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ABSTRACT

Employer Policies and the Immigrant-Native Earnings Gap*

We use longitudinal data from the income tax system to study the impacts of firms' employment and wage-setting policies on the level and change in immigrant-native wage differences in Canada. We focus on immigrants who arrived in the early 2000s, distinguishing between those with and without a college degree from two broad groups of countries – the U.S., the U.K. and Northern Europe, and the rest of the world. Consistent with a growing literature based on the two-way fixed effects model of Abowd, Kramarz, and Margolis (1999), we find that firm-specific wage premiums explain a significant share of earnings inequality in Canada and contribute to the average earnings gap between immigrants and natives. In the decade after receiving permanent status, earnings of immigrants rise relative to those of natives. Compositional effects due to selective outmigration and changing participation play no role in this gain. About one-sixth is attributable to movements up the job ladder to employers that offer higher pay premiums for all groups, with particularly large gains for immigrants from the "rest of the world" countries.

JEL Classification: J15, J31, J71

Keywords: wage differentials, immigrants, linked employer-employee data, firm effects

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1 Introduction

Average earnings of immigrants differ from those of natives, with gaps that depend on their country of origin and time in the host country. In the U.S., Canada, and Australia, immigrants from many countries earn *less* than natives with similar observed characteristics, though some immigrant groups earn more (see e.g., Clarke, Ferrer and Skuterud, 2019). Much of the existing literature attributes these gaps to differences to productivity associated with such factors as language skills (e.g., Chiswick and Miller, 1994), literacy (Ferrer, Green and Riddell, 2006), and the quality of schooling (Bratsberg and Terrell, 2007). A closely related literature explains the growth of immigrant earnings after arrival as the outcome of human capital investments (Chiswick, 1978; LaLonde and Topel, 1992; Baker and Benjamin, 1997), reinforced by the return migration of less successful immigrants (Yezer and Thurston, 1976; Dustmann and Gorlach, 2015).

While productivity differences between immigrants and natives are clearly important, a growing body of research originating with Abowd, Kramarz and Margolis (1999) suggests that firm's wage setting policies tend to magnify differences between groups and widen overall inequality (see Card, Cardoso, Heining and Kline, 2019 for a recent overview). In the presence of such firm-specific premiums, the immigrant-native pay gap will depend on the relative fractions of immigrants hired at high-wage firms – a between-firm *sorting effect* – and on the size of pay premiums offered by firms to immigrants versus natives – a *relative wage-setting effect*. Recent research suggests that both channels are quantitatively important for gender and race-related wage differences (Card, Cardoso and Kline, 2016; Gerrard, Lagos, Severnini, Card, 2019).

Several strands of existing research suggest that firm's hiring and wage setting policies may have a differential impact on immigrants. Oreopoulos (2011) showed that employers are less likely to call back job applicants with foreign names, particularly those with limited work experience in the host country. Using monthly labor force data to analyze transitions between higher and lower-paying jobs, Skuterud and Su (2012) showed that immigrants have lower upward-mobility rates than natives. Pendakur and Woodcock (2010) and Javdani and McGee (2018) compare job mobility rates and within-firm promotion rates in a longitudinal worker-firm data base and find immigrant-native gaps in both dimensions.

In this paper we use administrative earnings data for immigrants in Canada, along with parallel data for native-born workers, to quantify the impacts of employer policies on the level and trend in the immigrant-native pay gap.[1] We classify immigrants into four broad groups based on having

[1]An earlier study by Damas de Matos (2016) used a similar approach to study earnings assimilation of immigrants to Portugal, and concluded that movement to higher-paying firms was an important channel for the rise in relative

a college degree when applying for permanent residence status or not; and on being from either "advantaged" countries (the U.S., Northern Europe, Australia, New Zealand) – the source of about 10% of recent immigrant cohorts – or non-advantaged countries (India, China, other Asian countries, Southern and Eastern Europe, Africa, Latin America and the Caribbean) – the source of the vast majority of recent immigrants to Canada

Our main analysis relies on the Canadian Employer-Employee Dynamic Database (CEEDD), a longitudinal matched worker-firm database derived from tax records. CEEDD has information on taxable earnings for 100% of the Canadian population, and is matched to information for immigrants at the time they are granted permanent residence status, including country of origin and education.[2] A key advantage of CEEDD is sample size: we have earnings information for all workers in Canada - a fact that is particularly important for studying the outcomes of a specific immigrant arrival cohort. Relatedly, we can track individuals over time, allowing us to address concerns over selective emigration or changes in the share of a given immigrant cohort that works.[3] A limitation of CEEDD is the absence of detailed demographic information for *natives*, specifically on education. Like many other administrative data sets (e.g., Social Security earnings records in the U.S.) CEEDD also lacks information on weeks or hours, making it impossible to disentangle differences in labor supply from differences in wages per unit of time.

To set the stage for the analysis and provide some insights into the likely consequences of not being able to measure hours of work or natives' education, we therefore begin by analyzing data from the 2006, 2011 and 2016 Censuses. We reach two main conclusions. First, comparisons of immigrant-native wage gaps with and without controlling for education yield broadly similar conclusions about earnings assimilation patterns. Second, wage gaps in annual earnings are quite similar to the gaps in weekly earnings. Thus, we believe that the limitations of the CEEDD are unlikely to lead to major biases in our analysis.

With this background, we then turn to our main analysis. Using data for about 10 million

wages of immigrants in the period after arrival.

[2]Given this data source – known as the Longitudinal Immigration Data Base (IMDB) – we focus exclusively on immigrants with permanent residence status (equivalent to holding a Green Card in the U.S.) In contrast to the U.S., most immigrants receive permanent status when they first arrive in Canada. For the cohort of cohort of immigrants granted permanent residence between 2000 and 2004, only about 15% had entered Canada as temporary workers or students prior to obtaining permanent residence status.

[3]Recent studies of immigrant earnings growth in the U.S. that use administrative earnings records reach different conclusions about the importance of selective emigration, with Lubotsky (2007) finding that it contributes to positive earnings growth for stayers, and Rho and Sanders (2018) and Akee and Jones (2019) finding the opposite. Using tax record data similar to ours, Picot and Pirano (2013) find that selective emigration by immigrants is largely offset by selective non-participation by natives, leading to little net effect on the growth of immigrant earnings relative to natives.

natives and 2.5 million immigrants over the period from 2005 to 2013, we estimate separate Abowd, Kramarz and Margolis (1999) (AKM) models for annual earnings of natives and immigrants on their main jobs in each year. These models decompose earnings into a time-invariant person effect, a time-varying function of observed characteristics (including age and province of work), an earnings premium associated with the current employer, and a residual term. Consistent with findings from the U.S. and many other countries, we find that differences in the wage premiums paid by different firms explain an important share of the variation in earnings for both natives and immigrants in Canada.[4] We also find a strong pattern of assortative matching between higher-skilled workers and high-premium firms for both groups.[5] These matching patterns mean that firm-specific wage premiums tend to widen inequality between more- and less-skilled workers within both groups, as has been documented for Germany, the U.S., and other countries, and suggests that firm hiring patterns will widen immigrant-native gaps.

We then implement a simple decomposition of the difference in mean earnings between immigrants and natives that identifies the overall contribution of firm-specific pay premiums, and the sorting and relative pay-setting components of this total.[6] We find that the average workplace premiums earned by natives are higher than those earned by immigrants, accounting for about one-fifth of the immigrant-native pay gap for this cohort. Virtually all of this differential is associated with the between-firm sorting effect: we find that the firm-specific pay premiums for native and immigrant workers are on average the same, with no evidence that higher-paying firms compress their pay premiums for immigrants relative to natives. Looking within immigrant subgroups, we find heterogeneity in the contribution of firm hiring policies, with the largest magnitude for immigrants from non-advantaged countries who lack university education. Relative to natives (and better-educated immigrants) these workers are much less likely to be hired by high-wage firms - a gap that accounts for 7 percentage points of their 40 point earnings gap relative to natives.

Following this analysis of **average** pay gaps between immigrants and natives, we turn to an analysis of the **changes** in relative earnings from 2005 to 2013 for the 2000-2004 arrival cohort –

[4]Abowd, Creecy and Kramarz (2002) find that between-firm variation represents about 19% of the variance of hourly wages in Washington State and 30% of the variance of annual earnings in France. Card, Heining and Kline (2013), Card, Cardoso, and Kline (2016), and Macis and Schivardi (2016) estimate a 15%-20% share for establishment effects in the case of German workers, Portuguese male workers, and Italian manufacturing workers, respectively.

[5]Orefice and Peri (2020) find the immigration inflows lead to a higher degree of assortative matching between workers and firms in different districts in France.

[6]As explained in detail below, a key issue underlying this comparison is how to benchmark the estimated establishment effects for natives and immigrants. Following Card, Cardoso and Kline (2016) we use a normalization based on the set of firms that pay the lowest levels of wages to immigrants and natives. A similar method is used by Macis and Schivardi (2016), Gallen, Lesner and Vejlin (2017), Coudin (2018) and Bruns (2019).

i.e., the process of earnings assimilation. In our AKM-style framework, the "composition biases" that arise from selective outmigration or changing participation rates are summarized by changes in the mean of the person effects for those with positive earnings in a given year. Consistent with other recent evidence for Canadian and U.S. immigrants (Picot and Pirano, 2013; Rho and Sanders, 2018, Akee and Jones, 2019) we find that the composition effect is very small, with similar trends for immigrants and natives over time.[7]

On average we find that the growth in the sorting effect accounts for just under one-fifth of the 15 percentage composition-adjusted gain in earnings for the 2000-2004 arrival cohort between 2005 and 2013. Interestingly, the **gains** in relative wages attributable to moves up the job ladder are largest for university-educated immigrants from disadvantaged countries – a group who are often "over-educated" for the jobs they hold (Hou, Lu, and Schimmele, 2019). Adjusting for composition and age effects, this group's earnings rise by 22 percent relative to natives between 2005 and 2013; of this gain, nearly 4 percentage points are due to employment reallocation toward higher-paying employers. In contrast, university-educated immigrants from advantaged countries tend to work at high-paying firms when they first arrive, and make little further progress over the next decade. These patterns are consistent with a simple learning model in which higher-paying firms can readily evaluate the degrees of immigrants from advanced countries, but tend to downgrade the education credentials of immigrants from less advantaged countries, and only hire those who are revealed to be more productive over time.

Our findings make three main contributions. First, we contribute to the literature on the determinants of immigrant earnings (see e.g., Borjas, 1999)\ by quantifying the role of firm hiring and wage setting policies in observed immigrant-native pay gaps and earnings assimilation. To the best of our knowledge, only one earlier study by Damas de Matos (2016) – which focused more narrowly on assimilation – has studied the impact of firm-specific pay premiums on immigrant earnings outcomes. Second, we contribute to the growing literature that uses AKM-style models to study inter-group wage differences, including the gender pay gap (Card, Cardoso and Kline, 2016; Gallen, Lesner and Vejlin, 2017; Coudin, 2018; Bruns, 2019) and racial pay gaps (Gerrard, Lagos, Severnini, Card, 2019). We extend this literature by showing how ***changes*** in the sorting of workers to firms contribute to the evolution of pay gaps between groups. We also show how the estimated person effects from an AKM setup can be used to model the impacts of changing participation of

[7]We note that our immigrant population is comprised of people who are permanent migrants at the start of our observation period, and excludes those who enter the country as temporary migrants and never transition to permanent residents. We therefore miss any component of earnings growth associated with the selective emigration of lower-earning temporary immigrants.

one group relative to another. Finally we contribute to the large literature on immigrant earnings in Canada, complementing recent studies that have used longitudinal earnings data (e.g., Pendakur and Woodcock 2010; Picot and Pirano, 2013; and Javdani and McGee, 2018) to analyze the evolution of immigrant-native wage differences. We extend this literature by quantifying the impacts of differential sorting of immigrants from different source countries to higher-wage employers both cross-sectionally and over time.

2 Immigration to Canada

As background for our empirical analysis we begin with a brief overview of the institutional framework covering immigration to Canada.[8] Our focus is on "permanent immigrants" - those who have permission to work and stay indefinitely in the country. Canada also has a set of temporary immigration programs that includes temporary foreign workers and students, some of whom ultimately apply for permanent status. Since our key source for immigrants (including their source country and education) is derived from applications for permanent residency, we ignore temporary immigrants unless/until they become permanent residents.

Permanent immigrants to Canada fall into two main classes: economic immigrants and sponsored family members.[9] Economic immigrants apply to move to Canada and are evaluated through a point system that rewards factors including education, knowledge of French or English, having an occupation in high demand, having a pre-arranged job, and having prior work experience in Canada.[10] Candidates with higher numbers of points are invited to apply for permanent residence, with a cutoff that varies across years. Successful applicants and their family members can then become permanent residents upon arrival to the country.

Sponsored family members are parents, partners, children, and other relations of people who are already citizens or permanent residents of Canada (see Citizenship and Immigration Canada, 2014). The applicant and his or her sponsor submit a joint application under which the sponsor agrees to be responsible for all social assistance payments received by the applicant for a period of 3-10 years. The number of sponsored family members admitted varies from year to year, with highest priority for spouses and dependent children. In recent years the total number admitted has been

[8]See Green and Green (1995) for an historical overview of Canada's immigration policy.

[9]There are also two other groups: refugees, and immigrants entering under "Humanitarian/Compassionate Public Policy Considerations." On average these groups have made up about 10% of immigrants to Canada in recent decades.

[10]See Ferrer, Picot and Riddell (2014) for a discussion of how the points allocations have changed over time. Bonikowska and Hou (2015) show how various characteristics included in the point system help predict subsequent earnings in Canada.

about one-half as large as the number of economic immigrants admitted.

While the Canadian government sets the evaluation criteria and maximum inflows of each type of immigrant each year, the composition of the inflow pool is largely supply determined. Since the 1970s the main sources of immigrant supply have shifted from Western Europe to Asia. Coincident with this shift has been a decline in the earnings of immigrants relative to natives (Baker and Benjamin, 1994; Hou and Picot, 2016) that is widely attributed to differences in the skills brought to Canada by immigrants from these new source countries. Building on the existing literature, in our analysis below we form two broad groups of countries that reflect the "traditional" and "new" source countries. The first group, which for simplicity we call the *advantaged countrie*s, consists of the U.S., the U.K., Australia, New Zealand, and countries in Northern/Western Europe where most people have English as a second language, including Germany, France, the Netherlands, and the Nordic countries.[11] The second group, which we call the *non-advantaged countries*, includes all other countries, most importantly India, China, Africa, the Caribbean, and Southern and Eastern Europe. These "new" source countries account for close to 90% of immigrants to Canada in recent years.

Table 1 presents some descriptive statistics by country-of-origin group and admission class for immigrants age 20-59 observed in the 2016 Canadian census.[12] We also show parallel statistics for natives. Comparisons across the columns of the table show that immigrants from advantaged countries have considerably higher annual earnings than those from non-advantaged countries (or than natives), despite the fact that immigrants from disadvantaged source countries are **more likely** to hold at least a B.A. degree (47% versus 43%).[13] We suspect that this difference arises because applicants from advantaged countries are more likely to gain admission through factors like having a pre-arranged job that have an immediate payoff in the Canadian labor market, whereas those from non-advantaged countries are more likely to rely on having a university education – a credential that does not necessarily ensure labor market success given their language skills and lower quality schooling. Comparing immigrants admitted as sponsored family members to those admitted as economic immigrants, it is also clear that the family-based group have lower employment rates and lower earnings, regardless of source country, though some of these differences are presumably due to

[11]We have experimented with including Italy and Portugal in this group and found it makes little difference. Spain is not separately identified as a source country in the public use files of recent Canadian Censuses but we assume it is included in a category of other European countries that we add to the list.

[12]Information on admission class is not available in previous censuses.

[13]Both immigrant groups are substantially more likely to hold a B.A. than natives. Some of this gap reflects the fact that natives are older than immigrants, and university education is more prevalent among recent cohorts. Even among 30-39 year-old natives in 2016, however, only 29% have a B.A. or higher degree.

their lower education levels.

3 Immigrant-Native Wage Gaps Using the 2006, 2011, and 2016 Censuses

As noted above, a limitation of the CEEDD data that we use for our main analysis is the absence of information on hours or weeks worked and, in the case of native workers, on educational attainment. The first goal of this section is to assess whether the annual earnings differentials that can be computed using CEEDD are potentially misleading due to systematic differences between immigrants and natives in hours or weeks worked. Specifically, using census data, where we can observe weeks and a measure of hours per week, we follow other recent studies based on annual earnings records (e.g., Song et al., 2019) and impose a minimum annual earnings threshold of roughly \$14,000 for both natives and immigrants.[14] We then compare annual earnings gaps for workers who earn at least the threshold level to weekly wage gaps. To foreshadow our results, we find that the gaps constructed from the (above-threshold) annual earnings are broadly similar to the gaps constructed from weekly earnings, suggesting that the absence of hours data in CEEDD is potentially ignorable, provided we impose a threshold to eliminate very-low earning observations.

Our second goal is to assess the importance of missing education information for natives. Again, using census data we compare unadjusted annual earnings gaps to more conventional regression-adjusted gaps that control for education (and age). We find that controls for education shift the magnitudes of the immigrant-native wage gaps – particularly for immigrants from disadvantaged countries, who have high levels of education but relatively low earnings – but do not have much affect on the evolution of earnings gaps over time, as would be expected if individual education levels are constant.

Figure 1 shows immigrant-native gaps in mean log earnings for male and female immigrants from our two source country groups who arrived in Canada between 2000 and 2004 and were interviewed in the 2006, 2011, or 2016 Censuses. Panel a of the figure presents gaps in mean log annual earnings, right censoring earnings at (approximately) \$14,000 in each year. Panel b shows regression-adjusted versions of the gap in the same measure of annual earnings, with controls for education and age. Finally, panel c shows regression-adjusted gaps in log ***weekly*** earnings.

