NSM 2022
NORDIC STATISTICAL MEETING

A New Framework for Identifying the Drivers of Change in the Labor Market

Trond Christian Vigtel, Statistics Norway, tcv@ssb.no

Stine Bakke, Statistics Norway, eba@ssb.no

Øyvind Bruer-Skarsbø, Statistics Norway, obr@ssb.no

Magnus Berglund Johnsen, Statistics Norway, mjo@ssb.no

Knut Håkon Grini, Statistics Norway, gri@ssb.no

Thomas von Brasch, Statistics Norway, tly@ssb.no

Abstract

As statisticians we regularly publish information that show how aggregates change over time, often broken down by different subgroups. While this gives us information about the different subgroups, it is seldom clear to what extent factors like changing demographic composition are driving these changes in the aggregate.

After the outbreak of the covid-19 pandemic in 2020, separating these drivers of change became even more important for understanding the large changes that took place in the labor market. For example, the change in average earnings from one period to the next can be thought of as a combination of a change in the composition of subgroups (demographics), which is labeled a compositional effect, and a "pure" monetary change that reflects the actual change in earnings, labeled a price effect. This type of information can be of great value for end users, especially considering the expected demographic changes in the coming years.

Statistics Norway has, in a collaboration between our research department and the division for labor market and earnings statistics, developed an exact additive method for calculating these two effects from a change in any weighted arithmetic mean. This calculation proved vital for understanding how changes in the composition of the labor market through the covid-19 pandemic, which to a large extent was driven by the restrictions imposed by the Norwegian government, impacted the measurement of earnings. We argue that this method is easy to use and has a clear interpretation, which makes it very suitable for official statistics.

In this paper we present how this method works and how Statistics Norway has applied it in our publications on earnings and sickness absence. The method can be generalized to other areas and could prove useful for other countries as well. We will also present this method as an R-package, so that anyone can utilize this method either to examine their own data or by using published statistics.

Keywords: Labor Market Statistics, Earnings Statistics, covid-19, Research

1. Introduction

What are the driving forces underlying aggregate productivity growth? Why has the labor force participation rate changed during the last two decades? What has driven the change in annual earnings over the last year and why have import prices changed? To document these time trends, statisticians will often refer to headline average numbers. To answer the question of the driving forces behind these time trends, we can utilize the fact that the headline average numbers can be broken down by different subgroups.

2. What we do in this paper

In this paper, we derive a decomposition that identifies the size of two components of the change in the headline average number. The first component is a “compositional effect”, which shows the impact of a change in the composition of subgroups on the change in headline average number. The second component is a “price effect”, which shows the change in the headline average number which is not caused by changes in the composition of subgroups.

The decomposition that we present in this paper is useful for investigating the size of the compositional effects, and whether these effects can explain the observed time trend in the headline average number. In this paper we focus on how the method can be applied by statisticians, while the technical details are presented in a companion paper (see Brasch et al. 2022).

To illustrate the use of the decomposition in practice, we look at two well-known official statistics. We first use data on average earnings growth in Norway between 2020Q4 and 2021Q4 to derive the effect of changes in the number of full-time equivalents across industries on the average earnings growth. We find that most of the change in average earnings can be attributed to the price effect, and that only a small portion of the change is due to the change in composition of full-time equivalents across industries (the compositional effect).

In the second example, we use the decomposition for decomposing the change in the sickness absence rate over the period 2015–2020, using educational groups as the subgroup dimension. Here we also find that only a small share of the change in sickness absence rate can be attributed to the change in the composition of man-days across educational groups.

3. The decomposition method

Our point of departure is the headline average number measured at time t (P_t), which is a weighted sum of all numbers across units i (P_{it}),

$$P_t = \sum_{i=1}^{N} S_{it} P_{it}, \tag{1}$$

with weights $S_{it} = X_{it} / \sum_{j=1}^{N} X_{jt}$ and quantity variable X_{it}. Using earnings as an example, which we will investigate further in Section 4, the headline average number (P_t) is the average monthly earnings in the whole economy, while P_{it} shows the average monthly earnings for industry i. In industry i, there are X_{it} number of full-time equivalents, which means that a share S_{it} of all full-time equivalents in the economy work in industry i.

