Assignment 1 Bayesian Networks
Causality in the World Happiness Report

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1 Introduction

In our developed world, we often measure the welfare of a country and the success of governmental policies through the gross domestic product, or GDP. If the GDP increased, we assume policies were successful and the quality of life within a country increased. Even though it is nowadays well understood that the GDP is not an ideal measurement of social welfare and has thus been criticised as such, see for example [1, 2, 3, 4], it continues to be used as a dominating indicator of welfare in the Western world.

One of the first ones to question the use of the GDP as a measurement of social welfare was Easterlin [5], leading his findings to be named the Easterlin paradox. According to the Easterlin paradox, there is indeed a strong effect of income on happiness, if we look at one point in time, both within as also between nations. Looking at this relation over a long period of time, we see that growth rates of happiness and income are in fact *not* related [5].

One of the datasets that looks to compare countries according to life satisfaction and understand what life satisfaction means, in terms of other variables is the data collected for the World Happiness Report [6]. This report provides data on different countries on various variables every year. The goal of this assignment is to analyse this dataset to find causal relations between some of the variables and the overall life satisfaction to understand whether the GDP is an appropriate measure for life satisfaction within a country.

2 Data

The data we will use stems from the world happiness reports from 2005-2022 and contains 156 countries [6][1]. There are 2199 entries of data points (rows) over different countries and years with 11 variables (columns). See Table 1 for a description or Box 2.1 and Box 2.2 in [6] for more details. We decided to not use the variables country and year as those should not have any causal effects on life satisfaction, or at least not causal effects that we would be interested in as it is impossible to influence them.

[1] Data can be found at `https://worldhappiness.report/ed/2023/#appendices-and-data`

Variable	Description	Range	Notes
Country	The country of which the measurements are taken	165 countries	Not used in our model
Year	The year in which the measurements were taken	2005-2022	Not used in our model
GDP	Natural log of the GDP per capita	$0 - \infty$	Because of the natural log function, the GDP should already include the diminishing return effect
Health	Healthy Life Expectancy at Birth	$0 - \infty$	
Social Support	National average of the binary response to the question of social support, where 1=yes and 0=no	0-1	"If you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?"
Freedom	National average of the binary response to the question of freedom of life choices	0-1	"Are you satisfied or dissatisfied with your freedom to choose what you do with your life?"
Generosity	Residual of regressing the national average to the donation question on log GDP per capita	0-1	"Have you donated money to a charity in the past month?"
Corruption	National average of the binary response to the question of perceived corruption	0-1	"Is corruption widespread throughout the government (within businesses) or not?"
Positive Affect	Average of previous-day affect measures for laughter, enjoyment and interest	0-1	
Negative Affect	Average of previous-day affect measures for worry, sadness and anger	0-1	
Life Ladder	Life satisfaction measured by asking respondents to evaluate their current life as a whole using the image of a ladder (10=best possible life for them, 0=worst possible life for them)	0-10	

Table 1: Description of the variables present in our dataset

3 Building the Bayesian Network

In the following we will describe our process of using earlier research to propose a bayesian network structure. After that we will test it and improve it where needed and where research and reasoning lead us to believe the test results. After that we will end up with a bayesian network structure that we will investigate in the section hereafter.

3.1 Proposed Model according to earlier research

The first step to understanding the causal relationships between the variables is to build a Bayesian Network structure. To build such a structure, there are a few important things we need to consider. One is the temporality of variables (order of measurement), one is the results of earlier literature and research and another one is our own reasoning and understanding of the world [7]. It is important to note, that claiming there is no relationship between two variables (i.e. not drawing an error between two nodes) is a stronger claim than including the relationship [7]. To understand the relationships between our variables, we first turn to the World Happiness Report [6] itself (i.e. where the data was also collected) and see what interactions they assume and reason about. In the following, we list the interactions they discuss in the direction that the report seems to imply. Important to note, that everything that interacts with life satisfaction will automatically be a cause towards life satisfaction, as that is the dependent variable we want to understand (and learn what causes it).

