Unemployment shocks, cyclical prices and shopping behavior

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Abstract

We use rich data from Norway's biggest grocery chain to show how households and grocery stores react to changing economic conditions. We exploit the regional nature of a recession following the drop in the oil price in 2014 and find that when the local unemployment rate increases, households shift toward cheaper stores, and toward bulk and private label products. Households also buy more on sale and the average store level prices decreases. We then derive a novel decomposition of the changes in the prices households pay for products a in large number of product categories. The decomposition allows us to measure the relative importance of the different sources of price cyclicality. We find that a significant part of the cyclicality is explained by grocery stores responding to economic downturns by lowering their prices. Still, changes in household behavior are the main driver of price cyclicality, primarily through increased willingness to take advantage of sales.

1 Introduction

Do households and stores change their behavior over the business cycle? If so, which aspects of shopping behavior and store strategy change, and how large are the effects on average prices and total expenditure? Adverse economic conditions may affect shopping behavior and store strategy along several dimensions. First, individuals who become unemployed have more time available. Second, unemployment is associated with a fall in life-time earnings. These two effects tend to reduce the opportunity cost of time, and thus reduce search costs and thereby increase search effort and result in lower transaction prices. In addition, declines in life-time earnings may result in wealth effects on the composition of the consumption bundle, leading to substitution toward lower priced goods within a given product category. Furthermore, stores may respond to changes in the households' wealth and opportunity cost of time by adjusting their strategies with respect to pricing, campaigns and product assortment.

In this paper, we use two rich data sets from a large Norwegian grocery chain to provide new evidence on how shopping behavior, store choices, and household-level average prices vary over the business cycle. The first data set contains complete transaction histories for a large sample of households, while the second contains complete price-quantity data at the store level for a large set of product categories. Our empirical strategy exploits how the collapse of the oil price in the middle of the 2010s led to a severe worsening of the economic conditions and increasing unemployment rates in certain regions of Norway, while leaving other regions more or less unaffected.

Grocery expenditures are a potential source of cost savings for households when economic conditions deteriorate. Most households allocate a substantial part of their budget to groceries, and, in the short term, it is easier to save on groceries than on other substantial budget posts. According to Statistics Norway's consumer expenditure survey of 2012, expenditures on food and nonalcoholic beverages made up 11.8 percent of the total consumption expenditure, with alcohol and tobacco contributing a further 2.7 percent [Statistics Norway, 2013]. If we count that consumption on housing and transportation as fixed, food and nonalcoholic expenditures alone make up close to 25 percent of the variable consumption. With groceries being the dominant category in the households' variable consumption budget, major changes in income are very likely to affect this consumption category.

We find that households indeed adjust their shopping behavior in response to changes in the local economic conditions. In line with Griffith et al. [2009] and Nevo and Wong [2019], we provide strong evidence for reallocation of household expenditures toward generic brands, bulk items, items on sale, and low-price retailers when the local unemployment rate increases. Having established this evidence, we calculate average (per-unit) household-level prices in a large set of product categories, and find that the average price a household pays in a given category is responsive to business cycle fluctuations. Exploiting changes in prices and in the household's volume shares (at the product–store level), we derive a new decomposition that separates the change in the average price into a set of distinct factors: one component capturing changes in the prices charged by the store (holding the choices of the household unchanged), two components capturing changes in the store and product shares (holding prices charged by the store unchanged), and three components related to the customer's shopping intensity. Our decomposition is new to the literature on price cycles and shopping behavior. We find that while a part of the cyclicality is explained by grocery stores adjusting their prices, changes in household behavior are the main driver of price cyclicality. What we find particularly intriguing with this approach is that it allows us to incorporate the various aspects of household and store responses in the same framework, and to estimate the relative contribution of each component to the aggregate change in the category price.

Our evidence of significant shopping behavior responses to changes in economic conditions have consequences for a wide range of topics. For example, take the measurement of consumption inequality, which often relies on consumption expenditures. Aguiar and Hurst [2007] find that prices paid correlate with household characteristics. Hence, relying on expenditures alone is likely to give an imperfect picture of consumption inequality. Similarly, our results show that the price paid for the same product by a household varies with the business cycle. Thus, taking into account the cyclicality of transaction prices is important when studying consumption inequality (as in e.g., Coibion et al. [2012] and Bayer et al. [2020]).

The Boskin report [Boskin et al., 1996] highlighted four sources of bias in the household price index: i) product substitution, ii) store substitution, iii) quality change, and iv) new products. The current study sheds light on the two first sources. Specifically, we find that both product and store substitution are sensitive to business cycle fluctuations, and that in our data, store substitution is more important than product substitution.

In many theories of monetary nonneutrality and policy, and business cycles, the real interest rate is key in the transmission of shocks. Our results indicate that there may not be *one* inflation rate across households (as documented for the United States by Kaplan and Schulhofer-Wohl [2017]), and therefore the real interest rate will likely vary across households. Thus, our results should be of interest to policy makers. For instance, Kaplan and Menzio [2015] develop a model where shopping behavior plays a crucial role in generating self-fulfilling employment fluctuations. Hence, shopping behavior might not only affect the economy's response to shocks, but also the source of fluctuations itself.

The cyclical behavior of the markup over marginal cost is another key aspect of the transmission of shocks [Nekarda and Ramey, 2013]. While we do not study the markup directly, the cyclical behavior of households is an important co-determinant of the cyclicality of the markup. Finally, price dispersion, and heterogeneity in households' response margins may have implications for important political economy questions on adjustment of public benefits when measuring inequality and comparing real purchasing power [Griffith et al., 2009].

Main findings Overall, we find strong evidence of cyclicality in shopping behavior and store prices.

We estimate a number of household-level fixed effects regressions where we estimate the effect of the unemployment rate in the local market on different aspects of a household's shopping behavior. First, we find that the households substitute toward lower priced stores when local unemployment increases. Second, we consider the shares of total expenditure involving private label products, products bought in bulk, and products bought on sale. We find that all of these shares increase when there is an economic downturn, and that the effects are economically significant. For example, we estimate that a five percentage point increase in the local unemployment rate leads to an increase in the sales share of over two percentage points, which corresponds to over 40 percent of the average sales rate. Not only households but also stores may change their behavior in response to changes in local economic conditions, for example by reducing prices or running more campaigns to counter reductions in household demand. In addition to the household-level regressions, we run two store-level fixed effects regressions where we establish that the average price levels of the stores follow a cyclical pattern.

Both household and store responses to business cycle variations will have an impact on the average (per-unit) price a household pays for products in a given product category. Indeed, we find that household-level average prices for given categories is reduced substantially by an increase in the local unemployment rate. We then decompose the cyclicality of the category prices. An advantage of such a decomposition is that it allows us to estimate the effects stemming from changes both in store and household behavior in a unified model using large and detailed household-level data. This not only allows for high statistical precision but also makes it possible to quantify the relative contribution of the different channels through which the business cycle affects average prices. When decomposing the changes in the category prices, we find that over ten percent of the cyclicality of average prices can be explained by changes in the store prices alone (holding the households' choices fixed). However, most of the variation is due to factors that can be affected by the households. Of these, the component with the greatest contribution (accounting for over 50 percent of the total effect) is the households' propensity to take advantage of temporary price reductions. We also find that households allocate more of their expenditure in low-cost stores, contributing about ten percent of the total effect.

Related literature Our paper is related to a number of articles studying shopping behavior. Aguiar and Hurst [2007] study transaction prices over the life-cycle and find that households with higher incomes and those who spend more time shopping pay lower prices than other types of households. Similarly, Griffith et al. [2009] find that British households realize significant savings from buying in bulk and on sale, and by product and store substitution. Griffith et al. [2015] document how these effects were also present during the great recession in the UK: households decreased the average price paid per calorie by substituting towards generic brands and increasing shopping effort, among several adjustment margins. Studying shopping behavior in the US during the great recession, Nevo and Wong [2019] find that households systematically increased the use of coupons, purchases of generics, and the average size of units purchased when the local unemployment rate increased. Coibion et al. [2015] find that individual households allocated expenditure toward lower-price retailers when the local unemployment rate increased. Argente and Lee [2014] document large differences across income groups in how they adjusted consumption and shopping behavior during the great recession. While low income households already purchased the low price option within a product category, higher income households substituted towards lower priced options.

Missing data on actual consumption, economists are left to use consumption expenditure when imputing individual consumption. As expenditures reflect both price and quantity, interpreting declines in consumption expenditure as declines in consumption will exaggerate the actual decline in consumption if – as our findings suggest – individuals who enter unemployment realize significant price savings. Related to our paper is Campos and Reggio [2019], who find that roughly one sixth of the decline in consumption expenditure when entering unemployment is explained by a drop in transaction prices. Furthermore, this effect might vary across the income distribution.

Nekarda and Ramey [2013] argue that the common assumption of a countercyclical markup in New Keynesian models is based on inconclusive evidence. The authors review the literature, and revisit the methods that have tended to result in countercyclical markups. They conclude that using new data and methods, the evidence points toward procyclical or acyclical markups. Anderson et al. [2018] use scanner data from the retail sector, and find that product prices and replacement costs are acyclical in the United States and Canada. Additionally, for Canada, the authors find no discernible effect on these variables in response to oil price shocks across regions. While our results do not speak to the cyclicality of the markup for each product, they suggest that the average prices charged by stores is countercyclical and that the average household's purchasing prices contribute to a procyclical markup.

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The rest of the paper is organized as follows. In the next section, we present our empirical strategy, before we describe our data in Section 3. Section 4 presents reduced form evidence on business cycle changes and household behavior. Section 5 shows how we decompose a change in a household's average category price using product–store volume shares and prices. Section 6 presents the empirical results using our decomposition. Section 7 concludes.

