CENTER FOR ECONOMIC BEHAVIOR & INEQUALITY

CEBI WORKING PAPER SERIES

Working Paper 08/25

SUBJECTIVE UNEMPLOYMENT EXPECTATIONS AND PRECAUTIONARY BEHAVIOR IN THE SHADOW OF PEER JOB LOSS

Ida Maria Hartmann

ISSN 2596-447X

CEBI
Department of Economics
University of Copenhagen
www.cebi.ku.dk

Subjective Unemployment Expectations and Precautionary Behavior in the Shadow of Peer Job Loss

Ida Maria Hartmann*

August 2025

Abstract

I examine whether individuals' subjective unemployment expectations and self-insurance behavior are systematically related to unemployment experiences within their social networks. Using a combination of survey-elicited subjective unemployment expectations and Danish administrative data, I document three main findings. First, peer job loss is strongly predictive of individuals' own future unemployment risk, even after controlling for fixed effects and prior outcomes — suggesting that peer unemployment carries information about latent labor market conditions. Second, individuals' subjective unemployment expectations respond to recent unemployment among peers, particularly when the individuals have little experience of their own. Third, peer job loss exposure is associated with precautionary behavior, including higher take-up of private unemployment insurance and increased transitions to lower-turnover jobs.

Keywords: Expectations, Information, Unemployment, Self-Insurance

JEL classification: D83, J64

*PhD fellow at Center for Economic Behavior and Inequality (CEBI), University of Copenhagen. Email: imh@econ.ku.dk. The activities of CEBI are financed by the Danish National Research Foundation grant DNRF134.

1 Introduction

The labor market is inherently uncertain. Workers rarely possess full information about their individual unemployment risk, so how do they prepare for a potential adverse shock? A growing body of research shows that subjective expectations are one key input. For example, subjective unemployment expectations are important for precautionary behavior, shaping how people insure and save (Hendren, 2017; Lusardi, 1998; Carroll et al., 2003; Hartmann and Leth-Petersen, 2024). Consequently, understanding how these subjective expectations are formed offers an important insight into how people prepare. Prior research has shown that individuals often rely on their own past experiences to form such expectations (Kuchler and Zafar, 2019; Malmendier, 2021). However, these personal signals are often weak or entirely absent—particularly for younger workers or those with limited labor market experience. Formal labor market indicators, such as macroeconomic statistics or industry trends, are another potential source of information. Yet these signals are often published with delays, reported in aggregated form, and may not resonate well with the individual (Malmendier and Veldkamp, 2022). In such cases, social networks may play a critical informational role: The job loss of a sibling, a former classmate, or a coworker can serve as a salient and potentially informative signal. While these peer events may reflect localized disruptions, they may also carry broader signals about aggregate conditions that have not yet been captured in official statistics or widely reported indicators. 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.

In this paper, I examine whether individuals' subjective unemployment expectations and self-insurance behavior are systematically related to unemployment experiences within their social networks. To do so, I leverage a 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. I merge this information with a survey, conducted annually from 2010 to 2016, which elicited 11,500 representative respondents' subjective unemployment expectations in a probabilistic manner (Manski, 2004). The structure and timing of the data are critical for identification. For each survey wave, I observe realized unemployment among peers in the previous calendar year, before subjective unemployment expectations are elicited. Respondents are asked to state their expectations about unemployment in the coming year, allowing me to study how prior peer outcomes relate to expectations about future personal risk.

To identify patterns consistent with information transmission, I follow a standard approach in the peer effects literature (e.g., Bramoullé et al. (2009); De Giorgi et al. (2010)) and leverage variation in second-degree peer experiences, i.e., unemployment shocks among individuals who are connected to the respondent only indirectly through a mutual first-degree connection, such as a sibling's classmate or a coworker's partner. These second-degree ties are likely to be socially relevant, yet not subject to the same degree of endogenous formation or direct mutual influence, thereby reducing the risk of confounding from shared environments or other information sources. To further isolate informational effects from exposure to common shocks, I control for an extensive set of fixed effects (municipality×year, education×year, industry×year, and occupation×year), exclude second-degree peers who reside in the respondent's municipality, and account for the respondent's own unemployment history. This design substantially limits the potential for bias from geographic spillovers, industry-wide shocks, or shared labor market conditions that are easily observable through other sources of information.

I begin by documenting that peer unemployment is predictive of an individual's own unemployment risk. Specifically, a one pct. point increase in the share of unemployed second-degree peers in year t is correlated with a 0.7 pct. point increase in the individual's probability of becoming unemployed in year $t+1$. While the magnitude of the correlation decreases to 0.3 after conditioning on observable characteristics, individual unemployment history, and fixed effects, it remains positive and highly significant. Importantly, the use of second degree peers, together with the fixed effects and controls, substantially limits the potential for bias from other information sources. The finding thus suggests that peer unemployment serves as a proxy for latent changes in labor market conditions, changes that are difficult for individuals to observe directly through other sources.

Next, I show that individuals' expectations about their own unemployment risk are systematically related to recent unemployment shocks experienced by their peers. I find that a one percentage point increase in the share of unemployed peers is associated with a 0.2 percentage point increase in individuals' subjective unemployment expectations. This suggests that social networks may be an important channel for the transmission of labor market information, feeding into subjective unemployment expectations. I present a series of heterogeneity analyses that further support that this relationship is driven by information transmission. The relationship is particularly strong among individuals with limited labor market experience of their own, such as younger workers and those with low tenure, suggesting that peer signals serve as substitutes for personal information. Responsiveness is also greater when the information comes from a colleague rather than from other types of connections, consistent with individuals placing more weight on economically relevant signals. Finally, respondents with smaller social networks exhibit stronger expectation updates, indicating greater reliance on scarce informational input.