- GDP influences Life Satisfaction [6]
- Social Support influences Life Satisfaction [6]
- Social Support influences Positive Affect [6]
- Social Support influences Negative Affect [6]
- Healthy life expectancy influences Life Satisfaction [6]
- Healthy life expectancy influences Negative Affect [6]

- Freedom to make life choices influences Life Satisfaction [6]
- Freedom to make life choices leads to Positive Affect [6]
- Freedom to make life choices leads to Negative Affect [6]
- Generosity influences Positive Affect [6]
- Positive Affect influences Life Satisfaction [6]
- Corruption influences Life Satisfaction [6]
- Corruption influences Negative Affect [6]

While there are more interactions between variables implied in the World Happiness Report, there is no reasoning or description of causal direction implied anymore. Therefore, we turn to other research that investigated this dataset. For example, [8] finds that GDP, social support and health are also strongly correlated with each other. Similarly, [9] find that these three are the strongest cross-correlated variables. What is interesting, is that when looking at the table of cross-correlation in [9], we find that actually, the correlation between GDP and corruption is an even stronger one than the one between GDP and social support, while that is not mentioned in the article. Due to research on these variables, we argue for the following causal relationships between these four variables.

- GDP per capita causes healthy life expectancy to increase [10][2]
- Social support increases Health [11, 12]
- GDP leads to an increased feeling of social support [13]
- Corruption causes a lower GDP [14, 15]

As interactions that are not indicated in a model are a stronger claim than interactions that are indicated [7], we continue looking for research and literature that could explain causal relationships between the other cross-correlations that were found to be significant by [9] (in descending order). We make use of an array of fields such as psychology, public administration and philosophy as some of the concepts, such as freedom for example, are discussed in a lot of different contexts and fields. The research we found does not always explicitly state the causal relationship in the way that we do here or used slightly different concepts. In such cases, we provide our reasoning for why the implication of cause and effect seems valid to us or why we think the concept can be translated to the context in which we use it.

- Perceived corruption causes a decreased feeling of freedom as it takes away control of individuals over the government [15]
- Social Support causes an increased feeling of freedom as [16] found that increasing social support can prevent suicides. We reason, that one commits suicide only if one feels there is no other way (i.e. out of options means there is no freedom of choice). Additionally, the relationship seems valid to us as support makes it possible to make life choices that would not have been possible otherwise

[2]We found some contradicting literature here that also argued for a causal relationship in the other direction. We will further discuss this in section 5 "Limitations and Reflection"

- Perceived corruption causes a decreased generosity as one would not want to donate if it feels like the system is not honest [17, 18] (the research focuses on conspiracy theories and not on correctly perceived corruption, however, we argue that the effect would be similar as for a conspiracy theorist the perception of corruption is real)
- Health causes increased feelings of freedom as one has to be healthy to be able to make certain choices [19]. While the source is a philosophical discussion and argues about whether inability and 'unfreedom' are the same, it clearly implies the direction of the causal relationship
- Perceived corruption causes healthy life expectancy to go down due to the strain perceived corruption puts on mental health, as well as the real corruption that can lead to damages (e.g. faulty buildings) [20]
- Freedom increases Generosity as philosophically, generosity is seen as an expression of freedom [21, 22]
- Perceived corruption decreases the feeling of social support as there is no transparency and trust in the society [20]

Note that [9] also found a correlation between GPD and generosity, which we do not take into account. Donations to charities can go to either a different country (thus decreasing the GDP) or stay within the country (thus increasing the GDP). At the same time it seems logical to us that people in richer countries donate more (thus GDP could also influence generosity) and more to other countries (thus decreasing the GDP more). Because of the small correlation found, the complicated relationship and a lack of research clarifying our questions, we decide to not add an interaction between these two variables for now.

We used `dagitty` [23] to implement and visualise these causal relationships, which resulted in the graph that can be seen in Figure 1 which we will begin testing in the following section.

