# The importance of job loss risk for individual savings*

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**Abstract**

In this paper we use a novel natural experiment and Norwegian tax data to quantify the causal impact of job loss risk on individual savings. We show theoretically that higher job loss risk increases liquid savings and has an ambiguous impact on illiquid savings in partial equilibrium. In line with the model predictions, our empirical results confirm that a one percentage point increase in job loss rates increases liquid savings by 1.4-1.7 percent in the cross-section. Reassuringly, this effect is driven by low-tenured workers, who face the highest increase in job loss risk. Illiquid savings remain unaffected, implying an increase in the overall liquidity of individual saving portfolios. Using two independent approaches to quantify the overall importance of the job loss risk channel in explaining saving dynamics during recessions, we find that at least 80% of the recession-induced increase in liquid savings can be explained by higher job loss risk.

Key words: Precautionary savings, portfolio allocation, household finance, recessions, uncertainty

JEL Codes: D14, E20, E21

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## 1 Introduction

Saving rates typically increase during recessions, and the increases observed for the two most recent downturns have been especially striking. During the Great Recession, the US personal saving rate more than doubled, and remained elevated for an extended time period. The increase in savings was even larger during the recent pandemic, in which the saving rate almost tripled from one month to the next. These business cycle movements in saving rates are important for at least two reasons. First, large increases in savings, often accompanied by changes in portfolio allocations, may have important implications for asset prices (Gabaix and Koijen, 2021). Second, large increases in savings reduce household demand, potentially amplifying economic downturns (Mian and Sufi, 2014; Bayer et al., 2015).

Several factors may be important in explaining *why* saving rates increase during recessions. One such factor is uncertainty – a potentially important driver emphasized by both policymakers and academics.[1] In this paper, we focus on a specific form of uncertainty, namely *job loss risk*. Job loss risk is a key source of downside income risk for most households. We use Norwegian administrative data to document that the probability of large annual earnings losses, i.e. more than a 25% decline in wages and transfers, is less than three percent for those who stay employed, compared to more than sixty percent for those who experience job loss.[2]

Our main contribution to the literature is to provide a quantitative estimate of the causal impact of job loss risk on liquid and illiquid savings. We use this estimate to evaluate the relative importance of job loss risk for aggregate saving behavior during economic downturns. While several papers estimate the impact of labor-related risk on saving behavior, existing papers either do not use a treatment indicator which *quantitatively* measures job loss risk, or do not rely on exogenous variation in their risk measure. In this paper, we use the 2014 collapse of the international oil price as a novel natural experiment, along with rich administrative data, to estimate the causal impact of higher job loss risk on household savings and portfolio allocations. Our identification strategy allows us to control for the impact of other local recession effects, such as wealth effects, credit conditions, or sentiments, by comparing individuals who live in the same recession area but face different shocks to job loss risk.

Our analysis consists of four main steps. First, we document the overall importance of job loss for household income volatility.[3] We show that the expected change in real annual wage and

[1] See for instance the FOMC minutes from March 17-18 2009, Blanchard (2009), ECB (2009) and Mody et al. (2012).

[2] Regardless of the quantitative importance of job loss risk shocks however, the existing literature has devoted most attention to the role of pure uncertainty shocks, i.e. mean preserving spreads to future income, as these are the kind of shocks that generally enter into macro models. Job loss risk shocks are *not* mean preserving spreads to future income, as both the level and the variance of future income is affected.

[3] Income volatility is an often used proxy for income risk, see for instance Dynan et al. (2012). Ideally however, we would like to separate between voluntary and non-voluntary income changes. Given that income declines caused by unemployment are less likely to be voluntary than other income declines (caused for instance by changes in hours worked), our simple comparison is likely to *understate* the importance of job loss risk in accounting for individual

transfer income is -36% for those who experience unemployment, compared to 2.5% for job keepers. Moreover, the standard deviation of wage and transfer income for those experiencing unemployment is twice that of job keepers. In terms of large income falls, we find that the probability of experiencing annual income falls of at least 25% is less than three percent for job keepers, and more than sixty percent for those experiencing job loss. Overall, these findings illustrates the importance of job loss in accounting for substantial negative income changes and suggest that job loss risk is an important source of risk at the individual level.

Second, we explore the impact of job loss risk on household saving decisions in a stylized partial equilibrium model.[4] The model consists of three periods, in which the household faces unemployment risk in the intermediate period. The household can invest in two assets - liquid assets which are available in all periods and illiquid assets which are available only in the final period, but yield a higher return. We use the model to generate several testable predictions, as well as inform our empirical approach. A key prediction of the model is that an increase in future job loss risk increases liquid savings, while having an indeterminate impact on illiquid savings. The intuition is as follows. When the probability of becoming unemployed increases, the household wants to increase savings to smooth consumption across different states of the world. This is most efficiently done by increasing liquid savings, which are the assets that are readily available should the household become unemployed. All else equal, this leads to a reduction in illiquid assets. However, higher job loss risk also increases consumption risk in the final period, as unemployment reduces lifetime income. Since illiquid assets generate higher returns, this puts upward pressure on illiquid savings. As a result, the impact on illiquid savings is generally indeterminate. We note that this is in contrast to a mean preserving spread to future income, which will lead to a *decline* in illiquid assets (Bayer et al., 2019).

The theoretical framework further allows us to address a potential confounding factor in our empirical analysis, related to a possible decline in long term earnings potential resulting from human capital depreciation. This is important, as it is conceivable that an increase in job loss risk for certain groups may coincide with a deterioration in their long term earnings potential if the demand for their skills decline. In our setting, one might worry that the oil price collapse has negative long-term consequences for individuals working in the oil industry. In our model, this mechanism would be captured by lower income in the final period. However, we show that lower income in the final period unambiguously *decreases* liquid savings, as the household prefers to shift its investment into the high-return illiquid asset. The intuition being that hedging against income declines in the future is most efficiently done by investing in illiquid assets. An observed increase in liquid savings is therefore *not* consistent with the theoretical predictions of a permanent decline in human capital. Because the concern that job loss risk is positively correlated to human

income risk.

[4]Because our empirical results are cross-sectional, they do not capture general equilibrium effects. Hence, the partial equilibrium predictions of our model correspond to our empirical findings.

capital depreciation is a general feature, our theoretical result that the two channels have opposite predictions for the liquid asset share may be useful also in other empirical settings, and highlights the value of separating between liquid and illiquid savings.

Third, we turn to the main empirical analysis. The Norwegian administrative register data includes detailed information on income and wealth, allowing us to study the impact on overall savings as well as portfolio choice. We focus on the impact on liquid financial savings, measured by bank deposits, and illiquid financial savings, measured by stocks, bonds, mutual funds etc.,[5] but also consider illiquid real wealth such as housing. Bank deposits capture all forms of checking and saving accounts, and are by far the largest financial asset in our sample. In our treatment group, average (median) bank deposits are 1.5 (9) times as large as other financial assets. The tax data can be merged with labor market data as of year 2000, allowing us to observe labor market status and occupation, which is important for our identification of individual level job loss risk. We use the 2014 oil price collapse to obtain an exogenous increase in job loss risk which differs across occupations. The occupational group with the largest increase in job loss risk in response to the oil price collapse is engineers, which we use as our treatment group. As engineers have at least 1 - 3 years of higher education, we compare engineers to other high skilled workers in order to obtain a suitable control group. Prior to the oil price collapse, engineers and other high skilled workers have virtually identical levels of job loss risk, averaging roughly one percent per year. Following the oil price collapse, job loss risk for engineers increases sixfold, while job loss risk for other high skilled workers increases only moderately. We also make sure our results are robust to using an alternative control group consisting of high skilled *government* workers, who did not experience any increase in job loss risk.

To control for other recession effects which potentially affect savings, our baseline analysis compares individuals with different changes in job loss risk, but who all live in the recession area, in a dynamic difference in difference regression. Specifically, we define the recession area to be the two counties in the South-West of Norway which employ an unproportionally high share of oil workers. These are the counties in which the oil price collapse led to a local recession, with spikes in unemployment and house price declines. By comparing engineers and other high skilled workers who live in the recession area, we can control for any local recession effects which are common across these two groups. Our identifying assumption is that, in absence of the oil price collapse of 2014, engineers and other high skilled workers would have had similar *changes* in savings. We explicitly show that the two groups have identical changes in savings in the years prior to the shock, and perform various robustness checks to rule out any confounding factors we can think of for why the parallel trend assumption should cease to hold after the shock occurred.

To ensure that we do not capture the saving-effects of realized job loss, we use two alternative

[5]We use the terminology "liquid" and "illiquid" assets, but conceptually we do not distinguish between liquidity and risk. Bank deposits are both safe and liquid. Stocks and various other financial assets are in principle also quite liquid, but fast liquidation may require a low return, which reduces their *effective liquidity*.

approaches. First, we only include workers who are still employed in our sample. This could be problematic however, if those who never experience job loss have different saving responses from those who eventually become unemployed. To mitigate this concern we also use a different approach, in which we consider the initial saving response only, which materialized prior to the increase in unemployment rates. In this case we do not need to condition on job market status. Reassuringly, our findings are similar across the different specifications.

The results show an annual increase in liquid savings for engineers relative to other high skilled workers of roughly \$1,300, or just below four percent. Scaling this by the increase in job loss risk, we find that a one percentage point increase in the separation rate increases liquid savings by 1.4 - 1.7 percent. Reassuringly, the increase in liquid savings is driven by low-tenured engineers, who experienced the largest increase in job loss risk. Looking only at low-tenured individuals, the increase in liquid savings for every one percentage point increase in job loss rates rises to 1.4 - 2.7 percent. In line with our model predictions, we do not find any impact on other asset categories, implying that higher job loss risk contributes to a flight to liquidity effect at the individual portfolio level.

We consider a number of different robustness tests. First, our dynamic difference in difference specification allows us to explicitly test for parallel pre-trends, and we confirm that engineers and other high-skilled workers were on parallel saving trajectories prior to the oil price collapse. However, this does not rule out that the parallel trend assumption might cease to hold going forward. One important threat to identification is that the oil price shock might have caused both an increase in job loss risk for our treatment group, *and* a decline in their long-run earnings potential (not working though unemployment). To rule out that a decline in long run earnings potential is driving our results, we rely on our model predictions in combination with our empirical findings. First, we note that a decline in long run income should lead to a relative increase in *illiquid* savings, which is the opposite of what we find. This does not rule out that there is an impact working through lower long run income, but suggests that, if so, the job loss risk channel dominates. However, we can strengthen this result further, by using our findings for low-tenured workers. We show that low-tenured workers have larger increases in job loss risk and are likely to have smaller declines in their long run earnings potential. Based on this, the model predicts that *if* there is a decline in long run earnings potential, low-tenured workers should have larger declines in illiquid savings. This is, if anything, the opposite of what we observe in the data, leading us to conclude that declines in long run earnings potential have at most trivial impacts on individual saving behavior in our case. In addition, we make sure our results cannot be explained by differential house price changes across our treatment and control group, or different wealth shocks. We also explore alternative treatment and control groups, showing that our results are robust to these variations.

In the fourth and final step, we quantify the importance of job loss risk for saving rates during economic downturns. Conceptually, saving rates increase during recessions due to i) higher job loss risk and ii) other recession effects. In the latter group we include everything which is not job loss risk, for instance falling house prices, negative sentiments, wealth effects, credit availability etc. Our empirical findings isolate the impact of the job loss risk channel. To quantify the relative importance of this channel, we compare its magnitude to the total recession-induced saving increase using two independent approaches. First, we compare the saving behavior of our treatment group to a control group consisting of similar workers living *outside* of the recession area. Note that this comparison should capture both the impact of higher job loss risk and the impact of other recession effects. Using this approach, we find that the job loss risk channel can explain 83% of the liquid saving rate increase and 45% of the total saving rate increase. Second, we rely on the time series variation in the saving behavior of our treatment group to quantify the total saving increase. Although this approach relies on entirely different aspects of the data, it yields similar results, implying that the job loss risk channel can explain 93% of the liquid savings increase, and 54% of the total savings increase. We thus conclude that elevated job loss risk is by far the most important driver of higher liquid saving rates during recessions, and also explains about half of the total recession-induced increase in saving rates.

Applying our results to other recession periods, we find that the job loss risk channel can account for 3/4 of the observed saving response during the Great Recession, and 1/4 of the observed saving response during the COVID19-pandemic.

**Related literature** Our main contribution to the literature is to quantify the causal impact of job loss risk on individual savings. While several papers study the effect of employment-related risk on savings, the existing studies either do not use a treatment indicator which quantitatively measures job loss risk, or do not have exogenous variation in their risk measure. We fill this gap in the literature by using a natural experiment to estimate the quantitative impact of job loss risk on liquid and illiquid savings.

Several papers study the impact of subjective unemployment beliefs on savings (Guiso et al. 1992, Carroll and Dunn 1997, Lusardi 1998, Pettinicchi and Vellekoop 2019). The use of subjective unemployment beliefs has the advantage of potentially capturing risk as *perceived* by the household, but suffers from the usual challenges related to survey data. Moreover, because there is no exogenous variation in beliefs, one might worry that unemployment beliefs are correlated with omitted variables which also affect saving behavior. Another strand of the literature studies the impact of future unemployment spells on current savings (Chetty and Szeidl 2007, Ceritoğlu 2013, Basten et al. 2016, Hendren 2017), typically using mass layoffs to control for within-firm selection into unemployment.[6] These studies show that individuals have private information about upcoming job

[6] However, as pointed out by Hilger (2016), this does not necessarily control for potential across-firm selection

loss, and that this affects saving behavior. However, because the treatment indicator is a binary dummy-variable for future unemployment, the results do not give rise to a quantitative mapping between job loss risk and savings.[7]

A few papers use natural experiments to achieve an exogenous increase in employment-related risk. This methodology is attractive from an identification point of view. However, the existing studies do not use treatment indicators which capture the quantitative impact of job loss risk on savings. Fuchs-Schündeln and Schündeln (2005) use the German reunification as a natural experiment – an event which caused a massive structural shift in employment protection and income volatility. Their treatment indicator is a binary dummy-variable for being a civil servant, an occupational group with lower labor risk. While they provide qualitative evidence of precautionary saving behavior, their results do not provide a quantitative mapping between job loss risk and savings.[8] Barcelo and Villanueva (2016) use regional variation in employment protection in Spain. Their treatment indicator is the instrumented probability of having an open-ended employment contract. While their results show that employment protection affects saving behavior (at least for certain sub-groups), their findings are again not informative in predicting what the saving-impact of a $x$ percentage point increase in job loss risk would be.[9]

An alternative approach, followed by Carroll et al. (2003) and Harmenberg and Öberg (2021) using survey data, is to instrument for individual job loss risk using observable characteristics such as region and occupation. A similar approach is followed by Larkin et al. (2019) to study the liquid asset share. The estimates from these papers *do* give rise to a quantitative mapping between job loss risk and savings, but are not necessarily based on exogenous variation in job loss risk.[10] This could be problematic if higher unemployment risk is correlated with other local recession effects such as wealth effects, credit conditions or negative sentiments.

We contribute to this empirical literature by providing a quantitative estimate of the causal impact of job loss risk on savings. Our natural experiment allows us to explicitly control for the confounding impact of other local recession effects by comparing individuals who live in the same area and thus are subject to the same local recession effects. Moreover, we show that our results are not driven by an accompanying decline in long run earnings potential, a general concern if

[7] Also note that, because "treatment" in this case conditions on actual job loss, this analysis will not capture the (potentially different) saving behavior of the many individuals who never experience job loss – but who still face an increase in job loss risk.

[8] Indeed, this is not the main point on the paper, which is to highlight the potential challenges related to using occupation as a source of variation in income risk due to self-selection. We note that the issue of self-selection into occupations is unlikely to be problematic in our setting – see the discussion in Section 5.4.

