

# Human Capital Attainments of Refugee and Non-Refugee Intake Class Workers in Canada: An Analysis of Ethnic Cross-Classifications

Fernando Mata  
School of Sociology and  
Anthropology  
fmata@uottawa.ca



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# Overview of the Study



- ❑ The purpose of the paper was to examine the educational and income attainments of refugee and non refugee workers in Canada at the time of the 2016 Census
- ❑ Basic aim classify workers and detect clusters of surplus and deficits of human capital attainments
- ❑ Special tables from the 2016 Census containing ethnic classifications were used as data sources
- ❑ Exploratory study as a *precursor* of more in-depth analysis using individual micro-data

# Human Capital Attainments (1)



- ❑ **Human capital attainments : human outputs closely linked to workers' investments in knowledge, skills, education, and abilities (Garavan et al., 2001; Youndt et al., 2004.)**
- ❑ **Individuals who have the highest human capital endowments are best suited for competitive labour markets , thus, experiencing successful economic integration (Becker, 1993).**
- ❑ **Since their arrival to Canada immigrants from different intake classes have been attaining different types of human capital . Immigration policy selection criteria and the job market behind these outcomes**

# Human Capital Attainments (2)



- ❑ Refugee workers rank at the lowest levels in terms of human capital endowments (Silvus. 2016; 2016; Lamba. 2008, 2003; Yu, Oulette & Warmingon 2007).
- ❑ Refugees enter the labour market in a disadvantaged position facing numerous challenges they face such as discrimination, devaluation of educational credentials, government dependency and limited financial resources (Endicott, 2017).
- ❑ The lower human capital in refugees has been linked to negative outcomes such as inability to find jobs, experiencing longer spells of unemployment and "flatter" earnings trajectories over time (Wanner,2003; Devoretz, et. al. 2004; CIC, 2007; Connor,2010; Shields et al. 2010;Yu et. al, 2014,Mata and Pendakur, 2016 ).



# Research Questions



- ❑ What is the general picture regarding the human capital attainments' deficits and surpluses among ethnic immigrant workers of refugee and non refugee immigration intake categories in 2016?
- ❑ What major dimensions may underlie the indicators of deficits and surpluses?
- ❑ Will clusters of workers be observable by gender, particular ethnic origins and periods of arrival?



# Can ethnic classifications of workers from the 2016 Canadian Census be useful in addressing these research questions?



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# Ethnic Classifications (1)



- ❑ Ethnic classifications pertaining workers aged 25-54 years old and who reported some employment income in 2015 were drawn from two special tables from the 2006 Census of Canada
- ❑ These comprised approximately 233 ethnic origins
- ❑ Required minimal number of observations per ethnic classification: 500
- ❑ Ethnic origin referred to the ethnic or cultural origins of the person's ancestors which is usually more distant than a grandparent.
- ❑ Single and multiple origins of workers.

# Ethnic Classifications (2)



- ❑ Ethnic cross classifications ( $n_{\text{total}} = 1,312$ ) broken down by:
  - Gender: Male and Female ( $n_1 = 661, n_2 = 651$ )
  - Immigrant intake classes: economic, family, refugee. Census information linked to immigrant records.
  - Period of arrival cohorts (in or before 1980, 1981-1990, 1991-2000, 2001-2010, 2011-2016).
- ❑ Canadian-born workers' classifications were also included for comparison purposes





# Analytical Approach (1)



- ❑ Five human capital attainment indicators were calculated for the ethnic classifications:
  - A1: average % of high school degrees obtained ,
  - A2: average % of trade degrees obtained,
  - A3: average % of non university trade degrees obtained,
  - A4: average % of university degrees (bachelor and post bachelor) obtained,
  - A5: median employment income received from wage& salaries and self employment incomes in 2015 (in \$ thousands).
  
- ❑ Analysis was carried separately for male and female cross classifications

## Analytical Approach (2)



- ❑ The analytical approach of Ding and He (2004) was used to undertake the analysis of ethnic classifications
- ❑ This approach uses a combination of Principal Components Analysis (PCA) and k-means cluster analysis methods.
- ❑ Powerful visualizations of the relationships between variables and between units of analysis simultaneously
- ❑ Computer software used: SPSS , Stata and XLSTAT



# PCA Bi-plots as Exploratory Data Analytical Tools



- ❑ PCA bi-plots are graphs where vectors represent indicators and points the position of units in principal component space.
- ❑ The bi-plot of the second component on the first component (representing the major sources of variation in the data) displays the correlations of variables in terms of various vectors of different magnitudes, directions and positions.
- ❑ The length of indicators reflect the variances of the corresponding measuring variable while the angles between them reflect the size of their correlations, with small angles corresponding to high correlations where  $r = (\cos) \text{ angle } \theta$ .



