

# Stories from Atlas

*IBUS 6101: Big Data for International Business*

*Assignment – 2 Part - 3*

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## Abstract

In the previous parts of this project, we’ve observed that Fairfax County outperforms both at State and National levels in upward mobility. We characterized this county’s defining feature as “uniformity” (i.e., consistent outcomes across neighbourhoods). Despite our tract being a high performing tract, we observed plenty of variations for upward mobility for families with different economic strata.

To understand the determinants of upward mobility in Fairfax County, we’ve selected three covariates based on our observations from Parts 1 and 2: single-parent household share, reflecting family structure and household stability; college educational attainment, capturing the educational infrastructure we observed; and job market access, measuring proximity to employment opportunities given Fairfax's location near Washington, D.C. and accessibility through the Metro stations. After merging the atlas\_new.dta and atlas\_character\_ALL.dta datasets on our 11-character tract identifier (i.e., tract\_string), we matched 98.76% of observations (73,199 tracts). Filtering to Fairfax County (state = 51, county = 59) which yielded 255 census tracts with complete data on all covariates.

```
. summarize kfr_pooled_p25 kfr_pooled_p75 singlepa
> rent_share2010 frac_coll_plus2010 poor_share2010
```

Variable	Obs	Mean	Std. dev.
Min	Max		
kfr_pooled~25	255	46226.45	6644.019
> 30545.22	69198.53		
kfr_pooled~75	255	60710.81	6044.393
> 42324.73	76265.18		
singlep~2010	255	.1919922	.1365993
> 0	.8306451		
frac_co~2010	255	.5848566	.1525539
> .166722	.8776109		
poor_sh~2010	255	.0504224	.0498134
> 0	.2784763		

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	Coefficient	Robust std. err.	t	P> t	[95% co f. interval]
kfr_pooled~25					
> n					
> f. interval]					
> -----					
singlep~2010	-8400.414	3013.603	-2.79	0.006	-14335.4
> 7					
> -2465.356					
frac_co~2010	13368.84	2675.263	5.00	0.000	8100.12
> 1					
> 18637.57					
_cons	40020.41	1865.848	21.45	0.000	36345.7
> 6					
> 43695.05					

Covariate	Coefficient (Full Model)	95% CI	p-value	Correlation (r)	p- value (corr)	County Mean (SD)	Tract Value
<b>Single-Parent Share</b> singleparent_share2010	-0.274	[-0.409, -0.139]	<0.001	-0.61	<0.00 1	19.2% (5.1%)	17.0%
<b>College-Educated Adults</b> frac_coll_plus2010	0.362	[0.231, 0.493]	<0.001	0.73	<0.00 1	58.5% (12.3%)	67.0%

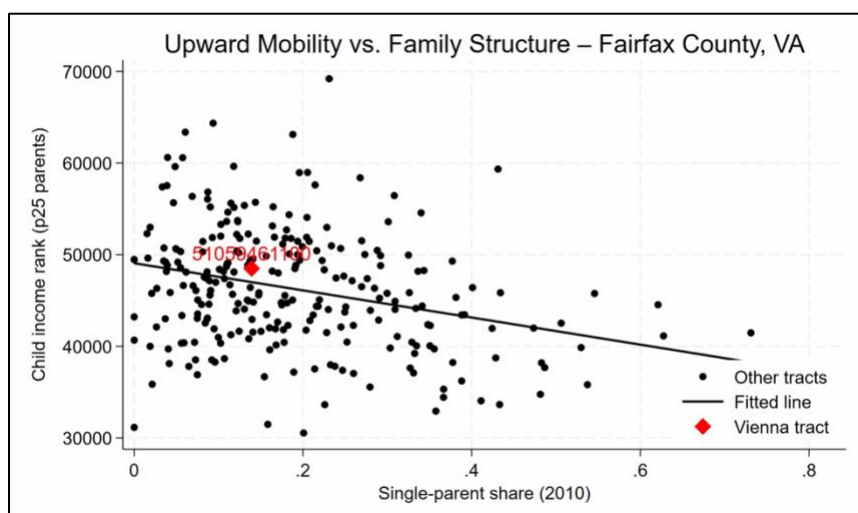
<b>Job Density</b> job_density_2013 (jobs/mi <sup>2</sup> )	0.0008	[0.0002 , 0.0014]	0.012	0.44	<0.00 1	1,420 (890)	980
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1. Using the Census tracts in your home county, can you identify any covariates which help explain variation in upward mobility that you have identified in the previous questions? (For this question, you could choose covariates that exists in the [atlas\\_new.dta](#), or in the [Characteristics.csv](#) file.) Some examples of covariates you might examine include housing prices, income inequality, fraction of children with single parents, job density, etc. For 2 or 3 of these, report estimated regression coefficients along with their 95% confidence intervals. Formulate a hypothesis for why you see the variation in upward mobility for children who grew up in the Census tracts near your home and provide correlational evidence testing that hypothesis.