[9] In addition, Engen and Gruber (2001) use a natural experiment to study the importance of unemployment insurance for household savings in a US context.

[10] Quantitatively comparing their results to ours is not straightforward, due to different outcome variables. Harmenberg and Öberg (2021) investigate the impact on durable consumption, and find that a 1 pp increase in unemployment risk reduces durable expenditure by 0.56%. Carroll et al. (2003) find that a 1 pp increase in unemployment risk reduces net wealth by about 1/2 of monthly income (although the estimate is imprecise and not statistically significant). This point estimate is larger than the effect we identify here, potentially because it also captures the impact of other recession effects.

higher unemployment risk and human capital depreciations are positively correlated in the data. We argue that knowing the quantitative impact of job loss risk on savings is important for at least three reasons. First, this quantification allows us to calculate how important job loss risk is in explaining the observed saving increases during economic downturns. Our results suggest that higher job loss risk is in fact the most important driver of recession-induced increases in savings, explaining more than 80 percent of the increase in liquid savings and half the increase in total savings.[11] Second, the strength of this relationship determines the degree of amplification resulting from job loss risk and precautionary savings in a range of recent theoretical papers (McKay and Reis 2016, Challe et al. 2017, Ravn and Sterk 2017, Den Haan et al. 2018, Heathcote and Perri 2018, Challe 2020, Albertini et al. 2021, Kekre 2021, Ravn and Sterk 2021). Our estimates could therefore be useful either to calibrate these models, or as identified moments to match when testing the model fit. Third, if this effect is sizable, which we argue that it is, it provides incentives for higher – and potentially time-varying – unemployment insurance (UI), or for other measures which curb effective job loss risk such as financial support to distressed companies during recession periods.[12]

While our main contribution is empirical, we also contribute to the theoretical literature mentioned in the previous paragraph, by providing analytical solutions of the liquid and illiquid saving responses to higher job loss risk in partial equilibrium. While our theoretical results do not necessarily speak to the general equilibrium effects, we note that it is the partial equilibrium responses which map into our cross-sectional empirical estimates, making them the relevant model predictions for our analysis. Our setup has similarities to Bayer et al. (2019), but differs in that while we consider job loss risk, they study mean preserving spreads to future income. We show that this distinction is important, as the two different types of uncertainty have different implications for the relative responses of liquid versus illiquid savings. Moreover, we use our model predictions for liquid vs illiquid savings, in combination with our empirical results, to rule out that the estimated saving-responses are driven by a confounding decrease in long-run income. This result generalizes to other settings, highlighting that as long as one observes both liquid and illiquid assets, one can distinguish between the impact of higher job loss risk and potential declines in long-run earnings potential.

[11] There are also some papers which use *macro* data to capture the importance of job loss risk during the Great Recession in explaining saving dynamics, see for instance Mody et al. (2012) and Carroll et al. (2019). Interestingly, both Mody et al. (2012) and Carroll et al. (2019) attribute a somewhat smaller share of the total saving increase to the job loss risk channel than we do (40 % and 27 % respectively). Mody et al. (2012) use a cross-country panel regression to estimate the impact of job loss risk on savings. Because they want to control for the first moment effect of job loss risk, they use one period ahead income growth as a control variable in their regression. This reduces the estimate and can at least partly explain why they find smaller effects than us. Carroll et al. (2019) rely on a structural estimation of the US personal saving rate. As the authors acknowledge, the impact of uncertainty may be understated in their analysis, as they also model the impact of assumed exogenous changes in wealth and credit conditions. If changes in job loss risk *causes* changes in household wealth and credit conditions, these indirect impacts will not be attributed to arising from changes to job loss risk.

[12] Kekre (2021) develops the argument for UI theoretically in a large scale general equilibrium model.

## 2 Sources of income volatility

In this section we investigate the importance of job loss risk in accounting for individual income volatility. We argue that, even though job loss risk is not a pure uncertainty shock (i.e. it has a first moment effect on future income), it's contribution to individual income volatility makes it an important shock to study. We show that the probability of large earnings losses are almost negligible at less than 3% conditional on staying employed, while the probability of large earnings losses conditional on becoming unemployed exceed 60%. Job loss risk is therefore crucial in explaining the substantial downside in individual income volatility. For the analysis, we rely on Norwegian administrative data. We postpone a full data description to Section 4, before outlining the main empirical analysis in Section 5.

We start by defining income as the sum of annual real wage income and transfer income, excluding retirees and students from our sample. In line with our upcoming analysis, and with existing literature, we focus on male earnings. We calculate the percent change in individual income from one year to the next, and plot the distribution of income changes for job keepers (in red) and job losers (in black) separately in Figure 1. Focusing first on the left panel, we see that the expected income growth of job keepers is positive at 2.5%, and the distribution is narrowly centered around the mean. For those who experience unemployment however, expected income growth is -36%, and the standard deviation is twice that of job keepers. Moreover, the probability of large income losses, defined as income growth below -25%, is less than three percent for job keepers, and more than sixty percent for those who become unemployed. This implies that, as long as job loss risk exceeds 4.6%, the overall probability of large income falls will be dominated by job loss risk.[13] If we consider even larger income losses, say of at least fifty percent, this is virtually only possible conditional on job loss occurring.[14]

How does this relate to income risk? Although the literature often uses income volatility as a proxy for income risk (see e.g. Dynan et al. (2012)), ideally, we would want to separate between voluntary and involuntary changes in income. Intuitively, we expect much of the negative wage growth for job keepers to be voluntary, for instance caused by a reduction in hours worked,[15] as nominal wage cuts in principle cannot be unilaterally decided upon by the employer.[16] Alternatively,

[13] To see this, let the job loss probability be denoted by x. The probability of a large annual income fall related to job loss is then 0.63x, while the probability of a large annual income fall unrelated to job loss is 0.03(1-x). The former dominates the latter if x>0.046.

[14] The UI replacement ratio in Norway is generally 62 percent, but the income which goes in to calculating UI is capped above. This means that high income earners will have a replacement ratio below 62 percent. We discuss the institutional setup in Section 4.

[15] Halvorsen et al. (2020) use Norwegian tax data and impute hours worked by merging administrative data with data from The Norwegian Labor Force Survey. They find that, for large income reductions, about half is explained by hours worked and half is explained by hourly wages.

[16] The Norwegian Labor Inspection Authorities writes on their website that "The employer's management prerogative is limited by the employment contract. Major or material changes [*such as wage cuts*] cannot take place unless the parties have agreed to enter into a new agreement, or the employer issues a formal redundancy notice - termination and offer of other employment.". Conceptually however, separating between voluntary and involuntary wage

the negative wage growth for the employed could be caused by individuals who switch firms due to unemployment, but who do not register for unemployment benefits.[17] In this sense, negative income *volatility* conditional on employment might overstate negative income *risk*.

Unemployment could in principle also be voluntary, although there are economic incentives to avoid this, as UI is less generous for those who voluntary quit their job.[18] In an attempt to isolate unemployment episodes which are likely to be non-voluntary, we restrict our sample to individuals residing in the oil producing region during the oil price collapse in the right panel of Figure 1. The distribution is similar, with a marginal increase in the mean income growth conditional on job loss and a marginal decrease in the standard deviation. Given that income volatility for job keepers might overstate negative income risk, while income volatility for job losers is a better risk proxy, the reported distributions, if anything, underestimate the importance of job loss in accounting for negative income risk.

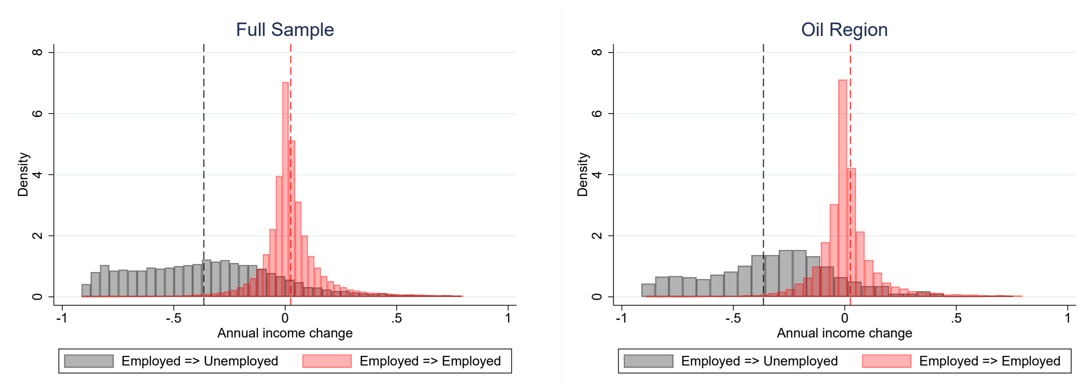


Figure 1: **Income changes for job losers and job keepers**. The distribution of annual income growth (wage income + transfer income) from one year to the next ($\frac{y_t - y_{t-1}}{y_{t-1}}$) for i) individuals who are employed in period $t-1$ and unemployed in period $t$ (Employed -> Unemployed) and ii) individuals who are employed in period $t$ and $t-1$ (Employed -> Employed). Left panel: Full sample. Right panel: The oil region in 2015 (i.e. the recession area).

## 3 Theoretical framework

Motivated by the importance of job loss in accounting for negative income volatility at the individual level, we now move on to exploring the impact of job loss risk on liquid and illiquid savings. We

cuts may be challenging, if for instance an employee agrees to a wage cut in the hope of avoiding being laid off if the firm is struggling financially.

[17]There has been a growing discrepancy between unemployment rates as measured based on UI and based on national survey responses in Norway, causing The Ministry of Finance to establish a working group to evaluate the reasons for this divergence. The working group concluded that a multitude of reasons probably contribute, including the rise in unemployment among groups who are not entitled to UI (students, recent graduates, immigrants etc.), as well as business cycle conditions (Andersen et al., 2017).

[18]If you quit your job without just cause, or if you are to blame for becoming unemployed, then you will generally not receive UI for the first 18 weeks of unemployment.

start by providing a theoretical framework. We consider a 3-period partial equilibrium model with unemployment risk. In this framework, we show that an increase in unemployment risk always increases liquid savings, but has an indeterminate impact on illiquid savings.

The setup has similarities with the partial equilibrium model in Bayer et al. (2019). Crucially however, our model has unemployment risk rather than a mean preserving spread to future income as the source of risk for households. This is important, as higher unemployment risk has both a variance and a level effect. That is, higher unemployment risk typically increases the volatility of future income, while at the same time reducing the level of expected future income. With a mean preserving spread however, expected future income is unchanged as income volatility rises. We show that the different shocks have different implications for household's asset allocations.

Empirically, a shock to unemployment risk may coincide with a reduction in long-term income. In the empirical analysis in Section 5, we study an exogenous increase in unemployment risk for oil workers resulting from the 2014 collapse in international oil prices. In this setting, it could be the case that oil workers experience both a short-term increase in unemployment risk, and a long-term decrease in future income – if the value of their human capital suddenly deteriorates. Motivated by this possible additional effect, we also use the partial equilibrium model to study the impact of long-term income changes on saving decisions today. We find that lower long-term income *reduces* liquid savings and increases illiquid savings. Hence, higher unemployment risk and lower long-term income have opposite impacts on liquid savings.

### 3.1 Setup

A representative household receives an endowment $y_i$ in period $i = \{1, 2, 3\}$. In the first period, the household decides between consumption $c_1$, investment in a liquid asset $b_1$ and investment in an illiquid asset $k_1$. The liquid asset pays a zero return in period 2, while the illiquid asset pays a positive return $r > 1$ in period 3. In the second period, the household is either employed and receives income $y_2$, or is unemployed and receives income $\eta y_2$, in which $\eta < 1$ is the replacement rate. The household decides between consumption $c_2$ and investing in the liquid asset $b_2$. We impose a borrowing constraint in all periods, so that the household can only save non-negative amounts. In the final period, the household faces no unemployment risk, and receives the endowment $y_3$ with certainty.

We abstract from discounting, so that households maximize the sum of utilities in period 1,2 and 3, and assume that the utility function takes the form $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$, i.e. there is constant relative risk aversion (CRRA). If the borrowing constraint binds in period 2, the household will consume all income and liquid assets in that period. If the constraint does not bind, the household will instead divide consumption equally between period 2 and 3. Note that, if the interest rate is not too large, or alternatively, income in period 2 is not too low, the household will never be constrained if employed in period 2, meaning that optimal consumption will have an interior solution. We formalize this in

Lemma 1 in Appendix A. Further, note that the household will only choose to hold liquid assets if it expects to be constrained if unemployed in period 2, as illiquid assets pay a higher return. We formalize this is Lemma 2 in Appendix A. Because we are interested in a setting in which the household does choose to hold liquid assets, we focus on this case here. Specifically, we assume that the conditions specified in Lemma 1 and 2 in the appendix hold, so that the household holds positive liquid assets and is not constrained in period 2 if employed. Under these assumptions, we arrive at the following consumption levels

$$c_{2E} = c_{3E} = \frac{b_1 + y_2 + y_3 + rk_1}{2}$$

$$c_{2U} = b_1 + \eta y_2$$

$$c_{3U} = rk_1 + y_3$$

in which $E$ denotes employment in period 2, while $U$ denotes unemployment in period 2. We restrict attention to this equilibrium in the analysis below.

Let $\rho < 1$ capture the probability of becoming unemployed in period 2. To capture the fact that unemployment is disadvantageous, we assume that the replacement ratio $\eta$ is sufficiently low so that $c_{2U} < c_{2E}$.

Optimal *liquid* savings in period 1 implies that the marginal utility of consumption in period 1 equals expected marginal utility in period 2. Optimal *illiquid* savings in period 1 implies that the marginal utility of consumption in period 1 equals the expected marginal utility of consumption in period 3, times the return on the illiquid asset. In other words, the function $F_1 = 0$ implicitly defines $b_1^*$ and the function $F_2 = 0$ implicitly defines $k_1^*$, in which

$$F_1 \equiv u'(c_1) - \rho u'(c_{2U}) - (1-\rho)u'(c_{2E})$$

$$F_2 \equiv u'(c_1) - r\rho u'(c_{3U}) - r(1-\rho)u'(c_{3E})$$

### 3.2 An increase in unemployment risk

We first consider what happens when unemployment risk $\rho$ increases. Holding the saving decisions in period 1 fixed, higher unemployment risk decreases expected consumption in period 2 by making the unemployment state more likely. Conversely, the expected marginal utility of consumption in period 2 increases. As a result, the household wants to increase $c_{2U} = b_1 + \eta y_2$. The only way to make this happen is by increasing liquid savings. Hence $b_1^*$ increases, as formalized in Proposition 1 and proved in the appendix.

**Proposition 1.** *Optimal liquid savings $b_1^*$ are increasing in unemployment risk $\rho$, i.e.* $\dfrac{\partial b_1^*}{\partial \rho} > 0$.

*Proof.* See Appendix A. □

While the impact on liquid savings is intuitive and unambiguous, the impact on illiquid savings is more complicated. First note that the increase in liquid savings, all else equal, implies a reduction in illiquid savings. This is intuitive, and says that higher unemployment risk makes the household want to substitute illiquid savings for liquid savings – which are readily available should the bad state of the world materialize in the next period.

However, there is an additional effect working on illiquid savings. Higher unemployment risk will generally also affect expected consumption in the period 3, by making unemployment in period 2 more likely. Specifically, if $c_{3U} < c_{3E}$, unemployment increases the expected marginal utility of consumption in period 3. As a result, the household wants to increase $c_{3U} = rk_1 + y_3$ when faced with higher unemployment risk. This can only be done by increasing illiquid savings. As a result, the total impact on $k_1^*$ is ambiguous.

Note that, in the special case where $c_{3U} \geq c_{3E}$, the motive to increase illiquid savings is eliminated. In this case, the impact on $k_1^*$ from higher unemployment risk is always negative. However, we view this as a strict assumption which might not hold in the data. As such, we conclude that in general, higher unemployment risk has an ambiguous impact on illiquid savings, as formalized in Proposition 2 and proved in the appendix.