# FINDINGS

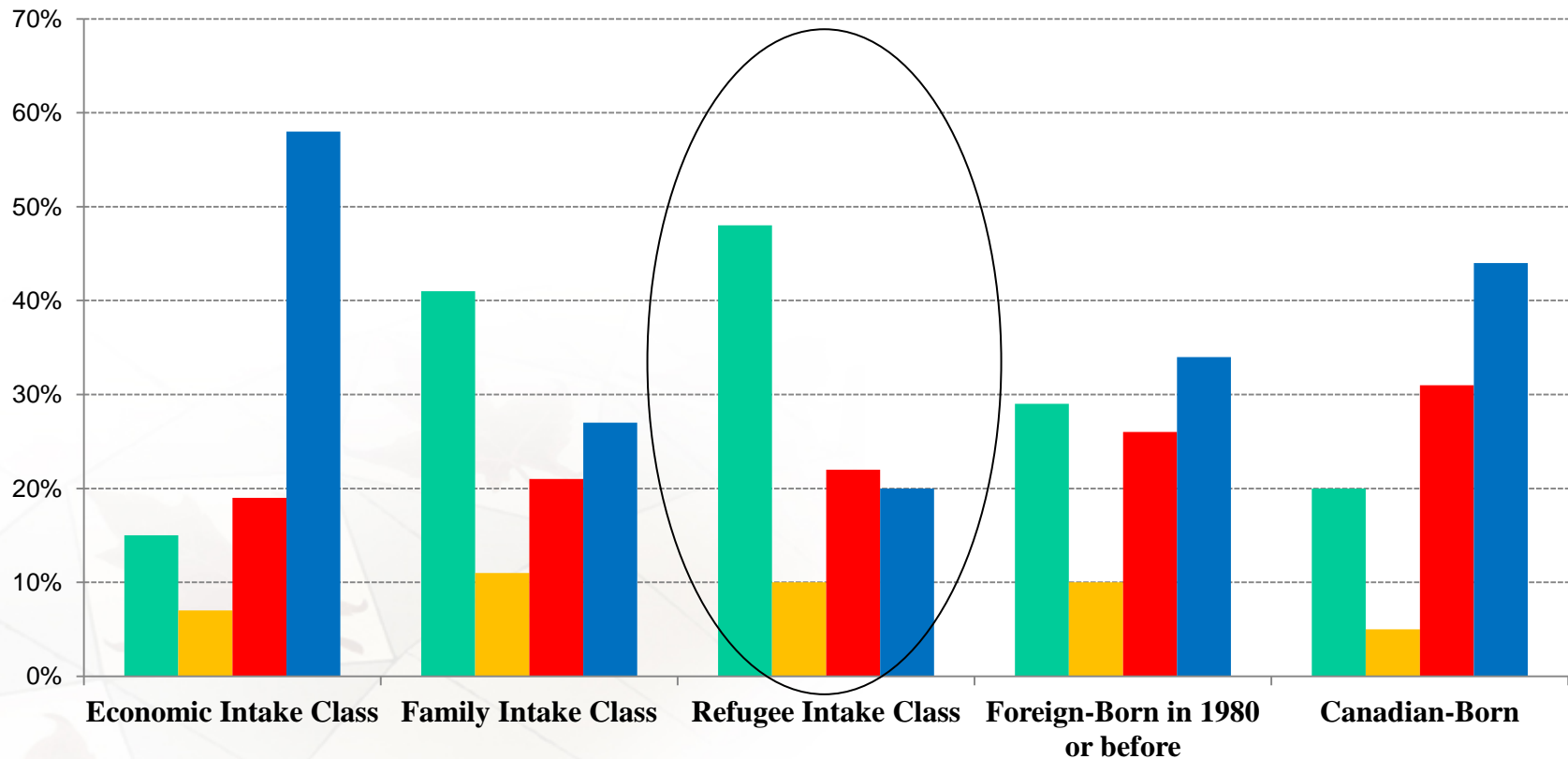


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# High School as the Modal Category in the Refugee Male Ethnic Classifications



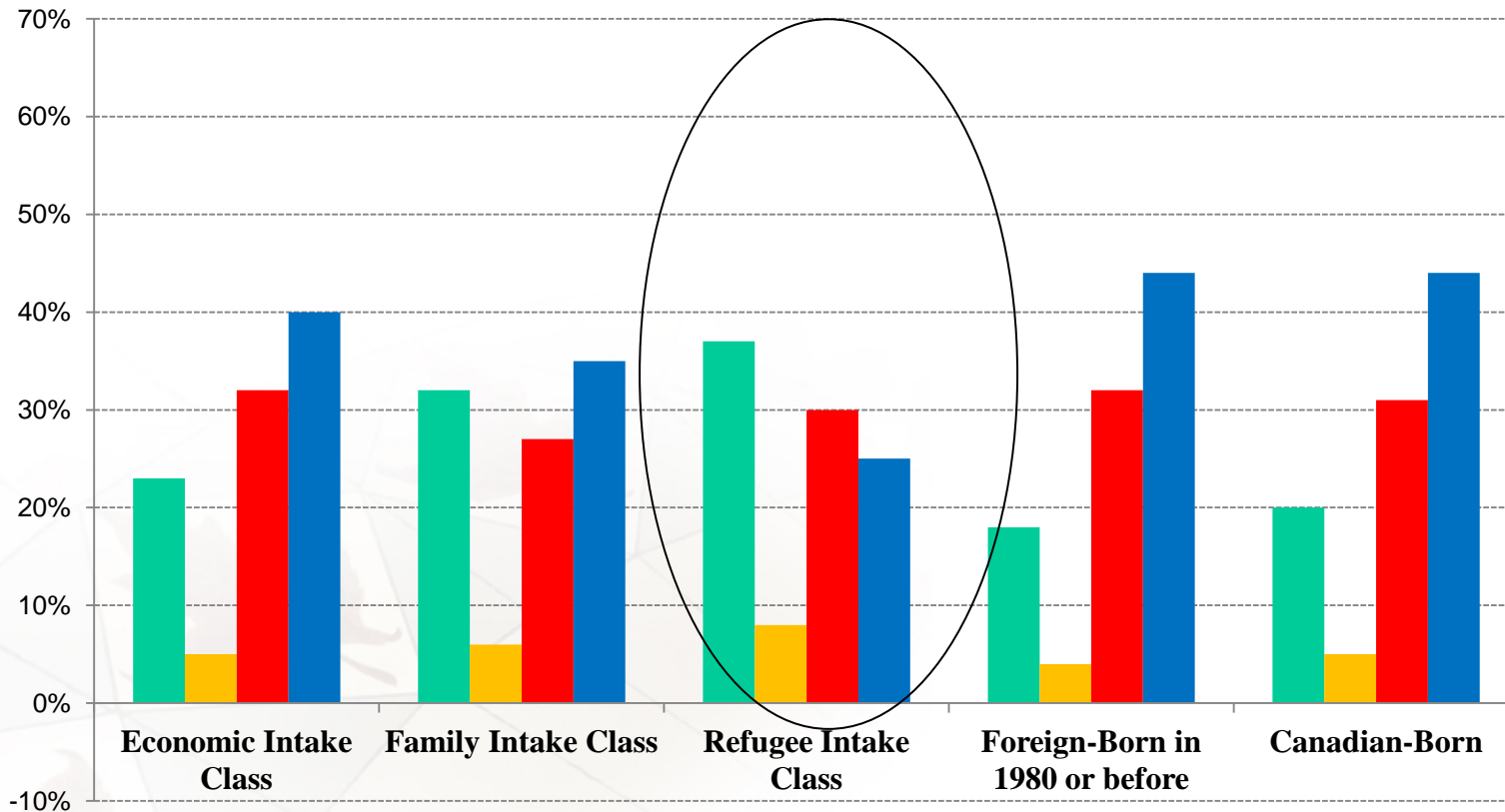
■ A1: Average % HS Degrees      ■ A2: Average % Trade Degrees  
■ A3: Average % Non Univ. Degrees   ■ A4: Average % University degrees