2 Empirical strategy: The oil shock and the Norwegian economy

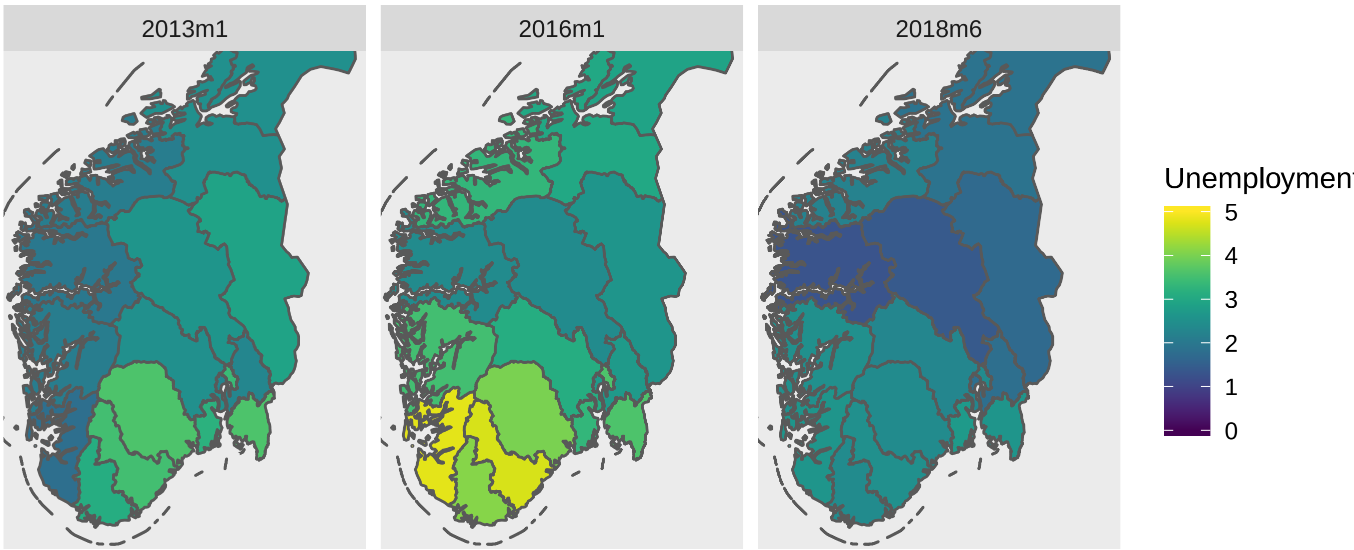
Our empirical strategy is to exploit how the collapse of the oil price in the middle of the 2010s led to a severe worsening of economic conditions and higher unemployment in certain regions of Norway, while leaving other regions largely unaffected. Using data on local unemployment rates together with data on households' transaction histories and store-level prices, we investigate how business cycle variation in prices can be explained by changes in household and store behavior. Specifically, we rely on fixed effects (and first differencing) to eliminate unobservable time-invariant effects (at e.g., the household and store levels). The geographical heterogeneity in the effect of the oil price shock allows us to efficiently control for country wide shocks using time fixed effects.

The petroleum industry is essential for the Norwegian economy, contributing 20 percent of GDP and 49 percent of exports in 2013 [Statistics Norway, 2020a,b]. In 2013, the petroleum industry directly or indirectly employed 8.7 percent of the Norwegian labor force [Hungnes et al., 2016]. However, the industry is largely concentrated along the southwestern coast, where it accounts for substantially larger shares of the economy. In Rogaland county, for example, the petroleum industry directly employs between 15 and 20 percent of the workforce in several municipalities [Ekeland, 2015, 2017].

In January 2013, the Europe Brent spot price was 112 USD per barrel. From the end of 2014 and through 2015, the price dropped dramatically, reaching a 12-year low of 30 USD by January 2016. The price then slowly increased, reaching 74 USD by June 2018 [U.S. Energy Information Administration, 2020]. Figure 1 plots county-level unemployment rate for the counties in South Norway, illustrating the regional nature of the effects of the oil price shock.[1] The highly oil-dependent coastal regions in the South and West experienced significant increases in the unemployment rate from January 2013 to January 2016. At the same time, other counties were unaffected by the shock–some even experienced a reduction in their unemployment rate in the same period. The county most severely hit by the oil price shock was Rogaland. In January 2013, Rogaland's unemployment rate of 1.8 percent was the lowest in the country. By January 2016, the unemployment rate had increased to 4.8 percent, which was the highest in the country. In June 2018, the unemployment had

[1] South Norway covers all but the three most northern counties. See also Table 9 in Appendix D.

Figure 1: County-level unemployment



Notes: The unemployment rate is the share of the workforce that, 1) is actively seeking a job, 2) has been without any work for the last two weeks, and, 3) has registered as unemployed at the Norwegian Labour and Welfare Administration. Data source: Norwegian Labour and Welfare Administration [2018]. See Appendix D for the underlying data.

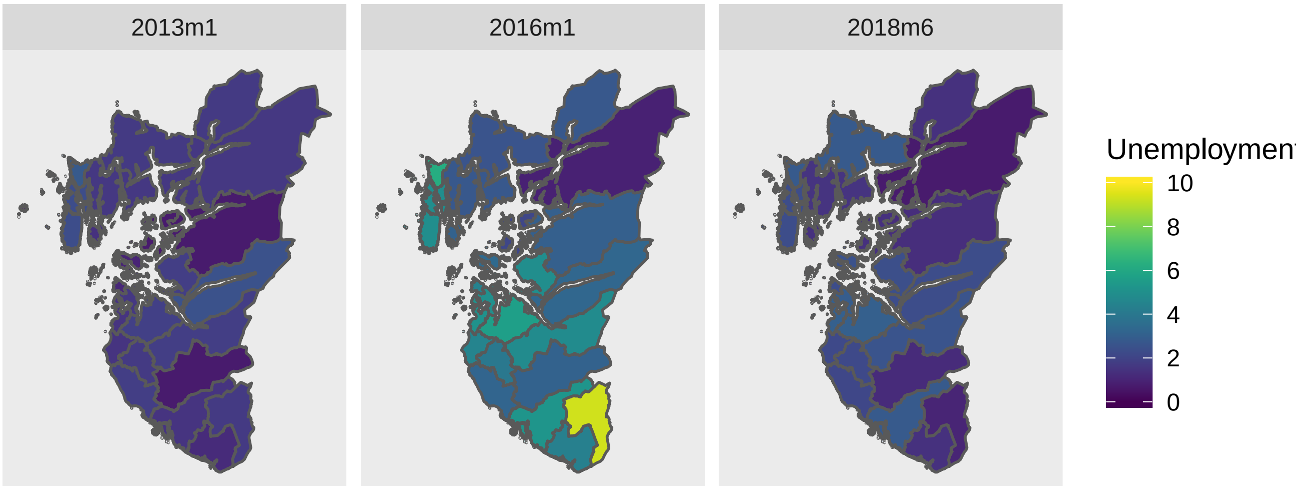
fallen to 2.6 percent. As illustrated in Figure 2, the recession was even more pronounced in some of the municipalities in Rogaland.[2] In the municipality of Sandnes, for example, the unemployment rate rose from 1.9 percent in January 2016 to 5.6 percent in January 2016, before falling back to 2.8 percent by June 2018.[3]

The oil-dependent regions also experienced weak developments in gross product, wage costs, and median income. Figure 3 shows the accumulated percentage increase in these quantities from 2013 to 2016. Rogaland stands out by performing worst by all three measures. In this county, the growth rate in median income was only 1.6 percent, compared with the unweighted average across all counties of 7.3 percent. Similarly, gross product grew only by 2.2 percent, compared with the average of 13.6 percent. Finally, wage costs grew by only 5.3 percent in Rogaland over the period, again significantly below the national average of 10.6

[2]See also Table 10 in Appendix D.

[3]The municipality with the most extreme difference between January 2013 and January 2016 is Lund, where the unemployment rate increased from 1.7 percent to 9.3 percent. However, this increase was not driven primarily by the oil price shock but by a flood in late 2015 that led to the temporary closure of a local factory.

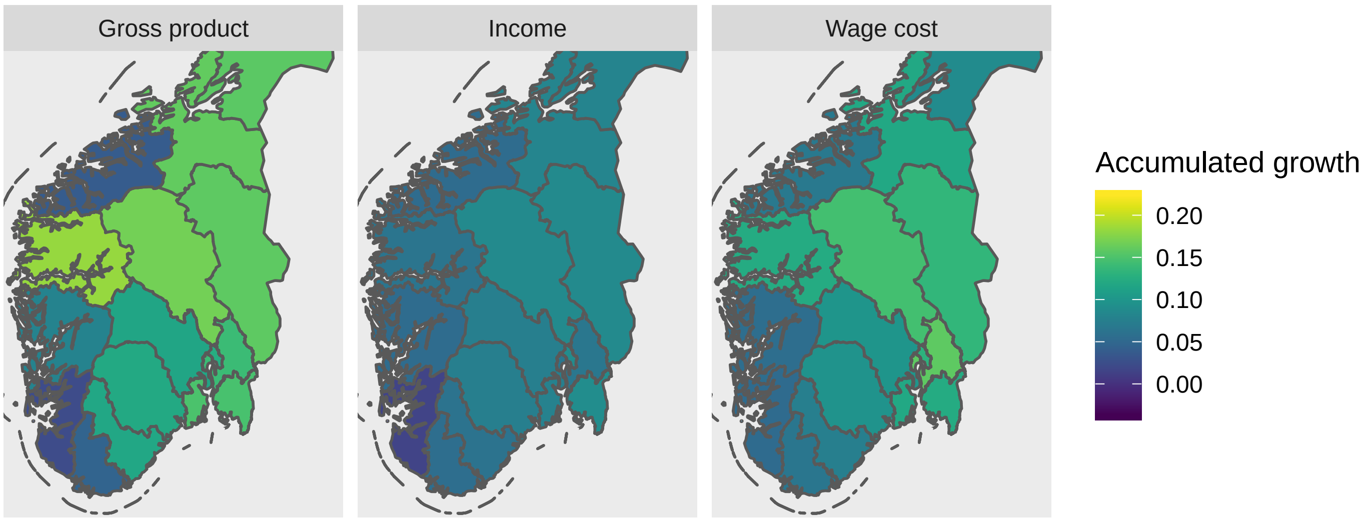
Figure 2: Municipality-level unemployment in Rogaland county



Notes: The unemployment rate is the share of the workforce that, 1) is actively seeking a job, 2) has been without work for the last two weeks, and, 3) has registered as unemployed at the Norwegian Labour and Welfare Administration. Data source: Norwegian Labour and Welfare Administration [2018]. See Appendix D for the underlying data.

percent.