**Proposition 2.** *The impact of unemployment risk $\rho$ on illiquid savings $k_1^*$ is generally indeterminate, i.e.* $\dfrac{\partial k_1^*}{\partial \rho} \lesseqgtr 0$ *. If however $c_{3U} \geq c_{3E}$, then* $\dfrac{\partial k_1^*}{\partial \rho} < 0$.

*Proof.* See Appendix A. □

How does the comparative statics discussed here differ from the comparative statics with respect to a pure uncertainty shock, i.e. a mean preserving spread? Bayer et al. (2019) find that higher income volatility increases liquid savings and unambiguously reduces illiquid savings. While the impact on liquid savings is qualitatively the same, the impact on illiquid savings could in principle differ. The reason for this discrepancy is that, in their case, an increase in volatility decreases expected consumption in period 2, but *increases* expected consumption in period 3. As such, households have no reason to transfer more resources to the final period by increasing liquid savings, and so $k_1^*$ declines. In our case however, the impact on expected consumption in period 3 is generally ambiguous, implying that the total impact on $k_1^*$ is also ambiguous.

A related way to think about the difference is that with the mean preserving spread to future income, the impact on expected consumption in period 2 and 3 exactly cancel each other out, meaning that there is no income effect. In our case however, it is possible – even plausible – that expected consumption falls both in period 2 and 3, implying a negative (future) income effect. To smooth consumption, the household therefore wants to increase savings today. For liquid savings, we thus have two forces working in the same direction. For illiquid savings however, we have one force working towards a reduction, i.e. the desire to substitute illiquid savings for liquid savings, and one force working towards higher savings, i.e. the desire to increase general savings in order to smooth consumption.

### 3.3 A decrease in long-term income

We now consider what happens when long-term income $y_3$ decreases. Consider first the impact on period 2 consumption, which is what matters for optimal liquid savings. While consumption if unemployed is unaffected, consumption if employed, $c_{2E} = \frac{b_1+y_2+y_3+rk_1}{2}$ , decreases. This makes the household want to transfer more resources to period 2 - but *only* in the employed state of the world. This is crucial, because consumption in period 2 if employed can be increased both by increasing liquid and illiquid savings. However, because illiquid savings pay a higher return, increasing $c_{2E}$ by increasing illiquid savings is less costly than by increasing liquid savings. As a result, $k_1^*$ increases. All else equal, this reduces $b_1^*$.

Consider now the impact on period 3 consumption, which is what matters for optimal illiquid savings. Lower long-term income reduces period 3 consumption in both states of the world. That is, $c_{3U} = rk_1 + y_3$ falls and $c_{3E} = \frac{b_1+y_2+y_3+rk_1}{2}$ falls. The only way to increase $c_{3U}$ is by increasing illiquid savings, and the most *efficient* way to increase $c_{3E}$ is by increasing illiquid savings. As a result, $k_1^*$ increases. All else equal, this again reduces $b_1^*$. Hence, there is no ambiguity in the case of lower long term income, which decreases liquid savings and increases illiquid savings. This is formalized in Proposition 3 and proved in the appendix.

**Proposition 3.** *Liquid savings increase and illiquid savings decrease in long-term income, i.e.* $\dfrac{\partial b_1^*}{\partial y_3} > 0$ *and* $\dfrac{\partial k_1^*}{\partial y_3} < 0$.

*Proof.* See Appendix A. □

To sum up, higher unemployment risk increases liquid savings and has an indeterminate impact on illiquid savings. The intuition being that higher unemployment risk induces a shift in savings from illiquid to liquid assets, while at the same time increasing optimal savings. This is in contrast to a mean preserving spread, in which the impact on illiquid savings is always negative.

A reduction in long-term income has the *opposite* impact on liquid savings compared to higher unemployment risk. That is, lower long term income reduces liquid savings. In addition, lower long-term income unambiguously increases illiquid savings. The intuition being that lower long term income increases optimal savings, and that this increase is most effectively achieved by increasing the high-return illiquid asset. Empirically therefore, an increase in unemployment risk should be distinguishable from a reduction in long-term income as long as one considers both liquid and illiquid assets.

## 4 Data and institutional background

In this section we first describe the data we use for our empirical analysis, before moving on to discussing the institutional background.

Our analysis is done using administrative data covering the universe of Norwegian tax filers. The tax data is a panel data set, covering the period 1993 to 2017. All data is annual, and variables are measured at the end of the year. The administrative data contains detailed information on individual income and wealth holdings, generally reported by third parties. Our main outcome variables are liquid financial assets and illiquid financial assets, measured at the individual level. Liquid assets are defined as bank deposits, and include all forms of saving accounts, checking accounts, fixed term deposits etc. Close to 100 percent of the sample have some positive holdings of bank deposits in a given year, while a substantially lower share own other financial assets or real wealth. Illiquid financial assets are defined as the remaining financial assets, including stocks, bonds and mutual funds. We also consider illiquid real wealth, in the form of housing wealth and other real wealth. From 2010 onward, real wealth can be divided into the market value of primary housing, secondary housing and other sources of real wealth. The data set also includes information on total debt, allowing us to measure net wealth.

The data further contains information on a broad range of income measures, including transfer income such as unemployment insurance. We use this to define individuals as unemployed if they receive unemployment benefits in a given year. Income is reported and taxed individually in Norway, whereas wealth is reported individually and taxed at the household level. Our unit of analysis is the individual, and so we cannot rule out that there is some misreporting of wealth within the household. However, we expect variables such as bank deposits to be relatively well measured also at the individual level, as it is reported by the bank and must be reported as belonging to the owner of the bank account. We follow much of the existing literature in focusing exclusively on men (see for example Basten et al. (2016) who also uses Norwegian administrative data).

The tax data can be merged with labor market data as of 2000, providing us with detailed information on labor market status and occupation. The latter will be important in identifying which individuals experience an increase in job loss risk. Our full data set therefore covers the period 2000 to 2017, but we focus most of the analysis on the period from 2010 and onward, in order to avoid any direct impacts of the financial crisis, which affected the Norwegian economy mainly in 2008 and 2009. Importantly, the labor market data allows us to match workers to firms, enabling us to calculate the observed tenure for each worker, which will be useful for identifying groups with especially large increases in job loss risk.

Occupation is only observed for employed individuals, and there are some instances of employed individuals not having a reported occupation. We therefore define an individual as belonging to an occupation $o$ if we observe the individual as being employed in that occupation for at least one of the three years leading up to the shock. We divide employed individuals into three occupational groups. The first group consists of engineers and civil engineers. The former requires 1-3 years of higher education, whereas the latter requires a minimum of four years of higher education. The second group consists of individuals who are employed in occupations requiring some higher education, and who are not engineers. We refer to this group as *other high skilled* workers. Managers, professionals, technicians and associate professionals belong to this group. In total, close to 50 percent of employed individuals are categorized as being either engineers or other high skilled workers, see Appendix Table C.1. The remaining working individuals are employed in occupations which do not require higher education, and are referred to as low skilled.

In addition to using only men, we make some further sample restrictions. First, we use a 25 percent random sample of the tax filing population. Second, we exclude individuals with business income in order to obtain a well defined concept of job loss risk. Third, we only include individuals who are employed at baseline and who can be matched to an occupation in one of the three years leading up to the shock. We also winsorize all variables at the 99 percent level, following Basten et al. (2016).

Summary statistics for the three occupational groups are reported in Table 1. Nearly everyone owns some liquid assets, although the average and median holdings are substantially larger for high skilled workers than for low skilled workers. Engineers and other high skilled workers hold similar amounts. Among the high skilled, just above 60 percent own illiquid financial assets, and other high skilled workers own somewhat more of these assets than engineers. As there is a substantial share of managers in this group, this could perhaps reflect that some of their labor compensation takes the form of financial assets. Among the low skilled, less than 40 percent own illiquid financial assets. Also note that these illiquid financial assets appear relatively skewed within groups, with average holdings far exceeding median holdings.

Engineers and other high skilled workers also look similar in terms of real wealth. Exactly 76 percent in both groups are homeowners, compared to less than 50 percent for low skilled workers. Just above 70 percent in both groups have positive net wealth. The average wage income among engineers is roughly $95,000, which is somewhat higher than for other high skilled workers, and substantially higher than for low skilled workers. High skilled workers are older than low skilled workers, but engineers and other high skilled workers have similar average and median ages at 44 to 45 years. We thus conclude that engineers and other high skilled workers look fairly similar along observable characteristics, and that both groups have substantially higher wealth and income levels than low skilled workers. While our identification strategy does not assume equality across observables, we restrict the analysis to a comparison of engineers and other high skilled workers.

| | Average | | | Median | | |
|---|---|---|---|---|---|---|
| | Engineers | High Skilled | Low Skilled | Engineers | High Skilled | Low Skilled |
| Liquid assets | 35,900 | 34,700 | 19,600 | 14,200 | 11,500 | 5,600 |
| Illiquid assets | 23,800 | 43,000 | 11,300 | 1,600 | 1,600 | 0 |
| Prim. Housing Wealth | 233,100 | 252,000 | 134,100 | 227,500 | 238,500 | 0 |
| Other Real Wealth | 44,600 | 52,300 | 23,200 | 8,300 | 7,700 | 100 |
| Debt | 183,600 | 197,400 | 104,200 | 153,200 | 161,000 | 33,200 |
| Wage Income | 94,600 | 85,600 | 55,400 | 90,300 | 78,800 | 55,600 |
| Age | 44 | 45 | 38 | 44 | 45 | 37 |
| Liquid assets > 0 (%) | 99 | 99 | 98 | | | |
| Illiquid Assets > 0 (%) | 61 | 64 | 39 | | | |
| Housing Wealth > 0 (%) | 76 | 76 | 48 | | | |
| Net Wealth > 0 (%) | 72 | 71 | 67 | | | |
| Observations | 21,901 | 74,113 | 160,223 | | | |

Table 1: **Summary statistics.** Summary statistics for 2013 in 2015 USD (rounded to closest 100 with exchange rate USD/NOK 7.5).

### 4.1 Institutional background

The impact of job loss risk on savings is likely to depend on the unemployment insurance (UI) scheme. That is, not only job loss risk matters, but also the expected income fall upon job loss – or what we might think of as effective job loss risk. OECD data on 2015 replacement rates from the *Tax and Benefit Systems: OECD Indicators* shows that out of the 40 countries included, Norway is ranked as number 18, i.e. close to the OECD median. For comparison, the US is ranked as number 37. All else equal, we would therefore expect job loss risk to have a smaller impact on savings in Norway than in the US.

Norwegian workers who become unemployed are generally entitled to unemployment insurance of 62 percent of pre-unemployment wages for a duration of two years. While there is a requirement to qualify, this is relatively low, and workers with a non-trivial position throughout the calendar year would all be expected to qualify. There is however an upper limit on pre-unemployment wages, meaning that income above a year-specific threshold does not enter into UI calculations. High income earners therefore have an effective replacement rate of less than 62 percent. This turns out to be relevant for our sample, as the treatment group will consist of relatively high-income individuals. Using the year specific thresholds, we calculate an effective replacement ratio of close to 50 percent for our sample.

With regards to the level of job loss risk, Norwegian unemployment rates are among the lowest in the OECD group. Appendix Figure B.1 depicts harmonized OECD unemployment rates by country, with the Norwegian unemployment rate typically falling below four percent.[19] While the unemployment rate in Norway has generally been below that in the US, this changed in the aftermath of the 2014 oil price collapse. At the same time as the US unemployment rate recovered from the Great Recession, the oil price collapse led to a deterioration of Norwegian labor market conditions. As a result, the unemployment rates in the two countries were at similar levels prior to the COVID19-pandemic.

Summing up, when interpreting the results of this study in a broader context, one should keep in mind that the setting is one of relatively low baseline job loss risk, and relatively generous unemployment insurance. That being said, the UI generosity is close to the OECD median, and because our treatment group consists of high-income individuals, their effective replacement ratio is lower than the national average.

# 5 Estimating the impact of job loss risk on savings

The main goal of the empirical analysis is to identify the impact of job loss risk on household savings and portfolio allocation. To obtain an exogenous increase in job loss risk, we use the 2014 oil price collapse as a novel natural experiment. By comparing asset allocations for individuals with different levels of job loss risk, but who are subject to the same local recession effects, we aim to isolate the impact of job loss risk from other recession effects.

## 5.1 Natural experiment: The oil price collapse of 2014

The sudden collapse of the oil price in the summer of 2014 led to an exogenous increase in job loss risk for certain regions and occupations. Job loss risk increased mainly in oil producing regions in the South-West of Norway, while the hardest hit occupational group was engineers.

The price of Brent crude oil fell from roughly \$110 to less than \$50 per barrel in the second half of 2014, as seen in Appendix Figure B.2. Popular explanations include a slowdown in global demand, especially from China, as well as high supply of shale oil from the US. Tokic (2015) notes that in contrast to the oil price busts of 1991 and 2008, the 2014 bust was not preceded by an oil price spike, and as such was "completely unexpected". To the best of our knowledge, there has been no suggestions that the oil price collapse of 2014 was in any way related to the Norwegian oil sector, which stands for only about two percent of world production. We thus feel comfortable assuming that the oil price shock was both unexpected and exogenous to the Norwegian economy.

At the start of 2014, the petroleum sector accounted for roughly 25 percent of Norwegian GDP and 40 percent of Norwegian exports. The large and unexpected decrease in oil prices therefore had an adverse effect on the Norwegian labor market. However, as documented below, the negative

[19] We restrict the comparison to the pre-COVID19 period, in order to avoid the challenges of measuring unemployment during the pandemic.

impact was to a large degree contained to certain regions and occupations.

**Regional and occupational variation** Oil production is concentrated in the South-West of Norway, as seen from Appendix Figure B.3. Two out of 19 counties employ a disproportionately high share of oil sector workers, and we define these two counties as the "oil region".[20] The combined population of these two counties in 2014 was close to one million, or 19 percent of the total population.

The left panel of Figure 2 depicts the percentage point change in unemployment rates by county. The red squares capture the average of the two counties defined as the oil region, while the blue dots capture the remaining seventeen counties. In 2015, the unemployment rate in the oil region increased by more than two percentage points, making it the largest increase in county level unemployment over the past fifteen years. At the same time, most other counties experienced moderate or no increase in unemployment. The unemployment increase in the oil region dampened somewhat in 2016, and started to reverse in 2017. As documented below however, the unemployment *level* in the oil region remained elevated in 2017. We will refer to the two oil counties as the *recession area* in the upcoming analysis.

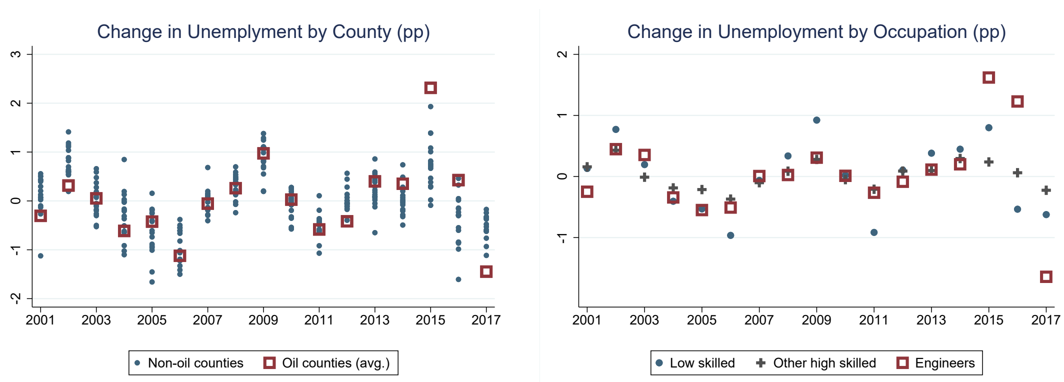


Figure 2: **Changes in unemployment rates (pp) by county and occupation.** Left panel: Every blue dot represents one county, while the average development across the two oil counties are captured by the red squares. Right panel: Blue dots represent low-skilled workers, gray plus-signs represent other high skilled workers than engineers, while red squares represent engineers.

