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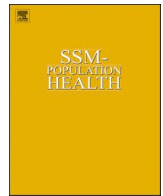
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# Does depression co-occur within households? The moderating effects of financial resources and job insecurity on psychological contagion<sup>☆</sup>

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## ABSTRACT

The empirically related psychopathologies of stress and depression exact an enormous economic toll and have many physical and behavioral health effects. Most studies of the effects of stress and depression focus on their causes and consequences for a *single, focal* individual. We examine the extent to which depression, as indicated by filling antidepressant prescriptions (SSRI and Benzodiazepines), co-occurs across spouses, constituting a negative spillover effect. To better understand the conditions that affect within-household contagion of depression, we examine whether the stress and uncertainty occasioned by job change and financial stress (net worth) increases spillover effects among spouses.

We use panel data from various Danish administrative registers from the year 2001–2015 with more than 4.5 million observations on more than 900,000 unique individuals and their spouses from Danish health registers.

Spouses in a household with their partner using antidepressants have a 62.1% higher chance of using antidepressants themselves, with the one year lagged effect being 29.3% and a two-year lagged effect of 15.1%. The effects become larger by 14.8% contemporaneously and 20% in the two-year lagged model if the focal individual changed employers. There was also a substantively unimportant effect of lower financial wealth to increase inter-spousal contagion.

## 1. Introduction

Even prior to the COVID-19 pandemic, workplace stress and depression were enormously costly both for individuals and society. Greenberg et al. (2015) estimated that depression costs the U.S. economy some \$210 billion per year, with 45% of that figure attributable to direct costs, 5% from costs associated with suicide, and 50% related to workplace costs such as absenteeism and diminished productivity. Kessler (2012) noted that “major depression is a commonly occurring, seriously impairing, and often recurrent mental disorder,” ranking as the fourth leading cause of disability worldwide. A recent review and meta-analysis (Konig et al., 2020) found that depression was associated with higher direct costs in adolescents, the elderly, in adults, and in participants with comorbid depression, and with higher indirect costs as

a result. The wide range of estimates of extra costs suggests that more study of excess costs is warranted. Depression results in mortality and morbidity, including from suicide, as well as diminished role performance.

Stress is also costly. Figures summarized by the University of Massachusetts at Lowell (n.d.) reported that job stress costs American companies more than \$300 billion a year in health costs, absenteeism, and reduced performance, with 40 percent of turnover related to stress and healthcare expenditures being 50 percent higher for employees who reported high levels of stress.

Research going back literally decades has consistently found that stress and depression are related, and has explored various mechanisms connecting the two distinct but interrelated behavioral health conditions. For instance, VanPraag (2005, p. 5) reported that stress can cause

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“brain disturbances thought to underlie certain forms of depression [...] or particular components of the depressive syndrome.” McGonagle and Kessler (1990) explored the relative importance of chronic versus acute stress on symptoms of depression, finding that the importance of chronic stress had been underestimated. Wurtman (2005), reviewing depression’s heritability, noted that among families exhibiting increased major depressive disorder, the risk of developing depression was enhanced in people exposed to stressful environments. Hammen’s (2005, p. 293) review of the relationship between stress and depression noted that “improved methods of assessment and research design have established a robust and causal association between stressful life events and major depressive episodes.” Stroud, Davila, and Moyer’s (2008) meta-analysis wrote that the relationship between stress and depression was well-established, and that particularly first onsets of depression were likely to be preceded by stressful life events.

Given the societal importance and cost of behavioral ill-health, our study seeks to examine the extent to which behavioral health problems co-occur—may be contagious—within households. Because our study uses prescription data as a marker of an underlying illness, our empirical focus is on the specific condition of depression, because depression is associated with specific medications used to treat that condition while there are less straightforward prescription drug implications of stress.

In economic terms, the social contagion of any behavioral illness such as depression can be categorized as a true negative spillover effect (Eisenberg et al., 2013) and economists have become increasingly interested in estimating spillover effects within social networks (Golberstein et al., 2014). Existing empirical literature on the contagious effects of mental health is relatively small (Monden, 2007; Eisenberg et al., 2013), and is largely based on surveys, experiments and empirical studies with small samples (see for a review, Joiner & Katz, 1999), diaries of single, minor daily events (e.g., Bolger et al., 1989), or with participants participating in scenario studies (e.g. Gurtman, 1990), which is why additional research employing large-sample research designs is needed (Meyler et al., 2007). Consistent with the idea that more research on the social contagion of behavioral health would be useful, Banerjee and Srivastana (2019) concluded that the contagious effect of stress was relatively unexplored and Gurtman et al. (1990) called for research on people that have important behavioral health problems, e.g. are depressed.

Prior studies have found a relationship between stress among entrepreneurs (owners of start-up companies) and their spouses (Dahl et al., 2010). Dahl et al. (2010) is the only prior study considering the relationship of stress between spouses that used prescription data. We seek to extend this line of research by studying another population, also using prescription data, as we focus on employees in mid-sized and large companies, i.e. over 250 employees, and their spouses. This population constitutes a great proportion of many countries and is important to the economy given their jobs inside corporations. Moreover, this sample differs from that studying entrepreneurs (Dahl et al., 2010), as employees have a different risk profile compared to entrepreneurs and also have different working environments, which may affect the extent of inter-spouse contagion. Using survey evidence, Eisenberg et al. (2013) found a contagious effect of perceived anxiety and depression among college roommates. Yet, they point to the fact that their results cannot be generalized to more intimate relations such as spouses.

We extend prior research by employing time-lagged models where the social contagion effect is not necessarily in the same period. This form of analysis will help to assess the causal effect of the relationship of depression between spouses and also begin to estimate the magnitude of lagged effects. Thereby, we also seek to respond to Golberstein et al.’s (2014) call for research on spillover effects of health service utilization behavior such as prescriptions.

In contrast to previous studies (e.g. Bolger et al., 1989; Eisenberg et al., 2013) on the contagion effect of behavioral health problems among spouses, we, like Dahl et al. (2010), use prescription data as a proxy for psychological ill-health. Prescription data has the advantage

that a medical evaluation has been made when the prescription has been ordered and the data are available in a large-scale database. This fact of medical examination prior to prescribing makes these data closer to being objective, or at least more consistent, as the data are less dependent on cognitive biases and self-reports. Moreover, prescriptions have the advantage that the people using medication are frequently actually unhealthy, a condition which can be difficult or ethically inappropriate to create in an experimental setting. Therefore, our methodological approach using longitudinal panel data of prescriptions can approximate a quasi-natural experimental setting.

