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The Saving and Employment Effects of Higher Job Loss Risk*

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Abstract

In this paper we use Norwegian tax data and a novel natural experiment to isolate the impact of job loss risk on saving behavior. We find that a one percentage point increase in job loss risk increases liquid savings by roughly 1.2 - 2.0 percent. Further, we show that employment falls in non-tradable industries not directly affected by the shock, also after controlling for intersectoral linkages and lower demand from affected industries, consistent with the household demand channel of recessions.

Key words: Precautionary savings, household finance, recessions

JEL Codes: D14, E20, E21

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1 Introduction

Saving rates tend to increase during recessions, and the increase following the recent financial crisis was especially large and long-lived. This has sparked a new interest in both the determinants and effects of higher saving rates during periods of economic distress. Policymakers and academics have linked the increase in savings to higher economic uncertainty. As future income becomes more volatile – for instance due to higher job loss risk – people may become less willing to consume today. The reduction in consumption implies a reduction in aggregate demand, making the increase in savings a potential amplifier of economic downturns.

A recent theoretical literature emphasizes the importance of higher savings in response to increased job loss risk in amplifying economic downturns (Bayer et al. 2015, Challe and Ragot 2016, Challe et al. 2017, Ravn and Sterk 2016, Ravn and Sterk 2017). However, little is known about the empirical effect of job loss risk on savings during periods of economic distress. Estimating this effect is challenging, as it requires both an exogenous increase in job loss risk and a strategy to isolate the impact of risk from other recession effects. Further, evaluating whether the saving response reduces overall employment through the household demand channel requires a strategy to separate the general equilibrium effects of higher household savings from other forces affecting employment.

In this paper we use administrative panel data from Norway and a novel natural experiment to study the impact of higher job loss risk on savings. The sudden collapse of the international oil price in 2014 led to an exogenous increase in risk for certain occupations and regions. Using our individual level data, we can compare workers who live in the same area, but who are subject to different changes in job loss risk, allowing us to separate the effect of higher job loss risk from other local recession effects. We find that a one percentage point increase in job loss risk increases liquid savings by 1.2 - 2.0 percent. In order to evaluate the aggregate demand effects of higher savings, we focus on employment in industries not directly affected by the oil price collapse. After accounting for lower demand from directly affected industries, we document that non-tradable sector employment declines more in regions in which the increase in individual savings is larger – consistent with the household demand channel.

The tax data includes information on income and wealth, and can be merged with labor market data as of 2000. We thus have detailed information on labor market status and occupation, which will be important in identifying individual level job loss risk. We use the 2014 oil price collapse to obtain an exogenous increase in risk which differs across occupations. The occupational group with the largest increase in job loss risk is engineers. 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 similar 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. As a robustness exercise, we also use an alternative control group consisting of high

skilled *government* workers, who did not experience any increase in job loss risk.

In order to control for other local recession effects which potentially affect savings, we start by comparing individuals with different changes in job loss risk, but who live in the same area, in a dynamic difference in difference regression. Specifically, we define the oil region to be the two counties in the South-West of Norway which employ an unproportionally high share of oil workers. By comparing engineers and other high skilled workers who live in the oil region, we can control for any local recession effects – such as falling house prices – which are common across these two groups. In order to evaluate the sign and the magnitude of other local recession effects, we compare the baseline results to an alternative specification in which the control group consists of high skilled individuals *not* residing in oil counties. Note that higher job loss risk necessarily has both a variance effect and a level effect on expected future income. Our empirical results capture both of these channels.

The results show an annual increase in savings for engineers relative to other high skilled workers of roughly \$1,200, or three and a half percent. Scaling this by the increase in job loss risk, we find that a one percentage point increase in job loss risk increases savings by 1.2 percent. Reassuringly, the increase in 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 savings for every one percentage point increase in job loss risk rises to 1.5 - 2.0 percent. Not controlling for local recession effects has a moderate, but positive impact on the results. This suggests that, if anything, not accounting for other recession effects would cause us to overstate the impact of job loss risk on savings.

When investigating the relevance of the household demand channel, we aggregate the outcome variables to the municipality level and categorize municipalities based on their share of oil sector engineers. We restrict the sample to the municipalities within the oil region. Not surprisingly, municipalities with a higher number of affected individuals experience an increase in average savings. In order to evaluate the overall employment impact of higher savings, we consider industries *not* directly affected by the shock. We find that non-oil sector unemployment increases more in the municipalities with a higher share of oil sector engineers, especially in the non-tradable sectors – assumed to be the most sensitive to local household demand.

Identifying the general equilibrium effects of the risk induced increase in savings on employment is challenging, as there are several factors at work. We attempt a rough decomposition of the increase in non-oil sector unemployment, considering three channels likely to be important. First, a negative shock to the oil sector implies lower demand for the firms producing inputs to the oil sector. Second, household demand is likely to be lower due to i) more people becoming unemployed and reducing consumption as a result of lower income, and ii) people reducing consumption in order to save more as a result of higher job loss risk.

We account for lower firm demand by using input output data and network analysis from Acemoglu et al. (2016). While lower firm demand can fully explain the unemployment increase in the

tradable sector, it cannot fully explain the unemployment increase in the *non*-tradable sectors – suggesting that some of the increase in unemployment is due to lower household demand. While we do not have an identification strategy to separate the impact of lower consumption resulting from realized unemployment from lower consumption resulting from higher job loss risk, we argue that the latter is quantitatively more important. Back of the envelope calculations suggest that the total consumption loss resulting from the risk channel is about four times as large as the total consumption loss resulting from realized unemployment. The reason being that, although unemployed individuals have larger consumption declines, there are relatively few of them compared to the many affected workers who keep their jobs but face an increase in risk. As a result, the decomposition exercise suggests that higher job loss risk is an important driver of increased unemployment in the non-tradable sectors. We thus conclude that the data is consistent with a risk induced increase in individual savings having a negative impact on employment.

1.1 Literature Review

Several papers study the connection between job loss risk and savings. Most of these papers do not focus on economic downturns specifically, and use either subjective unemployment beliefs (Guiso et al. (1992), Carroll and Dunn (1997), Lusardi (1998)) or future unemployment spells (Chetty and Szeidl (2007), Basten et al. (2016), Hendren (2017)) to capture job loss risk. This has the benefit of not confounding the impact of risk with other recession effects, but does not necessarily capture the impact of job loss risk on savings *conditional* on macroeconomic distress. In order to address endogeneity concerns, this literature has often used mass layoffs to control for within-firm selection into unemployment (see for example Basten et al. (2016)). However, as pointed out by Hilger (2016), this does not control for potential across-firm selection.

In order to obtain an exogenous increase in job loss risk, Fuchs-Schündeln and Schündeln (2005) use the German reunification as a natural experiment. The German reunification implied a permanent and “once-in-a-lifetime” reassignment of job loss risk across occupations however, and is therefore less relevant for understanding the implications of business cycle variations in job loss risk. An alternative approach is to instrument for (changes in) job loss risk with variables such as region of residence, occupation, sector and demographic characteristics. This approach is taken in Carroll et al. (2003) and Harmenberg and Oberg (2016). Due to the many variables used as instruments, it is not clear exactly what is driving the variation in risk. However, given that region and occupation are important determinants, the exercise may be conceptually similar to the one in this paper. We expand upon the analysis in these papers by separating the impact of job loss risk from other local recession effects, such as falling house prices etc.

Our analysis is also related to papers which use VARs to identify the impact of different types of uncertainty shocks on consumption and output, such as Alexopoulos et al. (2009), Jurado et al. (2015), Fernández-Villaverde et al. (2015), Leduc and Liu (2016), Larsen (2017) and Basu and

Bundick (2017). Basu and Bundick (2017) show that an uncertainty shock decreases both consumption and output, and develop a model in which output falls due to an increase in desired savings. We complement their analysis, by providing micro-level evidence in favor of this mechanism. Note that the VAR exercise cannot rule out that output falls as a direct response to the shock, and that this reduces employment and hence consumption. We contribute to this literature by directly showing that savings increase in response to higher uncertainty, and that this increase occurs prior to the employment fall. Further, we explicitly account for intersectoral linkages and show that the employment fall is found in non-tradable sectors only, supporting the household demand channel.

Finally, our paper relates to a literature which uses cross-sectional variation to uncover evidence on the local household demand channel. Mian and Sufi (2014) show that employment in the non-tradable sector declines in response to a fall in housing net worth, while Verner and Gyongyosi (2018) show that employment in non-exporting firms declines in response to an increase in household debt resulting from a sudden currency crisis. In addition to studying an uncertainty shock rather than a net wealth shock, we contribute to this literature by considering savings directly and documenting that the saving response precedes the employment decline - thereby offering further support for the household demand channel.

2 Data and Institutional Background

We use administrative data which covers the universe of Norwegian tax filers. The main outcome variable is liquid savings, measured by bank deposits. However, we also consider other financial assets. 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.

The tax data is a panel data set, covering the period 1993 to 2015. The data is annual, and variables are measured at the end of the year. It contains information on income from different sources, including transfers and taxes. We define individuals as unemployed if they receive unemployment insurance in a given year. In addition to income data, there is also rich information on household wealth. We observe financial wealth in the form of bank deposits and other financial assets. Real wealth is reported as primary housing wealth, secondary housing wealth and other real wealth. Prior to 2010 the value of real wealth which is reported for tax purposes is substantially below market value. From 2010 and onward, efforts are made to correctly report the market value of housing wealth. The data set also contains information on total debt, allowing us to back out net wealth.

Our main outcome variable is liquid savings, measured by bank deposits. As bank deposits is a highly liquid and safe financial asset, it seems like a good candidate for precautionary saving. However, we will also consider any adjustments that come through other financial assets or real

wealth. Bank deposits are reported by the bank, and include saving accounts, checking accounts, fixed term deposits etc. Bank deposits do not include investments in bonds and direct and indirect holdings of stocks, which belong to *other financial assets*. 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.

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 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)).

The tax data can be merged with labor market data as of 2000. Our full data set therefore covers the period 2000 to 2015. From the labor market data we obtain detailed information on occupation and sector, which is important for our identification strategy. The matched firm-worker data also allows us to calculate the observed tenure for each worker, which will be useful for identifying the 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. Similarly, the unemployment rate for an occupation o is defined as the unemployment rate for individuals in that occupation. We use the same type of assignment rule for assigning workers to a sector, and for calculating sector level unemployment rates.

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 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. The remaining working individuals are employed in occupations which do not require higher education, and are referred to as low skilled.

In addition to only using 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 the variables at the 99 percent level, following Basten

et al. (2016) who also use administrative data from Norway.

Summary statistics for the three occupational groups are reported in Table 1. Nearly everyone owns some bank deposits, 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 other 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 the labor compensation takes the form of financial assets. Among the low skilled, less than 40 percent own other financial assets. Also note that these other financial assets appear relatively skewed, 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. For this reason, 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
Bank Deposits	35,900	34,700	19,600	14,200	11,500	5,600
Other Financial 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
Bank Deposits > 0	99	99	98			
Other Fin. 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 2013 in 2015 USD (rounded to closest 100 with USD/NOK 7.5).

2.1 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. Figure 15 in Appendix A depicts harmonized OECD unemployment rates by country, with the Norwegian unemployment rate typically falling below four percent. While the unemployment rate in Norway has generally been below that in the US, this has changed in recent years. At the same time as the US labor market has finally recovered from the Great Recession, the oil price collapse in 2014 led to a deterioration of Norwegian labor market conditions. As a result, the unemployment rates in the two countries have been similar for the past three to four years.

When interpreting the results of this study in a broader context, it is useful to keep in mind that the setting is one of relatively low baseline job loss risk, and relatively generous unemployment insurance.