Third, I examine whether elevated perceived unemployment risk, informed by peer experiences, is associated with precautionary behavior. I begin by analyzing the uptake of private unemployment insurance (UI). A higher share of unemployed peers is associated with a significantly greater likelihood of purchasing private UI: specifically, a one percentage point increase in peer unemployment corresponds to a 0.05 percentage point increase in the probability that an individual holds private UI coverage. Next, I examine whether individuals engage in two types of informal self-insurance: Liquid savings and job-to-job transitions. I find no measurable effect on liquid savings. However, I document that individuals with a higher share of recently unemployed peers are more likely to transition between jobs, and that these transitions in particular happen toward positions with lower turnover rates. This pattern is consistent with a precautionary adjustment mechanism, in which individuals respond to perceived increases in labor market risk by reallocating toward more stable employment opportunities.

Together, these results suggest that individuals incorporate information about their peers' unemployment shocks into their subjective unemployment expectations, and that these expectations are associated with behavioral patterns consistent with forward-looking economic decision-making. These results support the interpretation that individuals treat peer job loss as an informative signal of their own latent labor market risk. Socially proximate experiences appear to shape not only expectations, but also the decisions individuals make to prepare for uncertain future outcomes. In this way, social networks may play a broader role in labor market adjustment than previously recognized, not only facilitating information flows about opportunities, but also transmitting signals that inform risk perception and behavioral adaptation.

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 peers shape important economic decisions including consumption, job search, voting, and re-employment opportunities (Kuchler and Stroebel, 2021; De Giorgi et al., 2020; Chetty et al., 2016; Dahl et al., 2014). The second is the literature on subjective expectations, from which we know that individuals' subjective unemployment expectations are predictive of realized outcomes 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 early insights into the interplay between peer effects and subjective expectations.

A number of studies document that individuals draw on peer information in labor market settings. Glitz and Vejlin (2021) and Kramarz and Skans (2014) show that referrals and peer networks influence job access and match quality. Eliason et al. (2023) demonstrate that displaced Swedish workers are more likely to be rehired at firms employing their peers. Cingano and Rosolia (2012) show that peer employment affects job-finding rates, consistent with information transmission. However, while these papers establish that peers shape outcomes, they do not comment on whether such experiences are internalized into subjective expectations.

Work in the expectations literature shows that individuals tend to overestimate their risk of unemployment, but that expectations remain predictive of actual outcomes and behavior (Balleer et al., 2023; Mueller and Spinnewijn, 2022). Expectations have also been found to relate to past experiences (Campbell et al., 2007; Kuchler and Zafar, 2019; Malmendier, 2021). However, less is known about whether subjective expectations are shaped by others' experiences, especially in the labor market. Recent studies provide first evidence that other types of subjective expectations are shaped by the experiences of peers. Bailey et al. (2018) find that peers' housing outcomes affect individual beliefs about home prices. Mayer (2023) show that beliefs about climate change are influenced by peer exposure to weather shocks. And Bailey et al. (2024) demonstrate that beliefs about health risks during COVID-19 were shaped by peer experience. In the labor market context, Alt et al. (2022) show that peer unemployment shocks shift political preferences, potentially by increasing personal risk perceptions.

This paper contributes by showing that subjective unemployment expectations are systematically related to peer unemployment experiences, particularly when information comes from coworkers and for individuals with limited personal experience. These patterns suggest that social networks act as informational environments through which individuals update their expectations, highlighting a previously understudied channel of expectations formation under uncertainty.

2 Social Networks and Information Transmission

Social networks arise across many different domains. In this paper, I focus on three peer groups that are both socially salient and relevant: family members, coworkers, and schoolmates. These groups are central to individuals' social environments and commonly serve as settings for information exchange about labor market conditions. Prior work emphasizes that peer groups are not just channels for exposure, but also shape how information is weighted and internalized. In particular, Malmendier and Veldkamp (2022) argue that information resonates more strongly when it comes from peers with shared characteristics or environments. This provides a rationale for why experiences within these peer domains may influence individuals' perceptions of their own economic risks.

For many, family is the core of the social network. 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 also represent a meaningful peer group 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 work-based networks frequently extend into broader social life. 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. The shared occupational setting may enhance both the perceived relevance and resonance of labor market related information.

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, expanding their networks geographically and demographically. Social ties in Denmark are typically stable throughout adulthood, with few individuals moving, and most moves being relatively short distance.[1]

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. Peers in these networks are not only frequent sources of interaction, but also likely to be seen as trustworthy and personally relevant sources of economic information.

3 Identification

In this section, I outline the empirical strategy used to isolate patterns consistent with information transmission through social networks. To this end, I follow the peer effects literature (Bramoullé et al., 2020; De Giorgi et al., 2010) and leverage variation in the experiences of second-degree peers, i.e., individuals connected to the respondent through a mutual first-degree peer but with no direct connection to the respondent themselves.

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

3.1 Second-Degree Peers and Intransitive Triads

A key challenge in estimating information transmission in peer groups is the presence of correlated and exogenous effects, as described in the reflection problem (Manski, 1993). Individuals often select into peer groups based on shared characteristics—such as education, occupation, or socioeconomic status which may independently influence their expectations or behavior (exogenous effects). Similarly, members of a peer group may be jointly exposed to macro or local shocks (correlated effects). These sources of endogeneity make it difficult to isolate the role of actual information transmission.