Besides focusing on an unexplored population, using lagged effects and using medical prescription data, we contribute to the estimation of contagion effects by introducing two moderators of the relationship of depression between spouses. The moderators are job change and personal financial equity. These factors are of interest, as the idea of social contagion for various health conditions has been empirically demonstrated (e.g., Monden, 2007), yet there is a need to understand contagion effects more broadly and also to begin to analyze under what circumstances the contagion effects are larger or smaller.

## 2. Background and hypotheses

Social psychology has long recognized that people learn what to do and model their behaviors from connected others, even when they underestimate the actual effects of normative social influence (e.g., Nolan, et al., 2008). Economics, too, understands that “the characteristics and behaviors of one individual influence the preferences, beliefs, or constraints of another” (Li & Gilleskie, 2021, p. 1025). For instance, Christakis and Fowler (2007; 2008; 2013) reported that smoking, obesity, and happiness may be contagious through social contacts. Oberle and Schonert-Reichl (2016) reported a social contagion effect of stress in elementary school classrooms from teachers to students. There have been studies of sibling effects on substance use (Rende et al., 2005) and Blok et al. (2013, p. 667) argued that “the spread of unhealthy behavior shows marked similarities with infectious diseases,” exhibiting patterns of social diffusion. Perry et al. (2016) reported partner concordance for physical activity, fruit and vegetable and fast food consumption, and Jackson et al. (2015) reported that when one partner changed to a healthier behavior (e.g., smoking cessation, physical activity, and weight loss), the other partner was also more likely to make a similar behavior change.

The inference problems of attributing similar health-relevant behaviors to social influence are substantial. Siblings and for that matter parents and children share genetic characteristics, making it difficult to distinguish hereditary from social influence effects on behaviors and medical conditions. And spouses and other cohabitating family members, and for that matter, members of the same social networks, often share characteristics such as income, education, and common environments that provide alternative explanations for patterns of similar behaviors and wellbeing. Thus, Li and Gilleskie (2021), among others, have found smaller social interaction effects than earlier studies. We use both longitudinal analysis and the hypothesized effects of factors that might interact with social contact to make social influences stronger to provide additional, and potentially more robust, understandings of the effects of social connection on, in this instance, depression.

There are at least two theoretical mechanisms posited to account for emotional contagion. Hatfield et al. (1992) posited what came to called primitive emotional contagion, in which people mimic the emotions of others to whom they are exposed almost automatically (see also, Wild et al., 2001). Mimicking or imitating the emotions of an interaction partner increases the similarity between the two, and similarity is of course an important basis of interpersonal attraction, and possibly therefore increases the pleasantness and other positive dimensions of the interaction. Consequently, imitating other’s emotions would be a behavior that is reinforced.

Second, as extensively explored by VanKleef, deDreu, and Manstead

(2010), people learn from observing others, and one thing individuals may learn is what emotions are appropriate in a given situation. For instance, following the arguments of informational social influence (e.g., Deutsch & Gerard, 1955), people may learn from others whether or not they should be depressed, or stressed, by environmental exigencies.

Traditionally, research has emphasized the positive health outcomes of being in a family or living with a partner (Monden, 2007). Yet, families not only promote good health. Health behaviors in a family depend on health status of other family members and their socioeconomic status (Monden, 2007).

The study of the diffusion of emotions, known as emotional contagion (Barsade et al., 2018; Parkinson & Simons, 2009), dates back to Le Bon (1903) research on sentiments in crowds. According to Schoenewolf (1990) emotional contagion occurs when an individual influences the emotions or behaviors of another person unconsciously or consciously, i. e. social contagion theory (Wethington et al., 2000; Oberle & Schonert-Reichl, 2016). To follow the approach of Eisenberg et al. (2013), we term the transmission of psychological stress or depression from the focal person to their spouse as a “contagion effect”. The term contagion effect is equivalent to what economists call “endogenous social interaction effects” (Manski, 1993), where variable A in one person causes changes in the same variable in another person. Hence, the term social contagion is somewhat more specific in its analysis than the spillover effect as spillovers can also include person 1’s variable A affecting person 2’s variable B.

As already noted, there are a number of mechanisms that might account for the contagion effect of depression across spouses. In addition to the two theoretical mechanisms of imitation and social learning, other logics also suggest that depression could be contagious. One source of contagion could be that the spouse empathizes with their partner, thereby coming to share that individual’s emotions (Parkinson & Simons, 2009), including depression (Hatfield et al., 1993). Another reason could be that the depressed person is not enjoyable to be around, which decreases the spouse’s mental health (Hokanson et al., 1989). Also, the depressed person could give negative feedback to their spouses and be unable to support them (Joiner & Katz, 1999). Hatfield et al. (1993) also suggested that people tend to mimic behaviors around them, and spouses are the immediate and closest environments for their partners, which also can explain why depression might be contagious. Lastly, having a depressed spouse may cause a sense of guilt, which in turn may lead to depression in the person not initially being depressed (Eisenberg et al., 2013).

From a behavioral perspective, when a spouse is depressed, that individual may do a smaller portion of the domestic duties, for instance, cleaning, cooking, childcare, and so forth. This withdrawal puts a larger workload on their spouse (Wethington, 2000), which can lead to mental health issues. A larger workload on one partner can increase the stress on their spouse (Karasek & Theorell, 1990) and influence their partner’s depressive condition. There are, therefore, numerous theoretical reasons and mechanisms that can potentially produce social contagion effects.

Our first hypothesis is, then:

**Hypothesis 1.** When an individual is depressed, there is an increased likelihood that his/her spouse will also be depressed.

### 2.1. Contagion and financial resources

Prior research shows that emotional contagion effects are stronger if people confront a greater threat as contrasted with being in low-threat circumstance (e.g., Gump & Kulik, 1997). The intuition is that higher threat conditions necessarily make people more vigilant, and that heightened vigilance increases people’s attention to, and therefore influence by, the behavior of others.

Research on the social determinants of health more generally and mental health specifically invariably speaks to the importance of economic circumstances (e.g., Lorant, et al., 2007; Meltzer et al., 2010),

including the effects of social class (e.g., Simandan, 2018). Sinkewicz et al. (2022), for instance, found that individuals with a lower socioeconomic position were more likely to be persistently depressed.