Our decomposition shows how the change between time t and time v in the headline average number, i.e. the left-hand side of Equation (1), can be split into a price effect (the first term) and a compositional effect (the second term):

$$\Delta P = \sum_{i=1}^{N} \bar{S}_i \Delta P_i + \sum_{i=1}^{N} \left(\frac{1}{\bar{\bar{Q}}}\right) \left(\bar{P}_i - \bar{\bar{P}}\right) \Delta X_i. \tag{2}$$

Here $\bar{\bar{P}} = \sum_{i=1}^{N} \bar{S}_i \bar{P}_i$ and $Q_t = \sum_{j=1}^{N} X_{jt}$, while Δ indicates the difference between time t and v ($\Delta x = x_t - x_v$), and a bar over a variable represents the average between time t and v ($\bar{x} = 1/2(x_t + x_v)$).

4. Empirical application

To illustrate the use of the decomposition method shown in the previous section, we consider two well-known official statistics: (i) monthly earnings and (ii) sickness absence.

Decomposing the change in monthly earnings

The data used in this empirical application are obtained through the “a-ordning”, which is a collaborative digital system shared by Statistics Norway, the Norwegian Tax Administration and the Norwegian Labour and Welfare Administration. It provides information about employment, remuneration in cash and in kind and taxes. Data for all industries and individuals are collected and compiled monthly, and this is the main source Statistics Norway utilize for producing statistics on earnings and the labor market.

We focus on the change in monthly earnings per full-time equivalent as the price variable from 2020Q4 to 2021Q4 and allow for compositional effects across industries, using the number of full-time equivalents in each industry as the quantity variable. Table 1 shows the average monthly earnings and the number of full-time equivalents in each industry and in the aggregate for 2020Q4 and 2021Q4.

Table 1 Monthly earnings per full-time equivalent and number of full-time equivalents, 2020Q4 and 2021Q4

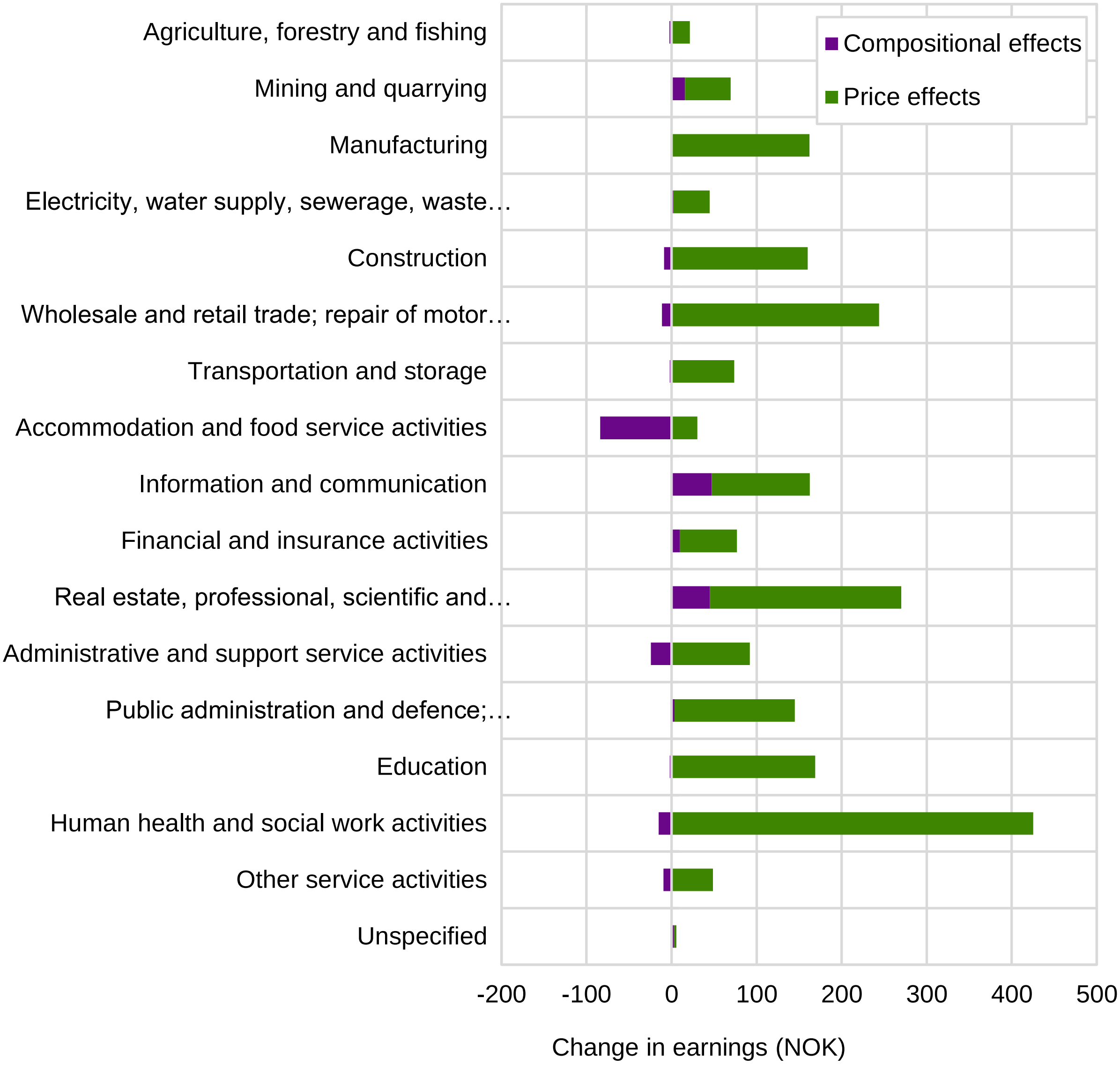
	2020Q4		2021Q4	
	Monthly earnings (NOK)	Number of full-time equivalents	Monthly earnings (NOK)	Number of full-time equivalents
All industries	48,750	2,242,706	50,790	2,320,214
Agriculture, forestry and fishing	41,880	24,838	43,830	25,664
Mining and quarrying	74,290	59,890	76,310	61,292
Manufacturing	49,090	197,800	50,940	201,393
Electricity, water supply, sewerage, waste management	54,450	32,012	57,430	32,846
Construction	46,110	221,718	47,730	228,745
Wholesale and retail trade; repair of motor vehicles and motorcycles	44,220	262,080	46,320	267,773
Transportation and storage	47,860	110,862	49,350	114,705
Accommodation and food service activities	33,340	60,593	34,380	72,623
Information and communication	63,270	93,626	65,980	100,882