3 Theoretical Predictions

What does higher uncertainty imply for savings and output in macroeconomic models? Under which conditions can an increase in uncertainty amplify an economic downturn? In this section we briefly discuss the implications of different types of models, and which assumptions are needed in order to generate amplification. In the appendix we set up and solve a search and match model with nominal frictions, and show how higher job loss risk can amplify economic downturns given assumptions about nominal frictions and monetary policy.

In general, higher uncertainty increases savings if there is prudence in the utility function

(Kimball, 1990) or if there are potentially binding borrowing constraints. In standard neoclassical models, the increase in savings leads to an increase in investment. In addition, higher uncertainty induces a precautionary labor supply response, making the overall impact on output positive. Higher uncertainty therefore increases both savings and output, and there is no amplification of economic downturns.

In New Keynesian models with nominal rigidities, the co-movement between savings and output can break down. If prices and interest rates do not fall sufficiently, the increase in investment will be insufficient to make up for the decline in consumption. If labor supply is inelastic, the precautionary labor supply response is also eliminated. As a result, higher uncertainty can increase savings while reducing output, see for example Kobayashi and Nutahara (2010) and Basu and Bundick (2017).

Macroeconomic models often introduce uncertainty as a mean preserving spread to future income. Job loss risk on the other hand, can both increase the variance of future income and reduce the expected level of future income, i.e. it is *not* a mean preserving spread. Both of these channels can lead to higher savings. Recently, a handful of papers have studied uncertainty in the form of job loss risk using search and match models with nominal frictions, see Bayer et al. (2015), Challe and Ragot (2016), Challe et al. (2017), Ravn and Sterk (2016) and Ravn and Sterk (2017). In these models, a shock to the separation rate increases job loss risk and induces individuals to save more. We now briefly discuss under what assumptions this type of model predicts amplification of economic downturns.

Search and match models with nominal frictions In the appendix, we set up and solve a model similar to Ravn and Sterk (2017). We briefly discuss the model setup here, and under which conditions higher job loss risk reduces output through an increase in savings.

Individuals receive a fixed wage income if employed and unemployment benefits if unemployed. At the time of consumption/saving decisions, individuals face idiosyncratic job loss risk. Firms post vacancies at a fixed vacancy posting cost, and the vacancy is filled with some probability that depends on the number of vacancies and the number of unemployed individuals. Firms maximize profits and are subject to a Rotemberg price adjustment cost. Matches between unemployed individuals and firms posting vacancies are governed by a matching function, and the interest rate follows a Taylor rule.

Consider a shock to the separation rate in this setting, which has two effects on output. First, a reduction in the number of employed individuals mechanically reduces output. Second, higher job loss risk induces households to save more, and thereby cut back on consumption. In order to increase consumption, prices and interest rates must fall. If prices do not fall sufficiently due to price rigidities, and if the interest rate does not fall sufficiently due to the monetary policy rule¹, firms are going to respond by reducing vacancies. As a result, there is an additional fall in

¹For a standard calibration of the Taylor rule, monetary policy is not able to fully offset the shock. In practice, one could think of monetary policy not being sufficiently accommodative due to the zero lower bound or because the

output, due to the risk induced increase in savings. The model exercise therefore shows that higher job loss risk in theory *can* amplify economic downturns through an increase in savings. However, with perfectly flexible prices or with sufficiently aggressive monetary policy, the amplification would break down.

We now move on to study these questions in the data, with the aim of evaluating the empirical relevance of the type of models outlined here. Note that these types of models often use complete market exercises to isolate the variance effect of job loss risk from the level effect of job loss risk. Our empirical analysis captures both the variance and the level effect. We proceed by first using administrative data and a natural experiment to investigate the impact of job loss risk on savings. After having confirmed that higher job loss risk increases savings, we show that there is a decline in employment in non-tradable industries not directly affected by the shock, consistent with the reduction in household demand amplifying the economic downturn.

4 Empirical Analysis

The empirical analysis consists of two main parts. First, we investigate the effect of higher job loss risk on savings, by comparing individuals who are subject to the same local recession effects, but who face different changes in risk. After having established that higher job loss risk increases individual savings, we consider the overall employment effects of higher savings, i.e. the household demand channel.

4.1 The effect of job loss risk on savings

The first goal of the empirical exercise is to identify the impact of job loss risk on savings. In order to obtain an exogenous increase in job loss risk, we use the 2014 oil price collapse as a novel natural experiment. By comparing liquid savings 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.

4.1.1 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 Figure 16 in Appendix A. 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

shock is regional.

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 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 Figure 17 in the appendix. Two out of nineteen counties employ a disproportionately high share of oil sector workers, and we define these two counties as the oil region.² 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 1 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.

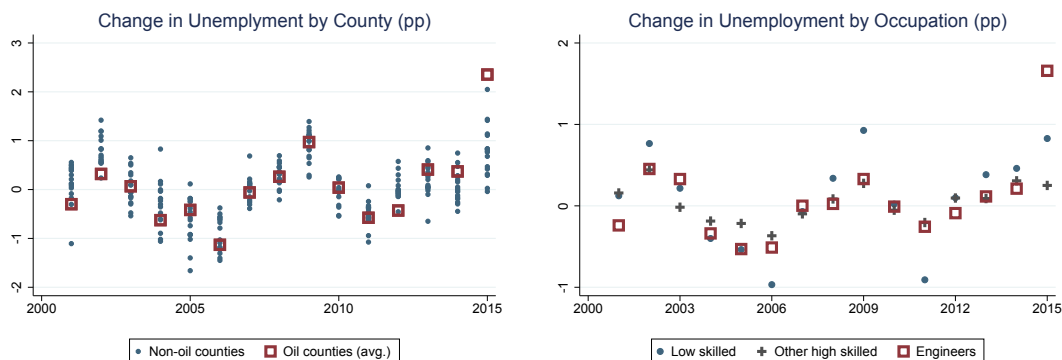


Figure 1: Changes in unemployment rates (pp).

No other occupational group received as much media attention as engineers following the oil price

²The two oil counties are Hordaland and Rogaland, and the largest city in the area is Stavanger - sometimes referred to as the oil capital.

collapse³, and the data suggests that this was indeed warranted.⁴ The tax data contains detailed 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*. High skilled individuals include managers, professionals, and technicians/associate professionals, and make up 47 percent of the work force, see Table 9 in Appendix B. Finally, individuals who do not belong to any of these groups, but who were employed in at least one of the years 2011-2013 are labeled low skilled.

The right panel of Figure 1 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. 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 1 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 2 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 two oil counties over time. After the oil price started

³Some 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 342 percent in one year - but many are finding new employment” *E24* March 2016.

⁴The 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 group in 2015 was the largest observed increase for any occupational group since their sample starts in 2003.

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 evaluate how salient the shock is in terms of labor market risk, the right panel of Figure 2 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.⁵

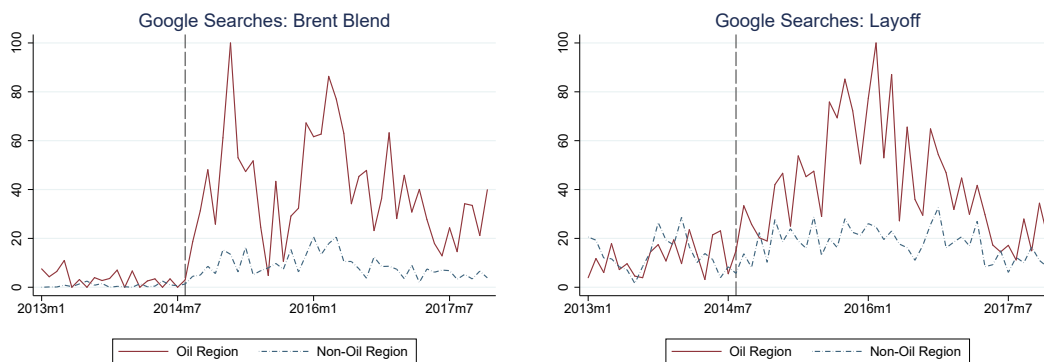


Figure 2: Google search data for the oil region and other counties. The index is set to 100 for the maximum search volume in the sample.

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.

4.1.2 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 savings for engineers to that of other high skilled workers in

⁵Unemployment 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.

oil producing regions. This within-region comparison allows us to control for the potential impact of other local recession effects on savings. Further, by contrasting the baseline findings to the results from an across-region comparison, we can explicitly evaluate the importance of other local recession effects.

The dynamic difference in difference regression is outlined in equation (1). The main outcome variable Y_{it} is bank deposits 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 oil producing regions, and $T_i = 0$ for other high skilled workers residing in oil producing regions. Treatment status is defined based on the years prior to the oil price collapse. Year fixed effects δ_k are included to capture time-varying aggregate effects which are common to all individuals, while individual fixed effects α_i are included to capture individual, time-constant factors. The coefficients of interest are the β_k 's, which capture the impact of the interaction term between treatment status and year indicator variables. Given that $\beta_k = 0$ for $k < 2014$, the dynamic treatment effect is captured by the β_k 's for $k \geq 2014$. We also estimate the more restrictive difference in difference regression given by equation (2), to obtain the average treatment effect, in which $I_t^{post} = 1$ if $t \geq 2014$. Standard errors are clustered at the individual level.

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

$$Y_{it} = \alpha_i + \sum_k \delta_k \mathbf{1}_{t=k} + \beta_k (T_i \times I_t^{post}) + \epsilon_{it} \quad (2)$$

Because we are interested in the impact of job loss risk, rather than the impact of realized unemployment, we restrict the analysis to only include individuals who are not (yet) unemployed.⁶ This turns out not to matter for the 2014 results, as the unemployment rate did not start increasing until the following year. It does however matter for the 2015 results, as some individuals had lost their job by that time and started to dis-save in order to smooth consumption.

In order to evaluate the importance of local recession effects in determining savings, we complement the baseline analysis with an across-region specification. That is, we compare engineers in oil producing regions to high skilled workers residing outside of oil producing regions. The results from this comparison should reflect both the impact of higher job loss risk and the impact of other local recession effects, such as a relative decline in house prices. Contrasting these results with the baseline findings allows us to also evaluate the sign and magnitude of the impact of other recession effects on savings.

⁶Specifically, we condition on job loss not occurring in 2014 or 2015. We have also tried conditioning on job loss not occurring for the full period, i.e. 2010-2015, and the results are very similar.

Selection into unemployment Before presenting the results, we briefly discuss the issue of selection into unemployment. In an event study in which job loss risk is identified by future unemployment, the main concern is that there is an individual level shock which is causing the upcoming job loss and affecting saving behavior. This concern is strongly mitigated in our setting, as job loss is caused by an exogenous fall in the oil price. 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 C 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 into unemployment following the oil price collapse.

4.1.3 Results

The empirical results confirm that higher job loss risk increases liquid savings. Reassuringly, the increase in savings is driven by low-tenured workers, who experienced an especially large increase in job loss risk. Not accounting for local recession effects produces larger estimates, suggesting that other recession effects might also contribute to higher savings.

Figure 3 depicts the unemployment rate and the separation rate in the oil region over the period 2001-2016, 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 going from employed to unemployed, and corresponds to the exogenous separation rate ρ_t in the model in Appendix D. 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 (q_t in the model). 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 an average of roughly six 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, 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 3. 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.