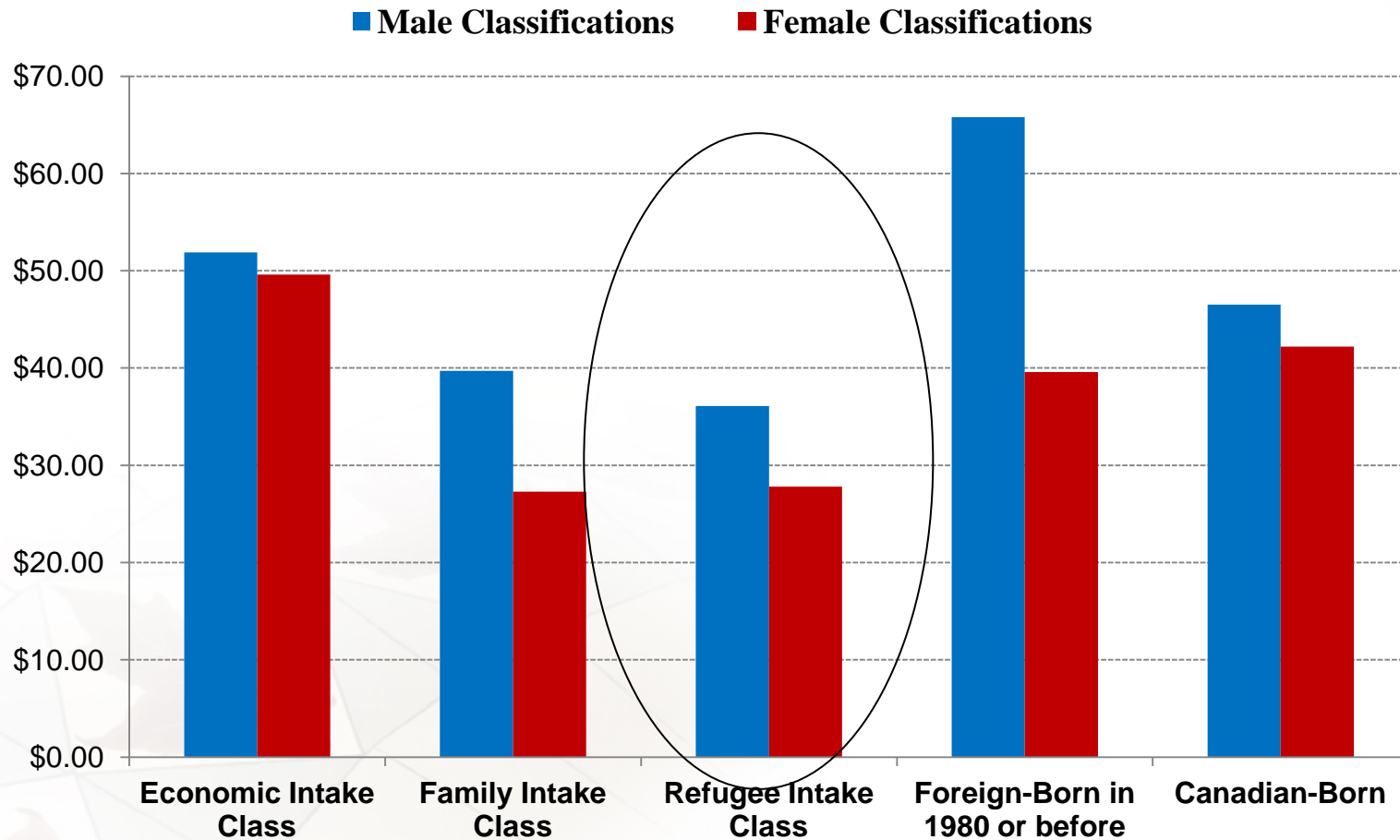
# More Diversified Modal Categories in the Refugee Female Ethnic Classifications



- A1: Average % HS Degrees
- A2: Average % Trade Degrees
- A3: Average % Non Univ. Degrees
- A4: Average % University degrees



# Higher Incomes among Economic Class Immigrants and More Established Ones



# Correlation Matrices of Male and Female Ethnic Classifications



Indicators	A1:% HS Degrees	A2:% Trades Degrees	A3: % Non Univ. degrees	A4: % University degrees	A5: Median Emp. Income (\$)
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## Male Classifications