Financial and insurance activities	70,360	45,928	73,670	46,890
Real estate, professional, scientific and technical activities	60,060	146,836	63,460	155,418
Administrative and support service activities	41,000	115,691	42,760	122,725
Public administration and defence; compulsory social security	52,210	157,396	54,240	159,831
Education	46,750	195,500	48,710	197,832
Human health and social work activities	44,860	446,720	47,010	455,729
Other service activities	43,830	70,212	45,360	74,466
Unspecified	63,440	1,003	68,490	1,403

Source: Statbank Table 11419, Statistics Norway.

Figure 1 shows the results from using the decomposition from Equation (2). The results illustrate that there were both positive and negative compositional effects present in aggregate earnings growth in Norway from 2020Q4 to 2021Q4. In the aggregate, these effects were negative, which is largely attributable to developments in the industry accommodation and food service activities. This industry was to a considerable extent impacted by the Norwegian government's actions to curb the spread of covid-19, as these measures particularly affected industries where social interaction is a necessity. However, the gradual softening of these measures throughout 2021 was accompanied by an increase in activity in these industries. As the industry accommodation and food service activities has a level of earnings lower than the weighted average earnings level (see Table 1), the compositional effect becomes negative when the volume variable of the industry increases. Conversely, the industries information and communication and real estate, professional, scientific and technical activities, in which the earnings level is higher than the aggregate earnings level, contributed to aggregate earnings growth with a noteworthy positive compositional effect, as these industries had an increase in the quantity variable. At the same time, several industries had a compositional effect that was close to zero.

Figure 1 Decomposition of change in monthly earnings (NOK), from 2020Q4 to 2021Q4



Source: Authors' own calculations using data from [Statbank Table 11419](), Statistics Norway.

Decomposing the change in sickness absence

The data used in this second empirical application are also obtained through the "a-ordning" (as described in the previous empirical example), as well as registers from the Norwegian Labour and Welfare Administration containing information about doctor-certified sickness absence.

Here, we use the sickness absence rate as the price variable, measured as the number of sickness absence man-days relative to the number of contractual man-days.[1] We allow for compositional effects across educational groups using the number of man-days in each educational group as the quantity variable. Table 2 shows the sickness absence rate and the number of contractual man-days in each educational group and in the aggregate for the period 2015–2020.

