The Wealth Position of Immigrant Families in Canada

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Abstract

The economic assimilation of immigrants is a key concern for policy makers. It is widely explored in terms of earnings assimilation of immigrants. This study attempts to look at the issue from the wealth perspective.

Using the 1999 Survey of Financial Security, I find that, among married families, immigrants have higher wealth than natives from the 40^{th} to the 90^{th} percentiles of the distribution, and the wealth gap ranges between $20,000 to $78,000, while among single families, immigrants have higher wealth than the natives from the 55^{th} to the 95^{th} percentiles, and the wealth gap ranges between $14,000 to $145,000. At the bottom of the distribution, however, there is evidence suggesting that immigrants have lower wealth than their native-born counterparts, although the gap is generally below $10,000.

Various decomposition results indicate that the age of the major income recipient and factor affecting permanent income explain the bulk part of the wealth gap between immigrant and native-born families, and MIR's (and spousal) age plays a more important role than other factors in explaining the wealth gap between married immigrants and natives. At the bottom of the wealth distribution, however, the wealth gap cannot be explained by MIR's age, permanent income, or family size alone or altogether.

The wealth gap between immigrant and native-born families are also explored along the cohort dimensions. Not surprisingly, recent immigrants have lower, and immigrants who arrived before 1976 generally have higher wealth than comparable native-born families, even after controlling a number of key factors. The widely agreed notion that immigrants arrived between 1976-1985 posses a poor earnings position is confirmed in terms of their wealth position.

Key words: immigrant, wealth gap, counterfactual decomposition, permanent income, life-cycle hypothesis, cohort effect.

1. Introduction

The economic assimilation of immigrants is a key concern for policy makers. Economists almost exclusively focus on the earnings assimilation of immigrants, little is known on the wealth position of immigrants in Canada and elsewhere.[1] Using Statistics Canada's 1999 Survey of Financial Security (SFS), this article takes on the first step to address some key issues pertaining the wealth position of immigrants in Canada. In particular, the study shall estimate the wealth gap between immigrant and native-born families and identify factors that may explain this gap. The cohort effect on wealth gap is also explored.

The importance of this topic can be seen firstly through the earnings assimilation of immigrants. Leading economists have painted a rather pessimistic picture on the earnings assimilation of immigrants. Using data from the 1971, 1981 and 1986 Canadian censuses, Baker and Benjamin (1994) fail to reject the zero assimilation hypothesis for male immigrants aged between 16-64, while Bloom, Grenier and Gunderson (1995) find negligible evidence of assimilation for male and zero assimilation for female immigrants with the same data sources.[2] If immigrants are able to catch up the wealth position of the natives, factors other than their earnings, such as savings rate, inheritance, and returns on investments, shall play significant roles in their wealth accumulation, and the zero earnings assimilation rate of immigrants needs not to be as disturbing as it has been perceived.

Furthermore, the wealth position of immigrants is not only an important aspect of the economic assimilation, it also plays a key role in the whole process of economic assimilation. This is the case since the wealth position of a family affects its access to the credit market, facilitates its members to venture into business activities, to pursue higher education, or to spend more time looking for better job matches. An established wealth position of immigrants may help them overcoming some disadvantages they face in the social networks and in the labour market. For example, until they are fully assimilated into the host economy, immigrants may face higher earnings uncertainty relative to the natives, wealthy immigrants will be in a better position than poorer immigrants in dealing with the uninsurable portion of this risk and achieve a higher rate of earnings assimilation.

Finally, according to the well-known life-cycle hypothesis, individuals accumulate wealth during their working age and consume these wealth upon retirement. So those who retire with a large amount of wealth will be less likely to rely on government transfers for their retirement consumption. If immigrants are unable to save enough for

[1] The only exception is perhaps Shamsuddin and DeVoretz (1998), in which the authors study wealth accumulation of Canadian and Foreign-born households.

[2] Borjas (1995) reaches similar conclusions with the 1970, 1980, and 1990 U.S. censuses. However, in a study using the 1981, 1986 and 1991 Canadian censuses, Grant (1999) finds evidences that male immigrants who arrived in Canada between 1980 to 1990 have experienced significant earnings growth during their first five years of arrival.

their retirement consumption, high immigrant intake will have negative effects for the public retirement funds.

This study confirms the existence of wealth gaps between immigrant and native-born families in Canada from the middle to the upper segments of the wealth distribution. Within these segments, immigrant families' wealth is significantly higher than that of native-born families. Decompositions of the wealth gap indicate that the age of the major income recipient (MIR) and family permanent income can explain the bulk part of the wealth gap. The notion that immigrants who arrived between 1976-1985 posses a poorer earnings position than their predecessors is also confirmed in terms of their relative wealth position.

In the next section, I describe the data source and present descriptive statistics of the variables involved. Section 3 examines the existence and the magnitude of the wealth gap between immigrants and native-born families. In Section 4, I attempt to identify factors that may explain the wealth gap by conducting some decompositions. Section 5 explores the cohort effect on wealth gap, and Section 6 contains a summary and the conclusion.

2. Data

The data source employed in this study is Statistics Canada's Survey of Financial Security (SFS). The survey was conducted from May to July 1999. It is based on Statistics Canada's Labour Force Survey sampling frame and represent all families and individuals in Canada except residents of the Yukon and the Northwest Territories, households located on Indian reserves, full-time members of the Armed Forces, and inmates of institutions. Information are collected for 15,933 family units, including data on all family members aged 15 or over. In this study, I delete observations in which the major income recipient (MIR) reports being married or living with a common-law partner, but provides no information on his/her spouse. This results in a sample of 15801 family units.[3]

There is no unique definition for an immigrant family. In this article, I refer to a family as an immigrant family if its major income recipient is an immigrant. If the major income recipient of a family is not an immigrant, the family is referred to as a native-born family, or a native family for short. As the study employs only cross-sectional data, there shall be no problem in determining whether a family is an immigrant or a native-born family using its MIR's immigration status. Wealth or net worth is defined as the difference between total assets and total debts. Total assets include all deposits, investments in mutual funds, bonds, and stock holdings, registered retirement savings plans (RRSP) or funds in locked-in retirement accounts (LIRA), principal residence and other real estate assets, vehicles, contents of principal residence, collectibles and valuables, business equity, and other assets such as registered education savings plans (RESP), deferred

[3] In the survey, an unattached individual is also viewed as a family unit. Detailed information on the survey is provided in a Statistics Canada publication "Assets and Debts of Canadians: An overview of the result of the Survey of Financial Security, 1999" (catalogue number 13-595-XIE).

profit sharing plans, homeownership savings plans, and annuities. Total debts include mortgage debts on principal residence and other real estates, outstanding balance on credit cards, deferred payment and instalment plans, student loans, loans for all vehicles, line of credits and other money owed. The value of work-related pension plans, entitlements to social security programs to be provided by governments such as the Canadian/Quebec Pension Plan and the Old Age Security are excluded from the total assets.[4]

Since the death of a partner or a marital breakup may have significant effect on family wealth, separate analyses for single and married families seem to be a reasonable choice. A family with a married MIR or the MIR lives with a common-law partner is defined as a married family. Among the 15801 family units, 9595 are married families. The remaining 6206 observations consist of families of unattached individuals and families with lone parents. They are referred to as single families. Hence, we have four types of families according to marital status and immigration status: married immigrant and native-born families, and single immigrant and native-born families. The non-parametric estimates of the wealth kernels (Figure 1) suggest that their wealth distributions are highly skewed to the right and data outliers are likely to be non-trivial. Indeed, Table 1 shows that the overall mean wealth of married families are roughly twice higher than their overall median wealth, while the overall mean wealth of single families are approximately four times higher than their overall median wealth. Likewise, the mean and median wealth of married immigrant families are 6.7% and 25.9% higher than the mean and median wealth of the native-born families, while the corresponding differences between single immigrant and native-born families are 33.1% and 12.0%, respectively. Hence the magnitude of the wealth gap between immigrant and native-born families will be different depending on which measure one adopts.

