Reading Results Tables

GHM (2010): Tables

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Outline for Today

1. **General layout of statistical results tables**
2. **Coefficients and standard errors – what they mean**
3. **Constructing confidence intervals: 90%, 95%, and 99%**
4. **Hypothesis testing: 10%, 5%, and 1% levels**
5. **What do the *s beside the estimates mean?**

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This Week

- Don't forget about the Difference-in-differences quiz

General layout of statistical results tables

- Top numbers are the estimates.
    - Usually these are coefficient estimates from a regression, but sometimes they are just means or differences in means.
    - These tell you the estimated effect, difference, etc.
    - These tell you the magnitude of the effect or difference – was it small or large? Negative or positive?

TABLE 4
INCUMBENT PLANT PRODUCTIVITY, RELATIVE TO THE YEAR OF AN MDP OPENING

Event Year	In Winning Counties (1)	In Losing Counties (2)	Difference Col. 1 − Col. 2 (3)
$\tau = -7$	.067	.040	.027
	(.058)	(.053)	(.032)
$\tau = -6$	.047	.028	.018
	(.044)	(.046)	(.023)
$\tau = -5$	.041	.021	.020
	(.036)	(.040)	(.025)
$\tau = -4$	−.003	.012	−.015
	(.030)	(.030)	(.024)
$\tau = -3$	.011	−.013	.024
	(.022)	(.022)	(.021)
$\tau = -2$	−.003	.001	−.005
	(.027)	(.011)	(.028)
$\tau = -1$	0	0	0
$\tau = 0$	.013	−.010	.023
	(.018)	(.011)	(.019)
$\tau = 1$	.023	−.028	.051**
	(.026)	(.024)	(.023)
$\tau = 2$	.004	−.046	.050
	(.036)	(.046)	(.033)
$\tau = 3$	.003	−.073	.076*
	(.047)	(.057)	(.043)
$\tau = 4$	.004	−.072	.076**
	(.053)	(.062)	(.033)
$\tau = 5$	−.023	−.100	.077**
	(.069)	(.067)	(.035)
R^2	.9861		
Observations	28,732		

NOTE.—Standard errors are clustered at the county level. Columns 1 and 2 report coefficients from the same regression: the natural log of output is regressed on the natural log of inputs (all worker hours, building capital, machinery capital, materials), year by two-digit SIC fixed effects, plant fixed effects, case fixed effects, and the reported dummy variables for whether the plant is in a winning or losing county in each year relative to the MDP opening. When a plant is a winner or loser more than once, it receives a dummy variable for each incident. Plant-year observations are weighted by the plant's total value of shipments 8 years prior to the MDP opening. Data on plants in all cases are available only 8 years prior to the MDP opening and 5 years after. Capital stocks were calculated using the permanent inventory method from early book values and subsequent investment. The sample of incumbent plants is the same as in cols. 1 and 2 of table 3.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

General layout of statistical results tables

- Under each estimate, in (), is the standard error (SE) of the estimate.
  - The SE tells us how precise the estimate is. How sure are we of this estimate?
  - Larger SE = less precise estimate, the estimate has a larger margin of error.
  - A confidence interval for this estimate would be wider (as we shall see).

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* Significant at the 10 percent level.
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More tables

- I will explain more about all these tables later, but for not just notice the typical format: estimate with standard errors underneath it. Also notice the use of *s, which I will explain shortly. These indicate how statistically significant an estimate is.

TABLE 6

CHANGES IN INCUMBENT PLANT OUTPUT AND INPUTS FOLLOWING AN MDP OPENING

	Output (1)	Worker Hours (2)	Machinery Capital (3)	Building Capital (4)	Materials (5)
Model 1: mean shift	.1200***	.0789**	.0401	.1327*	.0911***
	(.0354)	(.0357)	(.0348)	(.0691)	(.0302)
Model 2: after 5 years	.0826*	.0562	−.0089	−.0077	.0509
	(.0478)	(.0469)	(.0300)	(.0375)	(.0541)

NOTE.—The table reports results from fitting versions of eq. (8) for each of the indicated outcome variables (in logs). See the text for more details. Standard errors clustered at the county level are reported in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