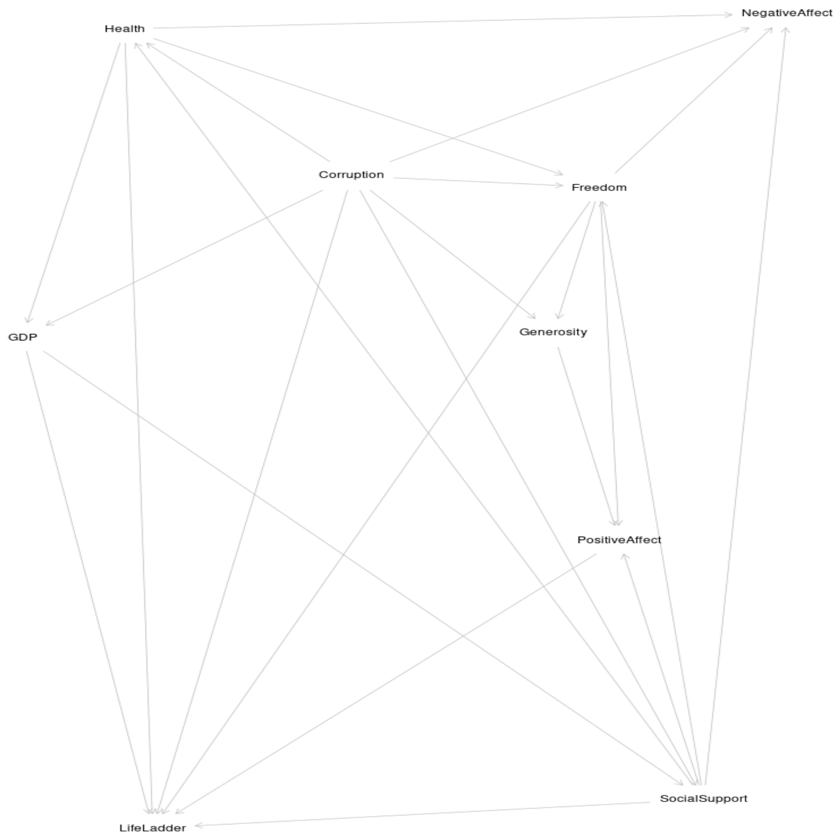

Figure 1: The bayesian network that results from our understanding of the data

3.2 Testing and Improving the Bayesian Network

We use the R function `localTests` to test the conditional independencies of our network, which we present graphically below (for the detailed output see the Appendix A "Test results of conditional independence for the first proposed structure", important to note is that all tests have a small p-value and are thus signficant). As the figure shows, not all of the conditional independencies are proven to be correct here. As we have a very large dataset (1958 observations) almost any correlation found will have a small p-value.

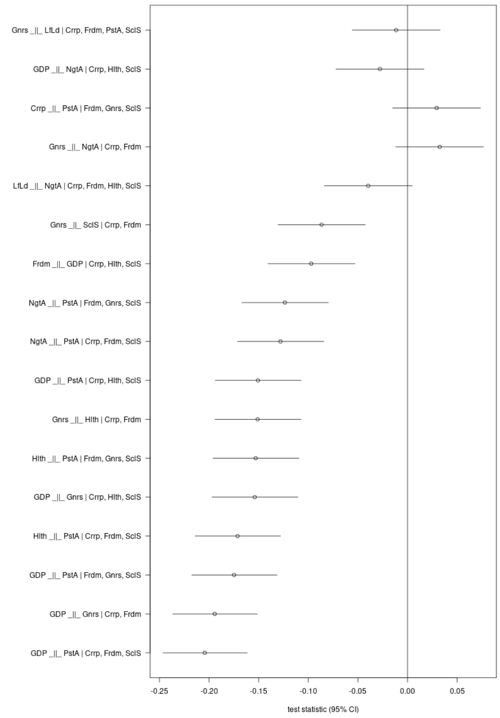

Figure 2: The tests of conditional independence for our proposed causal structure

The tests do make us notice that we have not properly inspected the relations between positive/negative affect and the other variables. We therefore aim at finding more research to see which interactions we can find. We reason the following:

- GDP and Positive Affect: Our test indicates a negative relationship, while research would indicate a positive relationship with success, income or similar measurements. Due to that discrepancy, we do not add that interaction in our model as we believe that peer-reviewed literature is more thorough than our test [24]
- Positive affect and health is also indicated to have a negative relationship with positive affect in our tests, while research shows the opposite. Just like above, we decide for that reason to not add the interaction [25]
- GDP and Generosity are also found to be an incorrect independence, while we have argued above for reasons to leave it out. As it is one of the "bigger problems" here, we decide to add an interaction despite our reasoning above. In a research about charitable donations [26] the dependant variables are being controlled for a few factors influencing them, among which the GDP. We therefore assume a causal relation from the GDP towards generosity
- Generosity and health are also indicated to have a negative relationship in our tests, which does not seem logical to us. Both of these are positively valued variables and we would thus think they positively influence each other. Generosity could, for example, mean a donation towards a health-related charity, which should in turn increase health. Similarly, we would assume that

one only donates if one is healthy themselves. Donations also increase one's self-image, so we also do not see a reason why generosity would decrease mental (or physical) health.