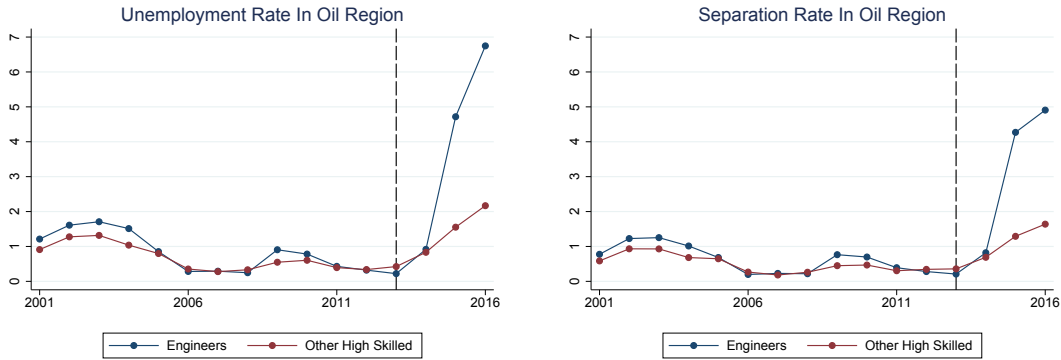


Figure 3: Unemployment rate and separation rate (%) for engineers in the oil region and other high skilled workers in the oil region.

The left panel of Figure 4 depicts bank deposits for engineers and other high skilled workers over time. Bank deposits for the two groups follow each other closely up until 2013, when there is a divergence which persists until 2015. Reassuringly, the divergence appears to be driven by an above trend increase in bank deposits for engineers rather than a below trend increase in bank deposits for other high skilled workers. Regression results from estimating equation (1) with $Y_{it} = \text{Bank Deposits}_{it}$ are depicted in the right panel of Figure 4. The pre-2014 coefficients are all very close to zero in magnitude and not statistically significant, suggesting that the parallel trend assumption is satisfied. In 2014, the coefficient is positive at roughly \$1,200 and statistically significant, implying that engineers in the oil region increased their bank deposits relative to that of other high skilled workers in the oil region.

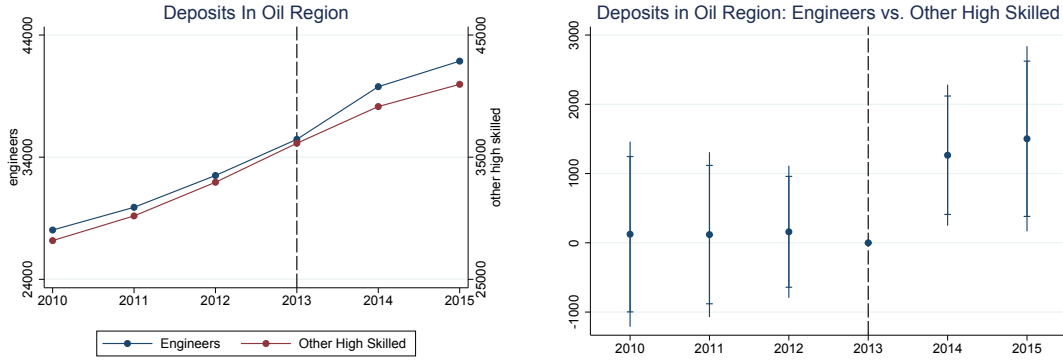


Figure 4: Bank deposits for engineers in the oil region relative to other high skilled workers in the oil region. Right panel: coefficient estimates from estimating equation (1) .

In the appendix, we further decompose engineers into those who lose their job and those who do not experience job loss.⁷ We show that while the average saving response occurs in 2014, engineers who lose their job in 2016 increase savings mainly in 2015.

The results in Figure 4 are further summarized in Table 2. As seen from the first column, engineers increased their bank deposits by roughly \$1,200 or 3.4 percent in 2014. In order to scale the saving response, we estimate the increase in unemployment rates and separation rates using a simple difference in difference regression as the one outlined in equation (2). Following the model outlined in the appendix, we use the next period increase in uncertainty to scale the current period saving response. The relative unemployment and separation rates increased by 3.0 and 2.9 percentage points respectively in 2015, and increased further the following year. 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 1.1 percent. Alternatively, we can scale the increase in bank deposits by the change in the separation rate. Doing so, we find that a one percentage point increase in the job loss rate increases liquid savings by 1.2 percent.

Results averaging over 2014 and 2015 are reported in the second column of Table 2, and show a similar increase. Focusing on the 2014 results has the advantage of capturing the initial saving response, which occurred before unemployment started to increase in the data and before any policy changes were implemented or even discussed. This makes it less likely that other forces are behind the relative increase in savings for engineers. However, the shock increased both in size and salience over time, and so we also include results which reflect the saving response in 2015 - the last year for which we have tax data. This increases the estimated saving response slightly, both in absolute terms and when scaled by the increase in uncertainty.

⁷Note that we are excluding those who lose their job in 2014-2015 from the analysis, as we do not want the effect of realized unemployment to influence our saving results. The decomposition is thus engineers who do not experience job loss during the period 2014-2016 and engineers who experience job loss in 2016.

	(1)	(2)
	Bank Deposits	Bank Deposits
$T_i^{2013} \times I_t^{post}$	1,187**	1,283**
	(2.12)	(2.32)
Increase in Bank Deposits (%)	3.37	3.64
per pp increase in unemployment rate (%)	1.14	0.992
per pp increase in separation rate (%)	1.18	1.21
Sample period	2010-2014	2010-2015
Clusters	19,370	19,370
N	95,332	114,370

t statistics in parentheses. Std. errors clustered at the individual level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Bank deposits. Within oil region analysis. Regression results from estimating equation (2).

Tenure While engineers residing in oil regions experienced a general increase in job loss risk post-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 a larger saving response.

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 oil regions is six years. We thus define individuals with less than six years tenure in 2013 as having *low tenure*. Figure 19 in Appendix A 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 are reported in Table 3, and show that the saving increase is driven by low-tenured workers. Low-tenured engineers increase their liquid savings by roughly \$2,000, while the increase for high-tenured engineers is not statistically significant. As low-tenured engineers have lower holdings of bank deposits to begin with, the percentage increase exceeds seven percent. Relative to other high skilled workers, low-tenured engineers experience an initial relative increase in unemployment rates and job loss risk of 4.8 and 4.6 percentage points respectively. 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 1.45 percent. Alternatively, a one percentage point increase in the job loss rate increases liquid savings by 1.51 percent. The relative saving response is somewhat higher when averaging over the 2014-2015 period, reaching an increase of 2.0 percent for every one percentage point increase in the separation rate.

Relative to the increase in job loss risk, the saving response of low-tenured engineers is higher than the baseline results. This is consistent with the simulation results in Engen and Gruber (2001), in which the percentage effect of risk on savings declines in age – which is positively associated with tenure – and increases in the level of risk.

	(1)	(2)
	Bank Deposits	Bank Deposits
$T_i \times I_t^{post}$	437	224
	(0.49)	(0.26)
$T_i \times Tenure_i^{low} \times I_t^{post}$	2,009*	2,637**
	(1.81)	(2.42)
Increase in Bank Deposits (%) (low tenure)	7.02	9.21
per pp increase in unemployment rate (%)	1.45	1.60
per pp increase in separation rate (%)	1.51	2.02
Sample period	2010-2014	2010-2015
Clusters	19,046	19,046
N	93,724	112,451

t statistics in parentheses. Std. errors clustered at the individual level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Bank deposits by tenure. Within oil region analysis. Regression results from estimating equation (2) by tenure.

Other recession effects 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. In this section we explore different specifications in order to gauge whether these other recession effects are quantitatively important in terms of affecting saving behavior.

The first column in Table 4 simply reproduces the baseline results, in which engineers in the oil region are compared to other high skilled workers in the oil region. In the second column, we compare engineers in the oil region to other high skilled workers everywhere. Finally, in the third column we compare engineers in the oil region to high skilled workers in the non-oil region. Both the coefficient estimates and the scaled increase in liquid savings increase as we move to the right in the table. This suggests that other recession effects are, if anything, contributing to higher saving

rates, and that not accounting for these effects would lead us to overstate the impact of job loss risk on savings.

Given that engineers in the oil region are affected by *both* higher job loss risk and local recession effects, other high skilled workers in the oil region are affected by local recession effects *only*, and that other high skilled workers in the non-oil region are *unaffected*, the impact of local recession effects can be found by comparing the results from column (3) to the baseline results in column (1). Both the regression coefficient and the scaled saving response is larger in the final column, suggesting that not accounting for local recession effects could lead us to overstate the impact of higher uncertainty on savings. However, the difference between the coefficient estimates is not statistically significant.

Note that the quantitative importance of local recession effects is likely to vary, and we do not attempt to measure the size of such effects for our given shock. It is therefore possible that other local recession effects would have larger implications for saving behavior in a different setting, simply because the other local recession effects would themselves be larger.

	(1)	(2)	(3)
	Bank Deposits	Bank Deposits	Bank Deposits
$T_i \times I_t^{post}$	1,187**	1,493***	1,560***
	(2.12)	(3.17)	(3.28)
Increase in Bank Deposits (%)	3.37	4.24	4.43
per pp increase in unemployment rate (%)	1.14	1.28	1.31
per pp increase in separation rate (%)	1.18	1.32	1.35
Control group: high skilled workers...	in oil region	in all regions	in non-oil region
Sample period	2010-2014	2010-2014	2010-2014
Clusters	19,370	78,388	65,241
N	95,332	387,296	322,387

t statistics in parentheses. Std. errors clustered at the individual level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Bank deposits. Across region analysis. Regression results from estimating equation (2).

Interpreting the increase in liquid savings Bank deposits are a safe and highly liquid way to save, and therefore a good candidate for precautionary saving. Basten et al. (2016) find that individuals respond to future unemployment by increasing both the level and the share of safe assets in their portfolio. We have rerun the baseline analysis using total financial wealth as the dependent variable, and the results are reported in Table 10 in the appendix. The increase in total financial wealth is virtually the same as the increase in bank deposits, indicating that non-deposit financial wealth was kept roughly unchanged. There was also no statistically significant decline in housing wealth or other real wealth for engineers relative to other high skilled workers following the oil price collapse.

Because there is no decrease in other forms of wealth – and no relative increase in wages – we find it likely that the increase in liquid savings implied a reduction in consumption. 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 discussed at this time. We therefore find it highly probable that the increase in liquid savings implied a reduction in consumption.

4.1.4 Robustness

In the robustness section we show that our results are robust to two alternative specifications. First, 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. Second, 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. We further show that the estimated saving response is unlikely to be driven by wealth effects or selection into occupation based on risk aversion.

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 now change the treatment group to only contain engineers which were employed in the oil sector prior to 2014. This leads to, if anything, a slightly higher saving response than in our baseline results.

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. The time series for unemployment and separation rates for the two groups are depicted in Figure 21 in the appendix, while the evolution of bank deposits is depicted below in Figure 5.

As seen from the left panel of Figure 5, engineers in oil sectors and other high skilled workers have almost identical holdings of bank deposits in the four years leading up to the oil price collapse. Following the oil price collapse, engineers in oil sectors increase their bank deposits relative to other high skilled workers. As reported in Table 11 in the appendix, the increase in bank deposits is similar to the baseline - both in absolute value and when scaling the response with the relative increase in job loss risk. A one percentage point increase in the separation rate is now found to increase liquid assets by 1.23 percent – compared to 1.18 in the baseline.

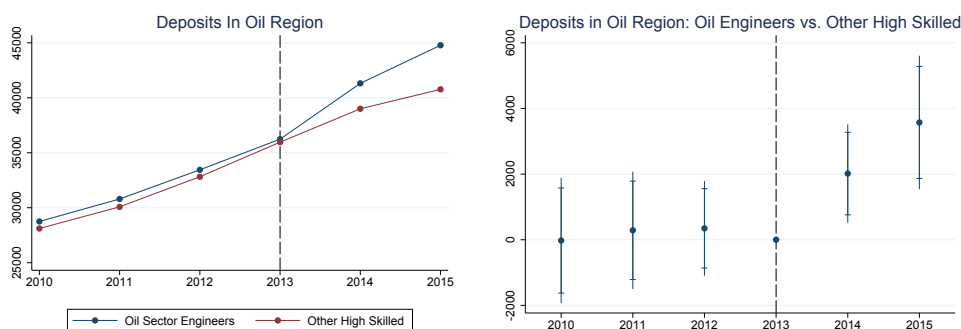


Figure 5: Bank deposits for oil sector engineers in the oil region relative to other high skilled workers in the oil region. Right panel: coefficient estimates from estimating equation (1).