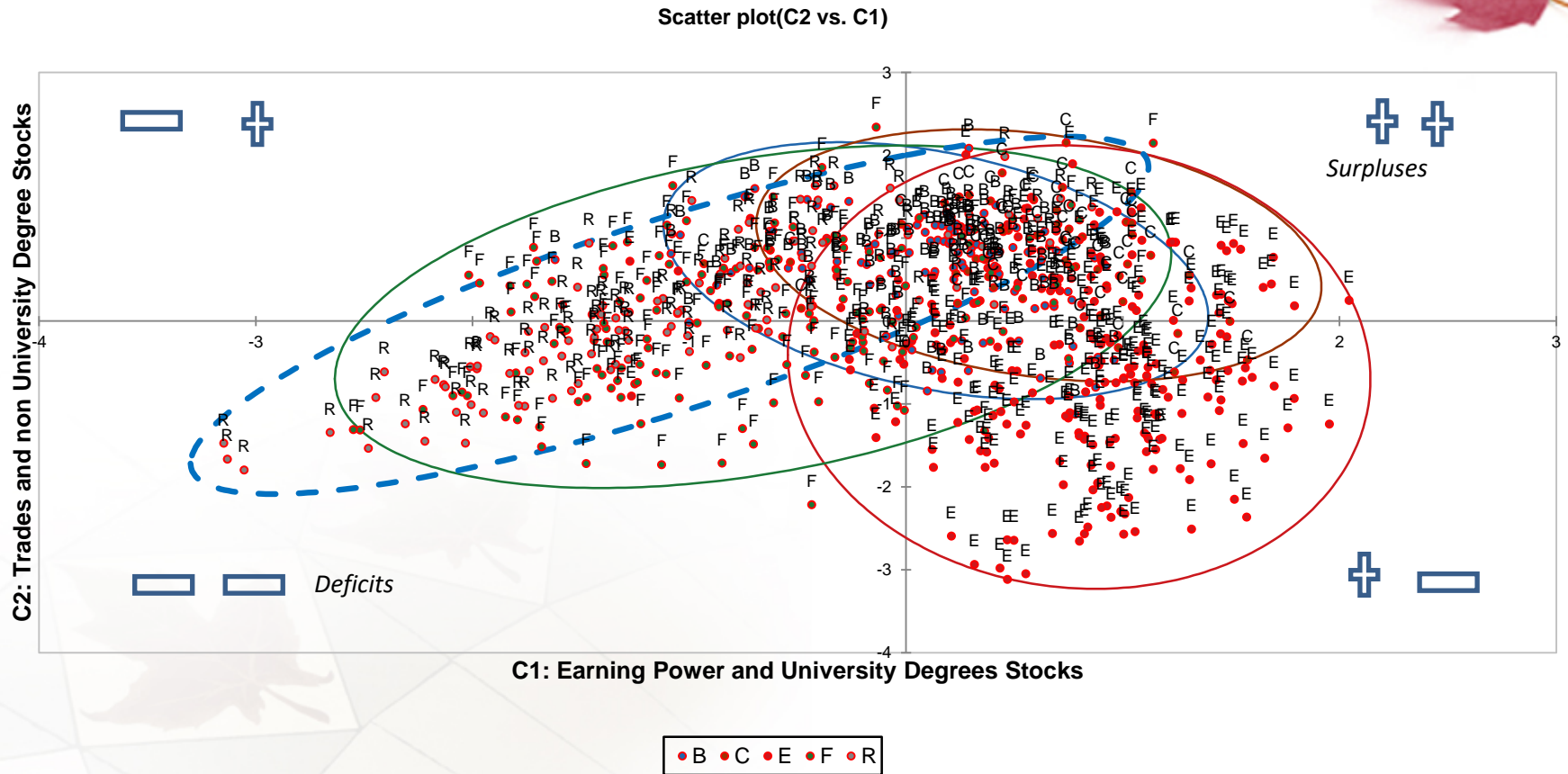
A1:% HS Degrees	1	.20**	.03ns	-.87**	<b>-.43**</b>
A2:% Trades Degrees		1	.43**	-.56**	<b>.06ns</b>
A3: % Non Univ. degrees			1	-.42**	<b>.23**</b>
A4: % University degrees				1	<b>.26**</b>
A5: Median Emp. Income (\$)					<b>1</b>

## Female Classifications

A1:% HS Degrees	1	.19**	.08*	-.83**	<b>-.34**</b>
A2:% Trades Degrees		1	.28**	-.52**	<b>-.18**</b>
A3: % Non Univ. degrees			1	-.57**	<b>.34**</b>
A4: % University degrees				1	<b>.14**</b>
A5: Median Emp. Income (\$)					<b>1</b>



