Unpacking Skill Supply and Wages

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Research Question and Motivation

- The response of the wages to changes in the supply of graduates is an important policy parameter. The college wage premium's response to graduate supply has been estimated to be large in the US[1].

[1] Autor et al., 2020; Card and Lemieux, 2001; Katz and Murphy, 1992

[2] Andrews et al, 2025; Bleemer and Mehta, 2022; Britton et al., 2022; Kirkeboen et al., 2016

Research Question and Motivation

- The response of the wages to changes in the supply of graduates is an important policy parameter. The college wage premium's response to graduate supply has been estimated to be large in the US[1].
- But, graduates studying different subjects have very different skillsets[2].
- How is the wage of a graduate affected by the supply of similar majors?

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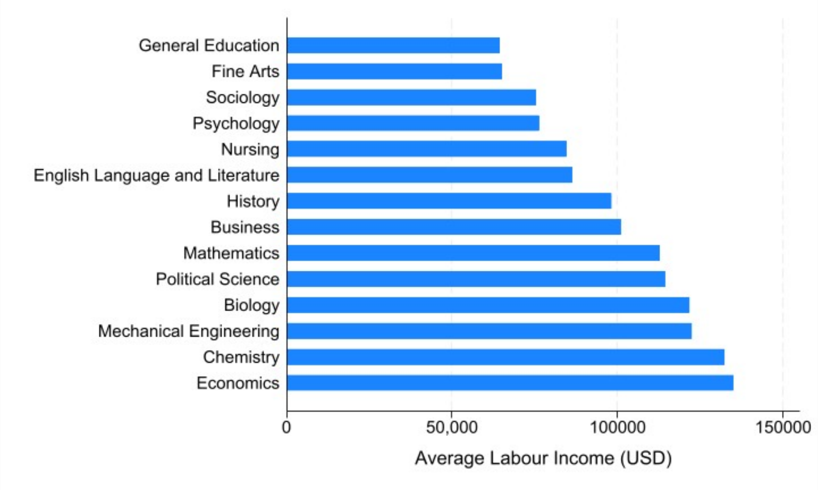
[2] Andrews et al, 2025; Bleemer and Mehta, 2022; Britton et al., 2022; Kirkeboen et al., 2016

Average Earnings for Full-Time Workers by Major (2019) [1]



[1] Source: American Community Survey, 2019

This Paper

- First general estimates of the elasticity of (US) graduate wages with respect to the supply of graduates from similar majors, using fixed effects and IV regression.[1]

[1] Qvist et al., 2021 provides some evidence on the supply of electrical and construction engineers.

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- First general estimates of the elasticity of (US) graduate wages with respect to the supply of graduates from similar majors, using fixed effects and IV regression.[1]
- We rule out elasticities stronger than about -0.3 and often weaker ones as well. This compares to a -0.6 value for graduates as a whole in previous work.[2]

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- Previous Katz and Murphy (1992) style estimates were too large due to unit root time series.
- Substitutability is explainable by graduates do not use degree or major-specific skills.

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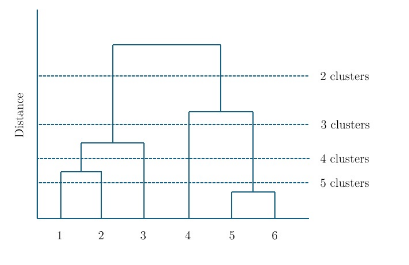
Data

- American Community Survey 2009-2019
- Annual cross-sectional survey covering a random 1% of the US population (3 million observations per year).
- Includes data on education including bachelor's degree major, labour income, hours of work, occupation, and basic demographic factors.

Grouping Degrees

- Data contains 175 majors. Some are very similar.
- Use hierarchical clustering to sort majors into similar groups based on occupation in a data-driven way.
- The number of groups is a choice. Validation metrics suggest that about 25 is optimal. Some of these are very small and some very large.
- Groupings are sensible e.g., Education degrees go together, Maths with Physics, Chemistry with Biology.