To address these concerns, I rely on the structure of *intransitive triads*. Specifically, I exploit cases where individual i is connected to individual k only through a mutual first-degree peer j, as illustrated in Figure 1. That is, i and k do not know each other directly, but both know j, who may transmit information about k's unemployment experience to i. This structure implies that any association between k's unemployment and i's beliefs must operate through information transmission, rather than direct exposure or joint selection into a peer group.

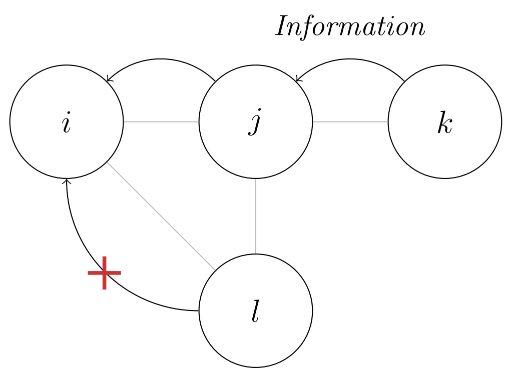


Figure 1: Intransitive Triads and Information Transmission

This design mitigates both correlated and exogenous effects in two key ways. First, second-degree peers are not directly connected to the respondent and are therefore less likely to share latent traits or unobserved shocks. Second, any influence of k's unemployment on i

must occur through information transmission via j. The intransitive triad design thus offers a plausible environment in which information transmission occurs, while minimizing bias from endogenous peer selection.

To further strengthen identification, I implement several steps to mitigate residual sources of confounding. First, I exclude all second-degree peers who reside in the same municipality as the respondent. This restriction serves two purposes. It reduces the likelihood of unobserved direct ties between the respondent and their second-degree peers. It also limits exposure to shared local labor market shocks, which the respondents is likely to receive information about through other channels.

In addition, I include a comprehensive set of respondent-level fixed effects to absorb common shocks that may simultaneously influence the outcomes of both the respondent and their extended network. Specifically, I control for fixed effects at the municipality-by-year, education-by-year, industry-by-year, and occupation-by-year levels. These dimensions capture systematic variation in unemployment risk that may arise from regional conditions, sectoral shocks, or occupational cycles. I also include controls for the respondent's own unemployment history, which helps account for heterogeneity in baseline risk exposure.

By conditioning on these factors, any residual variation in unemployment shocks among second-degree peers is unlikely to be observable to respondents through standard macroeconomic indicators or news sources, which tend to report information at aggregated levels. As such, if second-degree peer job loss remains predictive of individuals' expectations after these controls, it suggests that individuals are not simply reacting to publicly available information, but rather to information transmitted through their personal networks. In this sense, second-degree peer experiences may reflect otherwise latent variation in individual unemployment risk. Variation that becomes accessible to respondents only via social interaction. The identifying variation in this empirical strategy is thus driven by differential exposure to realized unemployment shocks among plausibly exogenous second-degree peers. While the design does not permit estimation of a causal effect of information transmission, it allows me to detect patterns consistent with individuals updating expectations in response to socially proximate signals, conditional on rich controls for shared shocks and observable characteristics. The use of intransitive triads, in combination with fixed effects and geographic restrictions, provides a conservative strategy for examining the role of peer experience in the formation of expectations.

3.2 Empirical Framework

To examine the relationship between peers' unemployment experiences and subjective unemployment expectations, I estimate equation 1:

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

Here, $E_{i,t}[U_{i,t+1}]$ denotes individual i's subjective unemployment expectation. The main regressor of interest, $USS_{i,t}$, captures the share of second-degree peers who experienced an unemployment spell in year t. The vector $X_{i,t}$ includes observable characteristics such as age fixed effects, gender, and immigrant background, while $U_{i,t}$ controls for the respondent's own unemployment experiences, which may predict both their subjective expectations and exposure to peer shocks.

The fixed effects $\omega_{m,t}$, $\phi_{w,t}$, $\delta_{o,t}$, and $\eta_{e,t}$ control for time-varying shocks at the municipality $\times$year, industry$\times$year, occupation$\times$year, and education$\times$year level, respectively. These fixed effects are designed to absorb regional or sectoral shocks that could jointly affect the respondent and their extended network. Conditioning on both $U_{i,t}$ and these fixed effects helps ensure that the variation in $USS_{i,t}$ used for identification is not confounded by common labor market exposures or baseline individual risk, which is observable to the individual through other sources of information.

Identification in this setting rests on the assumption that, conditional on these controls, second-degree peer unemployment affects the respondent's expectations only through information transmission shared by their first-degree peers. This assumption is strengthened by the network structure: respondents are not directly connected to their second-degree peers. The remaining variation in $USS_{i,t}$ is thus unlikely to be driven by endogenous network formation or exposure to local shocks.

While I cannot directly observe communication between peers, I rely on a structure that makes information exchange plausible and other forms of confounding less likely, as second-degree peers are socially proximate, but structurally distant. To the extent that some peer unemployment events go unobserved or uncommunicated, this measurement error should attenuate the estimates, making the results conservative.

4 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 an opportunity to identify not just 1st degree peers, but also second degree peers, which is crucial for my analysis. I combine this with survey elicited subjective unemployment expectations, for a representative sample of the Danish population.

4.1 Administrative Data

The administrative data covers the entire Danish population at the individual level and contains third-party reported information about labor market outcomes, finance and general demographic characterstics.