- As we have not added a lot of interactions between positive affect and negative affect and the ones that are suggested in these tests do mostly not seem valid to us, we do decide to add an interaction between these variables themselves. Literature shows that positive affect is seen as a positive factor in a lot of other aspects (e.g. improving health, reducing stress, increasing social connections) [27], where negative affect is usually not seen as a strong influence and only as a decreasing factor of positive affect. Because of that, we argue that negative affect influences positive affect.

With the above two connections added, we use the graph seen in **??** as a final model. While the tests of conditional independence are still not perfect, as seen in Figure 4, we reason that the correlations found are very small and as they do not seem in line with research we decide to leave them out for now (again, for details see Appendix B "Test results of conditional independence for the final structure". As our dataset is highly interrelated (due to the nature of social, subjective and wellbeing measurements), has a lot of datapoints resulting in almost all correlations to be significant and we want to keep our model useful (i.e. not overloaded), we decide that these tests are good enough for us to accept this.

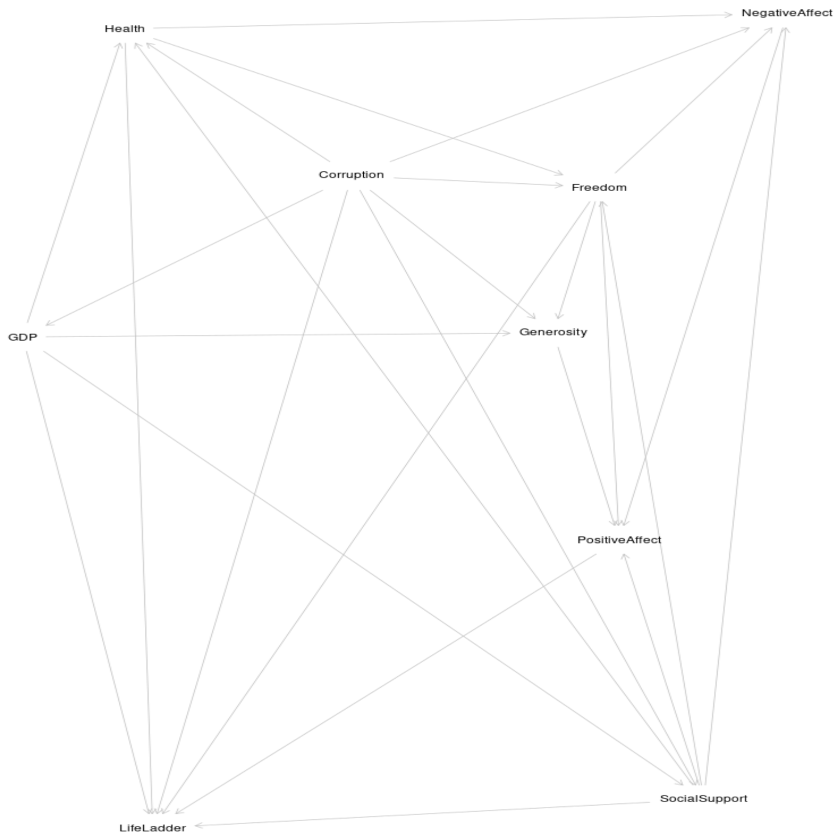

Figure 3: The final Bayesian network indicating causal relationships that we have identified