Figure 3: Additional business cycle measures



Notes: The figures shows the accumulated growth rates between 2013 and 2016. Gross product is measured in current prices. Income is the median total income at the household-level. Wage cost is measured in current prices. Data sources: Statistics Norway [2019a,b]. See Appendix D for the underlying data.

3 Data

Our main source of data is a large umbrella chain with several grocery chain concepts. The umbrella chain is present in all counties of Norway and has 13 chain concepts covering all market segments. We have two main data sets. The first contains complete transaction histories from January 2013 to June 2018 for a random sample of households that were members of the umbrella chain's frequent buyer program. Our sample covers roughly five percent of the households in the program.[4] For each transaction, we have information about the name of the product, the store at which it was bought, the price, a sales campaign indicator, and the product category (as defined by the umbrella chain). The second data set contains weekly sales expenditure and quantities at the product level from all the grocery stores in the umbrella chain. These weekly figures are based on transactions from all customers, not only the sample present in our transaction-level data set.

The main purpose of the paper is to investigate how households and stores respond to

[4]In 2018, more than two million Norwegians (out of a population of 5.3 million) were members of the program.

changing economic conditions, and how this translates into the average prices households pay for products in given categories, such as minced meat or soda. We are restricting attention to categories where we can calculate comparable unit prices across products.[5] This means that we do not include categories such as newspapers and ready-to-eat meals, where there is no straightforward and comparable measure of unit. We want to be able to compare prices for exactly the same products across stores and time periods. Therefore, we do not include fresh fruit and vegetables, because the quality of these products may vary between stores and time periods. See Appendix C for a list of the included categories and their expenditure shares. Transactions from all other categories are dropped from all the following analyses and descriptive statistics. In the transaction-level data set, the included categories account for about 32 percent of the total expenditure.

Table 1 reports some descriptive statistics on the households and stores in the data set. From the table, we see that there are 100,261 distinct households in the data set and 2339 distinct stores.

Let us first consider the monthly expenditures at the household-level. Here, we first calculate the average monthly expenditure for each household, before we calculate the average, median and standard deviation for this variable *across* households. When calculating the within household averages, we only use months where a given household had positive expenditure.[6] The average value (across households) of the average (within household) monthly expenditure is about 734 NOK, which corresponded to about 132 USD at the start of our sample period.[7] This monthly expenditure is well below what we would expect the average household to spend on groceries during a month. Note however that this expenditure only covers the categories we consider in the subsequent analysis. As mentioned above, these categories cover about 32 percent of the total expenditures of the households in our sample. In addition, monthly expenditures are only from one umbrella chain, while a household may

[5]To calculate unit prices, we need to determine the number of units of a product (e.g., the number of kilos or liters) from the product's name. We drop transactions of products that have a different measure of unit in their name than the mode of the category (e.g., products whose name describes the amount of liters while the mode unit of measurement of the category is kilos). We also exclude products where the product name does not contain information about the number of units.

[6]We exclude months with zero expenditure because many households appear in our data well into the sample period, presumably because they were not members of the frequent buyer program at the beginning of the sample period.

[7]In January 2013, the price of one USD was 5.56 NOK (monthly exchange rates from The Central Bank of Norway).

visit more than one umbrella chain in a given month. Turning to the number of stores visited, the average (across households) of the average (within household) number of distinct stores visited is 2.30, again only counting months where a given household visited at least one store. The months active variable indicates that on average the households made purchases in about 40 of the 66 months in the sample period, reflecting the fact that many households are not present in the data in the beginning of the sample period. Among the households present in the first quarter of the sample period, the average of the months active variable is about 54.

In the subsequent analysis, we keep only observations where we have information about the municipality of residence of the household, and where the household is registered as living in the same local market as the store. This is to avoid transactions where a customer no longer lives (and works) in the registered local market, and transactions made while travelling. We define local markets by local labor market regions. The labor market regions are defined by Statistics Norway using data on commuting patterns [Bhuller, 2009]. The 46 labor market regions nest the municipalities in Norway.[8] The reason for defining local markets by labor market regions rather than by municipalities is that consumers may live in one municipality but do much of their grocery shopping in neighboring municipalities. From Table 1, we see that this is indeed the case. The mean share of total expenditure that households spend in their home municipality is 0.73, while the mean share households spend in their home region is 0.87. Furthermore, 75 percent of the households spend 88 percent or more of their total expenditure in their home labor market region, while the corresponding figure for the home municipality is only 59 percent. As we will be analyzing households' willingness to switch to cheaper stores when economic conditions worsen, defining local markets by local labor market regions can be especially important in situations where the umbrella chain has few (if any) stores in a household's home municipality. While the umbrella chain has stores in all 46 labor markets, it is during our sample period never present in more than 370 municipalities. Furthermore, 75 municipalities have only one store from the umbrella chain (during the sample period), and 58 municipalities have only two stores, implying that the umbrella chain has two or fewer stores in about 45 percent of the municipalities.[9]

[8]In the beginning of our sample period there were 428 municipalities in Norway. At the end of our sample period, mergers had reduced the number of municipalities to 423.

[9]In addition, the umbrella chain is represented by either zero or one chain concepts in almost 40 percent of the municipalities. Since substituting toward cheaper stores typically involves substituting toward cheaper

Turning now to the store-level variables, we see that the average (across stores) of the average (within store) monthly revenue is about 1,175,937 NOK, which corresponded to about 211,499 USD at the start of our sample period.[10] The mean number of distinct months a store is active is about 44, and the median is 56.

chain concepts, this reinforces the impression that defining the relevant market by municipality is too narrow.

[10] Note that this is only the revenue coming from the subset of categories we consider in the subsequent analysis. The monthly revenue is calculated using the data set with weekly sales and quantities at the product–store level, so it covers revenue from all customers, not only the sample included in our transaction-level data set.

Table 1: Customer and store characteristics

	Mean	Median	Std. dev.	Observations
Households				
Monthly expenditure	733.79	498.51	730.72	100261
Stores visited	2.30	2.02	1.15	100261
Chains visited	1.72	1.59	0.60	100261
Stores in home municipality	29.05	9.00	48.80	100261
Stores in home region	159.55	53.44	169.42	100261
Chains in home municipality	4.30	4.00	2.52	100261
Chains in home region	8.08	8.00	2.87	100261
Home municipality share	0.73	0.87	0.32	100260
Home region share	0.87	0.97	0.24	100260
Months active	40.01	42	22.51	100261
Stores				
Monthly revenue	1175937	1019418	965686	2339
Months active	43.92	56	24.57	2339

Notes: Monthly expenditure is the average (within household) monthly expenditure in NOK, counting only months with expenditure above zero and only the categories considered in the subsequent analysis (see Table 8 in Appendix C). Stores visited is the average (within household) number of stores visited, counting only months with expenditure above zero. Chains visited is equivalently defined. Months active is the number of months where a household had expenditure above zero. Age is the age of a household's primary member. Monthly revenue is store-level revenue in NOK counting only the categories considered in the subsequent analysis. Months active is the number of months with revenue above zero. All household-level variables are calculated using the transaction-level data set. All store-level variables are calculated using the weekly store-level data set.

4 Household and store behavior over the business cycle

Aguiar and Hurst [2007] and Nevo and Wong [2019] argue that variation in the opportunity cost of time can induce households to increase effort to find items at lower prices. Furthermore, wealth effects may make households more price sensitive and more willing to substitute toward goods on sale. Wealth effects can also induce substitution toward generic brands, items bought in bulk, and lower priced stores. In Appendix B, we outline a theoretical framework based on Aguiar and Hurst [2007] and Nevo and Wong [2019]. This framework illustrates how business cycle variation in the opportunity cost of time can induce households to spend more time looking for items on sale.

As discussed earlier, stores may also adjust their behavior in response to an economic downturn. If households become more willing to hunt for bargains, stores may find it more profitable to run campaigns. A negative income shock that shifts the demand downwards may also induce price reductions by the stores. Finally, if the households become more inclined to buying generic brands or bulk items, stores may find it beneficial to give such items more exposure, e.g., through shelf space allocation. In this section, we will study how households and stores adjust their behavior along these dimensions over the business cycle. We will use simple reduced form fixed effects regressions to analyze the effect of changes in the unemployment rate on carefully designed variables measuring changes in household and store behavior.

We will start at the household-level. Table 2 reports descriptive statistics for a number of household-level measures that may be affected by the business cycle. We also report descriptive statistics on the unemployment rate.

Table 2: Household-level variables

	Mean	Median	75th pct.	25th pct.	Std. dev.
Generic PL share	0.0499	0.0052	0.0607	0.0000	0.0983
Sales share	0.0512	0.0000	0.0422	0.0000	0.1228
Bulk share	0.1910	0.1776	0.2520	0.1022	0.1464
Low price retailers share	0.3262	0.1004	0.6967	0.0000	0.3868
High price retailers share	0.0983	0.0000	0.0380	0.0000	0.2354
Unemployment rate	0.0275	0.0270	0.0333	0.0210	0.0086

Notes: The unit of observation is household-quarter. The number of observations with nonmissing values of all variables is 1,376,188. There are 97,379 distinct households. Markets are defined by labor market regions. The sample period is 2013q1 to 2018q2.

Generic PL share is the share of total expenditures that involved the umbrella chain's low-cost private label. Sales share is the share of total expenditures made on sale. To obtain the Bulk share, we follow Griffith et al. [2009] and rank all product (defined by EAN numbers) within each product category by size. For each category, we then calculate the share of purchases a given household makes that are in the top quartile of the category distribution.

To investigate whether households substitute towards low price stores when economic conditions worsen, we follow Coibion et al. [2015] and construct an aggregate measure of a store's price level, relative to the median price level in a given market and time period.[11] High price retailer share is the share of expenditure a consumer allocates to stores in the top quartile of the store distribution, while Low price retailer share is the share of expenditure the consumers allocate to stores in the bottom quartile of the store distribution.

