How Peers' Unemployment affect Subjective Unemployment Expectations and Self-Insurance Behavior

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PRELIMINARY DRAFT

Abstract

I examine how individuals' subjective unemployment expectations and subsequent economic behavior are affected by their peers' unemployment experiences. Using unique survey data on subjective unemployment expectations combined with comprehensive Danish administrative records, I find that a 1 percentage point increase in the share of unemployed second-degree peers raises individuals' subjective unemployment expectations by 0.2 percentage points. Individuals respond to this information by adjusting their economic behavior. In particular, I show that an increase in the share of peers who experience unemployment, leads to a higher probability of the individuals joining a private unemployment insurance fund and transitioning to more stable employment.

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1 Introduction

Individuals' expectations about future labor market prospects have important implications for their economic decisions and behavior. For example, subjective unemployment expectations affect decisions about unemployment insurance (Hendren, 2017), savings (Hartmann and Leth-Petersen, 2024), and consumption (Stephens, 2004). Despite the importance of subjective unemployment expectations, we know little about what shapes them. Previous literature indicates that individuals rely on their own experiences when forming their expectations (Malmendier, 2021; Campbell et al., 2007). Additionally, peers' experiences may provide a valuable source of information when individuals form their expectations, particularly in instances where individuals view their peers' experiences as predictive of their own future outcomes. This potential for information transmission has significant implications, especially when considering labor market risk. If individuals adjust their behavior based on what they learn from their peers, then peer effects in subjective unemployment expectations may amplify or mitigate the broader economic impact of labor market shocks. Despite these important consequences, comprehensive data prerequisites, i.e., a combination of information about social networks and elicited subjective expectations, means that we know very little about how the information shared between peers affect subjective expectations.

In this paper, I examine how peers' unemployment experiences influence individuals' subjective unemployment expectations and subsequent economic behaviors. To do so, I leverage a unique combination of survey elicited subjective unemployment expectations and high-quality Danish administrative data. As the Danish administrative data cover the entire Danish population, it provides a unique opportunity for mapping social peer groups in Denmark across several domains; family members, coworkers, and classmates. The administrative data further contain information about unemployment, thus providing a rare opportunity to investigate the transmission of information about unemployment risks within peer groups.

Using this unique dataset, I find that the unemployment experiences of peers significantly influence individuals' subjective unemployment expectations. Specifically, I show that a 1 pct. point increase in the share of second-degree peers who experience unemployment increases subjective unemployment expectations by 0.2 pct. points. This finding highlights that social networks are an important channel for the transmission of labor market information, feeding into subjective unemployment expectations. Incorporating information about peers' unemployment experiences into expectations may help individuals anticipate and prepare for a potential unemployment shock, allowing them to adjust their economic behavior in a precautionary manner.

Building on this, I next examine whether individuals adjust their economic behavior in response to their peers' unemployment expectations. First, I find that an increase in the share of peers who recently experienced unemployment has a positive effect on the respondents' probability of purchasing private unemployment insurance (UI). In particular, I find that a one-standard deviation increase in the share of unemployed peers leads to a 1.9 pct. point increase in the probability of having private UI. Second, I examine whether individuals also self-insure against a potential unemployment shock, by increasing their liquid savings. However, I find that this is not the case. While previous literature has pointed to precautionary savings as an important mean of self-insurance when individuals expect to become unemployed (Pettinicchi and Vellekoop, 2019), increasing one's savings often requires consistent, repeated effort. As highlighted by e.g. Thaler and Shefrin (1981), this level of commitment may be hard to obtain and this may help explain the lack of response in liquid savings. Third, I show that individuals with a higher share of recently unemployed peers are more likely to engage in job-to-job transitions and that these individuals change to jobs with lower turnover rates. Thus, it appears that upon learning of their peers' unemployment experiences, the respondents take actions to self-insure against a potential unemployment shock.

Identifying the causal effects of peers' experiences is inherently difficult due to potential selection into peer groups. For example, individuals often sort into social networks based on shared characteristics such as socioeconomic status, occupation, or geography, which may confound the relationship between peers' experiences and individuals' outcomes. To address this challenge, I follow Bramoullé et al. (2009) and De Giorgi et al. (2010), leveraging second-degree peers - peers of an individual's peers, who are not the individual's own peers. That is, second-degree peers are peers whom the individual do not know directly, and therefore does not interact with, but whom the individual may hear about through a common peer. The use of second-degree peers helps mitigate the risk that any estimated effect stems from selection, rather than information transmission. While selection effects are present at the first-degree level, I show that they are significantly attenuated at the second-degree level. Thus, the use of second-degree peers allows me to isolate the effect of information transmission from peers while minimizing the influence of shared unobservable characteristics.

To further strengthen identification, I incorporate a comprehensive set of fine-grained fixed effects, including municipality×year, education×year, industry×year, and occupation×year. These fixed effects control for common shocks that could simultaneously affect individuals' and their peers' labor market risks. Additionally, I exclude second-degree peers who reside in the same municipality as the respondent, to reduce the likelihood of local labor market shocks confounding the results. Finally, I control for the respondents' own unemployment experiences, to mitigate concerns about broader labor market trends and shared unobserved characteristics that may simultaneously affect both the individual's own unemployment risk and that of their peers. Together, these measures ensure that my estimates primarily reflect the causal effects of peer information transmission.

My findings highlight how social interactions act as informal channels for transmitting economic information, as information about peers' unemployment experiences not only affects individuals' subjective unemployment expectations, but also affect economic behavior. These results suggest that social networks can amplify or mediate the effects of economic shocks, with implications for individual resilience and aggregate labor market dynamics. Understanding these dynamics is crucial for designing policies that may help enhance individuals' ability to navigate economic uncertainty. [Results on shock propagation to be included in the next version of the paper.]

1.1 Related Literature

With this paper, I seek to bridge two strands of literature. The first is the literature on network effects, in which it is well established that an individual's peers have significant effects on the individual's outcomes (Kuchler and Stroebel, 2021; De Giorgi et al., 2020; Chetty et al., 2016; Dahl et al., 2014). The other is the literature on subjective expectations, from which we know that subjective unemployment expectations predict actual unemployment and economic behavior (Mueller and Spinnewijn, 2022; Hendren, 2017; Stephens, 2004). However, it is largely unexplored whether peers affect subjective expectations. This is likely due to the data prerequisites associated with an empirical investigation hereof. The data I utilize allow me to overcome this challenge and provide first insights into the interplay between peer effects and subjective expectations.

A large body of literature has shown that social peers and the information that passes between them have important implications for labor market outcomes and job search. Glitz and Vejlin (2021) study how referrals from former coworkers affect labor market outcomes. They show that referrals have positive effects on both wages and tenure. Kramarz and Skans (2014) show that graduates are more likely than their classmates to acquire a job in a plant where their parent works. Eliason et al. (2023) use Swedish administrative data to identify a wide range of social networks, and show that displaced individuals are more likely to find work in firms where they have a social peer. The authors find the largest effects for family members and past co-workers, while the effects from neighbors and former classmates are smaller, though still significant. Cingano and Rosolia (2012) show that an individual's unemployment spell duration is negatively dependent on the fraction of the individuals' former coworkers who are currently employed. The authors argue that the effect is driven by the transmission of job relevant information. All these studies indicate that individuals rely on information sharing from their network when they participate in the labor market. While a large body of literature examines how information transmission between peers may affect labor market outcomes, no work has, to the best of my knowledge, examined how such information affect labor market expectations. With this paper, I seek to fill this gap, by providing insights on how subjective unemployment expectations are affected by the information they receive from their peers.