A first conclusion that emerges from these simple comparisons is that individuals from the

[14] More precisely \$13,380 in \$2012 representing 48 weeks of full-time work paid at the average of the minimum wage across provinces, weighted by the number of employees in each province. See Galarneau and Fecteau (2014) for a study on the evolution of the minimum wage in Canada since 1975.

advantaged countries have on average much higher earnings than their counterparts from other countries. Indeed, males from the advantaged countries earn 10-20 percent ***more*** per year than natives, though much of this difference is explained by their higher education, so the adjusted annual and weekly earnings gaps are in the range of ± 5 percent. By comparison, males from less advantaged countries earn 20-30 percentage points less than natives per year. This gap widens by approximately another 15 percentage points when we control for education, reflecting the high levels of education among these immigrants (noted in Table 1).

A second observation is that the cross-year profiles of gaps in annual, adjusted annual, and adjusted weekly earnings are nearly parallel for all four groups. Regression adjustments for age and education lead to lower the gaps for all four gender $\times$ origin groups, but leave the *changes* in the gaps over time largely unaffected. These patterns suggest that an analysis of gaps in (right censored) annual earnings without adjustment for education will be informative about the earnings assimilation patterns of recent immigrant arrivals in Canada.

A third finding is that the earnings gaps for males and females from the same origin group are roughly parallel over time.[15] This is particularly true for the (much larger) group of males and females from less advantaged countries: both men and women from these countries experience about a 10% rise in earnings relative to natives between 2006 and 2011, then little further change between 2011 and 2016.

To check whether there might be something specific to the particular cohort of immigrants who entered the country between 2000 and 2004 or specific to the overall state of the labor market at that time, we computed a full set of analogous gaps for the cohort of immigrants that entered Canada between 1995 and 1999. The patterns in the immigrant-native wage differentials across the 2001, 2006, 2011, and 2016 censuses for these immigrants turn out to be very similar to the ones computed for the later cohort of entrants (though they experience only small changes in the levels of the gaps over time).

We also investigated how the earnings gaps of 2000-2004 immigant arrivals varied by their age at arrival in Canada. Appendix Figures 1a and 1b show the profiles of annual and weekly earnings gaps for men and women in 5-year age-at-arrival cohorts over the 2006, 2011 and 2016 censuses.[16]

[15]In an analysis of male and female immigration profiles, Baker and Benjamin (1997) argued that wives in immigrant families took on dead-end jobs at arrival in Canada to help finance human capital investments by their husbands, potentially leading to a divergence in earnings profiles after arrival. However, Blau et al. (2003) pointed out that the actual wage profiles estimated by Baker and Benjamin – and profiles for immigrants in the U.S. – show little or no divergence in rates of pay. Our findings on earnings are consistent with the conclusions of Blau et al. (2003).

[16]Appendix Table 1 provides a full tabulation of unadjusted and adjusted annual and weekly earnings gaps for the four gender $\times$country of origin groups, separately by 5-year age at arrival groups.

Given the small sample sizes for immigrants from advantaged countries we limit our attention in these figures to immigrants from the non-advantaged countries. Consistent with the patterns for the pooled set of age-at-arrival groups in Figure 1, we find that: (1) the profiles of annual and weekly wage gaps are very similar; and (2) the profiles for male and female immigrants are also similar. One new insight that emerges from a comparison of different age-at-arrival groups is that the gains in immigrant earnings relative to natives between 2006 and 2011 are particularly large for immigrants who arrived at older ages.

Other Labor Market Indicators

The comparisons in Figure 1 suggest that the earnings gaps between immigrants and natives are very similar whether we use mean log weekly earnings or mean log annual earnings for those with earnings above a minimum threshold. What about gaps in labor market participation? In Appendix Table 2 we report immigrant-native gaps by gender and source country group for three measures of participation: the fraction reporting postive earnings in the previous calendar year; the fraction who report working mainly full-time in the previous calendar year; and the fraction who worked at least 45 weeks over the previous year. As in Figure 1 these statistics pertain to immigrants who arrived in Canada between 2000 and 2004 and were interviewed in the 2006, 2011, or 2016 Census.

In brief, the data suggest that male immigrants from advantaged countries work about as much or slightly more than natives, while female immigrants from these countries work slightly ***less*** than native females. The modest gap for females is arguably consistent with standard findings on female labor supply, given the higher earnings of their husbands (who are mainly immigrants from advantaged countries too). By comparison, both male and female immigrants from non-advantaged countries work less than natives, with about a 5 percentage point gap in annual participation among men and a 10-15 point gap for women. Interestingly, for both gender groups we also see some closing of the gap relative to natives over the 2006-2016 period, suggesting that there is assimilation in hours of work for these immigrants, reinforcing the patterns for earnings conditional on work.

4 Impacts of Firm-Specific Hiring and Pay Policies on Immigrant Earnings

In this section we present a simple framework for measuring the impacts of firms' employment and wage setting policies on the earnings gap between immigrants and natives, and on the evolution of the gap as immigrants accumulate experience in the host economy.

4.1 A Job Ladder Model of Earnings

Building on AKM we assume that y_{git} – annual earnings of worker i from group g (either immigrant or native) in period t – is generated by a model of the form:

$$\ln y_{git} = \alpha_{gi} + \psi^{g}_{j(g,i,t)} + X_{git}\beta_g + \varepsilon_{git} \tag{1}$$

where α_{gi} is a person effect (capturing permanent differences in earnings capacity across workers), ψ^g_k is a group-specific *earnings premium* at workplace k, $j\,(g,i,t)$ is a function that identifies the workplace of worker (g,i) in year t, X_{git} is a vector of time varying controls (e.g., year effects, province effects, and controls for age), and β_g is a conformable vector of coefficients.[17] The final component ε_{git} captures all remaining determinants of earnings, including measurement errors, person-specific job match effects, and transitory shocks affecting the worker or the firm (e.g., employee health shocks or employer demand shocks). Note that the pay premiums offered by workplace j are allowed to vary by group, but are assumed to be the same for all workers in a given group.

There are a number of theoretical explanations for the pay premiums in equation (1), including variants of the equilibrium wage posting model developed by Burdett and Mortensen (1998) (e.g., Bassier, Dube and Naidu, 2019), search and matching models with wage bargaining (e.g., Postel-Vinay and Robin, 2006), and static models of monopsonistic wage setting (e.g., Card, Cardoso, Heining and Kline, 2018, henceforth CCHK). As a benchmark we follow CCHK and assume that workers have idiosyncratic valuations for jobs at different workplaces, leading to some degree of market power and to higher wages at more productive firms. In this setting, the wage premiums set by a given firm for workers in different groups can vary across groups, depending on the elasticity of supply of the group to the firm.

Specifically, CCHK show that under some simplifying assumptions, a firm's optimal policy is to set group-specific pay premiums:

$$\psi^g_j = \delta_g R_j \tag{2}$$

where R_j represents a measure of productivity at firm j (scaled relative to the reservation wage of workers) and δ_g is parameter that varies across groups and is related to the group's elasticity of supply to different workplaces.[18] Notice that this model is equivalent to a simple rent sharing model

[17] The person effects and the age profile component of X_{git} are not separately identified without a normalizing assumption. We follow Card, Heining and Kline (2013, CHK hereafter) in normalizing the age profiles to 0 at age 48, when the age profiles in our samples are relatively flat.

[18] Specifically, CCHK assume that the indirect utility that person i in group g places on a job at workplace j paying wage w_{gj} and offering non-wage amenities a_{gj} is $u_{igj} = \theta_g \ln(w_{gj} - b_g) + a_{gj} + \sigma_g \epsilon_{igj}$ where b_g represents the reservation wage of group g and $\sigma_g \epsilon_{igj}$ is a scaled extreme value variate (with variance proportional to σ^2) that

in which workplace j has rents R_j and group g has a rent-sharing coefficient of δ_g.

As noted by AKM, OLS estimation of (1) will only yield unbiased estimates of the workplace pay premiums if the conditional expectation of ε_{git} is independent of a worker's job history. Under this *exogenous mobility* assumption, workers who move from one firm to another will experience average earnings gains that are equal in size but opposite in sign to the gains of workers (from the same group) who move in the opposite direction. In contrast, simple models of mobility driven by idiosyncratic job match effects imply that job movers will tend to experience *positive* gains regardless of the pay premiums received by other workers at the origin or destination firm. Exogenous mobility also implies that transitory earnings fluctuations prior to a job move are unrelated to the change in ψ_j^g, ruling out the kinds of dips in earnings typically seen for workers enter a training program (Ashenfelter, 1978).

A series of specification checks proposed by CHK and evaluated in several later studies (e.g., Macis and Schivardi, 2016; Card, Cardoso and Kline, 2016; Gerrard et al. 2018) suggest that although exogeous mobility can be formally rejected, patterns of ***daily or hourly*** wage changes for movers are broadly consistent with a simple AKM-type model of wage setting. Evidence from Song et al. (2019) based on annual Social Security earnings data for U.S. workers points to the same conclusion, once allowance is made for the fact that annual earnings include pay from multiple employers in a year of job change, and are also impacted by spells of nonwork between jobs. In Section 5.1 below we present parallel evidence based on annual earnings changes for job movers in the CEEDD data. Consistent with the literature, we find that the patterns of earnings changes are broadly consistent with an AKM-type model.

4.2 Impacts on Immigrant-Native Earnings Gap

We now use equation (1) to analyze the impacts of employer hiring and pay policies on the wages of immigrants (group M) and natives (group N). Let D_{git} represent an indicator for the event that individual i in group g has observed earnings in year t, let $\overline{X}_{Mt}$ and $\overline{X}_{Nt}$ represent the means of the observed covariates among employed immigrants and natives in year t, and let π_{Mjt} and π_{Njt} represent the fractions of the two groups employed at workplace j in year t. Then, assuming that $E[\varepsilon_{git}|D_{git} = 1] = 0$ – i.e., ignoring any year-to-year variation in the mean of the *transitory* component of earnings – the mean log wages of immigrants and natives observed in any year t can

represents an idiosyncratic preference of worker i for workplace j. Starting from this specification of preferences and some simplifying assumptions on technology, they derive equation (2) with $\delta_g = \theta_g/\sigma_g$.

be decomposed as:

$$E[\ln y_{Mit}] = E[\alpha_{Mi}|D_{Mit}=1] + \overline{X}_{Mt}\beta_M + \sum_j \psi_j^M \pi_{Mjt} \quad (3)$$

$$E[\ln y_{Nit}] = E[\alpha_{Ni}|D_{Nit}=1] + \overline{X}_{Nt}\beta_N + \sum_j \psi_j^N \pi_{Njt}. \quad (4)$$

and the mean log wage gap between natives and immigrants in year t can be written as:

$$\begin{aligned} E[\ln y_{Nit}] - E[\ln y_{Mit}] &= E[\alpha_{Ni}|D_{Nit}=1] - E[\alpha_{Mi}|D_{Mit}=1] \\ &\quad + \overline{X}_{Nt}\beta_N - \overline{X}_{Mt}\beta_M \\ &\quad + \sum_j \psi_j^N \pi_{Njt} - \sum_j \psi_j^M \pi_{Mjt} \end{aligned} \quad (5)$$

The first term on the right hand side of equation (5) represents the difference in the means of the permanent component of individual skill between the two groups in year t. This difference will vary over time if there are changes in the relative participation of higher- or lower-skilled individuals in the two groups (for example, from selective emigration of low-skilled immigrants). The second term represents the difference in the observed, time-varying factors. If immigrants tend to live in higher-wage provinces than natives, for example, then this component will be nonzero and potentially changing with t. The third term is the net contribution of firm-specific pay premiums to the immigrant pay gap.

Following Oxaca (1973), the third term can be decomposed in one of two ways:

$$\begin{aligned} \sum_j \psi_j^N \pi_{Njt} - \sum_j \psi_j^M \pi_{Mjt} &= \sum_j \psi_j^N (\pi_{Njt} - \pi_{Mjt}) + \sum_j (\psi_j^N - \psi_j^M) \pi_{Mjt} \\ &= \sum_j \psi_j^M (\pi_{Njt} - \pi_{Mjt}) + \sum_j (\psi_j^N - \psi_j^M) \pi_{Njt} \end{aligned} \quad (6)$$

For simplicity, throughout this paper we focus on the first version, though conclusions from the alternative version are nearly identical. This equation expresses the difference in pay premiums as the sum of two terms: a weighted average of the differences in employment shares of the two groups (weighting by the pay premiums for natives at each workplace) and a weighted average of the differences in pay premiums (weighted by the share of immigrants employed at each firm). The first term – which we label the "***sorting effect***" – measures the contribution of differential sorting of natives and immigrants across employers. This will be positive – widening the pay gap between natives and immigrants – if natives are more likely to work at firms that offer higher pay premiums. The second term – which we label the "***pay setting effect***" – measures the contribution of differential pay setting for natives versus immigrants, and will be positive if on average $\psi_j^N > \psi_j^M$.

In the monopsonistic wage setting framework outlined in CCHK the pay premiums offered at each workplace are determined by equation (2) and $\psi_j^N - \psi_j^M = (\delta_N - \delta_M) R_j$. In this case the overall pay setting is just:

$$\sum_j (\psi_j^N - \psi_j^M)\pi_{Mjt} = (\delta_N - \delta_M) \sum_j R_j \pi_{Mjt}$$

which is proportional to the size of aggregate rents available across firms in economy, $\sum_j R_j \pi_{Mjt}$. If worker preferences are such that natives receive a larger share of the rents at each workplace, then $\delta_N > \delta_M$ and the pay setting effect will widen the gap between natives and immigrants.

4.3 Impacts on Immigrant Earnings Growth and Assimilation

The simple framework of equation (3) can also be used to analyze the determinants of immigrant earnings growth over time. Consider the change in mean log earnings for a cohort of immigrants between a base year ($t = 1$) and some later year ($t = 2$) :

$$\begin{aligned} \Delta_M \equiv E[\ln y_{Mi2} | D_{Mi2} = 1] - E[\ln y_{Mi1} | D_{Mi1} = 1] &= E[\alpha_{Mi} | D_{Mi2} = 1] - E[\alpha_{Mi} | D_{Mi1} = 1] \quad (7) \\ &+ (\overline{X}_{M2} - \overline{X}_{M1})\beta_M \\ &+ \sum_j \psi_j^M \Delta\pi_{Mj} \end{aligned}$$

where $\Delta\pi_{Mj} \equiv \pi_{Mj2} - \pi_{Mj1}$ is the change in the share of immigrants employed at workplace j. The first term on the right hand side of equation (7) is a selection effect arising if there is some change in the composition of the subset of immigrants observed working in different periods. As has been noted in the previous literature, this effect can be eliminated by focusing on the subset of workers who are present in both periods. The second term summarizes the effects of age, location, and changing macro-economic conditions, and will be positive if the cohort is on an upward-sloping age profile, or is moving toward higher-wage locations, or if there is overall wage growth in the economy. Finally, the third term summarizes the net impact of movements up or down the job ladder, and will be positive if immigrants tend to migrate toward higher-paying workplaces as they accumulate experience in the host labor market. Apart from Damas de Matos (2016), previous studies of immigrant earnings growth have ignored this term, subsuming the job ladder effect in the estimated age profile.

It is also possible to compare the change in earnings for a cohort of immigrants **relative to** a comparison cohort of natives, leading to an expression of the form:

$$\begin{aligned}\Delta_N - \Delta_M \quad = \quad & E[\alpha_{Ni}|D_{Ni2}=1] - E[\alpha_{Ni}|D_{Ni1}=1] \\ & -(E[\alpha_{Mi}|D_{Mi2}=1] - E[\alpha_{Mi}|D_{Mi1}=1]) \\ & +(\overline{X}_{N2} - \overline{X}_{N1})\beta_N - (\overline{X}_{M2} - \overline{X}_{M1})\beta_M \\ & +\sum_j \psi_j^N \Delta\pi_{Nj} - \sum_j \psi_j^M \Delta\pi_{Mj}\end{aligned} \tag{8}$$

Such relative changes are commonly referred to as "earnings assimilation." Chiswick (1978) argued that immigrants tend to invest in general skills when they first arrive in a host country – implying that the term in β_M measuring the effect of age for immigrants is larger than the corresponding term in β_N. Chiswick's original approach for measuring $\Delta_N - \Delta_M$ has been criticized for ignoring inter-cohort changes in the earnings capacity of successive cohorts of immigrants (Borjas, 1985) and selective outmigration of immigrants in a given arrival cohort (Dustmann and Gorlach, 2015). Picot and Piraino (2013) and Rho and Sanders (2018) also note that measures of assimilation will be affected by changing selectivity of the *natives* who work (captured in the first line of equation 8) Our framework suggests a third potential channel for this assimilation effect, arising from the changing contribution of workplace-specific pay premiums.

Following the logic underlying equation (6),the last component of equation (8) can be decomposed as:

$$\begin{aligned}\sum_j \psi_j^N \Delta\pi_{Nj} - \sum_j \psi_j^M \Delta\pi_{Mj} \quad = \quad & \sum_j \psi_j^N (\Delta\pi_{Nj} - \Delta\pi_{Mj}) \\ & +\sum_j (\psi_j^N - \psi_j^M)\Delta\pi_{Mj}\end{aligned} \tag{9}$$

The first term represents a *change* in the sorting effect, arising from differential reallocations of natives and workers across firms with higher or lower pay premiums for natives, while the second term represents a *change* in the pay setting effect arising from shifts of immigrants between firms that have bigger or smaller gaps in the pay premiums offered to natives versus immigrants.