# Two Domains of HC Attainments in Male Classifications (78% Variance Explained by C1 and C2)

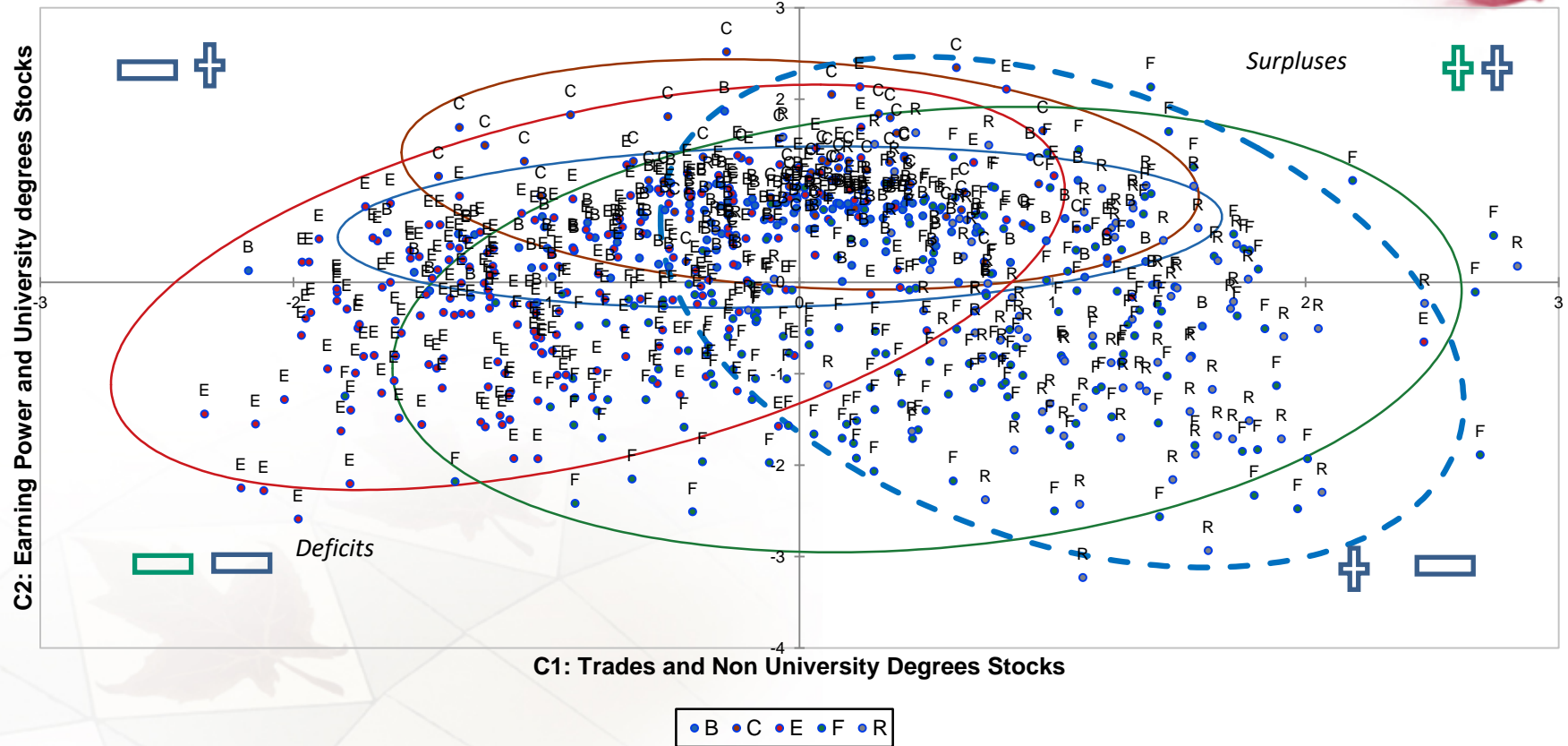


Symbols: B=Immigrants 1980 or before, C=Canadian-born, E=Economic intake class, F=family intake class, R=refugee intake class.

# Domains of HC Attainments in Female Classifications (76% Variance Explained by C1 and C2)



Scatter plot(C2 vs C1)



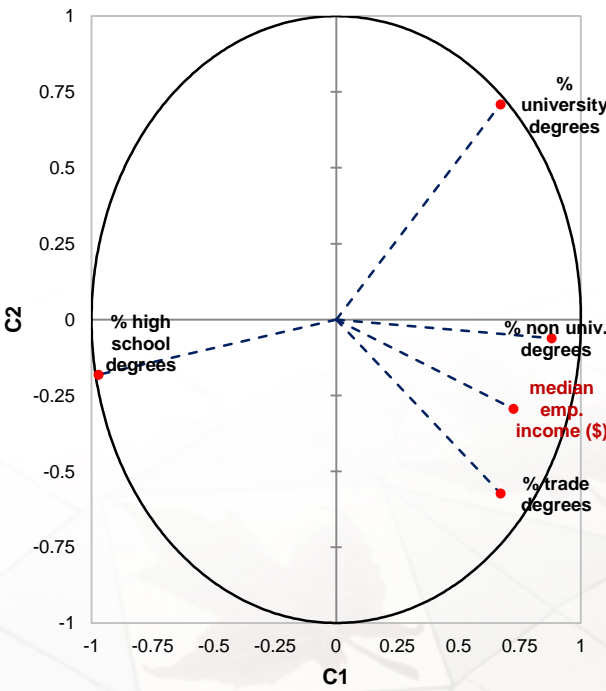
Symbols: B=Immigrants 1980 or before, C=Canadian-born, E=Economic intake class, F=family intake class, R=refugee intake class.

# Income Generation Patterns: Correlation Circles, Male Classifications



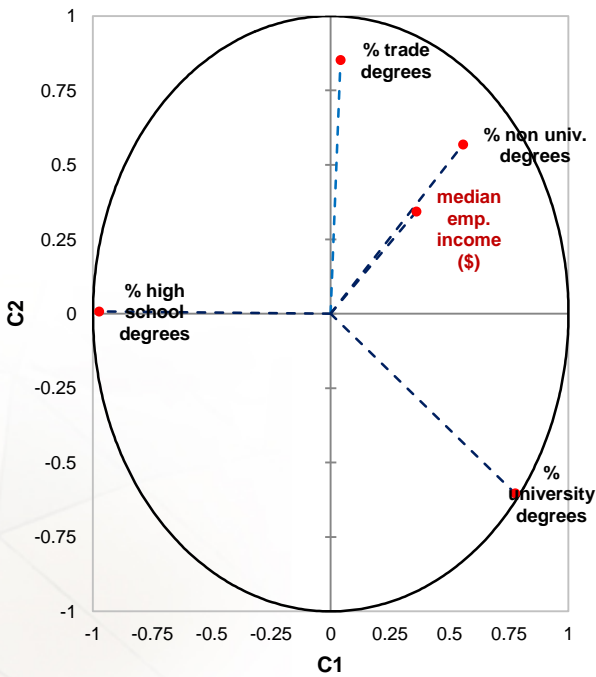
## Refugee Class

Variables (axes C2 vs. C1)