In the expectations literature, several papers have considered subjective unemployment expectations. They generally find that subjective unemployment expectations predict actual unemployment, but that individuals tend to overestimate the probability of becoming unemployed (Balleer et al., 2023; Mueller and Spinnewijn, 2022; Hendren, 2017; Stephens, 2004). Additionally, it has been shown that subjective unemployment expectations are positively correlated with unemployment experiences (Campbell et al., 2007).[1]

A small, but growing literature considers how subjective expectations are affected by the experience of peers. Using data from Facebook to identify peers, existing research shows that peers' house price experiences affect the subjective expectations about house prices (Bailey et al., 2018, 2019), that peers' experiences with Covid-19 affect beliefs about Covid-19 (Bailey et al., 2024), and that peers' experiences with temperature changes affect beliefs about climate change (Mayer, 2023). However, very little is known about how subjective labor market expectations are affected by peers' experiences. A notable exception of a paper which does consider this relationship is Alt et al. (2022). Based on the same data source as mine, they examine how transmission of information about unemployment shocks affect voters' policy preferences. Alt et al. (2022) show that information about unemployment shocks increases the probability to vote for a left-wing party and the support for unemployment insurance, and highlight that this effect likely travels through a positive effects on the voters' perception of national unemployment and their own unemployment prospects. I contribute to this literature by showing that peers' unemployment experiences do indeed affect subjective unemployment expectations, and that they further affect self-insurance behavior.

[1] Malmendier (2021) provides a broad overview of research that has shown that expectations are affected by past experiences and highlights that this positive relationship between past experiences and expectations are present across many domains.

2 Social Networks and Information Transmission

2.1 Social Networks in Denmark

Social networks arise across many different domains. Previous work has highlighted peers in three domains that are important for social interactions and sharing of information: Family members, coworkers, and school mates. For many individuals, family is a core social network, in which social interactions occur regularly. This is also the case in Denmark. The European Commission (2005) found that 88 pct. of respondents from Denmark reported that their family was very important to them and an additional 10 pct. reported that family was fairly important. Fielding a survey in Denmark with a focus on social interactions, Alt et al. (2022) find that more than 40 pct. of their respondents often discuss unemployment with their siblings and over 35 pct. of their respondents often discuss unemployment with their parents.

Coworkers form another network which is important for information sharing. The European Commission (2005) found that 44 pct. of their respondents from Denmark meet with their coworkers in a social setting outside of work, at least once a month. This indicates that individuals interact with their coworkers about topics not directly related to their work. Alt et al. (2022) support the claim that coworkers may be a relevant source of information, as they find that over 50 pct. of their respondents report discussing unemployment with their coworkers. Additionally, Glitz (2017) finds that former coworkers play an important role for re-employment when an individual is laid off, indicating that coworkers may stay in touch, even after their joint employment has been terminated.

In Denmark, social networks are also largely comprised of former school mates. Nearly everyone in the population completes 10 years of school, and 83 pct. of students continue to high school or vocational studies following elementary school (Statistics Denmark, 2017). As higher education is mainly offered in five larger cities, students often have to relocate when commencing tertiary education, at which point their social networks also expand. Social ties in Denmark are typically stable throughout adulthood, with few individuals moving, and most moves being relatively short distance.[2]

In summary, family members, coworkers, and schoolmates are all intrinsic members of social networks for most people in Denmark. The peers in these networks play vital roles in social interactions and information sharing. Consequently, it is likely that the experiences of these peers may affect an individual's expectations.

3 Data

To examine the effect of peers' unemployment experiences on subjective unemployment expectations, I use a combination of survey data and Danish administrative data. The administrative data covers the entire Danish population, and thus offers a unique opportunity to identify not just 1st degree peers, but also peers-of-peers, or second degree peers, which is crucial for my analysis (c.f., section 4. I combine this with survey elicited subjective unemployment expectations, for a representative sample of the Danish population.

3.1 Administrative Data

The administrative data covers the entire Danish population at the individual level and contains third-party reported information about income, assets, education, employment and general demographic characteristics.

The data covers the entire Danish population, yielding a unique opportunity of identifying extensive social networks across the population and different domains. To construct my networks, I identify an individual's family members, coworkers and former classmates using the following criteria:

[2] In 2018 there were 892,000 moves in Denmark. In 57 pct. of these, the move was less than 10 km (Statistics Denmark, 2019).

- Family members: Parents, siblings and partners. Partners are identified as being either married to, living with, or in a registered partnership with the individual. Siblings are identified through common parents. I include both full, half and adopted siblings.
- Coworkers: Individuals who have worked with the same employer, at the same plant, in the past two years. For individuals with more than 25 coworkers at a given employer, and for individuals who have accumulated more than 50 coworkers across employers, I only include coworkers with the same educational level as the individual. This restriction reflects the fact that individuals in large firms are more likely to interact with coworkers who perform similar tasks at the firm.
- Classmates: Individuals who graduated with the same degree, from the same institution, in the same year. I only consider the highest degree obtained for each individual, as relationships tend to attenuate when individuals move to new educational institutions.

The administrative data does not allow me to identify which peers the individual actually interacts with nor how often. This means that the potential inclusion of irrelevant peers is inevitable. The inclusion of potentially irrelevant peers should not pose a problem, though any estimated effect may be a lower bound of the actual effect as the inclusion of irrelevant peers may attenuate the estimates. While some of the identified peers are likely irrelevant, Sheridan (2019) shows that the identified groups of peers are significant predictors of regular bank transfers in the Danish transfer app, MobilePay.[3] Further, Alt et al. (2022) validate the use of these peers using a survey fielded in 2018 among a representative sample of the Danish population.

While the peers that I identify are highly relevant for the transmission of information, there are also some peers that the administrative data do not allow me to identify. These include non-educational and non-work friends as well as family members outside the nuclear family. However, if these peers live in close proximity of the individual, any bias that the

[3] MobilePay is the Danish equivalent of Venmo. In 2018, over 80 pct. of the Danish population older than 13 used MobilePay (Sheridan, 2019).

omission of these peers may cause should be mitigated by the geographical restrictions that I impose, cf. section 4.1.

Table 1 shows the number of first degree peers that I identify. The average individual has 213 peers, while the median individual has 82 peers. The fact that the average is more than twice as large as the median is driven by some individuals having a particularly large number of coworkers.

Table 1: Number of Identified Peers

	5^{th} Percentile	Median	95^{th} Percentile	Mean
Family Members	1.00	4.00	6.00	3.67
Classmates	0.00	29.00	226.00	61.42
Coworkers	0.00	20.00	752.60	147.71
All	4.00	82.00	897.00	212.97

The table shows the median and average number of 1st degree peers by domain. Due to regulation by Statistics Denmark, all percentiles are based on running averages over five observations.

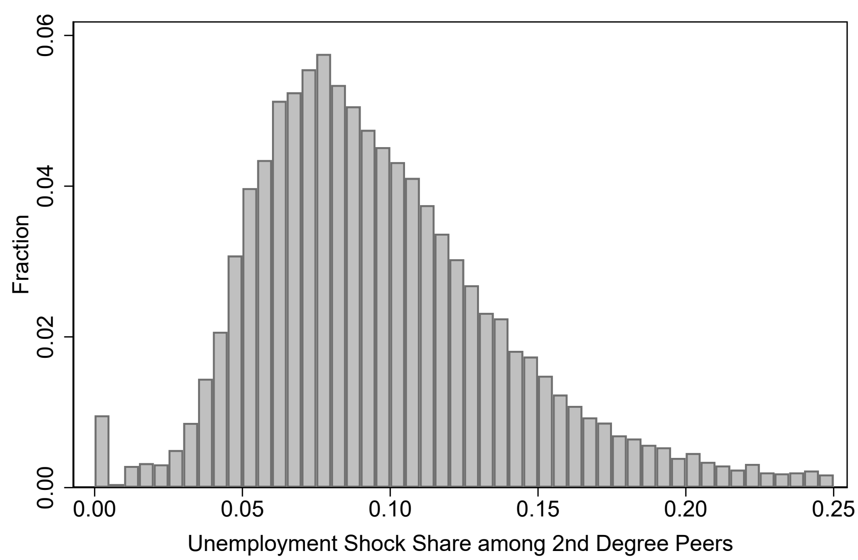
The main treatment in my analysis is unemployment shocks among second-degree peers. I obtain my measure of unemployment shocks from the central register for labor market statistics (CRAM).[4] The register includes individual unemployment at an annual level. I define an unemployment shock for individual i in year t with an indicator of the individual being unemployed for at least one month during year t. I restrict my focus to unemployment shocks longer than one month, to increase the probability that information about the unemployment shock is transmitted between peers. This may not be the case if the unemployment shock is very short. Additionally, if what I observe in the data is individuals switching between jobs, peers may talk about the event as a job transition rather than an unemployment shock, and this is not what I am interested in.[5]

[4] In Danish, the register is called Det Centrale Register for Arbejdsmarkedsstatistik.

