

# Research lab assignment 2

17 may 2020

## Group 9

11996277 Songhee Kim

12317594 Mai Phan

11968850 Jinhyun Kim

12014621 Rajeev Pandit

11996161 Dayeon Park

### QUESTION 1:

a)

The main research question is: Is the information content of earnings announcements (abnormal return volatility and abnormal trading volume) increased more in countries following mandatory IFRS adoption than non-IFRS adopting countries?

b)

One of the important goals of IFRS is usefulness of financial reporting, which can be operationalized by changes in price or volume. And these changes can be shown by the actions of investors-abnormal trade volume, abnormal returns- by reacting to the financial information. Surprisingly, no studies have researched the changes in the information content associated with the adoption of IFRS until recent. Thus, this study can give evidence of the effects of adopting IFRS from answering the above question.

c)

Following IFRS and Information content of earnings announcements

d)

X: Adoption of IFRS

Y: Information content of earnings announcements

e)

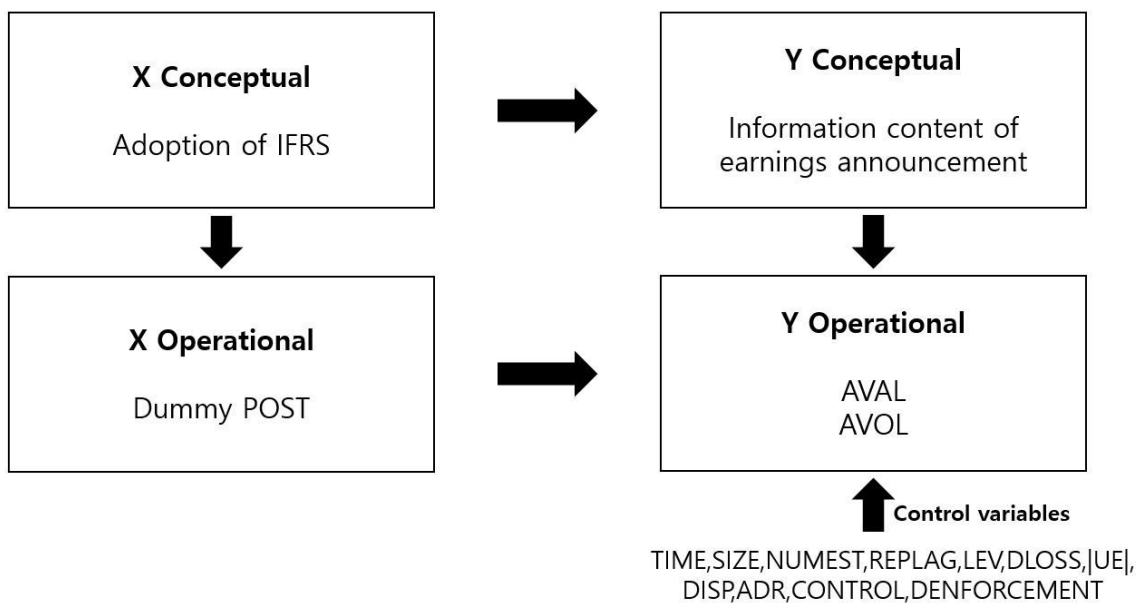
- Adoption of IFRS is measured by the dummy variable POST for country-level comparison. POST equals 0 to indicate an observation before the adoption of IFRS and equals 1 to indicate

an observation after the adoption year. Thus, it can compare periods when the country did not adopt IFRS and when they follow IFRS.

- Information content of earnings announcements is measured by abnormal return volatility and abnormal trading volume which is proxied by the variables of AVAL and AVOL respectively. First, daily market model-adjusted return(u) is calculated for the volatility. AVAL is based on the natural log of the mean of  $u$  divided by the variance of firm  $i$ 's market model residuals when there is no event. AVOL is measured by the natural log of the mean of the volume when the event occurs divided by the average estimation-period volume.

$$AVAR_i = \ln \left( \frac{\overline{u_{it}^2}}{\sigma_i^2} \right) \quad AVOL_{it} = \ln \left( \frac{\overline{V_{it}}}{V_i} \right)$$