There are numerous indicators of financial well-being, including both objective measures of financial standing and subjective attitudes about an individual’s financial condition. Because this study uses de-identified archival data, we do not have access to attitudes and there is no possibility of collecting people’s opinions. Reviews and analyses of objective indicators of financial position often mention income and wealth—net worth (e.g., Bruggen, et al., 2017; Greninger et al., 1996). We use net worth instead of income because income measures the flow of assets as contrasted with net worth that provides a measure of the total stock of wealth accumulated. Low net worth, an indicator of financial position, creates a greater sense of economic vulnerability. Poorer financial position may lead to more contagion of depression as there is no financial buffer available (Shoss, 2017). Not surprisingly, prior research has found an empirical relationship between mental health and the inability to pay home mortgages. However, prior empirical research has not studied the interaction effect between personal financial equity and the correlation of depression between spouses (See Hal, 2015 for a review).

People with scarce or negative personal equity have a lower likelihood of avoiding the consequences of being depressed. These consequences may be worry about whether they can maintain their individual performance and keep their job. A depressed person that is also financially insecure may be more able to influence the mental wellbeing of their spouse as the spouse also can become worried about the consequences of financial distress, such as losing their house, the ability to provide for their children and so forth. Diminished financial buffers add to a sense of not being in control which would make depression more contagious (Berker et al., 2019).

This line of reasoning leads us to hypothesize:

**Hypothesis 2.** The correlation of depression among spouses is higher when people’s personal financial equity—net worth—is lower

### 2.2. Contagion and job insecurity

Job change is another source of potential threat that can increase vigilance and therefore the likelihood of the social correlation of depression. The changing of a job by a partner may also be perceived as a negative surprise in the environment (Simandan, D. 2020) that affects mental health negatively when co-occurring with depression of their partner. Dahl’s (2011) study of organizational change as producing more depressive symptoms suggests that many forms of change, including job change, may be experienced as threatening and problematic. This is echoed by Wisse and Sleebos (2016). Recent research suggests that the symptoms of mental disorders can persist after a job change and be contagious (Kensbock et al., 2021).

A job change may change patterns and routines of a family, which can be perceived by the spouse as a change forced on them as they experience reduced control of their own situation and that of their partner. This reduced sense of control and unpredictability can lead to more social influence between the spouses (Peters et al., 2017).

This logic leads to the third hypothesis:

**Hypothesis 3.** The likelihood of depression being contagious between spouses is higher when individuals undergo a job change.

## 3. Methods and data

### 3.1. Registry data

To test our arguments, we used panel data from various Danish administrative registers. These are all controlled and maintained by official institutions under the Danish government and administered by Statistics Denmark. We were granted approval from The Danish Health

Data Authority to use data from the official and centralized Prescription database of Denmark. Demographic data is collected from the Integrated Database for Labor Market Research (IDA). Income and personal equity data is collected from the Income database (IND). The databases have been matched using the de-identified personal unique ID number to preserve full anonymity regarding these highly sensitive micro data.<sup>1</sup>

### 3.2. Sample

Our sample consists of employees of Danish organizations with more than 250 employees,<sup>2</sup> i.e. medium-sized and large organizations. These individuals we label “focal” persons. We also include their spouse in the panel. The panel spans the years from 2001 to 2015. The resulting data set consists of more than 4,500,000 observations on more than 900,000 different focal persons (unique individuals) – see Table 2. The panel of “focal” persons is complete and not a sampling of a larger population as the databases enable us to include all individuals employed in companies with more than 250 employees in Denmark. Thus, we do not use any particular sampling technique as we include all individuals and their spouses. Further descriptive information can be found in the results section.

Denmark is a welfare state with a social security system that is quite different from, for example, the US. This fact renders some of our analyses more conservative, as one would expect that effects such as job change or financial insecurity would be smaller in Denmark compared to a system like the US where there is a much smaller social safety net.

### 3.3. Measures

We use the same medical data as used in Dahl et al. (2010), Dahl (2011), and Dahl and Lamar (2020). They identified two main types of medication for depression– Benzodiazepines (ATC: N05CF; N05BA; N05CD) and selective serotonin reuptake inhibitor (SSRI – ATC: N06AB). Our independent variable *Both Types present year* equals 1 if the focal person filled at least one prescription for any antidepressant in a given year, and 0 otherwise. We construct the dependent variable *Spouse prescription usage* in an analogous way, taking the value of 1 if the spouse had at least one prescription in a given year, and 0 otherwise.

The focal individuals’ personal financial equity or net worth *Personal equity* is measured using annual data from Statistics Denmark, which have been reported by financial institutions. These data include personal financial assets such as houses, cars, investments, cash deposits, and similar assets, net of personal financial liabilities such as loans, mortgages, and similar items. The difference between total assets and liabilities measures individuals’ net worth. We consider this measure to be an objective measure of financial well-being as it is neither self-reported nor does it entail any subjective judgment.

We also assessed whether the focal person changed jobs to another company, which we label *Group 2 (to new job)* in the results section below. It is also possible that the focal person changed from being employed to being unemployed, which we label *Group 1 (to unemployment)* below. These changes are measured by Statistics Denmark and describe changes from one year to the next year. Most people do not change their job during the sample period.

We control for the focal person’s age, education measured in months of total education, personal income (measured in Danish Kroner), and gender. Prior studies (e.g. Dahl et al., 2010) have used similar demographic variables to statistically control for factors such as education (e.g., Bauldry, 2015) and income (Zimmerman & Katon, 2005) that research has shown affect people’s likelihood of being depressed.

### 3.4. Statistical analyses

To test our hypotheses, we used a conditional logit fixed effects model, following the recommendation of Allison (2009). This approach accounts for the time-invariant, unobserved characteristics of respondents by taking advantage of the longitudinal nature of the dataset (Allison, 2009), which is relevant to account for as our dataset is not based on a random assignment treatment. Using fixed-effects models provides an efficient way to methodologically cope with the problem of unmeasured, omitted variables. As the dependent variable of antidepressant use is binary, logistic regression was employed. To address causality, we examined whether the focal person was using either Benzodiazepine and/or SSRI before their spouse began filling antidepressant prescriptions, using a 1-year and 2-year lagged model to supplement the model where prescriptions to focal person and their spouse were filled in the same year. As robustness checks, we also run logit models with no fixed effects with and without interactions terms and year dummies. All analyses were conducted in STATA 17.