No other occupational group received as much media attention as engineers following the oil price collapse[21], and the data suggests that this was indeed warranted.[22] The tax data contains detailed

[20]The two oil counties are *Hordaland* and *Rogaland*, and the largest city in the area is *Stavanger* - sometimes referred to as the oil capital.

[21]Some examples of newspaper headlines: "Statoil is laying off more **engineers**" *Aftenposten* April 2015, "One out of three **engineers** are worried about losing their job" *Aftenposten* May 2015, "Union leader for the **engineers**: Worried unemployment will rise further" *Aftenposten* May 2015, "Solberg [the prime minister] wants to help unemployed **engineers**" *DN* September 2015. "New report on the oil **engineers**: Unemployment increased by 342 percent in one year - but many are finding new employment" *E24* March 2016.

[22]The Norwegian Labour and Welfare Administration (NAV) reports unemployment rates for fifteen different occupations, one of which is Engineers & IT workers. According to their data, the increase in unemployment for this

information on occupations for employed individuals. We categorize individuals as *engineers* if they were employed as engineers in the time leading up to the oil price collapse, i.e. if they were employed as engineers in at least one of the years 2011-2013. The individuals in this group are either civil engineers - which in Scandinavia is a protected title - or engineers. The former requires at least four years of higher education, while the latter requires 1-3 years of higher education. Individuals who do not belong to this group, but who are employed in other occupations requiring higher education, are labeled *other high skilled*.

The right panel of Figure 2 depicts the change in unemployment by occupational group. The change in unemployment rates for low skilled workers is captured by the blue dots. Note that the labor market outcomes of this group seem to be especially cyclical, with high peaks and low busts compared to other workers. The change in unemployment rates for engineers is captured by the red squares, while the change in unemployment rates for other high skilled workers is captured by the plus-signs. These two groups look fairly similar prior to the oil price collapse, but have very different employment outcomes in the year following the shock. In 2015, the unemployment rate for engineers increased by more than 1.5 percentage points - the highest increase observed - while the unemployment rate for other high skilled workers remained roughly unchanged. A similar increase was observed in 2016, with a partial reversal following in 2017. As will become evident in the upcoming analysis, this does not only reflect the geographical distribution of engineers and other high skilled workers.

**Salience** Figure 2 documented that the oil region experienced a sharp increase in relative unemployment in 2015. Google search data allows us to confirm that not only was the shock quantitatively large, it also appears to have been salient. Search volumes are indexed relative to the maximum search volume in the sample, which is assigned a value of 100. Further, search volumes are measured relative to the total amount of searches in a given area, allowing for meaningful comparisons across geographic areas of different sizes.

The left panel of Figure 3 depicts the volume of searches which Google classifies as belonging to the search category *Brent Blend*, i.e. oil price related searches. The solid red line depicts the volume of oil price related searches in the oil region over time. After the oil price started falling in August 2014, there is an immediate and sustained spike in oil price related searches. As seen from the dashed blue line, the rest of the country follows a very different pattern. Although there is some increase also in other counties, the magnitude is modest compared to that in the oil region. We thus conclude that individuals residing in oil producing areas are especially aware of, and are paying attention to, the collapse in the oil price.

Even though individuals living in affected areas are paying attention to the sudden oil price bust, they need not be aware of the negative consequences for the local labor market. In order to

group in 2015 was the largest observed increase for any occupational group since their sample starts in 2003.

evaluate how salient the shock is in terms of labor market risk, the right panel of Figure 3 depicts the volume of searches which Google classifies as belonging to the search category *Layoff*. Again, we see a rather striking pattern. While there is virtually no increase in layoff related searches in other counties, there is a large and persistent increase in the two oil counties. As before, the increase starts as the oil price begins falling in mid-2014, and then peaks in early 2016. Note that this means that individuals are googling layoffs even before unemployment rates start to rise in the data.[23]

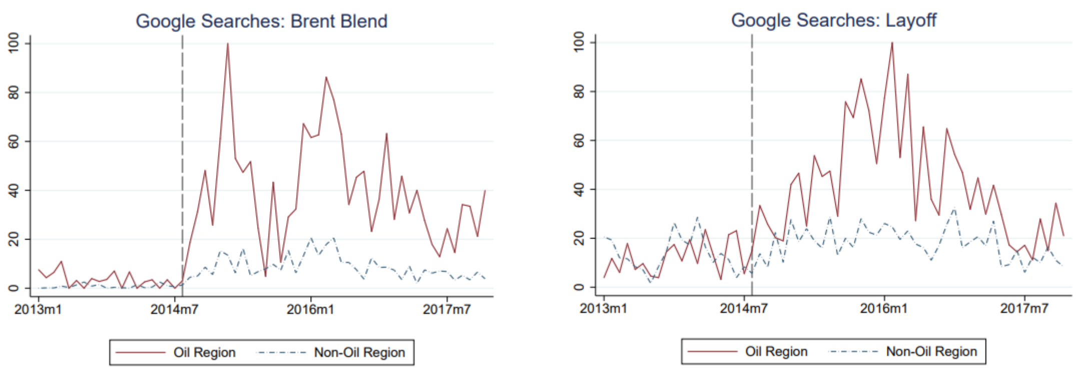


Figure 3: **Google search volumes for the oil region and other counties**. The index is set to 100 for the maximum search volume in the sample. Left panel: google searches related to the oil price (i.e. Brent Blend). Right panel: google searches related to layoffs.

Interestingly, search volumes for layoffs peak in January 2016 (and search volumes for the oil price reaches its second highest value), which is exactly when the oil price reaches its minimum value of $30 per barrel. Based on the Google search data, we thus conclude that not only are individuals living in oil producing areas immediately aware of the dramatic fall in the oil price, they also seem to understand that this implies an increase in job loss risk.

## 5.2 Methodology

In order to isolate the impact of job loss risk from other recession effects, we use a difference in difference approach to compare liquid and illiquid savings for engineers to that of other high skilled workers in the recession area. This within-region comparison allows us to control for the potential impact of other local recession effects on savings, provided that our treatment and control group have similar loadings on these effects. We provide supportive evidence for this in Subsection 5.4. Further, by contrasting the baseline findings to the results from an across-region comparison in

[23]Unemployment rates rise in 2015 according to the tax data, whereas layoff related Google searches increase also prior to 2015. Prior to the oil price collapse in August 2014, the search volume index has an average value of 12. After the oil price collapse, but prior to January 2015, the search volume index has an average value of 28. From January 2015 to December 2017 the search volume index has an average value of 45.

Section 6, we can explicitly evaluate the importance of other local recession effects and quantify the relative importance of the job loss risk channel.

We estimate a standard difference in difference regression, specified in equation (1), and a dynamic difference in difference regression, specified in equation (2). The main outcome variable $Y_{it}$ is either liquid financial assets or illiquid financial assets, for individual $i$ in year $t$. $T_i$ is an indicator variable equal to one if individual $i$ is in the treatment group, and equal to zero if individual $i$ is in the control group. In the baseline analysis, $T_i = 1$ for engineers residing in the recession area, and $T_i = 0$ for other high skilled workers residing in the recession area. Treatment status is defined based on the years prior to the oil price collapse. $I_t^{post}$ is an indicator variable which takes the value one from 2014 and onward, i.e. in the post oil price collapse period. Year fixed effects $\delta_k$ are included to capture time-varying aggregate effects which are common to all individuals, while individual fixed effects $\alpha_i$ are included to capture individual, time-constant factors.

The coefficient of interest in equation (1), which captures the relative savings of the treatment group in the post period, is $\beta_k$. In the dynamic difference in difference specification in equation (2), the coefficients of interest are the $\beta_k$'s, which capture the impact of the interaction term between treatment status and year dummies. Given that $\beta_k = 0$ for $k < 2014$, i.e. the parallel trend assumption holds prior to the shock, the dynamic treatment effect is captured by the $\beta_k$'s for $k \geq 2014$. Standard errors are clustered at the individual level.

$$Y_{it} = \alpha_i + \sum_k \delta_k \mathbf{1}_{t=k} + \beta \left( T_i \times I_t^{post} \right) + \epsilon_{it} \tag{1}$$

$$Y_{it} = \alpha_i + \sum_k \delta_k \mathbf{1}_{t=k} + \sum_k \beta_k \left( T_i \times \mathbf{1}_{t=k} \right) + \epsilon_{it} \tag{2}$$

Because we are interested in the impact of job loss risk, rather than the impact of realized unemployment, we restrict the baseline analysis to only include individuals who are not (yet) unemployed.[24] However, we also consider results using the full sample to avoid potential selection issues, and the estimated responses are similar. In fact, because the initial saving response precedes the increase in the unemployment rate, the coefficient estimates for the early saving response is virtually identical.

**Selection into unemployment** Before presenting the results, we briefly discuss the issue of selection into unemployment. In a typical event study in which job loss risk is identified by future unemployment, an important concern is that there is an individual level shock which is causing the upcoming job loss and affecting current saving behavior. This concern is strongly mitigated in our setting, as job loss is caused by an exogenous fall in the international oil price – and not by an individual

[24] Specifically, we condition on job loss not occurring between 2014 and 2017, and show saving responses up until 2016. As a result, our sample only consists of individuals who will not become unemployed for at least another year, and are therefore unlikely to have received severance pay or any extraordinary income related to job loss.

level shock. However, that does not mean that job loss (risk) is randomly distributed within the affected groups. For instance, as we show in the upcoming analysis, engineers with low tenure are more likely to experience job loss than engineers with high tenure. Our estimated saving response will reflect the behavior of people who experience a relatively large increase in job loss risk, which is not necessarily representative of the total population.

We show in Appendix D that after controlling for tenure, other observable characteristics are not informative in predicting which engineers experience job loss following the oil price collapse. Further, we show that a simple model based on observable characteristics has substantially less power in explaining job loss following the oil price collapse than in "normal" times. Hence, to the extent that observable characteristics are relevant for evaluating selection into unemployment, there appears to be relatively less selection following the oil price collapse. This suggests that studying the effects of unemployment during times of crisis may get us closer to identifying population representative responses.

### 5.3 Results

The empirical results in this section confirm that higher job loss risk affect household savings and asset allocations. Specifically, higher job loss risk increases holdings of safe and liquid financial assets, while leaving illiquid and more risky financial assets unaffected. Reassuringly, the increase in liquid savings is driven by low-tenured workers, who experience an especially large increase in job loss risk.

Figure 4 depicts the unemployment rate and the separation rate in the recession area over the period 2001-2017, for engineers and other high skilled workers. We include both the unemployment rate and the separation rate, as they capture different aspects of unemployment risk. The separation rate is defined as the probability of transitioning from employed to unemployed. While the separation rate captures the risk of job loss, the unemployment rate is closer to capturing the total risk of unemployment – as it also reflects the job finding rate. As seen from the figure, engineers and other high skilled workers have very similar unemployment and separation rates prior to 2014. This is important as it alleviates the concern that individuals are selecting into our control and treatment groups based on differences in risk aversion, a selection issue studied in detail in Fuchs-Schündeln and Schündeln (2005).

The unemployment rate for engineers increases from an average of roughly one percent prior to the oil price collapse, to a peak of almost seven percent after the oil price collapse. There is some increase in unemployment rates also for other high skilled workers. However, the increase is moderate compared to engineers. In the robustness section (Section 5.4), we use an alternative control group consisting only of high skilled *government* workers. This group experienced virtually no increase in job loss risk following the oil price collapse. Reassuringly, the results from this exercise are similar, suggesting that spillovers to the control group is not a concern.

The separation rate is depicted in the right panel of Figure 4. As was the case for the unemployment rate, the separation rate for engineers and other high skilled workers is similar prior to 2014. Post-2014, there is a large and sustained increase in the separation rate for engineers relative to that of other high skilled workers. Note that the separation rate increases by a similar magnitude as the unemployment rate in 2015, but by a smaller amount in 2016. This suggests that the initial increase in unemployment is driven almost exclusively by the separation rate, while a decline in the job finding rate is important in explaining the subsequent increase. By 2017, the separation rate for engineers has almost fallen back to its pre-crisis level, whereas the unemployment rate remains more visibly elevated.

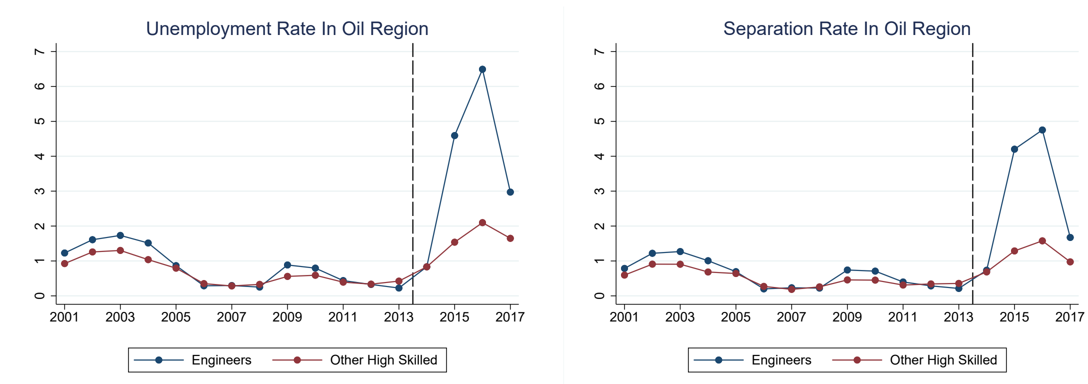


Figure 4: **Job loss risk for the control and treatment group.** Unemployment rate and separation rate (%) for engineers in the recession area and other high skilled workers in the recession area.

In order to estimate the impact of job loss risk on savings, we start by estimating the restrictive difference in difference specification in equation (1), with dependent variables $Y_{it} = \{\text{Liquid assets, Illiquid assets}\}$. The results are reported in Table (2). The first column captures the initial increase in liquid savings, when we restrict the sample to end in 2014. This has the benefit of capturing the saving response before unemployment rates started to increase, and before any policy reactions were implemented or even planned. In this case, liquid savings increase by an average amount of \$1,279 or 3.8 percent. In order to quantify the saving response, it is useful to express the saving estimate relative to the increase in unemployment risk. To be consistent with our theoretical framework in Section (3), and search and matching models such as Ravn and Sterk (2017), we use the next period increase in risk. Scaling the saving response by the relative increase in the unemployment rate, we find that a one percentage point increase in the unemployment rate increases liquid savings by 1.3 percent. Scaling the saving response by the relative increase in the job loss rate, we find that a one percentage point increase in the job loss rate increases liquid savings by 1.4 percent.

As an alternative, Column 2 reports the impact on liquid assets if we consider the saving response up until 2016. We stop in 2016, which is one year prior to the last year in our sample, in order to still be able to capture observed unemployment risk one period ahead. Considering this longer response period, the increase in liquid assets increases slightly in absolute value to \$1,327. The liquid saving response per percentage point increase in the unemployment rate also increases slightly, while the liquid saving response per percentage point increase in the job loss rate increases more noticeably. This is due to the relative dynamics of the unemployment rate and the job loss rate illustrated in Figure (4). Specifically, while the separation rate increases substantially from 2015 to 2016, the job loss rate increases only moderately, and is almost back to pre-crisis levels by 2017.

Columns 3 and 4 capture the response of illiquid savings to the increases in job loss risk. The coefficient estimates are negative, but economically small and statistically insignificant. We thus conclude that illiquid assets do not respond to the increase in job loss risk, implying an increase in the overall safety and liquidity of individual portfolios.