- + Libby boxes for this study



## QUESTION 2: PANEL DATA – EFFECTS OF CHANGES IN REGULATION

a)

```
. tab country if regulation==1
```

country	Freq.	Percent	Cum.
Finland	<b>1,317</b>	<b>13.82</b>	<b>13.82</b>
France	<b>5,408</b>	<b>56.76</b>	<b>70.58</b>
Poland	<b>2,803</b>	<b>29.42</b>	<b>100.00</b>
Total	<b>9,528</b>	<b>100.00</b>	

b)

```
. reg profit regulation, robust cluster(companysizegroup)
```

Linear regression	Number of obs	=	<b>31,004</b>
	F(1, 4)	=	<b>23.85</b>
	Prob > F	=	<b>0.0081</b>
	R-squared	=	<b>0.0131</b>
	Root MSE	=	<b>.05122</b>

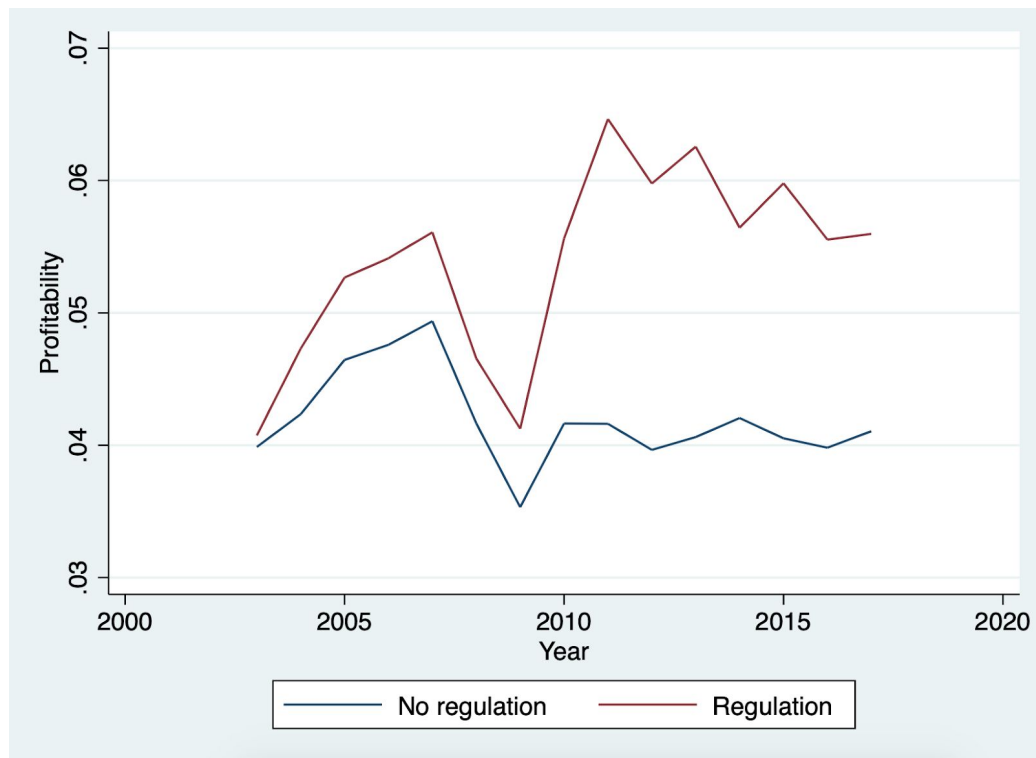
(Std. Err. adjusted for 5 clusters in companysizegroup)

profit	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
regulation	<b>.0128136</b>	<b>.0026235</b>	<b>4.88</b>	<b>0.008</b>	<b>.0055295</b>	<b>.0200976</b>
_cons	<b>.0419818</b>	<b>.0053342</b>	<b>7.87</b>	<b>0.001</b>	<b>.0271719</b>	<b>.0567918</b>

No, this regression does not allow us to analyse hypothesis 1 because it does not take into account timevalue (pre- or post-regulation). This regression regresses as if the regulated companies have been regulated for all the years that we have data for, however, we need to compare the difference in the profitabilities of the regulated and non-regulated companies *pre-regulation* to the difference between the two *post-regulation* (after 2010).

c)

Graph 2C: Average profitability of non-regulated and regulated companies over time



It can be observed from the graph that from the year 2010, the year of hypothetical implementation of regulation, the gap between the profitability of companies with and without regulation has increased dramatically. Whereas before 2010, the difference between the two groups was around 0.005 at its largest. We can see that around 2011 the average profitability of companies with regulation was about 0.020 higher than those without.