Spillovers to the control group The baseline analysis compared engineers residing in oil regions to other high-skilled workers residing in oil regions. It is likely that also the latter group experienced some increase in job loss risk following the oil price shock. Figure 3 showed that although other high-skilled workers in oil regions 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 1. 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 group 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 oil regions. As before, individuals are classified into occupations based on their occupational status in the years leading up to the oil price collapse. High skilled government workers have virtually no increase in unemployment rates or job loss risk following the oil price collapse, implying limited scope for spillover effects.

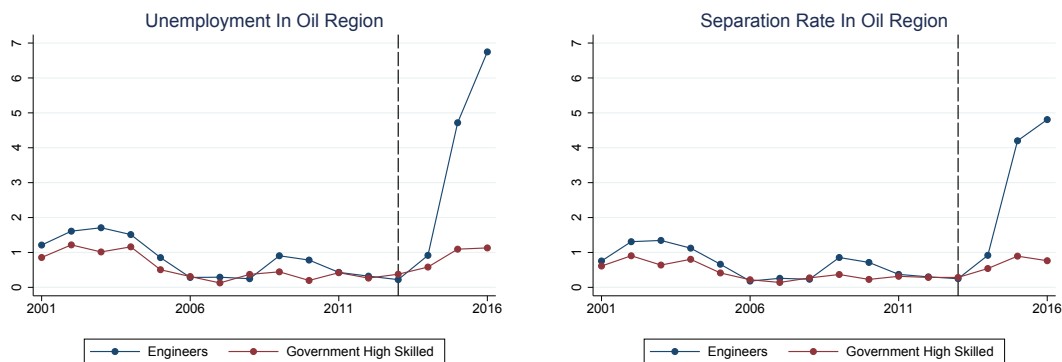


Figure 6: Unemployment rate and separation rate (%) for engineers in the oil region and high skilled government workers in the oil region.

Regression results when using only high skilled government workers in the control group are reported in Table 5. The coefficient estimate for 2014 is almost unchanged, but the increase in uncertainty is somewhat larger. As a result, a one percentage point increase in the separation rate is found to increase liquid savings by 1.00 percent - compared to 1.18 percent in the baseline. For the 2014-2015 results, the estimated saving response is virtually the same as in the baseline. Hence, we conclude that our results are robust to controlling for spillovers to the control group.

	(1)	(2)
	Bank Deposits	Bank Deposits
$T_i \times I_t^{post}$	1,108 (1.53)	1,449** (2.01)
Increase in Bank Deposits (%)	3.14	4.12
per pp increase in unemployment rate (%)	0.954	0.841
per pp increase in separation rate (%)	1.00	1.17
Sample period	2010-2014	2010-2015
Clusters	9,031	9,031
N	44,220	53,054

t statistics in parentheses. Std. errors clustered at the individual level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Bank deposits. Within oil region analysis. Regression results from estimating equation (2) using only high skilled government workers in the control group.

House prices Although the within region analysis controls for other “local” recession effects, the definition of local can be disputed. There might still be price differences within the two counties defined as the oil region. For example, engineers and their high skilled peers may live in systematically different areas, thereby being exposed to different changes in house prices. To explore this, 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.

Figure 22 in Appendix A 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 looks 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. 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 oil region.

Other wealth effects If local stock prices are affected, there could also be negative wealth effects coming from financial assets. While there was certainly a decline in stock prices for many oil firms, the overall impact on the Norwegian stock market was limited. As illustrated in Figure 23 in Appendix A, 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.

Figure 24 in Appendix A shows that there is no decline in the value of other financial assets for engineers or other high skilled workers following the oil price collapse. Note that other financial assets contain not only Norwegian stocks, which might have fallen slightly in value in 2016, but also other assets such as bonds and international stocks - typically held through global mutual funds. If the latter is not hedged against exchange rate movements, the value of these assets would have increased after the oil price collapse.

As long as any wealth effects are constant across the control and treatment group, they cannot be the driving force behind the estimated saving response. As previously discussed, there was no significant change in financial assets for engineers relative to other high skilled workers following the oil price collapse - see Table 10 in the appendix. We thus find it unlikely that the observed increase in bank deposits for engineers relative to other high skilled workers is driven by a negative wealth effect.

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 who had very similar levels of job loss risk prior to the oil price collapse. As shown in Figure 3, engineers and other high skilled workers had almost identical unemployment rates in the thirteen years leading up to the oil price collapse. Also, there has been a general shortage of engineers in Norway over the past years, and becoming an engineers has been considered a safe career choice. 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 a lower bound for the population wide response all else equal.

4.1.5 External validity

The treatment group considered so far consists of individuals with above average education, income and wealth. By doing an event study which includes all men who experience job loss, we find that high income individuals may exhibit stronger saving responses to heightened job loss risk than low income individuals. Hence, a shock which affected low income individuals could potentially have smaller effects on liquid savings than those identified in the previous subsection.

For the event study, we use a sample of men who become unemployed exactly once in the period 1995-2012. We run the regression in equation (3), where Y_{it} is the outcome variable for

individual i in year t . Individual fixed effects α_i capture time invariant individual characteristics, while time fixed effects δ_t capture common time trends. X_{it} is a fourth order polynomial in age. The coefficients of interest are the β_k 's, which capture the impact of being k years away from the start of an unemployment spell. Accordingly, U_{it}^k is a vector of dummies for nine years around job loss ($k = 0$). All results are reported relative to $k = -4$, i.e. four years prior to the beginning of the unemployment spell. Standard errors are clustered at the individual level.

$$Y_{it} = \alpha_i + \delta_t + X_{it}\beta + \sum_{k=-4}^{k=4} U_{it}^k\beta_k + \epsilon_{it} \quad (3)$$

The results for the full sample are depicted by the blue lines in Figure 7. Wage income is flat in the years leading up to job loss, while bank deposits increase. Basten et al. (2016) find similar results, and interpret the pre-unemployment increase in liquid assets as suggesting that at least some households are aware of the potential job loss several years in advance. We complement their findings by isolating the individuals who are likely to have lost their job during the second half of the calendar year, and who are therefore unlikely to have received formal notice of job loss at time $t = -1$.⁸ As illustrated by the red lines, the increase in deposits is similar, suggesting that the increase in savings is not driven by individuals who know for sure that they will lose their job in the near future.

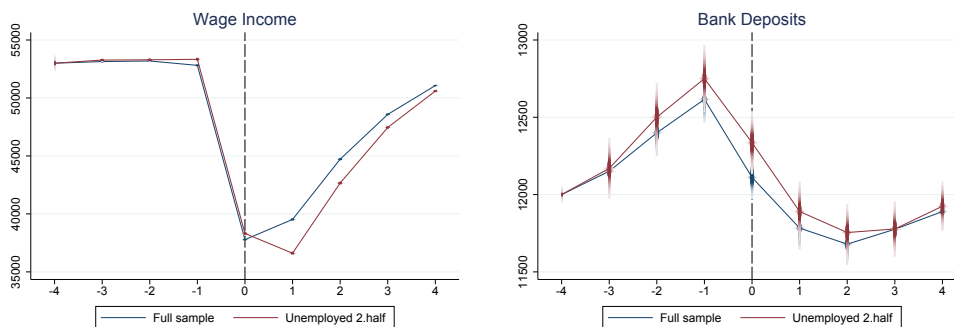


Figure 7: Event study - wage income and bank deposits. Full sample and individuals estimated to have experienced job loss in the second half of the calendar year.

How does the saving response vary with income? As seen from Figure 8, the increase in savings is driven by individuals with above median income. While there is some increase also for low income individuals, this is not statistically significant. This is consistent with the results in Carroll et al.

⁸We estimate the number of months an individual is likely to have received UI in year $t = 0$ based on pre-unemployment wages, the replacement rate, and the upper bound on income. Less than 1% are estimated to have received more than 12 months of UI, and these are dropped from the sample. The individuals who are estimated to have become unemployed during the second half of the calendar year are those who i) receive at most 6 months of UI in year $t = 0$ according to our estimates, and ii) received some UI also in year $t = 1$. This group makes up 55 % of the sample. Because the maximum required notice period is 6 months, these individuals are unlikely to have been notified of unemployment in year $t = -1$.

(2003), who find that savings increase in response to higher job loss risk only for those with medium or high income. However, we cannot rule out that the different responses (also) reflect differences in perceptions about future job loss risk between the two groups.

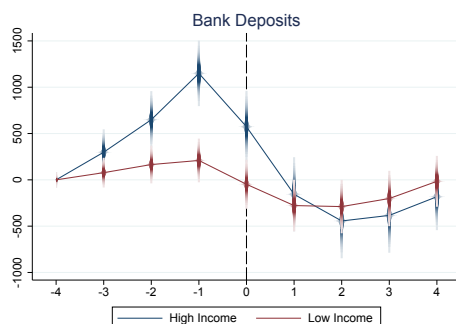


Figure 8: Event study - bank deposits by income level (above/below median income at time $t = -4$).

The event study results suggest that care should be taken when extrapolating results based on high income individuals to the full population. However, we believe studying high income individuals is interesting for two reasons. First, their saving behavior will have larger implications in terms of absolute amounts, due to their relatively high levels of liquid wealth. Second, and perhaps surprisingly, high-skilled individuals typically experience very similar percentage increases in job loss risk during recessions as low-skilled individuals - albeit starting from a lower level. Farber (2015) uses data from the Displaced Workers Survey (DWS) to study job loss during recessions in the US. He finds that the three-year job loss rate during the Great Recession increased by 85 percent for individuals with less than 12 years education, by 90 percent for those with 12 years education, by 83 percent for individuals with 13-15 years of education, and by 77 percent for those with 16 or more years of education. During the dot com bubble, individuals with 16 or more years of education actually experienced a larger percentage increase in job loss rates than other educational groups.

To summarize, we have found that a one percentage point increase in job loss risk increases liquid savings by 1.2 - 2.0 percent. This saving increase is driven by the individuals with the largest increase in job loss risk, i.e. individuals with low tenure. The results are robust to using an alternative control group with no increase in job loss risk, and are not driven by wealth effects.

What does this increase in savings imply for the macro economy? In the next section we use municipality level outcomes to study the household demand channel of recessions. That is, we evaluate to what extent the increase in savings is likely to have had a negative impact on employment.

4.2 The effect of higher savings on employment

In this section we investigate whether the increase in savings may have led to a decrease in employment. This is the second mechanism needed to produce amplification, as discussed in the theoretical motivation. Identifying general equilibrium effects such as this is challenging, as there are several effects at play. We show that *within* the oil region, non-oil sector unemployment increases more in areas with higher saving responses. We do a rough decomposition exercise, attributing the unemployment increase to either lower firm demand, or to lower household demand resulting from either realized unemployment or higher job loss risk. The decomposition exercise suggests that higher job loss risk contributed to higher unemployment in the non-tradable sector, consistent with the mechanism in the model.

Consider first the increase in unemployment for the oil region as a whole. As seen from Figure 9, unemployment in the oil sector increased by 3.5 percentage points from 2014 to 2015. However, unemployment increased also in sectors not directly affected by the shock, indicating some sort of spillover effects. Did the risk induced increase in individual savings contribute to this rise in non-oil sector unemployment? In order to account for any factors which are constant within the oil region, we consider the cross-sectional increase in unemployment. We then proceed by doing a rough decomposition of the increase in unemployment, considering three channels likely to be important. First, we consider the effect of lower *firm* demand, as firms in the oil industry are likely to demand fewer inputs for their production. Second, we consider the effect of lower *household* demand, which can take at least two forms: i) individuals who lose their job reduce consumption because their income is lower, ii) individuals who face higher job loss risk reduce consumption in order to save more.