Based on observable characteristics, I construct my network, by identifying an individual's family members, coworkers and former classmates using the following criteria:

- 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. While 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. Sheridan (2019) shows that the identified groups of peers are significant predictors of regular bank transfers in the Danish transfer app, MobilePay.[2] 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 omission of these peers may cause should be mitigated by the geographical restrictions that I impose, cf. section 3.1.

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

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

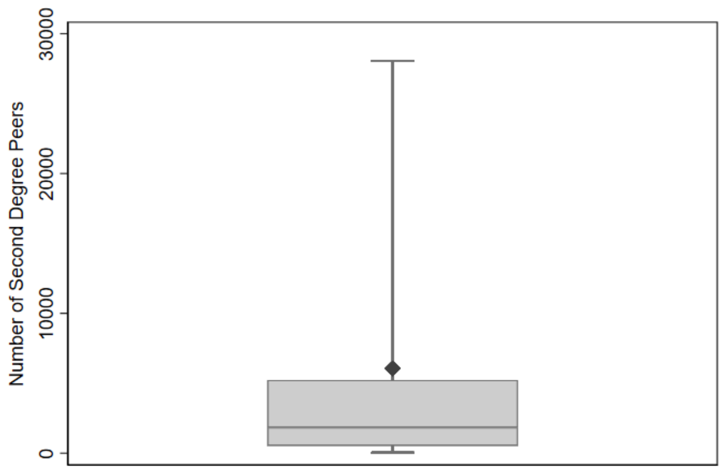
The table shows the median and average number of 1st degree peers by domain. Due to regulation by Statistics Denmark, all percentiles are based on running averages over five observations.

When moving from the first-degree peers to the second-degree peers, the number of peers increases vastly. The distribution of the sizes of the second-degree peer groups are shown in Figure 2. On average, each respondent is linked to 6,051 second-degree peers, with a median of 1,836. The distribution is right-skewed, with a small number of individuals linked to substantially larger networks due to highly connected first-degree peers.

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).[3] 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,

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

Figure 2: Distribution of Second-Degree Peers



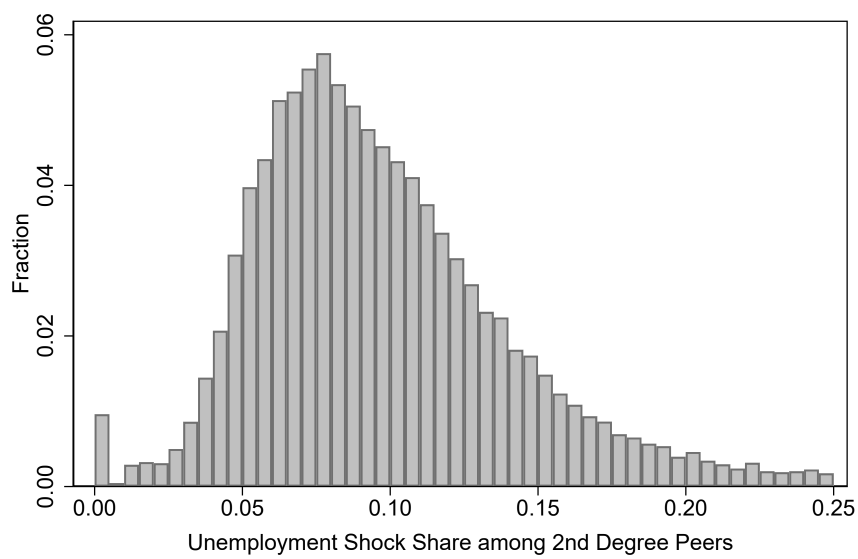
The boxplot shows the 5th, 25th, 50th, 75th and 95th percentiles of the number of second-degree peers for the survey respondents. The diamond depicts the average. Due to regulation by Statistics Denmark, all percentiles are based on running averages over five observations

peers may talk about the event as a job transition rather than an unemployment shock, and this is not what I am interested in.[4]

Figure 3 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 2. 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.

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

Figure 3: 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.

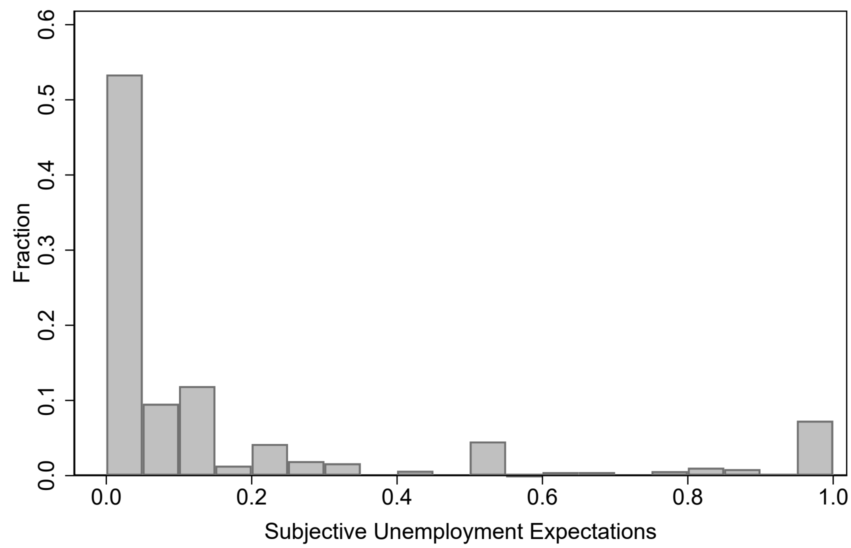
4.2 Survey Data

The administrative data is merged with the survey data using unique individual identifiers. 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 4. 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 4: 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.

4.3 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 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.