A number of factors may be used to explain the wealth gap between immigrant and native-born families. One theory widely employed in studying wealth accumulation is the life-cycle model. It is natural to expand this theory to family wealth accumulation by postulating that a family also has its own life-cycle. A family at an early stage of its life-cycle may have fewer assets but owes considerable amounts of debts, while a family at a latter stage of its life-cycle may have a substantial amount of assets and no debts. I shall use the age of the MIR of a family to capture the effect of family life-cycle in its wealth accumulation process. Table 1 shows that the wealth of married families reaches its maximum when MIR's age is between 56 to 65, and falls thereafter. While the wealth of single families changes in a more complex way. The mean wealth of single immigrant families increases to a maximum and then decrease, but the median wealth of single immigrant families, and the mean and median wealth of single native-born families seem to reach their maximums after MIR's age reaches beyond 65.[5]

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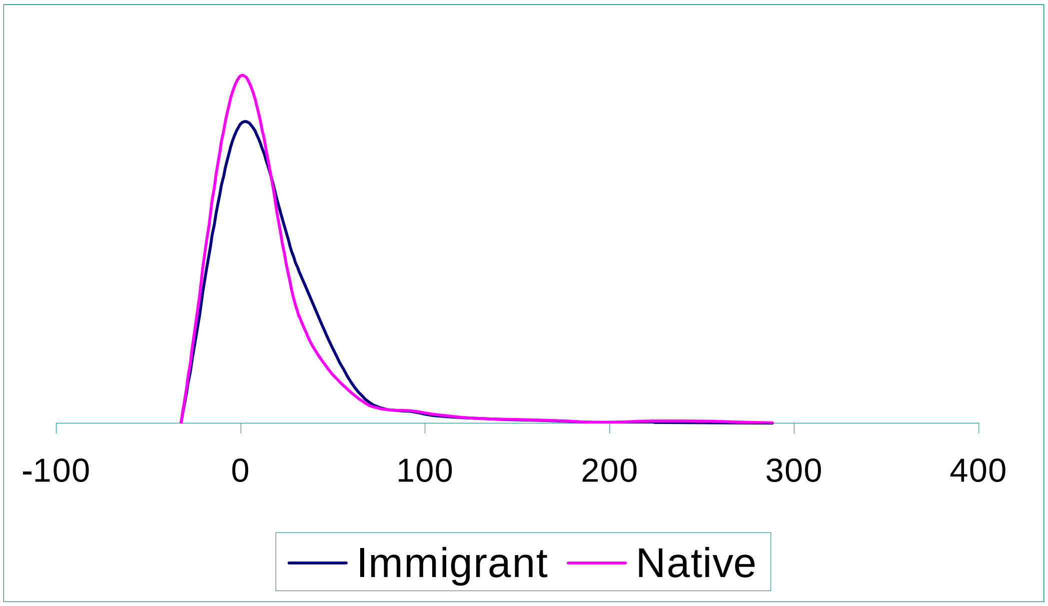
[4] Entitlements to work-related pension plans and social security incomes are excluded from family assets since they cannot be cashed out to repay family debts. Nevertheless, these future entitlements may have a negative (positive) effect on the wealth accumulation of natives (immigrants). For example, when natives anticipate higher entitlements to these incomes than immigrants do, they could save less than immigrants.

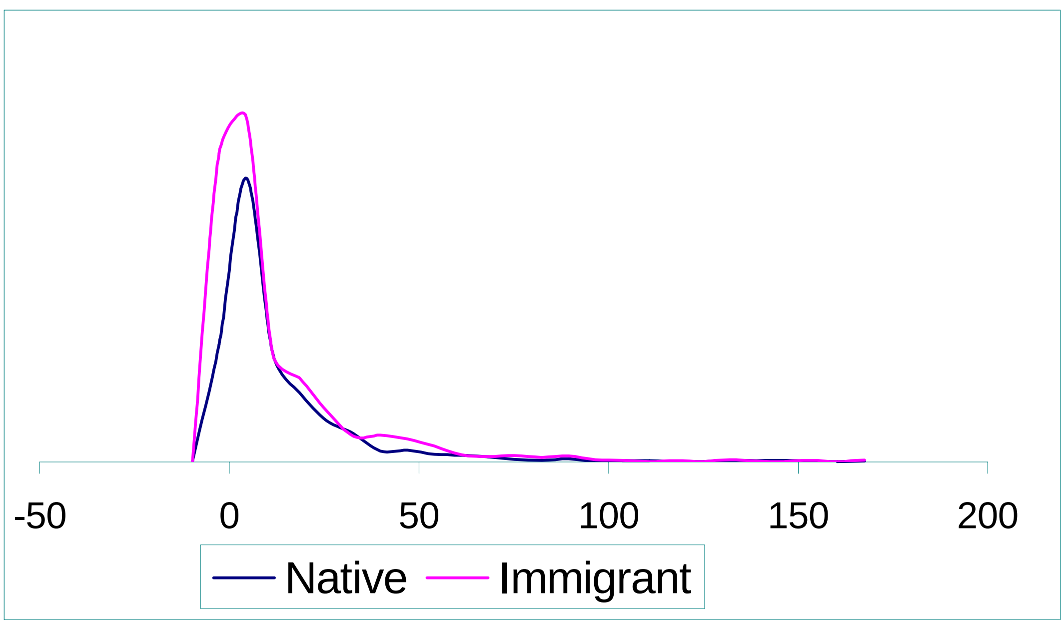
[5] A finer classification of 5-year age interval leads to the same observation.

Figure 1. Non-parametric estimates of wealth distributions

(1) Married families



(2) Single families



Another factor affects wealth accumulation, and hence the wealth gap between immigrant and native-born families, is family permanent income. Table 1 provides the mean and median wealth across different quintiles of family after-tax income. Apparently, family wealth raises as family income increases, except between the second and the third quintiles of income for married immigrant families, the mean and median wealth decrease somewhat. There are two potential concerns in analyzing the relationship between family income and wealth. On one hand, family income is potentially endogenous since a portion of family income may come from investment, and hence is affected by family wealth. On the other hand, we only observe the current income for a family and the current income is subject to random shocks since incidence of unemployment and fluctuations of the returns to investments are beyond the control of individual families. Theoretically, it is not the current income but the permanent income that affects wealth accumulation.[6] It is ideal to have observations of family income over a number of years to construct a permanent income measure, but given that we only have a cross-section data, we use age, education, and gender in place of permanent income to explain the wealth gap.

Aside from age and permanent income, I also look at difference in family size among married families and lone parents status among single families. From the intergenerational wealth transfer perspective (Blinder, 1973), it would be more coherent to look at difference in the number of children between immigrant and non-immigrant families. For transfer purposes, children of all ages must be taken into consideration in measuring the number of children. But SFS 1999 only provides accurate number of children aged below 25. Adult children aged 25 or older are considered as relatives to the MIR, even though these children are still living with the MIR and are future bequest recipients. Hence I use family size as an alternative for the number of children for married families.[7] Table 1 shows that the effect of family size on wealth is complex. Families of size two, presumably couples without children, have higher wealth than families of larger size. Among families consists of more than two persons, family size decreases the mean wealth of immigrants, but it increases the mean and median wealth of native families.

Lone parent status could have important negative effect on wealth accumulation for single families. Lone parents with small children often have no choice but to purchase child-care services in order to work. This will lower their savings and their wealth can be lower than single families which have no small children. Indeed, the sample shows that

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[6] Some authors choose to construct a measure of permanent income based on longitudinal income data (for example, see Altonji et al. (2001)), while other authors construct their permanent income measure based on cross-section income regression result (Blau and Graham (1990)). The latter approach uses the predicted income at a fixed age of the family head as a measure of family permanent income. Given that we only have a cross-section data, it seems plausible to follow this approach. But a particular difficult arises for calculating the permanent income for immigrant families. Since the "year since migration" (YSM) variable plays a key role in immigrants' earnings assimilation, it has to be included in the regression, but for some older immigrants who arrived in Canada more recently, if the fixed age chosen for calculating permanent income is low enough, these immigrants would not be immigrants yet. Some measurement error will be introduced.

[7] It should be admitted that family size itself also cannot fully measure the number of potential bequest recipients. For example, there is the case of married children living away from parents.

the mean and median wealth of lone parent families are approximately half of those for other families.

Table 1. Mean and median wealth vs. family characteristics

	Immigrant			Native-born		
	Median	Mean	Std. err.	Median	Mean	Std. err.
Married: overall	159,600	280,154	16,839	126,750	262,631	8,059
MIR's age						
<=25	10,275	25,007	6,865	14,700	60,452	13,277
26—35	52,000	102,267	14,317	57,701	103,087	7,061
36—45	87,800	184,464	33,544	120,120	243,558	18,150
46—55	222,904	345,595	23,605	180,200	349,893	19,915
56—65	322,000	449,547	44,485	215,500	403,179	26,726
>65	237,502	364,555	63,079	202,069	330,239	17,121
Single: overall	30,451	140,908	10,717	27,200	105,871	3,384
MIR’s age						
<=25	1,020	104,601	53,738	1,550	24,797	5,139
26—35	7,100	90,940	23,711	14,750	72,876	10,658
36—45	16,100	73,159	10,714	36,500	87,218	4,831
46—55	62,200	164,803	24,362	49,003	142,287	14,193
56—65	82,466	235,067	51,501	55,400	163,670	13,173
>65	101,540	184,247	18,078	90,353	170,944	7,567
Married: after-tax income						
q1 - q20	61,070	159,298	33,886	63,400	137,823	9,472
q21 – q40	149,105	214,333	14,381	85,272	161,690	6,500
q41 – q60	133,000	204,248	16,480	110,004	207,106	14,125
q61 – q80	158,000	279,129	25,555	146,455	266,393	15,539
q81 – q100	326,498	511,202	55,169	284,605	551,834	31,062
Single: after-tax income						
q1 - q20	1,020	31,041	10,784	1,497	31,721	6,008
q21 – q40	10,100	76,866	11,710	11,000	64,759	5,699
q41 – q60	18,100	93,006	11,192	26,000	78,762	4,152
q61 – q80	62,200	148,185	20,002	51,900	108,263	5,328
q81 – q100	167,201	310,923	36,233	121,200	253,078	15,663
Married: Family size						
2	200,000	343,935	36,510	151,000	281,512	10,810
3	125,000	257,823	43,967	104,100	238,378	17,568
4	148,260	252,714	18,473	118,000	245,071	19,897
>=5	124,300	236,142	25,904	123,521	274,230	22,625
Single: lone-parent status						
lone parent	15,100	71,415	15,815	13,550	68,744	9,682
other family	34,108	152,613	12,267	29,600	110,502	4,167

