Evaluation of the demand driven system in higher education

Evidence from ATO Longitudinal tax file data

Gabriela D'Souza

Monash University

dgab5@student.monash.edu

October 12, 2018

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Research Question

Did the expansion of subsidised domestic undergraduate places through the demand driven system have an effect on the higher education wage premium?

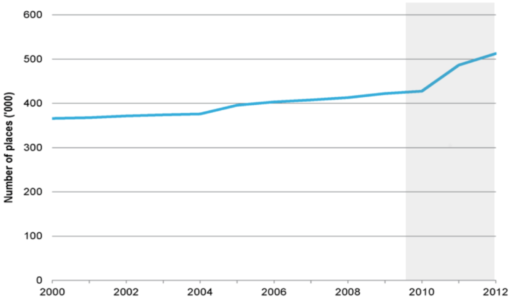
Figure: Is there a bubble?

Background

- Higher Education funding in Australia
  - mix of private and public spending
  - explicit subsidy through Commonwealth supported place and income contingent loan
- 2010 –introduction of the demand driven system
- Commonwealth Grants scheme costs the government up to $ 7 billion per year
- Total HECS debt $ 54 billion
- MYEFO cuts

Undergraduate subsidised places

Figure: Increase in undergraduate CSP places



Department of Education (2017) Student Contribution Bands

Data: ATO Longitudinal tax File

- Combines data from successive individual tax file returns from a 10 per cent sample, over 2010-16
- Advocated for by Dynarski (2014) to better answer questions relating to the returns to education
- Less measurement error in wages
- Allows merging of data with other variables like HELP modules and superannuation balances
- Geographical variables at the SA4 level
- Highly detailed occupation code (4 digit values)

Rules for dealing with administrative data

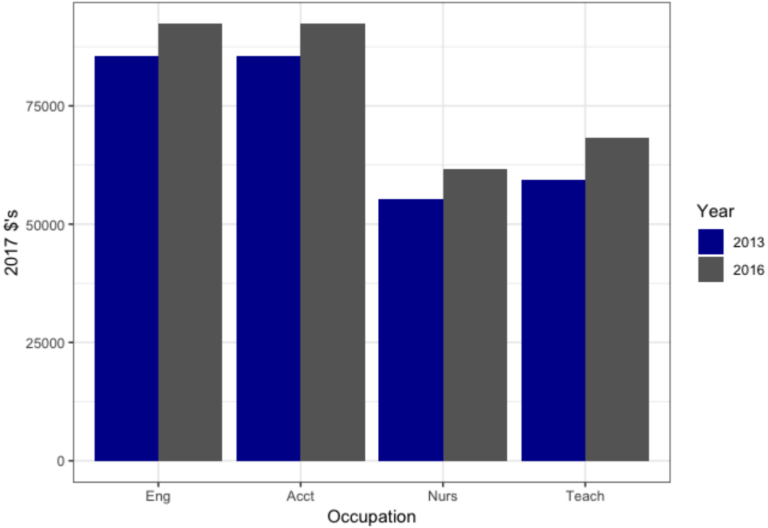
- Advantage: lots of data
- Disadvantage: cannot always get what you want

Solution: creating derived variables based on what you do have

`pmax_h_loan`	gives a max value for the `h_loan_year` variables
`highest_loan`	the year for which the loan was highest, thereby indicating possible completion (has to be over 15k- weed out non completers, but under 45k-to weed out PG)
`studying_3`	identifies if person was studying over the time period of the sample by looking at the outstanding help amount
`cohort_code`	assigns a cohort code based on `highest_loan`

Summary Stats

Figure: Increase in undergraduate CSP places



Research Methodology

- Base model

$$ln(Y_{it}) = \alpha_i + \beta_1 gender + \beta_2 primaryearner + \beta_3 dependents + \beta_4 partnered + \beta_5 Cohortdummy + \beta_6 State + \beta_7 Gender : Occupation + \beta_8 Cohort : Occupation + \beta_9 studying + \beta_{10} Male : Primary + \epsilon_i \quad (1)$$

- For each occupation (Accounting, Nursing, Engineering and teaching)

$$ln(Y_{it}) = \alpha_i + \beta_1 gender + \beta_2 primaryearner + \beta_3 dependents + \beta_4 partnered + \beta_5 Cohortdummy + \beta_6 State + \beta_7 Gender : Occupation + \beta_8 Cohort : Occupation + \beta_9 studying + \beta_{10} Male : Primary + \epsilon_i \quad (2)$$

	log Wage	
	(With Other)	(Without Other)
Male	-0.861^{***}	-0.480^{**}
Prim. Earner	0.518^{***}	0.381^{***}
Dependants	-0.372^{***}	-0.418^{***}
Cohort 2016	-0.442^{***}	-0.506^{***}
Age	-0.024^{***}	-0.017
Eng.	0.167	0.099
Nursing	-0.198	-0.196
Other	-0.958^{***}	-0.625^{***}
Teachers	-0.253^{*}	-0.140
Male:Primary	1.031^{***}	0.558^{***}
Male:Engineer	-0.040	0.046
Male:Nurse	0.282	0.311
Male:Teachers	0.182	0.204
Constant	11.812^{***}	11.956^{***}
Observations	48,783	11,627
R^2	0.073	0.070
Adjusted R^2	0.073	0.069
Residual Std. Error	2.733 (df = 48754)	2.022 (df = 11602)

Table: By Occupation: With other cohorts

	log Wage			
	(eng)	(acct)	(nurse)	(teaching)
Male	0.044	−0.031	0.133	0.086
Primary Earner	0.325***	0.320***	0.464***	0.326***
Dependants	−0.113***	−0.187***	−0.262***	−0.285***
studying_3	−0.577	−0.417	0.063	−2.500***
Cohort 2016	−0.297***	−0.122	−0.103	−0.222***
Cohort other	−0.098*	−0.207***	−0.219***	−0.300***
Age	0.060***	0.053***	0.016	0.020**
Male:Prim earner	0.030	0.119	0.091	0.106
Constant	9.277***	9.504***	10.490***	10.493***
Observations	856	1,055	1,266	1,815
R^2	0.138	0.115	0.171	0.182
Adjusted R^2	0.120	0.100	0.159	0.174
Residual Std. Error	0.699 (df=838)	0.790 (df=1036)	0.870 (df=1247)	0.748 (df=1795)

Table: By occupation: Without other

	Log wage			
	(eng)	(acct)	(nurse)	(teaching)
Male	0.110	−0.148	0.063	0.161*
Prim earner	0.283	0.337***	0.415***	0.294***
Dependants	−0.112**	−0.230***	−0.237***	−0.252***
Cohort 2016	−0.333**	−0.155	−0.137	−0.234***
Age	0.055**	0.034	−0.015	0.012
Male:Prime Earner	−0.034	0.177	0.214	−0.001
Constant	9.345***	10.192***	11.412***	10.691***
Observations	502	530	717	1,388
R^2	0.096	0.101	0.175	0.144
Adjusted R^2	0.068	0.075	0.158	0.134
Residual Std. Error	0.814 (df=486)	0.847 (df=514)	0.779 (df=701)	0.688 (df=1371)

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