5 Results

5.1 Peer Job Loss and Individual Unemployment Risk

A central premise of this paper is that social networks can serve as informal channels of information about labor market risk. Before evaluating whether individuals act on such information, I begin by asking whether peer job loss is predictive of individual unemployment outcomes. If peer experiences are to have informational value, they must reflect meaningful variation in respondents' own latent risk exposure. That is, peer unemployment must contain predictive power, not merely noise.

To test this, I regress realized unemployment in year $t+1$, $U_{i,t+1}$, on the share of second-degree peers who experienced unemployment in year t, $USS_{i,t}$, replacing the outcome variable in equation 1. Table 3 presents the results. Column 1 shows that a one percentage point increase in peer unemployment is associated with a 0.716 percentage point increase in the probability that the respondent becomes unemployed the following year. As expected, this correlation attenuates when including controls and fixed effects. 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, I include both controls and fixed effects in column 4, yielding a coefficient of 0.268, which remains statistically and economically significant.

This result is consistent with the interpretation that unemployment among second-degree peers serves as a proxy for otherwise latent changes in individual-level unemployment risk. Since these peers are not directly connected to the respondent, and they reside in different municipalities, their job loss experiences are unlikely to be correlated with the respondent's labor market outcomes through selection or shared environments. Moreover, the inclusion of the fine-grained fixed effects and individual unemployment history controls helps absorb macroeconomic, sectoral, and occupational shocks observable through other informational channels, such as aggregate statistics or news coverage. The remaining variation in $USS_{i,t}$ is

Table 3: 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.

thus unlikely to be visible to the respondent outside of their peer network.

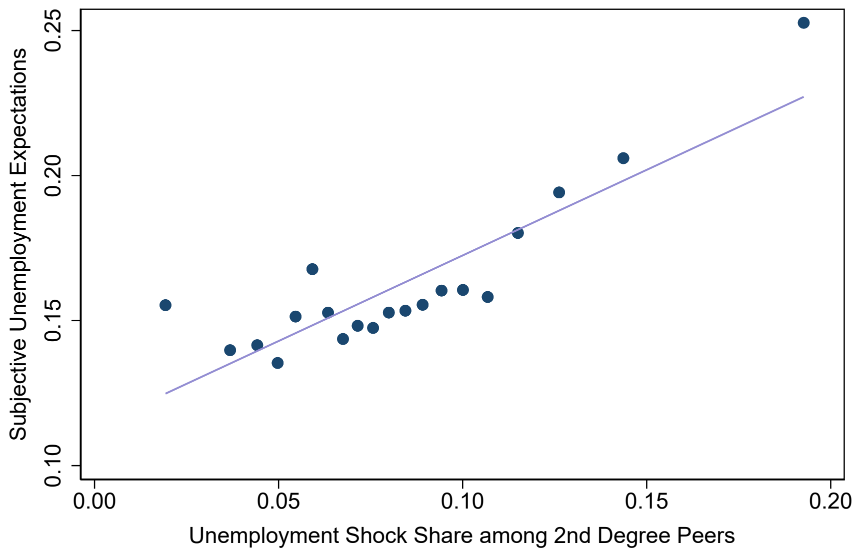
This raises the next question: Do individuals recognize the informational value of their peers' unemployment experiences? If so, we should expect to observe a systematic relationship between peer job loss and individuals' subjective unemployment expectations.

5.2 Peer Job Loss and Subjective Unemployment Expectations

To examine whether individuals treat peer experiences as informative signals, I first consider the raw correlation between peer unemployment in year t, $USS_{i,t}$ and subjective unemployment expectations in year $t+1$, $E_{i,t}[U_{i,t+1}]$, as shown in Figure 5. The two variables are strongly and positively correlated. Column 1 of Table 4 quantifies this relationship: A one percentage point increase in the share of unemployed second-degree peers in year t is associated with a 0.56 percentage point increase in the individual's subjective probability of becoming unemployed in the following year. This is a large correlation, given that the mean expectation is 11.6 pct.

Recognizing that this correlation could partially reflect shared shocks or compositional sorting, I proceed by conditioning on demographic controls and fixed effects. Column 2 of Table 4 adds demographic controls and the respondent's own unemployment experiences. This reduces the estimate to 0.356. Column 3 instead includes municipality$\times$year, education$\times$year, industry-by-year, and occupation$\times$year fixed effects to account for unobserved heterogeneity and shared labor market shocks. The estimate remains similarly stable at 0.366. Column 4 includes both controls and fixed effects, yielding a final estimate of 0.187. This implies that a one pct. point increase in peer unemployment is associated with a 0.2 percentage point increase in unemployment expectations, or roughly 2 pct. of the average subjective probability. The robustness of this relationship, even after absorbing personal histories and high-dimensional sources of confounding, suggests that peer job loss is not only predictive of risk exposure, it is also perceived as such by the individual. The fact that peer experiences appear to shift expectations, over and above what could be inferred from news, aggregate

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, $USS_{i,t}$.

statistics, or personal histories, suggests that social peers serve a informational role.

Table 4: 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.