Appendix Table 1 contains a descriptive summary of the above characteristics. It shows that, on average, MIRs of married immigrant families are older than those of married native families by 3 years, and MIRs of single immigrant families are older than those of single native families by 5 years. While average after-tax income of single immigrant families is 12% higher than that of single native families, the difference between married immigrant and native families is merely 1.4%. The average family size of married immigrants is 11.5% higher than that of married natives, and single immigrants is 30% more likely than single natives to live in a lone parent family. In terms of related to permanent income, immigrant families are more likely to have a female MIR than the native families, although the difference is not big, and immigrant MIRs (and spouses) have higher education than the natives. Remarkably, immigrants are almost twice likely than natives to have above-university education.

3. How Wide is the Wealth Gap?

As previously mentioned, the wealth distribution is highly to be skewed and outliers in wealth data are likely to be non-trivial. The non-parametric estimates of the wealth distributions (Figure 1) show that there are a small number of families whose wealth are extremely high. In such a situation, analysts usually smooth the data by taking the natural logarithm transformation. However, at the left side of the wealth distribution, there also exists a non-negligible number of families with very low or negative wealth. Some economists choose to exclude these families, while others choose to conduct some complex transformations.[8] Even if the outliers and non-normality issues are resolved, it is unclear if immigrants really have higher wealth than the native-born families and by how much when a single measure, such as the mean or the median, for the wealth gap is adopted. Hence, it seems more appropriate to measure the wealth gap along the whole distribution.

The wealth gaps at different points of the distribution may be simply calculated as the differences of wealth of immigrants and native-born families at different percentiles of the distribution. For example, one can find the median wealth of immigrant families and the median wealth of native-born families, the difference between the two medians is the wealth gap at the 50th percentile of their wealth distributions. Similarly, one can find the wealth levels at the 75th percentiles of the wealth distributions of immigrant and native-born families, and the difference is their wealth gap at the 75th percentile of their wealth distributions. This calculation is simple but it does not provide the standard errors to the estimated wealth gaps,[9] and tests such as the significance of the wealth gap at a point of the distribution, as well as tests on whether the wealth gaps at different points of the distributions are the same, cannot be conducted.

An alternative method that produces identical estimate of the wealth gaps and in which the above tests are feasible is the generalized quantile regression. The method is introduced by Koenkier and Bassett (1978), and more recently applied by Buchinsky (1998), Mueller (1998), and Garcia, Hernandez, and Lopez-Nicolas (2001), among others. The advantages of the generalized quantile regression method are: (1) it can

[8] For example, Shamsuddin and DeVoretz (1998) exclude all families with net worth less than $3,500, while Brbidge and Robb (1985) apply a modified Box-Cox transformation on all observations of wealth.
[9] But bootstrap standard errors may be calculated.

generate a wealth gap at any point of the distribution, not just a single measure such as the mean wealth gap; (2) the method is semi-parametric in which no distribution assumption of the dependent variable is needed; (3) the estimators are less sensitive to outliers than the OLS estimators; and (4) test of significance of the gap and test on whether the gaps are the same at different points of the distribution can be easily conducted.[10] The second and the third advantages of the generalized quantile regression method imply that we do not have to exclude any families from our analysis, and no complex transformation is needed to deal with data outliers or non-normality issues. This method can be easily understood from its special case--the least absolute deviation (LAD) regression. While the OLS regression fits the dependent variable as a linear function of some explanatory variables through the mean, the LAD fits the dependent variable as a linear function of explanatory variables involved through the median of the dependent variable. Extending the notion of the LAD, the generalized q^{th} quantile regression fits the dependent variable as a linear function of some explanatory variables through the q^{th} quantile of the dependent variable. As shown by Buchinsky (1998), the generalized quantile estimators are consistent and asymptotically normally distributed, and hence test of significance of an estimator and test on the difference between estimators can be conducted.

In order to estimate the wealth gap between immigrant and native-born families at the q^{th} quantile of the wealth distribution, all we need to do is to specify that the q^{th} quantile conditional expectation of wealth as a linear function of a constant and a dummy variable for immigration status.

$$w_i = \alpha^q + \beta^q IMG_i + \varepsilon_i^q \qquad (1)$$

where w_i is wealth level, IMG_i is a dummy variable which equals to 1 if family *i* is an immigrant family, and 0 if the family is native-born. The only assumption one needs to make is the restriction that $Q^q(w_i | IMG_i)$ -- the q^{th} quantile of the wealth density conditional on IMG_i -- is equal to $\alpha^q + \beta^q IMG_i$, or equivalently, $Q^q(\varepsilon^q | IMG_i) = 0$. The estimate for β^q represents the wealth gap between immigrant and native-born families at the q^{th} quantile of their wealth distributions.[11] Moreover, the above equation can be estimated simultaneously at different values of *q* to obtain the variance-covariance matrix for the βs at those different quantiles. Since these estimators are jointly normally distributed, the equality of the wealth gaps at different points of the distributions can be tested.

Table 2 presents the estimated wealth gaps between immigrant and native-born families at different locations of the wealth distributions. When all families are pooled together, immigrants have higher wealth than natives on average and over a large portion of the wealth distribution. The average wealth gap is estimated to be \$38,000, and along the distribution, the gap ranges between \$10,000 at 35th percentile to \$115,000 at the 95th percentile. Outside the 35th –95th percentile range, virtually no wealth gap can be found. Between married immigrant and native-born families, although the mean wealth gap of \$17,500 is not significantly different from 0, one cannot ignore the gaps along the wealth

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[10] The tests are asymptotic, however.

[11] When the equation is estimated by OLS regression, the estimated β measures the mean wealth gap.

distribution. From the 10th to the 20th percentiles, there is evidence suggesting that immigrant families have lower wealth than the native-born families. The wealth gap ranges between -$5,000 at the 10th percentile to -$8,000 at the 15th percentile. These differences are solid, although not huge. More remarkably, we see that married immigrant families have higher wealth than their native-born counterparts from the 35th to the 90th percentiles of the distribution. The wealth gap ranges between $20,000 at the 40th percentile to $80,000 at the 90th percentile, and the wealth gap generally widens along the distribution up to the 90th percentile of the distribution. A few tests based on results of simultaneous quantile regression[12] decisively rejects the hypothesis that the wealth gaps are the same along the distribution. For example, for testing the equality of the wealth gaps the 50th, 75th and the 90th percentiles, we obtain an F-statistic of 4.80 with a p-value of 0.0082, and for testing the equality of the wealth gaps at the 40th, 60th, and the 80th percentiles, the F-statistic is 12.65 and the p-value is close to 0.

Table 2. Observed wealth Gap between Immigrants and Natives ($10,000)

	All Families		Married families		Single families	
location	gap	t-stat.	gap	t-stat.	Gap	t-stat.
Mean	3.80	3.30	1.75	1.00	3.50	3.55
5th	-0.06	-0.54	-0.10	-1.03	-0.14	-0.65
10th	0.00	0.00	-0.52	-3.12	-0.10	-1.54
15th	-0.02	-0.24	-0.82	-3.46	0.00	-0.05
20th	-0.04	-0.26	-0.62	-1.54	-0.01	-0.32
25th	-0.02	-0.11	-0.07	-0.20	-0.06	-0.58
30th	0.33	1.30	0.30	0.81	-0.16	-1.79
35th	0.99	2.89	0.89	1.86	-0.18	-0.85
40th	1.63	5.22	1.98	3.72	-0.20	-0.85
45th	2.13	5.11	2.89	4.56	-0.30	-0.87
50th	3.44	7.27	3.29	4.79	0.33	0.70
55th	4.82	8.76	3.69	5.17	1.41	2.32
60th	5.06	8.67	4.77	6.16	1.49	2.33
65th	5.62	7.45	6.12	6.35	2.69	3.45
70th	7.08	8.93	6.58	5.68	5.25	4.94
75th	8.35	8.47	7.05	4.72	5.30	4.71
80th	9.89	8.85	6.68	3.43	6.51	5.59
85th	11.40	7.47	6.99	3.40	7.40	4.55
90th	10.99	4.96	7.79	2.29	13.94	5.63
95th	11.59	2.85	1.01	0.16	14.50	2.55
No. Obs.	15801		9595		6206	

The average wealth gap between single immigrant families and single native-born families is estimated at $35,000 and the estimate is significantly different from 0. Along

[12] Stata's SQREG procedure is employed to run the simultaneous quantile regression with 500 bootstrap replications to obtain an estimate of the variance-covariance matrix of the estimators.

the distribution, single immigrant families are found to have higher wealth than their native-born counterparts from the 55^{th} to the 95^{th} percentiles. The wealth gap ranges between \$14,000 at the 55^{th} percentile to \$145,000 at the 95^{th} percentile. On the other hand, there is no strong evidence indicates that poor single immigrant families have lower wealth than their native counterparts. The only points where single immigrant families may have higher wealth than the native-born single families are located at around the 10^{th} and the 30^{th} percentiles, and the wealth gaps at those points are negligible (-\$1,000 and -\$1,600). As in the case between married immigrants and native-born families, we also have strong evidence to reject the equal wealth gap hypothesis along the distribution. For example, the F-statistic for testing the equality of wealth gaps at the 55^{th}, 75^{th} and the 95^{th} percentiles is 10.36 and the p-value is practically 0. The equality of wealth gaps at the 65^{th}, 75^{th}, and 85^{th} percentiles is also decisively rejected.