While not reported in Table (2), we have also investigated whether there are any responses in real wealth holdings. We find mixed results for housing wealth, with some positive effect when considering the 2010-2014 period, and an insignificant effect when considering the 2010-2016 period. As there is some indication of pre-trends for housing wealth however, we do not focus on the housing results in our analysis. For non-housing real wealth we do not find any impact.

| | (1) Liquid assets | (2) Liquid assets | (3) Illiquid assets | (4) Illiquid assets |
|---|---|---|---|---|
| $I_t^{\text{post}} \times T_i^{2013}$ | 1,279** | 1,327** | -66.55 | -388.2 |
| | (566.6) | (571.6) | (801.7) | (902.2) |
| Percentage increase | 3.82 | 3.70 | -0.14 | -0.76 |
| per pp increase in unemployment rate | 1.34 | 1.36 | -0.05 | -0.028 |
| per pp increase in job loss rate | 1.40 | 1.74 | -0.05 | -0.36 |
| Mean of dependent variable | 33,405 | 35,886 | 47,433 | 51,387 |
| SD of dependent variable | 58,407 | 61,403 | 134,952 | 140,801 |
| Individual FE | Yes | Yes | Yes | Yes |
| Sample period | 2010 - 2014 | 2010 - 2016 | 2010 - 2014 | 2010 - 2016 |
| Clusters | 19,027 | 18,610 | 19,027 | 18610 |
| N | 93,699 | 128,133 | 93,699 | 128,133 |

Table 2: **The impact of job loss risk on liquid and illiquid savings.** Regression results from estimating equation (1) with $Y_{it} = \{\text{Liquid assets, Illiquid assets}\}$ for job keepers.

Having established the positive impact on liquid financial savings and the non-responsiveness of illiquid financial savings, we now move on to studying the dynamics. This allows us to both explicitly document that the parallel trend assumption is satisfied prior to the shock occurring, and to study how the saving responses evolve over time. Here we focus on the impact on liquid saving. In Appendix Figure B.5 we show that the parallel trend assumption is satisfied also for illiquid assets, for which there is no significant impact post-shock.

We start by simply plotting the raw data. The left panel of Figure 5 depicts liquid savings for engineers and other high skilled workers over time. Liquid assets for the two groups follow each other closely up until 2013, at which time there is a divergence which persists until 2016. Reassuringly, the divergence appears to be driven by an above trend increase in liquid savings for engineers rather than a below trend increase in liquid savings for other high skilled workers. Regression results from estimating equation (2) with $Y_{it}$ = Liquid savings$_{it}$ are depicted in the right panel of Figure 5. The pre-2014 coefficients are very close to zero in magnitude and not statistically significant, suggesting that the parallel trend assumption is satisfied prior to the oil price collapse. In 2014, the coefficient is positive at roughly $1,300 and statistically significant. This rise in liquid savings for engineers increases only very moderately after 2014. The dynamic saving responses thus show that nearly all of the saving response occurs at the onset of the recession, in which there is a spike in uncertainty. In Appendix Figure B.4 we show however, that for individuals who lost their job in 2016 or 2017, the largest increase in savings took place in 2015 – at which point their individual job loss risk probably peaked.

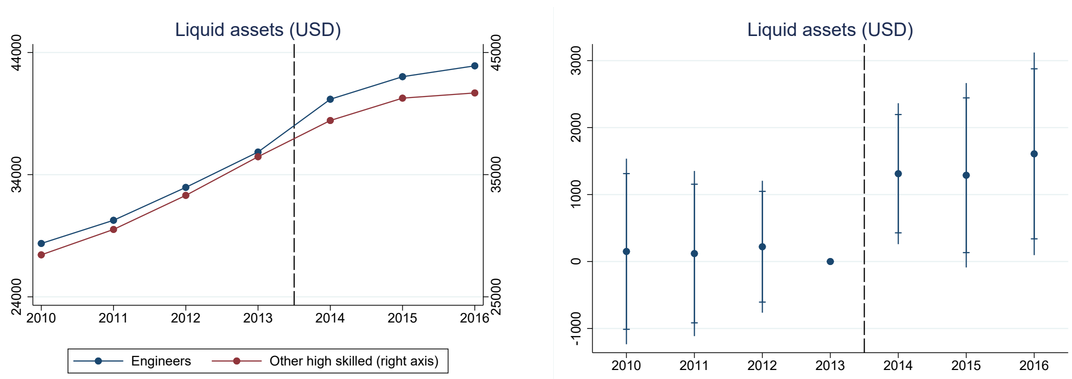


Figure 5: **Liquid assets for the control and treatment group.** Left panel: Liquid assets (USD) for engineers residing in the recession area and other high skilled workers residing in the recession area. Right panel: Regression results from estimating equation (2) with $Y_{it}$ = Liquid assets$_{it}$ for job keepers.

How do we interpret the magnitude of the liquid savings increase? One way of doing this is to imagine that all working-age individuals suddenly increased their liquid savings by $1,300, the approximate average of the results in Columns 1 and 2 in Table (2). What would this amount to in terms of household consumption and GDP? Using 2014-figures, we find that if all individuals aged 18-66 increased liquid savings by $1,300, this would amount to an increase in savings equal to 2.6% of household consumption and 1.0% of total GDP. For comparison, US household consumption fell by 1.6% in 2009 as a result of the financial crisis and by 3.3% in 2020, as a result of the COVID19 pandemic.[25] Hence, we view our estimated saving responses as being relatively large. That is, if the

[25] US consumption responses are calculated based on "Personal consumption expenditures: Household consumption

shock we were studying was a national shock that affected all working-age individuals, we would expect to see quite sizable effects on total consumption and output.[26]

**Tenure** While engineers residing in the recession area experienced a general increase in job loss risk after 2013, the increase in risk was not uniformly distributed. In particular, individuals with low tenure faced an especially large increase in the probability of job loss. The Basic Agreement between the Norwegian Confederation of Trade Unions (LO) and the Confederation of Norwegian Business and Industry (NHO) clearly states that tenure should be an important factor in deciding who gets laid off as a result of cutbacks or restructuring (§ *8-2 Seniority in the event of dismissal due to cutbacks*). The seniority or tenure principle should only be departed from when "there is due reason for this". Given that low-tenured individuals faced a particularly large and salient increase in job loss risk, one would expect these individuals to have larger saving responses.

We estimate tenure by calculating the number of years an individual has worked at the same firm. Because the individual tax data can only be matched to employer information as of 2000, the maximum observed tenure prior to the oil price collapse is fourteen years. In 2013, the median observed tenure of engineers residing in the recession area is six years. We thus define individuals with less than six years tenure in 2013 as having *low tenure*. Appendix Figure B.6 confirms that tenure is indeed an important predictor of unemployment. While the unemployment rate for high-tenured engineers increases to a maximum of almost four percent, the unemployment rate for low-tenured engineers increases to a maximum of nearly ten percent. A similar difference is seen in separation rates.

The results by tenure are reported in Table 3, and show that the saving increase is driven by low-tenured workers. Low-tenured engineers initially increase their liquid savings by $2,235, as seen from Column 1. The increase for high-tenured engineers is not statistically significant. As low-tenured engineers have lower holdings of liquid savings to begin with, the percentage increase is almost seven percent, i.e. almost twice the baseline increase. However, low-tenured engineers also have larger increases in risk, meaning that the difference in the scaled responses will be smaller. Scaling the estimated saving response by the relative increase in the unemployment rate, we find that a one percentage point increase in the unemployment rate increases liquid savings by 1.5 percent. Alternatively, a one percentage point increase in the job loss rate increases liquid savings by 1.4

expenditures (DPHCRC1A027NBEA)" from the FRED database.

[26]We do not attempt to impute consumption based on the tax data, but note that the documented increase in liquid assets is likely to imply a reduction in consumption. To see this, note that we have documented that there is no shift in illiquid financial wealth. As discussed above, the results for housing wealth are somewhat mixed, but if anything, indicate an increase. Other real wealth holdings do not change. We have also confirmed that initially there is no change in relative wages, and that over time relative wages, if anything, decline. While we cannot rule out that there were other adjustments which we do not observe, we find the 2014 increase in savings especially convincing. At this point there was still no increase in actual unemployment, and the full extent of the oil price collapse was not yet known. As a result, there were no policy measures being seriously discussed at this time. We therefore find it highly probable that the increase in liquid savings implied a reduction in consumption.

percent. The relative saving response is higher when averaging over the 2014-2016 period, reaching a maximum increase of 2.7 percent for every one percentage point increase in the separation rate – see Column 2. We note that the larger liquid saving impact for low-tenured engineers is consistent with the simulation results in Engen and Gruber (2001), in which the percentage effect of risk on savings increases in the level of risk.

Columns 3 and 4 shows that there is no significant impact on illiquid savings for low-tenured engineers. While the point estimates are now positive, and especially for the full sample period economically non-trivial, they remain noisy and statistically insignificant.

| | (1)<br>Liquid assets | (2)<br>Liquid assets | (3)<br>Illiquid assets | (4)<br>Illiquid assets |
|---|---|---|---|---|
| $I_t^{\text{post}} \times T_i^{2013}$ | 414.1 | 135.7 | 19.23 | -1,236 |
| | (892.0) | (863.2) | (1,246) | (1,358) |
| $I_t^{\text{post}} \times T_i^{2013} \times \text{Tenure}_i^{\text{low}}$ | 2,235** | 2,989*** | 141.6 | 1,899 |
| | (1,119) | (1,119) | (1,598) | (1,778) |
| Percentage increase | 6.79 | 8.43 | 0.30 | 3.69 |
| per pp increase in unemployment rate | 1.49 | 2.05 | 0.07 | 0.90 |
| per pp increase in job loss rate | 1.39 | 2.69 | 0.06 | 1.18 |
| Mean of dependent variable | 32,919 | 35,429 | 47,474 | 51,436 |
| SD of dependent variable | 57,720 | 60,789 | 135,112 | 140,952 |
| Individual FE | Yes | Yes | Yes | Yes |
| Sample period | 2010 - 2014 | 2010 - 2016 | 2010 - 2014 | 2010 - 2016 |
| Clusters | 18,710 | 18,294 | 18,710 | 18,294 |
| N | 92,126 | 125,966 | 92,126 | 125,966 |

Table 3: **The impact of job loss risk on liquid and illiquid savings by tenure.** Regression results from estimating equation (1) with $Y_{it} = \{\text{Liquid assets, Illiquid assets}\}$ by tenure for job keepers.

### 5.4 Robustness

In this section, we start by discussing an alternative driver of the estimated saving increase, specifically human capital depreciation, and argue that this interpretation is not supported by data. We proceed by showing that our results are robust to two alternative specifications. First, we change the control group to only consist of high skilled government workers, who did not experience any increase in job loss risk following the oil price collapse. Second, we change the treatment group to only consist of engineers who work in the oil sector, as these individuals may have been particularly effected by higher job loss risk. We further show that the estimated saving response is unlikely to be driven by wealth effects or selection into occupation based on risk aversion. Finally, we note that our results are not sensitive to whether or not we condition on employment.

### 5.4.1 Human capital depreciation

The sudden oil price collapse and the resulting macroeconomic consequences may have altered oil workers perception of their future earnings potential, and induced them to increase current saving in order to smooth consumption – regardless of current job loss risk. We refer to this alternative explanation as a decline in long run earnings potential or "human capital depreciation". In this section we argue that our results indicate that this channel, while ex-ante relevant, is not quantitatively important in our setting.

First note that the model in Section 3 showed that a decrease in long run income should lead to a *reduction* in liquid assets and an increase in liquid assets. This is not consistent with our results, which show an *increase* in liquid assets and a non-significant change in illiquid assets. While this does not rule out that savings may be affected by a decline in long run income, it does indicate that the impact of higher job loss risk must be substantially larger. By using our results for low-tenured workers however, we can strengthen this result and argue that lower long term earnings potential has at most a trivial role in explaining individual saving behavior in our setting.

For our results on low-tenured workers to be useful in distinguishing between job loss risk and human capital depreciation, we must first know how they are affected by these two channels relative to high-tenured workers. We have already documented that low-tenured workers experienced larger increases in job loss risk. We now argue that low-tenured workers, if anything, are likely to experience smaller human capital losses. This seems intuitive, as low-tenured workers are younger and likely to be more mobile both in terms of geography and industries. It is also the prediction of the labor literature, for instance Couch and Placzek (2010), who show that older workers with greater employment tenure experienced annual earnings reductions five years after job loss *more than double* those of younger workers.

To explore this further, Table 4 reports outcomes for low tenure and high tenure workers, both conditional on job loss and without conditioning on labor market status. Starting with the former, we see from the first two columns that, conditional on job loss, low-tenured workers outperform high-tenured workers in 2017, i.e. once unemployment rates have started to fall and the local economy is beginning to recover. Displaced low-tenured engineers have an income equal to 72 % of their 2013-income, compared to 68 % for displaced high-tenured workers. The difference is larger when considering only wage income. Among low-tenured engineers, 66 % are employed as wage takers in 2017, compared to 57 % for high-tenured workers. This is not explained by high-tenured workers transitioning into retirement, as a higher share of high-tenured workers are still unemployed in 2017. One reason why low-tenured engineers do better might be their willingness to move in order to gain employment. This is supported by 89 % of low-tenured engineers still living in the oil region in 2017, compared to 96 % of high-tenured engineers.

The two final columns show results without conditioning on job loss, and provide a similar picture. In total, low-tenured engineers have higher total income, higher wage income and a higher probably of being employed. This is despite a larger fraction of the low-tenured workers still being unemployed – which is not surprising as we documented in Appendix Figure B.6 that they are more than twice as likely to experience job loss as a result of the oil price collapse. To sum up, the data suggests that, in accordance with the labor literature, low-tenured workers if anything suffer smaller losses to their long run earnings potential.

| | Conditional on job loss | | Unconditional | |
|---|---|---|---|---|
| | Low tenure | High tenure | Low tenure | High tenure |
| Income 2017 / Income 2013 | 72 % | 68 % | 99 % | 93 % |
| Wage income 2017 / Wage income 2013 | 56 % | 44 % | 106 % | 83 % |
| Employment 2017 | 66 % | 57 % | 86 % | 85 % |
| Unemployment 2017 | 15 % | 21 % | 3.2 % | 2.0 % |
| Oil region residence 2017 | 89 % | 96 % | 94 % | 98 % |

Table 4: **2017 outcomes by tenure.** Engineers in the recession area, for those with below median and above median tenure. Conditional on job loss between 2014 and 2016 and unconditional.

Given the relative impacts on low-tenured engineers, we note that the only way in which our empirical findings are consistent with the model predictions in Section 3 is if lower long run earnings potential is not affecting saving behavior. To see this, suppose that there *is* both an increase in job loss risk and a decline in long run income. Because liquid savings increase in the data, this must mean that the job loss risk effect dominates the long run income effect. Moreover, since illiquid assets are unaffected in the data, this must mean that higher job loss risk decreases illiquid assets (in order to cancel out the positive effect working through lower long run income). Because low-tenured workers have larger increases in job loss risk and smaller human capital losses, they should have larger increases in liquid savings. This is consistent with data. However, they should also have smaller decreases in illiquid assets. This is *inconsistent* with data. As such, our findings indicate that human capital losses are not an important driver of observed saving behavior.

#### 5.4.2 Robustness tests

We proceed by showing that the estimated increase in liquid savings is robust to using an alternative control group consisting only of government workers, as well as an alternative treatment group consisting of only engineers in the oil sector. We also argue that our results are unlikely to be driven by wealth effects and that selection into unemployment based on risk aversion is probably not a concern in our setup.

