$
$$\text{where } \Delta = b_g + b_{aa} + (1-d)^2\,\beta\,(b_{as}+b_{ss}) > 0$$

The magnitude depends on the strength of the reinforcing nature of addictive consumption (b_{as}) relative to the magnitude of the accumulating harm from past consumption (b_{ss}).

The coefficient on current group consumption, γ_1, is positive. This implies that current individual and current group consumption are positively related, as expected. Current individual consumption is negatively related to future group consumption for the same reason it is positively related to future price, which was discussed above.

The long-run effect of a change in price in the forward-looking model is equal to

$$\frac{\partial a^*}{\partial p} = \frac{\pi_1 + \pi_2}{1 - \alpha_1\,(1-d)\,/d - \alpha_2 - \gamma_1 - \gamma_2}$$

Steady-state stability requires that

$$\alpha_1\,(1-d)\,/d + \alpha_2 + \gamma_1 + \gamma_2 < 1$$

Plugging in the relevant values for these coefficients yields the stability conditions presented in the main text.

Demand equation (12) from the main text can be equivalently written as

$$S_{t+2} - \frac{1+\alpha_2\,(1-d)}{\alpha_2} S_{t+1} + \frac{(1+\alpha_1)\,(1-d)}{\alpha_2} S_t = -\frac{1-d}{\alpha_2} h_{t+2} \tag{22}$$

where

$$h_{t+2} = \gamma_1 \overline{a}_t + \gamma_2 \overline{a}_{t+1} + \pi_1 p_t + \pi_2 p_{t+1} + \delta_1 x_t + \delta_2 x_{t+1} + k$$

Equation (22) is a second-order linear difference equation that can be solved using standard methods (Sargent, 1987). The solution provided below applies to both conformity and spillovers because these models both generate demand equations of the form (22). Rewrite (22) using lag operator notation:

$$\left(1 - \beta_1 L + \beta_2 L^2\right) S_t = -\beta_3 h_t \tag{23}$$

where

$$\beta_1 = \frac{1+\alpha_2(1-d)}{\alpha_2}$$
$$\beta_2 = \frac{(1+\alpha_1)(1-d)}{\alpha_2}$$
$$\beta_3 = \frac{1-d}{\alpha_2}$$

Factorizing the lag polynomial yields

$$\left(1-\beta_1 L+\beta_2 L^2\right) = (1-\phi_1 L)(1-\phi_2 L)$$

where

$$\phi_1 = \frac{2\beta_2}{\beta_1 - \sqrt{(\beta_1)^2 - 4\beta_2}}$$
$$\phi_2 = \frac{2\beta_2}{\beta_1 + \sqrt{(\beta_1)^2 - 4\beta_2}}$$

The general solution to (23) is

$$S_t = \frac{-\beta_3}{(1-\phi_1 L)(1-\phi_2 L)} h_t + c_1(\phi_1)^t + c_2(\phi_2)^t \tag{24}$$

where c_1 and c_2 are constants. I assume that $\phi_1 > 1$ and $\phi_2 < 1$ and set $c_1 = 0$ in order to ensure stability.[19] $\phi_1 \neq \phi_2$ implies the identity

$$\frac{1}{(1-\phi_1 L)(1-\phi_2 L)} = \frac{1}{\phi_1-\phi_2}\left(\frac{\phi_1}{1-\phi_1 L} - \frac{\phi_2}{1-\phi_2 L}\right)$$

which is used to rewrite (24) as

$$S_t = \left(\frac{-\beta_3\phi_1}{(\phi_1-\phi_2)(1-\phi_1 L)} + \frac{\beta_3\phi_2}{(\phi_1-\phi_2)(1-\phi_2 L)}\right) h_t + c_2(\phi_2)^t$$

[19]Most empirical analyses of addiction models have found "saddlepoint dynamics" like this (Ferguson, 2000). The conditions needed for steady-state stability in terms of demand equation parameters are given in the main text.

Using that $\frac{1}{1-\phi L}x_t = \sum_{j=0}^{\infty}\phi^j x_{t-j}$ (if $\phi < 1$) and $\frac{1}{1-\phi L}x_t = -\sum_{j=1}^{\infty}\phi^{-j} x_{t+j}$ (if $\phi > 1$) allows one to write the solution for S_t as a function of infinite sums:

$$\begin{aligned} S_t &= \frac{\beta_3 \phi_1}{\phi_1 - \phi_2}\sum_{j=1}^{\infty}(\phi_1)^{-j} h_{t+j} + \frac{\beta_3 \phi_2}{\phi_1 - \phi_2}\sum_{j=0}^{\infty}(\phi_2)^{j} h_{t-j} + c_2 (\phi_2)^t \\ &= K_1 \sum_{j=1}^{\infty}(\phi_1)^{-j} h_{t+j} + K_2 \sum_{j=0}^{t-1}(\phi_2)^{j} h_{t-j} + K_2 (\phi_2)^t \sum_{j=0}^{\infty}(\phi_2)^{j} h_{-j} + c_2 (\phi_2)^t \end{aligned} \tag{25}$$

where

$$\begin{aligned} K_1 &= \beta_3 \frac{\phi_1}{\phi_1 - \phi_2} \\ K_2 &= \beta_3 \frac{\phi_2}{\phi_1 - \phi_2} \end{aligned}$$