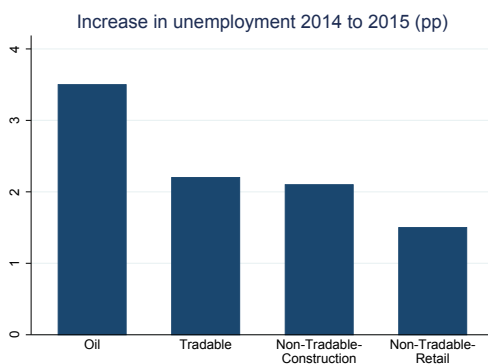


Figure 9: Increase in oil region unemployment by sector from 2014 to 2015 (pp).

4.2.1 Cross-sectional outcomes

In order to obtain cross-sectional variation, we aggregate saving and labor market outcomes to the municipality level and constrict the sample to only include the 59 municipalities in the oil region.

To construct our treatment and control groups, we calculate the share of oil sector engineers by municipality at the baseline. Municipalities with an above median share of oil engineers are classified as *oil intensive*, whereas municipalities with a below median share of oil engineers are classified as *non-oil intensive*.

Liquid savings Average bank deposits for the two municipality types are depicted in Figure 10. Oil intensive and non-oil intensive municipalities look very similar in the years leading up to the oil price collapse. In 2014 however, municipalities with an above median share of oil sector engineers increase their average bank deposits relative to other municipalities. Hence, the individual level saving response from the previous section is also observable at the municipality level.

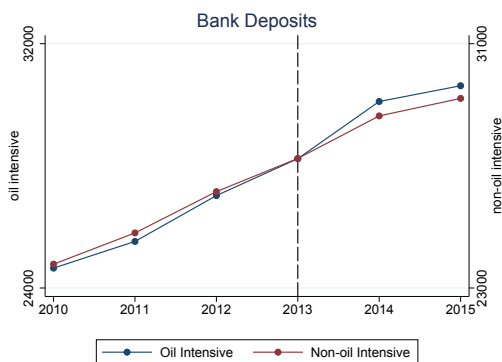


Figure 10: Bank deposits in oil intensive and non-oil intensive municipalities within the oil region.

Regression results are reported in Table 12 in the appendix. On average, bank deposits increase by just above \$400 per person. Because we only have 59 observations per year, and because we are averaging over all individuals who reside in a given municipality, the saving response is only statistically significant when the standard errors are not clustered.

Unemployment We follow the sector definitions used in Mian and Sufi (2014), and consider the tradable sector and the non-tradable sector separately. The tradable sector is defined as industries with export shares in the top 20th percentile. Following Mian and Sufi (2014), non-tradable industries are split into two groups. The first group consists of retail, food services and accommodation, and we refer to this as the *non-tradable-retail* sector. The second group consists of construction and real estate firms, and we refer to this as the *non-tradable-construction* sector.

Figure 11 depicts unemployment rates for oil intensive and non-oil intensive municipalities by sector. While unemployment rates are similar across municipalities up until 2014, there is a divergence in 2015 as unemployment rates increase faster in oil intensive municipalities. This is especially clear in the two non-tradable sectors, assumed to be the most dependent on local

household demand. The divergence is somewhat smaller in the tradable sector, and virtually non-existing in the oil sector itself.⁹

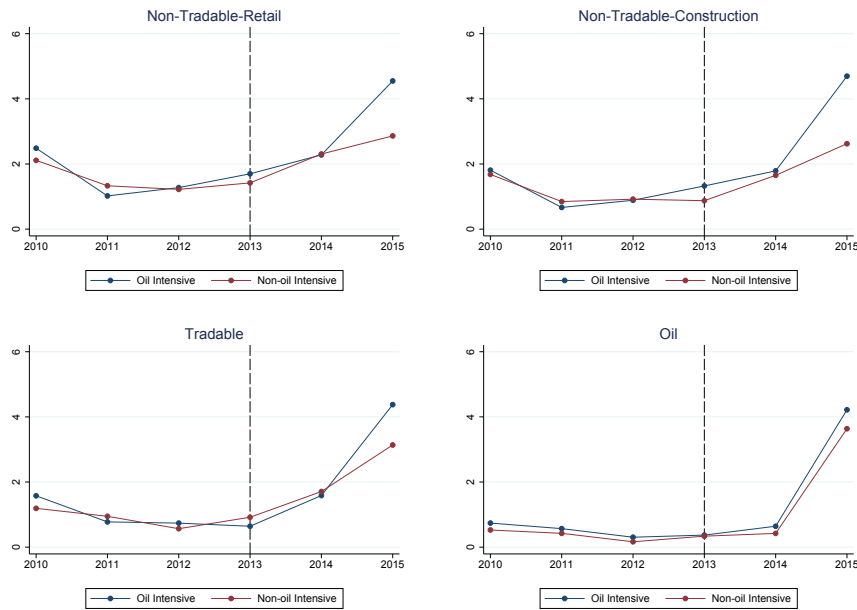


Figure 11: Increase in oil region unemployment by sector and municipality type.

Regression results are reported in Table 13 in the appendix. Unemployment increases by 1.7 percentage points in the non-tradable-retail sector, 2.0 percentage points in the non-tradable-construction sector, and 1.2 percentage points in the tradable sector. The relative increase in oil sector unemployment is small and not statistically significant.

4.2.2 Firm demand

In order to account for lower firm demand, we use network theory based on Acemoglu et al. (2016). Accounting for intersectoral linkages requires the use of input output data, which we obtain from Statistics Norway.¹⁰ Let $a_{ij} = \frac{p_j x_{ij}}{p_j y_j}$ be the value of inputs produced by sector j for use in sector

i , relative to the value of total output in sector j . The matrix $A = \begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{bmatrix}$ based on

national input output data is reported in Table 6. The bottom row is of special interest, as it tells us what share of production in each sector is used as inputs in the oil sector. For instance, $a_{51} = 0.03$ implies that three percent of production in the non-tradable-retail sector is used as an input in the

⁹Note that the oil sector has a substantially higher export share than the tradable sector, and should be relatively insensitive to local household demand.

¹⁰National input output data is available at <https://www.ssb.no/en/nasjonalregnskap-og-konjunkturer/tables/supply-and-use-and-input-output>.

oil sector. This compares to zero percent in the non-tradable-construction sector ($a_{52} = 0.00$) and five percent in the tradable sector ($a_{53} = 0.05$). Note that the tradable sector is the most reliant on demand from the oil sector, and should therefore experience the largest increase in unemployment as a result of lower firm demand.¹¹

	Non-tradable-retail	Non-tradable-constr.	Tradable	Other	Oil
Non-tradable-retail	0.02	0.03	0.02	0.02	0.00
Non-tradable-constr.	0.04	0.17	0.03	0.07	0.01
Tradable	0.06	0.01	0.19	0.08	0.10
Other	0.17	0.13	0.17	0.21	0.04
Oil	0.03	0.00	0.05	0.04	0.02

Table 6: Direct sectoral linkages 2013. A matrix.

The numbers reported in Table 6 do not capture the full extent of intersectoral linkages however. Lower demand from the oil sector will affect not only the firms which produce inputs for the oil sector, but also the firms which produce inputs for the firms producing inputs for the oil sector, and so on. Total intersectoral linkages are given by the matrix $H \equiv (I - A)^{-1}$, referred to as the Leontief inverse and reported in Table 7. The bottom row now tells us the share of production which is used as inputs in the oil sector – both directly and indirectly. The share of non-tradable-retail production which is used as an input in the oil sector increases from three to five percent when also the indirect linkages are taken into account ($h_{11} = 0.05$). In the non-tradable-construction sector, the share increases from zero to one percent ($h_{12} = 0.01$), and in the tradable sector the share increases from five to eight percent ($h_{13} = 0.08$).

	Non-tradable-retail	Non-tradable-constr.	Tradable	Other	Oil
Non-tradable-retail	1.03	0.04	0.03	0.03	0.01
Non-tradable-constr.	0.08	1.23	0.07	0.12	0.02
Tradable	0.11	0.04	1.28	0.14	0.14
Other	0.26	0.22	0.30	1.33	0.09
Oil	0.05	0.01	0.08	0.06	1.03

Table 7: Direct and indirect sectoral linkages 2013. H matrix.

Adjusting for the regional importance of the oil sector In order to account for corporate sector spillovers, we would ideally want municipality level input output data. Unfortunately, input output data is only available at the national level, and so we adjust the data ourselves to allow for a greater importance of the oil sector in the oil region. Note that if oil intensive and non-oil intensive municipalities in the oil region have the same input output matrices, corporate sector

¹¹It is possible that although the tradable sector produces the most inputs for the oil sector, these are the inputs which oil sector firms are the least likely to cut back on in the short term. When accounting for lower demand from the firm sector, we would then overstate the effect on the tradable sector.

spillovers would not be able to explain any of the cross-sectional increase in unemployment. We therefore allow for the possibility that firms in oil intensive municipalities are more reliant on oil sector demand than firms in non-oil intensive municipalities.

For our baseline adjustment, we assume that connections to the oil sector are proportional to oil sector employment. Because there are 3.5 times as many oil sector employees in oil intensive municipalities as the national average (adjusted for population size), we assume that firms in oil intensive municipalities have 3.5 times as large ties to the oil sector. Similarly, because there are 1.6 times as many oil sector employees in non-oil intensive municipalities, we assume that firms in non-oil intensive municipalities have 1.6 times as large ties to the oil sector. The adjusted input output tables are reported in Tables 14 and 15 in Appendix B.

We also use an alternative adjustment of the national input output data, in which we assume that only firms in oil intensive municipalities have an especially large connection to the oil sector. That is, we assume that firms in non-oil intensive municipalities have ties to the oil sector equal to the national average, whereas the additional connection to the oil sector loads only on firms in oil intensive municipalities.¹² We view this as an extreme assumption, used to provide an upper bound on the importance of corporate sector spillover in explaining the increase in cross-sectional unemployment.

The employment effects of lower firm demand As shown in Acemoglu et al. (2016), under some structural assumptions, the impact on sector i of a demand shock Z to the oil sector (sector 5), is given by $\Delta Y_i = h_{5i} Z$. Using the fact that this equation holds also for the oil sector itself, we can rewrite the expression to get rid of the shock: $\Delta Y_i = \Delta Y_5 \frac{h_{5i}}{h_{55}}$. For a constant labor share across sectors and a proportional adjustment of intermediate inputs versus labor, this same statement holds in terms of unemployment rates: $\Delta U_i = \Delta U_5 \frac{h_{5i}}{h_{55}}$.¹³ From Figure 9 we know the change in oil sector unemployment, i.e. $\Delta U_5 = 3.5$. Using the matrix elements from the adjusted H-matrix, we can then calculate the predicted increase in unemployment resulting from lower firm demand. The results are reported in Table 8, and range from 0.1 percentage points in the non-tradable-construction sector to 0.4 percentage points in the tradable sector under our baseline assumption.

¹²In this case firms in oil intensive municipalities are assumed to have $3.5 + 1.6 = 5.1$ times as large ties to the oil sector as the national economy.

¹³Following Acemoglu et al. (2016), let $\Delta Y_i = \alpha_i^L \Delta L_i + \Pi_{j=1}^5 \alpha_{ij} \Delta x_{ij}$. Assuming a proportional effect on labor relative to intermediate inputs (i.e. $\Pi_{j=1}^5 \alpha_{ij} \Delta x_{ij} = \frac{h_{5i}}{h_{55}} (\Pi_{j=1}^5 \alpha_{5j} \Delta x_{5j})$), we get that $\Delta L_i = \frac{h_{5i}}{h_{55}} \frac{\alpha_i^L}{\alpha_i^L} \Delta L_5$. For $\Delta L_i = -\Delta U_i$, we get that $\Delta U_i = \frac{h_{5i}}{h_{55}} \frac{\alpha_i^L}{\alpha_i^L} \Delta U_5$. In the data, the labor share in the oil sector is relatively low, so that $\frac{\alpha_i^L}{\alpha_i^L} < 1$ for $i = \{tradable, non - tradable, construction\}$. Hence, not accounting for sector specific labor shares creates an upward bias in our estimates of the firm demand channel.