In summary, the above results indicate the existence of wealth gaps between immigrant and native-born families along the distribution. At the lower tail of the distribution, there is evidence suggests that poor immigrants have lower wealth than the native-born families. But over a large range of the distribution, from the 40thth to the 90^{th} percentiles for married families, and from the 55^{th} to the 95^{th} percentiles for single families, there is strong evidence that immigrant families have higher wealth than their native-born counterparts, and that the wealth gaps are not equal at different points of the distribution: the gaps are small among the lower middle wealth class for married families and among middle class for single families, but they become considerably large among the upper and upper middle wealth classes.

4. Explaining the Wealth Gap

The previous section has demonstrated the existence and the magnitude of the wealth gap between immigrant and native-born families. I shall now attempt to explain the wealth gap with a few key variables that may have important effects on wealth accumulation. The wealth gap is explained first under the restriction that immigrant and native-born families have identical wealth distribution. I then relax this restriction and proceed with a semi-parametric analysis.

4.1 Results from Restricted Model

As discussed in Section 2 , factors such as age of the major income recipient, family size and lone parent status (for single families) as well as factors that affecting family permanent income play important roles in wealth accumulation. As a first step, I re-estimate the generalised quantile regression model by adding these variables to the simple model. The coefficient on immigrant status in those extended models can then be compared with the coefficient on immigrant status in the simple model. Three models are estimated. In model 1, only age dummies of MIR (and of spouse for married families) are included as additional explanatory variables. In model 2, family size (lone parent status for single families) is further added. And in model 3, gender of MIR, education level and the interaction between education level and gender of MIR (and spouse for married families) are added. The results are presented in Table 3.

As being expected, the wealth gaps between immigrant and native families become smaller when additional controls are introduced. This means that immigrant families would have lower wealth than they are observed conditional on given family characteristics. When only MIR's age (and spouse's age for married families) are controlled, the median wealth gap between married immigrant and native families is reduced from \$33,000 to \$6,000, which is only marginally significant. At the 75th percentile, the gap is reduced from \$70,500 to \$13,000 (t = 1.60), and at the 90th percentile, from \$78,000 to an insignificant amount. Between single families, at the 75th percentile, the gap is reduced from \$53,000 to \$12,000, and at the 90th percentile, it is reduced from \$139,000 to \$57,000. On the other hand, since the wealth gap at the bottom of the wealth distribution is negative, a smaller wealth gap means that the gap is actually widened. And some of the observed insignificant wealth gaps now become significant. At the 10th percentile for married families, the observed wealth gap of -\$5,200 is widened to -\$7,400, while at the 5th percentile, the observed wealth gap of -\$1,000 (not significant) now becomes -\$3,800 with t-statistics being equal to –2.56. Likewise, the wealth gap of -\$1,000 at the 10th percentile between single families becomes -\$1,300, and at the 25th percentile, the wealth gap of -\$600 (t = -0.58) becomes -\$2,500 (t = -2.61).

Result of model 2 shows that the wealth gaps are generally further reduced from those under model 1 when family size (lone parent status for single families) is also controlled. It is particularly so for married families along the portion of the distribution where immigrant families are observed to have higher wealth than natives (from the 35th to the 90th percentiles), and to a less extend for single families along the middle portion of the distribution (from the 55th to the 65th percentiles), all of the wealth gaps we examined are virtually reduced to insignificant quantities. But at the bottom portion of the wealth distributions, the negative wealth gaps are slightly widened from those of model 1. Both model 2 and model 3 performs better than model 1 in terms of their capability in reducing the observed wealth gaps, but model 3 does not perform very well compared to model 2 for married families. This may cast some doubts on the effects of factors related to permanent income on wealth accumulation. On the other hand, for single families, and in particular at the top portion of the wealth distribution, model 3 does perform better than model 2 in terms of the reductions of the wealth gaps, implying long parent status may not have very important effect in single family's wealth accumulation process.

Table 3. Effect of Key Variables on Wealth gap ($10,000)

I. Married family

		Model 1		Model 2		Model 3	
Location	Raw gap	Est. gap	t-stat	Est. gap	t-stat	est. gap	std. err.
5th	-0.10	-0.38	-2.56	-0.44	-2.97	-1.01	-5.48
10th	-0.52**	-0.74	-3.48	-0.72	-3.39	-1.47	-6.49
15th	-0.82**	-0.82	-3.71	-0.89	-4.17	-1.57	-9.12
20th	-0.65*	-0.80	-2.63	-0.83	-2.69	-1.35	-5.14
25th	-0.07	-0.29	-0.95	-0.37	-1.27	-1.05	-4.74
30th	0.30	-0.03	-0.10	-0.10	-0.34	-0.70	-2.13
35th	0.89**	0.02	0.06	-0.02	-0.06	-0.58	-1.48
40th	1.98**	0.21	0.47	0.02	0.05	-0.16	-0.43
45th	2.89**	**0.59**	1.72	0.41	0.93	0.50	0.13
50th	3.29**	**0.63**	1.71	0.37	0.84	0.24	0.45
55th	3.69**	**0.90**	1.78	**0.83**	1.61	**0.85**	2.00
60th	4.77**	**1.42**	2.32	**1.12**	1.86	**0.99**	2.11
65th	6.12**	**1.42**	2.09	**0.96**	1.50	**1.08**	1.94
70th	6.58**	**1.66**	1.91	**1.41**	1.57	**1.57**	2.42
75th	7.05**	**1.28**	1.60	0.49	0.56	**1.35**	1.73
80th	6.68**	0.86	0.73	0.33	0.29	1.09	1.20
85th	6.99**	-0.33	-0.22	-0.91	-0.60	0.67	0.51
90th	7.79**	1.30	0.64	0.66	0.31	-0.37	-0.22
95th	1.01	-3.92	-0.78	-5.17	-1.25	-3.00	-0.86
OLS	1.75	-0.75	-0.43	-1.25	-0.71	-3.03	-1.71
II. Single	**Family**						
5th	-0.14	-0.05	-0.80	-0.05	-0.80	-0.08	-0.80
10th	-0.10**	-0.13	-3.97	-0.14	-4.33	-0.19	-4.51
15th	0.00	-0.17	-4.60	-0.16	-4.26	-0.34	-8.26
20th	-0.01	-0.17	-2.76	-0.17	-2.73	-0.39	-5.35
25th	-0.06	-0.25	-2.61	-0.26	-2.79	-0.43	-5.28
30th	-0.16**	-0.36	-5.21	-0.39	-4.97	-0.57	-7.47
35th	-0.18	-0.49	-7.06	-0.48	-6.77	-0.59	-5.18
40th	-0.20	-0.44	-4.46	-0.37	-3.67	-0.60	-4.64
45th	-0.30	-0.31	-3.88	-0.35	-2.58	-0.60	-4.06
50th	0.33	-0.25	-1.61	-0.21	-1.00	-0.51	-3.30
55th	1.41**	-0.25	-1.00	-0.32	-1.23	-0.39	-2.39
60th	1.49**	-0.30	-1.12	-0.19	-0.73	-0.15	-0.63
65th	2.69**	0.34	1.31	0.41	1.31	0.52	2.09
70th	5.25**	1.02	2.56	0.79	1.77	1.67	6.34
75th	5.30**	1.21	2.89	1.35	3.37	2.55	9.47
80th	6.51**	3.25	4.84	3.27	4.49	2.94	5.65
85th	7.40**	4.92	4.27	4.74	5.12	2.87	3.55
90th	13.94**	5.67	2.72	5.16	3.15	5.02	6.61
95th	14.50**	10.54	2.53	9.85	2.55	6.09	2.45
OLS	3.50**	2.05	2.09	2.14	2.19	1.24	1.29

*. Significant at 10%. **. Significant at 5%.