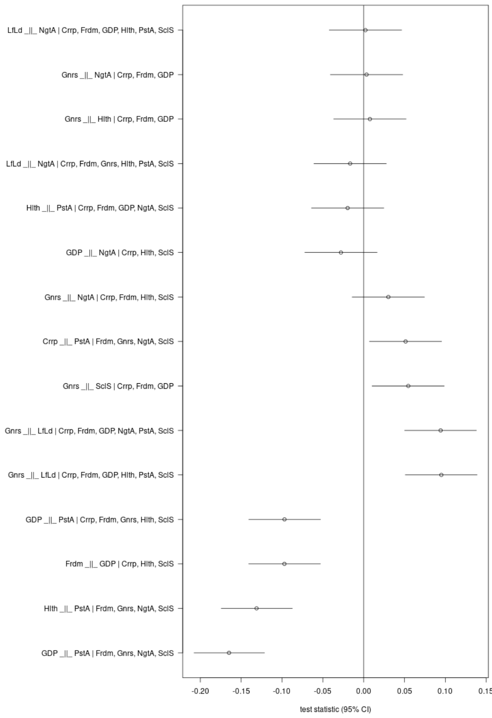

Figure 4: The tests of conditional independence in our final network

4 Causal Relations in our Model

Now that we have a final causal structure, we use the `bnlearn` package [28] with the `bn.fit` function to fit the coefficients to our scaled dataset. This gives us the output that can be found in Appendix C "Fitted coefficients of causal structure". To be able present it in a graphical way we used the `sem` function from the same named package [29] to fit a model and use the `semPlot` package [30] to visualise the graph. The resulting graph shows the same coefficients (besides a few rounding errors) as output, seen in Figure 5, where red arrows indicate negative effects, green arrows positive effects and the thicker an arrow, the stronger the absolute value of an interaction is.

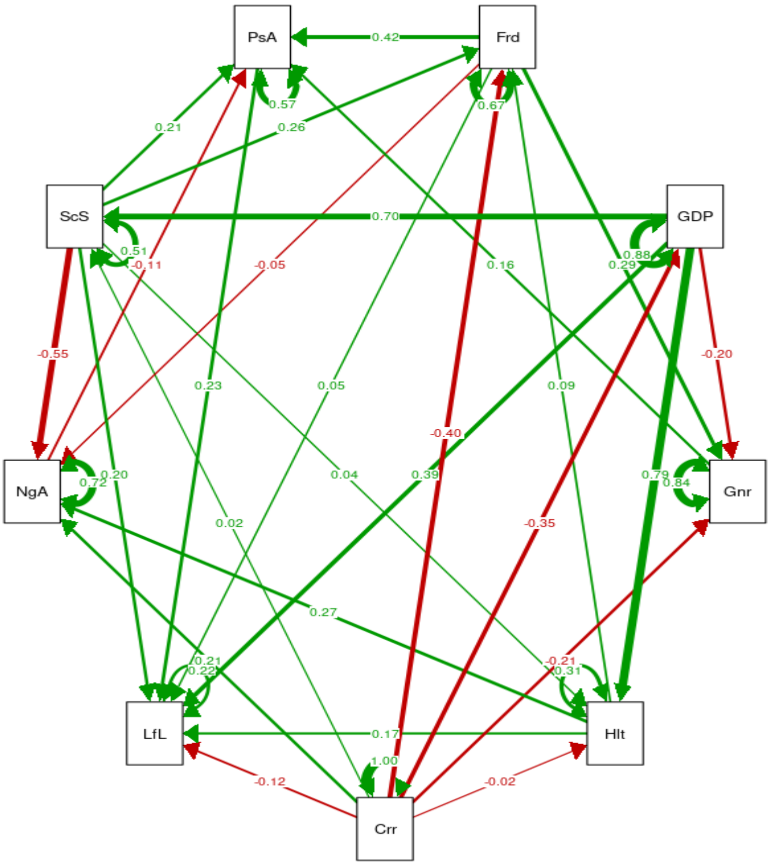

Figure 5: The coefficients in our causal structure

4.1 Discussion of Results

We see in this graph, that some of the connections we have added very early on (e.g. freedom and life satisfaction or freedom and negative affect as indicated in [6]) are negligible small now. Interestingly, however, even though it is a small effect the relationship between corruption and social support is slightly positive, while we had expected from earlier research that this would be a negative one [20].

The strongest causal effects seem to be from GDP towards health and from GDP towards social support. This is interesting as earlier research had indicated that there was a significant and strong correlation between GDP, social support and health [9, 8], however, now the causal relationship between social support and health is negligible small. This means that the correlation between social support and health is almost completely explained by the causal role the GDP plays in these interactions.

Next to the strong causation of the GDP towards social support and health, the strongest causal relationship is that of social support decreasing negative affect (-0.55). Freedom of choice on the

Causal relationship	Strength of effect
GDP → Health	0.79
GDP → Social Support	0.70
Social Support → Negative Affect	-0.55
Freedom → Positive Affect	0.42
Corruption → Freedom	-0.40
GDP → Life Ladder	0.39
Corruption → GDP	-0.35
Freedom → Generosity	0.29
Health → Negative Affect	0.27
Social Support → Freedom	0.26
Positive Affect → Life Ladder	0.23
Corruption → Negative Affect	0.21
Social Support → Positive Affect	0.21
Corruption → Generosity	-0.21
Social Support → Life Ladder	0.20
GDP → Generosity	-0.20
Health → Life Ladder	0.17
Generosity → Positive Affect	0.16
Corruption → Life Ladder	-0.12
Negative Affect → Positive Affect	-0.11
Health → Freedom	0.09
Freedom → Life Ladder	0.05
Freedom → Negative Affect	-0.05
Social Support → Health	0.04
Corruption → Social Support	0.02
Corruption → Health	-0.02

Table 2: Causal relationship sorted in descending order by strength of effect (i.e. absolute value of the coefficient)

other hand, strongly causes positive affect to increase (0.42). After that the negative causal relationships of perceived corruption towards freedom of choice (-0.40) and the GDP (-0.35) are the strongest effect.