Solving for the initial condition S_0 yields

$$S_0 = K_1 \sum_{j=1}^{\infty}(\phi_1)^{-j} h_j + K_2 \sum_{j=0}^{\infty}(\phi_2)^{j} h_{-j} + c_2 \tag{26}$$

Solving (26) for c_2 and plugging the result into equation (25) yields, after some algebra, the particular solution to (23):

$$S_t = K_1 \sum_{j=1}^{\infty}(\phi_1)^{-j} h_{t+j} + K_2 \sum_{j=0}^{t-1}(\phi_2)^{j} h_{t-j} + (\phi_2)^t \left(S_0 - K_1 \sum_{j=1}^{\infty}(\phi_1)^{-j} h_j \right) \tag{27}$$

The first term in equation (27) is a weighted average of future determinants of demand (p_{t+j} and x_{t+j}) and future group consumption. The second term is a weighted average of past determinants of demand and past group consumption. The third term represents the effect of an individual's initial condition and fades to zero over time. The parameters ϕ_1 and ϕ_2 dictate the sign and magnitude of the effect of a shock to past or future consumption on current consumption. Reindexing (27) so that the initial condition corresponds to S_1 rather than S_0 yields the particular solution corresponding to the model in the text.

The myopic demand equation (10) is a first-order difference equation in S_t and can be solved using similar methods as above:

$$S_t = (1-d) \sum_{j=0}^{t-2} (\phi)^j h_{t-j} + (\phi)^{t-1} S_1 \tag{28}$$

where $h_t = \pi p_{t-1} + \delta x_{t-1} + \gamma \overline{a}_{t-1}$; S_1 is the initial stock of past consumption; and $\phi = (1-d)(1+\alpha) < 1$.[20] The first term on the right-hand side of equation (28) is a weighted average of past determinants of demand and past group consumption. This provides the theoretical justification for using lagged determinants of demand as instruments for an individual's stock. The second term represents the effect of an individual's initial condition and fades to zero over time. The parameter ϕ dictates the magnitude of the effect of shocks to past consumption on current consumption. These shocks can be changes to any factor affecting the demand for the addictive good, e.g., prices.

B Simulations appendix

Figure 1 displays the range of consumption for one-hundred individuals from three different simulations. The data for all simulations are generated using equation (27). The parameters are set to arbitrary values:

$$\begin{aligned} \beta &= 0.75 \\ d &= 0.5 \\ \lambda &= 1 \\ b_a &= 15 \\ b_s &= 10 \\ b_{as} &= 0.2 \\ b_{aa} &= b_{ss} = b_{xx} = 0.3 \\ b_{ax} &= 2 \\ b_{sx} &= 4 \end{aligned}$$

[20]If the stability condition is met (see section II) then one can easily show that $\phi < 1$.

Prices p_t and covariates x_{it} are drawn i.i.d. $N(10,1)$ and $N(0,1)$, respectively. The initial stock of past consumption, S_{i0}, was drawn with a uniform distribution in $[0,10]$. Data for Figure 1a, which does not include social interactions, are generated directly by equation (27) by setting the parameter $b_g = 0$. Data for Figures 1b and 1c, which include social interactions, require a multi-step procedure:

1. Generate individual consumption data with equation (27) assuming no social interactions (i.e., $b_g = 0$).

2. Calculate mean consumption $\overline{a}_t^{'}$ for each period t.

3. Generate individual consumption data with equation (27) assuming social interactions and using the mean consumption $\overline{a}_t^{'}$ calculated in step 2. I set $b_g = 0.5$ for the conformity specification and $b_g = 0.05$ for the spillovers specification.

4. Calculate mean consumption $\overline{a}_t^{''}$ for each period t using the consumption data generated in step 3. Repeat steps 2-4 until $\left|\overline{a}_t^{'} - \overline{a}_t^{''}\right| < \varepsilon$ where $\varepsilon > 0$ is a tolerance parameter set arbitrarily close to 0. I set the tolerance parameter ε to 1×10^{-6} for my simulations.

The myopic demand regressions reported in Table 1 employ data generated using the method and parameter values outlined above, but with two minor modifications. First, β was set equal to 0 and the data generating process was based on equation (28) rather than equation (27). Second, I included an additional covariate in the data generating process that is generated in the same way as x_{it}, but is unobservable to the econometrician.

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