[5] In a robustness check, I define unemployment as any amount of unemployment in year t and perform the

Figure 1 shows the distribution of unemployment shock shares among second-degree peers for all respondents. The average unemployment shock share is 8 pct., and 95 pct. of the respondents have an unemployment shock share among their second-degree peers below 15 pct. The mass point at zero is driven by respondents with a small number of second-degree peers. In particular, respondents whose unemployment shock share is zero on average have 22 second-degree peers, well below the unrestricted average of 1836, cf. Figure 4. In my analysis, I winsorize the unemployment shock share at the 1st and the 99th percentiles, to account for these outliers in either end of the distribution.

Figure 1: Distribution of Unemployment Shock Shares



This figure shows the distribution of unemployment shock shares among second-degree peers for all respondents. Individuals with unemployment shock shares larger than 0.25 (approximately 0.5 pct. of the sample) are excluded in the figure due to data restrictions from Statistics Denmark.

analysis with this measure. I report the results of this robustness check in Appendix B, and show that the alternative measure of unemployment has no significant effect on the results.

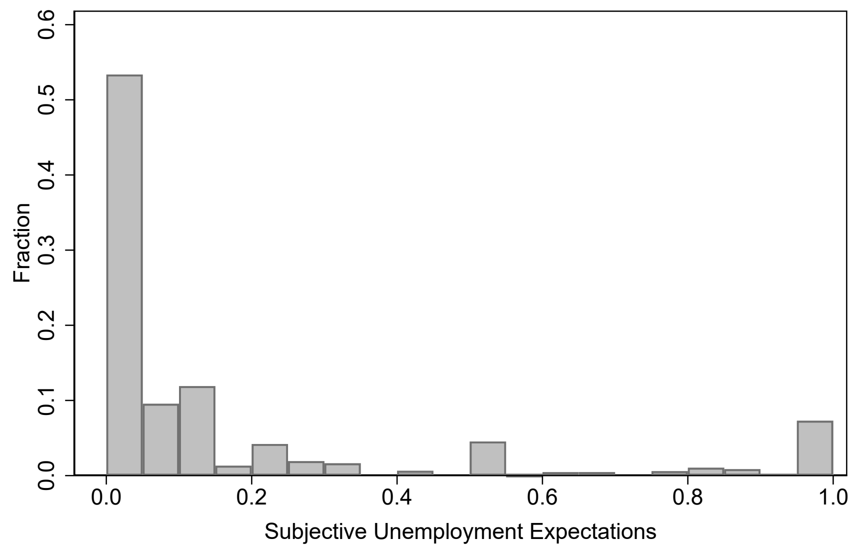
3.2 Survey Data

The administrative data is merged with the survey data using unique individual identifiers, ensuring that a given individual's survey responses are matched with the same individual's characteristics from the administrative data. The survey was fielded annually, in January, in the years 2010-2016. It was conducted by telephone and took 10 to 12 minutes to complete. The survey sampled respondents from a pool of randomly chosen Danes, who were active in the labor market at the time of the survey. From 2011 and forward, a subsample of respondents from the previous year were re-interviewed with a re-interview rate of approximately 75 pct. In total 11,511 individuals participated, yielding 33,624 observations due to the high re-interview rate. The survey included approximately 40 questions that covered a range of topics. To elicit subjective unemployment expectations, respondents were asked to report their estimated unemployment probability, inspired by Manski (2004). This yielded a probabilistic measure of subjective unemployment expectations. Specifically, the respondents were asked,

How do you assess the probability that you will experience a period without a job during the coming year? I would like you to state a number between 0 and 100, in which 0 means that you believe that, with certainty, the event will not occur and 100 means that you believe, with certainty, that the event definitely will occur.

The distribution of answers is shown in Figure 2. The distribution closely resembles the responses to a similar question from the Health and Retirement Study, in which respondents are also asked about their unemployment expectations in a probabilistic way (Hendren, 2017). We see mass points at 0 pct., 50 pct. and 100 pct. as well as a pattern of rounding in responses. These patterns are common in questions about probabilistic expectations, as highlighted by Bruine de Bruin et al. (2022). The average reported probability is 16.6 pct. Thus, individuals generally believe that there is a low probability that they will become unemployed. However, despite this fact, there is still great variation in expectations.

Figure 2: Distribution of Subjective Unemployment Expectations



This figure show the distribution of the survey elicited subjective unemployment expectations, $E_{i,t-1}[U_{i,t}]$ Answers have been scaled by 100.

4 Identification

In this section, I explain my strategy for identifying the effects of information about unemployment experiences passing between peers. I focus on unemployment shocks among second-degree peers in order to reduce the risk of any identified effect being driven by common shocks shared by both the individual and the peer experiencing the unemployment shock.

4.1 Identification of Information Transmission

A key challenge when identifying the effect of information transmission between peers is the presence of confounding factors that may drive a correlations in behavior between peers while not constituting an effect driven by the information transmission itself. This challenge mirrors the reflection problem (Manski, 1993), which differentiates between endogenous effects, exogenous effects, and correlated effects. Exogenous effects arise because individuals tend to select peers with similar observable and unobservable characteristics. For instance, peers with similar educational backgrounds or socioeconomic statuses may share other characteristics which cause them to behave similarly regardless of any direct influence between them. Correlated effects occur when peers experience shared shocks, such as local labor market downturns, which drive similar outcomes across individuals. Both exogenous and correlated effects complicate the identification of endogenous effects, which are the causal effects of information transmission. When examining the effect of peers' unemployment experiences on respondents' subjective expectations, the presence of exogenous and correlated effects make it difficult to isolate the role of information transmission.

To address the issue of exogenous and correlated effects, I follow Bramoullé et al. (2020) and De Giorgi et al. (2010) and rely on intransitive triads. Intransitive triads arise when the respondent, i and an individual k do not know each other, but share a common peer, j, as illustrated in figure 3. Consequently, k's unemployment experiences, can only affect i through information transmitted by j. By focusing on second-degree peers, I reduce the influence of selection into peer groups and common shocks, which are more likely to affect first-degree peers.

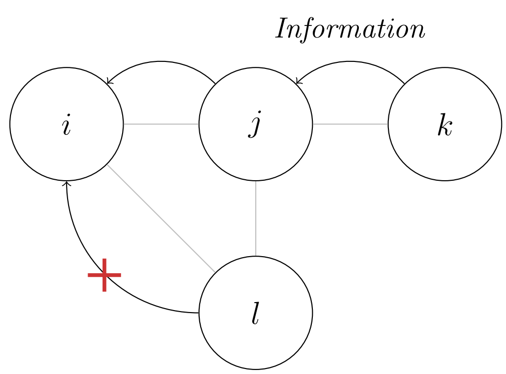


Figure 3: Intransitive Triads and Information Transmission

Relying on second-degree peers allows me to assume that their unemployment experiences are exogenous to the determinants of the respondents' subjective unemployment expectations.