Even though all these variables are measured at the household-level, some of them may

[11] First, we calculate for each product j in category c and local market m the log-difference, denoted $R_{mscj,t}$, between the average price at store s, calculated as total sales amount divided by the total quantity bought, and the median price of the product in the market in that time period. The average relative price of store s is given by $R_{ms,t} = \sum_c \Omega_{c,t} \sum_j \omega_{mscj,t} R_{mscj,t}$, where $\omega_{mscj,t}$ is product j's share of the expenditure in the category in the given market and time period, and $\Omega_{c,t}$ is category c's share of the total expenditure in the time period. We calculate $R_{ms,t}$ using only products that are sold by at least 90 percent of the stores in the market. We then rank the stores in a market by price level.

also reflect strategic decisions by the stores. A household's sales share may for example be affected by the local stores' sales campaign strategies. In addition, a household's bulk and private label shares may rise if the local stores give such items increased exposure through their shelf space and assortment decisions. However, low and high price retailer shares are less likely to be systematically affected by store-side responses.[12] For each of the household-level variables, we estimate a model of the following form,

$$Y_{hm,t} = \alpha_{hm} + \beta UR_{hm,t} + \lambda_t + \epsilon_{hm,t}, \tag{1}$$

where $Y_{hm,t}$ is the dependent variable of interest, α_{hm} are household fixed effects, $UR_{hm,t}$ is the unemployment rate in the home municipality of the household, and λ_t are time fixed effects. Table 3 reports the results for the household-level regressions.

[12] However, to the extent that there is variation in the economic conditions *within* the labor market regions and local store strategies are sensitive to this, the households' store shares could be systematically affected by store-side responses.

Table 3: Household-level regressions

	Unemployment rate
Generic PL share	0.109***
	(0.020)
Sales share	0.482***
	(0.041)
Bulk share	0.157***
	(0.030)
Low price retailers share	0.361***
	(0.078)
High price retailers share	−0.483***
	(0.056)
Observations	1376188
Households	97379

Notes: This table reports results from fixed effects estimation of models of the form specified in (1). The variables in the first column are dependent variables with the coefficients showing the effect of the unemployment rate on the dependent variable in question. The unit of observation is household-quarter. In the regressions, we only use observations with nonmissing values for all variables in the table. The standard errors reported in parentheses are clustered at the household-level. Markets are defined by labor market regions.

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

All variables are sensitive to the local business conditions as measured by the unemployment rate, and all coefficients have the expected signs. The private label, sale, and bulk shares increase significantly when local unemployment increases. Likewise, the low price retailer share increases and the high price retailer share decreases.

What is the economic significance of these results? Let us consider an increase in the unemployment rate of five percentage points to get a better understanding of our results. Such an increase is estimated to increase the private label share by 0.6 percentage points, implying a increase relative to the average reported in Table 2 of about 11 percent. Similarly, the sales share is estimated to increase by 2.4 percentage points, which is an increase of about 47 percent relative to the average. The expenditure share of bulk items is estimated to increase by roughly 0.8 percentage points, which is about four percent relative to the mean. The expenditure share allocated to low price stores is estimated to increase by nearly two percentage points, but because the average low price retailer share is above 32 percent, the relative increase is relatively modest at about five percent. The high price retailer share is estimated to fall by roughly 2.5 percentage points, which relative to the average share is about 25 percent.

In summary, we find both statistically significant and economically important effects from an increase in the local unemployment rate, suggesting that households do indeed adjust their behavior when hit by unemployment. Next we consider the price levels at the stores, and see whether we can find similar evidence of cyclicality. Table 4 reports descriptive statistics for two store-level price measures that may be affected by the business cycle.

Table 4: Store-level variables

	Mean	Median	75th pct.	25th pct.	Std. dev.
Chain deviation	−0.0025	−0.0015	0.0014	−0.0072	0.0134
Total deviation	−0.0093	−0.0271	0.0284	−0.0430	0.0418

Notes: The unit of observation is store-quarter. The number of observations with non-missing values for both variables is 33,830. There are 2313 distinct stores. The sample period is 2013q1 to 2018q2.

The variables Chain deviation and Total deviation measure the price level of a store, compared with the price level of the other stores in the store chain and all stores in the sample, respectively.[13] Even though these variables are measured at the store level, they

[13] The Chain deviation variable is constructed as follows. First, we calculate for each product j in category c

are constructed to also capture changes in household shopping behavior. Households may drive down the average price paid for a particular product in a particular store in a given time period (e.g., quarter) by concentrating their purchases in weeks when the product is relatively cheap, e.g., by taking advantage of sales campaigns.

For the two store-level variables, we estimate a model of the following form,

$$Y_{sm,t} = \alpha_{sm} + \beta UR_{sm,t} + \lambda_t + \epsilon_{sm,t}, \tag{2}$$

where $Y_{sm,t}$ is the dependent variable of interest, α_{sm} are store fixed effects, $UR_{sm,t}$ is the unemployment rate in the municipality of the store, and λ_t are time fixed effects.

Table 5 reports the results of the store-level regressions.

and chain k the log-difference, denoted $R_{kmscj,t}$, between the average price at store s in market m, calculated as total expenditure in period t divided by total quantities, and the median price of the product in the chain in that time period. The Chain deviation of store s is given by $R_{sm,t} = \sum_c \Omega_{c,t} \sum_j \omega_{kcj,t} R_{kmscj,t}$, where $\omega_{kcj,t}$ is product j's share of the monthly expenditure in category c in the given chain and time period, and $\Omega_{c,t}$ is category c's share of the expenditure in the given time period. We calculate $R_{sm,t}$ using only products that are sold by at least 90 percent of the stores in the chain. The variable Total deviation is defined in the same way, but here we are comparing the price level of the store with all the stores in the sample (rather than only the stores from the same chain).

Table 5: Store-level regressions

	Unemployment rate
Chain deviation	-0.028^{**}
	(0.014)
Total deviation	-0.080^{***}
	(0.024)
Observations	33830
Stores	2313

Notes: This table reports the results from fixed-effects estimation of the models of the form specified in (2). The variables in the first column are dependent variables with the coefficients showing the effect of the unemployment rate on the dependent variable in question. The unit of observation is store-quarter. In the regressions, only observations with nonmissing values of both variables are used. The standard errors reported in parentheses are clustered at the store level. Markets are defined by labor market regions.

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

We see from the table that average prices are indeed countercyclical. An increase in the unemployment rate of five percentage points is estimated to reduce Chain deviation by roughly 0.002, which is about 0.13 standard deviations. A similar increase in the unemployment rate is estimated to reduce Total deviation by roughly 0.05, which corresponds to about 0.11 standard deviations.

As mentioned above, this cyclicality in the store prices may reflect both household- and store-side responses, which was also the case for several of the household-level variables. In the next section, we propose a decomposition of changes in the average prices households pay in given categories which will allow us to better separate the relative contributions stemming from the stores and households.

5 Decomposing price changes

The previous section has indicated that both households and stores respond to changes in the local economic conditions. In this section, we develop a new framework for analyzing and decomposing the cyclicality of the average prices the households pay for goods in a given category, such as skimmed milk or filter coffee.

Let j refer to products (e.g., one liter of a specific brand of skimmed milk) and s to stores. In order to normalize prices across categories, we do the following. For household h in market m, we measure the log-difference, denoted $r_{hmscj,t}$, between the average price the household pays for product j belonging to category c in store s in period t, and the average price paid for products in category c, where the average is taken over all products, stores, households and time periods. We measure the category price as the share-weighted average of the normalized prices, which for a household in a given market for products in a given category and time period is given by

$$p_{hcm,t} = \sum_j \sum_s \alpha_{hmscj,t} r_{hmscj,t}, \tag{3}$$

where $\alpha_{hmscj,t} \geq 0$ is the proportion of total units bought in the category in period t the household allocated to product j in store s.

Within a time period such as a quarter, purchases of a given product in a given store can occur at different prices. By exploiting temporary price reductions, bundling or quantity discounts, a household may pay less than average for a given product in a given store in a given time period. Define

$$\delta_{hmscj,t} = r_{hmscj,t} - r_{mscj,t}, \tag{4}$$

where $r_{mscj,t}$ is the average price paid for product i in store j in the period in question. We can now write a household's category price as follows.

$$p_{hcm,t} = \sum_j \sum_s \alpha_{hmscj,t}(r_{mscj,t} + \delta_{hmscj,t}) \tag{5}$$

This average price can be decomposed as follows.

$$\begin{aligned} p_{hcm,t} &= \sum_j \sum_s \alpha_{hmscj,t}(r_{mscj,t} + \delta_{mscj,t}) \\ &= \frac{1}{2}\sum_j \alpha_{hmcj,t} r_{mcj,t} + \frac{1}{2}\sum_s \alpha_{hmsc,t} r_{msc,t} + \sum_j \sum_s \alpha_{ij}(r_{mscj,t} - \frac{r_{mcj,t} + r_{msc,t}}{2}) \\ &+ \sum_j \sum_s \alpha_{hmscj,t}\delta_{hmscj,t}, \end{aligned} \tag{6}$$

where $\alpha_{hmcj,t} = \sum_s \alpha_{hmscj,t}$ is the volume share of product j in period t (summed across stores), $\alpha_{hmsc,t} = \sum_j \alpha_{hmscj,t}$ is the volume share of store s in period t (summed across products), and $r_{hmcj,t}$ and $r_{hmsc,t}$ are the average prices in period t, market m and category c of product j and store s, respectively.

The first two terms of the last expression in (6) are weighted averages of the price levels of stores and products, where the weights are the volume shares the household allocates to each store and product. The third term accounts for the fact that some product–store combinations may be cheaper (or more expensive) than expected, based on the general price level of the store and the product. The fourth term accounts for the fact that not all purchases of a given product in a given store in a given time period take place at the same price. Equation (6) illustrates that a household can reduce its average price by buying products that in general are cheap (the first term), by buying at stores that in general are cheap (the second term), by choosing product–store combinations that, relative to the general price level of the store and the product, are cheap (the third term), and finally, by exploiting temporary price reductions and other special offers such as bundling or quantity discounts (the fourth term).