Empirical Strategy

Equation

$$\ln\left(\overline{Wage_{iact}}\right) = \alpha_{ia} + \beta \ln\left(\frac{\text{ClusterHours}_{ct}}{\text{TotalHours}_t}\right) + \mu \mathbf{X}_{icat} + \tau_t + year_t * \gamma_i + \varepsilon_{iact}$$

$\overline{Wage_{iact}}$=Average hourly wage for graduates of major i of five-year age-group a in skill cluster c at time t

$\frac{\text{ClusterHours}_{ct}}{\text{TotalHours}_t}$=Share of total hours worked by graduates in skill cluster c.

α_{ia} are major by age-group fixed effects.

$\mathbf{X}_{icat}$ are a vector of controls.

τ_t are year fixed effects.

$year_t * \gamma_i$ are major-specific time trends.

Standard errors are clustered at the skill cluster level and observations are weighted by cell size.

Potential Endogeneity

- Supply shifts around the time trend appear idiosyncratic. Change in one major's supply uncorrelated with changes in other majors within the cluster (e.g., economics and finance). Estimates
- Endogenous education choices - first difference
- Endogenous labour supply and migration decisions - instrument

Instrument

- Instrument $\ln\left(\frac{\text{ClusterHours}_{ct}}{\text{TotalHours}_t}\right)$ with its value among the US-born population if each US-born individual worked the number of hours typical of their age and sex within that major category as in the base period, 2009.
- Variation comes from new graduates and changes in labour supply from pre-determined lifecycle factors. No dependency on hours adjustments or migration.

Instrument

Instrument Definition

$$\ln\left(\frac{\text{PredictedClusterHours}_{ct}}{\text{PredictedTotalHours}_{t}}\right) = \ln\left(\frac{\sum_{x\in \text{MAS}} \mathbf{1}_{x\in C_c}(x)\left(\overline{\text{Hours}_{x,2009}}\cdot \text{NativePopShare}_{xt}\right)}{\sum_{x\in \text{MAS}}\left(\overline{\text{Hours}_{x,2009}}\cdot \text{NativePopShare}_{xt}\right)}\right)$$

C_c is the set of majors in skill cluster c.

MAS is the set of unique major, age, and sex combinations in the data.

$\overline{Hours_{x2009}}$ is the average hours worked among members of x in 2009.

$\mathbf{1}_{C_c}(x)=1$ when $x \in C$ and 0 otherwise

$NativePopShare_{xt}$ is the share of the US-born population who are a member of x

Graduate wages are inelastic to own major supply

Dependent variable:	$\ln(\overline{wage}_{iact})$			
	(1)	(2)	(3)	(4)
	FE	IV-FE	FD	IV-FD
$\ln\left(\frac{ClusterHours_{ct}}{TotalHours_t}\right)$	0.077	0.069	0.045	0.023
	(0.065)	(0.103)	(0.066)	(0.086)
	[-0.06, 0.21]	[-0.14, 0.28]	[-0.09, 0.18]	[-0.16, 0.20]
F-statistic		19.6		17.2
Major-by-age fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	18,515	18,515	16,817	16,817

Notes: Major-age (five year) combinations, the unit of analysis, are weighted proportionally to the sum of their members. Jackknife standard errors clustered at the skill cluster level are in parentheses and the resulting 95% confidence intervals are in square brackets. Controls cover the proportion of asian, hispanic, black, and female workers used to calculate the major-by-age group alongside their average age. The instrument is defined as proportion of hours worked by natives from within the same skill cluster if everyone worked the hours typical of their age-major-sex combination in the base period of 2009.

Previous approach

- Katz and Murphy (1992) approach regress a time series of college wage premium on relative supply and a time trend in a time series. Gets an elasticity of -0.6.