TABLE 5

CHANGES IN INCUMBENT PLANT PRODUCTIVITY FOLLOWING AN MDP OPENING

	ALL COUNTIES: MDP WINNERS − MDP LOSERS		MDP COUNTIES: MDP WINNERS − MDP LOSERS		ALL COUNTIES: RANDOM WINNERS
	(1)	(2)	(3)	(4)	(5)
			A. Model 1		
Mean shift	.0442*	.0435*	.0524**	.0477**	− 0.0496***
	(.0233)	(.0235)	(.0225)	(.0231)	(.0174)
				[$170 m]	
R^2	.9811	.9812	.9812	.9860	~0.98
Observations (plant by year)	418,064	418,064	50,842	28,732	~400,000
			B. Model 2		
Effect after 5 years	.1301**	.1324**	.1355***	.1203**	−.0296
	(.0533)	(.0529)	(.0477)	(.0517)	(.0434)
				[$429 m]	
Level change	.0277	.0251	.0255	.0290	.0073
	(.0241)	(.0221)	(.0186)	(.0210)	(.0223)
Trend break	.0171*	.0179**	.0183**	.0152*	− 0.0062
	(.0091)	(.0088)	(.0078)	(.0079)	(.0063)
Pre-trend	−.0057	−.0058	−.0048	−.0044	−.0048
	(.0046)	(.0046)	(.0046)	(.0044)	(.0040)
R^2	.9811	.9812	.9813	.9861	~.98
Observations (plant by year)	418,064	418,064	50,842	28,732	~400,000
Plant and industry by year fixed effects	Yes	Yes	Yes	Yes	Yes
Case fixed effects	No	Yes	Yes	Yes	NA
Years included	All	All	All	$-7 \leq \tau \leq 5$	All

NOTE.—The table reports results from fitting several versions of eq. (8). Specifically, entries are from a regression of the natural log of output on the natural log of inputs, year by two-digit SIC fixed effects, plant fixed effects, and case fixed effects. In model 1, two additional dummy variables are included for whether the plant is in a winning county 7 to 1 years before the MDP opening or 0 to 5 years after. The reported mean shift indicates the difference in these two coefficients, i.e., the average change in TFP following the opening. In model 2, the same two dummy variables are included along with pre- and post-trend variables. The shift in level and trend are reported, along with the pre-trend and the total effect evaluated after 5 years. In cols. 1, 2, and 5, the sample is composed of all manufacturing plants in the ASM that report data for 14 consecutive years, excluding all plants owned by the MDP firm. In these models, additional control variables are included for the event years outside the range from $\tau = -7$ through $\tau = 5$ (i.e., −20 to −8 and 6 to 17). Column 2 adds the case fixed effects that equal one during the period that τ ranges from −7 through 5. In cols. 3 and 4, the sample is restricted to include only plants in counties that won or lost an MDP. This forces the industry by year fixed effects to be estimated solely from plants in these counties. For col. 4, the sample is restricted further to include only plant by year observations within the period of interest (where τ ranges from −7 to 5). This forces the industry by year fixed effects to be estimated solely on plant by year observations that identify the parameters of interest. In col. 5, a set of 47 plant openings in the entire country were randomly chosen from the ASM in the same years and industries as the MDP openings (this procedure was run 1,000 times, and reported are the means and standard deviations of those estimates). For all regressions, plant by year observations are weighted by the plant's total value of shipments 8 years prior to the opening. Plants not in a winning or losing county are weighted by their total value of shipments in that year. All plants from two uncommon two-digit SIC values were excluded so that estimated clustered variance-covariance matrices would always be positive definite. In brackets is the value in 2006 U.S. dollars from the estimated increase in productivity: the percentage increase is multiplied by the total value of output for the affected incumbent plants in the winning counties. Reported in parentheses are standard errors clustered at the county level.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Coefficients and standard errors – what they mean

- Estimate (top number) tell us the effect that was estimated and what the magnitude of the effect was.
- The standard error tells us how precise that estimate is (how much margin of error does it have?)
- Here are some examples of coefficients that may make this easier to understand for those of you who haven't taken econometrics or any statistics courses that use regression.

Coefficients and standard errors – what they mean

- Suppose I estimated the mean (average) productivity of firms in county A and in county B. These are hypothetical numbers.
  - County A = 100, with a standard error of 10.
  - County B = 90, with a standard error of 12.
  - The difference (A – B) is 10, and suppose it has a standard error of 15.
  - Let’s focus on this estimate of 10, with a standard error of 15.
- The estimate of 10 tells us that county A’s productivity is estimated to be 10 higher than county B’s productivity, on average.
- The standard error is 15, which is fairly high.
- How do we use this standard error to tell us how precise our estimate is?
- The best way to do it is by using it to construct a confidence interval.