We are interested in the cyclicality of prices. Therefore, let us now consider the change in the average price from one period to the next. Note that we can write the category price paid by the household in period t as follows.

$$
\begin{aligned}
p_{hcm,t} &= \sum_j \sum_s \alpha_{hmscj,t}(r_{mscj,t} + \delta_{hmscj,t}) \\
&= \sum_j \sum_s (\alpha_{hmscj,t-1} + \Delta^{\alpha}_{hmscj,t})(r_{mscj,t-1} + \Delta^{r}_{mscj,t}) + \sum_j \sum_s \alpha_{hmscj,t}\delta_{hmscj,t},
\end{aligned} \tag{7}
$$

where $\Delta^{\alpha}_{hmscj,t} = \alpha_{hmscj,t} - \alpha_{hmscj,t-1}$ and $\Delta^{r}_{mscj,t} = r_{mscj,t} - r_{mscj,t-1}$. Subtracting $p_{hc,t-1}$ from (7) gives us the change in the category price as follows.

$$
\begin{aligned}
p_{hcm,t} - p_{hcm,t-1} &= \sum_j \sum_s (\alpha_{hmscj,t-1} + \Delta^{\alpha}_{hmscj,t})(r_{mscj,t-1} + \Delta^{r}_{mscj,t}) + \sum_j \sum_s \alpha_{hmscj,t}\delta_{hmscj,t} \\
&\quad - \sum_j \sum_s \alpha_{hmscj,t-1}(r_{mscj,t-1} + \delta_{hmscj,t-1}) \\
&= \sum_j \sum_s \alpha_{hmscj,t-1}\Delta^{r}_{mscj,t} + \sum_j \sum_s \Delta^{\alpha}_{hmscj,t} r_{mscj,t-1} + \sum_j \sum_s \Delta^{\alpha}_{hmscj,t}\Delta^{r}_{mscj,t} \\
&\quad + \sum_j \sum_s (\alpha_{hmscj,t}\delta_{hmscj,t} - \alpha_{hmscj,t-1}\delta_{hmscj,t-1})
\end{aligned} \tag{8}
$$

The first term in the last expression, $\sum_j \sum_s \alpha_{hmscj,t-1}\Delta^{r}_{mscj,t}$, is the change in the average category price that would result purely from changes in product–store prices (if the household did not reallocate consumption). The second term, $\sum_j \sum_s \Delta^{\alpha}_{hmscj,t} r_{mscj,t-1}$, is the change in the category price that would result purely from changes in volume shares (if prices were unchanged). The third term, $\sum_j \sum_s \Delta^{\alpha}_{hmscj,t}\Delta^{r}_{mscj,t}$, captures the interaction between price changes and volume changes. If the household reallocates toward products that have become relatively cheaper this term will be negative. The last term, $\sum_j \sum_s(\alpha_{hmscj,t}\delta_{hmscj,t} - \alpha_{hmscj,t-1}\delta_{hmscj,t-1})$, captures changes in the households' willingness and ability to take advantage of temporary price changes and other special offers.

To obtain the decomposition that we will take to the data, we write the change in the average price as follows.

$$
\begin{aligned}
p_{hcm,t} - p_{hcm,t-1} = & \overbrace{\sum_j \sum_s \alpha_{hmscj,t-1} \Delta^r_{mscj,t}}^{\Delta^{Laspeyre}} \qquad (9) \\
& + \overbrace{\frac{1}{2} \sum_j \Delta^\alpha_{hmcj,t} r_{mcj,t-1}}^{\Delta^{Products}} + \overbrace{\frac{1}{2} \sum_s \Delta^\alpha_{hmsc,t} r_{msc,t-1}}^{\Delta^{Stores}} \\
& + \overbrace{\sum_j \sum_s \Delta^\alpha_{hmscj,t} (r_{mscj,t-1} - \frac{r_{mcj,t-1} + r_{msc,t-1}}{2})}^{\Delta^{Shopping}} + \overbrace{\sum_j \sum_s \Delta^\alpha_{hmscj,t} \Delta^r_{mscj,t}}^{\Delta^{Interaction}} \\
& + \overbrace{\sum_j \sum_s (\alpha_{hmscj,t} \delta_{hmscj,t} - \alpha_{hmscj,t-1} \delta_{hmscj,t-1})}^{\Delta^{Discounts}}
\end{aligned}
$$

The average price a household pays for products in a given category may decrease because the prices of the products it buys decrease ($\Delta^{Laspeyre}$), because the household substitutes toward products and stores that in general are cheaper ($\Delta^{Products}$ and Δ^{Stores}), and because the household's shopping intensity has increased (the last three terms in (9)). $\Delta^{Shopping}$ captures changes in the household's propensity to choose combinations of products and stores that cost less than their individual product and store shares would indicate. $\Delta^{Interaction}$ tells us something about the household's willingness to take advantage of changing relative prices by substituting toward products that have become relatively cheaper, while $\Delta^{Discounts}$ captures changes in the changes in the household's willingness and ability to take advantage of temporary price changes and other special offers.

6 The cyclicality of grocery prices

Our main empirical specification is as follows

$$
Y_{hcm,t} = \theta_{hcm} + \beta UR_{hm,t} + \lambda_t + \epsilon_{hcm,t}, \qquad (10)
$$

where h, c, m, and t index households, categories, markets, and time period, respectively.

$Y_{hcm,t}$ is the variable of interest, $UR_{hm,t}$ is the unemployment rate in the home municipality of the household, θ_{hcm} denotes fixed effects at the household-category level, and λ_t denotes time fixed effects.

First differencing (10) gives us the following equation

$$Y_{hcm,t} - Y_{hcm,t-1} = \beta(UR_{hm,t} - UR_{hm,t-1}) + (\lambda_t - \lambda_{t-1}) + (\epsilon_{hcm,t} - \epsilon_{hcm,t-1}). \tag{11}$$

OLS estimation of (11) with the change in household-level category price, $p_{hcm,t} - p_{hcm,t-1}$, on the left-hand side gives us an estimate of the cyclicality of average category prices. Furthermore, by estimating (11) with each of the terms on the right-hand side of (9) as the dependent variable, we can decompose the cyclicality of the prices into the different components described in the previous section.

To calculate $p_{hcm,t}$, we use the average prices a household paid for each product–store combination in category c in period t. The average prices are calculated as the number of units bought divided by sales expenditure, including any discounts. We use quarters as time periods. When calculating the terms on the right hand side of (9), we need a measure of the general price of product j in store s in quarter t. Our measure is the (unweighted) average of the weekly product–store prices in the quarter, where the weekly price is sales value divided by the total number of units sold. When calculated in this way, the product–store prices will only to a limited extent be affected by household side responses. If we had calculated the quarterly price by dividing the total sales amount by the total number of units sold, the price would be responsive to the households' willingness and ability to concentrate their purchases of the product to the weeks where the price is relatively low.[14]

We now turn to the terms of the decomposition, and discuss to what extent each term captures household-side or store-side responses.[15]

[14]There are two ways the household still could affect the average price as we define it here. First, the average price would be reduced if the households exploit price variation at the product–store level *within* weeks, by concentrating their purchases in days where the price is relatively low. However, because the umbrella chain's sales campaigns tend to follow a weekly pattern, we believe that any such effects are limited. Second, households could reduce this average price by increasing their propensity to take advantage of special offers that are always available, such as quantity discounts. It should be noted, however, that the largest chain associated with the umbrella chain has an explicit policy of not offering quantity discounts, so we believe that this channel is of limited importance.

[15]In order to decompose the change in the category price according to (9), we need to know the (average) price in period t of all product–store combinations bought by the customer in period $t-1$, and likewise the

$\Delta^{Laspeyre}$ is calculated holding product–store shares fixed. As we argue above, the quarterly product–store price should not be much affected by household behavior, therefore, we view $\Delta^{Laspeyre}$ as measuring store-side responses to the business cycle. The variable will pick up price reductions stemming both from reductions in the regular price and increases in campaign activity at the store level. As Δ^{Stores} and $\Delta^{Shopping}$ are calculated holding prices fixed, they are unaffected by any cyclical pricing strategies at the store level. These two variables are therefore driven entirely by household-side responses. $\Delta^{Products}$ is also calculated holding prices fixed, but could to some extent be affected by store behavior, if for example, stores reacted to changing economic conditions through assortment and shelf space adjustments. We still believe that this variable is best viewed primarily as measuring household-side responses. $\Delta^{Interaction}$ measures the household's willingness and ability to reallocate consumption toward products that have become relatively cheaper. This variable is therefore entirely a measure of household-side response.

Finally, $\Delta^{Discounts}$ measures the change in the household's ability to take advantage of temporary price reductions, and thereby pay a lower price for product j in store s than the average price for the product in the store. Note that any cyclical variation in this variable will reflect an increase in the households' tendency to concentrate their purchases in weeks where the product is available at a relatively low price, e.g., by taking advantage of temporary sales campaigns. Increased propensity of households in local markets experiencing an economic downturn to take account of special offers that are available throughout the time period, such as quantity discounts, would not affect the variable because this would have the effect of reducing the average price. It should be noted that while it is natural to view this variable as primarily capturing a household-side response, cyclical variation in the households' willingness to exploit sales campaigns may be amplified by store-side responses, because, e.g., more frequent sales campaigns may make it easier for the households to reduce the price they pay for a given product in a given store (compared with the average price of the product in the store).

Table (6) reports our main empirical results. The first column of Table 6 is our preferred

(average) price in period $t-1$ of all product–store combinations bought by the customer in period t. Average prices at the product–store level are calculated using the store level data set with weekly sales and quantity information. We will therefore have a measure of the average product–store price in a given quarter, as long as the product was sold in the given store in the given time period, even if the product was not bought by any of the households in our transaction-level data set.

specification. We see that the category prices indeed are countercyclical: a five percentage point increase in the unemployment rate leads to a decrease in the category price of about 0.008,[16] Given that the (within-panel) standard deviation of the category price is about 0.21 this may seem like a relatively small effect. One should however keep in mind that while not all consumers in a given local market are (equally) affected by an economic downturn, the effect estimated in Table 6 is an average effects over all households. Among the households directly affected by an economic downturn, e.g., the ones becoming unemployed, the effect is likely to be greater.