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- Katz and Murphy (1992) approach regress a time series of college wage premium on relative supply and a time trend in a time series. Gets an elasticity of -0.6.
- These time series, using data from Autor, Goldin and Katz (2020), contain unit roots. Test Results
- Estimates collapse towards zero after first-differencing.

Katz and Murphy (1992) Approach

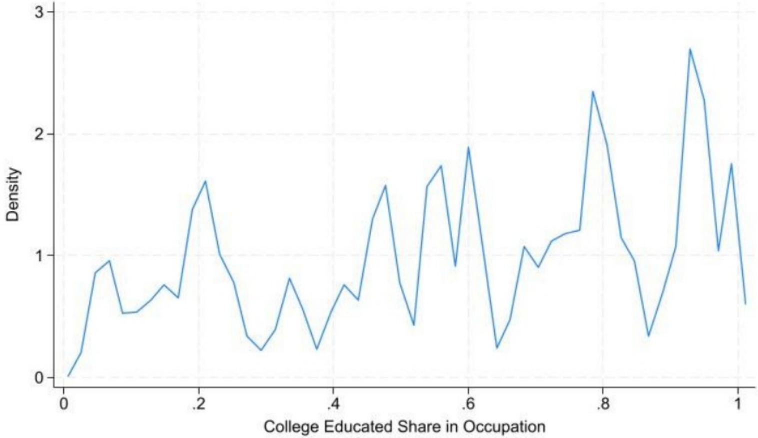
Dependent variable:	$\ln\left(\frac{w_{Skilled_t}}{w_{Unskilled_t}}\right)$				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Levels				
$\ln\left(\frac{L_{Skilled_t}}{L_{Unskilled_t}}\right)$	-0.254***	-0.644***	-0.688***	-0.609***	-0.125
	(0.048)	(0.057)	(0.070)	(0.074)	(0.167)
	Panel B: First Differences				
$\ln\left(\frac{L_{Skilled_t}}{L_{Unskilled_t}}\right)$	-0.096	-0.121	-0.120	-0.163	0.010
	(0.113)	(0.118)	(0.121)	(0.159)	(0.112)
Observations	54	54	54	28	26
Sample	1963-2017	1963-2017	1963-2017	1963-1991	1992-2017
Time trend	Linear	Linear spline	Quadratic	Linear	Linear

Notes: Heteroskedasticity-robust standard errors in parentheses. Data on college wage premiums and relative supplies are taken from Autor et al (2020). The linear spline fits a linear time trend between 1963 and 1992 and a different linear time trend between 1992 and 2017, as in many of Autor et al (2020)'s specifications. The first differenced regressions difference the time series and omit the constant to be analogous to the levels specification.

Why Small Elasticities?

- Many graduates work jobs that do not require their degree. This limits the potential elasticity.
- Even when the degree is highly relevant there may be other routes e.g., engineering apprenticeships.

Many graduates work jobs where they don't need a degree



Notes: Kernel density plot using an Epanechnikov kernel. Underlying data contains all college graduates in the American Community Survey from 2009-2019. College educated share is the proportion of workers in their four-digit occupation with at least a bachelor's degree.

Extensions and Robustness

- Main specification maps to a nested CES production function. Specifically, an upper nest of graduates and non-graduates with a lower nest of different types of graduates. Theoretical Framework
- Estimates more precise for lower return degrees. Heterogeneity by Returns
- Robust to altering the number of clusters. Results get more precise at greater disaggregation. No. Clusters
- Robust to alternative clustering approaches. Alternative clustering
- Results are not driven by measurement error. Errors-in-variables

Conclusions

- The elasticity of graduate wages to education is smaller than previously thought. Both at the specific and general level.
- We can rationalise this by many graduates not working jobs that require their degree.