Table 2 Sickness absence rate and number of contractual man-days, 2015–2020

	2015	2016	2017	2018	2019	2020
Sickness absence rate (percent)						
All	4.8	4.8	4.9	4.8	4.9	5.3
Compulsory	6.2	6.0	6.0	6.0	6.0	6.5
High school	5.2	5.2	5.3	5.3	5.3	5.8
University, 1–4 years	4.5	4.5	4.7	4.6	4.8	5.0
University, 4+ years	2.7	2.7	2.9	2.9	3.0	3.1
Unspecified	3.9	4.0	4.2	4.2	4.2	4.4
Contractual man-days (1,000)						
All	514,521	526,691	533,219	542,929	551,785	552,377
Compulsory	80,848	83,195	83,334	83,352	83,441	83,163
High school	204,754	206,779	206,643	207,528	208,851	207,734
University, 1–4 years	147,795	150,853	153,179	156,718	160,650	164,248
University, 4+ years	61,693	64,979	67,410	70,654	74,487	78,183
Unspecified	19,431	20,885	22,654	24,677	24,356	19,049

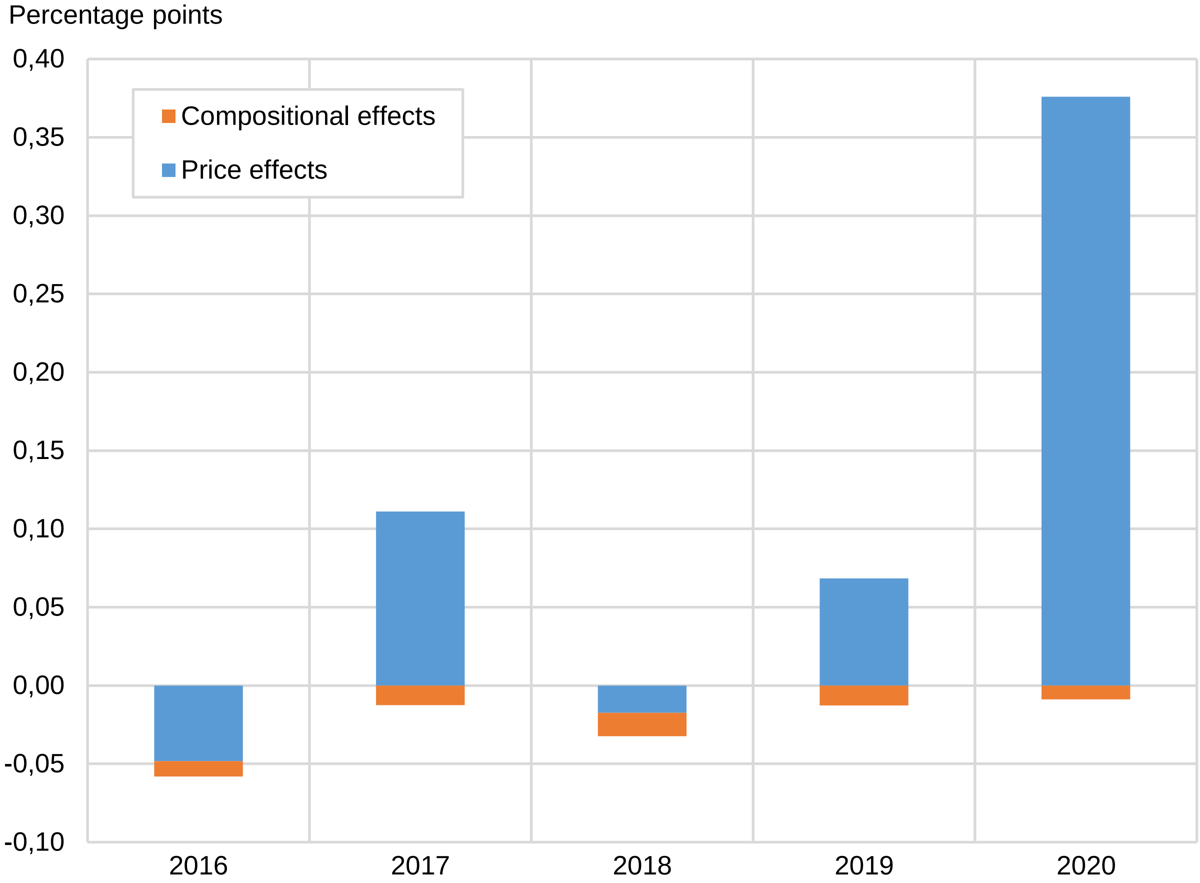
Source: Data from Statistics Norway.

Figure 2 shows the results from using the decomposition from Equation (2). The compositional effects across educational groups consistently contributes negatively to the change in the sickness absence rate each year. The reason for this is that the number of contractual man-days from individuals with university education between 1

[1] One man-day corresponds to the length in time of one working day for a person in a full-time position (100 percent position). A sickness absence man-day corresponds to one sickness absence day for a person in a full-time position (100 percent) and who is on full sick leave (100 percent degree of disability).

and 4 years and 4 years or more increased over time. These educational groups have a below-average sickness absence rate, and when the size of these two groups increased this led to a decrease in the aggregate sickness absence rate.