Since respondents and their second-degree peers have not selected into the same peer group, this structure reduces the risk that correlations between individuals' expectations and their second-degree peers' unemployment experiences are driven by shared characteristics or experiences. To further mitigate potential biases, I include a comprehensive set of fine-grained fixed effects in my regression model, as explained in Section 4.3.

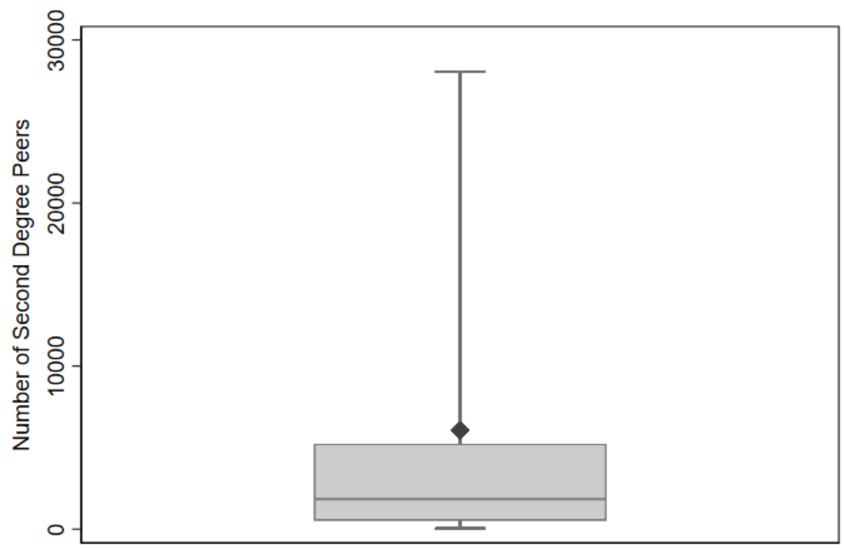
As the use of second-degree peers minimizes many confounding factors, the accuracy of my identification strategy hinges on correctly distinguishing between first- and second-degree peers (Bramoullé et al., 2020). If first-degree peers are misclassified as second-degree peers (e.g., l in Figure 3), their characteristics may have direct impacts on the respondent (i) which may bias the estimates. To increase the probability that intransitivity holds, I remove all second-degree peers who lives in the same municipality as the respondent. This step reduces the the risk that the respondent and their second-degree peers know each other directly through unobservable channels, while also minimizing the risk of shared local shocks, such as local aggregate demand shocks, which would give rise to spurious correlations.

After removing all second-degree peers who live in the same municipality as the individual, I find that the respondents, on average, have 6051 second-degree peers. The median is lower, at 1836. Figure 4 shows the distribution of the number of second-degree peers. While a vast majority of the respondents have fewer than 6000 second-degree peers, the distribution is right-skewed, with a small number of respondents having significantly larger peer groups.

4.2 Summary Statistics

Table 2 shows a summary of observable characteristics in 2016 for the full Danish population, the survey respondents, the survey respondents' first degree peers and the survey respondents' second-degree peers. The summary statistics show that survey respondents tend to be better educated and have higher income and savings than the general population. They are also less likely to experience unemployment and slightly more likely to be self-employed. This apparent selection in survey respondents is generally consistent with respondent patterns in

Figure 4: Distribution of Second-Degree Peers



The boxplot shows the 5th, 25th, 50th, 75th and 95th percentiles of the number of second-degree peers for the survey respondents. The diamond depicts the average. Due to regulation by Statistics Denmark, all percentiles are based on running averages over five observations other surveys. First degree peers show similar distinctions from the full population, which is to be expected, as individuals tend to sort into peer groups with similar individuals. However, second-degree peers more closely resemble the full population. This is particularly evident, when considering their education, income and wealth levels. The fact that the second degree peers most closely resemble the full population suggests that there is only little selection in second-degree peers and suggests that relying on second-degree peers do account for selection effects.

Table 2: Summary Statistics

	Full Population	Respondents	1^{st} Degree Peers	2^{nd} Degree Peers
Female	0.51	0.51	0.54	0.49
Age	49.96	51.19	46.65	46.30
Single	0.39	0.23	0.28	0.41
Unemployment	0.05	0.03	0.03	0.05
Self-Employed	0.04	0.06	0.03	0.05
Primary Educ. and High School	0.34	0.18	0.09	0.39
Vocational and Short Higher Educ.	0.37	0.43	0.41	0.38
Intermediate Higher Education	0.16	0.24	0.29	0.14
Long Higher Education	0.09	0.14	0.20	0.06
Gross Income (DKK)	330,942	437,852	463,022	310,173
Assets (DKK)	954,146	1,405,762	1,206,135	894,574
Debt (DKK)	561,133	867,442	819,072	546,685
Homeowner	0.47	0.69	0.63	0.45
Observations	4,437,851	11,511	930,598	3,174,845

The summary statistics are based on data from 2016. Female, single, unemployment, self-employment, homeowner and all education groups are indicators. All groups are restricted to only include individuals over the age of 20.

4.3 Estimating the Effect of Information Transmission on Expectations

To estimate the effect of information about unemployment experiences on the outcome of interest, $y_{i,t+1}$, I estimate equation 1.

$$y_{i,t+1} = \beta_0 + \beta_1 USS_{i,t} + \beta_2 U_{i,t} + \beta_3 X_{i,t} + \omega_{m,t} + \phi_{w,t} + \delta_{o,t} + \eta_{e,t} + \varepsilon_{i,t} \tag{1}$$

Here, i refers to individuals and t refers to years. $USS_{i,t}$ is the unemployment shock share among i's second-degree peers. $X_{i,t}$ is a vector of the individual's observable characteristics.

To address confounding factors, I include the individual's lagged unemployment status, $U_{i,t}$. This accounts for broader labor market trends and unobservable characteristics that simultaneously influence respondents' expectations and their exposure to peers' unemployment experiences. Lagged unemployment also captures path dependency, where prior unemployment affects both current expectations and future unemployment risks. Additionally, I include fixed effects for municipality×year, industry×year, occupation×year, and education×year.[6] These fixed effects control for common shocks, ensuring that any estimated effects of $USS_{i,t}$ on respondents' expectations are not driven by shared labor market conditions. The identification of the causal effect of second-degree peers' unemployment experiences rests on the assumption that, conditional on these controls and fixed effects, $USS_{i,t}$ affects the respondent only through information transmitted by first-degree peers. By focusing on second-degree peers and including an extensive number of controls, I aim to isolate the effects of information transmission while minimizing confounding from selection or shared shocks.

While my approach is designed to minimize biases from confounding and measurement error, certain limitations remain. Specifically, I cannot directly observe whether individuals communicate with their peers or the content of their discussions. Instead, I rely on second-degree peers' unemployment as a proxy for the information transmitted through so-

[6] I describe the classifications of education, occupation and industry used in table A1 in appendix A.

cial networks. This likely introduces measurement error, which should attenuate my estimates rather than inflating the estimated effects. Moreover, the causal interpretation of my results hinges on the assumption that I have adequately controlled for all potential confounders that could drive a positive correlation between peers' unemployment experiences and individuals' subjective unemployment expectations. By transparently acknowledging these potential limitations, I aim to provide cautious, but robust evidence on how information transmission shape subjective unemployment expectations. This should serve as a foundation for further investigation into the dynamics of social networks and expectations formation.