Turning to the decomposition, we observe that these sum to the total effect and that all coefficients are negative. The component with the largest contribution to the decrease in the category price is $\Delta^{Discounts}$, which accounts for about 57 percent of the total effect. This indicates that customers are more willing and able to take advantage of temporary price reductions when local unemployment increases. The second most substantial component, $\Delta^{Laspeyre}$ is statistically significant at the five percent level. This component accounts for about 12 percent of the decrease in the category price. As discussed above, we interpret $\Delta^{Laspeyre}$ as capturing store-side responses, and the negative sign of the coefficient indicates that stores do in fact respond to an economic downturn by reducing their prices. The parameter for Δ^{Stores}, which measures a household-side effect, is statistically significant at the one percent level, and represents about 12 percent of the total effect.

These findings are well aligned with the results reported in Table 3 and Table 5. In Table 3, we found that the share of expenditures involving sales increased when the unemployment rose. This is reflected directly in the negative sign of $\Delta^{Discounts}$, and also potentially in the negative sign of $\Delta^{Laspeyre}$, because this variable reflects both reductions in ordinary prices and price reductions due to more frequent or more substantial sales campaigns. The negative sign of Δ^{Stores} reflects the finding reported in Table 3 that households shift their trade from high-price stores to low-price stores when economic conditions worsen. Table 5 established that the price levels of the stores were cyclical, when average prices were calculated as quarterly expenditure divided by quarterly volume. This finding is reflected in the negative signs of $\Delta^{Laspeyre}$ and $\Delta^{Discounts}$. The negative sign and magnitude of $\Delta^{Discounts}$ indicates

[16] We choose to estimate Equation 10 by first differences rather than by fixed effects because this allows us to decompose the cyclicality of the average price. Estimating the model with fixed effects on the same samples as in Table 6 gives us nearly indistinguishable estimates of the main effect of unemployment on the category price.

Table 6: Cyclicality of category prices

	Category price	Category price	Category price	Category price
Unemployment rate	−0.14262***	−0.16083***	−0.16673***	−0.17479***
	(0.04038)	(0.04235)	(0.03941)	(0.04136)
Decomposition				
$\Delta^{Laspeyre}$	−0.01819**	−0.01872**	−0.01440*	−0.01489*
	(0.00772)	(0.00755)	(0.00811)	(0.00793)
$\Delta^{Products}$	−0.00198	−0.00158	−0.01054	−0.00582
	(0.01685)	(0.01624)	(0.01766)	(0.01704)
Δ^{Stores}	−0.01753***	−0.01340***	−0.02061***	−0.01520***
	(0.00542)	(0.00417)	(0.00571)	(0.00440)
$\Delta^{Shopping}$	−0.01338	−0.01966	−0.02480	−0.02730
	(0.01809)	(0.01740)	(0.01896)	(0.01826)
$\Delta^{Interaction}$	−0.00956	−0.00331	−0.00984	−0.00313
	(0.00715)	(0.00676)	(0.00751)	(0.00709)
$\Delta^{Discounts}$	−0.08199***	−0.11006***	−0.08064***	−0.10845***
	(0.02031)	(0.02044)	(0.02125)	(0.02139)
Observations	8,303,161	8,432,761	7,271,425	7,397,597
Panels	1,640,337	1,611,499	1,257,110	1,235,174
Households	87,300	87,165	54,211	54,206
Household set	Full	Full	Restricted	Restricted
Product set	Full	Restricted	Full	Restricted
Market span	Labor market	Labor market	Labor market	Labor market

Notes: The standard errors reported in parentheses are clustered at the household-level. Panels is the number of distinct household category combinations. The restricted household set only includes customers who were active in at least half of the months in the sample period. The restricted product set is derived as follows: we rank the products in each category (in descending order) by total expenditure in the entire sample period, and keep all products until the cumulative expenditure share reaches 0.95. Market is defined by labor market regions.

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

that the reduction in store prices to a large degree reflects that the households are more willing and able to concentrate their purchases of a given product in weeks where the price is relatively low. However, the negative sign of $\Delta^{Laspeyre}$ indicates that part of the cyclicality of the store prices are also driven by the stores themselves, through reductions in ordinary prices or through increased campaign activity.

While both household and store responses to business cycles have been studied in the literature, our detailed data and our new decomposition allows us to clearly disentangle and quantify the two responses. In sum, our results show a clear result: grocery prices are countercyclical. When unemployment increases, prices are reduced. When we decompose this cyclicality, we find that the aggregate effect is driven by both household-side and store-side responses, and that most of the cyclicality is driven by changes in the households' propensity to take advantage of sales campaigns.

To investigate the robustness of our results, we estimate several alternative specifications. First, households that buy most of their groceries from other chains may be a less reliable source of variation in category prices, because the category price calculated using transactions from the umbrella chain we have data from may differ substantially from the household's true average category price. In Column 3 and Column 4 of Table 6, we only include households that were active in at least half of the months in the sample period. This removes from the estimation sample households that only sporadically visited the umbrella chain's stores. Second, products that are infrequently bought may not be a reliable source of variation in prices because the weekly (and quarterly) prices at the store level may be based on few transactions and therefore be a noisy measure of the price at which the product is available in the store in the given period. In Column 2 and Column 4 of Table 6, we therefore exclude the least frequently bought products in each category when calculating and decomposing the average category prices. More specifically, we rank the products in each category (in descending order) by total expenditure in the entire sample period, and keep all products until the cumulative expenditure share reaches 0.95.

Comparing the results in Columns 2–4 with Column 1, we see that the results are qualitatively and quantitatively similar. The overall effects is similar, although the magnitude is slightly larger in the alternative specifications than in the Column 1. $\Delta^{Discounts}$ has the largest contribution in all specifications. $\Delta^{Laspeyre}$ and Δ^{Stores} still stands out among the other components, although $\Delta^{Laspeyre}$ is only borderline statistically significant in the specifications with the restricted household set.

Finally, we have re-estimated each model reported in Table 6 after dropping extreme observations. Specifically, when constructing the household-level average prices we drop transactions where the log-difference between the average quarterly price at the household-product-store level and the category-level average (across all products, stores, households and time periods) exceed two. This is to ensure that our results are not driven by a small number of transactions with extremely low (or high) prices. As can be seen from Table 7 in Appendix A, the results are both qualitatively and quantitatively similar to those reported in Table 6.

7 Conclusion

We utilize two data sets on household- and store-level grocery prices and sales to uncover how consumers' shopping behavior was affected by local economic downturns following the large drop in oil prices in 2014. The reduction in oil prices affected the Norwegian labor market very differently across regions, increasing local unemployment rates substantially in some areas.

We start by presenting reduced form evidence suggesting that both households and stores reacted to the economic downturn. Store prices are reduced when unemployment increases, and consumers react by reallocating expenditure toward cheaper products (more private label products, more bulk items) and stores.

We then develop a novel decomposition of changes in average category prices at the household-level. The decomposition captures changes in the prices charged by the stores (holding the choices of the households unchanged), changes in the store shares and product shares (holding prices charged by the stores unchanged), and changes in the households' shopping intensity. This decomposition allows us to incorporate household and store responses within the same framework, and thus measure also their relative contributions. We find that most of the cyclicality in prices are determined by household responses, but more than ten percent of the cyclicality in the average price is determined by stores' regional responses to the economic downturn. The single most important factor, accounting for more than half of the total effect, is the households' willingness to take advantage of temporary price reductions.

The results are consisitent with findings in the literature and indicate that knowledge of households' shopping behavior and the effect on prices can play a crucial role in understanding how shocks are transmitted in the economy (as in e.g, Jaimovich et al. [2019] and Kaplan and Menzio [2016]). The findings in the current paper are relevant for several important issues, such as how to measure consumption expenditures, and how local consumer responses affect the measurement of the aggregated real interest rate in an economy. Finally, the understanding of the scope for consumers to respond to economic shocks has implications for the measurement of consumption inequality and purchasing power in an economy.

It is important to note that while not all consumers in a given local market are (equally) affected by an economic downturn, the effects estimated in our paper are average effects over all households. An interesting venue for future research would be to combine detailed household-level data on shopping behavior with household-level data on employment status. This would allow a more direct measurement of the ways becoming unemployed affects shopping behavior.

Appendix A Alternative specification

Table 7: Cyclicality of category prices – extreme values dropped

	Category price	Category price	Category price	Category price
Unemployment rate	−0.13847***	−0.15163***	−0.16427***	−0.16765***
	(0.03964)	(0.04155)	(0.03882)	(0.04074)
Decomposition				
$\Delta^{Laspeyre}$	−0.01899**	−0.01990***	−0.01533*	−0.01620**
	(0.00768)	(0.00751)	(0.00807)	(0.00789)
$\Delta^{Products}$	−0.00358	−0.00315	−0.00920	−0.00427
	(0.01651)	(0.01593)	(0.01728)	(0.01670)
Δ^{Stores}	−0.01461***	−0.01074**	−0.01688***	−0.01242***
	(0.00530)	(0.00441)	(0.00559)	(0.00465)
$\Delta^{Shopping}$	−0.01526	−0.02203	−0.02401	−0.02660
	(0.01763)	(0.01704)	(0.01845)	(0.01786)
$\Delta^{Interaction}$	−0.01055	−0.00394	−0.01047	−0.00365
	(0.00709)	(0.00670)	(0.00744)	(0.00702)
$\Delta^{Discounts}$	−0.07549***	−0.10452***	−0.07573***	−0.10450***
	(0.02021)	(0.02034)	(0.02116)	(0.02130)
Observations	8,378,469	8,501,788	7,339,874	7,460,478
Panels	1,644,486	1,615,344	1,259,854	1,237,755
Households	87,307	87,172	54,211	54,206
Household set	Full	Full	Restricted	Restricted
Product set	Full	Restricted	Full	Restricted
Market span	Labor market	Labor market	Labor market	Labor market

Notes: The standard errors reported in parentheses are clustered at the household-level. Panels is the number of distinct household category combinations. The restricted household set only includes customers who were active in at least half of the months in the sample period. The restricted product set is derived as follows: we rank the products in each category (in descending order) by total expenditure in the entire sample period, and keep all products until the cumulative expenditure share reaches 0.95. Market is defined by labor market regions. We drop observations where the log-difference between the average quarterly price price at the household-product-store level and the category-level average (across all products, stores, households and time periods) exceeds two.