## 4. Results

### 4.1. Social influence effects on prescriptions for antidepressants

Table 1 presents descriptive statistics of the dataset. Pairwise correlations between all variables are shown in Panel A, whereas Panel B contains mean values, standard deviations, and min/max values. The “Spouse prescription usage” labels the filing of a prescription for the spouse, which is our dependent variable in our subsequent analyses.

Using conditional fixed effects logit regression, Table 2 presents the results of spouse’s use of either Benzodiazepine or SSRI prescription medications as the dependent variable in the same period (t) (Model 1) as their own spouse, one year later (t+1) (Model 2) and two years later (t+2) (Model 3) after the focal individual filled an antidepressant prescription. The conditional logistic models in Table 2, Model 1, are based on 255,442 observations from 31,682 focal individuals. 4,257,834 observations from 979,888 individuals<sup>3</sup> were dropped as conditional logistic fixed effects models estimate the likelihood of filling an antidepressant prescription conditional on some change in an independent variable—the spouse, for instance, starts taking an antidepressant. Because a large number of people never take antidepressants and nor do their spouses, these observations are dropped from the analyses as the variable of interest, taking an antidepressant, never changes.

Table 2 shows that if the focal person is using either Benzodiazepine or SSRI medications, this increases the probability relative to focal person not using Benzodiazepine or SSRI medications of the spouse also using either Benzodiazepine or SSRI medication by 63.5%, as the odds ratio is 1.635 in the same year (time t), and 62.1% in Table 3 where interaction effects are included.

To help untangle the question of causality, we examined whether the focal person was using either Benzodiazepine and/or SSRI before their spouse began filling antidepressant prescriptions, using a 1-year and 2-year lagged model. Those results are also presented in Table 2 in Models 2 & 3. The main effect of the focal person’s antidepressant use in the 1 year lagged model was statistically significant with a 1.291 odds ratio in Tables 2 and 1.293 when including interactions in Table 3. Hence, there is 29.1% increased probability that a spouse was using antidepressant medication the year after the focal person filled an antidepressant prescription. In Table 2, Model 3, we also found that the effect of the medication usage of the focal person is a statistically significant predictor of the spouse’s medication usage after 2 years. The odds ratio shows that there is an increased probability of 16.0% in Table 2, and 15.1% in Table 3 where interactions are included. We thus found

<sup>1</sup> <http://www.dst.dk/en/TilSalg/Forskningsservice>.

<sup>2</sup> Excluding employees in the pure public sector and the financial sector.

<sup>3</sup> In model 2, 4,259,992 observations (980,034 individuals) are dropped and in model 3, 4,268,912 observations (981,156 individuals) are dropped.

**Table 1**  
Descriptives statistics and correlations.

Panel A: Descriptive statistics	Mean	Median	S.D.	Min	Max
Spouse prescription usage t	0.29	0	0.45	0	1
Spouse prescription usage t+1	0.26	0	0.44	0	1
Spouse prescription usage t+2	0.24	0	0.43	0	1
Both types, present year t	0.08	0	0.27	0	1
Personal equity	249585.14	33963	3704869.54	-1,01,00,00,000	20,10,00,000
Job change	0.15	0	0.52	0	2
Education	159.24	168	38.92	0	252
Female	0.34	0	0.47	0	1
Age	44.11	44	9.21	14	88
Personal income	267675.12	237255.61	339475.79	-70,29,068	8,22,05,893

Panel B: Correlations	1	2	3	4	5	6	7
1 Spouse prescription usage t							
2 Both types, present year t	0.0607***						
3 Personal equity	0.0067***	0.0130***					
4 Job change	0.0274***	0.0129***	-0.0054***				
5 Education	0.001	-0.0107***	0.0298***	0.0116***			
6 Female	-0.0207***	0.0830***	-0.0103***	-0.0169***	-0.0591***		
7 Age	0.0745***	0.0684***	0.0686***	-0.0909***	-0.0516***	-0.0650***	
8 Personal income	0.0121***	0.0069***	0.1626***	0.0022	0.1009***	-0.0564***	0.0848***

Note: Panel A of this table presents descriptive statistics. Panel B presents correlations. 255,442 observations. Coefficients marked with \*\*\*, \*\*, or \* are significant at the  $p < 0.01$ ,  $0.05$ , or  $0.10$  level, respectively. Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK, EUR exchange rate fixed at 7.45).

**Table 2**  
Spouse prescription usage - Conditional fixed effects logistic regressions.

	Model 1		Model 2		Model 3	
	Spouse prescription usage, time t		Spouse prescription usage, time t+1		Spouse prescription usage, time t+2	
Both types, present year t	1.635***	(0.040)	1.291***	(0.032)	1.160***	(0.029)
Personal equity	1.00000000317	(0.00000000209)	1.00000000067	(0.00000000145)	1.00000000012	(0.00000000180)
Job change						
Group 1 (to unemployment)	1.027	(0.043)	1.086*	(0.046)	1.164***	(0.050)
Group 2 (to new job)	1.006	(0.019)	1.013	(0.020)	1.026	(0.020)
Education	1.007***	(0.001)	1.007***	(0.001)	1.008***	(0.001)
Age	1.081***	(0.002)	0.997*	(0.001)	0.934***	(0.001)
Personal income	0.99999997838	(0.00000002016)	0.99999999686	(0.00000001712)	1.000000010	(0.00000001671)
Observations	2,55,442		2,53,284		2,44,364	
Log likelihood	-89226.9		-89710.9		-86516.7	
Pseudo R-squared	0.019		0.001		0.012	

Note: This table presents the odds ratios and standard errors of conditional fixed effects logistic regressions of predictors on spouse prescription usage in time t, t+1, and t+2. Odds ratios marked with \*\*\*, \*\*, or \* are significant at the  $p < 0.01$ ,  $0.05$ , or  $0.10$  level, respectively. Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK, EUR exchange rate fixed at 7.45).

support for hypothesis 1.

To test the robustness of our results we also ran a similar model shown in Appendix A-1 using a logit regression, which is not based on fixed effects. These findings corroborate our main results (Tables 2 and 3). Average Marginal effects based on the full sample and based on the conditional sample are reported in Appendix B1 and B2, respectively. Appendix B1 is post calculated Appendix A2 logistics models, and Appendix B2 is calculated based on a similar logistics model yet only on the conditional sample used in Table 3 (individuals where spouse prescription is not 0 in whole period).