	Baseline Assumption			Upper Bound Assumption		
	Implied unemployment increase (pp)			Implied unemployment increase (pp)		
	oil-intensive	non-oil-intensive	diff.	oil-intensive	non-oil-intensive	diff.
Non-tradable-retail	$\frac{0.17}{1.11} \times 3.5 = 0.53$	$\frac{0.09}{1.06} \times 3.5 = 0.30$	0.23	$\frac{0.25}{1.16} \times 3.5 = 0.75$	$\frac{0.05}{1.03} \times 3.5 = 0.17$	0.58
Non-tradable-constr.	$\frac{0.07}{1.11} \times 3.5 = 0.22$	$\frac{0.03}{1.06} \times 3.5 = 0.10$	0.11	$\frac{0.08}{1.16} \times 3.5 = 0.24$	$\frac{0.01}{1.03} \times 3.5 = 0.03$	0.21
Tradable	$\frac{0.26}{1.11} \times 3.5 = 0.82$	$\frac{0.12}{1.06} \times 3.5 = 0.40$	0.42	$\frac{0.37}{1.16} \times 3.5 = 1.12$	$\frac{0.08}{1.03} \times 3.5 = 0.27$	0.85

Table 8: Predicted unemployment increases from network analysis.

Figure 12 illustrates the share of the unemployment increase attributed to lower firm demand. The coefficient estimates are the regression equivalences of Figure 11, i.e. the increase in unemployment in oil intensive municipalities relative to that of non-oil intensive municipalities. The blue bars are the predicted increases from the input output data reported in Table 8, with the dark blue referring to our baseline estimates and the light blue referring to our upper bound estimates. Two features are worth noticing. First, in the non-tradable sectors, lower firm demand appears to not fully account for the increase in unemployment, suggesting that there is some room for the impact of lower household demand. Second, in the tradable sector, the remaining unemployment increase after accounting for lower firm demand is not statistically significant, consistent with the tradable sector being less sensitive to local household demand.

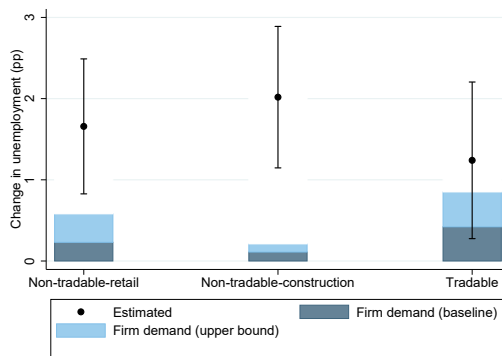


Figure 12: Estimated increase in unemployment by sector and predicted unemployment increase from network analysis.

4.2.3 Household demand

Figure 12 suggested that lower firm demand might not be able to fully account for the unemployment increase in the non-tradable sectors. Hence, lower demand from the household sector is likely to play a role. Household demand may be lower due to at least two reasons. First, individuals who experience job loss will decrease consumption because their income is lower. Second, individuals

who experience an increase in job loss risk will decrease consumption in order to save more.¹⁴ While we cannot isolate the effect of higher realized unemployment from the effect of higher job loss risk, we argue that the latter is quantitatively more important.

To see this, note that for every oil worker who experienced job loss in 2014-2015, twenty-four oil workers kept their job. With some back of the envelope calculations, we can compare the total consumption loss coming from job losers to the total consumption loss coming from job keepers. First, assume that job keepers in the oil sector reduce their consumption by \$1,200 reflecting the results in Table 2 in the previous section. Second, assume that job losers consume all of their after tax income, and that they reduce consumption by 14 percent upon job loss (Browning and Crossley, 2001).¹⁵ This implies that the total consumption loss from the job loss risk channel is $24 \times \frac{1,200}{0.14 \times 51,500} = 4.0$ times as large as the total consumption loss from the realized unemployment channel.

If we accept that the unemployment increase which is not accounted for by lower firm demand is due to lower household demand resulting either from increased unemployment or from increased job loss risk, we can back out the importance of the latter. This is done in Figure 13, using the back of the envelope calculations to determine the relative magnitude of the two household demand effects. The pink area captures the unemployment increase attributed to realized unemployment, while the red area captures the unemployment increase attributed to higher job loss risk. The latter is the quantitatively most important driver of higher unemployment in the non-tradable sectors according to our decomposition. We thus conclude that, although identifying the general equilibrium impact of a risk induced increase in savings is challenging, the data appears consistent with there being negative employment effects working through this channel.

¹⁴If house prices fell in oil intensive municipalities, this could also contribute to lower relative consumption. However, house price growth was roughly zero in 2015, and the difference between oil intensive and non oil intensive municipalities was not statistically significant - see Figure 25 in Appendix A.

¹⁵Several papers use food consumption from the PSID to estimate the consumption drop upon unemployment. These papers generally find consumption falls of less than ten percent, see for instance Chetty and Szeidl (2007). We use a consumption drop of 14 percent as estimated by Browning and Crossley (2001) using Canadian data, as they consider total consumption and Canada and Norway have similar replacement ratios.

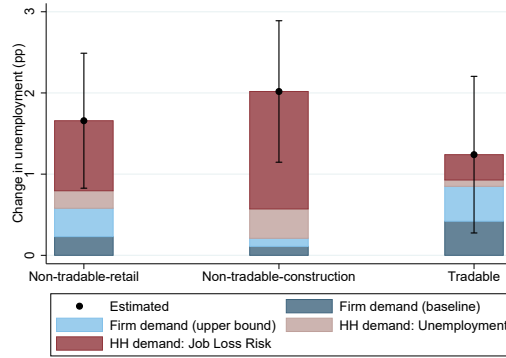


Figure 13: Estimated increase in unemployment by sector, predicted unemployment increase from network analysis and decomposition of the household demand effects.

5 Conclusion

We have used the oil price collapse of 2014 to identify an exogenous increase in job loss risk for certain segments of the population. By doing a within-region comparison of individuals across different occupations, we estimated that a one percentage point increase in job loss risk increases liquid savings by 1.2 - 2.0 percent. This effect was driven by low-tenured individuals, who faced the largest increase in job loss risk. We found no effect on other financial assets, suggesting that the saving response came through bank deposits only.

Further, we showed that unemployment in non-oil sectors increased more in municipalities with larger saving responses. For non-tradable sectors, the increase in unemployment was not (fully) accounted for by lower demand from the firm sector, suggesting that lower demand from the household sector was an important cause. Back of the envelope calculations suggested that lower household demand was largely driven by a risk induced increase in savings rather than realized job loss.

Hence, the data appears consistent with the mechanism from the motivating theory: individual savings increase as job loss risk rises, leading to a reduction in aggregate demand and potentially amplifying the economic downturn.

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Appendix A: Figures

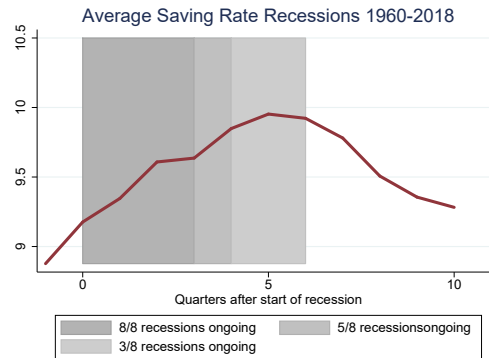


Figure 14: US personal saving rate. Savings as a share of disposable income. Average over past eight recessions (1960-2018). Three quarter moving average. Source: St. Louis FRED database.

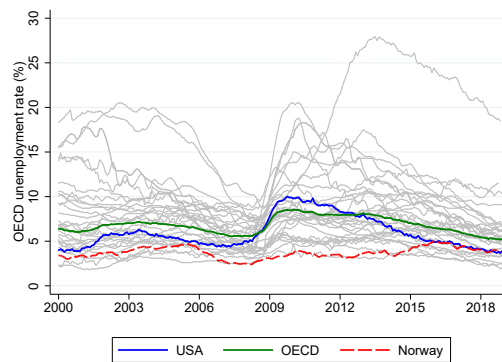


Figure 15: OECD harmonized unemployment rates by country (%).

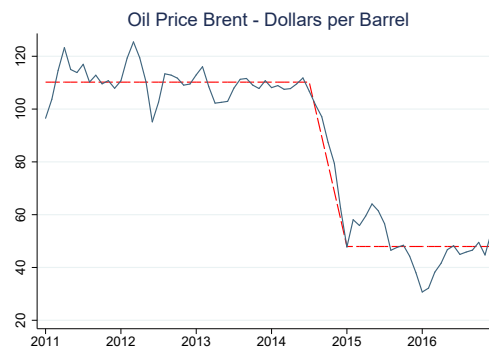


Figure 16: Oil price brent. USD per barrel.

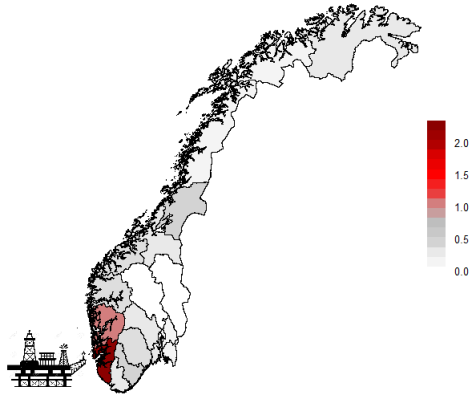


Figure 17: Share of workers employed in the oil sector relative to the share of total workers by county.

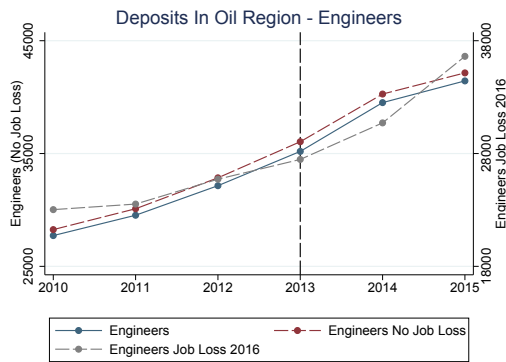


Figure 18: Bank deposits in oil regions for engineers, engineer who did not lose their job following the oil price collapse, and engineers who lost their job in 2016.

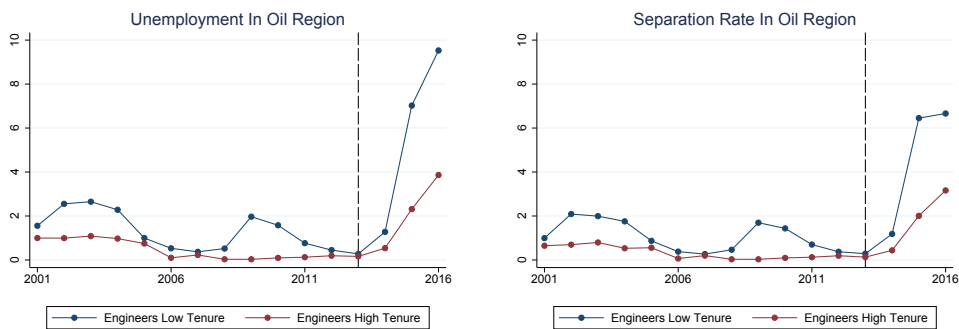


Figure 19: Unemployment rate and separation rate (%) for low tenure engineers in the oil region and high tenure engineers in the oil region.