5 Results

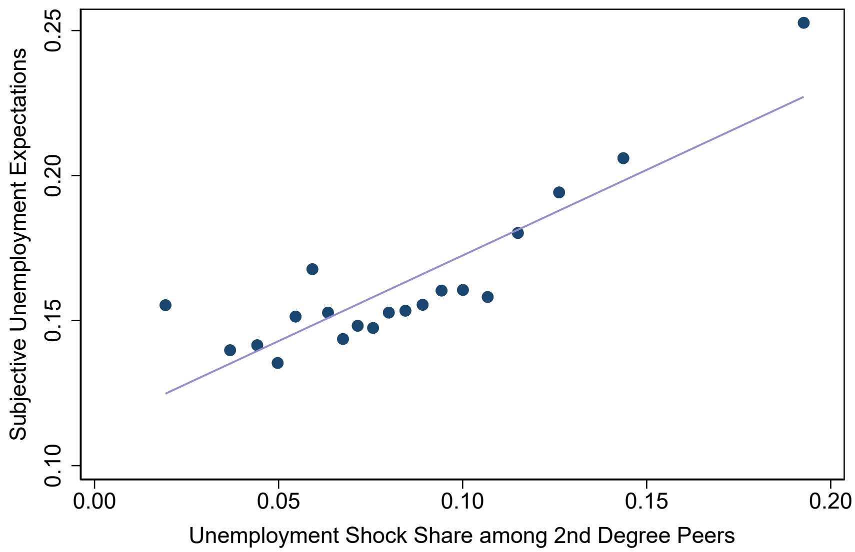
5.1 Peers' Unemployment Experiences Positively Affect Respondents' Expectations

I begin my results section by showing that information about unemployment shocks transmitted through social networks have significant effects on subjective unemployment expectations. Figure 5 shows the raw correlation between peers' unemployment experiences and the respondents' subjective unemployment expectations. The two are highly correlated. As reported in column 1 of table 3, a 1 pct. point increase in the share of peers who experienced unemployment in year t, is correlated with a 0.56 pct. point increase in the subjective unemployment expectations.[7]

Recognizing that this high correlation is likely driven, in part, by the presence of common shocks that influence both the respondent and their peers, I proceed by introducing controls and fixed effects to account for potential confounders. First, I control for the respondents' lagged unemployment status as well as observable characteristics such as gender, age, and

[7] In Appendix B, I define an unemployment shock share among the second-degree peers as any duration of unemployment during year t, rather than minimum one month of unemployment. As seen in table A2, this alternative measure of unemployment shocks does not qualitatively change the results.

Figure 5: Subjective Unemployment Expectations against Unemployment Shock Shares



This figure shows a binned scatterplot of the correlation between the respondents' expectations about their unemployment probability in year $t+1$, $E_{i,t}[U_{i,t+1}]$), against the share of their second-degree peers' who experience unemployment in t, $USS_{i,t}$.

immigration status (column 2). The correlation, which is now 0.36, remains strong and significant. Next, I instead include municipality×year, education×year, industry×year, and occupation×year fixed effects, which account for unobserved heterogeneity across local labor markets, educational backgrounds, industries, and occupations. The resulting estimate is 0.37 (column 3). Finally, I control for both observable characteristics and all fixed effects simultaneously (column 4). Even with this very extensive set of control variables included, the correlation remains robust and strong at 0.19. The robustness of the estimated effect, even after accounting for respondents' own unemployment history and potential common shocks, underscores the importance of information transmission through peer networks in shaping subjective unemployment expectations. The final estimate indicates that a one standard deviation increase in the share of unemployed second-degree peers leads to an increase in the subjective unemployment expectations of 0.7 pct. points which equals 6 pct. of the average reported level. This highlights the role of social networks as an informal channel for transmitting labor market information, with meaningful implications for how individuals perceive their own employment risks.[8]

[8]In appendix C I examine whether individuals with little labor market experience, rely more on the information they receive from their peers when forming their unemployment expectations. I find that younger respondents attach more weight to the information they receive about their peers' unemployment experiences than older respondents. This highlights the fact that peer effects play a larger role in expectations formation, for individuals with little experience of their own.

Table 3: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$

	(1)	(2)	(3)	(4)
$USS_{i,t}$	0.560***	0.356***	0.366***	0.187***
	(0.056)	(0.049)	(0.065)	(0.058)
Constant	0.069***	0.087*	0.085***	0.073
	(0.005)	(0.045)	(0.006)	(0.048)
Mean $E_{i,t}[U_{i,t+1}]$	0.116	0.116	0.116	0.116
Mean $USS_{i,t}$	0.083	0.083	0.083	0.083
Observations	23,159	23,159	23,159	23,159
R-squared	0.008	0.126	0.068	0.171
Controls		✓		✓
Municipality×Year FE			✓	✓
Education×Year FE			✓	✓
Industry×Year FE			✓	✓
Occupation×Year FE			✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second degree shares. Unemployment shocks measured as minimum one month of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's unemployment experience, gender, age dummies and immigration type dummies.

5.2 Do Peers' Unemployment Experiences Predict Actual Subsequent Unemployment Probabilities?

Having shown that peers' unemployment experiences affect subjective unemployment expectations, I next examine whether these experiences also predict the respondents' actual subsequent unemployment probabilities. Understanding this relationship is important for contextualizing the relevance of the information transmitted through social networks. The regression estimates are presented in table 4. Column 1 shows that the raw correlation between the share of peers' who experience unemployment and the respondents' realized unemployment is 0.72. Introducing controls for observable characteristics in column 2 reduces the estimate to 0.40, while including only the fixed effects in column 3 yields an estimate of 0.53. Finally, including both controls and fixed effects in column 4 further reduces the estimate to 0.27.

The decline in estimate size from 0.72 to 0.27 highlights the importance of addressing selection into peer groups and controlling for common shocks, as both factors drive a substantial portion of the observed correlation. However, the persistence of a positive and significant relationship suggests that peers' unemployment experiences contain information relevant to respondents' own unemployment risks, over and above what can be explained by the selection and common shocks which I account for by controlling for observables and fixed effects.

Additionally, the estimated effect of peers' unemployment experiences on subjective unemployment expectations (0.19) is not significantly different from the estimated effect on realized unemployment probabilities (0.27). The similarity in estimate size implies that individuals are, at least partially, able to internalize relevant information from their peers when forming expectations about their own unemployment risk. This finding underscores the informational value of social peers and their role in shaping individual perceptions of economic uncertainty.

Table 4: Realized Unemployment, $\mathbb{I}[U_{i,t+1} = 1]$

	(1)	(2)	(3)	(4)
$USS_{i,t}$	0.716***	0.403***	0.525***	0.268***
	(0.062)	(0.046)	(0.066)	(0.051)
Constant	-0.011**	-0.056	0.005	-0.069
	(0.005)	(0.043)	(0.005)	(0.044)
Mean $\mathbb{I}[U_{i,t+1}]$	0.048	0.048	0.048	0.048
Mean $USS_{i,t}$	0.083	0.083	0.083	0.083
Observations	23,159	23,159	23,159	23,159
R-squared	0.016	0.271	0.073	0.308
Controls		✓		✓
Municipality×Year FE			✓	✓
Education×Year FE			✓	✓
Industry×Year FE			✓	✓
Occupation×Year FE			✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second-degree peers. Unemployment shocks among second-degree peers measured as minimum one month of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's unemployment experience, gender, age dummies and immigration type dummies.

6 Behavioral Effects

Having established that information about peers' unemployment experiences affect subjective unemployment expectations, I now examine whether this translates into an effect the respondents' behavior. Previous literature has linked an increase in subjective unemployment expectations with self-insurance measures such as an increased probability of joining an unemployment insurance fund (Hartmann and Leth-Petersen, 2024), an increase in liquid savings (Pettinicchi and Vellekoop, 2019) and increased job search (Lizama and Villena-Roldán, 2019). I examine whether information about peers' unemployment experiences affect any of these outcomes, to identify whether the affect on subjective unemployment expectations translates into precautionary behavior.