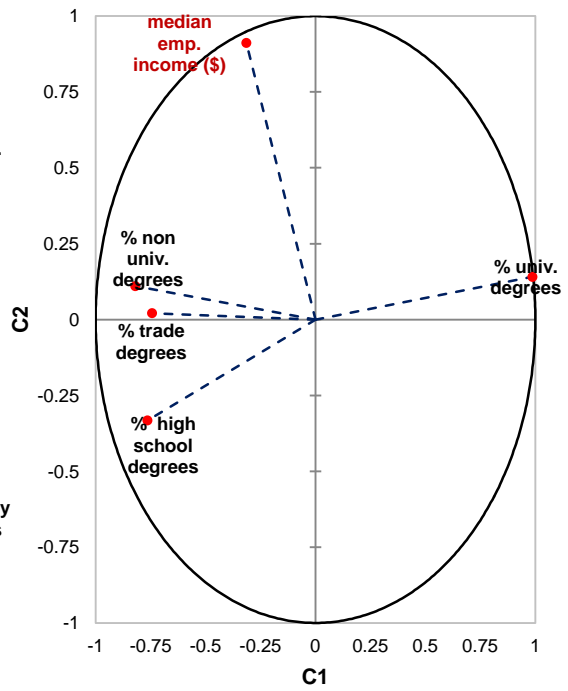
## Family Class

Variables (axes C2 vs. C1)



## Economic Class

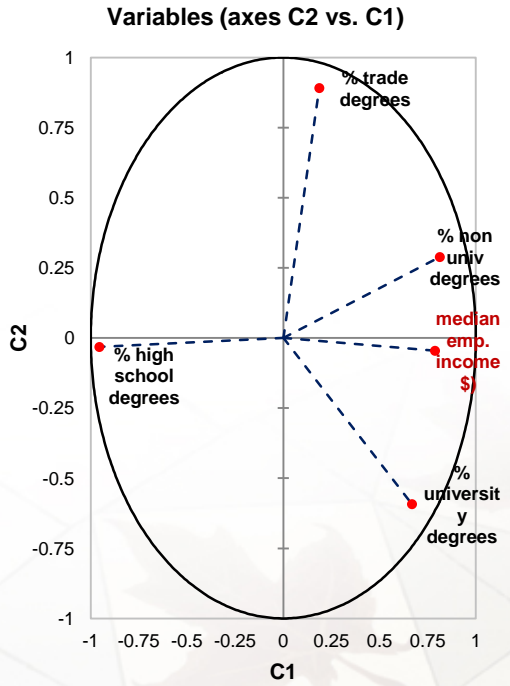
Variables (axes C2 vs. C1)



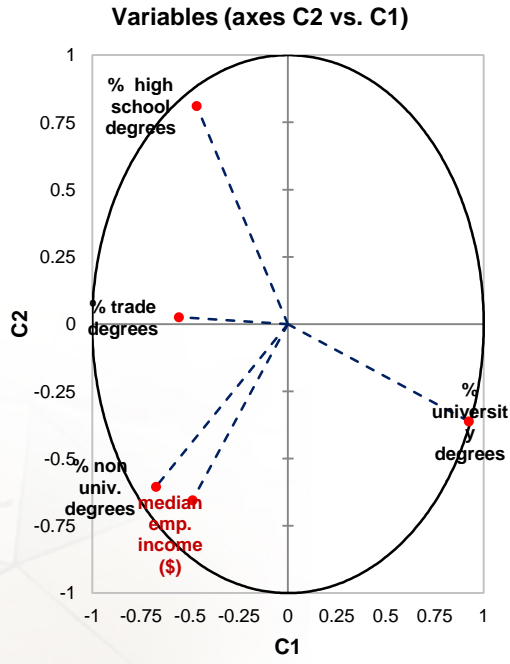
# Income Generation Patterns: Correlation Circles, Female Classifications