5.3 Heterogeneity by Age, Tenure and Source of Information

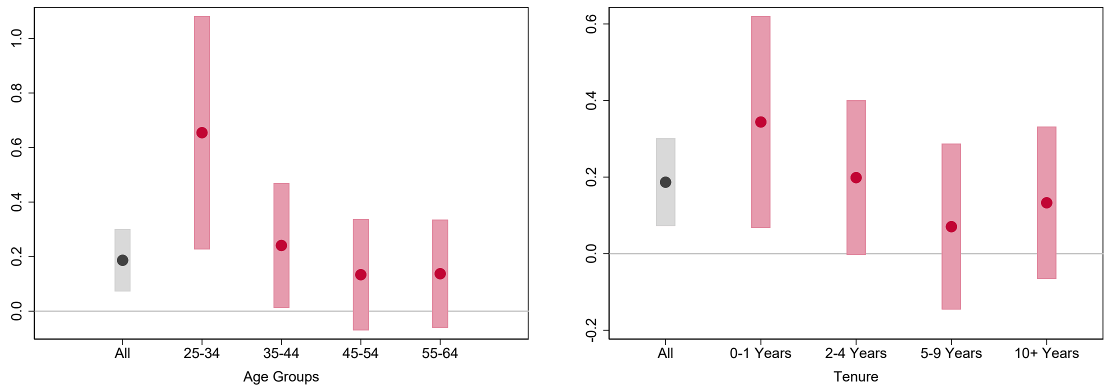
To further investigate the role of peer information in shaping subjective unemployment expectations, I explore heterogeneity in the estimated relationship along three dimensions: the respondent's experience, the source of the information and the size of the respondent's first degree network. Each of these dimensions speaks to the plausibility of an informational mechanism underlying the main results.

First, I test whether the responsiveness to peer job loss varies with the respondent's age. As shown in Figure 6a, the correlation between of peer unemployment and subjective unemployment expectations is substantially larger for younger individuals. A similar pattern emerges when stratifying the sample by labor market tenure: those with shorter tenure see a larger correlation between peer unemployment and subjective unemployment expectations (Figure 6b). These findings are consistent with the interpretation that individuals with limited labor market experience rely more heavily on external signals, when forming expectations about their own labor market risk. That is, peer information appears to act as a substitute for private experiences, becoming more influential when individuals lack informative priors of their own.

Second, I examine heterogeneity by the source of the information, i.e., the domain of the first degree peer. I estimate the relationship between peer unemployment and subjective unemployment expectations separately for second-degree peers connected to the respondent through a family member, a coworker or a classmate. The results are presented in Figure 7. The estimated effect is largest when the information is transmitted through coworkers, suggesting that information from peers who share a common labor market environment is perceived as more informative and credible. This aligns with prior findings that signals from institutionally or occupationally similar peers resonate more strongly and are more likely to be internalized (Malmendier and Veldkamp, 2022).

Finally, I examine whether the relationship varies by the size of the respondent's first-degree peer network. As seen in Figure 7, the correlation is largest for individuals with smaller

Figure 6: Estimate Size by Respondent Age and Tenure



(a) By Respondent Age

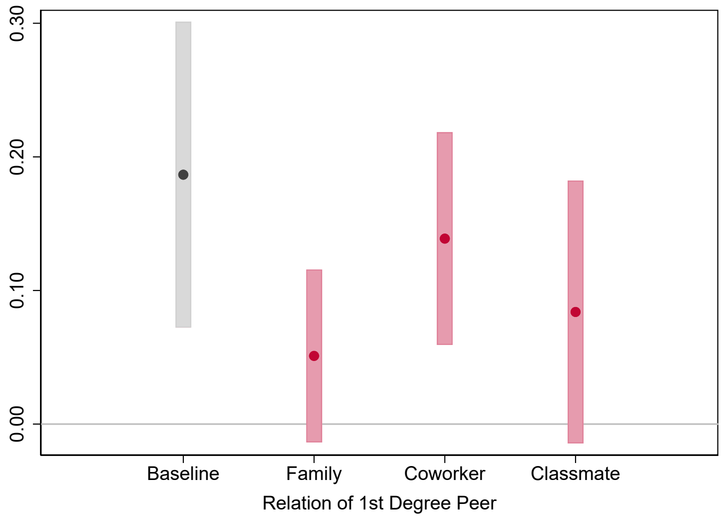
(b) By Respondent Tenure

This figures show the estimated relationship between subjective unemployment expectations, $E_{i,t}[U_{i,t+1}]$), and peer job loss, $USS_{i,t}$, by respondent age and tenure. The corresponding estimation results are depicted in tables A4 and A5, in the Appendix.

peer groups. This is consistent with the interpretation that individuals assign greater weight the information they receive, when this information is scarce. It may also reflect increased salience or perceived credibility of peer experiences when those peers are few but socially close. Both interpretations support the view that peer unemployment experiences serve as informational inputs into expectations, rather than merely reflecting common shocks.

These heterogeneity results strengthen the interpretation that the observed link between peer job loss and subjective unemployment expectations is driven by information transmission. If the correlation was primarily due to shared shocks or residual confounding, we would not expect the effects to vary systematically by experience or peer domain. Instead, the findings are consistent with a model of belief updating under uncertainty, in which individuals incorporate salient, socially proximate signals when other sources of information are limited or less personally relevant.