6.1 Unemployment Insurance

I first consider whether peers' unemployment experiences affect the uptake of private unemployment insurance (UI). Denmark has a voluntary unemployment insurance scheme, which is heavily subsidized by the government. This keeps membership costs low, at approximately 500 DKK[9] per month. Despite the low costs, UI benefits are relatively generous. For individuals with low income, the replacement rate is 90 pct. However, benefits are capped at 18,133 DKK per month (2016 level), which equals the earnings level of a full-time, unskilled worker, paid the minimum rate. Thus, UI benefits in Denmark are generous relative to the cost of membership[10].

Peers' unemployment experiences may affect the decision to buy private UI through two channels. First, peers' unemployment experiences may increase the respondents' subjective unemployment probability, as shown in section 5.1. Respondents may to wish insure themselves against the perceived increased risk of unemployment by purchasing private unemploy-

[9] 1 USD $\approx$ 7 DKK.

[10] More information about private UI in Denmark can be found here `https://lifeindenmark.borger.dk/working/work-rights/unemployment-benefits`

ment insurance. Second, respondents may learn about the benefits of private unemployment insurance from unemployed peers who are currently receiving UI benefits. Respondents may opt in or out of private UI depending on whether the information they receive from their peers is primarily positive or negative relative to their own prior knowledge.

To examine whether peers' unemployment experiences affect the uptake of private UI, I regress a dummy for having private UI, $\mathbb{I}[UI_{i,t+1}]$ on $USS_{i,t}$,

$$\mathbb{I}[UI_{i,t+1}] = \gamma_0 + \gamma_1 USS_{i,t} + \gamma_2 X_{i,t} + \omega_{m,t} + \phi_{w,t} + \delta_{o,t} + \eta_{e,t} + \varepsilon_{i,t} \tag{2}$$

I present the results in table 5. I find an initial positive correlation of 0.65 which is highly significant. Controlling for observables and including fixed effects lowers the correlation slightly. In column (4) I include both controls and fixed effects and I find an effect size of 0.51. This indicates that a one standard deviation in $USS_{i,t}$ leads to a 1.9 pct. point increase in the probability of having $\mathbb{I}[UI_{i,t+1}]$. This is an economically significant effect, especially in light of the fact that on average 84 pct. of wage earning respondents have private UI in the years 2010-2016, and that there is little change in this statistics from year to year.

In column (5), I estimate the effect of $E_{i,t}[U_{i,t+1}]$ on $\mathbb{I}[UI_{i,t+1}]$ using $USS_{i,t}$ as an instrument for $E_{i,t}[U_{i,t+1}]$, in order to examine the effect of peers' unemployment experiences that affect UI uptake through an effect on subjective unemployment expectations. This relies on the assumption that the uptake of UI is only affected by $USS_{i,t}$ through unemployment expectations. As stated above, this may not be the case. Using this instrumental approach, I find that an increase in $E_{i,t}[U_{i,t+1}]$ of 1 pct. point leads to an 0.05 pct. point increase in the probability of having private UI.

6.2 Liquid Savings

Next, I examine whether peers' unemployment experiences affect liquid savings. As UI provides limited coverage for most individuals, liquid savings may act as a complementary resource to UI. Consequently, they may increase their liquid savings in response to learn-

Table 5: Unemployment Insurance, $\mathbb{I}[UI_{i,t+1}]$

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	IV
$USS_{i,t}$	0.649***	0.600***	0.626***	0.505***	
	(0.090)	(0.085)	(0.108)	(0.098)	
$E_{i,t}[U_{i,t+1}]$					0.045**
					(0.023)
Constant	0.831***	0.590***	0.833***	0.637***	-2.629
	(0.009)	(0.078)	(0.010)	(0.076)	(1.926)
Mean $\mathbb{I}[UI_{i,t+1}]$	0.885	0.885	0.885	0.885	0.885
Mean $USS_{i,t}$	0.083	0.083	0.083	0.083	0.083
Observations	23,159	23,159	23,159	23,159	23,159
R-squared	0.006	0.189	0.060	0.237	
Controls		✓		✓	✓
Municipality×Year FE			✓	✓	✓
Education×Year FE			✓	✓	✓
Industry×Year FE			✓	✓	✓
Occupation×Year FE			✓	✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second-degree peers. Unemployment shocks measured as minimum one month of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's gender, age dummies and immigration type dummies. Individuals who experience unemployment in year $t+1$ excluded.

ing about their peers' unemployment experiences (Pettinicchi and Vellekoop, 2019). While previous work has found that subjective unemployment expectations affect liquid savings, it is important to consider the practical implications of this relationship. Unlike purchasing private UI, which provides a direct and pre-defined form of protection, increasing one's liquid savings requires ongoing effort and discipline, as individuals must actively and repeatedly deposit funds into savings accounts over a period of time. Such discipline may be hard to obtain (Thaler and Shefrin, 1981). Consequently, it is not immediately obvious whether one should expect to find an effect of peers' unemployment experiences on liquid savings.

I estimate equation 3, in which $LA_{i,t+1}$ is individual i's cash holding in banks in year t and $\bar{Y}_{i,2008-2009}$ is their average disposable income in 2008-2009.

$$LA_{i,t+1}/\bar{Y}_{i,2008-2009} = \tau_0 + \tau_1 USS_{i,t} + \tau_2 X_{i,t} + \omega_{m,t} + \phi_{w,t} + \delta_{o,t} + \eta_{e,t} + \varepsilon_{i,t} \tag{3}$$

The regression results are presented in table 6. It is immediately clear that the analysis reveals no statistically significant association between peers' unemployment experiences and liquid savings. However, it is important to note that the estimates exhibit imprecision. There does appear to be a negative effect of the replacement rate, suggesting that individuals facing greater income loss in the event of unemployment tend to maintain higher savings rates. Given that UI offers only partial protection, augmenting it with liquid savings may serve to mitigate consumption fluctuations across employment states. However, the estimated effect of the replacement rate is insignificant for liquidity constrained individuals when I include fixed effects in the regression, and even becomes insignificant when controlling for both observable characteristics and fixed effects for individuals who are not liquidity constrained.

6.3 Job Search

Finally, I consider whether whether peers' unemployment experiences affect job-to-job transitions. As shown by Lizama and Villena-Roldán (2019) and Fujita (2012), an increase in the perceived risk of layoff is positively correlated with on-the-job search effort. As I have

Table 6: Liquid Assets, $LA_{i,t+1}/\bar{Y}_{i,2008-2009}$

	Liquidity Constrained			Not Liquidity Constrained		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
$USS_{i,t}$	-0.152	-0.013	-0.070	-0.493	-0.227	-0.174
	(0.122)	(0.143)	(0.139)	(0.412)	(0.550)	(0.538)
$rr_{i,t}$	-0.093***	-0.003	-0.001	-0.555***	-0.245***	-0.022
	(0.023)	(0.021)	(0.020)	(0.070)	(0.082)	(0.099)
Constant	0.257***	0.183***	0.123	1.394***	1.168***	0.794***
	(0.015)	(0.015)	(0.081)	(0.048)	(0.058)	(0.149)
Average $LA_{i,t+1}/\bar{Y}_{i,2008-2009}$	0.196	0.180	0.180	1.088	1.030	1.030
Average $USS_{i,t}$	0.086	0.085	0.085	0.082	0.082	0.082
Observations	14,458	10,334	10,334	18,248	12,783	12,783
R-squared	0.003	0.085	0.095	0.014	0.094	0.116
Controls			✓			✓
Municipality×Year FE		✓	✓		✓	✓
Education×Year FE		✓	✓		✓	✓
Industry×Year FE		✓	✓		✓	✓
Occupation×Year FE		✓	✓		✓	✓

Liquid assets, $LA_{i,t+1}$ measured as cash in banks. $\bar{Y}_{i,2008-2009}$ is average disposable income in the years 2008-2009. Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second-degree peers. Unemployment shocks measured as minimum one month of unemployment in year t. Both $USS_{i,t}$ and $LA_{i,t+1}/\bar{Y}_{i,2008-2009}$ are winsorized at 1st and 99th percentiles. Controls include i's unemployment experience, gender, age dummies and immigration type dummies.

shown that peers' unemployment experiences positively affect subjective unemployment expectations, I hypothesize that they also have a positive effect on search effort. While I cannot observe search effort in my data, I can observe job-to-job transitions. As noted by Fujita (2012), job-to-job transitions occur more often for individuals who engage in on-the-job search, than for those who do not, and consequently, I consider job-to-job transitions as a proxy for on-the-job search.