**Spillovers to the control group** The baseline analysis compared engineers residing in the recession area to other high-skilled workers residing in the recession area. It is likely that also the latter group experienced some increase in job loss risk following the oil price shock. In fact, Figure 4 showed that although other high-skilled workers in the recession area experienced a very modest increase in unemployment relative to engineers, they too were subject to an increase in job loss risk. This could be because some workers in this group are directly employed in the oil sector and/or because there are spillover effects to other sectors. Note that the largest spillover effects occur for low skilled workers, as alluded to by Figure 2. Hence, this issue is less of a concern when using only high-skilled workers in the control group.

If the impact of job loss risk on saving behavior is homogeneous and linear, spillover effects should not be an issue. To see this note that we are not assuming that there is no increase in job loss risk for the control group. Rather, we are using the difference in job loss risk between the two groups, to scale the impact on liquid savings. If the control and treatment groups have the same underlying linear saving response to a given increase in job loss risk, spillover effects should not affect our estimates. However, if the saving response is non-linear and/or non-homogeneous, spillover effects could be an issue.

To reduce the likelihood that spillover effects are influencing our results we redo the baseline analysis with a control group consisting only of high skilled *government* workers. This has the benefit of only including individuals whose employment security should not be affected by (short-term) economic conditions, but has the disadvantage of producing a control group with less similar employment outcomes pre-2014. Figure 6 depicts unemployment rates for engineers and high skilled government workers in the recession area. High skilled government workers have virtually no increase in unemployment rates or job loss rates following the oil price collapse, implying limited scope for spillover effects.

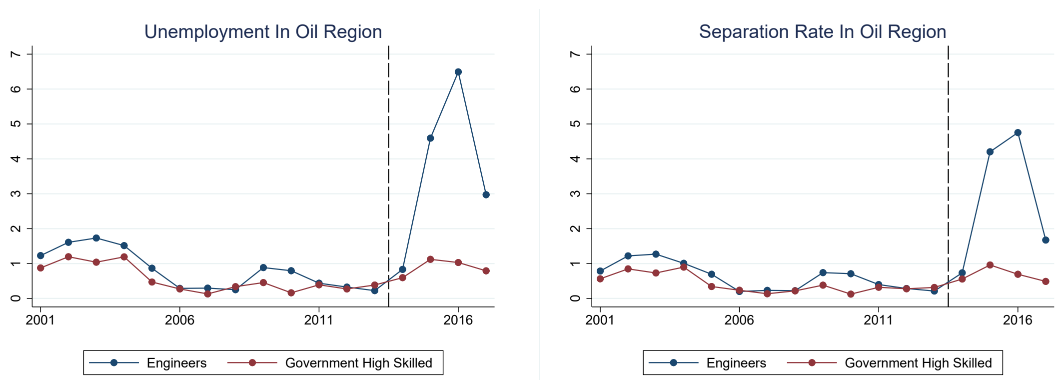


Figure 6: **Job loss risk for the treatment group and an alternative control group consisting of high skilled government workers.** Unemployment rate and separation rate (%) for engineers in the recession area and high skilled government workers in the recession area.

Regression results when using only high skilled government workers in the control group are reported in the first two columns of Table 5. The coefficient estimates for the initial saving response decreases very slightly, while the coefficient estimates for the full saving response increases very slightly. While the results based on the sample period 2010-2014 become borderline insignificant –

as a result of the sample size being roughly cut in half – the full sample results remain statistically significant. The results show that engineers increase liquid savings relative to government workers by $1,428 or 4.2 percent. This implies that a one percentage point increase in the unemployment rate (separation rate) increases liquid savings by 1.3 (1.6) percent. Hence, the baseline increase in liquid savings is robust to using a control group which did not experience any increase in job loss risk, despite residing in the recession area.

| | (1) Liquid assets | (2) Liquid assets | (3) Liquid assets | (4) Liquid assets |
|---|---|---|---|---|
| $I_t^{\text{post}} \times T_i^{2013}$ | 1,167 | 1,428* | 2,765*** | 4,008*** |
| | (729.6) | (753.1) | (805.3) | (849.6) |
| Percentage increase | 3.70 | 4.20 | 10.8 | 14.3 |
| per pp increase in unempl. rate | 1.19 | 1.25 | 2.68 | 3.47 |
| per pp increase in job loss rate | 1.22 | 1.60 | 2.60 | 4.30 |
| Mean of dependent variable | 31,498 | 34,099 | 25,678 | 27,767 |
| SD of dependent variable | 53,568 | 56,917 | 49,277 | 51,951 |
| Individual FE | Yes | Yes | Yes | Yes |
| Sample period | 2010 - 2014 | 2010 - 2016 | 2010 - 2014 | 2010 - 2016 |
| Treatment group | Baseline | Baseline | Oil sector engin | Oil sector engin. |
| Control group | Gov. workers | Gov. workers | Baseline | Baseline |
| Clusters | 8,861 | 8,598 | 46,472 | 45,306 |
| N | 43,420 | 58,890 | 222,850 | 306,341 |

Table 5: **The impact of job loss risk on liquid savings with alternative control and treatment groups.** Regression results from estimating equation (1) with $Y_{it}$ = Liquid assets$_{it}$ for job keepers. Alternative control group: high-skilled government workers residing in the recession area. Alternative treatment group: engineers working in the oil sector residing in the recession area.

**Engineers in the oil sector** So far, our classification of individuals into treatment and control groups have relied only on occupations. However, we also know in which sector individuals work. We can therefore change the treatment group to only contain engineers which were employed in the oil sector prior to 2014. This leads to somewhat higher liquid saving response than in our baseline results. Again, this is consistent with the findings in Engen and Gruber (2001), in which the relative saving responses increases in risk.

Statistics Norway defines the oil sector to contain what they refer to as petroleum sectors and petroleum related sectors. The petroleum sector includes the following sectors: extraction of crude petroleum and natural gas (06), support activities for petroleum and natural gas extraction (09.1), transport via pipeline (49.5) and support activities pipeline (52.215). In addition, Statistics Norway defines petroleum related sectors to include the following industries: building of oil-platforms and modules (31.113), installation and completion work on platforms and modules (30.116) and offshore supply terminals (52.223). According to Statistics Norway, around 84,000 individuals were employed in the oil sector in 2014 (Ekeland, 2017) – which constitutes just above three percent of all employed workers. However, a high number of individuals work in industries which produce output used in the oil sector, but which are not included in this definition. Attempts by Statistics Norway to calculate the number of workers directly or indirectly employed in the oil sector based on input output data produces a number of 239,000 – which constitutes just above nine percent of all employed workers (Prestmo et al., 2015). Hence, only 35% of oil related workers are actually employed in the oil sector.

We follow the standard Statistics Norway definition and create an alternative treatment group, consisting of engineers employed in the oil sector. The new treatment group is thus a subset of our baseline treatment group, while the control group is left unchanged. In Appendix Figure B.7, we depict unemployment rates and job loss rates for this alternative treatment group. The result from this exercise are reported in the last two columns of Table 5. Both the absolute savings increases and the scaled saving responses increase in size and remain statistically significant.

**House prices** Because our estimates are based on a comparison of individuals living in the recession area, general house price declines should not be problematic. However, if engineers and their high skilled peers live in systematically different areas, they could be exposed to different changes in house prices. To explore whether this is a concern, we use house price data on the municipality level from Statistics Norway. This data is not available for the smallest municipalities, but still covers 96 percent of engineers and other high skilled workers residing in the oil region.

Appendix Figure B.8 depicts average house prices in the oil region over time for engineers and their high skilled peers separately. The change in house prices for engineers and other high skilled workers appears very similar. Prices are roughly constant from 2013 to 2015 for both groups, while house prices in the rest of the country are increasing. House prices in the oil region fall noticeably in 2016, but the decrease is not significantly different across engineers and other high skilled workers.

We also note that the home ownership rates are identical across engineers and other high skilled workers, as showed in the summary statistics in Table 1. Hence, we find it unlikely that house price changes are driving the increase in savings of engineers relative to other high skilled workers, within the recession area.

**Other wealth effects** Another potential wealth effect might come about through differential stock holdings across our treatment and control group. For instance, one might worry that engineers to a larger extent own equity in oil firms. While this would be sub-optimal from a hedging point of view, given the positive correlation with labor income, it is not uncommon for workers to own equity in the company they work for. However, because there is no significant impact on illiquid financial wealth, which includes stocks, any relative decrease in stock value for engineers would have to be counteracted by an increase in the quantity of illiquid assets.[27] That is, engineers must be reacting to the negative wealth shock by increasing illiquid savings. This could perhaps come about if they have some sort of target value for illiquid wealth holdings. However, we can think of no sound reason for why this would further induce them to increase their liquid savings. As such, we find it unlikely that differential exposure to oil firm stocks should be driving our saving results.

More generally, the overall impact of the oil price collapse on the Norwegian stock market was limited. As illustrated in Appendix Figure B.9, there was some decline in the Oslo Stock Exchange overall index in the second half of 2014, but at an annual level – the relevant level for our tax data – stock prices increased from 2014 to 2015. Moreover, the increase was similar to that of the S&P 500 index in the US. There was a modest fall in stock prices in the following year, but this was also a low growth year for US stock markets. One reason why the oil price collapse appears to have had a relatively modest impact on average stock prices might be the large exchange rate movements, which increased the international competitiveness of Norwegian firms.

Finally, we note that median holdings of financial assets such as stocks, bonds, mutual funds etc. is modest in both our control and treatment group. In fact, as seen from Table 1, the median holdings of illiquid financial wealth in both the control and treatment group is exactly the same at $1,600. This implies that for the median worker, any wealth shocks working though financial asset prices must be of limited magnitude. Average holdings of illiquid financial wealth are also similar, but somewhat larger for other high skilled workers than for engineers.

**Selection into occupations** We have used pre-2014 occupations in order to identify groups with different changes in job loss risk. However, occupations are not randomly assigned and engineers may be systematically different from their high skilled peers. Fuchs-Schündeln and Schündeln (2005) argue that individuals self-select into occupations based on their level of risk aversion, thereby potentially biasing occupation based estimates of precautionary saving. We believe this concern to be of limited importance in our case for two reasons. First, we are comparing two groups which had very similar levels of job loss risk prior to the oil price collapse. As shown in Figure 4, engineers and other high skilled workers had almost identical unemployment rates in the thirteen years leading up to the oil price collapse. Second, we are not simply comparing wealth levels across occupations. Rather, we are considering a sudden change in job loss risk, and the following change in liquid savings. Still, if engineers are less risk averse than the general population, this would mean that the estimated saving response is likely to be a lower bound for the population wide response, all else equal.

[27]In fact, stock prices for Statoil (i.e. the largest Norwegian oil company, now called Equinor) followed a U-shaped pattern, falling after the oil price collapse, and then increasing again from 2015 onward. If engineers to a (substantially) larger extent than other high skilled workers owned oil stocks, they would have to increase their illiquid asset holdings in 2014 and 2015, and then decrease them again in 2016, in order for the observed change in the total value of illiquid assets to be constant, as illustrated in Appendix Figure B.5.

**Conditioning on employment** Finally, we note that our estimates only capture the saving responses of the still employed. Intuitively, we expect individuals who experience job loss to dis-save in order to smooth consumption in the face of lower income. However, we have rerun our estimations without conditioning on job status, to capture the aggregate saving responses. Doing this for the period 2010-2014, i.e. the initial saving response, the coefficient estimates are virtually identical. This is not surprising, as unemployment rates did not start to rise until 2015. However, even for the 2010-2016 results, including unemployed individuals in our estimations has a very limited impact on our estimates. The reason is partly driven by modest dis-saving for job losers, and partly by the fact that the still-employed individuals vastly outnumber the individuals who experience job loss.

# 6 The importance of the job loss risk channel for saving dynamics during recessions

In this final section we use two different approaches to quantify the importance of the job loss risk channel in explaining why saving rates increase during recessions. Reassuringly, the two approaches, which rely on different aspects of the data, provide similar results. In both cases, we find that the increase in unemployment risk can explain more than 80% of the liquid saving increase due to the oil price collapse, and about half of the *total* saving increase. In other words, our results indicate that job loss risk is the main driver of increased savings during economic downturns.

**Within-region versus across-region results** Local economic downturns can affect saving behavior not only through increased job loss risk. For instance, falling house prices may induce people to cut back on consumption and increase savings. One could also imagine a local recession leading to negative sentiments or beliefs, which might make individuals save more regardless of their employment prospects. In the baseline analysis we did a *within* region comparison, in order to control for such local recession effects. This way, we isolated the increase in savings due to job loss risk.

In order to better understand the economic magnitude of this channel, we are also interested in knowing the impact of other recession effects on savings. To get a measure of this, we complement our baseline findings with an *across* region analysis. That is, we compare engineers in the recession area to high-skilled workers outside of the recession area. The intuition is as follows. Engineers in the oil region should be subject to both the unemployment risk effect and the local recession effects, while high-skilled workers outside of the oil region should be subject to neither. Comparing these two groups thus gives us the total saving response to the recession. Contrasting this to our baseline estimate, which isolated the unemployment risk effect, we can back out the saving impact of these other recession effects as well.

The first column in Table 6 simply reproduces the baseline result for liquid assets, in which engineers in the recession area are compared to other high skilled workers in the recession area. In the second column, we compare engineers in the recession area to high skilled workers *not* residing in the recession area. In order to evaluate the magnitudes of the different channels, we compare the coefficient estimates in Columns 1 and 3. The coefficient estimate in Column 1 ($1,279) captures the unemployment risk channel, and accounts for 83 % of the total saving impact, captured by the coefficient estimate in Column 3 ($1,542). That is, according to this approach, the job loss risk channel can explain more than 80% of the overall increase in liquid savings for workers affected by the oil price collapse.

Columns 3 and 4 provide the same comparison for illiquid assets. Interestingly, we find a significant increase in illiquid assets in the across-region comparison in Column 4, suggesting that other recession effects than job loss risk *do* lead to an increase in illiquid assets. Combining the liquid and illiquid saving responses, we find that the job loss channel can account for 45% of the total recession-induced increase in savings.

| | (1)<br>Liquid assets | (2)<br>Liquid assets | (3)<br>Illiquid assets | (4)<br>Illiquid assets |
|---|---|---|---|---|
| $I_t^{\text{post}} \times T_i^{2013}$ | 1,279** | 1,542*** | -66.55 | 1,278** |
| | (566.6) | (481.5) | (801.7) | (606.6) |
| Mean of dependent variable | 33,405 | 32,635 | 47,433 | 42,157 |
| SD of dependent variable | 58,407 | 57,892 | 134,952 | 128,517 |
| Individual FE | Yes | Yes | Yes | Yes |
| Sample period | 2010 - 2014 | 2010 - 2014 | 2010 - 2014 | 2010 - 2014 |
| Control group area | Recession | Non-recession | Recession | Non-recession |
| Clusters | 19,027 | 63,854 | 19,027 | 63,854 |
| N | 93,699 | 315,671 | 93,699 | 315,671 |

Table 6: **The impact of job loss risk and other recession effects on liquid and illiquid savings.** Regression results from estimating equation (1) with $Y_{it} = \{\text{Liquid assets, Illiquid assets}\}$ for job keepers with different control groups. Columns 1 and 3: control group as in baseline (i.e. high skilled government workers in the recession area). Columns 2 and 4: alternative control group consisting of high skilled workers outside of the recession area.

Note that the quantitative importance of local recession effects is likely to vary, and we do not attempt to directly measure the size of such effects for our given shock. It is therefore possible that other local recession effects would have smaller/larger implications for saving behavior in a different setting, simply because the other local recession effects would themselves be smaller/larger. For example, if there were larger declines in house prices, or larger changes in sentiments, the local recession effects could plausibly be larger.