From this we can infer that hypothesis 1, that states Regulation Random did not change the profitability of companies, would be rejected.

d)

	Pre	Post	Difference
Regulation=1	0.0486152	0.0587295	0.0101143
Regulation=0	0.0434769	0.0408727	-0.0026042
Difference	0.0051383	0.0178568	0.0127185

The positive difference-in-difference, as seen by 0.0127185, tells us that the regulation had a positive effect on the average profitability of the treated companies.

e)

```
. reg profit regulation post int_post_regul, robust cluster(compansiz~p)
```

```
Linear regression               Number of obs   =    31,004
                                F(3, 4)         =    173.40
                                Prob > F           =    0.0001
                                R-squared          =    0.0164
                                Root MSE       =    .05114
```

(Std. Err. adjusted for 5 clusters in companysizegroup)

profit	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
regulation	.0051383	.0031263	1.64	0.176	-.0035417	.0138183
post	-.0026042	.0025582	-1.02	0.366	-.009707	.0044986
int_post_regul	.0127185	.0009781	13.00	0.000	.0100028	.0154342
_cons	.0434769	.0044551	9.76	0.001	.0311076	.0558462

It can be seen that int\_post\_regulation is significant with the p-value of 0.000. We can consider that there would be a positive outcome from implementing the new regulation. It is expected that the regulation implementation would increase the profitability by 1.2785 percentage point on average. Thus, we reject Hypothesis 1.

HYPOTHESIS 1 (null): Regulation Random did not change the profitability of companies

f)

The name of the test is difference in difference test. DID or DD is one type of statistical technique for areas such as econometrics or quantitative research. This test is done through comparing the average outcome difference in the treatment group with the difference in the control group within a selected time period. This DID model uses panel data which make it different with time-series estimate or cross-section estimate. Time -series estimate simply analyzes overtime difference, and cross-section estimate measures only treatment effect differences between treatment group and control group.

g)

The difference-in-difference model has an advantage in estimating the regulation effect without any intervention of other factors such as political situation, economical level, and population density. It is very likely that the profit rate will change without the treatment factors. It is highly possible that simply focusing on the difference after implementation would under- or overestimate the regulation effect. Additionally, it is probable that the regulation effect can be changed with the way of selecting groups. For example, if control groups consist of companies with high profitability rates, it is possible that the regulation effect would be undervalued. This potential overestimation or underestimation problem can be solved through dividing and comparing the treatment group with the control group within a selected time period. Concisely, this method can reduce the effect of extraneous factors and selection bias.

### QUESTION 3:

a)

Hypothesis 2 (null): Accounting information contains information that is not relevant for the stock market valuation of companies.

Hypothesis 2 (alternative): Accounting information contains information that is relevant for the stock market valuation of companies.

```
. reg bhar01 surprise, robust cluster(compustatcode)
```

```
Linear regression               Number of obs   =   219,847
                                F(1, 8036)       =    30.92
                                Prob > F          =    0.0000
                                R-squared          =    0.0053
                                Root MSE       =    .07829
```

(Std. Err. adjusted for 8,037 clusters in compustatcode)

bhar01	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
surprise	.1232517	.0221648	5.56	0.000	.0798029	.1667005
_cons	-.000016	.0001893	-0.08	0.932	-.000387	.000355

According to the regression above, we can reject the null hypothesis and accept the (alternative) hypothesis 2 since there is a significant positive relationship between *surprise* (the news in the earnings announcement) and *bhar01* (stock returns) around the announcement. The p-value of the surprise variable is 0.000 which is less than a significance level of 0.01. It can be seen that the stock return variable *bahr01* would increase by 0.1232517 when the surprise variable increases by 1.

b)

HYPOTHESIS 3 (alternative): Accounting information is less relevant for stock market valuations when companies do not have a Big 4 auditor.

```
. reg bhar01 surprise big4auditor surprise_big4auditor , robust cluster(compustatcode)
```

```
Linear regression              Number of obs   =    219,847
                              F(3, 8036)        =     26.97
                              Prob > F          =     0.0000
                              R-squared         =     0.0056
                              Root MSE      =     .07828
```

(Std. Err. adjusted for 8,037 clusters in compustatcode)