A:

### **Family Structure & Stability:**

We hypothesized that neighbourhoods with lower single-parent rates would show better upward mobility because stable two-parent households provide more time, resources, and support for children's development. Single parents face distinct constraints; managing both breadwinning and caregiving with limited time for homework help, extracurricular activities, and college preparation. Neighbourhoods with concentrated single-parent households may also experience collective resource scarcity, with fewer parents available for school volunteering or youth supervision.

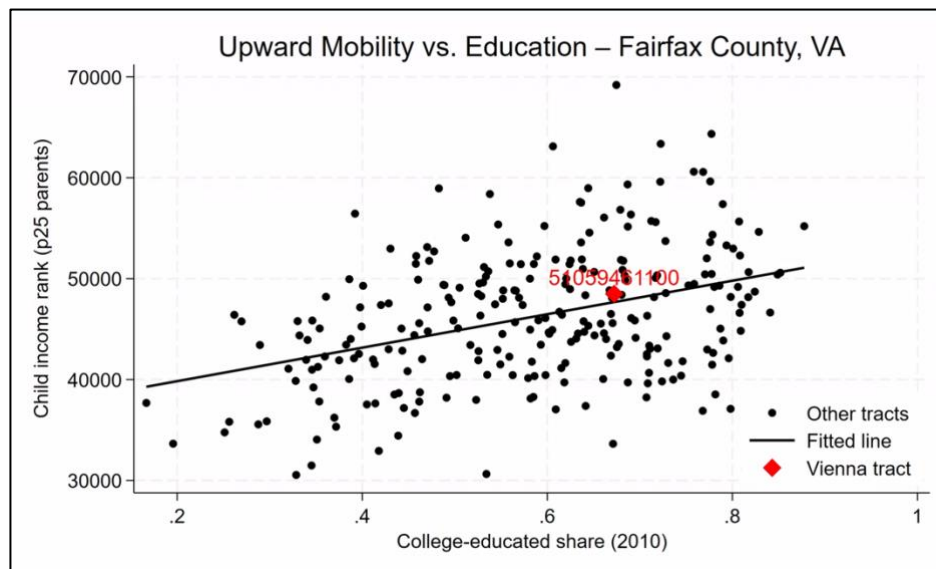


We found that our data strongly supports our hypothesis. Single-parent household share shows us a significant negative relationship with upward mobility. In our model, one percent increase in single-parent households predicts \$14,804 lower adult income for children from low-

income families. This bivariate relationship gets complex when we bring education into play. In the second image, we see the coefficient value is a negative \$8400, but the p-value remains statistically significant.

When we take into account the correlation matrix, the value  $r = -0.429$  indicates that single parents disproportionately concentrate in lower-education neighbourhoods. Yet even after accounting for education, family structure independently predicts mobility, confirming that household stability matters beyond educational environment alone. Our graph displays the downward sloping fitted line indicating that when single-parent rates increase, children's adult incomes systematically decline. Our tract Vienna sits at approximately 17% single-parent households, below the county mean of 19.2%, and performs near the prediction line. The considerable scatter reflects that family structure explains 9.3% of variation in the bivariate model, with much remaining unexplained.