**Total versus explained increase in saving rates** In the approach outlined above, we relied on a comparison of engineers in the recession area to high skilled workers outside of the recession area to quantify the total saving impact of the oil price collapse, i.e. the sum of the unemployment risk channel and the other recession effects. We now take a different approach, and rely only on the time series dimension of savings for the affected workers. In order to do so, we define the saving rate for an individual $i$ at time $t$ as

$$s_{i,t}^{j} \equiv \frac{\text{Assets}_{i,t}^{j} - \text{Assets}_{i,t-1}^{j}}{\text{Wage income}_{i,t}} \text{ for } j = \{\text{Liquid}, \text{Total}\} \tag{3}$$

The change in the saving rate from time $t-1$ to $t$ is then simply

$$\Delta s_{i,t}^{j} = s_{i,t}^{j} - s_{i,t-1}^{j} \tag{4}$$

As seen in Figure 5, savings tend to increase every year, with a visible above-trend increase in 2014. In order to only capture the increase relative to trend, we consider the observed saving increase after we correct for a linear time trend in savings. Focusing on our sample of (job-keeping) engineers in the recession area, the average (above-trend) observed changes in saving rates from 2013 to 2014 are

$$\overline{\Delta s_{2014}}^{liquid} = 1.5 \text{ pp and } \overline{\Delta s_{2014}}^{total} = 2.6 \text{ pp}$$

While our estimated saving increase of \$1,300 implies saving rate increases of

$$\widehat{\Delta s_{2014}}^{liquid} = 1.4 \text{ pp and } \widehat{\Delta s_{2014}}^{total} = 1.4 \text{ pp}$$

These simple calculations thus indicate that the job loss risk mechanism can explain 1.4 / 1.5 = 93% of the observed increase in liquid saving rates and 1.4 / 2.6 = 54% of the observed increase in total saving rates. Although relying on entirely different aspects of the data, these figures are quite similar to the ones reported above of 83% and 45% respectively. The empirical evidence thus suggests that the job loss risk channel is by far the most important driver of liquid saving increases during recessions, and also accounts for about half of the total saving increase.

### 6.1 Other recessions

In this sub-section, we apply our saving estimates to other recession periods, and provide rough estimates of the importance of job loss risk in explaining US saving dynamics during the Great Recession and the COVID19-pandemic. We find that job loss risk can account for 3/4 of the observed saving increase during the Great Recession, and 1/4 of the observed saving increase during the recent pandemic.

We showed in the previous subsection that the predicted saving rate increase from our analysis equaled 1.4 percentage points. Scaling this by the relative increase in unemployment rates, we find that for every one percentage point increase in unemployment, saving rates are predicted to increase by 0.5 percentage points.[28] How does this compare to other recession periods? To answer this, we consider aggregate US unemployment and saving rates from the FRED Database.[29] During the Great Recession, the maximum increase in unemployment rates from the onset of the recession was 4.5 percentage points. Our estimates suggest that this should lead to a 2.3 percentage point increase in the saving rate through the job loss risk channel. Comparing this to the observed saving rate increase over the same time period of 3.0 percentage points, we find that the job loss risk channel can explain 3/4 of the observed saving increase during the Great Recession – see Table 7.

The unemployment and saving dynamics during the recent pandemic were less typical, and we would be more cautious in applying our results to this setting. While the unemployment rate increased rapidly after the outbreak of the virus, the observed increase in the saving rate was even more dramatic. The unemployment rate increased by a maximum of 10.3 percentage points, leading to a predicted saving increase of 5.2 percentage points. Observed saving rates however, increased by 21 percentage points, meaning that the job loss risk channel can only explain 1/4 of the increase. This could be partly driven by challenges in correctly measuring unemployment rates and job loss risk during the pandemic. However, we also find it plausible that the strict infection control measures had a substantial direct impact on savings, making the relative importance of the job loss risk channel smaller than in more typical economic downturns (see e.g Baker et al. (2020), Coibion et al. (2020) and Immordino et al. (2022)).

| US Recession | $\Delta$u-rate | $\Delta$s-rate$^{predicted}$ | $\Delta$s-rate$^{observed}$ | Share explained |
|---|---|---|---|---|
| Great Recession | 4.5 pp | 2.3 | 3.0 | 75 % |
| COVID-19 | 10.3 pp | 5.2 | 21 | 25 % |

Table 7: **Predicted and observed saving rates during recessions**. $\Delta$u-rate is the change in the unemployment rate from the start of the recession to the maximum observed unemployment rate within the recession period. $\Delta$s-rate$^{observed}$ is the change in the saving rate over the same time period. $\Delta$s-rate$^{predicted}$ is the predicted increase in the saving rate based on $\Delta$u-rate and the empirical findings from Section 5.3, which results in the prediction that the saving rate increases by 0.5 percentage points for every 1 percentage point increase in the unemployment rate.

We end this section by noting that while our estimates only capture the saving responses of the still employed, our results are quite similar when not conditioning on employment – as discussed in Section 5.4. We find this result interesting with regards to the household demand channel of recessions. While household demand might decline during recessions due to lower consumption among the unemployed (Schaal and Taschereau-Dumouchel, 2016; Petach and Tavani, 2022), household de-

[28] Technically, this only captures the job loss *risk* effect, and not the effect working though individuals who experience actual unemployment. If many workers get laid off, and if these workers have large negative saving responses, this will dampen the total increase in aggregate savings resulting from unemployment (i.e. the sum of the unemployment risk channel and the realized unemployment channel). Hence, what we are capturing here is the importance of the job loss *risk* channel in accounting for *net* savings.

[29] Specifically, we use the U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED and the U.S. Bureau of Economic Analysis, Personal Saving Rate [PSAVERT], retrieved from FRED, at a monthly frequency. Recession periods are defined based on NBER based Recession Indicators.

mand might also decline due to lower consumption among the still-employed (who face an increase in job loss *risk*). Our findings suggest that the latter channel clearly dominates the former.

# 7 Conclusion

Using a novel natural experiment along with Norwegian administrative data, we have shown that higher job loss risk increases liquid savings while leaving illiquid savings unaffected. This is in line with our model predictions. For every one percentage point increase in job loss rates, we estimate a liquid savings increase of 1.4-1.7 percent. Reassuringly, this increase in liquid savings is driven by low-tenured workers, who faced the largest increase in job loss risk. Comparing our estimates to the overall increase in savings, we find that the job loss risk channel can explain more than 80 percent of the recession-induced increase in *liquid* savings, and about half of the recession-induced increase in *total* savings.

Quantifying the causal impact of job loss risk on savings is important for understanding movements in asset prices (Gabaix and Koijen, 2021) and amplifications of economic downturns through the household demand channel (e.g. Challe et al. 2017). We believe our estimates could be useful as identified moments to match for the recent theoretical literature emphasizing amplification of shocks through job loss risk. Moreover, our findings suggest that the job loss risk channel is quantitatively the most important channel in explaining recession-induced increases in savings. This has implications for stabilization policies, and suggests that measures which aim to curb (effective) job loss risk are likely to be effective. Examples of such measures include (time-varying) UI-policies and financial support to distressed companies. Our findings also highlight the importance of job loss *risk* relative to realized unemployment in explaining aggregate demand declines during recessions – an implication being that solely stimulating the consumption of the unemployed, might not be sufficient to stabilize household demand.

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# Appendix A: Proofs

**Assumption 1**

$$y_2 > \left(y_1 + \frac{y_3}{r}\right) \frac{r^{\frac{1}{\sigma}}}{1 + r^{\frac{1-\sigma}{\sigma}}}$$

This assumption puts a lower bound on income if employed in period 2, which ensures that the borrowing constraint does not bind in period 2 if the household is employed (Lemma 1).

**Lemma 1.** *Suppose Assumption 1 holds. In this case, the household will not be constrained if employed, i.e.* $b_2^* \neq 0$.

*Proof.* Suppose otherwise, i.e. $b_2 = 0$. In this case, the household is always constrained in period 2, and so period 3 consumption no longer depends on employment status in period 2. Rather, consumption in period 3 is now given by

$$c_3 = y_3 + rk_1$$

While consumption in period 2 if employed is given by

$$c_{2E} = y_2 + b_1$$

If $b_2 = 0$, then we must have that $c_{2E} < c_3$, i.e. the marginal utility of consumption in period 2 as employed is strictly higher than the marginal utility of consumption in period 3. If this was not the case, the household would want to save in liquid assets in period 2. At the same time, optimality for illiquid assets requires that

$$u'(c_1) = ru'(c_3)$$

which implies

$$c_3 = c_1 r^{\frac{1}{\sigma}}$$

We insert for $c_3$ in this expression, solve for $k_1$, and insert the expression for $k_1$ into first period consumption $c_1 = y_1 - b_1 - k_1$. Rearranging, this gives us that

$$c_1 = \left(y_1 - b_1 + \frac{y_3}{r}\right) \frac{1}{1 + r^{\frac{1-\sigma}{\sigma}}}$$

which further implies

$$c_3 = \left(y_1 - b_1 + \frac{y_3}{r}\right) \frac{r^{\frac{1}{\sigma}}}{1 + r^{\frac{1-\sigma}{\sigma}}}$$

Note that this means that $c_3 < c_{2E}$ if

$$y_2 + b_1 > \left(y_1 - b_1 + \frac{y_3}{r}\right) \frac{r^{\frac{1}{\sigma}}}{1 + r^{\frac{1-\sigma}{\sigma}}}$$

A sufficient condition for this to hold is that

$$y_2 > \left(y_1 + \frac{y_3}{r}\right) \frac{r^{\frac{1}{\sigma}}}{1 + r^{\frac{1-\sigma}{\sigma}}}$$

, which holds by Assumption 1. This contradicts $c_{2E} < c_3$, as so $b_1^* \neq 0$. $\square$

Next, we show that the borrowing constraint binds in period 2 if unemployed whenever the household holds both liquid and illiquid assets.

**Lemma 2.** *If $b_1^* > 0$, $k_1^* > 0$ and $r \neq 1$, then the borrowing constraint binds in period 2 if unemployed.*

*Proof.* Since $b_1 > 0$ and $k_1 > 0$, the following two optimality conditions must hold

$$u'(c_1) = \mathbb{E}u'(c_2)$$

$$u'(c_1) = r\mathbb{E}u'(c_3)$$

Suppose that the household is unconstrained in the unemployed state in period 2. In that case, consumption in period 2 and 3 is always the same, so that

$$c_{2E} = c_{2U} = c_{3E} = c_{3U}$$

This implies that $\mathbb{E}u'(c_3) = r\mathbb{E}u'(c_3)$, which only holds if $r = 1$ and so we have a contradiction. Hence, the household is constrained if unemployed in the second period. $\square$

## Proof of Proposition 1

*Proof.* By the implicit function theorem:

$$\begin{bmatrix} \frac{\partial b_1^*}{\partial \rho} \\ \frac{\partial k_1^*}{\partial \rho} \end{bmatrix} = - \begin{bmatrix} \overbrace{\frac{\partial F_1}{\partial b_1}}^{\equiv A_1} & \overbrace{\frac{\partial F_1}{\partial k_1}}^{\equiv A_2} \\ \underbrace{\frac{\partial F_2}{\partial b_1}}_{=A_2} & \underbrace{\frac{\partial F_2}{\partial k_1}}_{\equiv A_3} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial F_1}{\partial \rho} \\ \frac{\partial F_2}{\partial \rho} \end{bmatrix}$$

$$= - \frac{1}{A_1 A_3 - A_2^2} \begin{bmatrix} A_3(u'_{2E} - u'_{2U}) - A_2 r(u'_{2E} - u'_{3U}) \\ A_1 r(u'_{2E} - u'_{3U}) - A_2(u'_{2E} - u'_{2U}) \end{bmatrix}$$

In which $A_1 = -\left[u''_1 + \rho u''_{2U} + \frac{1-\rho}{2} u''_{2E}\right] > 0$, $A_2 = -\left[u''_1 + \frac{r(1-\rho)}{2} u''_{2E}\right] > 0$ and $A_3 = -\left[u''_1 + r^2 \rho u''_{3U} + \frac{r^2(1-\rho)}{2} u''_{2E}\right] > 0$.

Consider first the determinant. The fraction $-\frac{1}{A_1 A_3 - A_2^2}$ can be expressed as follows

$$-\frac{1}{r^2 \rho u''_{3U} u''_1 + \rho u''_{2U} u''_1 + \rho^2 r^2 u''_{2U} u''_{3U} + \frac{r^2 \rho(1-\rho)}{2}\left(u''_{2U} u''_{2E} + u''_{2E} u''_{3U}\right) + u''_1 u''_{2E} \frac{1-\rho}{2}\left[r^2 + 1 - 2r\right]}$$

Note that the product of two second order derivatives are positive, so that the denominator is positive as long as the last term in square brackets is positive, i.e. $r^2 + 1 - 2r \geq 0$, which is always the case. This means that $-\frac{1}{A_1 A_3 - A_2^2} < 0$.

Hence, $\frac{\partial b_1^*}{\partial \rho} > 0$ if $A_3(u'_{2E} - u'_{2U}) - A_2 r(u'_{2E} - u'_{3U}) < 0$.

Inserting for $A_2$ and $A_3$ we have that:

$$A_3(u'_{2E} - u'_{2U}) - A_2 r(u'_{2E} - u'_{3U}) = r^2 \rho u''_{3U}(u'_{2U} - u'_{2E}) + \frac{r^2(1-\rho)}{2} u''_{2E}(u'_{2U} - u'_{3U}) + u''_1(u'_{2U} - u'_{2E} + r(u'_{2E} - u'_{3U}))$$

The first term on the right-hand side is negative, as $u'_{2U} - u'_{2E} > 0$.

The second term on the right-hand side is also negative, as $u'_{2U} - u'_{3U} > 0$. To see this, note that from the Euler equations we know that $u'_1 = E u'_2$ and $u'_1 = r E u'_3$, which implies that $u'_{2U} - r u'_{3U} = \frac{(1-\rho)(r-1)}{\rho} u'_{2E} > 0$ and so $u'_{2U} - u'_{3U} > 0$.

The third and final term is negative if $u'_{2U} - u'_{2E} + r(u'_{2E} - u'_{3U}) > 0$. Again using the fact that $u'_{2U} - r u'_{3U} = \frac{(1-\rho)(r-1)}{\rho} u'_{2E} > 0$, this condition can be rewritten as $u'_{2E} \frac{r-1}{\rho} > 0$, which we know to be true.

Hence, it must be the case that $A_3(u'_{2E} - u'_{2U}) - A_2 r(u'_{2E} - u'_{3U}) < 0$, which implies $\frac{\partial b_1^*}{\partial \rho} > 0$.

$\square$

### Proof of Proposition 2

*Proof.* We know from Proposition 1 that $-\frac{1}{A_1A_3-A_2^2}<0$. The sign of $\frac{\partial k_1^*}{\partial \rho}$ therefore depends on

$$A_1r(u'_{2E}-u'_{3U})-A_2(u'_{2E}-u'_{2U})=u''_1\left(u'_{2E}(1-r)+ru'_{3E}-u'_{2U}\right)-\rho ru''_{2U}\left(u'_{2E}-u'_{3U}\right)+\frac{1-\rho}{2}ru''_{2E}\left(u'_{3U}-u'_{2U}\right)$$

From the optimality condition $u'_{2U}-ru'_{3U}=\frac{(1-\rho)(r-1)}{\rho}u'_{2E}>0$, the first term on the right-hand side is positive.

From the same condition, we know that $u'_{2U}-u'_{3U}>0$, implying that the final term on the right-hand side is also positive.