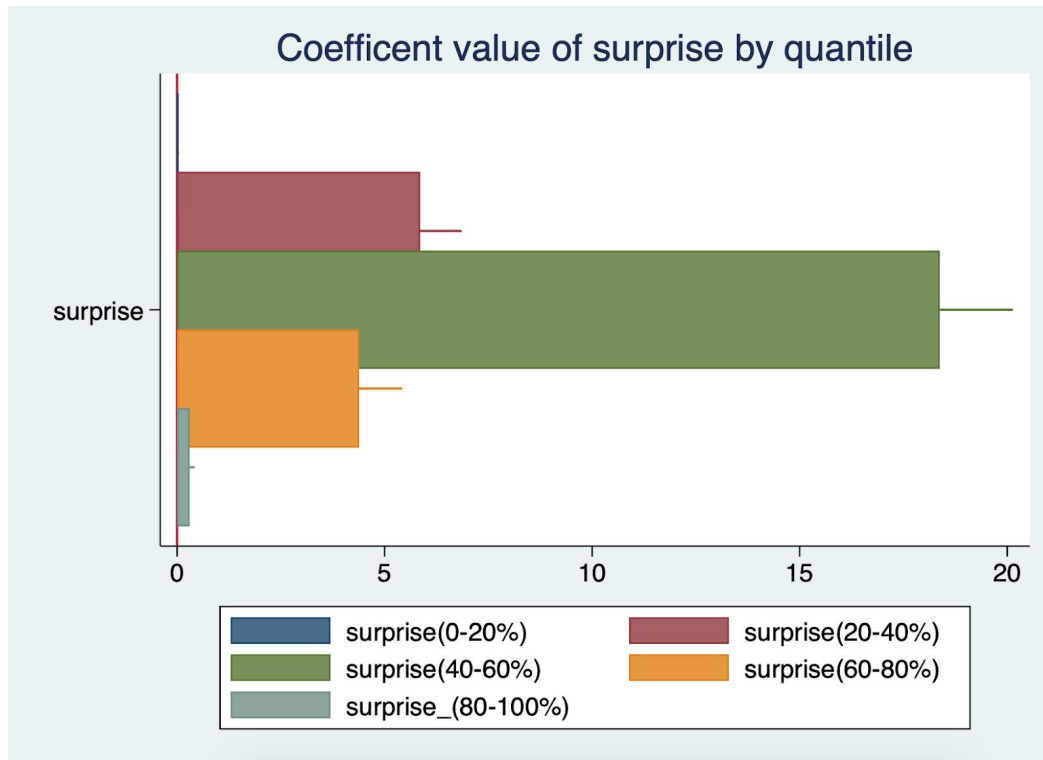
bhar01	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
surprise	.1361221	.0303698	4.48	0.000	.0765894	.1956548
big4auditor	.0029148	.00054	5.40	0.000	.0018562	.0039734
surprise_big4auditor	-.0177704	.040534	-0.44	0.661	-.0972276	.0616868
_cons	-.0024504	.0005025	-4.88	0.000	-.0034354	-.0014654

The interaction term surprise\_big4auditor tests the effect of surprise on the stock returns when there is a Big 4 auditor. The result shows that the interaction term is not significant with the p-value of 0.661, given an alpha of 0.05. This means that the effect of surprise does not depend on whether or not the company's financial statements were audited by a Big 4 firm. Thus, we have failed to reject the null hypothesis and do not accept (the alternative) hypothesis 3.



c)

Graph 3c: Coefficient value of surprise by quantile



The differences in coefficients depict the magnitude of stock market reactions. The surprise coefficient in the first quintile was 0.0226699 which meant that the stock returns had barely changed. This coefficient then increased to 8.393113 in the second quintile (20-40%) and to 22.80094 in the third quintile (40-60%). This pattern suggests that when the difference between the actual and expected EPS was close to zero, the subsequent impact on the stock return was higher and vice versa. This can be reiterated in the observations above the third quintile as the surprise coefficient decreased from 22.80094 to 7.432923 in the fourth quintile (60-80%), decreasing further to 0.47768716 in the last quintile (80-100%).

Therefore, it can be inferred that news of a greater difference between the actual and expected EPS will portray the shares of the company as volatile and less appealing, thereby inducing a lower stock market reaction. Consequently, resulting in a smaller surprise coefficient, as seen in the first and last quintiles. News of more stable earnings, as depicted by the observations in the third quintile, on the other hand would result in a bigger stock market reaction as the shares of such companies will be seen as more valuable.