4.4 Normalizing the Pay Premiums

As was noted by AKM, a key feature of equation (1) is that the person effects and the pay premiums are only identified up to a normalizing constant. One can add a constant to all the person effects and subtract the same constant from all the firm effects and leave the fitted values from the model unchanged. This observation is particularly salient for models that allow separate workplace pay effects for different groups of workers: the magnitudes of the pay premiums for one group are only identified relative to those of another group by making a normalization **across the groups.** In essence, one has to take a stand on which firms pay a 0 premium to native workers, and which pay a 0 premium to immigrants. As a consequence, the relative pay-setting effect in equation (6) is only identified after normalizing the pay premiums for natives and immigrants relative to each other. In contrast, the sorting component in this decomposition is invariant to renormalization.[19] We discuss our approach to the normalization issue in Section 6, below.

5 Longitudinal Tax Data from CEEDD

To implement the analyses outlined in the previous section we use data from the Canadian Employer-Employee Dynamic Database (CEEDD), an administrative data set with information on workers and firms drawn from the tax system.[20] CEEDD reports the total annual earnings received by each employee from each employer, but has no information on the start/end date of the job, or hours per week. Characteristics of workers include age, gender, marital status and province of residence. At the firm level it includes annual payroll and value added, the total number of employees, and the firm's industry classification.[21] Our data use agreement provides access to CEEDD data for 2005-2013.

Critically for this project, we are able to link CEEDD with the IMDB, which is derived from the records of individuals who successfully apply for permanent immigrant status. IMDB includes information on education, marital status, country of origin, and admission class. We use these data to classify immigrants by country-of-origin group (using the same groupings as in Table 1 and Figure 1), and by whether they have a bachelor's degree (BA) or not at the time of application for permanent residence.

Table 2 provides a descriptive overview of the characteristics of workers age 25-59 who have earnings in at least one year in CEEDD in the 2005-2013 period. Building on the results from our analysis of earnings in the censuses, we only count the earnings received from a given employer in a

[19]To see this, consider transforming the pay premiums for natives by an additive factor $\rho : \widetilde{\psi}_j^N = \psi_j^N + \rho$. Since $\sum_j \rho(\pi_{Mjt} - \pi_{Njt}) = 0$ for any ρ, the transformed pay premiums imply the same numerical value of the sorting effect.

[20]Specifically, the data on individual earnings are derived from personal, family and business declaration files - known as "T1" records – as well as corporate and firm owner's tax returns ("T2" files) and supplementary ("T4") files. See the Data Appendix for more details.

[21]Value added is measured as the sum of T4 payrolls and net income before taxes and extraordinary items.

year if they are above our "full-time-at-minimum-wage" threshold of roughly $14,000. In cases where an individual earned >$14,000 from two employers in the same year, we select the one that paid more as the main employer in that year. This procedure leads to a mechanical ***dip*** in earnings in the last year of any "main job" that ends part-way through the year, and similarly a ***rise*** in earnings from the first to the second year of any main job that commences part-way through the year. It also creates "gap years" for individuals who spend a substantial share of the year out of employment.

Columns 1 and 2 show the characteristics of native-born and permanent immigrant workers in our CEEDD sample. As noted in the bottom row, we have data on around 10 million natives and 2.5 million immigrants. Given our focus on a single cohort of immigrants entering the country, on average we have about 5 years of earnings data for each individual (out of a possible maximum of 9 years). This limited fraction reflects the dropping of data from any year in which an individual earns less than $14,000 from at least one employer, as well as the aging-in and aging-out of younger and older people.

The samples of natives and immigrants are both about 60% male, with a mean age of just over 40. Mean earnings (on the main job) for an individual who earns at least our minimum threshold are $50,700 for natives and $41,800 for immigrants - implying a native-immigrant earnings gap of around 20%. The geographic distributions of natives and immigrants are also different, with 71% of immigrants in Ontario or B.C. versus only 47% of natives. Immigrants tend to be employed at slightly larger firms, and to work at firms that have a relatively high share of immigrants in their overall workforce (62% versus 21% for natives). Some of this gap is driven by the concentration of Canadian immigrants in Toronto and Vancouver, where immigrants comprise over 50% of the local population.[22]

Column 3 of Table 2 shows the subset of immigrants who obtained permanent residency (i.e., "landed", in Canadian terminology) in the period from 2000 to 2004. This group - most of whom arrived in Canada for the first time in the 2000-2004 period – is observed over their first decade as permanent residents in our CEEDD sample, and is our main focus. Reassuringly, recently landed immigrants look quite similar to the broader population of immigrants, with very similar gender, age, and geographic distributions, and similar mean earnings.

As is well known, the worker and firm fixed effects in AKM style models are only identified within "connected sets" of workers and firms (see e.g. Abowd, Creecy, and Kramarz, 2002). Column 4 shows the characteristics of natives in the connected set of native workers, while column 5 shows the characteristics of immigrants in the connected set of immigrant workers. For natives, the connected

[22]About 55% of Canadian immigrants live in Toronto or Vancouver. Immigrants make up 55% of the adult population in Toronto and 49% in Vancouver - comparable to shares in cities like Los Angeles and Miami.

includes 97% of all person-year observations and 96% of all persons, but only 75% of firms, reflecting the exclusion of firms with no employees who worked at other firms in the connected set at some point between 2005 and 2013. The connected set for immigrants is slightly more selective, containing 94% of person-year observations, 92% of all persons, and 65% of firms that ever have an immigrant employee in the connected set. Nevertheless, the characteristics of the connected sets are quite similar to those of the corresponding populations in columns 1 and 2. The one difference is that the mean firm sizes are larger in the connected subsets. We also show in column 6 the characteristics of the 2000-2004 arrival cohort who are included in the connected set of immigrants. Again, this set is not very different from the overall sample of such immigrants in column 3.

To be able to make comparisons ***between*** the firm effects for natives and immigrants (such as those in equation 6) we need to further limit attention to firms in the "dual-connected set" – i.e., the set of firms that are in the connected sets for both natives and immigrants – and to the corresponding sets of workers at these firms. Columns 7-9 of Table 2 show the characteristics of natives, immigrants, and 2000-2004 arrivals in this dual connected set. The dual connected set drops firms that have no connected native employees or no connected immigrant employees. The restriction on having at least one connected immigrant worker is particularly stringent and ends up eliminating about 70% of firms that are in the connected set for natives. By comparison the restriction on having at least one connected native worker is less severe, and 80% of firms in the connected set for immigrants end up in the dual connected set.

The ability to construct connected sets depends critically on sample size. The fact that we have such large samples of natives and immigrants in the CEEDD gives us the unique opportunity to study the processes by which immigrants transition between firms in the context of an AKM style model.

The relative selectivity of natives in the dual connected set is illustrated by their mean earnings, which are about 8% higher than mean earnings of all natives (column 1) or those in the connected set of natives (column 4). Even more remarkable is the effect on median firm size, which rises from 170 full time equivalents for all natives (and 196 for natives in the connected set) to 743 full time equivalents for those in the dual connected set. The dual connectedness restriction has less impact on immigrants and those in the dual connected set are fairly similar to those in the connected set of immigrants.

5.1 Exogenous Mobility

In this section we present some evidence on the plausibility of the exogenous mobility restrictions needed to ensure that OLS estimation of AKM style models using CEEDD data will yield unbiased estimates of the worker and firm effects. Specifically, following CHK, we group workers into quartiles based on the average pay of the coworkers at their firm and examine the changes in mean earnings for workers who move up or down the coworker "pay ladder". In CHK's original analysis the earnings measures were based on **daily** wages (similarly, CCK examine hourly wages). Unfortunately, in our case, we only observe total earnings received during the year from a given employer. This means that we confound changes in the rate of pay with variation in the number of days worked at a given job. This is especially problematic in the year of a job change, since our "main job" definition will assign the worker to either the beginning-of-year or end-of-year employer, with no adjustment for the fraction of the year worked, creating a temporary dip in earnings in either the last year on the old job or the first year in the new job. It is even worse for people who lose a job in one year, spend some time out of work, then start a new job in the following year. For such workers, earnings in the last year of the old job and earnings in the first year of the new job will **both** be temporarily depressed.

With this caveat in mind Figures 2a and 2b show mean earnings in the two years before and two years after an employer switch for natives and immigrants in our CEEDD samples. The analysis is limited to individuals who are observed in two consecutive years at both the origin and destination firms. Workers are grouped by quartiles of coworker pay, using wages of all coworkers (i.e., both immigrants and natives) in the year of separation (for the origin firm) and year of hiring (for the destination firm). For clarity, only the earnings profiles of workers who move from jobs in quartile 1 and quartile 4 are shown in the figures.

Focusing first on people who leave first-quartile firms, we see little or no change in average earnings per year for those who move to first quartile firms, but rises for those who move up the ranks. As expected, there is some indication of a temporary dip in earnings in the last year of the old job. Moreover, earnings in the new job tend to rise between the first and second years on this job, particularly if the new job has higher co-worker pay. We interpret this rise as evidence that many movers work only part of the year in their first year at the new firm.[23] What it means is that for workers who move up the job ladder there is a negative correlation between the transitory component of earnings in the year after a job change and the change in mean pay offered by the

[23] Note that for people moving to higher-paying firms it is more likely that their first part-year on the new job pays at least $14,000, and is included in our sample. For those who move to lower-paying firms, however, many of the part-year observations will be excluded.

origin and destination firms – a violation of the exogenous mobility assumption.

Looking next at people who leave fourth-quartile firms, we see a dip in earnings in the last year of the old job that is particularly deep for those who end up moving to first or second quartile firms, then a rise between the first and second years on the new job. Again, we believe the dip and rise are both attributable to the losses of work time in the transition years between jobs. Such dips will be larger for workers who have longer spells of non-work between jobs. Assuming that job losers initially search for new jobs at higher-ranked firms and only take jobs further down the job ladder if nothing else is available, we would expect a longer gap between jobs for workers from quartile 4 who move further down the job ladder, leading to larger average losses in work time in the last year on the old job for those workers and larger "anticipatory dips" in measured annual earnings just prior to job change. This pattern appears to be true for both natives and immigrants in the CEEDD. Thus, for job losers from higher-paying firms, there is a positive correlation between the transitory component of earnings in the year prior to changing jobs and the direction of change in the "quality" of jobs - another violation of the exogenous mobility assumption.

A second specification test suggested by CHK is to compare the earnings gains for people who move up the job ladder to the losses for those who move down. Under the exogenous mobility assumption these should be symmetric (i.e., movers from quartile 2 to quartile 1 should experience average wage losses that are the same size but opposite sign to the gains who move from quartile 1 to quartile 2). Figure 3 presents some evidence that is broadly supportive this prediction: we show the percentage changes in mean earnings (from 2 years before a job change to 1 year after) by origin and destination quartile for natives (panel a) and immigrants (panel b).[24] While not perfectly symmetric, the gains for up-movers and down-movers are very strongly negatively correlated ($\rho = -0.96$ for natives, $\rho = -0.99$ for immigrants).

Overall, we interpret the evidence in Figures 2 and 3 as suggesting that the patterns of wage changes in the CEEDD for between-firm movers are relatively consistent with exogenous mobility, apart from the "dips" induced in the period of job transition by our inability to control for the duration of time worked on jobs that start or end part-way through the year.

6 Estimation Results

In this section, we present the results from estimating the two-way fixed effects model in equation (1) for natives and immigrants using the connected sets described in columns 4 and 5 in Table 2.

[24] Movers' wage changes are adjusted for trends by deviating the changes from the mean change for people who switch firms but remain in the same quartile of coworker pay.

We then discuss our procedure for normalizing the worker and firm effects for the two groups and provide a measure of the degree of assortative matching between workers and firms.

Estimation Results and Model Fit

Table 3 summarizes the estimation results. We show the standard deviations of the estimated person effects, estimated firm effects, and estimated covariate index $X'_{git}\widehat{\beta}_g$, as well as the root mean squared error (RMSE) and adjusted R-squared of the models. For reference, we also show comparable fit statistics for a more general "job match" model that includes a separate fixed effect for each worker-firm match.

The two-way fixed effects models fit relatively well, with adjusted R-squared statistics of around 80% and RMSE's of around 0.25. By comparison the adjusted R-squared statistics for the match effects model are around 0.85, and the RMSE's are around 0.23. The difference in the two RMSE's indicates the magnitude of the variance of the "match component" in the residuals of the AKM model – i.e., the component of ε_{git} that is shared by all observations of a given worker at a given firm. This component has a standard deviation of about 0.12 for natives and 0.11 for immigrants – large enough to account for about 4% of the overall variance of wages for the two groups. This small magnitude may help to alleviate concerns over the potential role of match effects in accounting for patterns of mobility.

The bottom panel of Table 3 shows simple "plug-in" estimates of the variance shares of the model components. Person effects account for around 65% of the variance of log earnings (conditional on having earnings above our minimum threshold) while firm effects account for 11-14% of the variance. The covariance between these two components accounts for another 3-4% of overall variance, while the covariates (and their covariances with the person and firm effects) account for about 5% of the variance of earnings of natives but less than 1% of the variance of earnings of immigrants.

It is well known that estimation error in the worker and firm effects leads to at least two problems in interpreting the variances and covariance of the estimated worker and firm effects reported in Table 3. The first is that the sampling errors in the estimated worker and firm effects are negatively correlated (Andrews et al., 2008) leading to a downward bias in the estimated correlation between these effects. The second is that the variance shares of the *estimated* worker and firm effects will tend to overstate the importance of these components (Kline, Saggio and Solvsten, 2019). Our reading of recent research is that these biases are likely to be larger in settings with smaller numbers of observations per worker and relatively "thin" networks of workers (i.e., settings where many firm effects are identified by only a single worker that connects a particular firm to the broader connected set). This suggests some degree of caution in interpreting the higher variance share of firm effects for immigrants than natives, and the lower correlation between the worker and firm effects for immigrants.

Appendix Table 3 shows the estimated coefficients associated with two of the most interesting components included in the covariate index X : marital status of the individual, and province. (The other components of X are year effects and a quartic in age). We include 6 categories of marital status relative to an omitted category of married. None of the estimated coefficients are large in magnitude: among the largest is widow/widower status, which is associated with about 3-4 percent lower earnings. The province variables are larger in magnitude, especially for native workers. Our estimates suggest that working in the Atlantic provinces reduces earnings for natives by about 15% relative to Ontario, while working in Alberta raises earnings by 4%. We note that these estimated provincial earnings premiums differ from others in the literature in two ways. First, we control for person effects, so our estimates are based on earnings differentials for people who move between provinces. Second, we also control for firm effects: thus we are measuring earnings differences between jobs <u>at the same firm</u> but in different provinces.

Appendix Figure 2 shows the estimated age profiles of earnings for natives and immigrants. As noted earlier, we normalize these profiles at age 48. The estimates suggest that earnings of natives rise by about 27 percent from age 25 to 48, then fall off slightly. The age profile for immigrants is much steeper, rising by about 46 percent from age 25 to 48. The difference is an estimate of <u>average</u> earnings assimilation across the various cohorts in our immigrant sample (controlling for worker and firm characteristics), which leads to approximately a 20 percentage point gain in mean log earnings between ages 25 and 48 for immigrants relative to natives. We return to the issue of how to measure earnings assimilation for a specific cohort in our analysis below of earnings growth for immigrants who landed in the 2000-2004 period.

Normalizing the Worker and Firm Effects

The next step in our analysis is to normalize the estimated worker and firm effects in the two AKM models summarized in Table 3. Our approach builds on the interpretation developed by CCHK of firm-specific pay premiums as "rent shares", as specified by equation (2). Specifically, CCHK show that marginally viable firms with no rents to share will pay workers their outside option (i.e., the wage they could earn in the non-market sector), whereas more productive firms will pay premiums that vary with their productivity R_j. We use the log of measured value added per worker over the 2005-2013 period at a given firm ($\overline{S}_j$) as a proxy for R_j (so $R_j \propto \eta \overline{S}_j$) and assume that the true pay premiums paid to natives and immigrants can be written as:

$$\begin{aligned}\psi_j^N &= \delta'_N \max\left\{0, \overline{S}_j - \tau\right\} \\ \psi_j^M &= \delta'_M \max\left\{0, \overline{S}_j - \tau\right\}\end{aligned}$$

where $\delta'_g = \eta\delta_g$ and τ is some minimum threshold level of value added per worker beyond which firms are productive enough to offer pay premiums. These equations imply that the arbitrarily normalized estimated pay premiums coming from our AKM estimation procedure should be related to $\overline{S}_j$ by a pair of non-linear threshold regression functions of the form:

$$\begin{aligned}\hat{\psi}_j^N &= c_N + \delta'_N \max\left\{0, \overline{S}_j - \tau\right\} + e_j^N \\ \hat{\psi}_j^M &= c_M + \delta'_M \max\left\{0, \overline{S}_j - \tau\right\} + e_j^M.\end{aligned} \tag{10}$$

In principle the threshold τ should be the same in the two equations. However, we estimate the models separately and verify that in fact the estimated thresholds are (approximately) the same.

Estimation results for equations (10) are presented in Table 4.[25] We note first that among firms with higher levels of value added per worker there is a strong positive relationship between $\overline{S}_j - \tau$ and the estimated firm effects for both natives and immigrants, with a slightly smaller estimate for δ'_M than δ'_N. Second, the estimated breakpoints for natives and immigrants are quite close, consistent with the model leading to equations (10). Based on this similarity, we set $\widehat{\tau} = 9.432$ which is equivalent to a threshold of around \$12,500 in value added per worker.

Overall about 6% of all native and immigrant person-year observations are accounted for by jobs at firms with $\overline{S}_j < \widehat{\tau}$. We then determine the values of the normalizing constants such that the re-normalized effects for both natives and immigrants have a weighted average of zero across all firms with $\overline{S}_j < \hat{\tau}$, where the weight for firm j is the total number of person-year observations for natives and immigrants in the dual connected set with j as the employer.[26]

Assortative Matching

As reported in Table 3, the correlations across person-year observations between the estimated person effects and the estimated firm effects are positive for both natives ($\rho = 0.07$) and immigrants ($\rho = 0.04$). These correlations have to be interpreted carefully because the sampling errors in the

[25]The standard errors in this table are approximations that attempt to adjust for correlations between estimated firm effects.