This puts the causation between GDP and life satisfaction only at the seventh position regarding strength of effect (0.39). While this is still the biggest causal effect towards life satisfaction, it is already almost as strong as the effect of social support and health towards life satisfaction (0.20 and 0.17 respectively), which are largely explained through the GDP. So while in our model one could conclude that the GDP is the strongest stand-alone measure to predict life satisfaction (at least from the variables of the World Happiness Report), it is also clearly visible that it is in no way a complete predictor.

We already talked about the strong negative effect perceived corruption has on the freedom that is felt to make life choices. Perceived corruption seems to additionally play a role in the way the GDP develops in the way that it causes it to decrease the GDP (-0.35). Considering how many weak causal relationships we have, that seems to be an important factor in our model.

One startling observation we make in our model, is that healthy life expectancy at birth positively influences negative affect (0.27). Even though, the Happiness Report [6] had also found a slightly positive correlation, that one was very small (0.003 with p-value at the 0.001 level). Here, the effect is not as small anymore, which would mean our model would lead us to conclude, that increasing healthy life expectancy at birth within a country, increases the amount of negative affect that individuals experience in that country. Additionally, we had in the process of building the model already decided to not add an interaction between positive affect and health because our the tests of our model seemed to indicate that this was a negative relation, which was contradicting to research [25][3]. One of the ways we could have explained this seemingly contradictory relation was that we have misplaced the causal relationship, meaning that people who worry more would increase their life expectancy. However, we also tried that in a model and the causal relationship then reduced by a lot (from the 0.27 before to 0.13), leading us to abandon that theory. Our other explanation for this causal effect is that a longer life expectancy causes people to worry more because they live longer, meaning there is a longer future to worry about. This would, however, not yet explain why the relationship of positive affect and health are negative in our model, so future research into this relation will be needed.

5 Limitations and Reflection

When looking at earlier research that would indicate the directions of causal relationships within our dataset, we encountered quite a few contradicting results. For example [31] and [32] reason that not only does the GDP increase healthy life expectancy, but it also works the other way round as only someone who is healthy can contribute to the GDP of a country. Similarly, there is research that suggests that while the feeling of social support increases positive affect, there is also research that suggests that positive affect increases likablity of people and thus their quality of social relationships [33] which may in turn also effect whether there is a social support net to rely on or not. These "virtuous circles" are not uncommon in these social settings as we are considering with this dataset. This means, that while we followed the assumptions and implication of what we found to be the most closely related research, it is possible that we have made mistakes in the directing of causal relationships. Similarly, we did see in subsection 3.2 "Testing and Improving the Bayesian Network" that our tests of conditional independence were not yet perfect. At the time it seemed reasonable to us to leave some of these interactions out in light of the size of our dataset and to increase the usefulness of our model. However, now that there are some interactions that we did not expect, we are wondering whether those were the right choices. Future research may want to focus on comparing different models to see whether there are improvements to be made.

[3]Out of curiosity we also tried the model once with an arrow from health to positive affect and it indeed showed a negative causal relationship.