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

Appendix B Theoretical Framework

To organize thinking about the transmission mechanism from local economic conditions to shopping behavior, we present the model from Aguiar and Hurst [2007] and Nevo and Wong [2019] used for the study of life-time prices and shopping behavior over the business cycle respectively. The underlying assumption is that business cycle variation in the opportunity cost of time induces households to spend more time looking for lower prices, and that unemployment induces substitution in the consumption bundle. These mechanisms are captured in the comparative statics of s and Q with respect to C and μ below.

Within a period the household minimizes the cost of reaching a consumption level, C, at a given cost of time, μ. To reach the desired level of consumption the household exerts effort, h, to enhance inputs purchased in the market, Q, in order to produce the final consumption good. Furthermore, the household can exert effort, s, to search for lower prices, $p(s, \mathbb{N})$. We assume that the marginal gross return to search is always positive and declining in search effort, i.e., $\partial p(s, \mathbb{N})/\partial s < 0$ and $\partial^2 p(s, \mathbb{N})/\partial s^2 > 0$. As in Aguiar and Hurst [2007] and Nevo and Wong [2019] the price vector can be described by aspects other than price, these are captured in $\mathbb{N}$. Among the properties are the product itself, Q. We assume that the conditions for an interior maximum are satisfied. This implies that η is a positive Lagrange multiplier measuring the marginal cost of consumption. The described problem results in the following optimization problem and first-order conditions

$$\begin{aligned} \underset{Q,h,s}{\text{minimize}} \quad & p(s, \mathbb{N})Q + \mu\,(h + s) \\ \text{subject to} \quad & f(Q, h) = C \end{aligned}$$

$$-\frac{\partial p}{\partial s} Q = \mu \tag{12}$$

$$\frac{\partial f}{\partial h} \eta = \mu \tag{13}$$

$$p(s, \mathbb{N}) + \frac{\partial p}{\partial Q} Q = \frac{\partial f}{\partial Q} \eta \tag{14}$$

The optimal allocation of time is described by the agent equating the marginal returns to shopping and household production to the opportunity cost of time, μ. In the following I assume that $\partial p/\partial Q = 0$. Dividing equation 13 by equation 14 gives the familiar result that the inputs to production are chosen such that their marginal rate of transformation equals their relative price.

$$\frac{\partial f/\partial h}{\partial f/\partial Q} = \frac{\mu}{p(s)} \tag{15}$$

Business Cycle: Comparative Statics with respect to μ and C

μ

If the opportunity cost of time decreases, we would expect the household to spend more time to produce the same level of consumption. However, whether both time in home production and search effort increase is not obvious. For prices to decrease when the opportunity cost of time decreases, time and market goods must be sufficiently “unsubstitutable” in home production. To see why, assume that the household does not change its search effort such that the price of market goods $p(s)$ is unchanged. By equation 15, the household increases the use of time relative to market goods in production. This will come about as an increase in h and a decrease in Q. When the purchased quantity of market goods falls, the marginal benefits of search decline. However, there is a direct effect of the opportunity cost of time on search effort which will tend to increase the effort spent looking for lower prices. Hence, the substitutability of time and market goods in home production versus the elasticity of the price with respect to search effort is crucial in determining the effect of changed opportunity cost of time on prices paid by households.

C

Assume that the desired level of final consumption falls. Holding time spent searching for low prices constant, this reduces the time needed in home production and the amount of goods purchased in the market. This in turn reduces the returns to search for low prices and we would expect to see a decline in search effort and higher prices. A higher price of market goods will lead to substitution toward time in home production, further reducing the incentives to search for low prices.

Sources of Business Cycle Variation in μ and C

We consider variation in household income and available time to be the main sources of variation in the opportunity cost of time and consumption over the business cycle. Here we consider how changes in current and future employment prospects might affect the within-period opportunity cost of time and desired final consumption. We first consider the case when labor supply is along the intensive margin and then along the extensive margin. In both cases we abstract from potential search effort in the labor market as a consequence of being unemployed.

To understand the potential sources of business cycle variation in the opportunity cost of time and consumption, we embed the home production model of Aguiar and Hurst [2007] and Nevo and Wong [2019] in an intertemporal setting as follows. Assume that the household derives utility from final consumption and leisure and can save in a bond. If the employment is along the extensive margin, hours worked and income are given by $n_t = \bar{n}\mathbb{I}_t, y_t = \bar{y}\mathbb{I}_t$, where $\mathbb{I}_t = 1$ and $\mathbb{I}_t = 0$ if unemployed. If employment is along the extensive margin, the household chooses hours optimally given a wage rate w_t and labor income $w_t n_t$. This results in the following maximization problem

$$\begin{aligned}
&max && \sum_{t=0}^{\infty} \beta^t u\left(c_t, l_t\right) && && (16)\\
&s.t. && p\left(s_t\right) q_t + b_t = R b_{t-1} + y_t && (\lambda_t) && (17)\\
& && c_t = f\left(h_t, q_t\right) && (\kappa_t) && (18)\\
& && l_t = 1 - n_t - s_t - h_t && &&
\end{aligned}$$

The variables q, p, s and h have the same interpretation as previously. b_t is the amount saved in period t, y_t is labor income, and n_t is the share of the time endowment devoted to market work. The problem has the following first-order conditions

$$\begin{aligned}
b_t: && \lambda_t = R\beta\lambda_{t+1} && (19)\\
c_t: && \frac{\partial u}{\partial c_t} = \kappa_t && (20)\\
n_t: && \frac{\partial u}{\partial l_t} = w_t\lambda_t && (21)\\
q_t: && \left[p\left(s_t\right) + \frac{\partial p}{\partial q_t}q_t\right]\lambda_t = \frac{\partial f}{\partial q_t}\kappa_t && (22)\\
s_t: && -\frac{\partial p}{\partial s_t}q_t\lambda_t = \frac{\partial u}{\partial l_t} && (23)\\
h_t: && \frac{\partial f}{\partial h_t}\kappa_t = \frac{\partial u}{\partial l_t} && (24)
\end{aligned}$$

Define $\eta_t \equiv \kappa_t/\lambda_t$ and $\mu_t \equiv \frac{\partial u/\partial l_t}{\lambda_t}$ such that equations 22, 23, and 24 can be rewritten as

$$\begin{aligned}
p\left(s_t\right) + \frac{\partial p}{\partial q_t}q_t &= \frac{\partial f}{\partial q_t}\eta_t\\
-\frac{\partial p}{\partial s_t}q_t &= \mu_t\\
\frac{\partial f}{\partial h_t}\eta_t &= \mu_t
\end{aligned}$$

Conditional on a value of c_t and μ_t these equations along with equation 18 make up a system of four equations in four unknowns (q_t, h_t, s_t, η_t), mirroring the first-order conditions of the cost minimization problem. Intuitively, maximizing life-time utility implies minimizing costs within periods. The intertemporal problem allows us to consider how employment status and real wages affect the within-period consumption level and opportunity cost of time.

When labor supply is along the intensive margin, the opportunity cost of time is equal to the real wage. That is, μ moves one-for-one with the real wage in each period. Based on the comparative statics above, we would predict lower real wages, ceteris paribus, lead to greater search effort and lower transaction prices for the affected households. Depending on how strong the effect of temporary real wage changes are on labor supply, and therefore life-time income, the effect on transaction prices might be undone through effects on desired consumption. A decline in desired consumption reduces purchases of market goods and therefore reduces the marginal benefit of looking for lower prices. For this channel to dominate, the decline in income would have to be long-lasting and/or uninsured.

For households that determine labor supply on the extensive margin, the opportunity cost of time is given by the marginal rate of substitution between leisure and market goods. That is, the ratio of marginal utility of leisure to the marginal utility of market income. Assume that a household is employed and expects to be employed at the same salary for the foreseeable future. The household then becomes unemployed. Becoming unemployed increases time available, allowing for more leisure. Holding the marginal utility of market income/wealth constant and assuming leisure increases, the marginal utility of leisure falls and the opportunity cost of home production/search falls. In addition, job loss will tend to decrease life-time income, which in turn will increase the marginal utility of market income and lead to a further decline in the opportunity cost of time. As before, the decline in consumption of market goods will reduce the returns to search in product markets and the effect on transaction prices might be ambiguous.

To conclude, the two models have similar predictions regarding business cycle fluctuations in final consumption, but they differ in how the opportunity cost of time is determined. This might be clearer if we consider the response to an anticipated future reduction in real wages or expected transition to unemployment. When labor supply is determined along the intensive margin, there is no change in the opportunity cost of time in response to the news of lower future wages as today's opportunity cost is equal to the current real wage. We would therefore expect to see an increase in transaction prices as final consumption is reduced. In contrast, a household that supplies labor along the extensive margin will reduce final consumption and experience a fall in the opportunity cost of time.

Appendix C Product categories

The table lists the categories included in the analysis. The Total column reports the expenditure share of the category in the transaction-level data set (including all categories), while Included column reports the expenditure share of the category in the data set used for the main analyses.