The fact that age and income have modest effects (and opposite to our expectations) is a consequence of our using an estimation procedure that accounts for changes, and there is not likely to be substantial changes in either of these variables over a one or even two-year period.

#### 4.2. Effects of focal Person's use of antidepressants on their spouse conditional on job change and financial condition

To test hypotheses H2 and H3, we expand the models presented in Table 1 by including two interactions. One interaction is between the variable measuring antidepressant use and personal net worth (H2). The second is between antidepressant use and job change (either job change to another company, group 1, or to unemployment, group 2) (H3). The results are presented in Table 3.

The main effect of antidepressant use is very similar in Tables 2 and 3, with the probabilities of spouse antidepressant use conditional on the focal person's use of antidepressants contemporaneously and with a one and two year lag virtually identical across the two models.

There is a significant interaction effect between the focal person using either Benzodiazepines and/or SSRI (labeled "both types" in the Tables) and the personal equity of the focal person on the spouse's use of

**Table 3**  
Spouse prescription usage - Conditional fixed effects logistic regressions including interactions.

	Model 1		Model 2		Model 3	
	Spouse prescription usage, time t		Spouse prescription usage, time t+1		Spouse prescription usage, time t+2	
Both types, present year t	1.621***	(0.041)	1.293***	(0.033)	1.151***	(0.030)
Personal equity	1.0000000037	(0.00000000254)	1.00000000112	(0.00000000158)	1.0000000020	(0.00000000233)
Both types present year t × Personal equity	0.9999999877	(0.00000000813)	0.99999997506**	(0.00000001062)	0.99999997509**	(0.00000001055)
Job change						
Group 1 (to unemployment)	1.034	(0.047)	1.097**	(0.050)	1.184***	(0.055)
Both types present year t × Group 1 (to unemployment)	0.958	(0.114)	0.932	(0.111)	0.895	(0.110)
Group 2 (to new job)	0.993	(0.020)	1.006	(0.020)	1.008	(0.021)
Both types present year t × Group 2 (to new job)	1.148**	(0.073)	1.075	(0.069)	1.200***	(0.079)
Education	1.007***	(0.001)	1.007***	(0.001)	1.008***	(0.001)
Age	1.080***	(0.002)	0.997*	(0.001)	0.934***	(0.001)
Personal income	0.9999999824	(0.00000001991)	1.00000000315	(0.00000001722)	1.00000001657	(0.00000001699)
Observations	2,55,442		2,53,284		2,44,364	
Log likelihood	-89223.2		-89706.2		-86508.4	
Pseudo R-squared	0.019		0.001		0.012	

Note: This table presents the odds ratios and standard errors of conditional fixed effects logistic regressions of predictors and interactions on spouse prescription usage in t, t+1, and t+2. Odds ratios marked with \*\*\*, \*\*, or \* are significant at the  $p < 0.01$ ,  $0.05$ , or  $0.10$  level, respectively. Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK, EUR exchange rate fixed at 7.45).

antidepressants in the lagged models (Models 2 and 3) but not in the one measuring usage in the same year (Model 1). The effects, however, as assessed by the odds ratios, are trivially small, so we conclude that a focal person's net worth does not affect the likelihood of their spouse's use of antidepressants.

In Table 3, we also present the results testing the interaction between the use of antidepressants and "job change" of the focal person on the spouse's use of medication. The interaction between focal person usage of medication and job change to a new job (from this year to the next year – group 2) in a new company is statistically significant ( $p < 0.05$ ) with an odds ratio of 1.148 in the same year model (Time t - Model 1) suggesting a 14.8%<sup>4</sup> increased probability of the spouse's use of antidepressants, if the focal person both uses medication and changes job in that year. Interestingly, there is no effect for a one-year lag but the effect for a two-year lag is slightly larger (20.0%).

However, becoming unemployed has no effect on the social contagion of antidepressant use.

Appendix A-2 report the results of similar models as those in Table 3 using logistic regression. These tests support the results presented in Table 3 with one exception. The logit regression in Appendix A-2 r show an opposite sign for the odds ratio of the interaction between personal equity and antidepressant use.

These results suggest that our two measures of stress or threat—net worth and job change—have at best limited effects, especially in the case of net worth, on the extent of social contagion of antidepressant use. Changing job of the focal person has an interaction effect, yet that effect is substantially smaller than the main effect.

## 5. Discussion

There is growing interest in whether behavioral health and, for that matter, behaviors that affect behavioral health (Jackson et al., 2015) are contagious (e.g., Katz, Beach & Joiner, Jr., 1999) in that they are correlated among spouses, close network connections, and roommates. The interest in contagion or spillover in health reflects the reality that studies that consider only the effects of factors affecting behavioral

<sup>4</sup> Without adjusting for the main effect of job change (group 2), yet this is close to an odds ratio of 1 (insignificant), hence effect is around 14% increase.

health on a single, focal individual can underestimate costs and other effects if, in fact, the behavioral health of one individual affects the health of connected others. The present study contributes to this interest in and research attempting to estimate the degree of social contagion in several ways.

First, we provide evidence that inter-spousal social influence for depression exists for people working in larger companies with over 250 employees, not just for the spouses of entrepreneurs (Dahl et al., 2010). Moreover, our analyses rely on a large population analyzed over time, and in that way contributes to the growing body of evidence on within-couple and within-household correlations of health-relevant attitudes and behaviors (e.g., Eisenberg, et al., 2013; Perry et al., 2016). Although theories of emotional and behavioral social influence have existed for many years (see Christakis & Fowler, 2008; 2013 for reviews), this study is the first to use longitudinal prescription data and, a large sample with fixed-effects modeling to explore the social contagion of depression.

Second, we find some evidence that the stress from changing jobs can magnify the social influence of depression between spouses. However, we did not find evidence of much effect of financial condition on the social contagion of stress. Our findings suggest that job change may be more of a stressor than low financial net worth, possibly because job change is a particularly psychologically salient event while financial condition may be more of a chronic condition to which people adapt.