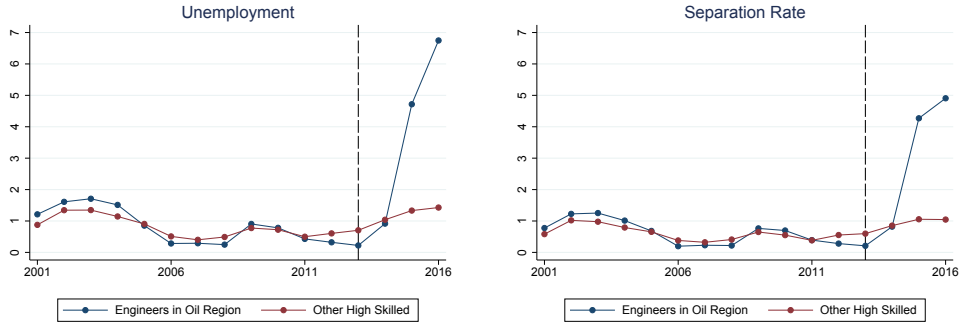


Figure 20: Unemployment rate and separation rate (%) for engineers in the oil region and other high skilled workers in all regions.

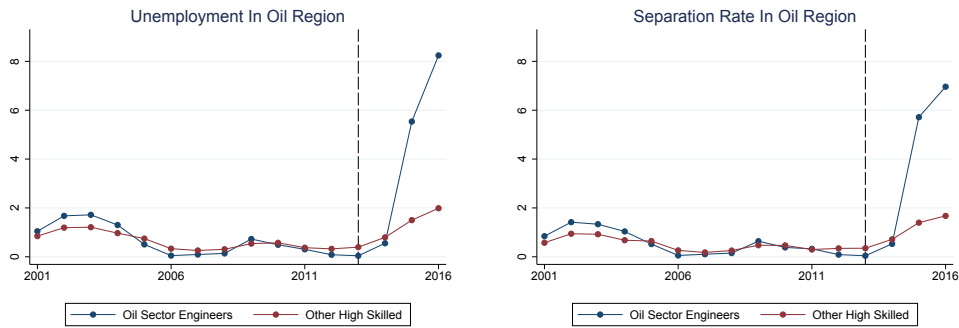


Figure 21: Unemployment rate and separation rate (%) for oil sector engineers in the oil region and other high skilled workers in the oil region.

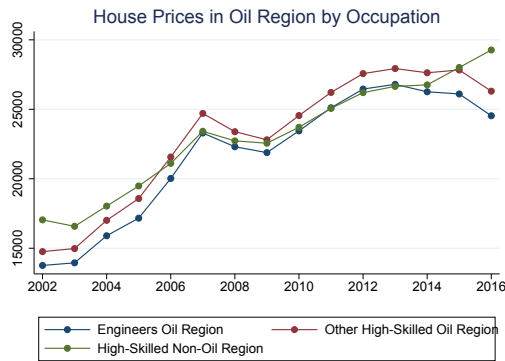


Figure 22: House prices single family homes. Municipality level. Average for engineers and other high skilled workers in the oil region.

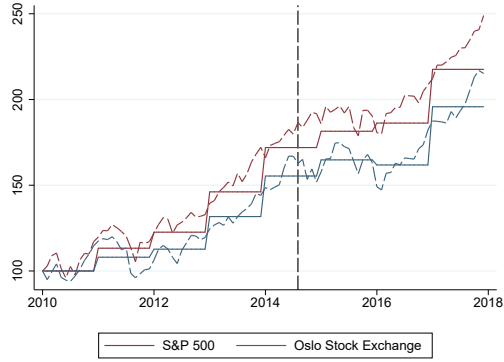


Figure 23: Stock prices. S&P 500 index and Oslo Stock Exchange index. Solid lines are annual data, whereas dashed lines are monthly data.

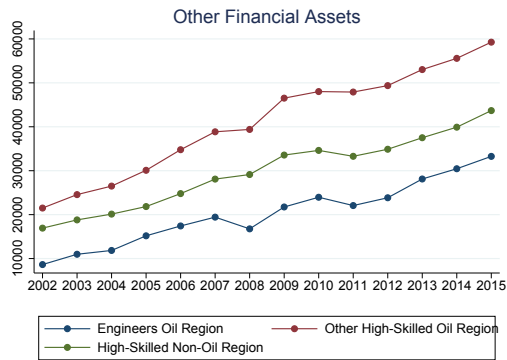


Figure 24: Other financial assets by occupation-region.

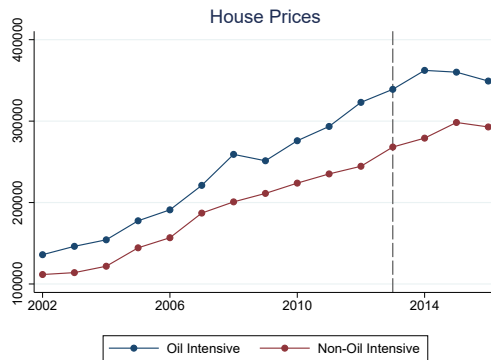


Figure 25: Average house prices for oil intensive and non-oil intensive municipalities.

Appendix B: 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 9: Occupations. Occupations 1-3 are classified as high skilled.

	(1)	(2)	(3)	(4)
	Deposits	Deposits	FW	FW
$T_i^{2013} \times I_i^{post}$	1,187**	1,283**	1,281	1,221
	(2.12)	(2.32)	(1.33)	(1.24)
Increase in Deposits/FW (%)	3.37	3.64	1.98	1.89
per pp increase in unemployment rate(%)	1.14	0.992	0.669	0.515
per pp increase in separation rate(%)	1.18	1.21	0.692	0.630
Sample period	2010-2014	2010-2015	2010-2014	2010-2015
Clusters	19,370	19,370	19,370	19,370
N	95,332	114,370	95,332	114,370

t statistics in parentheses. Std. errors clustered at the individual level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Bank deposits and total financial wealth (FW). Within oil region analysis. Regression results from estimating equation (2) with $Y = \{\text{Bank Deposits, Total Financial Wealth}\}$.

	(1)	(2)	(3)	(4)
	Bank Deposits	Bank Deposits	Bank Deposits	Bank Deposits
$T_i \times I_t^{post}$	1,187** (2.12)	1,283** (2.32)	1,869** (2.21)	2,636*** (3.11)
Increase in Bank Deposits (%)	3.37	3.64	5.27	7.43
per pp increase in unempl. rate (%)	1.14	0.992	1.26	1.35
per pp increase in sepr. rate (%)	1.18	1.21	1.23	1.55
Treatment group:	Engineers	Engineers	Oil Engineers	Oil Engineers
Sample period	2010-2014	2010-2015	2010-2014	2010-2015
Clusters	19,370	19,370	15,638	15,638
N	95,370	114,370	77,105	92,488

t statistics in parentheses. Std. errors clustered at the individual level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Bank deposits. Within oil region analysis Regression results from estimating equation (2), comparing engineers in the oil sector to other high-skilled workers.

	(1)	(2)	(3)	(4)
	Bank Deposits	Bank Deposits	Bank Deposits	Bank Deposits
$T_m \times I_t^{post}$	431.0 (1.38)	404.6 (1.13)	431.0* (1.84)	404.6** (2.07)
Sample period	2010-2014	2010-2015	2010-2014	2010-2015
Clusters	59	59	-	-
N	295	354	295	354

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Bank deposits at the municipality level within the oil region. $T_m = 1$ if municipality m is an oil intensive municipality in the oil region, and $T_m = 0$ if municipality m is a non-oil intensive municipality in the oil region.

	(1)	(2)	(3)	(4)
	Non-Tradable	Construction	Tradable	Oil
$T_m \times T_t^{2015}$	1.658*** (3.91)	2.018*** (4.54)	1.240** (2.52)	0.423 (1.17)
Clusters	59	59	59	59
N	354	353	349	349

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Sectoral unemployment rates at the municipality level within the oil region. $T_m = 1$ if municipality m is an oil intensive municipality in the oil region, and $T_m = 0$ if municipality m is a non-oil intensive municipality in the oil region.

	Non-tradable-retail	Non-tradable-constr.	Tradable	Other	Oil
Non-tradable-retail	0.02	0.03	0.01	0.01	0.00
Non-tradable-constr.	0.03	0.17	0.02	0.05	0.00
Tradable	0.04	0.01	0.13	0.06	0.06
Other	0.12	0.13	0.11	0.16	0.02
Oil	0.12	0.02	0.18	0.13	0.08

Table 14: Direct sectoral linkages 2013. A matrix. Baseline adjustment for oil intensive municipalities in the oil region. Created by taking Table 6 and assuming that $a_{5j}^{adjstuted} = 3.5a_{5j} \forall j$ and adjusting all other a_{ij} 's with the same factor $\sum_{i=1}^4 a_{ij}^{adjusted} = x \sum_{i=1}^4 a_{ij} \forall j$ such that the total input share is unchanged $\sum_{i=1}^5 a_{ij}^{adjusted} = \sum_{i=1}^5 a_{ij}^{adjstuted} \forall j$.

	Non-tradable-retail	Non-tradable-constr.	Tradable	Other	Oil
Non-tradable-retail	0.02	0.03	0.02	0.02	0.00
Non-tradable-constr.	0.04	0.17	0.03	0.07	0.01
Tradable	0.06	0.01	0.18	0.08	0.09
Other	0.16	0.13	0.15	0.20	0.04
Oil	0.06	0.01	0.08	0.06	0.04

Table 15: Direct sectoral linkages 2013. A matrix. Baseline adjustment for low oil intensive municipalities in the oil region. Created by taking Table 6 and assuming that $a_{5j}^{adjstuted} = 1.6a_{5j} \forall j$ and adjusting all other a_{ij} 's with the same factor $\sum_{i=1}^4 a_{ij}^{adjusted} = x \sum_{i=1}^4 a_{ij} \forall j$ such that the total input share is unchanged $\sum_{i=1}^5 a_{ij}^{adjusted} = \sum_{i=1}^5 a_{ij}^{adjstuted} \forall j$.

	Non-tradable-retail	Non-tradable-constr.	Tradable	Other	Oil
Non-tradable-retail	0.01	0.03	0.01	0.01	0.00
Non-tradable-constr.	0.02	0.16	0.01	0.04	0.00
Tradable	0.03	0.01	0.09	0.05	0.04
Other	0.09	0.12	0.08	0.12	0.02
Oil	0.18	0.02	0.27	0.20	0.12

Table 16: Direct sectoral linkages 2013. A matrix. Upper bound adjustment for high oil intensive municipalities in the oil region. Created by taking Table 6 and assuming that $a_{5j}^{adjstuted} = 5.1a_{5j} \forall j$ and adjusting all other a_{ij} 's with the same factor $\sum_{i=1}^4 a_{ij}^{adjusted} = x \sum_{i=1}^4 a_{ij} \forall j$ such that the total input share is unchanged $\sum_{i=1}^5 a_{ij}^{adjusted} = \sum_{i=1}^5 a_{ij}^{adjstuted} \forall j$.