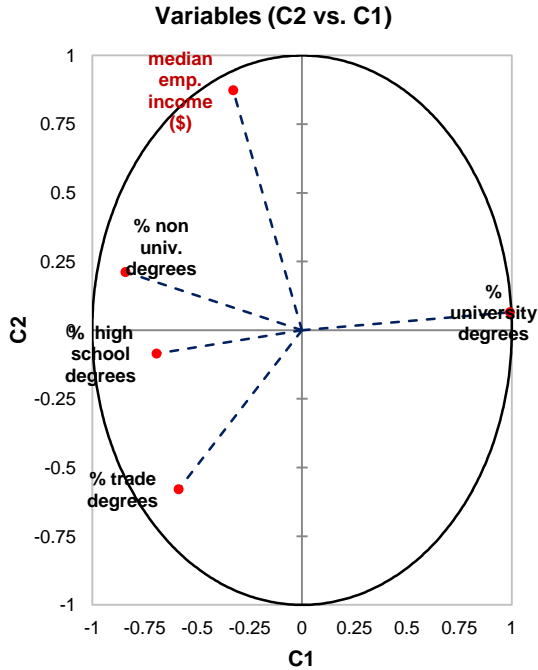
## Refugee Class



## Family Class



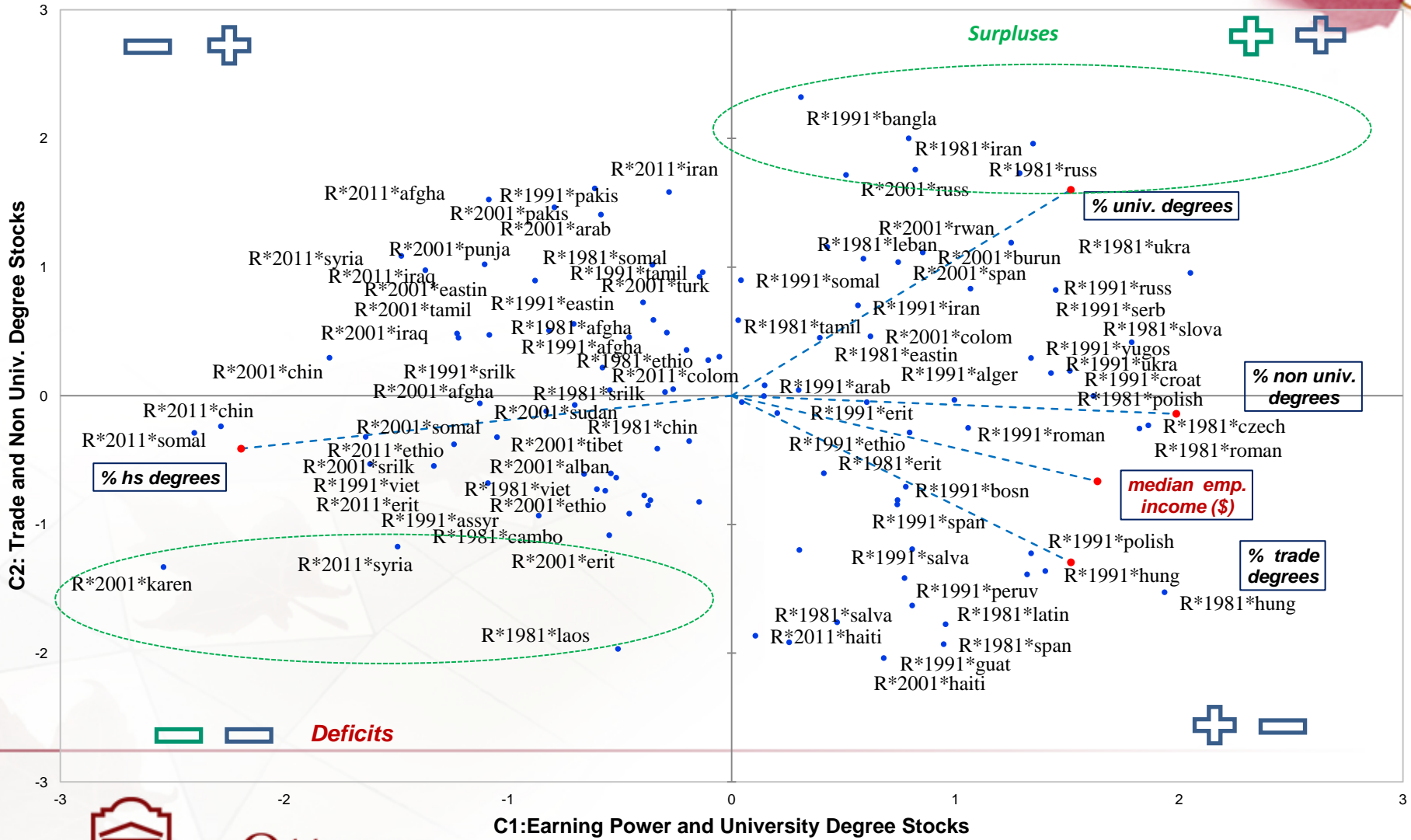
## Economic Class



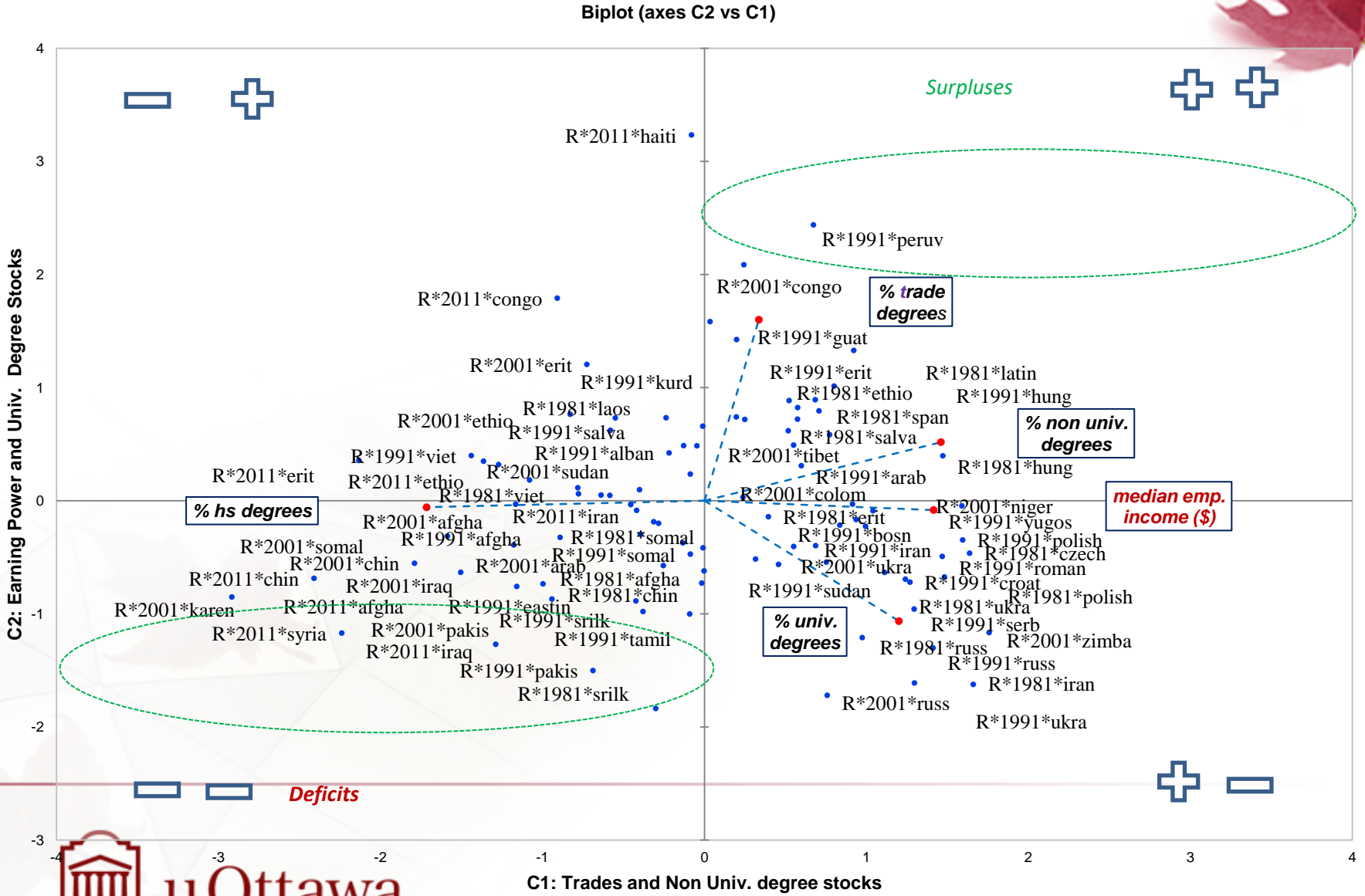
# Ethnic Groups in Component Space: Refugee Male Classifications