[26]These constants are approximately the same as the estimated constants c_N and c_M in the threshold regression models. Since we estimate those models without weighting, however, they are not exactly the same.

estimated worker and establishment effects are negatively correlated, leading to a downward bias (Mare and Hyslop, 2006; Andrews et al., 2008). Previous studies have shown that the magnitude of the bias is larger for weakly connected networks – a problem that is likely more severe for immigrants than natives in our samples. For example, there are 14.5 natives per firm in the connected set of natives, but only 8.7 immigrants per firm in the connected set of immigrants.

While procedures are available to derive bias-corrected correlations (Kline, Saggio and Solvsten, 2019), we follow the simpler approach to measuring assortative matching discussed by Gerrard et al. (2018). Specifically, consider a regression of the estimated person effect for a member of group g on the estimated firm effects for the workplaces she or he works at:

$$\widehat{\alpha}_{gi} = \lambda_{0g} + \lambda_{1g}\widehat{\psi}^{g}_{J(g,i,t)} + \xi_{git}. \tag{11}$$

The coefficient λ_{1g} is closely related to the correlation of the worker and firm effects, and provides a metric for assessing assortative matching. Since the sampling errors in the person and establishment effects are negatively correlated, we expect OLS estimates of λ_{1g} to be negatively biased. However, we can use the estimated firm effects for the *other* origin groups as an instrumental variable, yielding corrected estimates of λ_{1g}.

Table 5 presents estimates based on equation (11) for natives and immigrants in the dual-connected set, and for subset of immigrants in the dual-connected set who were landed (i.e., received permanent residency) in the 2000-2004 period. We present both OLS and IV results for all three groups. Inspection of the table points to three interesting conclusions. First, as expected, a comparison of OLS and IV estimates suggests that the attenuation bias in the OLS estimate of λ_{1M} (for immigrants) is substantially larger than the corresponding bias in the OLS estimate of λ_{1N} (for natives). Second, after accounting for this bias it appears that the degree of positive assortative matching between high-skill workers and high-wage employers is if anything larger for immigrants. Third, the degree of assortative matching for both groups is high: a firm that pays a 10% higher earnings premium has employees whose average earnings capacity is 8-9 percentage points higher. The implication of this sorting is that firm policies will tend to magnify pay differences between groups with higher and lower "skills" as measured by their mean person effects.

6.1 Decomposing the Average Immigrant-Native Pay Gap

Next, we use the framework of equation (6) to evaluate the contribution of firm-specific pay premiums to the average earnings gap between natives and immigrants, and decompose this total effect into a between-firm sorting effect and a within-firm relative wage-setting effect. Table 6 presents the results for the overall population of natives and immigrants in the dual-connected set, and for subgroups classified by gender and age. We present the overall wage gap for the subgroup in column 1, the mean estimated firm effects for natives and immigrants in columns 2 and 3, respectively, the difference in the firm effects in column 4, and the sorting and relative pay-setting effects in columns 5 and 6, respectively.

Beginning with the results in the first row, our AKM models and normalization procedure implies that native workers earn an average firm-specific pay premium of 20.2 percent, whereas immigrant workers earn and an average pay premium of 16.4 percent. The difference (3.8 percentage points) accounts for about one fifth of the overall native-immigrant wage gap. The entries in columns 5 and 6 imply that the under-representation of immigrants at high-premium firms drives the entire contribution of firm pay policies; the relative pay setting effect is essentially zero. As noted earlier, the value of the pay-setting effects depends on the normalization of the firm effects. Our baseline normalization assumes that firms with low value added per worker (i.e., $\overline{S}_j < \widehat{\tau}$) pay zero premiums to both natives and immigrants. If we were to assume instead that these low-productivity firms actually pay a p% wage premium for natives relative to natives, then the pay setting effect would increase by p percentage points and the total contribution of firm premiums to the wage gap would rise from 3.8 percentage points to $3.8 + p$ percentage points.

The next two rows of Table 6 show how the effects of firm pay policies vary by gender. The immigrant-native pay gap is larger for men than women, and the sorting effect explains a somewhat larger share of the male gap (22% versus 15% for women). Interesting, among both natives and immigrants in Canada, men earn higher average pay premiums than women, implying that firm hiring policies also contribute to the gender pay gap. Indeed, the 5.5 percentage point gap in mean pay premiums for native men versus women represents about 17% of the 32 log point gender gap in earnings for natives, while the 3.3 percentage point gap in mean pay premiums for immigrant men versus women represents about 12% of the 27 log point gender gap for immigrants. We emphasize that these estimates are not strictly comparable to others in the literature (e.g. Card, Cardoso and Kline, 2016; Gallen, Lesner and Vejlin, 2017; Coudin, 2018; and Bruns, 2019) for two important reasons. First, our earnings measures do not adjust for gender differences in hours per week (or weeks per year). This presumably leads is to overstate the gross pay gaps between men and women and understate the *relative contribution* of firm policies. Second, we do not fit separate AKM models for males and females - thus, we are ignoring the possibility that firms set different wage premiums for men and women, which other studies have found also contribute to the gender gap.

The bottom three rows of Table 6 show the heterogeneous impacts of firm pay policies by age. Looking across the overall workforce, the native-immigrant pay gap widens with age, despite the evidence in Figure 1 that the gap narrows as immigrants remain in the country longer. This seeming paradox is explained by the fact - noted in the discussion of Appendix Figures 1a and 1b – that the pay gap is wider for people who arrive in the country at later ages. The mean pay premiums earned by natives rise somewhat with age but actually follow an inverse-U shape for immigrants, implying that the total contribution of firms' pay policies is largest for older workers, explaining about 5.5 percentage points of the 24.4 percentage point earnings gap.

Earnings Gaps for the 2000-2004 Cohort

As a final step before turning to our analysis of ***changes*** in earnings gaps, we present a decomposition similar to the one in Table 6 for the subset of immigrants who landed in the 2000-2004 period. Table 7 shows results for all workers in the 2000-2004 cohort, for males and females, and for the four immigrant groups defined by country-of-origin group and education above or below a bachelor's degree (BA).

The results for all workers in the 2000-2004 cohort, and for males and females, closely parallel the results in Table 6, though the contribution of firm pay policies is slightly smaller for the recently arrived group.

The results for the four origin and education subgroups, shown in the last four rows of Table 7, show some interesting patterns. Most notably, the overall contribution of firm pay policies is close to zero for immigrants with a BA from either the advantaged countries or the non-advantage countries. In fact, mean pay premiums earned by BA holders from the advantaged countries are actually slightly higher than those earned by natives, explaining about 1.3 percentage points of the 29.1 percentage point earnings *advantage* of these immigrants relative to natives. Similarly, the mean pay premiums earned by BA holders from non-advantaged countries are nearly the same as those earned by natives. A potential concern with comparisons between highly educated immigrants and all natives (as we are making in Table 7) is that the assumed counterfactual ignores the evidence of assortative matching in Table 5. Arguably, it would be more appropriate to compare highly educated immigrants to highly educated natives, who might be expected to work at firms with higher than average pay premiums. Given the absence of data on education for natives in the CEEDD, however, we are unable to make such comparisons.

In contrast to the situation for highly educated immigrants, for less-educated immigrants the mean pay premiums are smaller than for natives, potentially explaining about one-quarter of the mean earnings gap between natives and less-educated immigrants from advantaged countries, and 17% of the pay gap between natives and less-educated immigrants from non-advantaged countries.

The latter group appears to face the most difficulty in gaining jobs at high-premium firms, pushing down their earnings relative to natives. As benchmark, the 6.6 percentage point sorting effect in the bottom row of Table 7 is comparable to the earnings effect of having a vocational college degree for immigrants in Canada (see e.g., Ferrer and Riddell, 2008, Tables 3a and 3b).

Before proceeding, it is worth pointing out one further limitation of the decompositions in Table 7. These comparisons are based on averages over the 2005-2013 period for immigrants that only recently obtained permanent residency status. To the extent that newly-arrived immigrants move up the job ladder relatively quickly, comparisons of their average pay premiums to those of natives may miss an important dynamic role of sorting between firms. We turn to this next.

6.2 Earnings Assimilation

Our final set of analyses address the sources of earnings assimilation for recently-landed immigrants in Canada, using data on the cohort who obtained permanent-residency status in the 2000-2004 period.[27] To set the stage for this analysis, Figure 4 shows the changes in mean log earnings for four subgroups of the 2000-2004 cohort, classified by country-of-origin group and education level, as well as the changes for natives. In this figure and all the analysis in this subsection we focus on members of the 2000-2004 cohort in the dual-connected set as well as natives in this set (i.e., the subgroups of about 7.7 million natives and 328,000 immigrants whose characteristics are presented in columns 7 and 9 of Table 2).

Mean log earnings of all four immigrant groups rise faster than those of natives, with around a 34% gain for highly educated immigrants from disadvantaged countries, 20-25% gains for the other three immigrant groups, and only a 7% rise for natives. We note that our estimates of relative earnings gains for this cohort are substantially larger than the (negligible) gains reported by Baker and Benjamin (1994) for cohorts of immigrants who arrived in Canada in the 1970s but are more similar to estimates reported by Grant (1999) for immigrants who arrived in Canada between 1981 and 1985. They are are also quite similar in magnitude to estimates reported by Abbott and Beach (2011), who use IMDB data linked to tax records to examine earnings growth in the first 10 years in Canada for those who were landed in 1982, 1988 and 1994. Appendix Figure 3 shows earnings profiles based on their tabulations. For comparability with our analysis, we scale median earnings of each group by their median earnings in the third year after landing. Abbott and Beach's (2011) data show earnings gains of between 30 and 40 percent for males and females in the period from 3

[27]As noted early about 15% of this group entered Canada prior to 2000 as students or temporary workers; the remainder presumably arrived in the 2000-2004 period.

to 10 years after landing. Interestingly, as we have found, their data also show earnings profiles that are quite similar for males and females in a given arrival cohort, providing further support for our choice to pool the genders.

Equation (8) suggests three main sources of this growth: relative changes in the composition of workers (summarized by the change in the mean of the person effects for the subset who are observed working); relative changes in the observable skill components (mainly age); and relative changes in the mean firm premiums earned by immigrants versus natives. Figure 5 presents some evidence on the composition effect, based on the means of the estimated person effects for individuals in a given subgroup that have earnings above the $14,000 threshold on at least one job in a given year. Notice first that the mean of the person effects for natives is falling slightly over time (-2.3 percentage points) while the mean of the person effects across all immigrants in the cohort falls a little more quickly (-3.5%). The faster fall for immigrants means that the changing relative composition of the immigrant workforce actually contributes to a decline in earnings for immigrants in the cohort relative to natives. This is the opposite of the prediction arising from models of selective return migration (Yezer and Thurston, 1976; Dustmann and Gorlach, 2015) which hypothesize that immigrants who enter a host country and experience relatively low earnings in their first few years will return home, leading to a rise in mean earnings for the subset of immigrants who stay, and the (false) impression of assimilation.

Comparing across the four immigrant subgroups, we see that for three groups the mean of the person effects trend downward over time, with a particularly large fall for immigrants from advantaged countries with a BA or higher education. We conjecture that this fall is driven by a relative rise in participation by females within the group, coupled with selective emigration by the *most successful* earners in the group, particularly to the U.S. (see Damas de Matos and Parent, 2019). In contrast, for less-educated immigrants from non-advantaged countries we see a rise over time in the mean of the person effects for those with earnings. The gain is small (3.5 percentage points) and concentrated in the 2008-2010 period, potentially reflecting the effects of the recession, which caused the unemployment rate to rise from 6.0 percent in late 2008 to 8.5% in mid-2009, and may have led to selective job losses for the least skilled on this subgroup of immigrants.

To account for changes in the permanent skill characteristics of the subset of immigrants working in each year, and to adjust for expected differences arising from normal wage growth with age and changes in macro conditions, we constructed a simple "composition-adjusted" estimate of mean earnings for immigrant subgroup S in year t:

$$A_{St} = \sum_{i \in S} \left(\ln y_{Mit} - \widehat{\alpha}_{mi} - X_{Mit} \widehat{\beta}_N \right) \tag{12}$$

Notice that this adjustment applies the estimated coefficients for natives, $\widehat{\beta}_N$ to the observed characteristics of the particular immigrant (X_{Mit}). We then calculated the change $A_{St} - A_{S2005}$ to derive a composition-adjusted change in mean log earnings for group S from 2005 to year t. By using the native age effects we are incorporating the portion of earnings growth that would be expected for group S if their age profile was the same as natives. We are also subtracting off the estimated year effects for natives, thus deriving an estimate of earnings assimilation that incorporates age and year effects as well as any composition bias arising from selective participation.

Figure 6 shows the composition adjusted earnings profiles for each of our four immigrant subgroups. We note two key features of these adjusted profiles. First, for all groups except highly-educated immigrants from non-advantaged countries the growth in adjusted earnings from 2005 to 2013 is around 8-10 percent. For immigrants from non-advantaged countries with a BA adjusted growth is about twice as large (21.6 percent). Second, the pace of assimilation appears to have slowed in the 2009-2010 period – again, potentially reflecting the impact of the recession - but resumed again by 2012.

What role did movements up the job ladder play in this assimilation process? We provide a graphical illustration in Figure 7, which plots

$$\sum_j \widehat{\psi}_j^N (\pi_{Sjt} - \pi_{Njt})$$

for each subgroup S and year t. This is an estimate of the (negative) sorting effect for group S in year t, based on the estimated firm-specific wage premiums for natives and the difference in employment shares between group S and natives in year t. (We show the negative sorting effect to make it easier to compare to the upward-sloping assimilation profiles in Figures 4 and 6). All four immigrant groups show some gain in wages relative to natives from movements to higher-paying firms. The gain is largest for immigrants from non-advantaged countries with a BA (3.6 percentage points) and smallest for immigrants with a BA from the U.S., U.K. and Northern Europe (1.3 percentage points), who are already working at relatively high-paying firms in 2005 and make little subsequent progress.

Our findings from Figures 4-7 are summarized in Table 8. The first column of this table shows the change in mean log earnings for each group from 2005 to 2013 relative to natives. The second column shows our estimate of earnings assimilation – the growth in A_{St} from equation (12) – for each group. Column 3 shows the growth in earnings arising from the changing distribution of immigrants across firms - i.e., the first term in equation (9). Finally, the fourth column shows the percentage of estimated assimilation that is attributable to movements up the job ladder. This ranges from 13 to 32 percent, with an overall average of 18%. The magnitude of the job ladder effect is largest for immigrants from non-advantaged countries that have a BA, but as a share of total assimilation the job ladder component is largest for those without a BA from these same countries.

7 Discussion

We have used rich administrative data from tax records, along with the simple "job ladder" model specified by AKM, to provide a series of new insights about the level and growth of immigrant earnings in Canada. Consistent with a growing literature that applies the AKM framework to understand inter-group pay differences, we find that firm-specific pay and hiring policies contribute to the gap in earnings between immigrants and natives. Immigrants as a group are less likely to be hired at firms that offer higher pay premiums, explaining about one-fifth of the average pay gap between immigrants and natives in our sample period. Looking within subgroups of immigrants, we find that this sorting effect is particularly large for immigrants from non-traditional source countries who lack a university-level education – a subgroup that earns about 40% less than natives, on average, and is widely seen as "less successful" in the Canadian labor market.

We also use our longitudinal data and AKM-based framework to help understand the sources of the relatively rapid earnings growth that recently arrived cohorts of immigrants experience in their first years in the host country. The AKM framework provides a natural metric for measuring changes in earnings due to selective emigration or non-participation within a cohort. In the context of the model, these changes are represented by changes in the average of the person effects for those with earnings in a particular year. For the cohort we study, who became permanent residents in the 2000-2004 period, we find that selectivity biases associated with movements in or out of the workforce actually contribute to a slight decline in earning of immigrants relative to natives – a finding that has been echoed in a few other recent studies for Canada and the U.S. (Picot and Pirano, 2013; Rho and Sanders, 2019).

Using the estimated AKM models for immigrants and natives to derive the "true" earnings assimilation rate of the cohort, adjusting for selective composition effects, age-related earnings growth, and macro shocks, we conclude that immigrants in the 2000-2004 cohort experienced about a 15 percentage point growth in mean log earnings between 2005 and 2013. Comparing assimilation rates across country-of-origin and education subgroups, the one group that stands out are immigrants from the "new" source countries (i.e., Asia, Eastern Europe, Africa and Latin America) with a university education. This group experiences earnings growth of about 20% relative to natives. Interestingly, they are also the group with the largest movements up the job ladder between 2005 and 2013 - shifts between employers that can explain about one-sixth of their rapid earnings gains.

Overall, our findings complement and extend existing results in the literature by showing the time profile in the progress of the immigrants' average earnings relative to natives and by identifying part of the source of the average gain from having a B.A. or more, namely the movement from employer to employer. In addition, the results for those from the new source countries with a university education are consistent with some learning in the labor market by employers. Although the credentials of those immigrants are discounted upon arrival, their productivity is eventually revealed and recognized by employers, and part of this paper's contribution is to characterize this process by which foreign credentials are valued in the labor market.

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Table 1: Characteristics of Adult Natives and Immigrants, 2016 Census

		Immigrants from US/UK/Northern Europe[a]			Immigrants from Rest of World		
	Natives	All	Economic Class	Family Reunification Class	All	Economic Class	Family Reunification Class
Share Female	0.51	0.50	0.52	0.46	0.46	0.49	0.41
Share with B.A. or More	0.23	0.42	0.46	0.36	0.47	0.60	0.27
Share with Postive Earnings	0.81	0.78	0.81	0.74	0.75	0.77	0.71
Share Working Mainly Full Time	0.74	0.77	0.82	0.69	0.70	0.73	0.66
Mean Annual Earnings	46,797	54,969	60,354	46,889	35,641	40,280	28,352
Number Observations	320,349	7,334	4,401	2,933	72,488	44,299	28,189

Notes: Entries are tabulations from 2016 Census for individuals age 20-59.