### 5.1. Limitations

Using prescription data for antidepressants is one limitation for our analyses. People may be depressed and not see a physician to receive antidepressant prescriptions, and depression can be treated non-pharmacologically with counseling, meditation, and other similar interventions. Moreover, antidepressants may be prescribed for conditions other than depression. For instance, Trazadone, originally developed as an antidepressant, is now widely prescribed (and evaluated) as a sleep aid (e.g., Jaffer, et al., 2017). Thus, there is inevitably some measurement error introduced by using prescription data as a marker of depression. Such measurement error should, however, not be systematically correlated with other measures and would reduce our effect sizes but probably not change the fundamental conclusions. Moreover, we note that virtually all methods of assessing behavioral health also

may have some error, as self-reports may not be accurate and even physician diagnoses of mental health conditions are not error-free.

Our study relies on data from Denmark. As already noted, Denmark is a country with a strong social safety net and also comprehensive medical coverage that differs, for instance, not only from less-developed countries but also from the United States where coverage for mental health issues is much more limited. We note that the social contagion of behavior and attitudes is a general phenomenon that relies on mechanisms such as the effects of common environments, similarity, and social influence that are unlikely to be country specific. Nonetheless, it is important to replicate our results in other countries and cultures.

Importantly, as Luo (2017) has argued, there are a number of mechanisms that can account for similar health and behaviors among spouses, including spouses choosing others who are similar and the operation of the marriage market in ways that cause similarity among spouses. Fu et al. (2012) modeled the evolutionary advantages of homogamy, the tendency for individuals to mate with similar others, and homophily, the tendency for individuals to interact with similar others. These mechanisms at once complement but also offer a different explanation for concordance between spouses than the one we and others have focused on, social convergence or contagion. As in similar studies of social influence among spouses, we are not able to fully rule out the alternative explanations of common environmental conditions or associative similarity—although the longitudinal analyses partially mitigate this concern. It is unlikely that similarity or associative mating can account for the fact that once one spouse starts taking antidepressants, the other spouse is much more likely to do so, also. However, it is quite possible that a change in the household environment that would increase depression risk would affect both spouses.

5.2. Future directions

As already note as we discussed limitations, one important future direction for research is to more adequately disentangle the underlying theoretical mechanisms that lead to the correlation of depression and, for that matter, other behavioral and physical health outcomes among connected others, including spouses and partners. And the large body of evidence demonstrating the existence of correlations of behavioral and physical health and health-relevant behaviors suggests some important avenues for extending this subject.

First, as noted, most studies of the costs of ill-health focus on the costs arising from individuals. It would be useful to extend and expand those analyses, for instance on how work environments affect stress and ill-health (e.g., Goh et al., 2016) to consider the economic and other

costs such as morbidity and mortality considering also the effects of social contagion across people.

Second, while the existence of social contagion seems reasonably well-established, the factors making interpersonal correlations larger or smaller remain to be theorized and empirically examined. In this study we examined job change and financial stress as represented by net worth. But there are a large number of factors that might affect interpersonal contagion of depression and other health outcomes. The presence of children, the amount of time people spend interacting, whether or not both people work, are among the factors that affect underlying stress and might make the other’s depression or other behavioral health symptoms more or less salient. The point is that it is now time to explore not just the existence of interpersonal health correlations but what makes those relationships larger or smaller.

6. Conclusion

The fact that spouses, and possibly others who are socially connected, share indicators of depression is important for understanding where to allocate behavioral health resources and also for estimating the full costs of depression. The fact that we found that the likelihood of a spouse taking an antidepressant if their partner increases by about 63 percent contemporaneously and by about 20 percent with a one- or two-year lag means that the costs of depression estimated from focusing only one focal person are seriously underestimated. The toll of depression, already thought to be large, is actually higher when the social contagion effects of depression are considered.

This study contributes to the growing literature on the evidence of social influences on behavioral and physical health, a topic that remains important not just for depression or stress but for other psychological and physical health outcomes as well. People, particularly spouses, have important influences on the other, so behavioral health and, for that matter, physical health and health-relevant behaviors are socially influenced. Recognizing and estimating the economic and health consequences of such social influence remains an important task for research on all aspects of health.

Declaration of competing interest

No conflicts to report.

Data availability

The authors do not have permission to share data.

Appendix A1 and A2. Logistic regression (non fixed effects) with and without

Table A1  
Spouse prescription usage - Logistic regressions

	Model 1		Model 2		Model 3	
	Spouse prescription usage, time t		Spouse prescription usage, time t+1		Spouse prescription usage, time t+2	
Both types, present year t	1.927***	(0.020)	1.859***	(0.020)	1.840***	(0.021)
Personal equity	0.99999996430***	(0.00000000266)	0.99999996920***	(0.00000000262)	0.99999997730***	(0.00000000249)
Job change						
Group 1 (to unemployment)	0.953**	(0.022)	0.963	(0.022)	0.977	(0.023)
Group 2 (to new job)	0.887***	(0.010)	0.878***	(0.010)	0.869***	(0.010)
Education	1.001***	(0.000)	1.000***	(0.000)	1.000***	(0.000)
Female	0.949***	(0.007)	0.948***	(0.007)	0.938***	(0.007)
Age	1.049***	(0.000)	1.046***	(0.000)	1.043***	(0.000)
Personal income	1.00000003840***	(0.00000000533)	1.00000001366	(0.00000000859)	0.99999999983	(0.00000000371)
Observations	45,13,276		45,13,276		45,13,276	
Log likelihood	-448583.6		-433818.7		-417275.9	
Pseudo R-squared	0.040		0.035		0.032	
Year fixed effects	No		No		No	
	Model 4		Model 5		Model 6	

(continued on next page)



**Table A1 (continued)**

	Model 1		Model 2		Model 3	
	Spouse prescription usage, time t		Spouse prescription usage, time t+1		Spouse prescription usage, time t+2	
	Spouse prescription usage, time t		Spouse prescription usage, time t+1		Spouse prescription usage, time t+2	
Both types, present year t (0.020)		1.920***	(0.020)	1.768***	(0.020)	1.707***
Personal equity	0.9999996170***	(0.00000000272)	0.9999994335***	(0.00000000310)	0.9999992538***	(0.00000000348)
Job change						
Group 1 (to unemployment)	0.953**	(0.022)	0.944**	(0.022)	0.936***	(0.022)
Group 2 (to new job)	0.885***	(0.010)	0.880***	(0.010)	0.874***	(0.010)
Education	1.001***	(0.000)	1.001***	(0.000)	1.001***	(0.000)
Female	0.949***	(0.007)	0.950***	(0.007)	0.941***	(0.007)
Age	1.049***	(0.000)	1.048***	(0.000)	1.047***	(0.000)
Personal income	1.0000004095***	(0.00000000539)	1.0000006377***	(0.00000000713)	1.0000007566***	(0.00000000734)
Observations	45,13,276		41,82,607		38,57,295	
Log likelihood	-448377		-425894.4		-402161	
Pseudo R-squared	0.040		0.038		0.036	
Year fixed effects	Yes		Yes		Yes	