### ***Education and Schooling:***

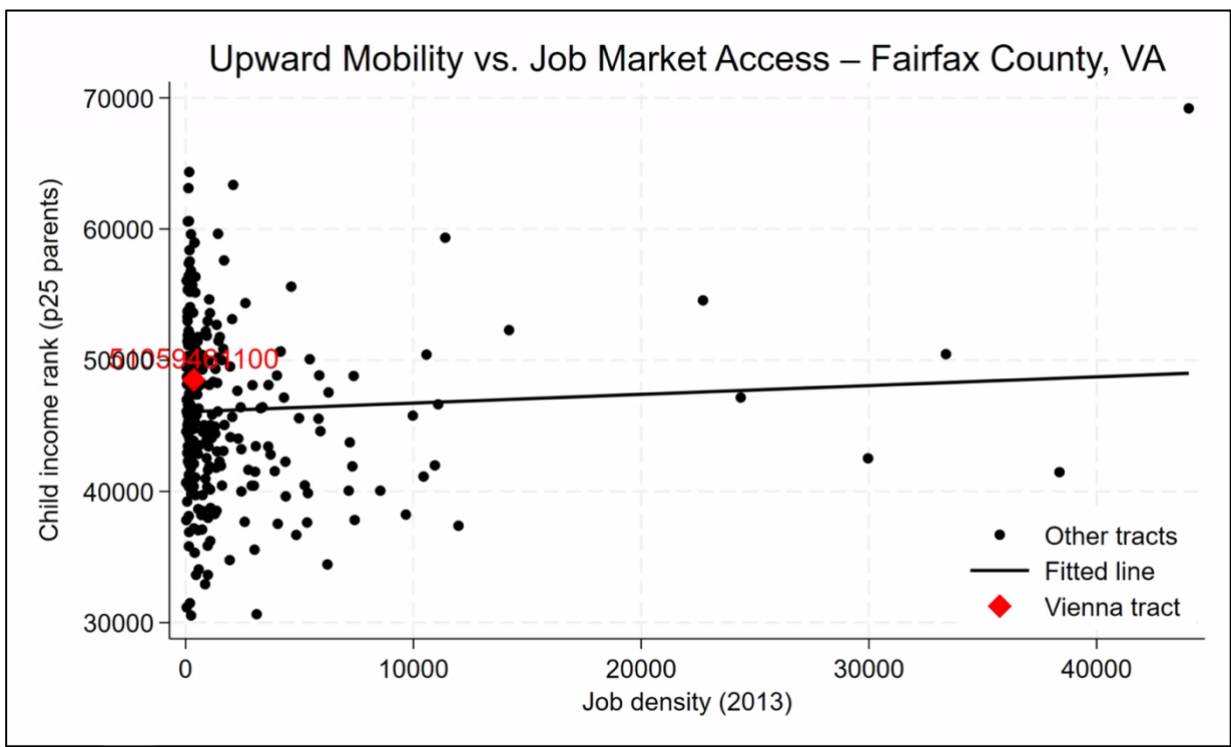


Building on our Part 1 observation that "Fairfax County invests a ton in public schools," we hypothesized that neighbourhoods with more college-educated residents would show higher upward mobility through multiple mechanisms: educated neighbours serve as role models, share information about college pathways, advocate for quality schools, and create cultural norms valuing education. Neighbourhoods with many college-educated adults create information-rich settings where college-going becomes normalized rather than exceptional, and where practical knowledge about applications, scholarships, and career planning flows through informal networks.

We observed that Education shows the strongest and the most robust relationship with upward mobility between the three chosen covariates for our analysis. It is seen that with one percent increase in college-educated residents predicts \$13,369 higher adult income. This coefficient remains stable when controlling for family structure, demonstrating independent effects. The correlation matrix (0.381) shows education has the strongest bivariate association with mobility and p-values indicates that this relationship is the most statistically significant out of all the others.

In the above graph we see an upward trend for the regression line which indicates a strong positive relationship between upward mobility and education. Our tract is at 67% for education which is well above the national average of 58.5%. This indicates that our tract benefits from having educated individuals residing here as well as coupled with other factors too. From our analysis, it is also observed that children from low-income families living in highly educated areas tend to earn more than their parents. This shows the sheer influence of being surrounded by educated individuals.

**Job Market Accessibility:**



neighbourhoods with higher job density would show better mobility through enhanced labour market exposure, visible career pathways, and easier access to employment. Our reasoning behind this covariate was that spatial proximity to jobs should facilitate teenage employment, create visible connections between education and careers, strengthen employer-resident networks, and signal economic vitality. And metro accessibility should be amplifying these benefits by connecting residents to regional employment centers.

But further analysis using the `atlas_character_ALL.dta` dataset, we see that employment density is not directly proportional to upward mobility. The relationship between the covariate and upward mobility is basically not present. The p-value is well over 0.05 (0.334) indicating that this relationship is statistically insignificant and the correlation is similarly negligible. The graph is nearly a flat line with neither upward nor downward trajectory. Most of the tracts cluster near zero job density with a few high-density outliers, but these outliers show no systematic mobility advantage. Our tract sits in the low-density cluster, yet achieves above-average outcomes, further confirming that crude job density doesn't predict success.