Appendix C: 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 (4). 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.

$$I_i^{jobloss} = \alpha + \beta Tenure_i + \gamma X_i + \epsilon_i \quad (4)$$

The regression results are reported in Table 17. 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 (4). We then compare the pseudo R^2 's to the pseudo R^2 reported in Table 17. The results are depicted in Figure 26. The pseudo R^2 's during the oil crisis is the lowest in the sample, suggesting that the simple statistical model outlined in equation (4) has 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 26. 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)	(2)
	Job Loss	Job Loss
Tenure	-0.0737*** (-10.54)	
Age	0.00402* (1.71)	-0.00490** (-2.22)
Wage Income	0.000000240 (0.22)	-0.000000971 (-0.82)
Total Income	-0.000000957 (-1.09)	-0.000000244 (-0.24)
Primary Housing Wealth	5.77e-08 (0.21)	-6.37e-08 (-0.24)
Real Wealth	-0.000000151 (-0.58)	-0.000000202 (-0.80)
Financial Wealth	-0.000000621 (-1.63)	-0.000000810** (-2.12)
Bank Deposits	9.80e-08 (0.14)	0.000000144 (0.21)
Debt	0.000000202 (1.41)	0.000000236* (1.68)
Constant	-1.082*** (-10.76)	-1.009*** (-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 17: Regression results from estimating equation (4) with dependent variable $I_i^{jobloss} = 1$ if engineer i experienced job loss in 2015-2016. Probit regression.

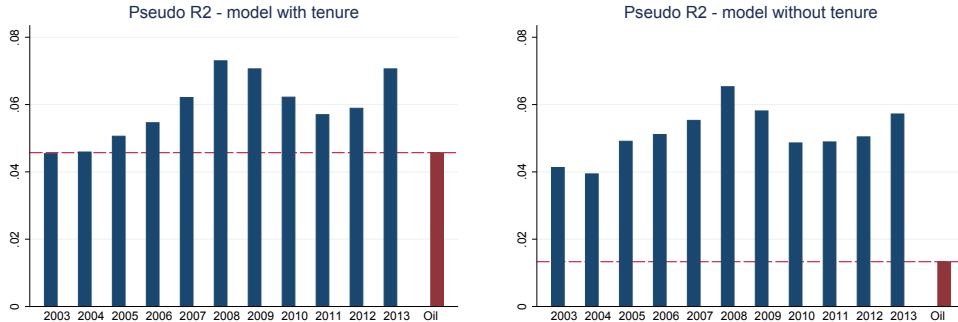


Figure 26: Pseudo R2 from probit regression.

Appendix D: Model

Households Individual i chooses a consumption index $c_{i,t}$ and savings $b_{i,t}$ in order to maximize utility $U(c_{i,t})$ subject to a borrowing limit $b_{i,t} \geq b^{min}$ and the budget constraint outlined in equation (5). Employed individuals receive a wage income w_t , while unemployed individuals receive unemployment benefits ξ_t . Employed individuals lose their current job with an exogenous probability $\rho_t \in [0, 1]$. Unemployed individuals find a new job with probability q_t , which is endogenously determined by the number of unemployed individuals and the number of vacancies.

$$c_{i,t} + b_{i,t} = n_{i,t}w_t + (1 - n_{i,t})\xi_t + \frac{R_{t-1}}{1 + \pi_t}b_{i,t-1} \quad (5)$$

Entrepreneurs Entrepreneur j produces output $y_{j,t}$ using a linear production function with labor $l_{j,t}$ as the only input. To hire workers the entrepreneur posts vacancies $v_{j,t}$, which costs a fixed cost μ and are filled with a probability ψ_t . The entrepreneurs marginal costs are outlined in equation (6).

$$mc_{j,t} = w_t + \frac{\mu}{\psi_t} - \beta \mathbb{E}_t \left[(1 - \rho_t) \frac{\mu}{\psi_{t+1}} \right] \quad (6)$$

The entrepreneur maximizes profits, given by equation (7). As seen from the last term of the profit expression, we assume Rotemberg price frictions, so that entrepreneurs face a quadratic price adjustment cost. Due to monopolistic competition, the entrepreneur also faces the demand constraint $y_{j,t} = \left(\frac{P_{j,t}}{P_t} \right)^{-\gamma} y_t$. The entrepreneurs are the sole claimants to the profits they produce, which they use for consumption and to cover production costs and taxes.

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left(\left(\frac{P_{j,t+s}}{P_{t+s}} - mc_{j,t+s} \right) y_{j,t+s} - \frac{\phi}{2} \left(\frac{P_{j,t+s}}{P_{j,t+s-1}} - 1 \right)^2 y_t \right) \quad (7)$$

Labor Market The wage is assumed to be perfectly rigid so that $w_t = \bar{w}$, in which \bar{w} is consistent with the joint matching surplus being non-negative. The matching technology is given by equation (8), in which u_t is the number of unemployed individuals, v_t is the number of vacancies and \bar{m} and α are constant parameters.

$$m_t = \bar{m} u_t^\alpha v_t^{1-\alpha} \quad (8)$$

Government The government runs a balanced budget, so that the amount spent on unemployment benefits each period equals revenues from taxing entrepreneurs. Monetary policy follows the Taylor rule given by equation (9), in which \bar{R} is the long run nominal interest rate target and $\bar{\pi}$ is the long run inflation target.

$$R_t = \bar{R} \left(\frac{1 + \pi_t}{1 + \bar{\pi}} \right)^\eta \quad (9)$$

Timing The timing is as follows: i) the state of the world is realized, i.e. (the aggregate) separation rate ρ_t becomes known to everyone, ii) matching occurs between firms with vacancies and individuals searching for a job, iii) production and consumption occur, and iv) job separation occurs.

Solving the model When solving the model we follow Ravn and Sterk (2017) in imposing $b^{min} = 0$, so that there is no saving or borrowing. This implies a degenerate wealth distribution, greatly simplifying the computations. Importantly, the precautionary saving motive is still present through the households Euler equation. In order to solve the model numerically we log-linearize the equilibrium conditions around steady state values.

Non-linear equilibrium

Endogenous variables: $\{R_t, \pi_t, q_t, m_t, u_t, v_t, l_t, y_t, \theta_t, \psi_t, \rho_t\}$

Shocks: ϵ_t

The 11 equilibrium conditions are

$$\bar{w}^{-\sigma} = \beta \mathbb{E}_t \frac{R_t}{1 + \pi_{t+1}} \{(1 - \rho_t) \bar{w}^{-\sigma} + \rho_t \xi^{-\sigma}\} \quad (10)$$

$$R_t = \bar{R} \left(\frac{1 + \pi_t}{1 + \bar{\pi}} \right)^\eta \quad (11)$$

$$1 - \gamma + \gamma \left(\bar{w} + \mu \bar{m}^{-\frac{1}{1-\alpha}} q_t^{\frac{\alpha}{1-\alpha}} - \beta \mathbb{E} \left[\mu \bar{m}^{-\frac{1}{1-\alpha}} q_{t+1}^{\frac{\alpha}{1-\alpha}} \right] \right) = \phi \pi_t (1 + \pi_t) - \phi \beta \mathbb{E}_t \left[\pi_{t+1} (1 + \pi_{t+1}) \frac{y_{t+1}}{y_t} \right] \quad (12)$$

$$u_t = (1 - q_t) (u_{t-1} + \rho_{t-1} l_{t-1}) \quad (13)$$

$$l_t = 1 - u_t \quad (14)$$

$$\rho_t = \rho_{t-1} \bar{\rho}^{1-\delta} \epsilon_t \quad (15)$$

$$\psi_t = \bar{m}^{-\frac{1}{1-\alpha}} q_t^{-\frac{\alpha}{1-\alpha}} \quad (16)$$

$$\theta_t = \bar{m}^{-\frac{1}{1-\alpha}} q_t^{\frac{1}{1-\alpha}} \quad (17)$$

$$v_t = \theta_t u_t \quad (18)$$

$$m_t = \bar{m} u_t^\alpha v_t^{1-\alpha} \quad (19)$$

$$y_t = l_t \quad (20)$$

Steady state

$$\pi = 0 \quad (21)$$

$$q = \bar{m}^\alpha \left(\frac{\gamma^{-1}(\gamma - 1) - \bar{w}}{\mu(1 - \beta)} \right)^{\frac{1-\alpha}{\alpha}} \quad (22)$$

$$\rho = \bar{\rho} \quad (23)$$

$$u = \frac{\rho(1 - q)}{\rho + q - \rho q} \quad (24)$$

Log-linearized equilibrium

Define $X_t = \frac{X_t - X}{X}$, where X is the steady state value of X_t .

Endogenous variables: $\{\hat{R}_t, \hat{\pi}_t, \hat{q}_t, \hat{m}_t, \hat{u}_t, \hat{v}_t, \hat{l}_t, \hat{y}_t, \hat{\theta}_t, \hat{\psi}_t, \hat{\rho}_t\}$

Shocks: $\hat{\epsilon}_t$

The 11 equilibrium conditions are:

$$\hat{\pi}_{t+1} = \hat{R}_t + \frac{\xi^{-\sigma} - \bar{w}^{-\sigma}}{\xi^{-\sigma} + \frac{1-\rho}{\rho}\bar{w}^{-\sigma}} \hat{\rho}_t \quad (25)$$

$$\hat{R}_t = \eta \hat{\pi}_t \quad (26)$$

$$\frac{\alpha}{1-\alpha} \gamma \mu \left(\frac{q^\alpha}{\bar{m}} \right)^{\frac{1}{1-\alpha}} (\hat{q}_t - \beta \hat{q}_{t+1}) = \phi (\hat{\pi}_t - \beta \hat{\pi}_{t+1}) \quad (27)$$

$$\hat{u}_t = (1-q)\hat{u}_{t-1} - \frac{q}{1-q}\hat{q}_t + q(\hat{\rho}_{t-1} + \hat{l}_{t-1}) \quad (28)$$

$$\hat{l}_t = -\frac{u}{1-u}\hat{u}_t \quad (29)$$

$$\hat{\rho}_t = \delta \hat{\rho}_{t-1} + \hat{\epsilon}_t \quad (30)$$

$$\hat{\psi}_t = -\frac{\alpha}{1-\alpha}\hat{q}_t \quad (31)$$

$$\hat{\theta}_t = \frac{1}{1-\alpha}\hat{q}_t \quad (32)$$

$$\hat{v}_t = \hat{\theta}_t + \hat{u}_t \quad (33)$$

$$\hat{m}_t = \hat{u}_t + (1-\alpha)\hat{\theta}_t \quad (34)$$

$$\hat{y}_t = \hat{l}_t \quad (35)$$

Amplification of shocks due to job loss risk

Higher job loss risk and incomplete markets can amplify this economy's response to initial shocks. Consider, for instance, an exogenous increase in job loss risk as captured by an increase in the separation ratio $\hat{\rho}$. All else equal, this reduces employment and thereby reduces output. The overall effect comprises of the direct effect and the amplification effect due to higher savings in response to higher job loss risk. In order to quantify the additional output fall, i.e. the amplification, it is useful to compare the baseline model to a complete markets version of the model. In the complete markets version, every individual receives the average income, thereby shutting down the risk channel. Figure 27 illustrates the additional output drop resulting from the risk channel, as a function of the UI replacement ratio. For a replacement ratio of 0.4 in line with US levels (Mitman and Rabinovich, 2015), and a Taylor coefficient of 1.5 (Ravn and Sterk, 2017), output falls by 22 percent more due to the risk induced increase in savings.

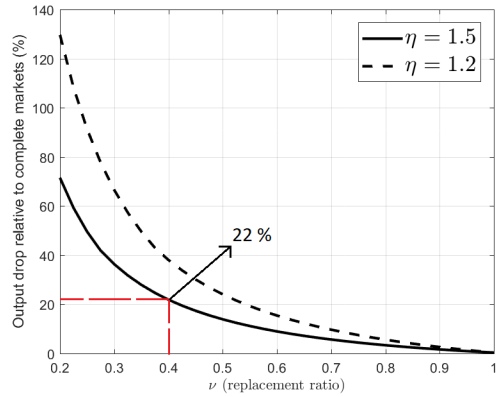


Figure 27: Amplification as a function of the unemployment benefit replacement ratio ν , for two different values of the Taylor coefficient η .

The model exercise shows that higher job loss risk in theory *can* amplify economic downturns through an increase in savings. However, with perfectly flexible prices or with sufficiently aggressive monetary policy, the amplification would break down.