The complete set of coefficient estimates of the three models is contained in Table A2. Except at the very bottom of the distribution, the results show that the effect of MIR age constantly increases along the wealth distribution, and the effect of spousal age constantly increases to the upper middle of the wealth distribution, and then starts to decrease. As well, the effect of MIR's education increases at each point of the distribution. Although the effect of spousal education is not significant at the lower portion of the wealth distribution, it starts to increase from the middle of the wealth distribution. The effect of family size on wealth of married families also increases along the distribution, but the effect of gender on wealth is by and large constant along the distribution. Finally, lone parent status does not seem to play any important role in the wealth accumulation process of single families.

Overall, the wealth gap between immigrant and native-born diverges from the observed wealth gap at the bottom of the distribution when a number of key variables are controlled. This implies that low-wealth immigrant families will have lower wealth than they are observed, and the negative wealth gap would become even larger (in absolute terms) when factors other than immigration status alone is controlled. While along the portion of the distribution where immigrants have higher wealth than native-born families, the observed wealth gaps are substantially reduced by controlling the life-cycle aspect of a family, the family size and factors related to permanent income. Among the factors examined, it seems that MIR and spousal age, MIR's education, and family size may play important roles in explaining the wealth gap between immigrant and native families, while gender of MIR and lone parent status may not have any substantial effect.

4.2 Semi-parametric Decomposition

The above result is subjected to the restriction that the wealth of immigrant and native-born families is identically distributed. To see the effect of this restriction, a decomposition analysis with this restriction being relaxed is necessary. The widely followed approach is the Oaxaca decomposition. It attributes the mean difference of the dependent variables between two groups into an explained component that is due to differences in observed characteristics and an unexplained component that is due to differences in unobserved characteristics. One difficulty with respect to this approach is that a parametric specification has to be made for the conditional expectation of the dependent variable (wealth in our case). As Barsky, bound, Charles and Lupton (2001) have shown, the mis-specification of the regression function is likely to result in erratic inferences regarding the portion attributable to differences in the explanatory variables. To avoid this problem, the semi-parametric decomposition approach proposed by DiNardo, Fortin and Lemieux (1996, DFL) will be modified and applied in this study. This approach is much the same in spirit of the Oaxaca decomposition. The key question is what would be the wealth distribution of immigrant families if they were given the characteristics of native-born families, or what would be the wealth distribution of native-born families if they were given the characteristics of immigrant families? A slight modification of the DFL principle enables us to answer the counterfactual above questions. Using conditional probability rule, the marginal density of wealth (*w*) of a family with character(s) *x* is,

$$f(w) = \int f(w \mid x) g(x) dx$$

The observed density of wealth for an immigrant family can be written as,

$$f(w \mid IMG = 1) = \int f^{IMG}(w \mid x) g(x \mid IMG = 1) dx.$$

The counterfactual density of wealth for an immigrant family if it were given the characteristics of the native-born family can be defined as,

$$\begin{aligned} f_{CF}^{IMG}(w) &= \int f^{IMG}(w \mid x) g(x \mid IMG = 0) dx \\ &= \int f^{IMG}(w \mid x) g(x \mid IMG = 1) \psi(x) dx. \end{aligned}$$

where,

$$\psi(x) = \frac{g(x \mid IMG = 0)}{g(x \mid IMG = 1)}.$$

is a "re-weighting" factor. Applying Bayes' rule for the unconditional density function *g(x)*, we obtain the following identity,

$$\frac{g(x \mid IMG = 0) P(IMG = 0)}{P(IMG = 0 \mid x)} = \frac{g(x \mid IMG = 1) P(IMG = 1)}{P(IMG = 1 \mid x)}.$$

This implies that the re-weighting factor $\psi(x)$—a ratio of two conditional densities--can be written as,

$$\psi(x) = \frac{P(IMG = 1)}{P(IMG = 0)} \frac{P(IMG = 0 \mid x)}{P(IMG = 1 \mid x)} \qquad (2)$$

One can construct statistics such as the weighted mean, weighted variance and weighted quantiles, as well as weighted density function (non-parametrically) of wealth for immigrant families, using estimated values of $\psi(x)$ as the weights.[13] They are referred to as counterfactual mean, counterfactual variance, counterfactual quantiles and counterfactual density function, respectively. The first part of the right-hand-side of Equation (2) can be approximated by the ratio of immigrant over native-born families,

[13] Statistics surveys usually have their own survey weights. In estimating the counterfactual density of a variable, the survey weight and the "re-weighting" factor will be used together. The new weight is simply the product of these two weights, each of which is normalised to sum to 1.

while the second part is the ratio of two conditional probabilities, each can be calculated from a logit (or probit) regression on explanatory variable(s) *x*.

While the wealth gap decomposition can be based on the counterfactual mean or the counterfactual density, I shall conducted the decomposition using the counterfactual quantiles. The quantile-based decomposition results are directly comparable to those obtained in the previous two sections.[14] The wealth gaps between immigrant and native-born families at different quantiles of the distribution may be decomposed into an explained portion and an unexplained portion as the following,

$$W_q^{IMG} - W_q^{CND} = \left[W_q^{IMG} - \omega_q^{IMG}\right] + \left[\omega_q^{IMG} - W_q^{CND}\right] \qquad (3)$$

where ω_q^{IMG} is the q^{th} counterfactual quantile of wealth for immigrant families estimated with the re-weighting factor.

Table 4 contains the decomposition results for three specifications of the logit model. Model 1 includes only MIR's (and spousal) age dummies, Model 2 adds family size for married family and lone parent status for single family, and Model 3 further adds education, gender and their interactions. The decomposition is performed first by using the counterfactual wealth quantiles of immigrant families. The explained percentage is calculated as the ratio of the explained portion (first item on the right hand side of equation (3)) of the wealth gap to the observed gap (the left hand side of equation (3)). The alternative decomposition is performed using the counterfactual wealth quantiles of native-born families. For this alternative decomposition, the logit models regress native-born status on the same explanatory variables as above.

The result shows that among married families, at the bottom of the distribution where immigrant have lower wealth than the native-born families, none of the factors we explored can explain the negative wealth gap between immigrants and natives. Indeed, results from all of the three models indicate that immigrant families would have lower wealth than they are observed if they were given the characteristics of their native-born counterparts. Over the remaining segment of the wealth distribution (40^{th} to 90^{th} percentiles) where immigrant families have higher wealth than the native-born families, MIR's (and spousal) age plays a prominent role in explaining the wealth gap. When MIR's age alone is controlled (Model 1), a minimum of 42% of the wealth gap can be explained if the counterfactual wealth quantiles for immigrants are employed for the decomposition (Panel A), and a minimum of 31% of the gap is explained if the counterfactual wealth quantiles for native families are employed (Panel B). When family size is also controlled (Model 2), the first decomposition scheme (Panel A) shows that it explains at least 52% of the wealth gap, while the alternative decomposition scheme

[14] Since the mean wealth gap between married immigrant and native-born families is insignificant, a mean-based decomposition is not very interesting in the current case. On the other hand, the density-based decomposition requires us to estimate the density non-parametrically in which the estimate can be very sensitive to the choice of bandwidth when the true density is highly skewed.

(Panel B) indicates that a minimum of 37% of the gap is explained. When MIR's age, family size, and factors affecting permanent income are all controlled (Model 3), at least 58% of the wealth gap can be explained in Panel A, at a minimum of 71% of the gap is explained in Panel B.

Table 4. Semi-parametric decomposition (% of raw wealth gap explained)

		Panel A. Immigrant CF			Panel B. Native CF		
I. Married families							
Locations	raw gap	model 1	model 2	model 3	model 1	model 2	model 3
10th	-0.52	-34.6	-40.4	-42.3	-77.7	-75.2	-81.6
15th	-0.82	-46.7	-52.9	-56.6	-81.5	-88.6	-104.0
40th	1.98	125.9	158.7	170.1	70.2	73.7	112.3
45th	2.89	92.7	110.2	124.6	56.8	62.7	91.2
50th	3.29	75.5	98.2	111.8	53.1	62.7	92.9
55th	3.69	72.1	94.8	102.5	47.2	57.7	85.4
60th	4.77	66.5	87.0	97.4	38.4	46.1	80.9
65th	6.12	60.0	72.9	85.9	34.3	40.8	70.5
70th	6.58	50.2	60.8	69.9	30.6	36.9	72.6
75th	7.05	41.8	54.6	58.4	34.8	46.1	92.3
80th	6.68	44.2	52.1	59.3	37.1	62.6	113.1
85th	6.99	54.4	70.1	73.7	45.2	59.9	142.0
90th	7.79	86.8	91.9	99.0	59.4	71.4	199.5
II. Single family							
mean	3.50	27.2	22.9	37.8	42.2	40.7	76.3
55th	1.41	144.2	144.2	149.9	97.2	90.1	119.9
60th	1.49	74.5	73.8	87.9	87.7	83.1	121.5
65th	2.69	74.9	72.9	79.4	60.8	58.2	84.6
70th	5.25	70.3	69.1	69.5	39.1	36.0	48.8
75th	5.30	35.9	33.6	36.8	46.2	44.2	61.3
80th	6.51	57.9	55.3	58.4	32.1	28.1	47.7
85th	7.40	34.3	28.4	48.6	31.1	27.0	43.9
90th	13.94	19.1	17.7	35.8	18.8	17.6	32.3
95th	14.50	0.0	-1.3	1.8	32.4	27.1	55.4

For single families, the result is consistent with that of the restricted model where lone parent status does not contribute much in explaining the wealth gap. So in what follows, our discussion will focus on Models 1 and 3. The wealth gaps along the upper middle portion of the distribution are well explained under both decomposition schemes. Between the 55th to the 85th percentiles, a minimum of 31% of the wealth gap is explained with model 1, and at least 37% of the gap is explained with model 3. Over the top portion of the distribution (at the 90th and 95th percentiles, in particular) the decomposition scheme (Panel A) employing immigrant counterfactual wealth does not perform well.