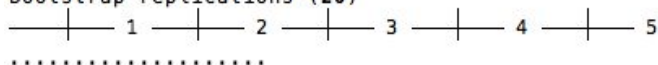
```
.
. tabstat surprise, stat(n mean min max sd p50) by (Surprise_5)
```

Summary for variables: surprise  
by categories of: Surprise\_5 (5 quantiles of surprise )

Surprise_5	N	mean	min	max	sd	p50
1	43970	-.0213614	-6.66009	-.0020182	.1011674	-.0064439
2	43969	-.0006611	-.0020181	.0000313	.0005925	-.0005142
3	43970	.0004571	.0000313	.0009408	.0002549	.00044
4	43969	.0017752	.0009409	.0029907	.0005787	.0016824
5	43969	.0091005	.0029909	.05	.0078652	.0061133
Total	219847	-.002138	-6.66009	.05	.0465134	.00044

```
.
. sqreg bhar01 surprise if Surprise_5==1
(fitting base model)
```

Bootstrap replications (20)



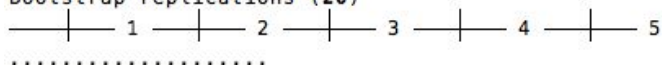
Simultaneous quantile regression  
bootstrap(20) SEs

Number of obs = 43,970  
.50 Pseudo R2 = 0.0003

bhar01	Coef.	Bootstrap Std. Err.	t	P> t	[95% Conf. Interval]	
<b>q50</b>						
surprise	.0261267	.0081618	3.20	0.001	.0101293	.0421241
_cons	-.025045	.0002957	-84.69	0.000	-.0256246	-.0244653

```
.
. sqreg bhar01 surprise if Surprise_5==2
(fitting base model)
```

Bootstrap replications (20)



Simultaneous quantile regression  
bootstrap(20) SEs

Number of obs = 43,969  
.50 Pseudo R2 = 0.0023

bhar01	Coef.	Bootstrap Std. Err.	t	P> t	[95% Conf. Interval]	
<b>q50</b>						
surprise	5.8537	.3426939	17.08	0.000	5.182013	6.525386
_cons	-.0088446	.0003556	-24.87	0.000	-.0095417	-.0081476

```
. sqreg bhar01 surprise if Surprise_5==3
(fitting base model)
```

```
Bootstrap replications (20)
```

```
-----|----- 1 -----|----- 2 -----|----- 3 -----|----- 4 -----|----- 5
.....
```

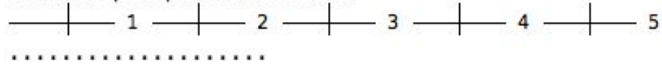
```
Simultaneous quantile regression
bootstrap(20) SEs
```

```
Number of obs =    43,970
.50 Pseudo R2 =    0.0046
```

bhar01	Coef.	Bootstrap Std. Err.	t	P> t	[95% Conf. Interval]	
<b>q50</b>						
surprise	18.37203	1.053289	17.44	0.000	16.30757	20.4365
_cons	-.0062082	.0004198	-14.79	0.000	-.0070311	-.0053853

```
. sqreg bhar01 surprise if Surprise_5==4
(fitting base model)
```

Bootstrap replications (20)



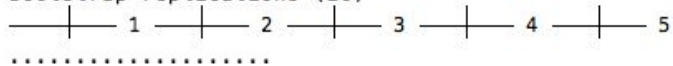
Simultaneous quantile regression  
bootstrap(20) SEs

Number of obs = 43,969  
.50 Pseudo R2 = 0.0010

bhar01	Bootstrap		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
q50						
surprise	4.383773	.574917	7.63	0.000	3.256926	5.510621
_cons	.0063603	.0010792	5.89	0.000	.004245	.0084755

```
. sqreg bhar01 surprise if Surprise_5==5
(fitting base model)
```

Bootstrap replications (20)



Simultaneous quantile regression  
bootstrap(20) SEs

Number of obs = 43,969  
.50 Pseudo R2 = 0.0005

bhar01	Bootstrap		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
q50						
surprise	.3011218	.064635	4.66	0.000	.1744361	.4278076
_cons	.0215543	.0005113	42.16	0.000	.0205522	.0225564