Digital Economics PS1

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Part 1

Question 1

I define `coauthorship` as `TRUE` if $allcoauths > 0$. When both institutions have access to Bitnet, they have a higher probability of coauthorship — however, the probability of coauthorship is always low, only around 0.223% on average.

Table 1: Q1 Model

	Dependent variable:
	Coauthorship
l_distance	-0.00104^{***}
	(0.00028)
both_have_bitnet	0.00215^{***}
	(0.00063)
totsoloauths	0.00001^{***}
	(0.000004)
Observations	36,315
R^2	0.01269
Adjusted R^2	0.00527
Residual Std. Error	0.04705 (df = 36043)
Note:	*p<0.1; **p<0.05; ***p<0.01

Here, $R^2 \approx 0.013$ for the full model. Choosing a 5% significant level, all coefficients are statistically significant. These results indicate that, on average, those universities which are 1% farther apart have a 0.001% lower probability to have a coauthored publication in the given year. In other words, universities which are 2x farther apart have a 10% lower probability of coauthorship.

We are not really able here to identify any causal effect of Bitnet access; all we know is that university pairs that have Bitnet are more likely to have coauthored papers — this could, for example, mean that universities that coauthor more papers with one another are more likely to justify the purchase of Bitnet.

Question 1A

Let's look at the probability of coauthorship as a function of $\log(distance)$ by running a logistic regression of `coauthorship` on the same variables as before and checking the predicted probabilities:

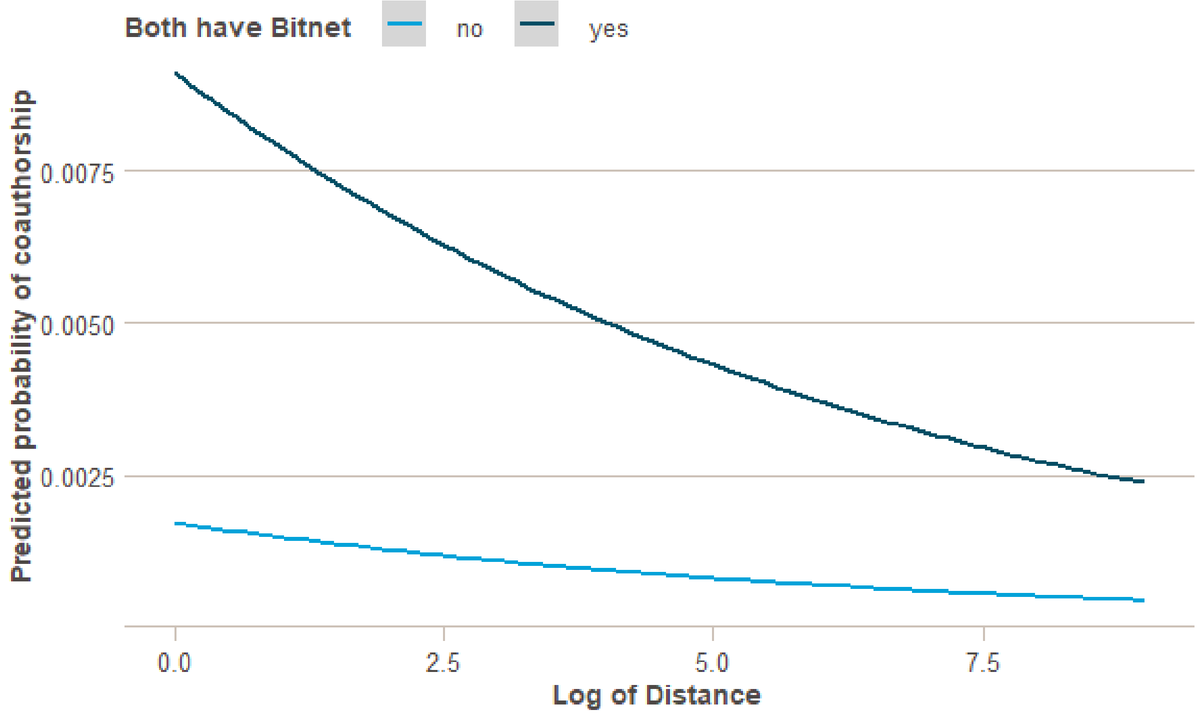

Figure 1: Probability of Coauthorship vs Log of Distance

Question 2

The above model is not the same as considering the probability of researcher i choosing to coauthor with researcher j; it is simply the probability that institution pair i, j have at least one shared paper.