[a] Includes U.S., U.K., Australia, New Zealand, Germany, Netherlands, France, Denmark, Sweden, Norway, Finland, Spain.

Table 2: Descriptive Statistics for Subsamples of Individuals in CEEDD 2005-2013

	Overall Analysis Sample			Connected Sets of Workers/Firms: All			Connected Sets of Workers/Firms: Dual-Connected		
	Natives (1)	Immigrants (2)	Landed 2000-2004 (3)	Natives (4)	Immigrants (5)	Landed 2000-2004 (6)	Natives (7)	Immigrants (8)	Landed 2000-2004 (9)
Percent Male	59.7	57.5	58.7	60.0	57.8	59.0	59.8	57.9	59.4
Mean age	42.1	41.2	39.9	42.0	41.1	40.0	42.2	41.3	39.9
Percent <= 30 years old	16.2	14.5	12.6	16.4	14.7	11.9	15.6	13.9	11.9
Percent >= 50 years old	27.6	20.7	12.6	27.2	20.3	12.6	27.4	20.6	12.2
Mean earnings (if ≥ threshold)	50 732	41 774	40 976	51 011	42 239	41 633	55 671	43 790	42 992
Percent in Québec	26.3	13.3	14.2	26.5	13.1	14.1	23.9	13.4	14.5
Percent in Ontario	36.1	54.8	55.9	36.1	55.3	56.1	39.5	55.8	56.5
Percent in British Columbia	11.3	15.7	14.6	11.2	15.5	14.6	11.4	14.7	13.6
Median firm size (estimated labor units)	170	201	218	196	258	229	738	297	326
Fraction of immigrants at firm (estimated labor units)	21.2	62.4	65.6	21.4	62.1	64.9	26.9	55.9	58.2
Mean log sales/estimated labor unit	10.7	10.6	10.6	10.7	10.6	10.7	10.8	10.7	10.7
Number of person-year obs	52 004 007	11 430 335	1 840 022	50 511 526	10 744 641	1 770 032	35 502 198	9 555 501	1 542 143
Number of persons	10 097 344	2 466 523	376 131	9 717 699	2 269 452	315 382	7 035 252	1 898 212	294 621
Number of firms	888 781	401 223	140 732	668 892	259 353	118 782	220 948	220 948	90 129

Notes: Based on authors' tabulations of CEEDD. Estimated labor units are computed using the average number of employees at the firm, representing the mean of all non-zero monthly employment submissions from the Payroll Deductions and Remittances. Annual earnings are set to missing if less than $14,000 threshold (in real dollars) -- see text.

Table 3: Summary of Estimated AKM Models for Natives and Immigrants

	Natives (1)	All Immigrants (2)
Standard deviation of log earnings	0.637	0.591
Number of person-year observations	50,457,400	10,935,636
Summary of parameter estimates:		
Number of person effects	8,631,009	2,127,628
Number firm effects	605,155	221,540
Std. dev. of person effects (across person-yr obs.)	0.489	0.460
Std. dev. of firm effects (across person-yr obs.)	0.202	0.211
Std. dev. of Xb (across person-yr obs.)	0.130	0.133
Correlation of person/firm effects	0.071	0.042
RMSE of model	0.259	0.250
Adjusted R-squared of model	0.818	0.802
Corr. of estimated native/immigrant firm effects[a/]	0.601	
Comparison with job-match effects model:		
Number of job-match effects	10,097,344	4,144,024
RMSE of match-effects model	0.228	0.226
Adjusted R-squared of match-effect model	0.856	0.836
Standard deviation of job match effect	0.123	0.107
Share of variance of log-wages due to:		
Person effects	0.649	0.672
Firm effects	0.111	0.141
Covariance of person and firm effects	0.038	0.026
XB and associated covariances	0.054	0.003
Residual	0.149	0.158

Note: table presents summary of estimated two-way fixed effects model. Model is estimated separately for natives (column 1) and immigrants (column 2).

[a/] Correlation of estimated firm effects for native workers and immigrant workers across all firms In dual connected set.

Table 4: Regressions of Estimated Firm Effects on Mean Log Value Added per worker

	Natives (1)	Immigrants (2)
Constant	-0.206	-0.155
	(0.010)	(0.020)
Slope coefficient	0.141	0.125
	(0.010)	(0.010)
Break Point (τ)	9.432	9.465
	(0.130)	(0.170)

Note: Table displays coefficient estimates for nonlinear regression of *unnormalized* estimated firm effects for firms in dual connected set on max{ mean log value added per worker - m, 0 }, where m is an estimated breakpoint. Approximate standard errors in parentheses.

Table 5: Relationship Between Estimated Person Effects and Estimated Firm Effects

	Natives		Immigrants		Immigrants (Landed 2000-2004)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Regression Coefficient	0.434	0.779	0.188	0.902	0.257	0.869
(Pers. Eff. = a +b Firm Eff)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)

Note: table entries are coefficients from regression of estimated person effect on estimated firm effect for the firm of person's main job in the year. In column 2 instrumental variable for estimated firm effect for native workers is estimated firm effect for immigrant workers. In columns 4 and 6 instrumental variable for estimated firm effect for immigrant workers is estimated firm effect for native workers. Sample for columns 1-2 is person-year observations for natives working at firms in dual-connected set of natives and immigrants. Sample for columns 3-4 is person-year observations for immigrants working at firms in dual-connected set of immigrants and natives. Sample for columns 5-6 is person-year observations for immigrants who landed in the period 2000-2004 working at firms in dual-connected set of immigrants and natives.

Table 6: Contribution of Firm-specific Pay Premiums to the Immigrant Wage Gap at Dual Connected Firms

	Immigrant-Native Earnings Gap	Mean Firm Premium for Natives	Mean Firm Premium for Immigrants	Total Contribution of Firm Premiums to Earnings Gap	Sorting Effect (Weighted by Native Premiums)	Pay-Setting Effect (Weighted by Immigrant Shares)
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.199	0.202	0.164	0.038	0.040	-0.002
				(0.19)	(0.20)	(-0.01)
By gender:						
Male	0.217	0.224	0.178	0.045	0.048	-0.003
				(0.21)	(0.22)	(-0.01)
Female	0.158	0.169	0.145	0.024	0.026	-0.002
				(0.15)	(0.16)	(-0.01)
By age group:						
Up to age 30	0.112	0.186	0.164	0.022	0.028	-0.005
				(0.20)	(0.25)	(-0.03)
Ages 31-50	0.207	0.204	0.169	0.035	0.038	-0.003
				(0.17)	(0.18)	(-0.01)
50 or over	0.244	0.206	0.151	0.055	0.054	0.001
				(0.22)	(0.22)	(0.00)

Note: Column (1) shows the mean log earnings gap between immigrants and natives in the dual-connected set. Columns (2) and (3) show the mean (normalized) pay premiums received by natives and immigrants. Column (4) is the difference between columns (2) and (3) and measures the total contribution of firm-specific hiring and wage setting policies to the immigrant-native gap. Columns (5) and (6) decompose the total in column (4) into a between-firm sorting effect (column (5)) and a differential pay-setting effect (column (6)). See text. Entries in parentheses are shares of overall gap explained by component in columm.

Table 7: Contribution of Firm-specific Pay Premiums to the Wage Gap for Immigrants Landed 2000-2004

	Immigrant-Native Earnings Gap (1)	Mean Firm Premium for Natives (2)	Mean Firm Premium for Immigrants (3)	Contribution of Firm Premiums to Gap (4)	Sorting Effect (Weighted by Native Premiums) (5)	Pay-Setting Effect (Weighted by Immigrant Shares) (6)
All	0.203	0.202	0.172	0.029	0.034	-0.004
				(0.14)	(0.17)	(-0.02)
By gender:						
Male	0.215	0.224	0.189	0.035	0.039	-0.005
				(0.16)	(0.18)	(-0.02)
Female	0.183	0.169	0.148	0.021	0.025	-0.004
				(0.11)	(0.14)	(-0.03)
By source country group and BA or not:						
US/UK/Northern Europe with BA+	-0.291	0.202	0.214	-0.013	0.001	-0.014
				(0.04)	(0.00)	(-0.04)
US/UK/Northern Europe without BA	0.121	0.202	0.168	0.033	0.055	-0.021
				(0.27)	(0.45)	(-0.18)
Other Countries with BA+	0.077	0.202	0.201	0.000	0.008	-0.007
				(0.01)	(0.10)	(-0.09)
Other Countries without BA	0.410	0.202	0.133	0.068	0.066	-0.002
				(0.17)	(0.16)	(0.00)

Note: Column (1) shows the mean log earnings gap between immigrants who landed 2000-2004 and natives in the dual-connected set for natives and immigrants. Columns (2) and (3) show the mean (normalized) pay premiums received by natives and immigrants. Column (4) is the difference between columns (2) and (3) and measures the total contribution of firm-specific hiring and wage setting policies to the immigrant-native gap. Columns (5) and (6) decompose the total in column (4) into a between-firm sorting effect (column (5)) and a differential pay-setting effect (column (6)). See text. Entries in parentheses are shares of overall gap explained by component in columm.

Table 8: Contribution of Changes in Firm Premiums to Adjusted Earnings Growth for Immigrants Landed 2000-2004

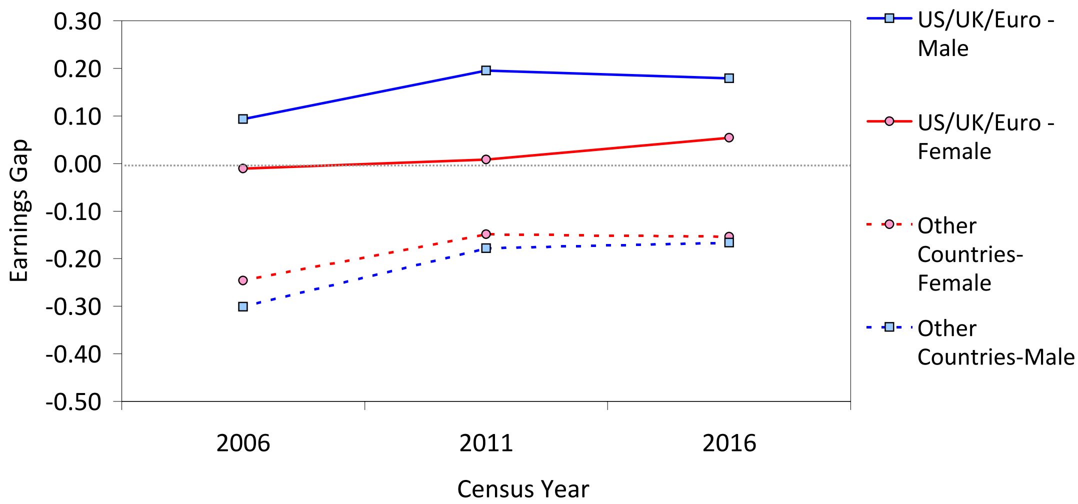
	Growth in Mean Log Earnings Relative to Natives (1)	Adjusted Growth in Mean Log Earnings Relative to Natives (2)	Change in Mean Firm Premiums Relative to Natives (Sorting Effect)[a] (3)	Contribution of Sorting Effect to Adjusted Earnings Growth (percent) (4)
All	0.199	0.149	0.027	18.1
By source coutry group:				
US/US/Northern Europe	0.120	0.091	0.014	15.4
Other Countries	0.212	0.154	0.028	18.2
By source coutry group and BA or not:				
US/US/Northern Europe with BA+	0.158	0.100	0.013	13.0
US/US/Northern Europe without BA	0.135	0.090	0.020	22.2
Other Countries with BA	0.274	0.216	0.036	16.7
Other Countries without BA	0.184	0.084	0.027	32.1

Note: Column (1) shows growth in mean log earnings for immigrants that landed 2000-2004 relative to natives over the 2005-2013 period. Column (2) shows an estimate of composition-adjusted earnings growth for immigrants (adjusting for changes in permanent component of earnings and age differences). Column (3) shows the change in the estimated between-firm sorting effect (i.e., the change in the difference in average native firm premiums at firms employing immigrants versus natives). Column (4) shows the percentage of adjusted total earnings growth explained by the change in the sorting effect.

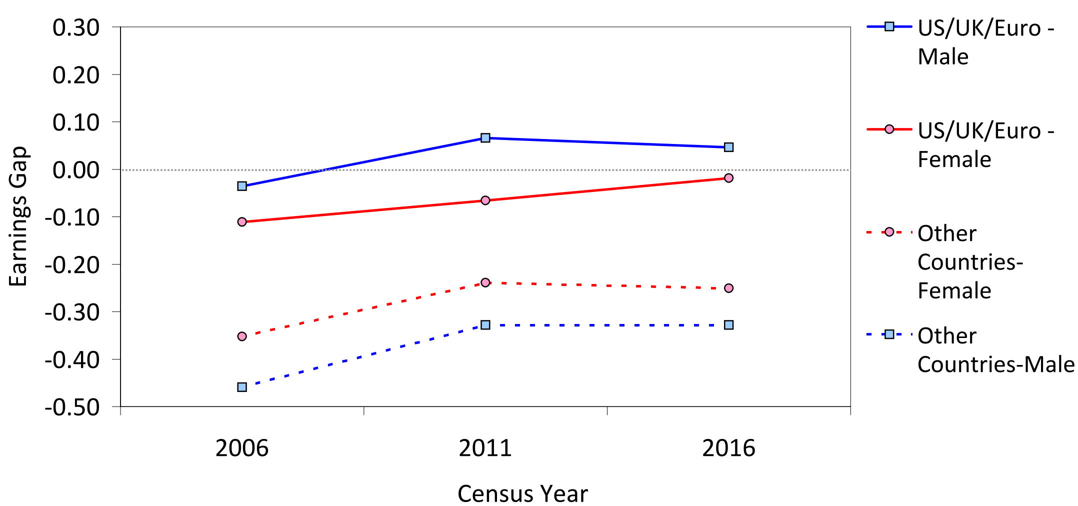
[a] Sorting effect is defined as difference in shares of immigrants and natives working at different firms, weighting by the estimated firm-specific pay premium for natives. This is the negative of the sorting effect defined in earlier tables and figures.

Figure 1: Immigrant-Native Gaps in Earnings

a. Annual Earnings Gap



b. Adjusted Annual Earnings Gap



c. Adjusted Weekly Earnings Gaps

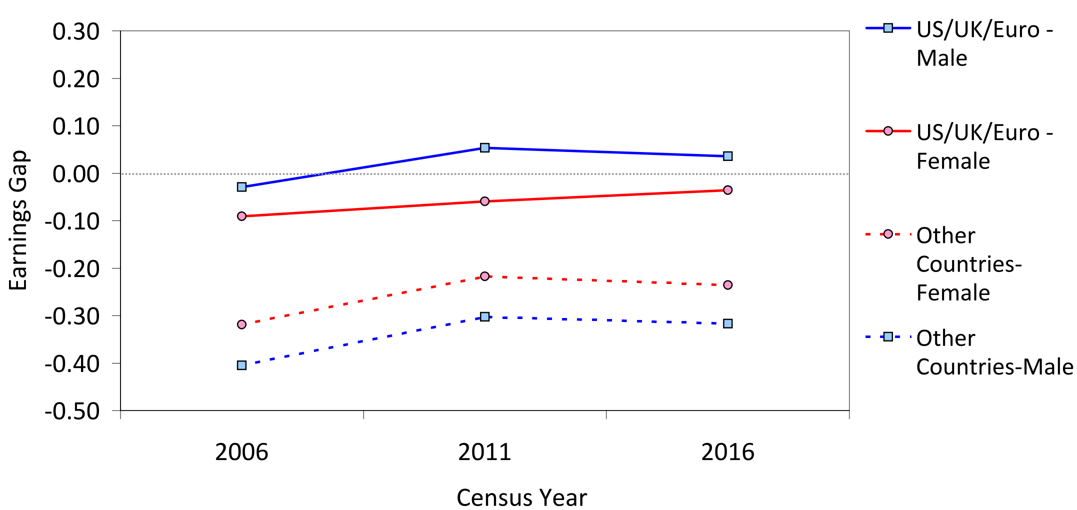


Figure 2a: Earnings Trends for Natives Around Job Changes Classified by Co-worker Earnings Quartiles Pre and Post