Appendix

Supply of one major uncorrelated with similar majors

Back

Dependent variable:	$\ln\left(\frac{ClusterHours_{ct} - MajorHours_{ict}}{TotalHours_t}\right)$	
	(1)	(2)
	FE	IV-FE
$\ln\left(\frac{MajorHours_{ict}}{TotalHours_t}\right)$	0.015	-0.013
	(0.026)	(0.029)
	[-0.04, 0.07]	[-0.08, 0.05]
F-statistic		450.4
Major-by-age fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Controls	Yes	Yes
Time trend	Yes	Yes
Observations	17,435	17,435

Notes: Major-age (five year) combinations, the unit of analysis, are weighted proportionally to the sum of their members. Jackknife standard errors clustered at the skill cluster level are in parentheses and the resulting 95% confidence intervals are in square brackets. Controls cover the proportion of asian, hispanic, black, and female workers used to calculate the major-by-age group alongside their average age. The instrument is defined as proportion of hours worked by natives from within the same skill cluster, excluding those from the same major, if everyone worked the hours typical of their age-major-sex combination in the base period of 2009.

Unit Root and Cointegration Tests

Back

Panel A: Augmented Dickey-Fuller Test with Time Trend

Series:	Sample	ADF Statistic	5% Critical Value	P-value
Relative Wage	1963-2017	-1.253	-3.496	0.899
Relative Supply	1963-2017	-1.357	-3.496	0.873
Relative Wage	1963-1992	-0.541	-3.584	0.982
Relative Supply	1963-1992	-0.627	-3.584	0.977
Relative Wage	1993-2017	-2.046	-3.600	0.566
Relative Supply	1993-2017	-2.150	-3.600	0.518

Panel B: Engle-Granger Test for Cointegration

Sample	ADF Statistic	5% Critical Value	10% Critical Value
1963-2017	-2.012	-3.961	-3.630
1963-1992	-2.661	-4.070	-3.711
1993-2017	-2.382	-4.180	-3.790

Notes: These statistics are calculated from the replication data provided by Autor et al (2020). The Engle-Granger test for cointegration critical values are calculated from the MacKinnon (2010) formula for N=2 with a time trend.

Theoretical Framework

Back

Upper nest with skilled and unskilled labour alongside factor augmenting technology and a scale parameter:

$$Y_t = [\alpha_t(A_{U_t})U_t)^{\rho} + (1-\alpha_t)(A_{S_t}S_t)^{\rho}]^{(1/\rho)}$$

Lower nest of n graduate skill groups:

$$A_{S_t}S_t = \left[\sum_{i=1}^{n} \beta_{it}\left(b_{it}L_{it}\right)^{\rho_S}\right]^{\frac{1}{\rho_S}}$$

Under perfect competition, wage is equal to marginal product. Differentiating and log-linearising gets us with σ_S the elasticity of substitution between skill groups:

$$\ln w_{it} = -\frac{1}{\sigma_S}\ln L_{it} + \ln\left(\beta_{it}\, b_{it}^{\rho_S}\right) + F(\alpha_t, A_{S_t}, S_t, \rho, Y_t)$$

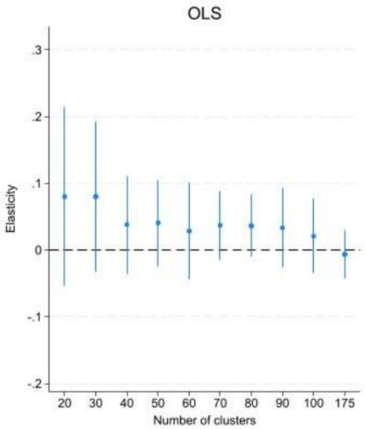
Effects less precise for higher-return majors

Back

Dependent variable:	$\ln(\overline{wage}_{iact})$			
Major wage in 2009:	Below Mean		Above Mean	
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE	IV-FE
$\ln\left(\frac{ClusterHours_{ct}}{TotalHours_t}\right)$	0.181	0.132	-0.039	-0.009
	(0.086)	(0.117)	(0.117)	(0.182)
	[-0.01, 0.37]	[-0.13, 0.39]	[-0.30, 0.22]	[-0.41, 0.39]
F-statistic		122.1		24.0
Major-by-age fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	9,006	9,006	9,509	9,509