In this researcher-specific model, we need to consider that the researcher always has outside option of solo-authoring. This implies that all researchers which choose to solo-author have a utilty less than zero for coauthoring.

Value of collaboration is given by:

$$v(c) = \beta \log(d) + \alpha b + \mu_{ij} + \varepsilon_{ij}$$

An author chooses to coauthor a paper if it is more 'profitable' than the outside option of solo-authoring a paper, $v(c) \geq v(s) = 0$.

So the probability of coauthoring is given by:

$$\Pr(v(c) \geq 0) = \Pr(\beta \log(d) + \alpha b + \mu_{ij} + \varepsilon_{ij} \geq 0)$$

We can write this as:

$$\Pr(v(c) \geq 0) = \frac{\exp(\beta \log(d) + \alpha b + \mu_{ij} + \varepsilon_{ij})}{1 + \exp(\beta \log(d) + \alpha b + \mu_{ij} + \varepsilon_{ij})}$$

For this model I calculate the `fraction_coauthored` which is equal to:

$$fraction\_coauthored_{i,j} = \frac{allcoauths_{i,j}}{allcoauths_{i,j} + totsoloauths_i}$$

Question 3

The `fraction_coauthored` as shown above is the observable empirical analogue of the probability that researcher i chooses to collaborate with researcher j.

Table 2: Fraction Coauthored

	both_have_bitnet	mean	sd	max
1	0	7.92e-06	0.000463	0.040
2	1	0.00152	0.0298	0.881

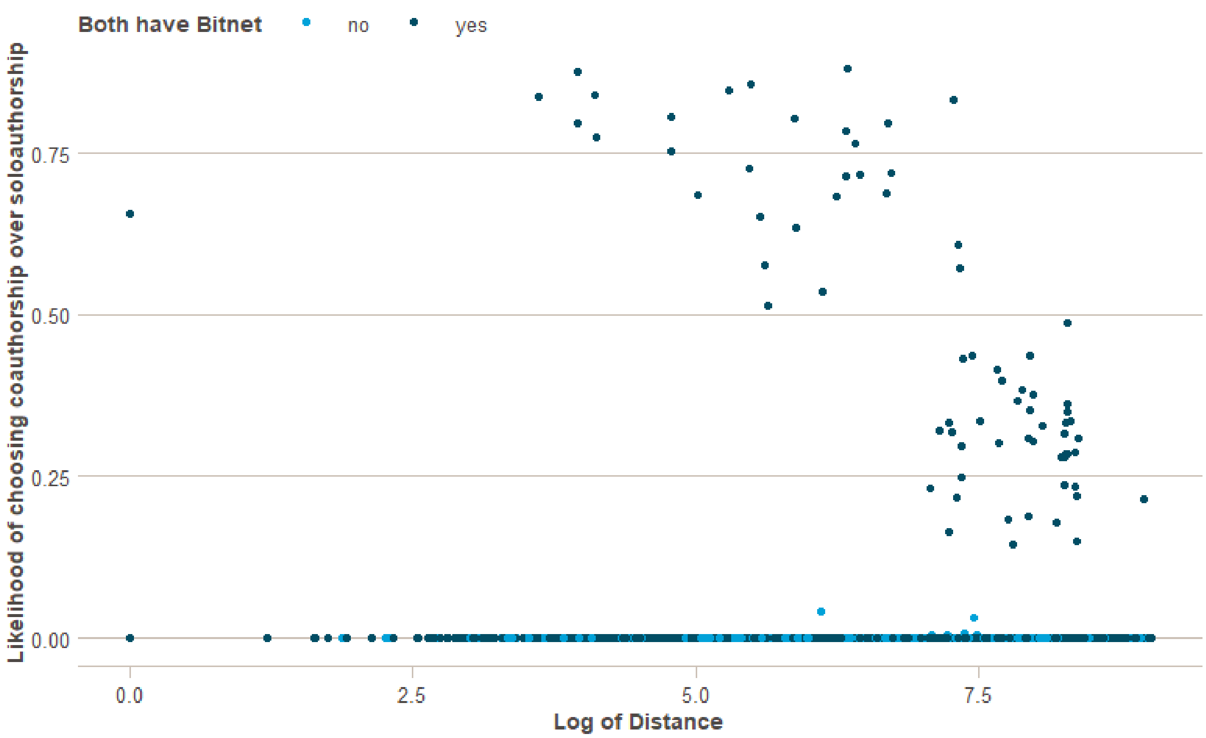

Figure 2: Fraction Coauthored vs Log of Distance

Question 4

There are a couple different ways to estimate this model with OLS. For example, we could create a dummy variable `choose_coauthorship_over_soloauthorship` which is `TRUE` when `fraction_coauthored >= 0.50`.