I estimate equation 4, in which $EE_{i,t+1}$ is an indicator for individual i's changing jobs in year $t+1$, with no unemployment spell in between employments.

$$EE_{i,t+1} = \tau_0 + \tau_1 USS_{i,t} + \tau_2 X_{i,t} + \omega_{m,t} + \phi_{w,t} + \delta_{o,t} + \eta_{e,t} + \varepsilon_{i,t} \tag{4}$$

The regression results are presented in table 7. In the first two columns, where I do not include any fixed effects, I find no significant correlation between the share of peers who have recently experienced unemployment and the probability of job-to-job transitions. However, this changes when I do include fixed effects. The inclusion of fixed effects permits a positive and significant estimate of the relationship between the share of peers who have recently experienced unemployment and the probability of job-to-job transitions. In particular, when including both fixed effects and controlling for observables, as I do in column 4, I find that a one pct. point increase in $USS_{i,t}$ leads to a 0.17 pct. point increase in the probability of a job-to-job transition.

Table 7: Employment to Employment, $EE_{i,t+1}$

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	IV
$USS_{i,t}$	0.062	0.028	0.223***	0.171**	
	(0.058)	(0.058)	(0.071)	(0.072)	
$E_{i,t}[U_{i,t+1}]$					0.017*
					(0.010)
Constant	0.085***	0.147**	0.072***	0.150**	-0.464
	(0.005)	(0.068)	(0.006)	(0.071)	(0.605)
Mean $EE_{i,t+1}$	0.090	0.090	0.090	0.090	0.090
Mean $USS_{i,t}$	0.082	0.082	0.082	0.082	0.076
Observations	21,355	21,355	21,355	21,355	21,355
R-squared	0.000	0.016	0.048	0.062	
Controls		✓		✓	✓
Municipality×Year FE			✓	✓	✓
Education×Year FE			✓	✓	✓
Industry×Year FE			✓	✓	✓
Occupation×Year FE			✓	✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second-degree peers. Unemployment shocks measured as minimum one month of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's gender, age dummies and immigration type dummies. Individuals who experience unemployment in year $t+1$ excluded.

To investigate whether respondents change jobs in response to their peers' unemployment experiences as a strategy to enhance their job security, I examine whether respondents are more likely to switch to an employer with a lower turnover rate when they learn of their peers' unemployment experiences. I calculate turnover rates for each employer by dividing the number of employees who leave the employer between November in year t and November year $t+1$ by the total number of employees in November, year t. Based on these turnover rates, I construct an indicator, $\mathbb{I}[LT_{i,t+1}]$, that is equal to one when an individual changes employer, and the new employer has a lower turnover rate than the old employer.

I estimate the relationship between peers' unemployment experiences and the probability of the individual transitioning to an employer with a lower turnover rate. The resulting estimates are presented in table 8. As seen in column 1, there is a positive and highly significant correlation between $USS_{i,t}$ and the probability of transitioning to an employer with a lower turnover rate. In column 2, I control for observable characteristics, which turns the estimated correlation insignificant. However, also including fixed effects, as I do in column 4, I find a significant effect of 0.14. This means that a 1 pct. point increase in the share of peers who have recently experienced unemployment, leads to a 0.14 pct. point increase in the probability that the individuals will transition to an employer with a lower turnover rate. This indicates that individuals who increase their subjective unemployment expectations due to information they receive about their peers' unemployment experiences, may search for more stable employment in response. However, using an IV approach, in which I use $USS_{i,t}$ as an instrument for unemployment expectations, I find a smaller effect, which is only significant at a 10 pct. significant level. This may be due to the fact that $USS_{i,t}$ only explains part of the variation in $E_{i,t}[U_{i,t+1}]$. However, it is reassuring that the estimate is still positive, and weakly significant, and thus still indicates that individuals who increase their unemployment expectations upon learning of their peers' unemployment experiences, subsequently seek more stable employment.

Table 8: New Job, Lower Turnover Rate, $\mathbb{I}[LT_{i,t+1}]$

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	IV
$USS_{i,t}$	0.188***	0.013	0.283***	0.136**	
	(0.049)	(0.047)	(0.059)	(0.058)	
$E_{i,t}[U_{i,t+1}]$					0.008*
					(0.004)
Constant	0.038***	0.015	0.030***	0.000	-0.475
	(0.004)	(0.036)	(0.005)	(0.039)	(0.364)
Mean $\mathbb{I}[LT_{i,t+1}]$	0.054	0.054	0.054	0.054	0.054
Mean $USS_{i,t}$	0.083	0.083	0.083	0.083	0.083
Observations	20,163	20,163	20,163	20,163	20,163
R-squared	0.001	0.068	0.045	0.109	
Controls		✓		✓	✓
Municipality×Year FE			✓	✓	✓
Education×Year FE			✓	✓	✓
Industry×Year FE			✓	✓	✓
Occupation×Year FE			✓	✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second-degree peers. Unemployment shocks measured as minimum one month of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's unemployment experience, gender, age dummies and immigration type dummies.

7 Conclusion

In this paper, I have examined how information about peers' unemployment experiences affects subjective unemployment expectations and subsequent self-insurance behavior. To do so, I combined survey elicited subjective unemployment expectations with Danish administrative data. I exploited the Danish administrative data to map social networks for all the survey respondents, and further identity unemployment experiences for all individuals in the social networks.

I showed that peers' unemployment experiences predict the respondents' subjective unemployment expectations. This holds even when I include a number of controls and fine grained fixed effects that capture common shocks that affect both the respondents and their peers. I find that a 1 pct. point increase in the share of peers' who experience unemployment, predicts a 0.19 pct. point increase in the respondents subjective unemployment expectations. This highlights the role of social networks as an informal channel for transmitting labor market information, with meaningful implications for how individuals perceive their own employment risks. Next, I examined whether individuals take action to self-insure against potential unemployment after learning of their peers' unemployment experiences. I showed that upon learning of their peers' unemployment experiences, individuals self-insure against the perceived increase in the unemployment risk, by joining a private unemployment insurance fond and transitioning to jobs with lower turnover rates.

References

Alt, J. E., A. Jensen, H. Larreguy, D. D. Lassen, and J. Marshall (2022). Diffusing Political Concerns: How Unemployment Information Passed between Social Ties Influences Danish Voters. *Journal of Politics 84*(1), 383–405.

Bailey, M., R. Cao, T. Kuchler, and J. Stroebel (2018). The Economic Effects of Social Networks: Evidence from the Housing Market. *Journal of Political Economy 126*(6), 2224–2276.

Bailey, M., E. Dávila, T. Kuchler, and J. Stroebel (2019). House Price Beliefs and Mortgage Leverage Choice. *Review of Economic Studies 86*, 2403–2452.

Bailey, M., D. Johnston, M. Koenen, D. Russel, and J. Stroebel (2024, 6). Social Networks Shape Beliefs and Behavior: Evidence from Social Distancing During the COVID-19 Pandemic. *Journal of Political Economy Microeconomics 2*(3), 463–494.

Balleer, A., G. Duernecker, S. Forstner, and J. Goensch (2023). Biased Expectations and Labor Market Outcomes : Evidence from German Survey Data and Implications for the East-West Wage Gap. *CESifo Working Papers 10336*, 1–29.