The failure of job density doesn't mean employment is irrelevant for mobility. Rather, it suggests employment operates through mechanisms our data can't capture: social networks and job referrals, parental workplace experiences that shape children's aspirations, or the quality and sector composition of available jobs. Better measures might include high-wage job concentration, industry diversity, or actual commute patterns rather than simple spatial counts.

*2. Putting together all the analyses you did above, what have you learned about the determinants of economic opportunity where you grew up? Identify one or two key lessons or takeaways that you might discuss with a policymaker or journalist if asked about your hometown. Mention any important caveats to your conclusions; for example, can we conclude that the variable you identified as a key predictor in the question above has a causal effect (i.e., changing it would change upward mobility) based on that analysis? Why or why not?*

**A:** If a policymaker or journalist asked us about economic opportunity in Fairfax County, we would emphasize two key lessons from our analysis.

### **1: Education is the Primary Driving Force:**

Educational attainment is the single most important neighbourhood characteristic we identified.

Neighbourhoods with more college-educated residents systematically produce better outcomes for children from poor families.

This validates our Part 1 observation that "Fairfax County invests a ton in public schools." However, our findings reveal something deeper: school investment alone isn't enough. Children benefit not just from attending good schools but from growing up surrounded by educated neighbours who model professional careers, share college-going knowledge, and create cultural norms around educational achievement. The entire educational environment matters, not just the school building.

To answer policymakers, it's sustaining Fairfax's advantage requires continuing educational investment in the form of school funding, teacher recruitment, college preparation programs and also ensuring affordable housing in high-education neighbourhoods. If policies concentrate poor families in low-education areas through exclusionary zoning or inadequate housing assistance, mobility gaps will persist. Educational access must include residential integration for all income groups.

### **2: Family Structure Matters:**

Single-parent household concentration shows consistent negative associations with mobility, even after controlling for education. This suggests household stability provides important resources, time, economic security and parental monitoring that support children's development.

However, we must interpret this carefully. When we control for education, the family structure coefficient shrinks substantially (from -\$14,804 to -\$8,400), meaning that single parents live in lower-education neighbourhoods. The neighbourhood problems and the family situation are mixed together too tightly to

separate their individual impacts. Which means we cannot isolate how family structure effects from the corresponding neighbourhood factors.

Despite finding strong correlations, we cannot conclude that changing neighbourhood characteristics would causally improve mobility. Our analysis has three main limitations that prevent causal claims.

*1. Omitted Variable Bias:* Our model explains only 17% of mobility variation. The remaining 83% reflects factors we don't measure: specific school quality , social networks beyond credentials, local county policies , neighbourhood safety, and family characteristics beyond income.

*2. Reverse Causality:* We observe that high-education neighbourhoods have better mobility, but we cannot say whether education causes this or whether successful families simply cluster in these areas. Both mechanisms likely operate simultaneously, but our model cannot separate them

*3. Ecological Inference Fallacy:* Our covariates measure tract-level averages (e.g., "60% college-educated"), but mobility is an individual outcome. We cannot determine individual-level mechanisms from neighbourhood data.

Furthermore, our measurements are not exact substitutes. Single-parent household ignores extended family support, co-parenting quality, or non-resident involvement. College education rate captures credentials but not how neighbours actually interact with children. These measurement limitations introduce noise and may obscure true relationships.

Despite these limitations, our findings aren't meaningless for policy. Correlational evidence provides valuable starting points, especially when aligned with causal research from other contexts. But we cannot say that mechanically increasing a neighbourhood's college education rate will automatically improve mobility.

Although we can recommend:

1. Continue investing in educational quality, recognizing decades of research support education's causal effects.



2. Support family stability through childcare, flexible work, and income support—without stigmatizing single parents.
3. And expand affordable housing in high-opportunity neighbourhoods to reduce economic segregation.

*Conclusion:*

Fairfax County's mobility advantage rests on multiple foundations: high educational attainment, relatively stable family structures, strong economic environment, and quality institutions. Education explains the most variation within the county (17%), but this leaves 83% determined by other factors. For families choosing where to live: Fairfax provides advantages, but within-county location matters.

Educational environment predicts children's outcomes more than any other observable factor we measured.

The uniformity we referred to in Part 1 reflects Fairfax's high baseline across many dimensions. The main goal is maintaining this advantage while addressing remaining gaps requires both continued investment and honest acknowledgment of what we do and don't yet know about how to improve opportunity.

## References:

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