However, as `fraction_coauthored` is already a decent empirical analogue, it's more straightforward to use this as the dependent variable and allows us to have more variation in the likelihood of choosing coauthorship. Running the regression with `instit2` fixed effects:

```
univ_innov %>%
  felm(formula = fraction_coauthored ~ l_distance + both_have_bitnet
  + totsoloauths | instit2)
```

Alternatively, incrementing `allcoauths` and `totsoloauths` by 1, we can calculate the `log_fraction_coauthored` and run:

```
univ_innov %>%
  felm(formula = log_fraction_coauthored ~ l_distance + both_have_bitnet
  + totsoloauths | instit2)
```

Considering the second log specification, we have:

Table 3: Log Linear Model with Institution FE

	Dependent variable:
	log_fraction_coauthored
l_distance	-0.0060^{***}
	(0.0013)
both_have_bitnet	0.0152^{***}
	(0.0030)
totsoloauths	-0.0046^{***}
	(0.00002)
Observations	36,315
R^2	0.7026
Adjusted R^2	0.7004
Residual Std. Error	0.2192 (df = 36043)
Note:	*p<0.1; **p<0.05; ***p<0.01

Question 5

Part 2

Question 1

The treated group is patent classes where there exist some German-filed patents, and the control is the patent classes without German-filed patents. The treated group covers 284 out of 399 class IDs (71.2%).

We are told that "ways of mass producing indigo dyes were pioneered by German chemists in the early years of the 20th century" — maybe it is not right to assume that these groups are the same. German chemists or manufacturers could have some particular advantage in this domain that may even change over time differently than in the USA. Also, maybe the US specialized in different patent classes for a reason specific to some characteristics of the USA or of USA companies or individuals.

Question 2

The treated group and control groups look relatively similar, with 159 patents filed in the control and 204 in the treated group. Before treatment, the treated and control group are closer to being equal.

After the TWEA law was passed, patent filings in both the treatment and the control group went up. And, this increased more in the treated group than in the control.

The number of German-filed patents also went up after the passing of the TWEA. This may be because all patents filed pre-1919 were now invalid in the US; we would expect German firms then to re-file different, updated patents post-1919 (when the war ended, and after which the TWEA would not apply to newly-filed patents).

Table 4: Ten Year Patent Filings, US and DE

	TWEA Passed	Treated Group	Mean US	SD US	Count US	Mean DE	SD DE	Count DE
1	0	0	0.029	0.169	29	0	0	0
2	0	1	0.024	0.159	24	0.242	0.972	244
3	1	0	0.33	0.578	130	0	0	0
4	1	1	0.446	1.483	180	0.535	0.927	216

Question 3

Table 5: Linear Model (no FE)

	Dependent variable:
	Ten Year Count USA
twea_passed	0.301***
	(0.037)
treated_group	−0.006
	(0.028)
did	0.121**
	(0.052)
Constant	0.029
	(0.020)
Observations	2,793
R^2	0.067
Adjusted R^2	0.066
Residual Std. Error	0.620 (df = 2789)
F Statistic	67.164*** (df = 3; 2789)
Note:	*p<0.1; **p<0.05; ***p<0.01

In Table 4, we find that the coefficient of treated group is not different from zero, but that that of the treatment time (passing of TWEA), is positive and significant. This could just mean that over that period, patent filings in the US were on the rise. The DiD coefficient gives us more insight, indicating that over that same treatment period, patent filings increased more for treated firms compared to control. This is precisely the number we get by calculating it from Table 3: $0.446 - 0.330 - (0.024 - 0.029) = 0.121$. This coefficient is significant at the 5% level.

By adding `class_id` and `ten_yr` fixed effects, the results do not change. This is expected, since `treated_group` is an indicator function of `class_id` and `twea_passed` is an indicator function of `ten_yr`; they are collinear.