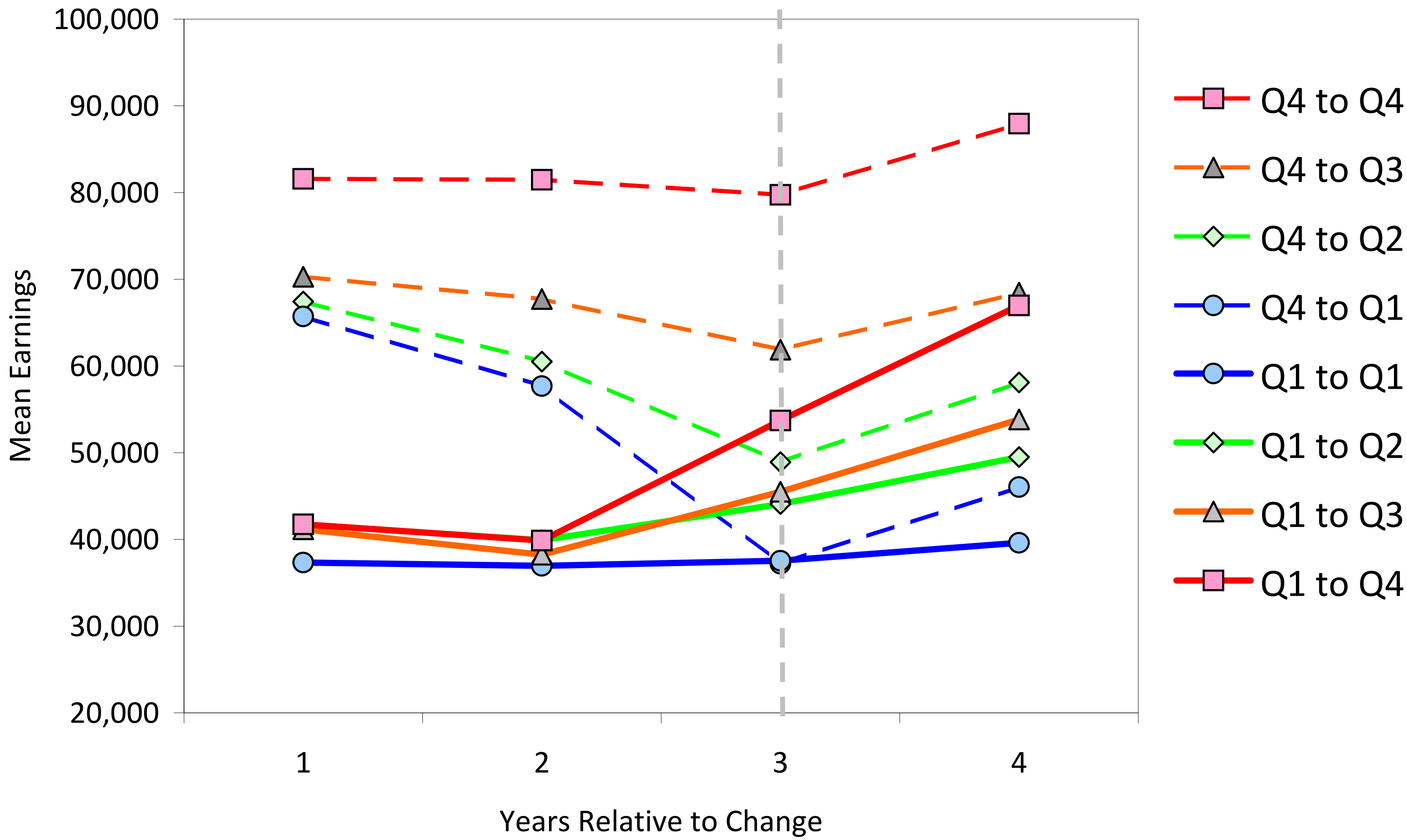


Figure 2b: Earnings Trends for Immigrants Around Job Changes Classified by Co-worker Earnings Quartiles Pre and Post

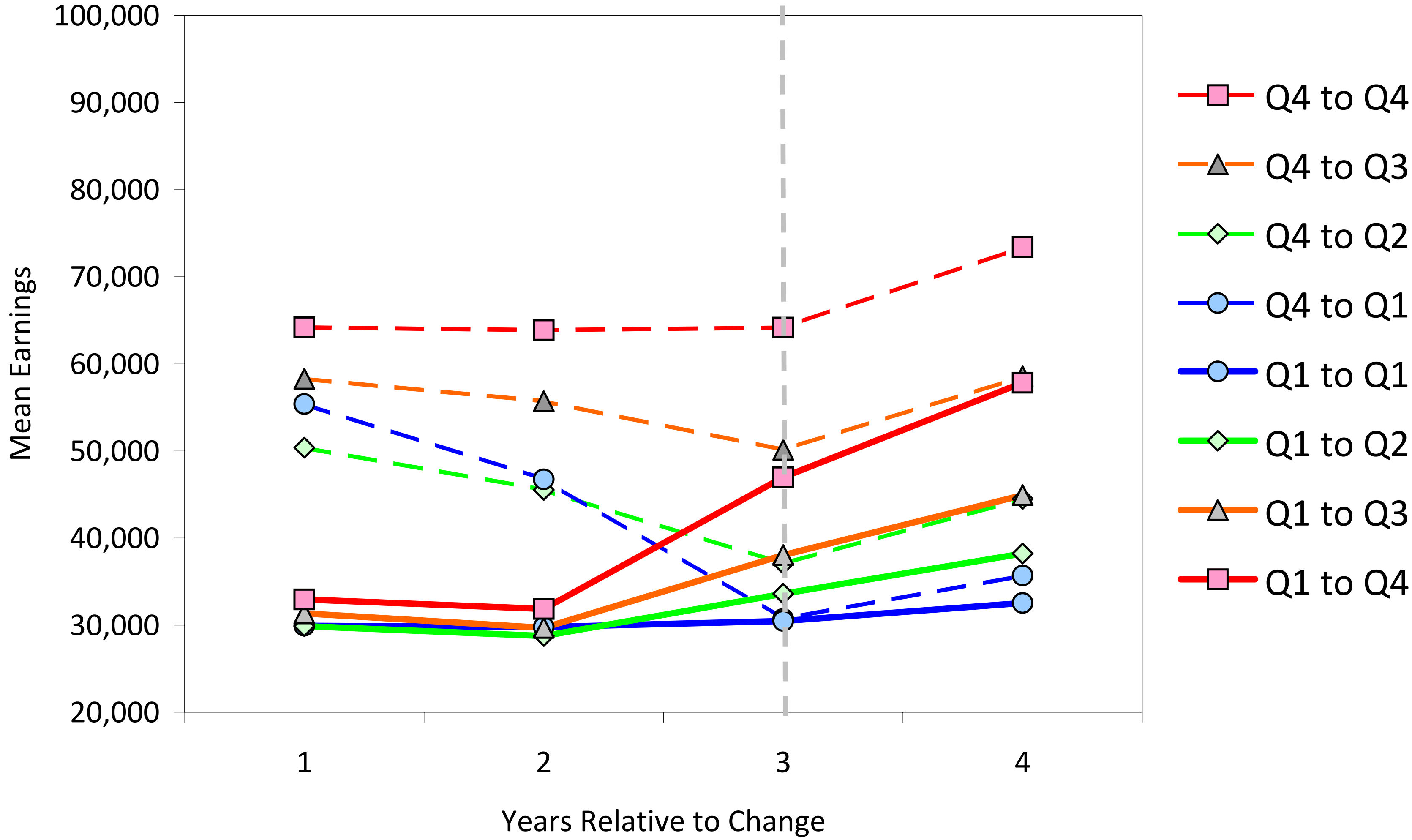
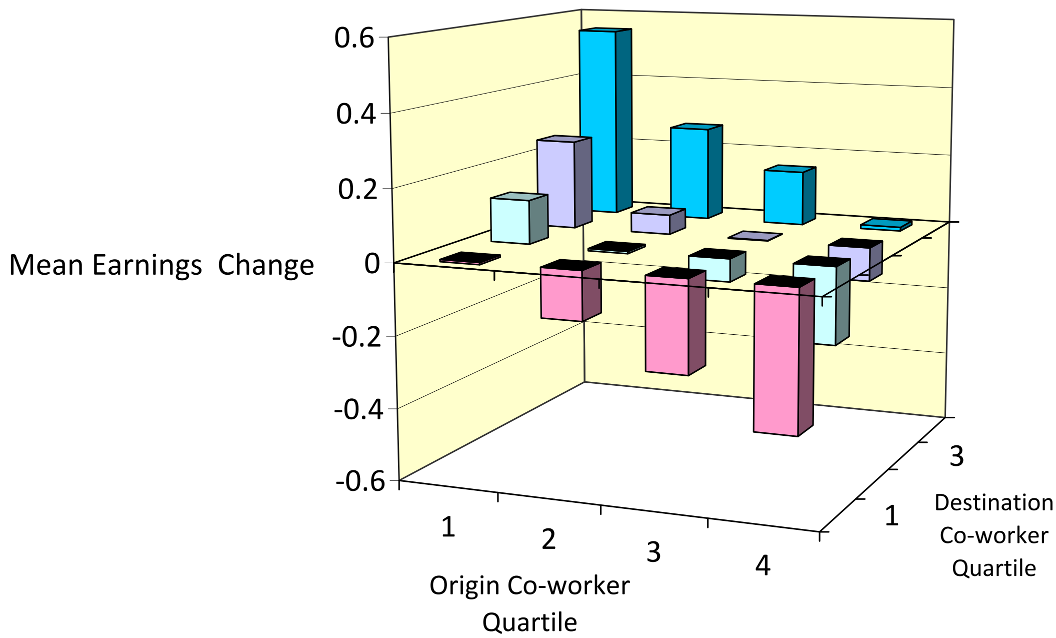
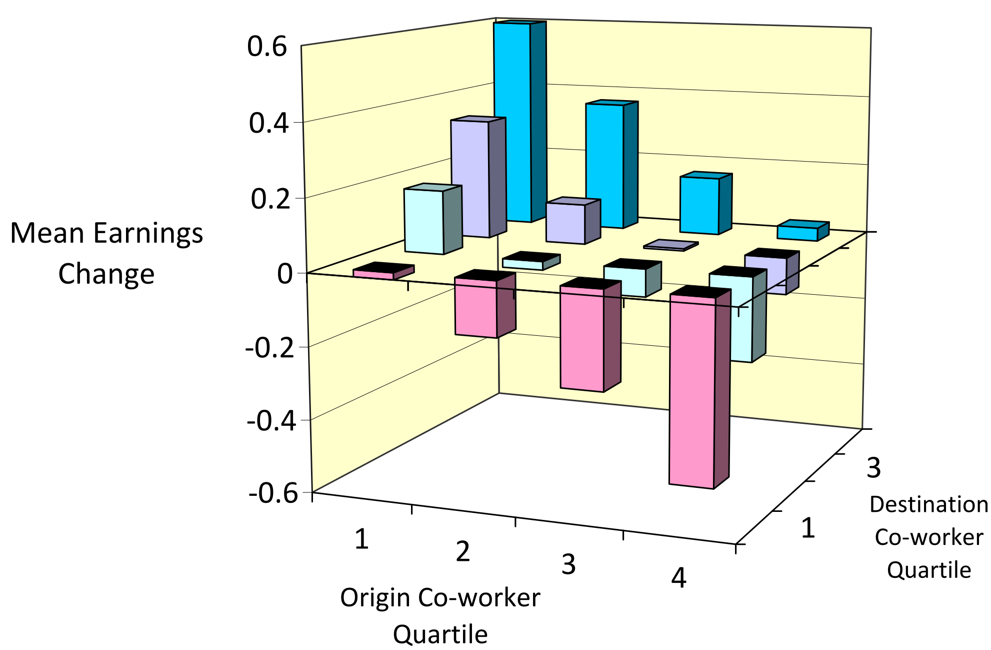


Figure 3: Earnings Changes of Firm Movers by Co-worker Earnings Quartile of Origin and Destination Firm

a. Natives



b. Immigrants



Note: earnings changes are deviated from mean earnings changes of movers who remain in same co-worker quartile.

Figure 4: Mean Earnings Growth of Natives and Subgroups of Immigrants in 2000-2004 Landed Cohort

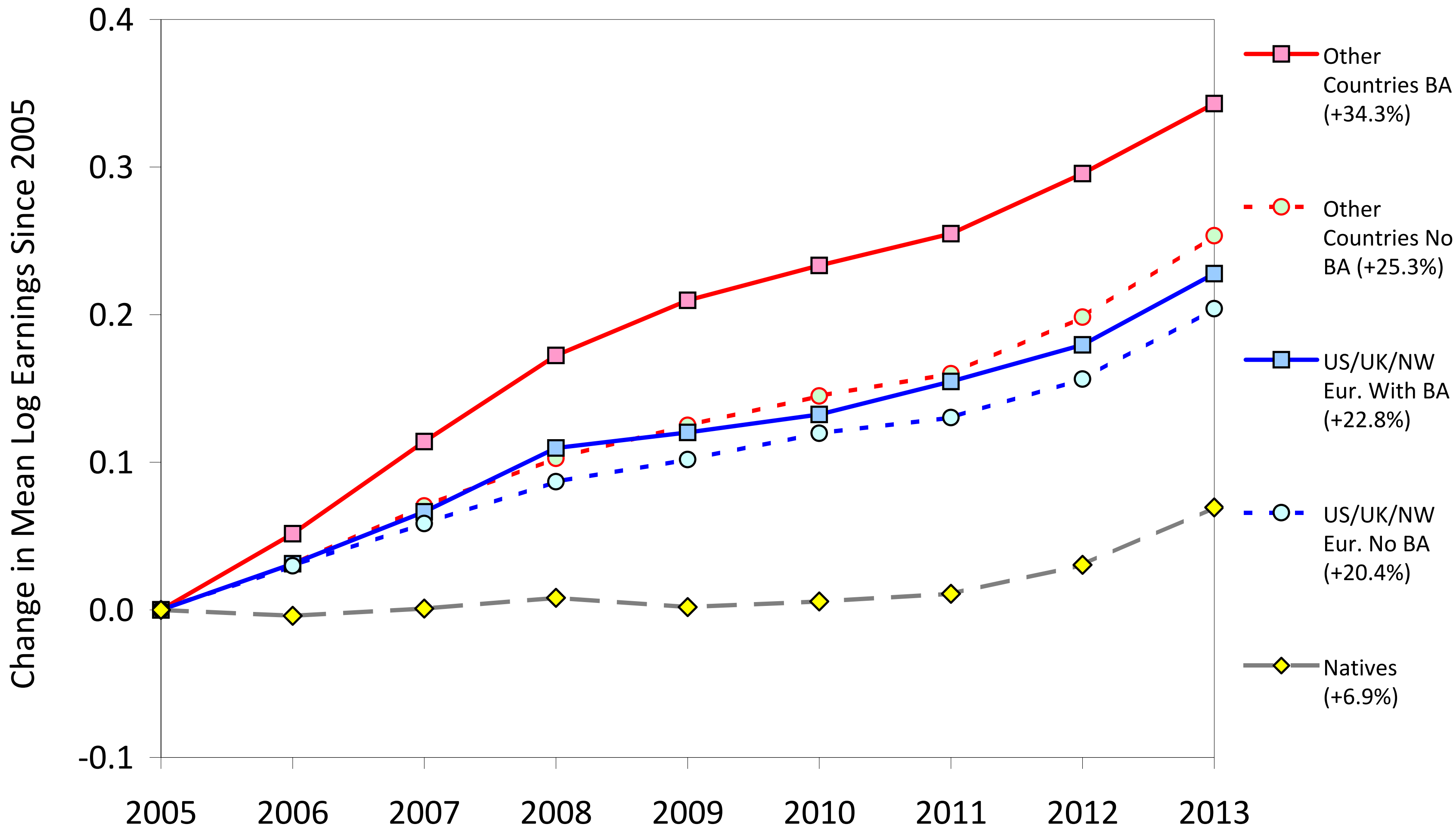


Figure 5: Changes in the Mean Person Effects of Workers Employed Over Time - Estimates of Composition Bias

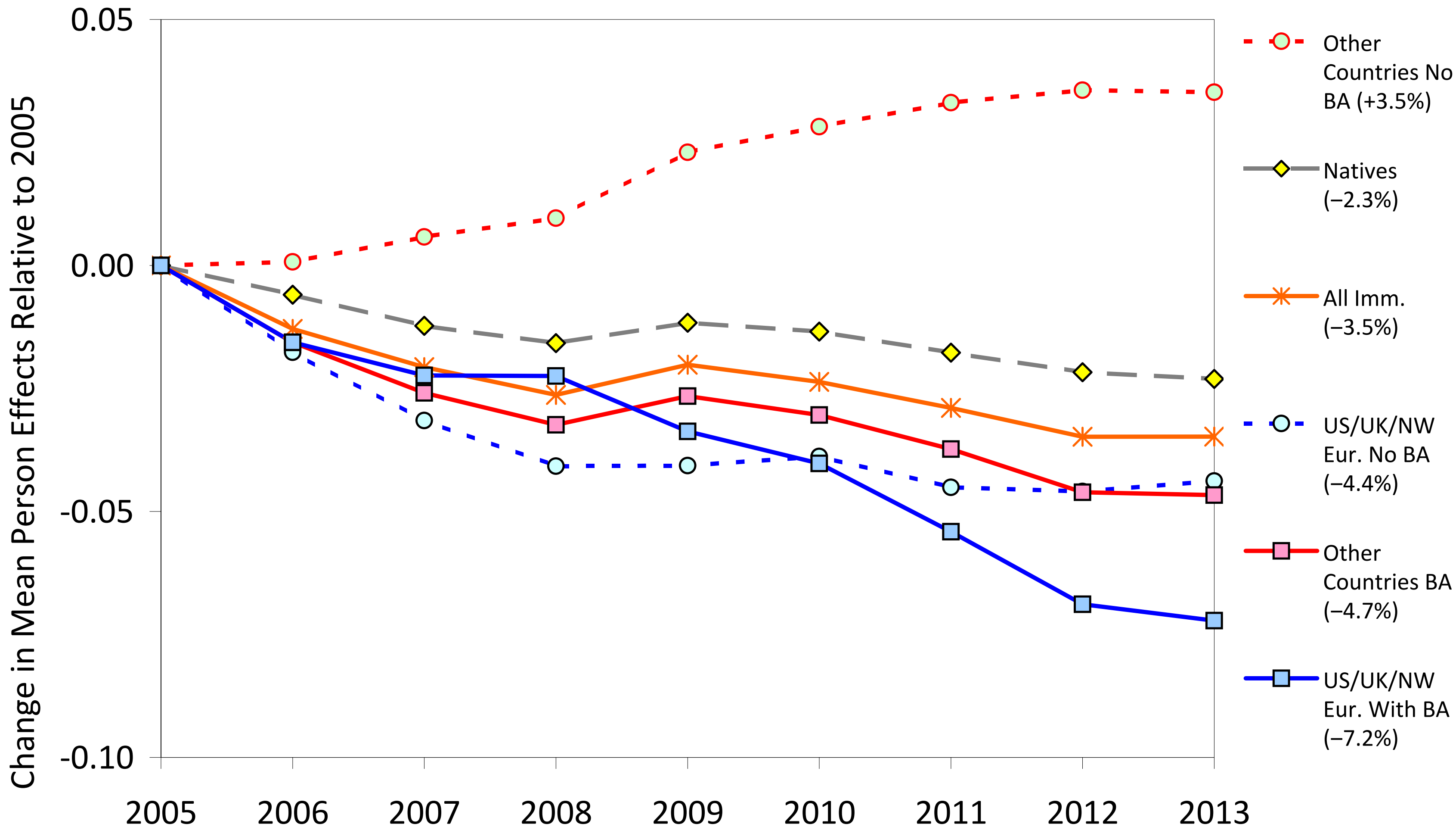


Figure 6: Composition-Adjusted Earnings Growth of Subgroups of Immigrants in 2000-2004 Landed Cohort