Constructing confidence intervals

- There are usually three confidence intervals that (social) scientists create: 90%, 95%, and 99% confidence intervals.
- The intuitive* way to understand these is:
  - The 90% (95%, 99%) confidence interval tells us that, under the assumption that our statistical model is correct, the true effect we are measuring lies within our confidence interval 90% (95%, 99%) of the time.
  - For example, suppose the 95% confidence interval of an estimate was (-0.3 to 0.1). Then we are 95% confident that the true effect, the thing we are estimating, lies between -0.3 and 0.1.
- Thus, this confidence intervals tell us how sure we are of our estimates, since it's impossible to be sure what they are exactly, given randomness and noise in the data.[1]

* For those with more theoretical stats training, you'll know that this intuitive explanation isn't technically correct, but I am not looking to explain to beginners the difference between frequentist and Bayesian statistics or the repeated sampling nature of classical statistics.

Constructing confidence intervals

- How do we make 90%, 95%, and 99% confidence intervals?
- The general formula is:
- Lower bound: Estimate – critical value * standard error
- Upper bound: Estimate + critical value * standard error
- Where the critical value is 1.645 for a 90% interval, 1.96 for 95%, and 2.576 for 99%.
- Going back to our original example, we had an estimate of 10 and a standard error of 15
- Lower bound: 10 – critical value * 15
- Upper bound: 10 + critical value * 15
- Where the critical value is 1.645 for a 90% interval, 1.96 for 95%, and 2.576 for 99%.
- Lower bound: 10 – critical value * 15 = 10 – 1.645*15 = 10 – 24.675 = -14.675
- Upper bound: 10 + critical value * 15 = 10 + 1.645*15 = 10 + 24.675 = 34.675
- Therefore, the 90% confidence interval is (-14.675, 34.675).

Constructing confidence intervals – 90%

- Lower bound: 10 – critical value * 15 = 10 – 1.645*15 = 10 – 24.675 = -14.675
- Upper bound: 10 + critical value * 15 = 10 + 1.645*15 = 10 + 24.675 = 34.675
- Therefore, the 90% confidence interval is (-14.675, 34.675).

Constructing confidence intervals – 95%

- Lower bound: 10 – critical value * 15 = 10 – 1.96*15 = 10 – 29.4 = -19.4
- Upper bound: 10 + critical value * 15 = 10 + 1.96*15 = 10 + 29.4 = 39.4
- Therefore, the 95% confidence interval is (-19.4, 39.4).

Constructing confidence intervals – 95%

- Lower bound: 10 – critical value * 15 = 10 – 1.96*15 = 10 – 29.4 = -19.4
    - Upper bound: 10 + critical value * 15 = 10 + 1.96*15 = 10 + 29.4 = 39.4
    - Therefore, the 95% confidence interval is (-19.4, 39.4).
    - **1.96 is very close to 2**, so you can calculate an "eye-ball" confidence interval (not a technical term) by using 2:
    - Lower = 10 – 2*15 = 10 – 30 = -20
    - Upper = 10 + 2*15 = 10 + 30 = 40