Table 6: Linear Model (FE)

	Dependent variable:
	Ten Year Count USA
did	0.121**
	(0.049)
Observations	2,793
R^2	0.287
Adjusted R^2	0.166
Residual Std. Error	0.585 (df = 2387)
Note:	*p<0.1; **p<0.05; ***p<0.01

Question 4

This data and these results imply nothing about the effects of removing copyrights, as these are industrial or technical patents and not copyrights.

These results seem to suggest that more patents were filed in the US post-1919, when the TWEA lost effect on newly-filed German patents but remained in effect on patents filed pre-1919. More importantly, the results suggest that this increase in patent filings was higher for treated class IDs than for control IDs – in patent classes were there were German-filed patents, the number of US-filed patents increased more over the same period of time.

On average, for treated class IDs, 0.121 more patents were filed in the USA post-TWEA than were filed in the USA pre-TWEA. There is no evidence that the two groups were statistically different before the law was introduced.

Question 5

From Table 4, I find the effects for the 1920-1930 period are lower than for the 1930-1940 period:

$$\hat{Z} = \frac{\hat{\beta}_{1920,y} - \hat{\beta}_{1930,y}}{\sqrt{SE(\hat{\beta}^2_{1920,y}) + SE(\hat{\beta}^2_{1930,y})}} = -4.99$$

where $\hat{\beta}_{year,y}$ indicates the coefficient for treated ($y = yes$) groups in $year$.

The strongest effects take place in 1930; this is when there is the greatest increase in US-filed patents among both treated and non-treated groups, and with the largest difference for treated groups.

Question 6

From the "placebo" DiD regressions in Tables 5 and 6, the DiD coefficient is not different from zero. In Table 5, I regress `Ten Year Count USA` using the presence of French-filed patents in a subclass as the treated group instead of German-filed patent presence.

In Table 6, I show the coefficients from regressing `Ten Year Count FR` on the same treated group (German-filed patent presence in a subclass) as done initially. From their coefficients and standard errors, both estimates are neither economically nor statistically different from zero.

Table 7: Treatment Effects by Year

	Dependent variable:
	Ten Year Count USA
treated_group	
ten_yr1880	0.030
	(0.059)
ten_yr1890	−0.000
	(0.059)
ten_yr1900	0.005
	(0.059)
ten_yr1910	0.036
	(0.059)
ten_yr1920	0.107*
	(0.059)
ten_yr1930	0.523***
	(0.059)
treated_group:ten_yr1880	−0.021
	(0.083)
treated_group:ten_yr1890	−0.010
	(0.083)
treated_group:ten_yr1900	−0.0001
	(0.083)
treated_group:ten_yr1910	−0.021
	(0.083)
treated_group:ten_yr1920	0.027
	(0.083)
treated_group:ten_yr1930	0.195**
	(0.083)
Observations	2,793
R^2	0.289
Adjusted R^2	0.166
Residual Std. Error	0.585 (df = 2382)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8: Placebo DiD 1

	Dependent variable:
	Ten Year Count USA
french_presence	0.004
	(0.043)
twea_passed	0.350***
	(0.028)
placebo_did_french	0.099
	(0.081)
Constant	0.026*
	(0.015)
Observations	2,793
R^2	0.066
Adjusted R^2	0.065
Residual Std. Error	0.620 (df = 2789)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9: Placebo DiD 2

	Dependent variable:
	Ten Year Count FR
treated_group	0.022***
	(0.007)
twea_passed	−0.002
	(0.010)
did	−0.015
	(0.014)
Constant	0.012**
	(0.005)
Observations	2,793
R^2	0.004
Adjusted R^2	0.003
Residual Std. Error	0.166 (df = 2789)
Note:	*p<0.1; **p<0.05; ***p<0.01

Question 7

These results are probably not generalizable to patents more broadly. This forfeiture of patent rights was an unanticipated "random" event that happened in wartime. It is because of this pseudo-randomness and transience that we can extrapolate from it; but if countries were routinely ignoring each other's patent laws, then the effects would likely decay.

The results are probably more likely to generalize to older patents, those in certain sectors (biomedicine, manufacturing processes, STEM fields, and so on) than to more recent developments. It would make sense that opening up process-based patents would be more beneficial than some other more esoteric patents; with it, any firm could use (and improve upon) an existing patent, which could lead to more patents through some spillover effects.

For more cutting-edge patents (for example, MRNA vaccine production), opening up patents wouldn't be as beneficial — at least in the short term — since few companies in the world could replicate the technical process even if they had the legal rights to do so.