A Test results of conditional independence for the first proposed structure

```
                                      estimate      p.value        2.5%
Crrp _||_ PstA | Frdm, Gnrs, SclS   0.02931049 1.951993e-01 -0.01504168
Frdm _||_ GDP | Crrp, Hlth, SclS   -0.09704721 1.698579e-05 -0.14077788
GDP _||_ Gnrs | Crrp, Frdm         -0.19429069 3.413834e-18 -0.23662516
GDP _||_ Gnrs | Crrp, Hlth, SclS   -0.15397173 7.020891e-12 -0.19697994
GDP _||_ NgtA | Crrp, Hlth, SclS   -0.02782953 2.187472e-01 -0.07207336
GDP _||_ PstA | Frdm, Gnrs, SclS   -0.17479122 6.062111e-15 -0.21747186
GDP _||_ PstA | Crrp, Frdm, SclS   -0.20435801 5.298249e-20 -0.24651972
GDP _||_ PstA | Crrp, Hlth, SclS   -0.15076270 1.918698e-11 -0.19381849
Gnrs _||_ Hlth | Crrp, Frdm        -0.15106930 1.724085e-11 -0.19410964
Gnrs _||_ LfLd | Crrp, Frdm, PstA, SclS -0.01146005 6.127064e-01 -0.05577571
Gnrs _||_ NgtA | Crrp, Frdm         0.03242263 1.517584e-01 -0.01191578
Gnrs _||_ SclS | Crrp, Frdm        -0.08663943 1.238087e-04 -0.13046229
Hlth _||_ PstA | Frdm, Gnrs, SclS  -0.15300282 9.532620e-12 -0.19602548
Hlth _||_ PstA | Crrp, Frdm, SclS  -0.17131100 2.103454e-14 -0.21404864
LfLd _||_ NgtA | Crrp, Frdm, Hlth, SclS -0.03966259 7.963270e-02 -0.08385935
NgtA _||_ PstA | Frdm, Gnrs, SclS  -0.12361136 4.032963e-08 -0.16703741
NgtA _||_ PstA | Crrp, Frdm, SclS  -0.12803560 1.285237e-08 -0.17140531
                                          97.5%
Crrp _||_ PstA | Frdm, Gnrs, SclS    0.073547686
Frdm _||_ GDP | Crrp, Hlth, SclS    -0.052942391
GDP _||_ Gnrs | Crrp, Frdm          -0.151277360
GDP _||_ Gnrs | Crrp, Hlth, SclS    -0.110393747
GDP _||_ NgtA | Crrp, Hlth, SclS     0.016523480
GDP _||_ PstA | Frdm, Gnrs, SclS    -0.131480048
GDP _||_ PstA | Crrp, Frdm, SclS    -0.161495817
GDP _||_ PstA | Crrp, Hlth, SclS    -0.107147160
Gnrs _||_ Hlth | Crrp, Frdm         -0.107468532
Gnrs _||_ LfLd | Crrp, Frdm, PstA, SclS  0.032900640
Gnrs _||_ NgtA | Crrp, Frdm          0.076633970
Gnrs _||_ SclS | Crrp, Frdm         -0.042481284
Hlth _||_ PstA | Frdm, Gnrs, SclS   -0.109413397
Hlth _||_ PstA | Crrp, Frdm, SclS   -0.127952419
LfLd _||_ NgtA | Crrp, Frdm, Hlth, SclS  0.004689623
NgtA _||_ PstA | Frdm, Gnrs, SclS   -0.079715796
NgtA _||_ PstA | Crrp, Frdm, SclS   -0.084181082
```

Listing 1: Tests of conditional independence for the first proposed causal structure

B Test results of conditional independence for the final structure

```
> res2
```

```
                                                                   estimate        p.value
Crrp _||_ PstA | Frdm, Gnrs, NgtA, SclS                         0.051374852  2.313286e-02
Frdm _||_ GDP | Crrp, Hlth, NgtA, SclS                         -0.098491766  1.273886e-05
GDP _||_ PstA | Frdm, Gnrs, NgtA, SclS                         -0.164891137  1.976606e-13
Gnrs _||_ Hlth | Crrp, Frdm, GDP                                0.007657686  7.351113e-01
Gnrs _||_ LfLd | Crrp, Frdm, GDP, Hlth, PstA, SclS              0.095140730  2.520391e-05
Gnrs _||_ LfLd | Crrp, Frdm, GDP, NgtA, PstA, SclS              0.094272403  2.989240e-05
Gnrs _||_ NgtA | Crrp, Frdm, GDP                                0.003545052  8.755395e-01
Gnrs _||_ SclS | Crrp, Frdm, GDP                                0.054621826  1.570605e-02
Hlth _||_ PstA | Frdm, Gnrs, NgtA, SclS                        -0.131138760  5.678278e-09
Hlth _||_ PstA | Crrp, Frdm, GDP, NgtA, SclS                   -0.019625113  3.860884e-01
LfLd _||_ NgtA | Crrp, Frdm, GDP, Hlth, PstA, SclS              0.002174797  9.235111e-01
                                                                       2.5%        97.5%
Crrp _||_ PstA | Frdm, Gnrs, NgtA, SclS                         0.007046939   0.09550178
Frdm _||_ GDP | Crrp, Hlth, NgtA, SclS                         -0.142218514  -0.05438536
GDP _||_ PstA | Frdm, Gnrs, NgtA, SclS                         -0.207742465  -0.12143686
Gnrs _||_ Hlth | Crrp, Frdm, GDP                               -0.036687396   0.05197269
Gnrs _||_ LfLd | Crrp, Frdm, GDP, Hlth, PstA, SclS              0.050989299   0.13892449
Gnrs _||_ LfLd | Crrp, Frdm, GDP, NgtA, PstA, SclS              0.050115350   0.13806500
Gnrs _||_ NgtA | Crrp, Frdm, GDP                               -0.040793989   0.04787017
Gnrs _||_ SclS | Crrp, Frdm, GDP                                0.010314179   0.09871603
Hlth _||_ PstA | Frdm, Gnrs, NgtA, SclS                        -0.174479047  -0.08730281
Hlth _||_ PstA | Crrp, Frdm, GDP, NgtA, SclS                   -0.063924861   0.02475175
LfLd _||_ NgtA | Crrp, Frdm, GDP, Hlth, PstA, SclS             -0.042195968   0.04653701
```