Constructing confidence intervals – 99%

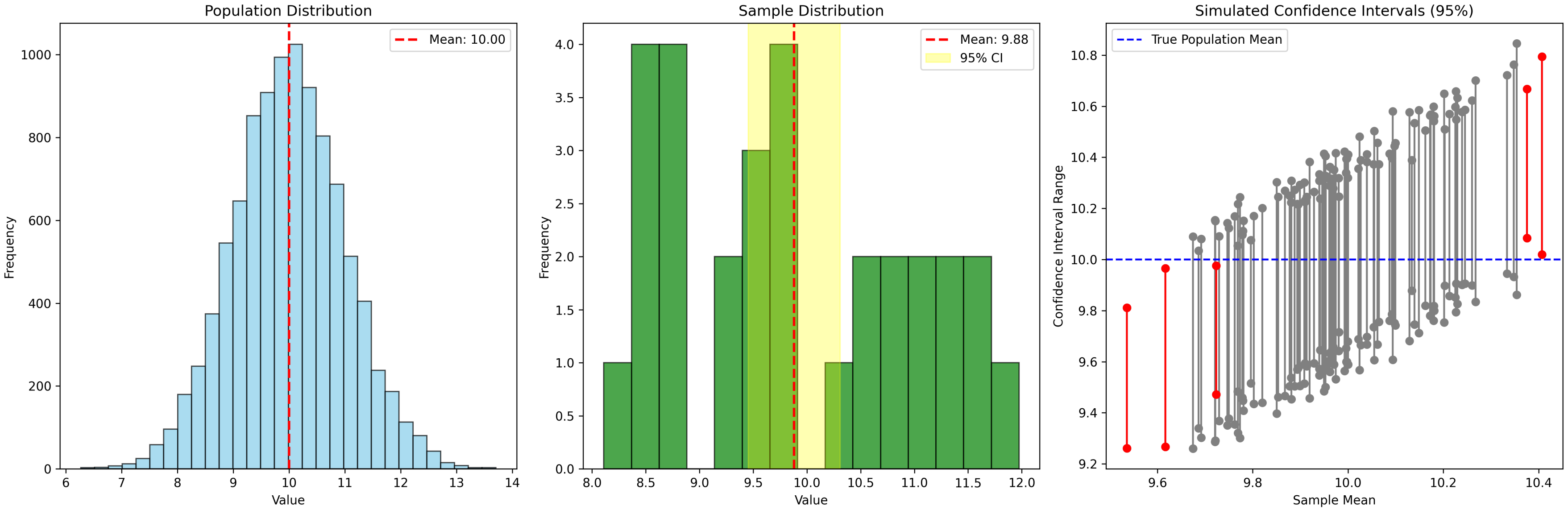
- Lower bound: 10 – critical value * 15 = 10 – 2.576*15 = 10 – 38.64 = -28.64
- Upper bound: 10 + critical value * 15 = 10 + 2.576*15 = 10 + 38.64 = 48.64
- Therefore, the 99% confidence interval is (-28.64, 48.64).

Comparing confidence intervals

- For our example of an estimate of 10, with a standard error of 15, our confidence intervals are:
- The 90% confidence interval is (-14.675, 34.675).
- The 95% confidence interval is (-19.4, 39.4).
- The 99% confidence interval is (-28.64, 48.64).
- Notice how as we move higher in confidence, the confidence interval grows.
- To be more sure that our interval contains the true value (higher % confidence), we have to increase the interval.

Confidence Intervals Examples

Example of confidence intervals



Confidence Intervals Activity

Activity break – Calculating confidence intervals

- Let's take a break from lecture to calculate some intervals.
- For this, I'm going to have you calculate "eye-ball" 95% confidence intervals, i.e. using 2 instead of 1.96 for the critical value.
- Therefore, the formula is:
  - Lower bound = estimate – 2*SE, Upper bound = estimate + 2*SE
- Remember order of operations -> multiply SE by 2 first!
- I'll give you five minutes to do the short quiz "Confidence Interval Calculation" on Canvas. I'll put you into breakout rooms so you can more easily ask each other or me (by summoning me) questions.

05:00

Hypothesis Testing

Hypothesis testing

- In addition to calculating confidence intervals, we often do hypothesis testing.
- Mostly, we test to see if our estimates are statistically significantly different from zero.
    - This is, are we reasonably sure that the true value, which we estimated, is different from zero?
- Different from zero is useful to test because if it is different from zero, then it implies that there is likely an effect or a difference.
- If an estimate is not statistically significantly different from zero, we don't have enough statistical evidence to claim that there is an effect.

Hypothesis testing: 10%, 5%, and 1% levels

- We typically test for statistical significance at the following levels:
  - 10%, which corresponds to a 90% confidence interval,
  - 5%, which corresponds to a 95% confidence interval,
  - 1%, which corresponds to a 99% confidence interval.
- The 10%, 5%, and 1% here refer to the amount of what is called “Type 1 error”, which can be interpreted as a false positive rate (finding an effect that does not exist).
  - Under 10% (5%, 1%), you will find an effect (difference from zero) that does not actually exist 10% (5%, 1%) of the time.

Balancing Type 1 and Type 2 Error

- Statistics tries to balance to types of error:
- Type 1 error -> “false positive”
  - E.g., finding an effect where there is actually no effect.
  - A positive test result when really the person is negative.
- Type 2 error -> “false negative”
  - E.g., finding no effect (not statistically different from zero) when really there is an effect.
  - A negative test result when really the person is positive.

Balancing Type 1 and Type 2 Error

Actual Result↓ | Estimated Result→	There is an effect	There is no effect
There is an effect		Type 2 Error False Negative
There is no effect	Type 1 Error False Positive	

If we decrease the level that we test at (e.g., from 5% to 1%, which would be the same as moving from a 95% confidence interval to a 99% confidence interval) then we decrease the probability of making Type 1 Errors (fewer false positives) but we increase the probability of making Type 2 Errors (more false negatives).