Note: This table presents the odds ratios and standard errors of logistic regressions of predictors on spouse prescription usage in t, t+1, and t+2. Models 4, 5, and 6 include Year fixed effects. Odds ratios marked with \*\*\*, \*\*, or \* are significant at the p < 0.01, 0.05, or 0.10 level, respectively. Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Female is an indicator variable, taking the value of 1, if the focal person is female, and 0 otherwise. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK).

**Table A2**

Spouse prescription usage - Logistic regressions including interactions

	Model 1		Model 2		Model 3	
	Spouse prescription usage t		Spouse prescription usage t+1		Spouse prescription usage t+2	
Both types, present year t	1.882***	(0.022)	1.815***	(0.022)	1.790***	(0.022)
Personal equity	0.9999995693***	(0.00000000293)	0.9999996111***	(0.00000000294)	0.9999997034***	(0.00000000281)
Both types present year t × Personal equity	1.00000003653***	(0.00000000477)	1.00000003828***	(0.00000000457)	1.00000002810***	(0.00000000493)
Job change						
Group 1 (to unemployment)	0.954*	(0.024)	0.962	(0.024)	0.986	(0.025)
Both types present year t × Group 1 (to unemployment)	1.000	(0.060)	1.007	(0.063)	0.952	(0.062)
Group 2 (to new job)	0.873***	(0.011)	0.869***	(0.011)	0.855***	(0.011)
Both types present year t × Group 2 (to new job)	1.151***	(0.039)	1.107***	(0.040)	1.160***	(0.042)
Education	1.001***	(0.000)	1.000***	(0.000)	1.000***	(0.000)
Female	0.949***	(0.007)	0.948***	(0.007)	0.937***	(0.007)
Age	1.049***	(0.000)	1.046***	(0.000)	1.044***	(0.000)
Personal income	1.00000003904***	(0.00000000616)	1.0000001045*	(0.00000000569)	0.9999999675	(0.00000000488)
Observations	45,13,276		45,13,276		45,13,276	
Log likelihood	-448529.6		-433768.8		-417232.8	
Pseudo R-squared	0.040		0.036		0.032	
Year fixed effects	No		No		No	
	Model 4		Model 5		Model 6	
	Spouse prescription usage t		Spouse prescription usage t+1		Spouse prescription usage t+2	
Both types, present year t	1.873***	(0.022)	1.745***	(0.021)	1.654***	(0.021)
Personal equity	0.9999995410***	(0.00000000298)	0.9999993377***	(0.00000000334)	0.9999991364***	(0.00000000373)
Prescription usage × Personal equity	1.00000003856***	(0.00000000487)	1.00000006142***	(0.00000000489)	1.00000008480***	(0.00000000497)
Job change						
Group 1 (to unemployment)	0.953*	(0.024)	0.940**	(0.024)	0.941**	(0.024)
Both types present year t × Group 1 (to unemployment)	1.005	(0.061)	1.027	(0.064)	0.981	(0.064)
Group 2 (to new job)	0.872***	(0.011)	0.874***	(0.011)	0.864***	(0.011)
Both types present year t × Group 2 (to new job)	1.149***	(0.039)	1.105***	(0.040)	1.160***	(0.042)
Education	1.001***	(0.000)	1.001***	(0.000)	1.001***	(0.000)
Female	0.949***	(0.007)	0.951***	(0.007)	0.941***	(0.007)
Age	1.049***	(0.000)	1.048***	(0.000)	1.047***	(0.000)
Personal income	1.00000004194***	(0.00000000615)	1.0000006389***	(0.00000000607)	1.0000007530***	(0.00000000628)
Observations	45,13,276		41,82,607		38,57,295	
Log likelihood	-448321.2		-425812.4		-402066.7	
Pseudo R-squared	0.040		0.038		0.037	
Year fixed effects	Yes		Yes		Yes	

Note: This table presents the odds ratios and standard errors of logistic regressions of predictors and interactions on spouse prescription usage in t, t+1, and t+2. Models 4, 5, and 6 include Year fixed effects. Odds ratios marked with \*\*\*, \*\*, or \* are significant at the p < 0.01, 0.05, or 0.10 level, respectively. Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's

net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Female is an indicator variable, taking the value of 1, if the focal person is female, and 0 otherwise. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK).