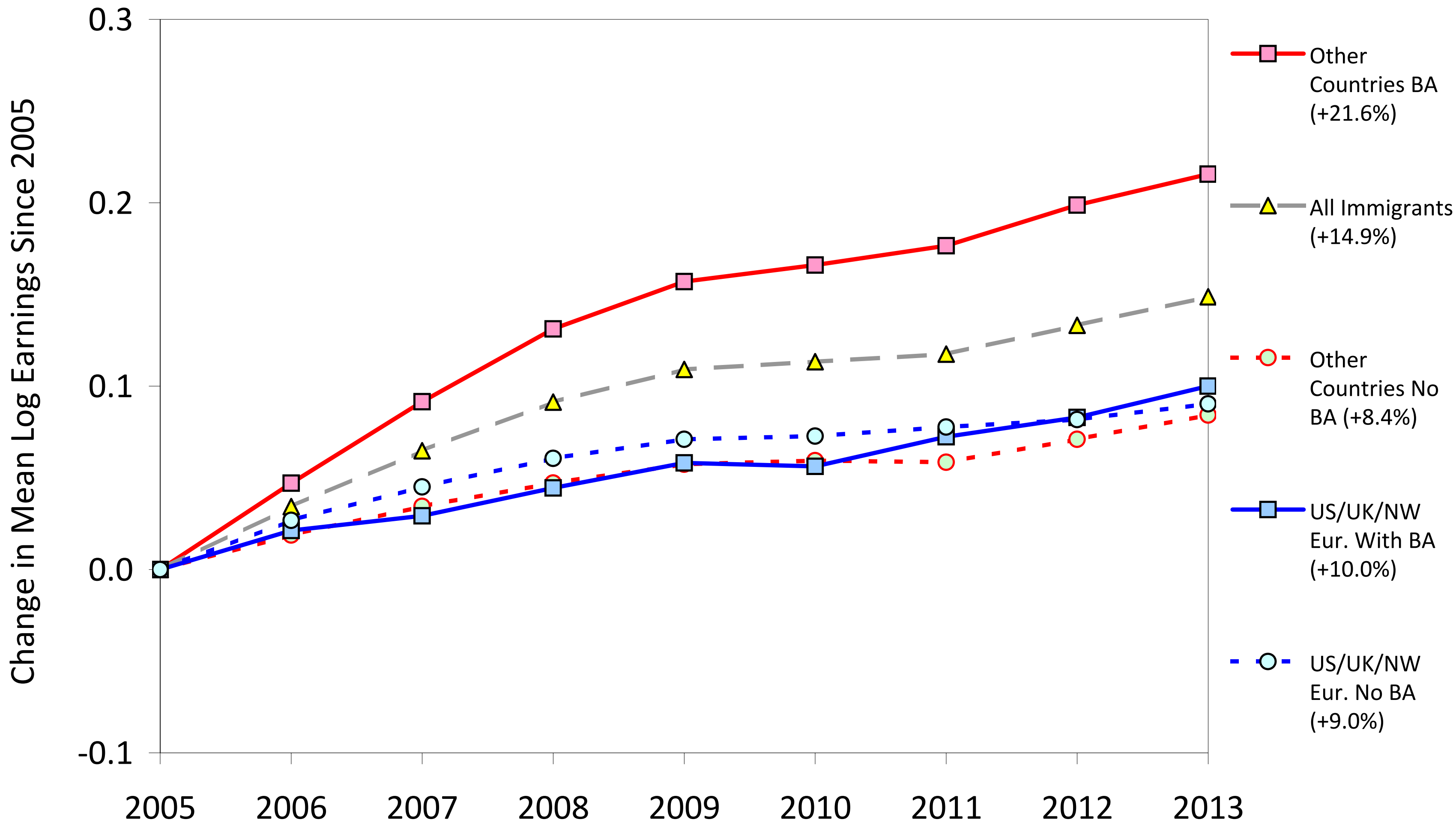
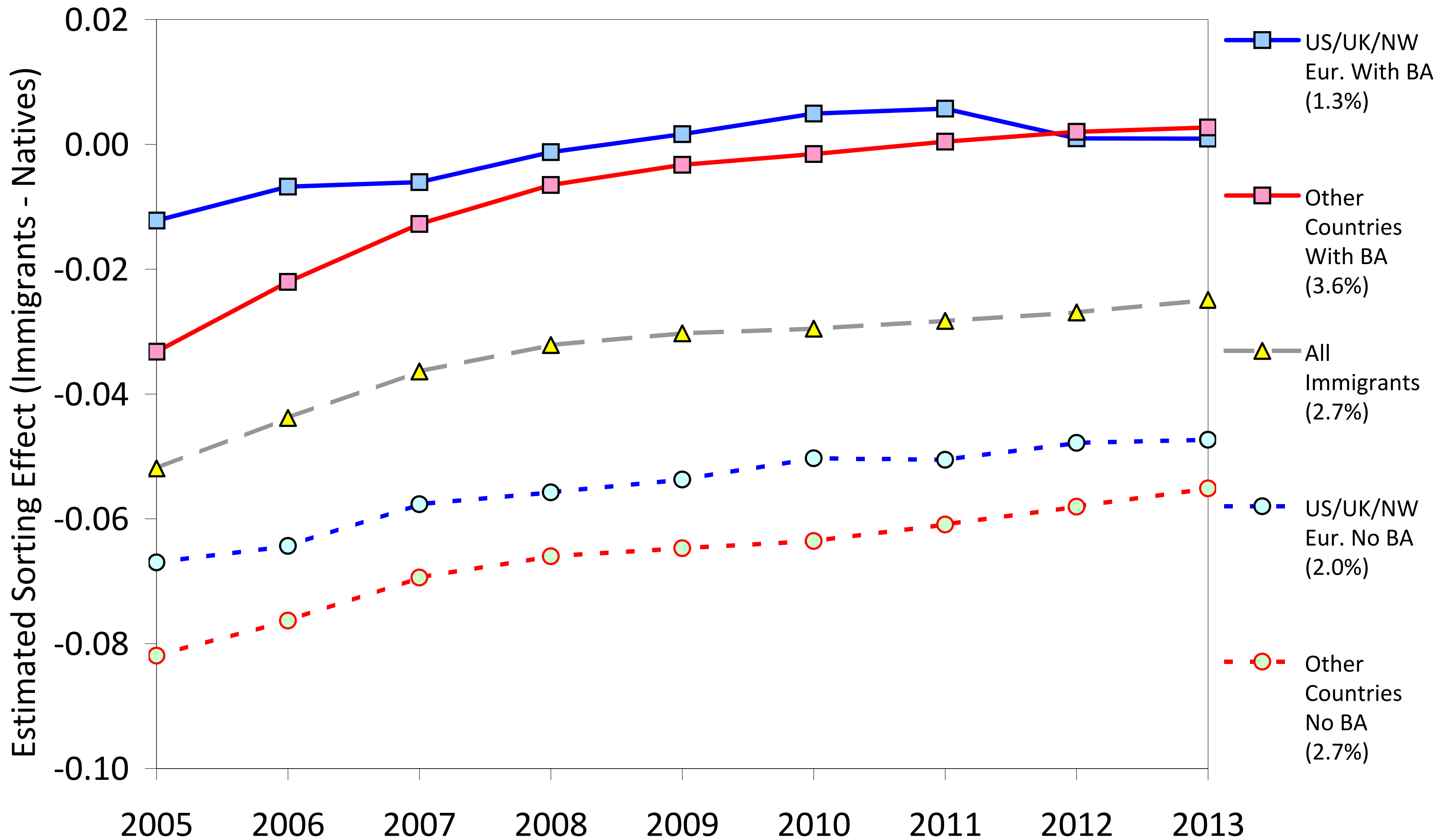


Figure 7: Evolution of Sorting Effect for Subgroups of Immigrants in 2000-2004 Landed Cohort



Data Appendix

Our study makes use of the Canadian Employer-Employee Dynamics Database (CEEDD) – a matched employer-employee database built from large-scale administrative data in a linkable file environment. The CEEDD covers the universe of individual tax filers and their families, employees receiving Statements of Remuneration Paid (T4) slips, unincorporated businesses and corporations, unincorporated business owners reporting self-employment income, and owners of Canadian-controlled Private Corporations.[1,2]

Our dataset focuses on employees in the business sector whose primary income sourcing from employment. Several steps are taken before arriving at the full set as reported in columns 1-3 in Table 2. First and foremost, our sample keeps individuals with their primary source of income being employment only. To determine the main source of income for a given individual, we define income sources into four categories: 1) employment income; 2) self-employment income; 3) indifferent between employment and self-employment income; and 4) no income. Employment income is aggregated from all T4 slips. Self-employment income sources from business, farming, fishing, rental, commissions, and professional income. Our full set includes scenarios 1) and 3) only.

Second, our sample limits Canadian businesses to ones with a valid business number (BN) only, removing unincorporated (T1) businesses without BN as a result.[3] BN is a number the Canadian Revenue Agency assigns to a business when it files any or all of T4, Payroll Deductions and Remittances (PD7), GST/HST, and exports/imports.[4] As such, BNs establishes employer-employee relationship. Limiting our sample to businesses with a valid BN is a particularly important and necessary step for T1 businesses to retain a longitudinal structure in this relationship between employees and their employers. While all incorporated (T2) businesses have a valid BN, only a fraction of T1 businesses does so. Moreover, other T1 business identifiers, while exist, are not meaningful in creating our sample for the following reasons. The unique business identifier (BI) used in collecting T1 Business Declaration (T1BD) is cross-sectional in nature. Moreover, other longitudinal business identifiers (e.g., partnership business number and parent operating entity) cannot be used to match employees with their employers.

Finally, our sample covers Canadian businesses in the business sector only and with two or more employees. We limit our focus to the business sector for two reasons. First, the average firm size in the public services (NAICS 91) is found significantly larger than the rest of industries. Second, most public-sector employees are unionized which in turn may contaminate the wage-setting effect in the business

[1] The data are accessed at the Canadian Centre for Data Development and Economic Research (CDER), Statistics Canada in Ottawa. The current production cycle of the core CEEDD file covers reference years 2001-2017.

[2] The CEEDD provides comprehensive information on employees and their employers. For employees, this includes 1) demographics (e.g., age, gender, marital status, immigrant status, province of residence); 2) family (e.g., spouse and children); and 3) employment (e.g., earnings, job separation, workplace). For businesses, this includes 1) detailed financial information (e.g., revenue, expense, assets, liabilities); 2) employment, payroll, workforce characteristics; and 3) performance related to productivity, research and development expenditures, industry, province of operation, and trade.

[3] The unit of analysis for firms is different between T1 and T2 businesses. A T1 business is identified by BN whereas a T2 business is identified by enterprise – a statistical identifier that could correspond to multiple BNs for a more complex business entity. T1 businesses are in general smaller than T2 business in size, defined by employment. Using BN as the unit of analysis in T1 reinforces this result as each T2 business could have one or more BNs.

[4] PD7 is filled out by the employer to indicate the amount of the employee's and employer's benefits sent to CRA. This information is generally reported monthly.

sector. Moreover, we include businesses with two employees or more in our final sample. Consequently, we exclude over half of all Canadian businesses with limited labour market implications.[5]

The resulting dataset include all workers in the business sectors employed at firms with a valid BN and with at least two employees. For a given year, each worker has one job gives rise to his/her highest employment income. Effectively, this dataset also excludes self-employment or individuals with zero employment income.

Key variables considered for employees are annual earnings, gender, and province of residence. For a given employee, annual earning is derived from T4 income by BN. Province of residence and gender information are sourced from T1 personal tax filings. Gender information from the Longitudinal Immigration Database is used to supplement any missing values from T1.

Key variables on firm characteristics include value added per worker, employment and immigrant participation rate (or shares).[6] For each firm, value added is a sum of T4 payrolls and net income before taxes and extraordinary items. Employment is the average number of employees. For T2 businesses it is the mean of all non-zero monthly employment submissions from PD7 whereas for T1 businesses it is the total headcount of employees who receive T4 slips.[7] Immigrant share is calculated according to these employment measures for a given firm.

Reference

Li, J., Grekou, D. and H. Liu. 2018. "The Measurement of Business Ownership by Gender in the Canadian Employer-Employee Dynamics Database." Analytical Studies: Methods and References, Catalogue no. 11-633-X — No. 017, Statistics Canada.

[5] On average, there are 2.3 million firms annually between 2005 and 2013; about 1.2 million of them – incorporated and unincorporated – have no employment (see columns 1-3 in Table 1-1 in Grekou, Li and Liu 2018).

[6] In T1BD, payroll information is not reported. Instead, T1 payroll is created by aggregating all T4 employment income for a given BN. This is identical to the concept of T2 payroll.

[7] While conceptually similar, PD7-based employment is a preferred measure. As an average of non-zero monthly employment, PD7 employment captures annual full-time employment figure instead of T4 headcount which does not adjust for part-time employment and seasonal operations.

Appendix Table 1: Mean Earnings Gaps Relative to Natives by Birth Cohort, Age and Year

				Earnings Gaps Relative to Natives:			
Birth Cohort	Age	Year	Sample Size	Weekly	Adjusted Weekly	Yearly	Adjusted Yearly
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
a) Males from Other Countries							
81-85	20-24	2006	56	0.114	0.055	-0.055	-0.12
81-85	25-29	2011	91	-0.122	-0.134	-0.172	-0.182
81-85	30-34	2016	117	-0.144	-0.161	-0.165	-0.185
76-80	25-29	2006	320	-0.151	-0.202	-0.152	-0.207
76-80	30-34	2011	441	-0.068	-0.131	-0.129	-0.195
76-80	35-39	2016	472	-0.181	-0.216	-0.195	-0.234
71-75	30-34	2006	691	-0.173	-0.313	-0.217	-0.369
71-75	35-39	2011	936	-0.105	-0.232	-0.139	-0.279
71-75	40-44	2016	988	-0.129	-0.277	-0.138	-0.299
66-70	35-39	2006	817	-0.232	-0.406	-0.268	-0.457
66-70	40-44	2011	996	-0.168	-0.33	-0.159	-0.335
66-70	45-49	2016	1083	-0.135	-0.314	-0.138	-0.332
61-65	40-44	2006	634	-0.304	-0.499	-0.354	-0.565
61-65	45-49	2011	774	-0.164	-0.346	-0.167	-0.364
61-65	50-54	2016	760	-0.166	-0.361	-0.163	-0.376
56-60	45-49	2006	367	-0.331	-0.489	-0.416	-0.584
56-60	50-54	2011	482	-0.22	-0.384	-0.232	-0.412
56-60	55-59	2016	426	-0.248	-0.422	-0.217	-0.406
51-55	50-54	2006	217	-0.448	-0.582	-0.478	-0.621
51-55	55-59	2011	275	-0.339	-0.452	-0.33	-0.453
51-55	60-64	2016	188	-0.303	-0.436	-0.272	-0.41
46-50	55-59	2006	109	-0.621	-0.635	-0.605	-0.613
46-50	60-64	2011	106	-0.404	-0.452	-0.359	-0.408
46-50	65-69	2016	52	-0.398	-0.46	-0.271	-0.338
b) Males from US/UK/Northern Europe							
81-85	20-24	2006	4	-0.128	-0.041	-0.055	0.037
81-85	25-29	2011	2	0.301	0.242	0.404	0.338
81-85	30-34	2016	6	0.271	0.216	-0.147	-0.207
76-80	25-29	2006	49	0.019	-0.109	-0.049	-0.188
76-80	30-34	2011	36	-0.026	-0.133	0.026	-0.091
76-80	35-39	2016	47	-0.016	-0.125	-0.005	-0.124
71-75	30-34	2006	89	-0.048	-0.162	-0.041	-0.165
71-75	35-39	2011	72	0.294	0.132	0.306	0.129
71-75	40-44	2016	89	0.206	0.049	0.246	0.077
66-70	35-39	2006	91	0.143	0.011	0.147	0.007
66-70	40-44	2011	69	0.025	-0.083	0.072	-0.047
66-70	45-49	2016	87	0.179	0.093	0.177	0.083
61-65	40-44	2006	60	0.063	-0.003	0.1	0.03
61-65	45-49	2011	52	0.223	0.119	0.201	0.088
61-65	50-54	2016	58	0.176	0.039	0.198	0.048
56-60	45-49	2006	46	0.079	-0.053	0.045	-0.098
56-60	50-54	2011	31	0.261	0.159	0.302	0.19
56-60	55-59	2016	30	0.127	-0.005	0.185	0.033
51-55	50-54	2006	24	0.405	0.149	0.444	0.166
51-55	55-59	2011	12	0.341	0.249	0.333	0.213
51-55	60-64	2016	14	0.508	0.319	0.603	0.399
46-50	55-59	2006	14	0.56	0.494	0.675	0.603
46-50	60-64	2011	6	0.278	0.232	0.369	0.319
46-50	65-69	2016	7	-0.39	-0.34	-0.155	-0.102

Note: Based on 2006, 2011, and 2016 Canadian Census files. Adjusted wage gaps control for education and experience.