Since the observed mean wealth gap between single immigrant and native families is significant, both the DFL and the Oaxaca decompositions are feasible. From Table 4, The DFL decompositions show that between 27% - 42% of the mean wealth gap can be explained in model 1 where only MIR's age are employed in constructing the re-weighting factor, and between 38% - 76% of the total gap is explained in model 3 in which MIR's age, lone parent status and permanent income factors are all employed in the logit regressions. Although the Oaxaca decomposition has some limitations as discussed earlier, it can be used to compare with that of the DFL decomposition of the mean wealth gap. The Oaxaca decomposition results are reported in Table 5. Surprisingly, they are almost the same as that of the DFL decomposition, and suggest that MIR,s age is the most important factor in explaining the wealth gap, and factors related to permanent income may also play an important role.

Table 5. Oaxaca decomposition of the mean gap between single families

	scheme I			Schem II		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Total % explained	27.2	23.5	32.8	42.3	40.3	71.1
% explained by MIR age	27.2	27.2	33.1	42.3	42.1	49.4
% explained by lone parent status	--	-3.7	-2.6	--	-1.8	1.2
% explained by perment income factors	--	--	2.4	--	--	20.5

In summary, the unrestricted analysis shows the main result of the restricted model is still valid when the restriction is relaxed. Over the range of the wealth distribution where immigrant families have higher wealth than the native-born families--from the 40th to the 90th percentiles for married families, and from the 55th to the 90th percentiles for single families--the bulk part of the wealth gap between immigrants and natives can be explained by MIR's (and spousal) age and factors related to permanent income. But at the bottom of the wealth distribution where immigrant families have lower wealth than the native-born families, the observed wealth gap cannot be explained by any of the factors we have explored. This signifies that the low-wealth families may behave differently from families of other wealth classes in their wealth accumulation process.

5. The Cohort Effect

The generalised quantile regression model can also be employed to investigate the cohort effect on wealth gap. When the dummy variable of immigration status is replaced by a few dummy variables indicating periods of entry in Canada for immigrants, the coefficient on a cohort dummy can be interpreted as observed wealth gaps between a typical native-born family and an average immigrant family from this cohort. I divide immigrant families here into four different cohorts according to years since migration of the major income recipient: those arrived before 1976, those arrived between 1976 and

1985, those arrived between 1986 to 1999. Particular attention will be paid to the 1976-1985 cohort of immigrants which is the cohort with worse entry position than their predecessors and a zero earnings assimilation rate, according to Baker and Benjamin (1994) and Bloom et. al. (1995). The results are contained in Table 5.

Table 6. Wealth gap by period of immigration (t-statistics in parentheses)

Cohort	5th	10th	25th	40th	50th	60th	75th	90th	95th	mean
				Married Familes						
1986—1999	-0.64	-1.09	-3.8	-5.84	-7.1	-9.5	-14.3	-25.07	-38.61	-13.9
	(-3.42)	(-4.41)	(-8.63)	(-6.73)	(-7.04)	(-8.07)	(-6.62)	(-5.17)	(-4.07)	(-4.93)
1976—1985	-0.05	-0.49	-1.25	-0.09	0.44	0.25	0.5	-1.22	-6.94	-4.29
	(-0.17)	(-1.42)	(-2.03)	(-0.08)	(0.32)	(0.16)	(0.17)	(-0.19)	(-0.54)	(-1.09)
before 1976	1.29	3.64	9.55	12.31	14.44	15.87	18.7	23.33	18.42	13.53
	(8.62)	(17.79)	(26.39)	(17.32)	(17.52)	(16.39)	(10.53)	(6.03)	(2.46)	(5.88)
				Single Families						
1986--1999	-1.22	-0.6	-0.2	-1.07	-2.38	-4.41	-8.93	-12.91	-19.45	-6.43
	(-3.39)	(-6.78)	(-1.28)	(-3.23)	(-3.54)	(-5.24)	(-4.27)	(-3.31)	(-2.01)	(-3.80)
1976--1985	-0.53	-0.25	-0.14	-0.69	-1.69	-2.44	-1.32	18.35	30.57	3.04
	(-1.09)	(-2.18)	(-0.71)	(-1.70)	(-2.01)	(-2.41)	(-0.52)	(3.44)	(2.75)	(1.42)
before 1976	0.56	0.1	1.5	5	7.45	10.68	14.05	18.6	25.71	9.56
	(3.11)	(1.90)	(15.84)	(23.07)	(16.40)	(18.76)	(9.76)	(6.54)	(4.04)	(7.26)

Some clear patterns shown by Table 5. On average and along the wealth distribution, immigrant families arrived before 1976 all have higher wealth, while immigrant families arrived after 1985 all have lower wealth than a typical native-born family, and the wealth gaps are wider at the top of the distribution than those at the bottom of the distribution. The wealth position of the 1976-1985 cohort of immigrant families is seen better than their earnings position. Except small portions of the distributions where immigrant families have lower wealth than the native families, the wealth gaps are generally insignificant, the magnitude of these gaps are not large. Moreover, at the top of the distribution, it seems that this cohort of single immigrant families have significant higher wealth than their native-born counterparts.

However, the above framework is different from that of Section 3. In section 3, the observed wealth gap measures the difference in wealth level between a typical immigrant family and a typical native-born family. In this section, comparison is made between a typical native-born family and a typical family of a specific cohort of immigrants. The wealth gaps estimated here is likely to be biased since the MIR of an early cohort of immigrants are also likely to be older than the MIR of a typical native family, the estimated wealth gap between them can be biased upwards due to the age differences. On the other hand, if recent cohorts of immigrants are younger than a typical native-born, the estimated wealth gap can be biased downwards. Table 6 presents the result when some key variables are controlled.[15]

[15] To save space, the coefficients on MIR's age, permanent income and family size etc. are not presented. They are available upon request.

Table 7. Cohort effect on wealth gap (t-statistics in parentheses)