**Appendix B1 and B2. Average Marginal Effects in full sample & conditional sample**

**Table B1**

Spouse prescription usage – Average Marginal Effects in full sample

	Time t	Time t+1	Time t+2	Time t	Time t+1	Time t+2
Months of education	.0000134** (1.65e-06)	9.45e-06** (1.60e-06)	5.16e-06** (1.55e-06)	.0000139** (1.66e-06)	.0000161** (1.75e-06)	.0000179** (1.85e-06)
Female	-.00108*** (.00014)	-.00105*** (.00014)	-.00122*** (.00014)	-.00109*** (.00014)	-.00108*** (.00015)	-.00133*** (.00016)
Age	.000988*** (6.75e-06)	.000891*** (6.51e-06)	.00080*** (6.26e-06)	.00099*** (6.78e-06)	.000997*** (7.11e-06)	.00100*** (7.50e-06)
Both types, present year t = 1	.0179*** (.0003)	.0159*** (.0003)	.0147*** (.0003)	.0178*** (.0003)	.0160*** (.0003)	.0150*** (.0003)
Personal equity	-.8.11e-10*** (5.55e-11)	-.6.91e-10*** (5.29e-11)	-.5.04e-10*** (4.83e-11)	-.8.65e-10*** (5.65e-11)	-.1.28e-09*** (6.51e-11)	-.8.11e-10*** (5.55e-11)
(Personal equity) at Both types = 0 &	-8.50e-10*** (5.80e-11)	-7.36e-10*** (5.56e-11)	-5.34e-10*** (5.06e-11)	-9.06e-10*** (5.89e-11)	-1.35e-09*** (6.83e-11)	-1.82e-09*** (7.88e-11)
Both types = 1	-2.38e-10* (1.43e-10)	-2.07e-10 (1.21e-10)	-4.96e-10 (1.31e-10)	-2.66e-10* (1.46e-10)	-1.69e-10 (1.34e-10)	-5.44e-11 (1.25e-11)
Job change:						
Group 1 (To unemployment)	-.00096** (.00046)	-.00075** (.00045)	-.00035** (.00045)	-.00098** (.00046)	-.00123** (.00045)	-.00135** (.00050)
Group 2 (to new job)	-.00237*** (0.0002)	-.00245*** (0.0002)	-.00250*** (0.0002)	-.00241*** (0.0002)	-.00253*** (0.0002)	-.00273*** (0.0002)
Both types at Job change (no change)	.01777*** (.00039)	.01580*** (.00039)	.01449*** (.00038)	.01758*** (.00039)	.01588*** (.00041)	.01475*** (.00042)
Job change (group 1)	.01697*** (.00194)	.01548*** (.00188)	.01279*** (.00181)	.01699*** (.00194)	.01589*** (.00197)	.01332*** (.00197)
Job change (group 2)	.02046*** (.0011)	.017022*** (.0011)	.01690*** (.0010)	.02022*** (.0011)	.01728*** (.0011)	.017746*** (.0012)
Personal income	8.10e-10*** (1.28e-10)	2.07e-10*** (1.13e-10)	-6.21e-11*** (9.19e-11)	8.71e-10*** (1.28e-10)	1.36e-09*** (1.30e-10)	1.65e-09*** (1.38e-10)
Year dummies	No	No	No	Yes	Yes	Yes
Observations	4513276	4513276	4513276	4513276	4182607	3857295

Notes: Six models – Average Marginal effects reported (dy/dx) post-calculated after tests in Appendix A-2 r. Standard errors (Delta method) in brackets. P-values: \*\*\*, \*\*, or \* are significant at the p < 0.01, 0.05, or 0.10 level, respectively.

Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Female is an indicator variable, taking the value of 1, if the focal person is female, and 0 otherwise. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK).

**Table B2**

Spouse prescription usage – Average Marginal Effects in conditional sample

	Time t	Time t+1	Time t+2	Time t	Time t+1	Time t+2
Months of education	.0000449* (.000023)	.0000176 (.000023)	-.0000118 (.000024)	.0000106 (.000023)	.0000295 (.000025)	.0000337* (.000026)
Female	-.019*** (.00019)	-.026*** (.00020)	-.026*** (.00019)	-.021*** (.00019)	-.028*** (.00020)	-.027*** (.00022)
Age	.0035*** (.00009)	.0024*** (.0001)	.0009*** (.0001)	.0028*** (.0001)	.0028*** (.0001)	.0027*** (.0001)
Both types, present year t = 1	.0949*** (.003)	.0757*** (.003)	.0639*** (.003)	.0967*** (.003)	.0758*** (.003)	.0606*** (.003)
Personal equity	7.51e-12 (2.31e-10)	1.96e-10 (2.65e-10)	1.78e-09** (7.91e-10)	1.96e-10 (2.59e-10)	7.95e-11 (2.96e-10)	-2.13e-10 (4.50e-10)
(Personal equity) at Both types = 0 &	1.12e-10 (2.78e-10)	1.12e-10 (2.78e-10)	1.64e-09* (8.42e-10)	1.38e-10 (2.71e-10)	-4.16e-12 (3.11e-10)	-3.28e-10 (4.80e-10)
Both types = 1	1.17e-09 (7.78e-10)	1.17e-09 (7.78e-10)	3.34e-09*** (9.33e-10)	8.89e-10 (7.71e-10)	1.03e-09 (8.68e-10)	1.08e-10 (9.75e-10)
Job change:						
Group 1 (To unemployment)	.0861*** (.0087)	.0604*** (.0087)	.0586*** (.0087)	.0795*** (.0086)	.0566*** (.0089)	.0551*** (.0094)
Group 2 (to new job)	.0529*** (.0003)	.0352*** (.0003)	.0296*** (.0003)	.0495*** (.0003)	.0434*** (.0003)	.0460*** (.0004)
Both types at						

(continued on next page)

Table B2 (continued)

	Time t	Time t+1	Time t+2	Time t	Time t+1	Time t+2
Job change (no change)	.0921*** (.00373)	.0749*** (.00373)	.0624*** (.00375)	.0924*** (.00373)	.0751*** (.00386)	.0592*** (.00403)
Job change (group 1)	.0889*** (.0256)	.0562** (.0252)	.0145 (.0252)	.0889*** (.0255)	.0569*** (.0259)	.0876*** (.0268)
Job change (group 2)	.133*** (.0131)	.0898*** (.0131)	.0923*** (.0131)	.133*** (.013)	.0891*** (.014)	.0888*** (.014)
Personal income	4.68e-09*	-4.64e-09	-3.37e-08***	-4.37e-09	-4.47e-10	2.67e-09*
	(2.61e-09)	(3.30e-09)	(5.83e-09)	(3.18e-09)	(2.92e-09)	(3.05e-09)
Year dummies	No	No	No	Yes	Yes	Yes
Observations	255442	253284	244364	255442	237393	214510

Notes: Six models – Average Marginal effects reported (dy/dx) post-calculated after tests using logitics (non-fixed effects) on conditional sample (not full sample). Standard errors (Delta method) in brackets. P-values: \*\*\*, \*\*, or \* are significant at the  $p < 0.01$ ,  $0.05$ , or  $0.10$  level, respectively.

Spouse prescription usage in t, t+1, t+2, are indicator variables taking the value of 1, if the spouse had at least one prescription in the respective year, and 0 otherwise. Both types, present year t is an indicator variable taking the value 1, if the focal person had at least one prescription in the given year, and 0 otherwise. Personal equity is the focal person's net worth (in DKK). Job change is a categorical variable with Group 1 taking the value of 1, if the focal person changes to unemployment and Group 2 taking the value of 2, if the focal person changes to a new job, and 0 otherwise. Education denotes the months of education of the focal person. Female is an indicator variable, taking the value of 1, if the focal person is female, and 0 otherwise. Age is the focal person's age (in years). Personal income is the focal person's income (in DKK).

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