Hypothesis testing formula

- To do a hypothesis test, at any level (10%, 5%, 1%), to see if our estimate is statistically different from zero, we first calculate a t-statistic as follows:

$$t = \frac{\text{estimate} - 0}{\text{SE}}$$

- The formula for hypothesis testing is:
  - Test statistic = (estimate – null hypothesis value) / standard error
  - The null hypothesis value is usually zero, but it can be any value.
  - The standard error is the standard error of the estimate.

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- The formula for hypothesis testing is:
    - Test statistic = (estimate – null hypothesis value) / standard error
    - The null hypothesis value is usually zero, but it can be any value.
    - The standard error is the standard error of the estimate.
- E.g., if the coefficient is 0.2 and the standard error is 0.1, the t-statistic is 2.
- E.g., if the coefficient is -2 and the standard error is 2, the t-statistic is -1.

Hypothesis testing formula

- Once we have our t-statistic, we compare it to a critical value.
- These are the same critical values used to create confidence intervals.
- The critical values are…
  - 1.645 for a test at the 10% level of significance (90% confidence interval)
  - 1.96 for a test at the 5% level of significance (95% confidence interval)
  - 2.576 for a test at the 1% level of significance (99% confidence interval)
- If our critical value is, in **absolute value**, greater than that critical value, then it is at least significant at that level.
- $|t - statistic| \geq \text{critical value}$
  - The | | means “take the absolute value of”
  - So, if your t-statistic is negative (i.e. your estimate is negative), then just multiply it by -1 to make it positive.

Hypothesis testing Example

- 1.645 for a test at the 10% level of significance
- 1.96 for a test at the 5% level of significance
- 2.576 for a test at the 1% level of significance
  - $|t - statistic| \geq \text{critical value}$
  - Suppose our t-statistic is 2.2.
- It's greater in absolute value than 1.645 and 1.96, but not 2.576.
- Therefore it is significant at the 5% level, but not the 1% level.
  - Suppose our t-statistic is -1.7.
- It's greater in absolute value than 1.645, but not 1.96 or 2.576.
- Therefore it is significant at the 10% level, but not the 5% or 1% levels.

Hypothesis testing Example

- Instead of using 1.96 as the critical value to test at the 5% level, use 2.
- The "eye-ball" t-test at the 5% level is just dividing the coefficient by the standard error and seeing if that t-statistic is greater than 2 in absolute value.
- You can often do this just by looking at coefficient estimates with their standard errors in tables.
- E.g., 0.038 (0.017)
- I can see that that's bigger than 2.

Activity break – t-statistics and hypothesis testing

- Let's take a break from lecture to calculate some intervals.
- For this, I'm going to have you do hypothesis tests ("t-tests") using the "eye-ball" method, i.e. using 2 instead of 1.96 for the critical value.
- Therefore, the formula is:
  - $|t - statistic| \geq 2$
- I'll give you five minutes to do the short quiz "t-statistics and hypothesis testing" on Canvas. Ask each other or me questions.

What do the *s beside the estimates in tables mean?

- Usually statistical tables have notes under them that detail what *, **, ***
    - More *s means more statistically significant -> we are even more sure that there is an effect (i.e. that the estimate is different). The risk of Type 1 error (false positive) is lower as significance increases.

TABLE 6

CHANGES IN INCUMBENT PLANT OUTPUT AND INPUTS FOLLOWING AN MDP OPENING

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	(.0478)	(.0469)	(.0300)	(.0375)	(.0541)

NOTE.—The table reports results from fitting versions of eq. (8) for each of the indicated outcome variables (in logs). See the text for more details. Standard errors clustered at the county level are reported in parentheses.

* Significant at the 10 percent level.
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TABLE 5

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Effect after 5 years	.1301**	.1324**	.1355***	.1203**	−.0296
	(.0533)	(.0529)	(.0477)	(.0517)	(.0434)
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Level change	.0277	.0251	.0255	.0290	.0073
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Trend break	.0171*	.0179**	.0183**	.0152*	− 0.0062
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Pre-trend	−.0057	−.0058	−.0048	−.0044	−.0048
	(.0046)	(.0046)	(.0046)	(.0044)	(.0040)
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Plant and industry by year fixed effects	Yes	Yes	Yes	Yes	Yes
Case fixed effects	No	Yes	Yes	Yes	NA
Years included	All	All	All	$-7 \leq \tau \leq 5$	All

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