Cohort	5th	10th	25th	40th	50th	60th	75th	90th	95th	mean
Model 1				Married Familes						
1986—1999	-0.9	-1.56	-3	-3.64	-4.62	-4.81	-5.75	-9.05	-8.12	-10.5
	(-4.21)	(-3.84)	(-6.77)	(-5.63)	(-7.23)	(-5.11)	(-4.14)	(-2.86)	(-0.95)	(-3.56)
1976—1985	-0.19	-0.82	-1.48	-1.49	0.03	-0.45	-0.32	-2.41	-6.7	-4.98
	(-0.66)	(-1.40)	(-2.42)	(-1.69)	(0.04)	(-0.35)	(-0.17)	(-0.60)	(-0.67)	(-1.27)
before 1976	0.84	2.2	6.55	7.09	8.65	9.03	8.75	11.77	5.18	6.76
	(4.74)	(6.38)	(17.86)	(13.19)	(16.15)	(11.35)	(7.61)	(4.72)	(0.75)	(2.89)
				Single Families						
1986—1999	-0.81	-0.25	-0.37	-1.08	-1.6	-2.53	-2.91	-5.93	-7.6	-4.45
	(-6.31)	(-4.02)	(-1.94)	(-7.26)	(-5.17)	(-5.36)	(-3.38)	(-2.00)	(-1.02)	(-2.67)
1976—1985	-0.1	-0.27	-0.58	-1.02	-1.04	-1.09	0.02	19.22	28	3.12
	(-0.90)	(-3.72)	(-2.23)	(-5.39)	(-2.73)	(-1.92)	(0.02)	(4.69)	(2.79)	(1.47)
before 1976	0	0	1.14	3.36	4.51	6.28	8.24	10.69	12.22	5.72
	(0)	(0)	(9.59)	(33.88)	(21.69)	(19.75)	(13.65)	(4.46)	(2.28)	(4.28)
Model 2				Married Familes						
1986—1999	-0.97	-1.63	-3.16	-3.72	-4.61	-5.46	-5.99	-10.83	-10.9	-10.83
	(-4.15)	(-4.49)	(-6.64)	(-5.44)	(-6.76)	(-5.49)	(-4.34)	(-3.64)	(-1.51)	(-3.81)
1976—1985	-0.26	-1	-1.32	-1.36	-0.39	-0.81	-1.15	-2.38	-7.44	-5.68
	(-0.78)	(-2.00)	(-2.01)	(-1.47)	(-0.43)	(-0.61)	(-0.64)	(-0.60)	(-0.84)	(-1.44)
before 1976	0.84	2.11	6.44	7.08	8.66	8.91	7.81	12.15	3.86	6.36
	(4.22)	(6.82)	(16.40)	(12.51)	(15.28)	(10.75)	(6.82)	(4.93)	(0.67)	(2.71)
				Single Families						
1986—1999	-0.81	-0.25	-0.39	-1.05	-1.7	-2.51	-2.67	-5.4	-8.22	-4.36
	(-6.21)	(-3.93)	(-2.01)	(-5.84)	(-3.98)	(-5.69)	(-3.04)	(-2.00)	(-1.11)	(-2.62)
1976—1985	-0.1	-0.27	-0.58	-1.02	-0.91	-0.63	0.1	19.51	29.8	3.37
	(-0.90)	(-3.64)	(-2.19)	(-4.47)	(-1.70)	(-1.16)	(0.09)	(5.18)	(2.86)	(1.59)
before 1976	0	0	1.15	3.4	4.4	6.39	8.25	10.38	10.7	5.74
	(0)	(0)	(9.55)	(28.50)	(15.20)	(21.36)	(13.08)	(4.74)	(1.87)	(4.30)
Model 3				Married Familes						
1986—1999	-1.96	-3.1	-4.98	-5.37	-5.38	-5.68	-5.67	-9.9	-12.87	-14.25
	(-5.91)	(-9.32)	(-10.41)	(-7.89)	(-7.71)	(-6.60)	(-5.38)	(-5.06)	(-2.84)	(5.00)
1976—1985	-0.73	-1.28	-1.34	-2.27	-2.03	-1.76	0.38	-2.75	-5.71	-7.97
	(-1.55)	(-2.62)	(-2.04)	(-2.48)	(-2.18)	(-1.54)	(0.28)	(-1.07)	(-1.12)	(-2.04)
before 1976	0.7	1.86	5.05	7.18	7.9	8.65	10.04	10.17	9.27	5.67
	(2.40)	(6.38)	(12.52)	(12.78)	(13.70)	(12.10)	(11.50)	(6.32)	(2.46)	(2.42)
				Single Families						
1986--1999	-1.24	-0.37	-0.8	-1.37	-2	-2.63	-2.56	-3.86	-0.66	-5.41
	(6.73)	(-4.04)	(-4.74)	(-6.15)	(-6.96)	(-6.90)	(-4.05)	(-2.15)	(-0.13)	(-3.30)
1976--1985	-0.2	-0.42	-0.86	-1.35	-1.35	-1.09	0.35	19.34	25.43	2.18
	(-1.30)	(-5.38)	(-3.47)	(-5.01)	(-3.75)	(-2.36)	(0.47)	(9.05)	(3.43)	(1.05)
before 1976	0	-0.05	0.79	3.22	3.9	5.86	7.69	13.01	10.86	5.04
	(-0.02)	(-0.83)	(6.96)	(21.61)	(19.79)	(22.62)	(17.59)	(11.13)	(2.66)	(3.85)

As expected, the estimated wealth gaps are substantially reduced when MIR's age alone is controlled. Given MIR's (and spousal) age, recent immigrants still have lower wealth, and most immigrants arrived before 1976 still have higher wealth than the natives. However, some immigrant families arrived between 1976—1985, in particular, the lower middle class single immigrants are now seen to have lower wealth than a similarly aged native family. When MIR's age, family size (lone parent status for single families), permanent income related factors are controlled, the notion that immigrants arrived between 1976-1985 posses a disadvantaged earnings position is now confirmed in terms of the wealth position for a large portion of them. In particular, among immigrants arrived in this period, married families with wealth below the median and single families with wealth below the 75th percentile now have lower wealth than their native-born counterparts. The result for immigrant families arrived before 1976 when some key variables are controlled, shows that immigrants are able to outpace natives in wealth accumulation as their years in Canada increase.

6. Summary and Conclusions

The economic assimilation of immigrants is a key concern for economists and policy makers. Most studies are focused on the earnings assimilation of immigrants. This article attempts to asses the assimilation issue from the wealth perspective. It studies wealth differences between immigrant and native-born families and tries to uncover the factors that may explain the wealth gap.

This study found that, on average and along the upper segment (from the 55th to the 95th percentiles) of the wealth distribution, single immigrant families have higher wealth than their native-born counterparts. The wealth gap ranges from $15,000 to $145,000, with an mean gap of $35,000. Among married families, immigrants have higher wealth than the natives from the 40th to 90th percentiles of the distribution. The wealth gap ranges between $20,000 to $80,000. However, at the lower tail of the distribution, there is evidence suggesting that low-wealth immigrants can have lower wealth than their native-born counterparts, though the gaps themselves are well below $10,000. Various decompositions indicate that the age of the major income recipient, which captures the effect of a family's life-cycle and permanent income related factors such as education and gender can explain the bulk part of the wealth gap between immigrant and native-born families, and MIR's age seems to play a more important role than permanent income related factors in explaining the wealth gap. However, at the bottom of the wealth distribution where immigrants have lower wealth than native families, none of the wealth gap can be explained by MIR's age, permanent income factors and family size. This seems to indicate that poor families may behave differently from families of other wealth classes in wealth accumulation. The notion that immigrants arrived between 1976-1985 posses poorer earnings position than their predecessors is confirmed in terms of their poorer wealth position. Even after controlling a number of key factors, we still find that recent immigrants have lower wealth and immigrants arrived before 1976 have higher wealth than the native-born families.

There are a few caveats in this study. With a cross-section survey, our ability to identify and estimate some key parameters are limited, a longitudinal wealth data with additional information on pension and savings will be helpful for further researches.

References

Baker, M., and D. Benjamin (1994) 'The performance of immigrants in the Canadian labor market.' *Journal of Labor Economics* 12, 369-405.

Baker, M., and D. Benjamin (1995) 'The receipt of transfer payments by immigrants to Canada.' *Journal of Human Resources* 30, 650-676

Barsky, R., J. Bound, K. Charles and J. Lupton (2001) 'Accounting for the black-white wealth gap: a nonparametric approach.' NBER working paper #8466, 2001

Blau, F. D. and J. W. Graham (1990) 'Black-white differences in wealth and asset Composition.' *Quarterly Journal of Economics* 105, 321-339.

Blinder, A. S. (1973) 'A model of inherited wealth.' *Quarterly Journal of Economics* 87, 608-626

Bloom, D. E., G. Grenier, and M. Gunderson (1995) 'The changing labour market position of Canadian immigrants.' *Canadian Journal of Economics*, 28, 987-1005, 1995.

Borjas, G. (1995) 'Assimilation and changes in cohort quality revisited: what happened to immigrant earnings in the 1980s?' *Journal of Labor Economics* 13, 201-245.

Buchinsky, M. (1998) 'Recent Advances in Quantile Regression Models.' *Journal of Human Resources*, 33, 88-126.

Burbidge, J. and A. L. Robb (1985) 'Evidence on wealth-age profiles in Canadian cross section data.' *Canadian Journal of Economcis*, 18, 854-75, 1985.

Butcher, K., and J. diNardo (1998) 'The immigrant and native-born wage distributions: evidence from united states censues' *NBER working paper* No. 6630.

Dinardo, J., N. Fortin, and T. Lemieux (1996) 'Labor Market Institutions and the Distribution of Wages, 1973 – 1992: A Semiparametric Approach.' *Econometrica*, Vol. 64, No. 5, 1001 – 1044.

Garcia, J., P. Hernandez, and A. Lopez-Nicolas (2001) 'How wide is the gap? An investigation of gender wage differences using quantile regression.' *Empirical Economics* 26, 149-167.

Grant, M. (1999) 'Evidence of new immigrant assimilation in Canada.' *Canadian Journal of Economics* 32, No. 4, 930-953.

Koenker, R. and G. Bassett (1978) 'Regression quantiles.' *Econometrica* 46, 33-50.

Mueller, R. E. (1998) 'Public-private sector wage differentials in Canada: evidence form quantile regressions.' *Economics Letters* 60, 229-235.

Oaxaca , R. (1973) 'Male-female wage differentials in urban labour markets.' *International Economic Review* 14, 693-709.

Shamsuddin, A. F. M., and D. J. DeVoretz (1998) 'Wealth accumulation of Canadian and foreign-born households in Canada.' *Review of Income and Wealth* 44, 515-33, 1998.

Statistics Canada (2001) 'Assets and Debts of Canadians: An overview of the result of the Survey of Financial Security, 1999.' Catalogue number 13-595-XIE.