Figure 2 Decomposition of change in sickness absence rate, 2015–2020



Source: Authors' own calculations using data from Statistics Norway.

5. Practical application

Application in statistical products and acceptance by users are important measures for statistical quality. After the onset of the covid-19 pandemic and the implementation of governmental restrictions, the need for a tool that enabled decomposition of, amongst other things, the effect on earnings was in high demand. A process to establish an intuitive tool for decomposing change in earnings was initialized and adopted in the winter of 2020–2021. The Norwegian Technical Calculation Committee for Wage Settlements has now adopted the method described in this paper in their latest report (NOU, 2022).

Statistics Norway has also made use of the decomposition to describe consequences of governmental shutdown on the labor market and the measurement of changes in average earnings specifically (Grini et al. 2021). Furthermore, the decomposition method has proven useful for studying the effect of changes in the composition of the labor market on the measurement of sickness absence (Bruer-Skarsbø and Vigtel, 2022).

In interpreting statistics, compositional effects have always been of special interest. This is especially the case when the economy has been subject to some sort of shock. Such shocks can either be a consequence of natural shifts in supply or demand, or come as an external shock as most recently exemplified by the governmental intervention in response to the spread of covid-19. In Norway, the second most recent case of a large shock to the economy was the fall in oil prices in 2014, which impacted the Norwegian economy heavily for several years. Other relevant examples of situations where the decomposition of a change in a headline average number could be of interest includes changes in demographic composition, either as a short- or long-run trend, and changes in consumer behaviour, for example regarding the shift from physical shops to online shopping.

The method presented in this paper makes its case first and foremost because of its simple application and ease of use. There is no lack of alternative methods in the economic literature for decomposing changes, but this method allows for interpretation and comparison of each single compositional effect, with the additional strength of straightforward additivity.

Notes of caution and utilization

Before the implementation and use of this method for decomposition, statistical and topic-related judgement should be applied, as in most situations concerning the production and dissemination of statistics. Choosing variables for the decomposition is important, but so is the level of detail needed (NOU, 2022).

In the case of earnings, as an example, both occupation and industry have been utilized. The obvious reason for choosing a specific variable is that it carries information about the phenomenon where the effects are to be found. As stated earlier, the covid-19 pandemic and the related governmental measures had an asymmetrical impact on the different industries, but certain occupations were also more severely affected than others (Grini et al., 2021).

As such, it is important to note that the calculated aggregate price and compositional effects will be different depending on the variables used in the decomposition.

6. Discussion

In this paper, we have presented a method for decomposing the change in a headline average number into two distinct components. The first component is a “compositional effect”, which shows the impact of a change in the composition of subgroups on the change in headline average number. The second component is a “price effect”, which shows the change in the headline average number which is not caused by changes in the composition of subgroups. We have furthermore illustrated the use of this method by applying it to two well-known official statistics: (i) monthly earnings and (ii) sickness absence rate.

The method is a useful tool for statisticians in communicating the driving forces behind changes in the labor market. In connection with annual wage settlements in Norway, the Norwegian Technical Calculation Committee for Wage Settlements, a significant national consumer of statistics on earnings, have over many years been describing the change in average earnings and its compositional effects (NOU, 2022). Especially in the context of shocks to the economy, which require analyses to assess their impact on the labor market and the measurement of earnings, the decomposition has been used to isolate the underlying growth in earnings from other short- and medium-term business cycle phenomena.

When communicating the results from the proposed decomposition to consumers of official statistics, it should however be noted that the choice of dimension along which the change in the headline average number is decomposed is by no means arbitrary. When choosing this dimension, it is critical that it inherently captures the nature of the changes in the quantity variable.

7. References

Brasch, T. v., Grini, H., Johnsen, M. B. and Vigtel, T. C. (2022). A Two-Stage Bennet Decomposition of the Change in the Weighted Arithmetic Mean, forthcoming in *Journal of Official Statistics*.

Grini, K. H., Johnsen, M. B., Konci, E. (2021). Arbeidslivet og smitteverntiltak – Hva skjedde etter 12. mars 2020? SSB Rapporter 2021/38.

Bruer-Skarsbø, Ø., Vigtel, T.C. (2022). Sykefravær og frafall fra arbeidsmarkedet. Betydningen av sammensetningen av sykemeldte. SSB Rapporter 2022/10.

NOU (2022). Grunnlaget for inntektsoppgjørene 2022 [Online report from the Norwegian Technical Calculation Committee for Wage Settlements].