Bramoullé, Y., H. Djebbari, and B. Fortin (2009). Identification of Peer Effects Through Social Networks. *Journal of Econometrics 150*(1), 41–55.

Bramoullé, Y., H. Djebbari, and B. Fortin (2020). Peer Effects in Networks: A Survey. *Annual Review of Economics 12*, 603–629.

Bruine de Bruin, W., A. Chin, J. Dominitz, and W. van der Klaauw (2022). Household Surveys and Probabilistic Questions. In *Handbook of Economic Expectations*, pp. 3–31. Elsevier Inc.

Campbell, D., A. Carruth, A. Dickerson, and F. Green (2007). Job Insecurity and Wages. *The Economic Journal 117*(518), 544–566.

Chetty, R., N. Hendren, and L. F. Katz (2016). The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment. *American Economic Review 106*(4), 855–902.

Cingano, F. and A. Rosolia (2012). People I Know: Job Search and Social Networks. *Journal of Labor Economics 30*(2), 291–332.

Dahl, G. B., K. V. Løken, and M. Mogstad (2014). Peer Effects in Program Participation. *American Economic Review 104*(7), 2049–2074.

De Giorgi, G., A. Frederiksen, and L. Pistaferri (2020). Consumption Network Effects. *The Review of Economic Studies 87*, 130–163.

De Giorgi, G., M. Pellizzari, and S. Redaelli (2010). Identification of Social Interactions through Partially Overlapping Peer Groups. *American Economic Journal: Applied Economics 2*(2), 241–275.

Eliason, M., L. Hensvik, F. Kramarz, and O. N. Skans (2023). Social Connections and the Sorting of Workers to Firms. *Journal of Econometrics 233*(2), 468–506.

Fujita, S. (2012). An Empirical Analysis of On-the-Job Search and Job-to-Job Transitions. *Federal Reserve Bank of Philadelphia, Working Paper 10-34*, 1–28.

Glitz, A. (2017). Coworker Networks in the Labour Market. *Labour Economics 44*, 218–230.

Glitz, A. and R. Vejlin (2021). Learning Through Coworker Referrals. *Review of Economic Dynamics 42*, 37–71.

Hartmann, I. M. and S. Leth-Petersen (2024, 10). Subjective Unemployment Expectations and (Self-)Insurance. *Labour Economics 90*.

Hendren, N. (2017). Knowledge of Future Job Loss and Implications for Unemployment Insurance. *American Economic Review 107*(7), 1778–1823.

Kramarz, F. and O. N. Skans (2014). When Stong Ties are Strong: Networks and Youth Labour Market Entry. *Review of Economic Studies 81*(3), 1164–1200.

Kuchler, T. and J. Stroebel (2021). Social Finance. *Annual Review of Financial Economics 13*, 37–55.

Lizama, C. and B. Villena-Roldán (2019). Avoiding Layoffs: On-the-job Search and Partial Insurance. *Working Paper*, 1–31.

Malmendier, U. (2021). Exposure, Experience, and Expertise: Why Personal Histories Matter in Economics. *NBER Working Paper 29336*, 1–55.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies 60*(3), 531–542.

Manski, C. F. (2004). Measuring Expectations. *Econometrica 72*(5), 1329–1376.

Mayer, M. (2023). Climate Change Concerns and Information Spillovers from Socially-Connected Friends. *IWH Discussion Papers 2*(2023), 1–25.

Mueller, A. I. and J. Spinnewijn (2022). Expectations Data, Labor Market and Job Search. In *Handbook of Economic Expectations*.

Pettinicchi, Y. and N. Vellekoop (2019). Job Loss Expectations, Durable Consumption and Household Finances: Evidence from Linked Survey Data. *SAFE Working Paper 249*.

Sheridan, A. (2019). Learning About Social Networks from Mobile Money Transfers. *Working Paper*, 1–35.

Statistics Denmark (2017). Statistisk Tiårsoversigt. Technical report.

Statistics Denmark (2019). DST Analyse: De Fleste Flytninger er Over Korte Afstande. Technical Report November.

Stephens, M. (2004). Job Loss Expectations , Realizations , and Household Consumption Behavior. *The Review of Economics and Statistics 86*(1), 253–269.

Thaler, R. H. and H. M. Shefrin (1981, 4). An Economic Theory of Self-Control. *Journal of Political Economy 89*(2), 392–406.

The European Commission (2005). Special Eurobarometer: Social Capital. Technical report, European Commission.

Appendices

to

Information Transmission and Subjective Unemployment Expectations

Ida Maria Hartmann

A Education, Occupation and Industry Classification

Table A1 shows the education, occupation and industry classification that I use to absorb fixed effects in the regressions.

B Robustness Checks

B.1 Alternative Measure of Unemployment

To ensure that the results in section 5.1 are robust to different measures of unemployment shocks, I perform the analyses with an alternative measure. In the main analysis, I define an unemployment shock as any unemployment spell, with a duration longer than one month. Here, I define an unemployment shock as any duration of unemployment in a given year. I then estimate equation 1 with the measure as the outcome. The results are shown in table A2. The sign and significance levels of the estimates are the same as in table 3. However, the size of the β_1 estimate is smaller. This may be due to the fact, that when I define unemployment as any duration of unemployment, I also include some very short unemployment shocks in the unemployment shock shares among second degree peers, $USS_{i,t}$. If individuals do not talk about very short unemployment shocks, using any duration of unemployment as the outcome may add noise to the regression, and thus attenuate the estimates. A similar issue arises if the very short unemployment spells are mainly experienced by individuals who are in between jobs, in which case peers may not refer to these experiences as unemployment. Despite these concerns, the fact that the estimates in table A2 are not significantly different from those in table 3 is reassuring.

Table A1: Education, Occupation and Industry Classification

Education Classification
1: Primary school
2: Regular high school
3: Business high school
4: Vocational school
5: Short higher education
6: Intermediate higher education
7: Bachelor's degree
8: Long higher education (university)
9: Research
Occupation Classification
1: Military
2: Management
3: Work that requires knowledge at the highest level within that field
4: Work that requires knowledge at the intermediate level within that field
5: Office work and customer service
6: Service and sales
7: Agriculture, forestry and fishery
8: Craftsmanship
9: Machine operator, installation and transportation
10: Other manual work
Industry Classification
1: Agriculture and fishery
2: Industry
3: Construction
4: Trade and transport
5: Information and communication
6: Finance and insurance
7: Real estate and rental service
8: Service business
9: Public administration, teaching and healthcare
10: Culture and other services

Table A2: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$

	(1)	(2)	(3)	(4)	(5)
$USS_{i,t}$	46.759***	25.414***	29.271***	28.497***	15.192***
	(4.654)	(3.912)	(4.825)	(5.206)	(4.637)
Constant	11.409***	18.871***	8.530***	8.607***	7.187
	(0.502)	(4.811)	(0.510)	(0.550)	(4.777)
Mean $E_{i,t}[U_{i,t+1}]$	16.286	16.237	11.564	11.560	11.560
Mean $USS_{i,t}$	0.105	0.105	0.104	0.104	0.104
Observations	33,217	33,126	23,169	23,159	23,159
R-squared	0.006	0.145	0.040	0.068	0.171
Controls		✓			✓
Municipality FE			✓		
Education FE			✓		
Industry FE			✓		
Occupation FE			✓		
Year FE			✓		
Municipality×Year FE				✓	✓
Education×Year FE				✓	✓
Industry×Year FE				✓	✓
Occupation×Year FE				✓	✓

Standard errors in parentheses, clustered by individual, *** p<0.001, ** p<0.05, * p<0.1. $USS_{i,t}$ is unemployment shock shares among second degree shares. Unemployment shocks measured as any duration of unemployment in year t. Unemployment shock share winsorized at 1st and 99th percentiles. Controls include i's unemployment experience, gender, age dummies and immigration type dummies.