Listing 2: Tests of conditional independence for the final causal structure

C Fitted coefficients of causal structure

```
 Bayesian network parameters

  Parameters of node Corruption (Gaussian distribution)

Conditional density: Corruption
Coefficients:
 (Intercept)
1.637994e-16
Standard deviation of the residuals: 1

  Parameters of node Freedom (Gaussian distribution)

Conditional density: Freedom | Corruption + Health + SocialSupport
Coefficients:
  (Intercept)     Corruption         Health   SocialSupport
-1.700849e-17   -3.950653e-01    8.954434e-02    2.599741e-01
Standard deviation of the residuals: 0.8207477
```

```
  Parameters of node GDP (Gaussian distribution)

Conditional density: GDP | Corruption
Coefficients:
  (Intercept)     Corruption
 4.485708e-16  -3.498796e-01
Standard deviation of the residuals: 0.9370341

  Parameters of node Generosity (Gaussian distribution)

Conditional density: Generosity | Corruption + Freedom
Coefficients:
  (Intercept)     Corruption        Freedom
 3.195474e-17  -1.665048e-01   2.392339e-01
Standard deviation of the residuals: 0.9368232

  Parameters of node Health (Gaussian distribution)

Conditional density: Health | Corruption + GDP + SocialSupport
Coefficients:
  (Intercept)     Corruption            GDP  SocialSupport
-3.726951e-18  -1.658898e-02   7.942063e-01   4.470104e-02
Standard deviation of the residuals: 0.5553833

  Parameters of node LifeLadder (Gaussian distribution)

Conditional density: LifeLadder | Corruption + Freedom + GDP + Health +
       PositiveAffect + SocialSupport
Coefficients:
   (Intercept)     Corruption        Freedom            GDP         Health
 -6.127135e-16  -1.237647e-01   5.494385e-02   3.927728e-01   1.715309e-01
PositiveAffect  SocialSupport
  2.283762e-01   1.970655e-01
Standard deviation of the residuals: 0.4720566

  Parameters of node NegativeAffect (Gaussian distribution)

Conditional density: NegativeAffect | Corruption + Freedom + Health + SocialSupport
Coefficients:
  (Intercept)     Corruption        Freedom         Health  SocialSupport
-2.138571e-16   2.136356e-01  -4.827751e-02   2.746516e-01  -5.491578e-01
Standard deviation of the residuals: 0.8481268

  Parameters of node PositiveAffect (Gaussian distribution)

Conditional density: PositiveAffect | Freedom + Generosity + SocialSupport
Coefficients:
  (Intercept)        Freedom     Generosity  SocialSupport
```

```
 2.314690e-16   4.326916e-01   1.665747e-01   2.516566e-01
Standard deviation of the residuals: 0.7641265

  Parameters of node SocialSupport (Gaussian distribution)

Conditional density: SocialSupport | Corruption + GDP
Coefficients:
  (Intercept)     Corruption            GDP
-3.493436e-16   2.137981e-02   7.036751e-01
Standard deviation of the residuals: 0.7179405
```

Listing 3: Coefficients of the causal structure as fitted by bn.fit

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