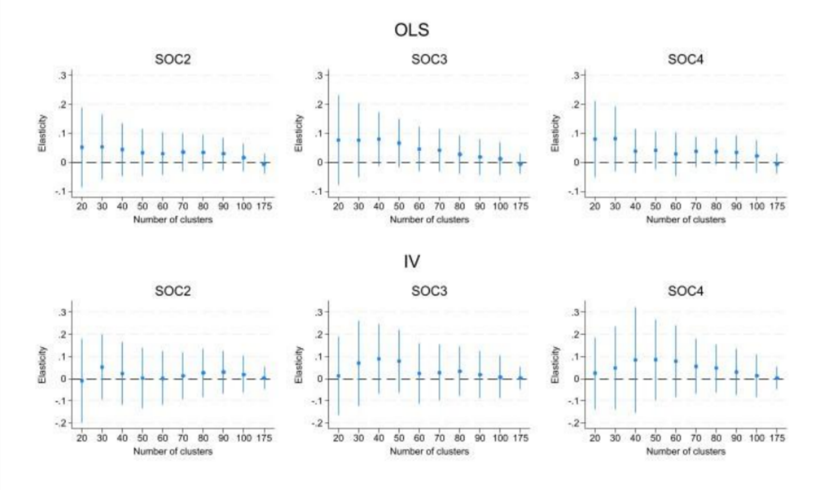
Notes: Major-age (five year) combinations, the unit of analysis, are weighted proportionally to the sum of their members. Jackknife standard errors clustered at the skill cluster level are in parentheses and the resulting 95% confidence intervals are in square brackets. Controls cover the proportion of asian, hispanic, black, and female workers used to calculate the major-by-age group alongside their average age. Below mean average wage means that the average wage of graduates from that skill cluster was below the mean graduate's wage in 2009. The instrument is defined as proportion of hours worked by natives from within the same skill cluster if everyone worked the hours typical of their age-major-sex combination in the base period of 2009.

Different Number of Skill Clusters Back



Notes: Point estimates come from estimating equation (7). The IV estimates use the instrument in equation (2) in a two-stage least squares setup. The 95% confidence intervals come from jackknife standard errors, clustered at the skill cluster level. The number of clusters is the number of clusters we tell the hierarchical clustering algorithm to sort the majors into.

Alternative clustering approaches Back



Errors-in-variables approach

Back

Dependent variable:	$\ln(\overline{wage_{iact}})$			
Model:	ORIV-FE		ORIV-FD	
	(1)	(2)	(3)	(4)
$\ln\left(\frac{ClusterHours_{ct}}{TotalHours_t}\right)$	0.099	0.051	0.036	-0.003
	(0.110)	(0.112)	(0.169)	(0.114)
	[-0.13,0.33]	[-0.18,0.28]	[-0.31,0.39]	[-0.24,0.23]
F-statistic	24.3	21.6	10.0	13.3
Instruments	Internal	External	Internal	External
Major-by-age fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	37,030	37,030	33,634	33,634

Notes: All regressions estimate equation (7) or a first-differenced analogue using the obviously related instrumental variables approach from Gillen et al (2019). Major-age (five year) combinations, the unit of analysis, are weighted proportionally to the sum of their members. Jackknife standard errors clustered at the skill cluster level are in parentheses and the resulting 95% confidence intervals are in square brackets. Controls cover the proportion of asian, hispanic, black, and female workers used to calculate the major-by-age group alongside their average age. The external instrument is defined as proportion of hours worked by natives from within the same skill cluster if everyone worked the hours typical of their age-major-sex combination in the base period of 2009 from the other half of the sample. The internal instrument is the independent variable calculated in the other half of the sample. Either instrument is also interacted with the log of the skill cluster's size in 2009, to account for the structure of the measurement error.