Biplot (axes C2 vs. C1)



# Ethnic Groups in Component Space: Refugee Female Classifications



# K-Means Clustering Results



- ❑ Five solutions were carried out:  $k=3$  to  $k=7$ .
- ❑ The reduction of the Wilk's lambda statistic (ratio of within to total variance) was used as a criteria for determining for the number of clusters where a lower lambda ( $\lambda < .05$ ) is always preferred.
- ❑ As the  $k=5$  solution was the most parsimonious, this one was chosen for both the male and female classifications.
- ❑ To validate the optimal  $k=5$  solution, discriminant analyses was additionally undertaken (Punj and Stewart, 1983).
- ❑ All of the four discriminant functions for the male and female classifications were found to be statistically significant using the  $X^2$  statistic test

# 5 Main Clusters: Male Classifications



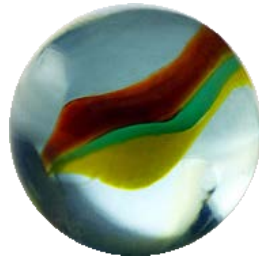
n=89



Univ. Degree Stocks

- 87% Non European
- 93% Economic
- 47% 2001-2010 arrival

n=147



Earning Power

- 52% Non European
- 65% Economic
- 26 % 2001-2010 arrival

n=84



HCA Deficits

- **92% Non European**
- **49% Refugee**
- **50% Family**
- **41 % 2001-2010 arrival**
- **29 % 2011-2016 arrival**

n=187



HCA Surpluses

- **34 % Non European**
- **35% in or before 1980 arrival**

n=155



Non P.S. Degree Stocks

- 74 % Non European
- 48% Family
- 25% 1991-2000 arrival



# 5 Main Clusters: Female Classifications



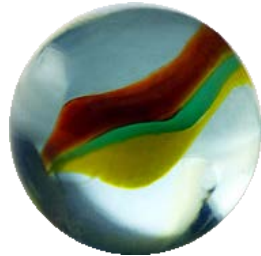
n=202



Non Univ.  
Degree Stocks

- 41% Non European
- 34% in or before 1980 arrival

n=87



HCA  
Deficits

- **89% Non European**
- **62% Family**
- **39% Refugee**
- **37 % 2001-2010 arrival**

n=111



Trade  
Degree Stocks

- 77% Non European
- 41% Family
- 32% Refugee
- 33% 1991-2000 arrival

n=159



HCA  
Surpluses

- **57 % Non European**
- **59% Economic**
- **39% 2001-2010 arrival**

n=92



Univ.  
Degree Stocks

- 78 % Non European
- 64% Economic
- 59% 2011-2016 arrival

## Group Rankings in the Clusters: Male Classifications



### Surpluses Cluster

(Factor Scores  $> 2.00$ )

1. Economic, 2001-2010, S. African
2. Economic, 1991-2000, Colombian
3. Economic, 2001-2010, Brazilian
4. Economic, 2001-2010, Slovak
5. Economic, 2001-2010, Tamil
6. Economic, 1991-2000, Berber
7. In or before 1980, Jewish
8. Economic, 2001-2010, Italian
9. Economic, 1991-2000, Egyptian
10. Economic, 2011-2016, Australian

### Deficits Cluster

(Factor Scores  $< 2.00$ )

1. Refugee, 2011-2014, Chinese
2. Refugee, 2001-2010, Karen
3. Refugee, 2011-2016, Somali
4. Refugee, 2001-2010, Chinese
5. Family, 2011-2016, Vietnamese
6. Family, 2011-2016, Afghani
7. Refugee, 2011-2016, Syrian
8. Refugee, 2011-2016, Eritrean
9. Refugee, 2011-2016, Sri Lankan
10. Refugee, 2001-2010, Burmese



## Group Rankings in the Clusters: Female Classifications



### Surpluses Cluster

(Factor Scores  $> 2.00$ )

1. In or before 1980, Croatian
2. Economic, 1981-1990, Jamaican
3. Economic, 1991-2000, Jamaican
4. In or before 1980, Filipino
5. In or before 1980, S. African
6. In or before 1980, Czech
7. In or before 1980, Guyanese
8. In or before 1980, Egyptian
9. In or before 1980, Haitian
10. Refugee, 1991-2000, Polish

### Deficits Cluster

(Factor Scores  $< 2.00$ )

1. Refugee, 2011-2016, Syrian
2. Refugee, 2011-2016, Chinese
3. Economic, 2011-2016, Bangladeshi
4. Family, 2011-2016, Vietnamese
5. Family, 2011-2016, Punjabi
6. Family, 2011-2016, Sri Lankan
7. Refugee, 2011-2016, Afghani
8. Family, 2011-2016, Pakistani
9. Refugee, 2011-2016, Iraqi
10. Family, 2001-2010, Vietnamese



# Conclusions: Towards Micro-data Analysis



- ❑ **Surpluses and deficits in human capital reflect significant stratifications present in the Canadian labour force**
- ❑ **Situation where particular ethnic immigrant groups may be more economically vulnerable than others.**
- ❑ **HCA deficits clearly visible across refugee and family class groups of immigrants regardless of period of arrival**
- ❑ **Statistical analysis with micro-data as next step to explain income generation processes and educational outcomes**





**THANK-YOU!**



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