Appendix Table 1, continued

Birth Cohort	Age	Year	Sample Size	Earnings Gaps Relative to Natives: Weekly	Adjusted Weekly	Yearly	Adjusted Yearly
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
c) Females from Other Countries							
81-85	20-24	2006	45	-0.048	-0.076	-0.108	-0.136
81-85	25-29	2011	91	-0.146	-0.112	-0.199	-0.167
81-85	30-34	2016	118	-0.184	-0.125	-0.238	-0.179
76-80	25-29	2006	300	-0.149	-0.187	-0.175	-0.207
76-80	30-34	2011	516	-0.085	-0.101	-0.153	-0.167
76-80	35-39	2016	610	-0.184	-0.197	-0.216	-0.226
71-75	30-34	2006	525	-0.141	-0.256	-0.19	-0.3
71-75	35-39	2011	795	-0.096	-0.193	-0.126	-0.218
71-75	40-44	2016	929	-0.07	-0.174	-0.11	-0.209
66-70	35-39	2006	503	-0.2	-0.342	-0.232	-0.366
66-70	40-44	2011	746	-0.087	-0.216	-0.106	-0.226
66-70	45-49	2016	882	-0.118	-0.248	-0.132	-0.255
61-65	40-44	2006	382	-0.224	-0.384	-0.286	-0.436
61-65	45-49	2011	628	-0.164	-0.3	-0.176	-0.305
61-65	50-54	2016	608	-0.138	-0.299	-0.15	-0.301
56-60	45-49	2006	216	-0.326	-0.448	-0.364	-0.478
56-60	50-54	2011	347	-0.189	-0.321	-0.2	-0.324
56-60	55-59	2016	319	-0.181	-0.329	-0.179	-0.32
51-55	50-54	2006	117	-0.357	-0.435	-0.373	-0.439
51-55	55-59	2011	144	-0.166	-0.242	-0.194	-0.266
51-55	60-64	2016	129	-0.218	-0.339	-0.207	-0.309
46-50	55-59	2006	47	-0.423	-0.449	-0.446	-0.461
46-50	60-64	2011	59	-0.202	-0.184	-0.167	-0.161
46-50	65-69	2016	23	-0.204	-0.298	-0.14	-0.227
d) Females from US/UK/Northern Europe							
81-85	20-24	2006	4	0.603	0.43	0.231	0.065
81-85	25-29	2011	1	-0.01	-0.272	-0.003	-0.253
81-85	30-34	2016	8	-0.244	-0.094	-0.134	0.007
76-80	25-29	2006	36	0.008	-0.095	0.048	-0.051
76-80	30-34	2011	41	0.183	0.129	0.152	0.1
76-80	35-39	2016	55	0.021	-0.002	0.008	-0.015
71-75	30-34	2006	67	0.05	-0.08	-0.024	-0.149
71-75	35-39	2011	53	-0.003	-0.121	-0.055	-0.166
71-75	40-44	2016	74	0.102	-0.02	0.15	0.036
66-70	35-39	2006	54	0.133	0.051	0.088	0.009
66-70	40-44	2011	43	0.039	-0.026	0.078	0.011
66-70	45-49	2016	58	0.104	0.02	0.061	-0.02
61-65	40-44	2006	30	0.143	0.034	0.158	0.055
61-65	45-49	2011	33	-0.069	-0.116	-0.063	-0.108
61-65	50-54	2016	39	-0.098	-0.175	-0.069	-0.134
56-60	45-49	2006	18	-0.253	-0.341	-0.23	-0.314
56-60	50-54	2011	18	-0.204	-0.274	-0.19	-0.257
56-60	55-59	2016	20	0.156	0.094	0.09	0.03
51-55	50-54	2006	14	-0.297	-0.4	-0.253	-0.35
51-55	55-59	2011	9	-0.001	-0.048	0.069	0.024
51-55	60-64	2016	18	0.051	-0.027	0.127	0.036
46-50	55-59	2006	10	-0.557	-0.612	-0.534	-0.587
46-50	60-64	2011	4	0.092	-0.085	-0.044	-0.214
46-50	65-69	2016	6	-0.162	-0.545	-0.057	-0.335

Note: Based on 2006, 2011, and 2016 Canadian Census files. Adjusted wage gaps control for education and experience.

Appendix Table 2: Immigrant-Native Gaps in Work Activity, 2000-4 Arrivals

	Immigrant-Native Gap in:		
	Share Working (1)	Share Full Time (2)	Share 45+ Weeks (3)
a. Males from US/UK/Northern Europe:			
2006	-0.006	0.001	0.008
2011	0.001	0.025	0.032
2016	-0.006	0.063	0.045
b. Males from Other Countries:			
2006	-0.056	-0.063	-0.098
2011	-0.033	-0.019	-0.012
2016	-0.039	0.014	-0.003
c. Females from US/UK/Northern Europe:			
2006	-0.033	-0.019	-0.012
2011	-0.039	0.014	-0.003
2016	-0.096	-0.063	-0.021
d. Females from Other Countries:			
2006	-0.151	-0.163	-0.076
2011	-0.118	-0.104	-0.017
2016	-0.083	-0.068	-0.021

Note: table entries represent gaps relative to natives in share working last year (column 1), working full time last year (column 2) and working 45 or more weeks last year (column 3).

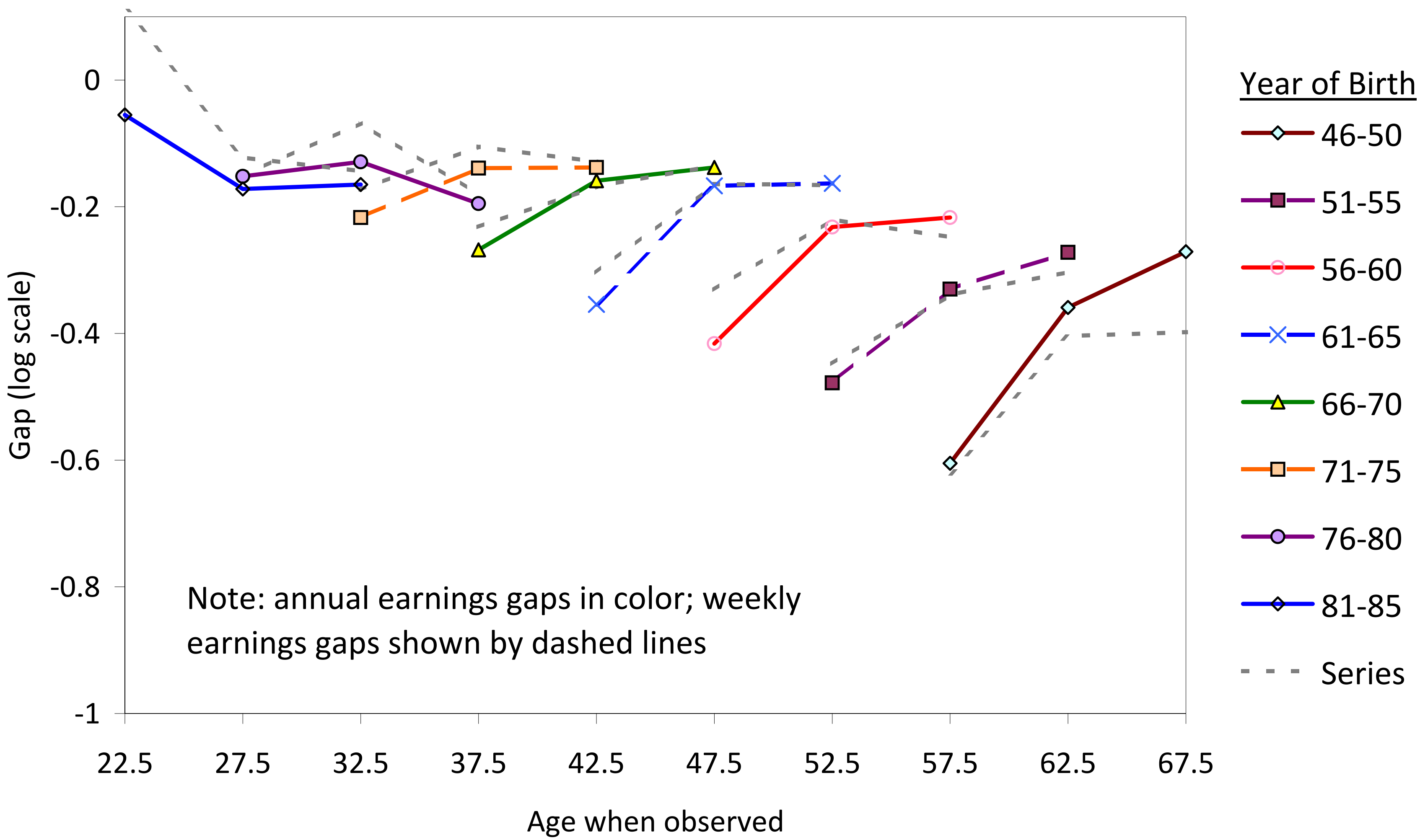
Appendix Table 3: Estimated Coefficients from AKM Models

	Natives (1)	Immigrants (2)
Marital Status (Relative to Married):		
Common Law	-0.008	-0.004
Widowed	-0.036	-0.028
Divorced	-0.002	0.008
Separated	-0.007	-0.001
Single	-0.01	-0.002
Unstated	-0.016	-0.04
Province (Relative to Ontario):		
Newfoundland and Labrador	-0.181	-0.043
Prince Eward Island	-0.196	-0.065
Nova Scotia	-0.148	-0.066
New Brunswick	-0.129	-0.037
Quebec	-0.038	-0.023
Manitoba	-0.015	0.041
Saskatchewan	-0.027	-0.005
Alberta	0.036	0.028
British Columbia	0.009	0.02
NorthWest Territories	0.136	0.147
Yukon	0.018	0.045
Nunavut	0.142	0.021
Year Effects	yes	yes
Quartic in Age, Person and Year Effects [a/]	yes	yes

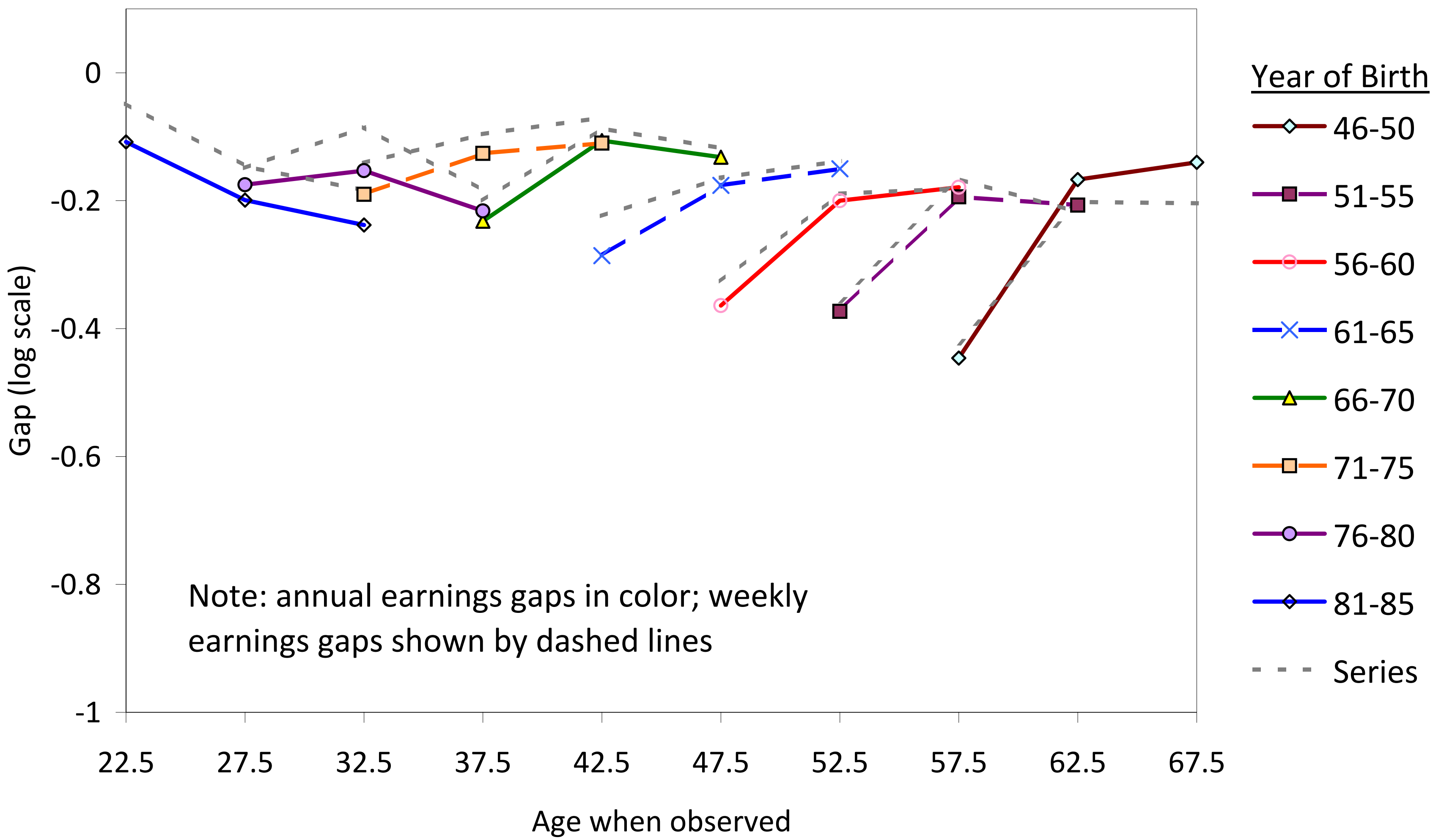
Note: table shows estimated coefficients of marital status and province from estimated AKM models for natives and immigrants.

[a/] See Table 3 for summary of estimated person and firm effects in these models, and Appendix Figure 2 for graph of estimated age profiles

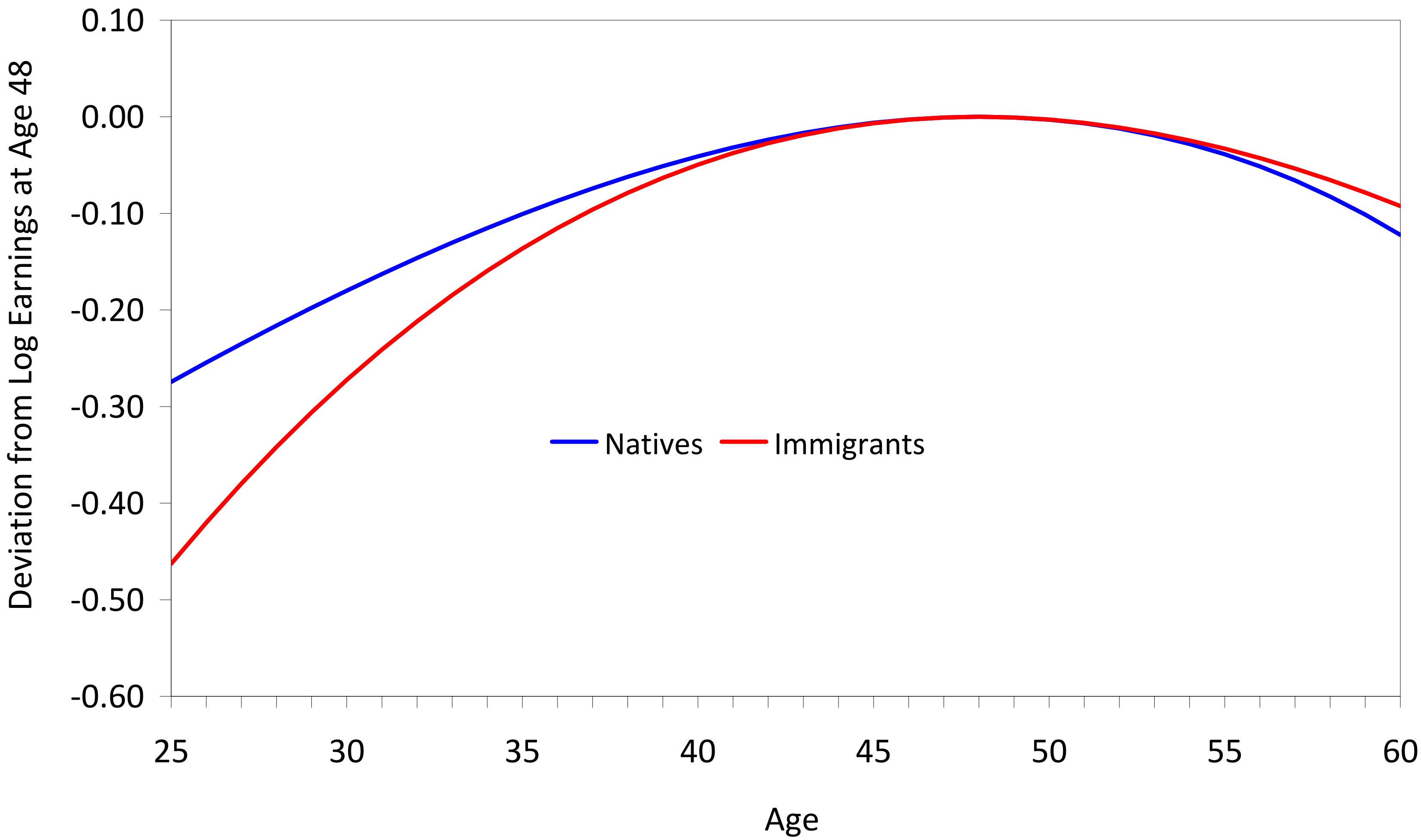
Appendix Figure 1a: Annual vs. Weekly Earnings Gaps Relative to Natives: Males from Outside US/UK/Northern Europe, Arrived 2000-2004



Appendix Figure 1b: Annual vs. Weekly Earnings Gaps Relative to Natives: Females from Outside US/UK/Northern Europe, Arrived 2000-2004



Appendix Figure 2: Estimated Age Profiles from AKM Models



Appendix Figure 3: Earnings Growth of Immigrant Arrival Cohorts from Beach and Abbott (2011)