Figure 7: Effect Size by by Type of 1^{st} Degree Peer

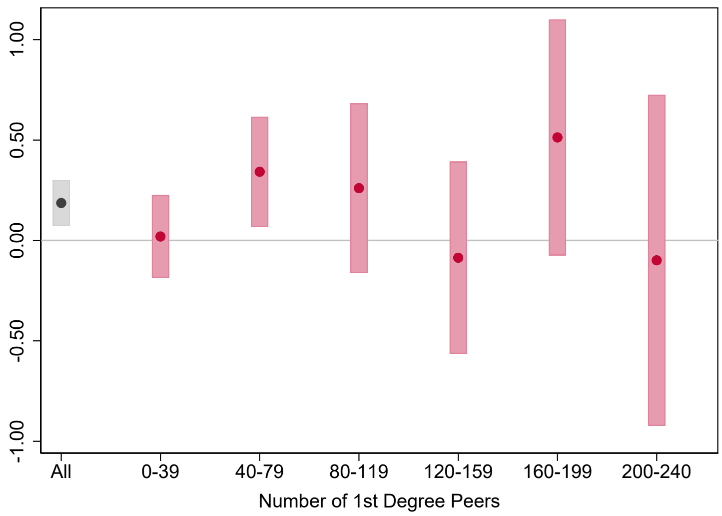


The figure shows the estimated relationship between subjective unemployment expectations, $E_{i,t}[U_{i,t+1}]$), and peer job loss, $USS_{i,t}$, by the information source. The corresponding estimation results are depicted in tables A6 in the Appendix.

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 (Hendren, 2017), an increase in liquid savings (Hartmann and Leth-Petersen, 2024) 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 effect on subjective unemployment expectations translates into precautionary behavior.

Figure 8: Effect Size by Number of First Degree Peers



The figure shows the estimated relationship between subjective unemployment expectations, $E_{i,t}[U_{i,t+1}]$), and peer job loss, $USS_{i,t}$, by the size of the individual's first-degree peer group. The corresponding estimation results are depicted in tables A7 in the Appendix.

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[5] 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[6].

[5] 1 USD $\approx$ 7 DKK.

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

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 5.2. Respondents may to wish insure themselves against the perceived increased risk of unemployment by purchasing private unemployment 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 UI. 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.

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 learning about their peers' unemployment experiences. 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

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

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Probit
$USS_{i,t}$	0.649***	0.600***	0.626***	0.505***	0.518***
	(0.090)	(0.085)	(0.108)	(0.098)	(0.100)
$E_{i,t}(U_{i,t+1})$					
Constant	0.831***	0.590***	0.833***	0.637***	
	(0.009)	(0.078)	(0.010)	(0.076)	
Average $I[UI_{i,t+1}]$	0.885	0.885	0.885	0.885	0.894
Average $USS_{i,t}$	0.083	0.083	0.083	0.083	0.077
Observations	23,159	23,159	23,159	23,159	21,786
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. Probit estimate in column 6 is average marginal effect.

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 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

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.

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) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Probit
$USS_{i,t}$	0.050	0.019	0.204***	0.150*	0.187**
	(0.062)	(0.062)	(0.077)	(0.077)	(0.075)
$E_{i,t}(U_{i,t+1})$					
Constant	0.090***	0.144**	0.078***	0.147**	
	(0.006)	(0.069)	(0.007)	(0.071)	
Average $EE_{i,t+1}$	0.095	0.095	0.095	0.095	0.104
Average $USS_{i,t}$	0.082	0.082	0.082	0.082	0.076
Observations	20,395	20,395	20,395	20,395	18,614
R-squared	0.000	0.017	0.050	0.065	
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. Probit estimate in column 6 is average marginal effect.

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.

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

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	Probit
$USS_{i,t}$	0.188***	0.013	0.283***	0.136**	0.196***
	(0.049)	(0.047)	(0.059)	(0.058)	(0.060)
$E_{i,t}(U_{i,t+1})$					
Constant	0.038***	0.015	0.030***	0.000	
	(0.004)	(0.036)	(0.005)	(0.039)	
Average $I[LTR_{i,t+1}]$	0.054	0.054	0.054	0.054	0.067
Average $USS_{i,t}$	0.083	0.083	0.083	0.083	0.077
Observations	20,163	20,163	20,163	20,163	16,010
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 whether individuals' subjective unemployment expectations and self-insurance behavior are systematically related to unemployment experiences within their social networks. To do so, I relied on a combination of Danish survey and administrative data. I showed that peer unemployment experience are systematically associated with individuals' subjective unemployment expectations and actual unemployment outcomes. These patterns are consistent with the interpretation that individuals rely on social information to assess their personal labor market risk, and that peer job loss may serve as an informal, but informative, signal of future exposure. Notably, I find that the predictive power of peer experiences remains strong even after conditioning on fine-grained fixed effects and individuals' own labor market histories, suggesting that these signals reflect latent risk factors that are otherwise difficult for individuals to observe directly. In turn, individuals appear to internalize this information: their subjective unemployment expectations respond to recent peer unemployment, particularly when the information comes from socially or professionally relevant sources such as coworkers, and when personal experience is sparse, as is the case for younger or low-tenure individuals.

I also document behavioral responses that align with forward-looking precautionary behavior. Individuals exposed to higher degree of peer job loss are more likely to purchase private unemployment insurance and to switch jobs, disproportionately toward positions with lower turnover risk. These findings suggest that peer experiences do more than shape expectations, they also influence individual decisions with real economic consequences.

Combined, the evidence supports a view of social networks as informal information environments through which individuals interpret and respond to labor market risk. This points to a broader role for social networks in mediating the flow of economic information and shaping adaptive behavior, particularly when formal indicators are limited, delayed, or difficult to personalize.

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., 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.

Carroll, C. D., K. E. Dynan, and S. D. Krane (2003). Unemployment Risk and Precautionary Wealth: Evidence from Households' Balance Sheets. *Review of Economics and Statistics 85*(3), 586–604.

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.

Kuchler, T. and B. Zafar (2019). Personal Experiences and Expectations about Aggregate Outcomes. *Journal of Finance 74*(5), 2491–2542.

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

Lusardi, A. (1998). On the Importance of the Precautionary Saving Motive. *The American Economic Review 88*(2), 449–453.