Table 8: Product categories

Product category	**Total**	**Cum. total**	**Included**	**Cum. included**
Beer	0.0477	0.0477	0.1472	0.1472
Soft drinks	0.0351	0.0828	0.1083	0.2555
White cheese, semi-hard	0.0221	0.1049	0.0681	0.3236
Milk, low-fat	0.0192	0.1240	0.0592	0.3828
Beef, minced	0.0137	0.1378	0.0424	0.4252
Ham	0.0132	0.1510	0.0408	0.4661
Eggs	0.0117	0.1627	0.0361	0.5022
Coffee, ground	0.0103	0.1730	0.0316	0.5338
Pizza, frozen	0.0099	0.1828	0.0304	0.5643
Chocolate, bars	0.0095	0.1923	0.0293	0.5936
Bread, whole grain	0.0090	0.2013	0.0278	0.6214
Chicken, raw fillets	0.0089	0.2102	0.0275	0.6488
Orange juice	0.0086	0.2188	0.0265	0.6754
Potato chips	0.0085	0.2273	0.0263	0.7016
Beef, steaks	0.0080	0.2354	0.0248	0.7264
Sausages	0.0065	0.2419	0.0201	0.7465
Toilet tissue	0.0058	0.2477	0.0178	0.7643
Fish, fresh	0.0057	0.2534	0.0176	0.7819
Bread, semi whole-grain	0.0053	0.2586	0.0163	0.7982
Sour cream	0.0052	0.2638	0.0160	0.8142
Milk, full	0.0043	0.2682	0.0134	0.8276
Chocolate, snack bars	0.0041	0.2723	0.0126	0.8402

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Table 8 – continued from previous page

Product category	Total	Cum. total	Included	Cum. included
Yoghurt, fruit	0.0039	0.2762	0.0121	0.8523
Butter	0.0031	0.2793	0.0096	0.8619
Mackerel, tinned	0.0030	0.2822	0.0092	0.8711
Milk, skimmed	0.0029	0.2852	0.0091	0.8801
Toothpaste	0.0027	0.2879	0.0085	0.8886
Fish, frozen salmon and trout	0.0026	0.2906	0.0081	0.8967
Carbonated water, flavoured	0.0024	0.2930	0.0074	0.9041
Tortillas	0.0024	0.2953	0.0073	0.9114
Diapers	0.0023	0.2976	0.0071	0.9186
Pork, steaks	0.0022	0.2998	0.0068	0.9253
Fish, frozen whitefish	0.0019	0.3017	0.0057	0.9311
Coffee, instant	0.0018	0.3034	0.0054	0.9365
Dishwasher detergent, tablets	0.0017	0.3052	0.0053	0.9418
Shampoo	0.0017	0.3068	0.0051	0.9470
Laundry detergent, liquid	0.0016	0.3084	0.0049	0.9518
Breakfast cereals	0.0015	0.3099	0.0046	0.9565
Beer, alcohol free	0.0015	0.3114	0.0046	0.9611
Carbonated water, not flavoured	0.0015	0.3129	0.0046	0.9657
Laundry detergent, powder	0.0015	0.3144	0.0045	0.9702
Ketchup	0.0013	0.3156	0.0039	0.9741
Müsli	0.0012	0.3168	0.0037	0.9778
Salsa	0.0011	0.3179	0.0034	0.9812
Dishwasher detergent, powder	0.0011	0.3190	0.0033	0.9845
Tomatoes, tinned	0.0009	0.3199	0.0029	0.9874
Still water, not flavoured	0.0008	0.3208	0.0026	0.9900
Sanitary napkins	0.0008	0.3216	0.0026	0.9926
Pantyliners	0.0008	0.3224	0.0026	0.9951
Spaghetti	0.0007	0.3232	0.0022	0.9973
Still water, flavoured	0.0006	0.3237	0.0018	0.9991

Continued on next page

Table 8 – continued from previous page

Product category	Total	Cum. total	Included	Cum. included
Laundry detergent, tablets	0.0003	0.3240	0.0009	1.0000

Appendix D Business cycle measures

Table 9: County-level unemployment

County	Month	Unemployment
Akershus	2013m1	2.3
Aust-Agder	2013m1	3.5
Buskerud	2013m1	2.5
Finnmark	2013m1	3.7
Hedmark	2013m1	2.9
Hordaland	2013m1	2.1
Møre og Romsdal	2013m1	2.1
Nord-Trøndelag	2013m1	2.5
Nordland	2013m1	3.1
Oppland	2013m1	2.6
Oslo	2013m1	3.4
Østfold	2013m1	3.6
Rogaland	2013m1	1.8
Sogn og Fjordane	2013m1	2.0
Sør-Trøndelag	2013m1	2.5
Telemark	2013m1	3.6
Troms	2013m1	2.3
Vest-Agder	2013m1	3.1
Vestfold	2013m1	3.2
Akershus	2016m1	2.7
Aust-Agder	2016m1	4.7
Buskerud	2016m1	3.1
Finnmark	2016m1	3.8
Hedmark	2016m1	2.6
Hordaland	2016m1	3.5
Møre og Romsdal	2016m1	3.3

Continued on next page

Table 9 – continued from previous page

County	Month	Unemployment
Nord-Trøndelag	2016m1	2.9
Nordland	2016m1	2.9
Oppland	2016m1	2.4
Oslo	2016m1	3.6
Østfold	2016m1	3.6
Rogaland	2016m1	4.8
Sogn og Fjordane	2016m1	2.4
Sør-Trøndelag	2016m1	3.0
Telemark	2016m1	4.0
Troms	2016m1	2.3
Vest-Agder	2016m1	4.1
Vestfold	2016m1	3.3
Akershus	2018m6	1.8
Aust-Agder	2018m6	2.5
Buskerud	2018m6	2.3
Finnmark	2018m6	2.7
Hedmark	2018m6	1.7
Hordaland	2018m6	2.5
Møre og Romsdal	2018m6	2.2
Nordland	2018m6	1.7
Oppland	2018m6	1.4
Oslo	2018m6	2.4
Østfold	2018m6	2.6
Rogaland	2018m6	2.6
Sogn og Fjordane	2018m6	1.3
Telemark	2018m6	2.4
Troms	2018m6	1.5
Trøndelag	2018m6	1.9
Vest-Agder	2018m6	2.4

Continued on next page

Table 9 – continued from previous page

County	Month	Unemployment
Vestfold	2018m6	2.7

Table 10: Municipality-level unemployment in Rogaland

Municipality	**Month**	**Unemployment**
Bjerkreim	2013m1	0.7
Bokn	2013m1	1.4
Eigersund	2013m1	1.5
Finnøy	2013m1	0.7
Forsand	2013m1	2.5
Gjesdal	2013m1	1.8
Hå	2013m1	1.8
Haugesund	2013m1	2.8
Hjelmeland	2013m1	0.7
Karmøy	2013m1	2.3
Klepp	2013m1	1.5
Kvitsøy	2013m1	1.9
Lund	2013m1	1.7
Randaberg	2013m1	1.1
Rennesøy	2013m1	1.0
Sandnes	2013m1	1.9
Sauda	2013m1	1.7
Sokndal	2013m1	1.2
Sola	2013m1	1.5
Stavanger	2013m1	1.6
Strand	2013m1	1.8
Suldal	2013m1	1.6
Time	2013m1	1.7
Tysvær	2013m1	1.6
Utsira	2013m1	0.8
Vindafjord	2013m1	1.7
Bjerkreim	2016m1	3.1
Bokn	2016m1	3.1

Continued on next page

Table 10 – continued from previous page

Municipality	**Month**	**Unemployment**
Eigersund	2016m1	5.2
Finnøy	2016m1	2.1
Forsand	2016m1	3.3
Gjesdal	2016m1	4.8
Hå	2016m1	3.2
Haugesund	2016m1	6.2
Hjelmeland	2016m1	3.0
Karmøy	2016m1	4.9
Klepp	2016m1	4.5
Kvitsøy	2016m1	2.1
Lund	2016m1	9.3
Randaberg	2016m1	4.4
Rennesøy	2016m1	3.4
Sandnes	2016m1	5.6
Sauda	2016m1	2.7
Sokndal	2016m1	4.3
Sola	2016m1	5.1
Stavanger	2016m1	5.0
Strand	2016m1	4.9
Suldal	2016m1	0.9
Time	2016m1	4.0
Tysvær	2016m1	2.7
Utsira	2016m1	NA
Vindafjord	2016m1	2.6
Bjerkreim	2018m6	1.2
Bokn	2018m6	1.4
Eigersund	2018m6	2.8
Finnøy	2018m6	1.4
Forsand	2018m6	2.3

Continued on next page

Table 10 – continued from previous page

Municipality	Month	Unemployment
Gjesdal	2018m6	2.6
Hå	2018m6	2.1
Haugesund	2018m6	2.8
Hjelmeland	2018m6	1.3
Karmøy	2018m6	2.3
Klepp	2018m6	2.2
Kvitsøy	2018m6	1.4
Lund	2018m6	1.0
Randaberg	2018m6	2.3
Rennesøy	2018m6	2.5
Sandnes	2018m6	3.0
Sauda	2018m6	1.4
Sokndal	2018m6	1.4
Sola	2018m6	3.0
Stavanger	2018m6	2.9
Strand	2018m6	2.4
Suldal	2018m6	0.7
Time	2018m6	2.2
Tysvær	2018m6	1.5
Utsira	2018m6	NA
Vindafjord	2018m6	2.8

Table 11: Additonal business cycle measures

Municipality	**Year**	**Disposable income**	**Gross product**	**Wage cost**
Akershus	2013	536000	224537	143125
Aust-Agder	2013	462000	33750	22398
Buskerud	2013	465000	94282	62130
Finnmark	2013	454000	26063	17659
Hedmark	2013	430000	59093	38156
Hordaland	2013	488000	226218	141186
Møre og Romsdal	2013	480000	108996	65959
Nord-Trøndelag	2013	462000	41824	27878
Nordland	2013	452000	83443	52057
Oppland	2013	436000	56313	36562
Oslo	2013	410000	459605	273353
Østfold	2013	442000	81475	54222
Rogaland	2013	532000	226278	150557
Sogn og Fjordane	2013	486000	40746	25338
Sør-Trøndelag	2013	463000	123555	79044
Telemark	2013	442000	55764	35318
Troms	2013	457000	59616	38158
Vest-Agder	2013	468000	68798	43063
Vestfold	2013	455000	74917	50452
Akershus	2016	573000	255988	165857
Aust-Agder	2016	489000	37728	24074
Buskerud	2016	500000	105219	68259
Finnmark	2016	493000	31874	18995
Hedmark	2016	463000	68471	43283
Hordaland	2016	517000	244246	149038
Møre og Romsdal	2016	509000	113118	70447
Nord-Trøndelag	2016	497000	48397	30307
Nordland	2016	485000	98737	57447

Continued on next page

Table 11 – continued from previous page

Municipality	Year	Disposable income	Gross product	Wage cost
Oppland	2016	472000	65780	41868
Oslo	2016	446000	516690	308924
Østfold	2016	477000	93495	60838
Rogaland	2016	547000	231403	158615
Sogn og Fjordane	2016	516000	48187	28429
Sør-Trøndelag	2016	500000	143387	88442
Telemark	2016	473000	62445	38737
Troms	2016	493000	71758	44217
Vest-Agder	2016	495000	71959	45866
Vestfold	2016	489000	86107	56465

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