***If***, $c_{3U}>c_{3E}$, so that $u'_{3U}<u'_{3E}$, then the second term on the right-hand side is also positive. In this case, $\frac{\partial k_1^*}{\partial \rho}<0$**.**

Without this assumption, the sign of the second term and therefore the sign of the entire right-hand side of the equation, is ambiguous, implying $\dfrac{\partial k_1^*}{\partial \rho}\lesseqgtr 0$. $\square$

### Proof of Proposition 3

*Proof.* By the implicit function theorem:

$$\begin{bmatrix}\frac{\partial b_1^*}{\partial y_3}\\ \frac{\partial k_1^*}{\partial y_3}\end{bmatrix}=-\begin{bmatrix}\overbrace{\dfrac{\partial F_1}{\partial b_1}}^{\equiv A_1} & \overbrace{\dfrac{\partial F_1}{\partial k_1}}^{\equiv A_2}\\ \underbrace{\dfrac{\partial F_2}{\partial b_1}}_{=A_2} & \underbrace{\dfrac{\partial F_2}{\partial k_1}}_{\equiv A_3}\end{bmatrix}^{-1}\begin{bmatrix}\frac{\partial F_1}{\partial y_3}\\ \frac{\partial F_2}{\partial y_3}\end{bmatrix}$$

$$=-\frac{1}{A_1A_3-A_2^2}\begin{bmatrix}A_2\left(r\rho u''_{3U}+\frac{r(1-\rho)}{2}u''_{2E}\right)-A_3\frac{(1-\rho)}{2}u''_{2E}\\ A_2\frac{(1-\rho)}{2}u''_{2E}-A_1\left(r\rho u''_{3U}+\frac{r(1-\rho)}{2}u''_{2E}\right)\end{bmatrix}$$

We know that $-\frac{1}{A_1A_3-A_2^2}<0$. In order for $\frac{\partial b_1^*}{\partial y_3}>0$ it must therefore be the case that

$$A_2\left(r\rho u''_{3U}+\frac{r(1-\rho)}{2}u''_{2E}\right)-A_3\frac{(1-\rho)}{2}u''_{2E}<0$$

Inserting for $A_2$ and $A_3$, and rearranging this condition can be rewritten as

$$u_1''u_{3u}''r\rho + u_1''u_{2e}''\frac{1}{2}\left(1-\rho\right)\left(r-1\right) > 0$$

and so $\frac{\partial b_1^*}{\partial y_3} > 0$.
In order for $\frac{\partial k_1^*}{\partial y_3} < 0$ it must similarly be the case that

$$A_2\frac{(1-\rho)}{2}u_{2E}'' - A_1\left(r\rho u_{3U}'' + \frac{r(1-\rho)}{2}u_{2E}''\right) > 0$$

Inserting for $A_1$ and $A_1$, and rearranging this condition can be rewritten as

$$r\rho u_1''u_{3U}'' + \frac{(1-\rho)(r-1)}{2}u_1''u_{2E}'' + \rho^2 r u_{3U}''u_{2U}'' + \frac{r\rho(1-\rho)}{2}u_{2E}''u_{2U}'' + \frac{r\rho(1-\rho)}{2}u_{2E}''u_{3U}'' > 0$$

As all the terms on the left-hand side are positive, this inequality must hold. Hence $\frac{\partial k_1^*}{\partial y_3} < 0$
. $\square$

## Appendix B: Figures

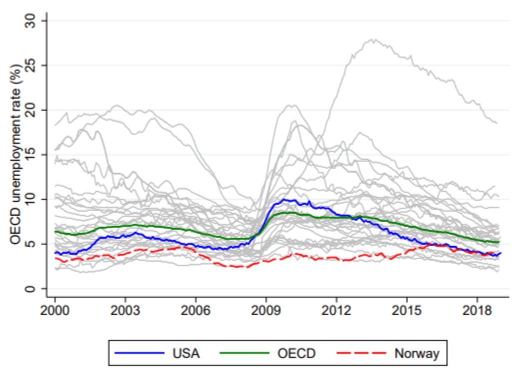


Figure B.1: **OECD harmonized unemployment rates by country (%).** 2000-2019.

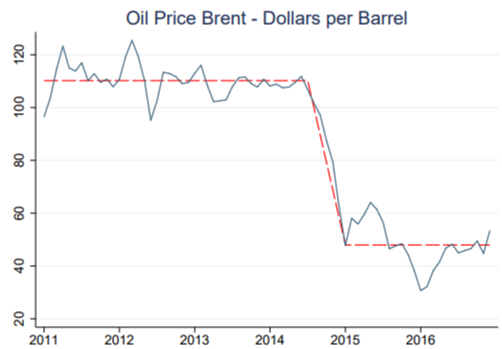


Figure B.2: **Oil price**. Brent Blend (USD per barrel). 2011-2017.


Figure B.3: **Geographical distribution of oil workers.** Share of workers employed in the oil sector relative to the share of total workers by county (%).

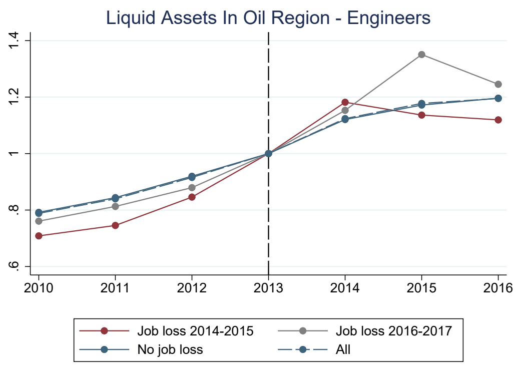


Figure B.4: **Liquid assets by job status for treatment group.** Normalized to 1 in 2013. Liquid assets for engineers in the recession area who i) experience job loss in 2014-2015, ii) experience job loss in 2016-2017, iii) do not experience job loss in this period, and iv) all of the above.

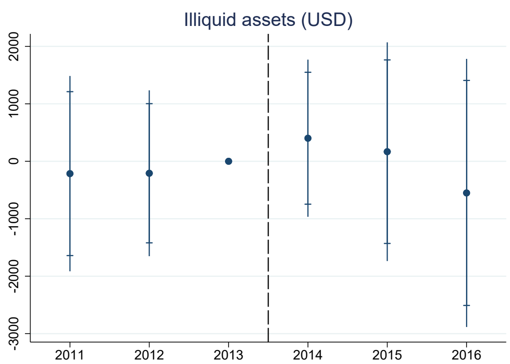


Figure B.5: **The impact of job loss risk on liquid assets.** Regression results from estimating equation (2) with $Y_{it}$ = Illiquid assets$_{it}$ on a sample of job keepers.

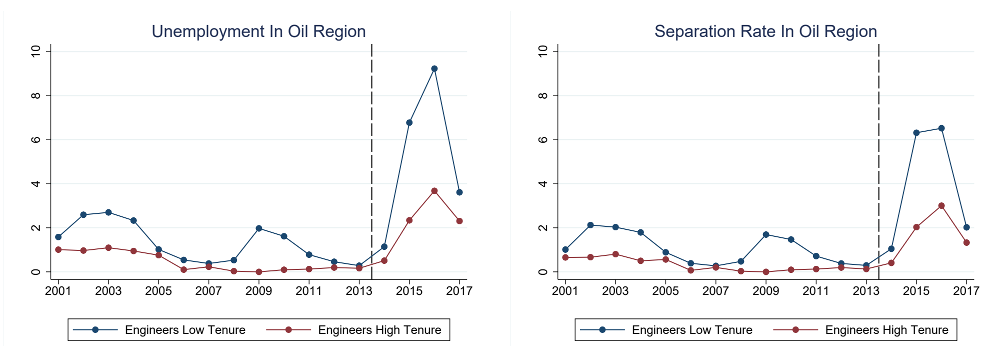


Figure B.6: **Job loss risk for treatment group by tenure.** Unemployment rate and separation rate (%) for low-tenured engineers in the recession area and high-tenured engineers in the recession area.

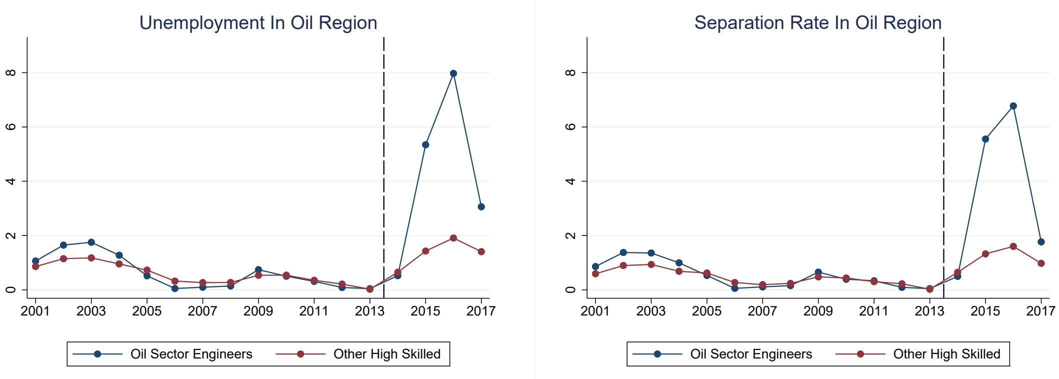


Figure B.7: **Job loss risk for control group and alternative treatment group.** Unemployment rate and separation rate (%) for oil sector engineers in the recession area and other high skilled workers in the recession area.

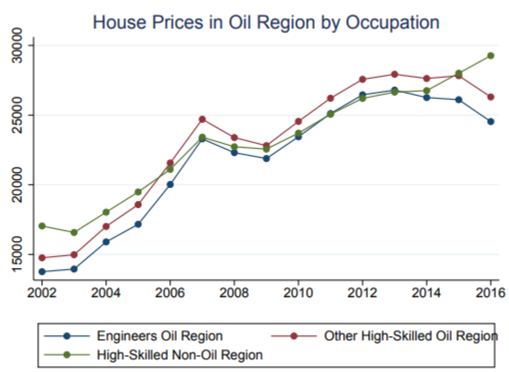


Figure B.8: **Average house prices in municipality of residence.** Average house prices for single family homes based on the municipality of residence for i) engineers in the recession area, ii) other high skilled workers in the recession area, iii) other high skilled workers outside of the recession area.

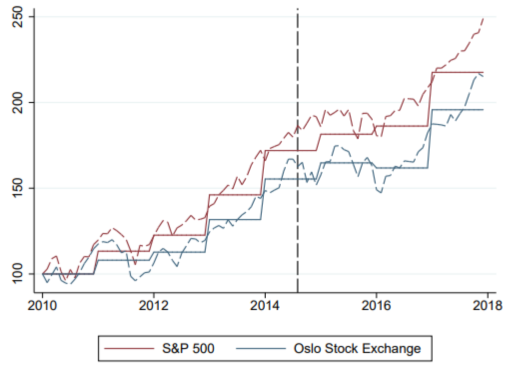


Figure B.9: **Stock prices.** S&P 500 index and Oslo Stock Exchange index. Solid lines are annual data, whereas dashed lines are monthly data.

## Appendix C: Tables

| Occupations | Education/Skills | Share of Workers (%) |
|---|---|---|
| **1 - Managers** | **Not specified** | 11 |
| **2 - Professionals** | **Min. 4y of higher educ.** | 15 |
| **3 - Technicians/Associate prof.** | **1y-3y of higher educ.** | 21 |
| 4 - Clerical support workers | High school | 6 |
| 5 - Service and sales workers | High school | 12 |
| 6 - Skilled agriculture | High school | 1 |
| 7 - Craft and related trade workers | High school | 17 |
| 8 - Plant and machine operators | High school | 11 |
| 9 - Elementary occupations | Not specified | 4 |
| 0 - Armed forces and unspecified | Not specified | 2 |

Table C.1: **Occupations.** Occupations 1-3 are classified as high skilled.

## Appendix D: Selection into unemployment

In this appendix, we attempt to quantify the amount of selection into unemployment based on observable characteristics among engineers in the years following the oil price collapse.

We start by evaluating to what extent we can predict job loss during the oil crisis based on baseline characteristics. Specifically, we define an indicator variable $I_i^{jobloss} = 1$ if engineer $i$ experienced job loss in 2015 or 2016, and zero otherwise. We then regress this indicator variable on 2013 characteristics in a probit regression, according to equation (5). Ex-ante, we expect tenure to be an important variable in explaining job loss, as firms are obliged to follow the seniority principle in determining layoffs. Other control variables are captured in $X_i$, and include age, wage income, total income, housing wealth, real wealth, financial wealth, bank deposits, and debt.

$$I_i^{jobloss} = \alpha + \beta Tenure_i + \gamma X_i + \epsilon_i \tag{5}$$

The regression results are reported in Table D.1. As expected, tenure has a negative and significant effect on the probability of job loss. However, after controlling for tenure, information on income, wealth and debt does not have a significant impact on the probability of job loss. The only other variable that is statistically significant – at the ten percent level – is age. When tenure is not included in the regression, both age, financial wealth and debt has a significant effect on the probability of job loss. The pseudo $R^2$ is low in both cases, but especially so when tenure is excluded from the analysis.

In order to compare the amount of selection during the oil crisis to selection into unemployment during "normal times", we repeat the above analysis for job loss prior to the oil price collapse. Specifically, we let $I_i^{jobloss}$ indicate job loss in one of the years 2003-2013 and rerun the regression specified in equation (5). We then compare the pseudo $R^2$'s to the pseudo $R^2$ reported in Table D.1. The results are depicted in Figure D.1. The pseudo $R^2$'s during the oil crisis is the lowest in the sample, suggesting that the simple statistical model outlined in equation (5) has somewhat less explanatory power in predicting job loss during the oil price crisis than in normal times.

Note however, that because we can only calculate tenure back until year 2000, the comparison is somewhat misleading (as the tenure variable contains more information towards the end of the sample). In order to undertake a more fair comparison, we exclude tenure from the model, and redo the analysis. The resulting pseudo $R^2$'s are depicted in the right panel of Figure D.1. The pseudo $R^2$ during the oil price collapse is now *much* lower than in normal times, suggesting less selection on observables into unemployment.

| | (1) Job Loss | (2) Job Loss |
|---|---|---|
| Tenure | -0.0737*** | |
| | (-10.54) | |
| Age | 0.00402* | -0.00490** |
| | (1.71) | (-2.22) |
| Wage Income | 0.000000240 | -0.000000971 |
| | (0.22) | (-0.82) |
| Total Income | -0.000000957 | -0.000000244 |
| | (-1.09) | (-0.24) |
| Primary Housing Wealth | 5.77e-08 | -6.37e-08 |
| | (0.21) | (-0.24) |
| Real Wealth | -0.000000151 | -0.000000202 |
| | (-0.58) | (-0.80) |
| Financial Wealth | -0.000000621 | -0.000000810** |
| | (-1.63) | (-2.12) |
| Bank Deposits | 9.80e-08 | 0.000000144 |
| | (0.14) | (0.21) |
| Debt | 0.000000202 | 0.000000236* |
| | (1.41) | (1.68) |
| Constant | -1.082*** | -1.009*** |
| | (-10.76) | (-10.09) |
| Pseudo R2 | 0.0457 | 0.0133 |
| *N* | 6,732 | 6,732 |

$t$ statistics in parentheses
$^{*}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table D.1: **Predicting job loss.** Regression results from estimating equation (5) with dependent variable $I_i^{jobloss} = 1$ if engineer $i$ experienced job loss in 2015-2016. Probit regression.

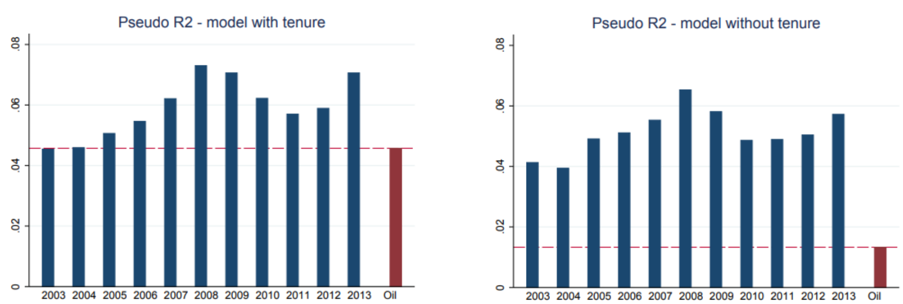


Figure D.1: **Share of job loss explained by observable characteristics**. Pseudo R2 from the probit regression reported in Table D.1 by year of job loss.