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

Malmendier, U. and L. Veldkamp (2022). Information Resonance. *Working Paper*, 1–40.

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.*

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

Subjective Unemployment Expectations and Precautionary Behavior in the Shadow of Peer Job Loss

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.

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

B Robustness Checks

B.1 Alternative Measure of Unemployment

To ensure that the results in sections 5.1 and 5.2 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 tables A2 and A3. The sign and significance levels of the estimates are the same as in the main analyses, seen in tables 3 and 4. However, the sizes of the β_1 estimate are slightly 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 A3 are not significantly different from those in the main text is reassuring.

Table A2: Realized Unemployment, $\mathbb{I}[U_{i,t+1} = 1]$

	(1)	(2)	(3)	(4)
$USS_{i,t}$	0.579***	0.344***	0.255***	0.237***
	(0.049)	(0.036)	(0.041)	(0.041)
Constant	-0.012***	-0.061	-0.003	-0.072
	(0.005)	(0.043)	(0.004)	(0.044)
Mean $\mathbb{I}[U_{i,t+1}]$	0.048	0.048	0.048	0.048
Mean $USS_{i,t}$	0.104	0.104	0.104	0.104
Observations	23,159	23,159	23,159	23,1599
R-squared	0.016	0.272	0.303	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 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.

Table A3: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$

	(1)	(2)	(3)	(4)
$USS_{i,t}$	0.431***	0.278***	0.289***	0.152***
	(0.045)	(0.039)	(0.052)	(0.046)
Constant	0.071***	0.086*	0.085***	0.072
	(0.005)	(0.045)	(0.005)	(0.048)
Mean $E_{i,t}[U_{i,t+1}]$	0.116	0.116	0.116	0.116
Mean $USS_{i,t}$	0.104	0.104	0.104	0.104
Observations	23,159	23,159	23,159	23,1599
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 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.

C Heterogeneity Analyses

Table A4: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$, by Age

	(1)	(2)	(3)	(4)	(5)
Ages	All	25-34	35-44	45-54	55-64
$USS_{i,t}$	0.187***	0.654***	0.241**	0.134	0.137
	(0.058)	(0.218)	(0.117)	(0.104)	(0.101)
Constant	0.073	0.026	0.068***	0.077***	0.074***
	(0.048)	(0.046)	(0.015)	(0.012)	(0.012)
Mean $E_{i,t}[U_{i,t+1}]$	0.116	0.171	0.119	0.109	0.094
Mean $USS_{i,t}$	0.083	0.085	0.083	0.083	0.083
Observations	23,159	2,631	5,894	7,703	6,129
R-squared	0.171	0.366	0.250	0.212	0.281
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.

Table A5: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$, by Tenure

	(1)	(2)	(3)	(4)	(5)
Tenure (Years)	All	0-1	2-4	5-9	10+
$USS_{i,t}$	0.187***	0.344**	0.199*	0.071	0.133
	(0.058)	(0.141)	(0.103)	(0.111)	(0.102)
Constant	0.073	0.125*	0.145	0.098*	-0.106
	(0.048)	(0.071)	(0.090)	(0.051)	(0.068)
Average $E_{i,t}[U_{i,t+1}]$	0.116	0.199	0.095	0.084	0.071
Average $USS_{i,t}$	0.083	0.086	0.082	0.082	0.083
Observations	23,159	5,378	6,151	5,019	4,664
R-squared	0.171	0.272	0.217	0.243	0.205
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.

Table A6: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$

	(1) All	(2) Family	(3) Coworkers	(4) Classmates
$USS_{i,t}$	0.187***			
	(0.058)			
$USS_{i,t}$ among Family		0.051		
		(0.033)		
$USS_{i,t}$ among Coworkers			0.149***	
			(0.045)	
$USS_{i,t}$ among Classmates				0.084*
				(0.050)
Constant	0.073	0.101**	0.117*	0.099**
	(0.048)	(0.048)	(0.069)	(0.048)
Average $E_{i,t}[U_{i,t+1}]$	0.116	0.116	0.113	0.115
Average Number of Peers	266.188	4.123	205.149	73.571
Average $USS_{i,t}$	0.083	0.033	0.083	0.071
Observations	23,159	21,384	19,012	21,361
R-squared	0.171	0.176	0.111	0.172
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.

Table A7: Subjective Unemployment Expectations, $E_{i,t}[U_{i,t+1}]$

	(1)	(2)	(3)	(4)	(5)	(6)
Number of Peers	0-39	40-79	80-119	120-159	160-199	200-240
$USS_{i,t}$	0.020	0.342**	0.261	-0.086	0.513*	-0.099
	(0.105)	(0.140)	(0.216)	(0.244)	(0.300)	(0.421)
Constant	-0.138**	0.050	-0.083	0.049	0.243*	0.400**
	(0.065)	(0.103)	(0.092)	(0.085)	(0.132)	(0.177)
Average $E_{i,t}[U_{i,t+1}]$	0.141	0.118	0.112	0.114	0.106	0.110
Average $USS_{i,t}$	0.086	0.088	0.083	0.083	0.083	0.084
Observations	4,881	4,257	3,082	2,178	1,493	890
R-squared	0.313	0.282	0.348	0.429	0.502	0.523
Controls	✓	✓	✓	✓	✓	✓
Municipality×Year FE	✓	✓	✓	✓	✓	✓
Education×Year FE	✓	✓	✓	✓	✓	✓
Industry×Year FE	✓	✓	✓	✓	✓	✓
Occupation×Year FE	✓	✓	✓	✓	✓	✓

Standard errors, clustered by individual, in parentheses, *** 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.