Appendix

Table A1. Descriptive Statistics

	Married families				Single families			
	Immigrant		Native-born		Immigrant		Native-born	
	Mean	std.err.	Mean	std.err .	Mean	std.err.	Mean	std.err.
MIR's age	49.7	0.34	46.9	0.17	50.5	0.6	45.8	0.26
spouse age	47.9	0.33	45.5	0.16	--	--	--	--
female MIR	0.25	0.01	0.22	0.01	0.58	0.02	0.55	0.01
female spouse	0.76	0.01	0.78	0.01	--	--	--	--
family size	3.45	0.03	3.09	0.01	1.7	0.04	1.4	0.01
lone parent	--	--	--	--	0.14	0.01	0.11	0.01
MIR ed: 0-8 yr.	0.123	0.008	0.096	0.003	0.153	0.012	0.123	0.005
MIR ed: 9 -13 yr.	0.104	0.007	0.159	0.004	0.11	0.01	0.182	0.005
MIR ed: hgh schl	0.151	0.009	0.158	0.004	0.149	0.012	0.134	0.005
MIR ed: P.S.	0.32	0.011	0.376	0.006	0.362	0.016	0.378	0.007
MIR ed: Univ.	0.168	0.009	0.143	0.004	0.149	0.012	0.139	0.005
MIR ed: abv Uni.	0.134	0.008	0.068	0.003	0.077	0.009	0.043	0.003
spo ed: 0-8 yr.	0.143	0.008	0.092	0.003	--	--	--	--
spo ed: 9 -13 yr.	0.121	0.008	0.175	0.004	--	--	--	--
spo ed: hgh schl	0.202	0.01	0.199	0.005	--	--	--	--
spo ed: P.S.	0.306	0.011	0.369	0.006	--	--	--	--
spo ed: Univ.	0.151	0.009	0.131	0.004	--	--	--	--
spo ed: abv Uni.	0.078	0.006	0.034	0.002	--	--	--	--
IMG 86--99	0.33	0.011	--	--	0.31	0.015	--	--
IMG 76--85	0.16	0.009	--	--	0.18	0.013	--	--
IMG before 1976	0.52	0.012	--	--	0.51	0.017	--	--

Table A2. Selected generalised quantile regression results: restricted models

1. Model 1: Married families

OLS regression

Source	SS	df	MS
Model	1269444.43	11	115404.039
Residual	47320300.6	9583	4937.94225
Total	48589745.1	9594	5064.59715

Number of obs =	9595
F(11, 9583) =	23.37
Prob > F =	0.0000
R-squared =	0.0261
Adj R-squared =	0.0250
Root MSE =	70.27

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.7448278	1.73745	-0.43	0.668	-4.150596	2.660941
age_1m	-9.372401	5.312285	-1.76	0.078	-19.7856	1.0408
age_2m	-8.015865	2.710782	-2.96	0.003	-13.32957	-2.702159
age_4m	5.320138	2.569418	2.07	0.038	.2835346	10.35674
age_5m	10.55492	3.652153	2.89	0.004	3.395926	17.71391
age_6m	5.671805	4.718975	1.20	0.229	-3.578383	14.92199
age_1s	-10.32146	4.514527	-2.29	0.022	-19.17089	-1.472034
age_2s	-4.879969	2.648117	-1.84	0.065	-10.07084	.3109003
age_4s	9.206334	2.606652	3.53	0.000	4.096743	14.31592
age_5s	8.044998	3.765699	2.14	0.033	.6634317	15.42657
age_6s	3.982364	4.912349	0.81	0.418	-5.646878	13.61161
_cons	23.30265	1.576913	14.78	0.000	20.21157	26.39374

.1 Quantile regression — Number of obs = 9595

Raw sum of deviations 51650.59 (about 1.005)

Min sum of deviations 50703.63 — Pseudo R2 = 0.0183

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.735	.2112352	-3.48	0.001	-1.149066	-.3209344
age_1m	-1.386	.5710028	-2.43	0.015	-2.505286	-.2667138
age_2m	-.7325	.3125107	-2.34	0.019	-1.345087	-.1199129
age_4m	1.035	.3407789	3.04	0.002	.3670013	1.702999
age_5m	.7419999	.4591873	1.62	0.106	-.1581044	1.642104
age_6m	1.0016	.612227	1.64	0.102	-.1984944	2.201694
age_1s	-1.4245	.5064777	-2.81	0.005	-2.417304	-.4316965
age_2s	-.704	.3141529	-2.24	0.025	-1.319806	-.0881939
age_4s	.318	.3361553	0.95	0.344	-.3409355	.9769354
age_5s	2.025	.4660822	4.34	0.000	1.11138	2.93862
age_6s	1.4584	.6353818	2.30	0.022	.2129171	2.703883
_cons	1.74	.1892232	9.20	0.000	1.369083	2.110917

```
.25 Quantile regression                             Number of obs =      9595
  Raw sum of deviations 120281.7 (about 4.8221998)
  Min sum of deviations   114883                    Pseudo R2     =    0.0449

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |  -.2890999   .3052363    -0.95   0.344    -.8874276    .3092278
      age_1m |    -1.9109   .8837824    -2.16   0.031      -3.6433   -.1784996
      age_2m |    -1.2352   .4807481    -2.57   0.010    -2.177568    -.292832
      age_4m |     2.0945   .4769762     4.39   0.000     1.159526    3.029474
      age_5m |       2.18   .6516262     3.35   0.001     .9026746    3.457325
      age_6m |   2.013799   .8235855     2.45   0.014     .3993976    3.628201
      age_1s |    -3.5741   .7895041    -4.53   0.000    -5.121695   -2.026505
      age_2s |     -2.145   .4674449    -4.59   0.000    -3.061291   -1.228709
      age_4s |      1.175   .4871468     2.41   0.016     .2200894    2.129911
      age_5s |   4.170301   .6608849     6.31   0.000     2.874826    5.465775
      age_6s |   3.591201   .8573057     4.19   0.000       1.9107    5.271701
       _cons |      5.345   .2684985    19.91   0.000     4.818686    5.871314
------------------------------------------------------------------------------


Median regression                                   Number of obs =      9595
  Raw sum of deviations   206408 (about 13.3461)
  Min sum of deviations 191865.2                    Pseudo R2     =    0.0705

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   .6299992    .368098     1.71   0.087    -.0915507    1.351549
      age_1m |      -4.83   1.053709    -4.58   0.000    -6.895493   -2.764507
      age_2m |     -2.555   .5795081    -4.41   0.000    -3.690958   -1.419041
      age_4m |   4.260001   .5285768     8.06   0.000     3.223879    5.296123
      age_5m |     6.7918   .7423165     9.15   0.000     5.336703    8.246898
      age_6m |   3.860001   .9598669     4.02   0.000     1.978459    5.741544
      age_1s |  -6.417301   .9259151    -6.93   0.000     -8.23229   -4.602311
      age_2s |  -3.637301   .5624277    -6.47   0.000    -4.739778   -2.534823
      age_4s |     4.0327   .5395898     7.47   0.000      2.97499     5.09041
      age_5s |   5.902699   .7711626     7.65   0.000     4.391057     7.41434
      age_6s |   5.242699   1.003002     5.23   0.000     3.276603    7.208795
       _cons |    11.8373   .3270133    36.20   0.000     11.19629    12.47832
------------------------------------------------------------------------------


.75 Quantile regression                             Number of obs =      9595
  Raw sum of deviations 238098.9 (about 28.941)
  Min sum of deviations 218763.9                    Pseudo R2     =    0.0812

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   1.279999   .8007605     1.60   0.110     -.289661    2.849659
      age_1m |     -9.483   2.295516    -4.13   0.000     -13.9827   -4.983303
      age_2m |       -5.6   1.183798    -4.73   0.000    -7.920494   -3.279506
      age_4m |   8.249998   1.070475     7.71   0.000     6.151641    10.34836
      age_5m |      14.04   1.551039     9.05   0.000     10.99963    17.08036
      age_6m |   7.519995   2.162903     3.48   0.001     3.280247    11.75974
      age_1s |    -11.907   1.963169    -6.07   0.000    -15.75523   -8.058775
      age_2s |  -6.599901    1.15326    -5.72   0.000    -8.860535   -4.339266
      age_4s |   6.900002   1.092731     6.31   0.000     4.758017    9.041986
      age_5s |       7.59   1.629468     4.66   0.000     4.395899     10.7841
      age_6s |   5.460003   2.284075     2.39   0.017     .9827323    9.937274
       _cons |      24.12   .7018604    34.37   0.000     22.74421     25.4958
------------------------------------------------------------------------------
```

.9 Quantile regression — Number of obs = 9595

Raw sum of deviations 200718.2 (about 55.599998)

Min sum of deviations 184809.2 — Pseudo R2 = 0.0793

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	1.3025	2.034944	0.64	0.522	-2.686421	5.29142
age_1m	-15.5955	6.473944	-2.41	0.016	-28.2858	-2.905201
age_2m	-11.233	2.925668	-3.84	0.000	-16.96793	-5.498072
age_4m	16.8501	2.674183	6.30	0.000	11.60814	22.09207
age_5m	38.6226	4.049418	9.54	0.000	30.68488	46.56032
age_6m	27.4901	5.412002	5.08	0.000	16.88143	38.09877
age_1s	-23.1309	4.955043	-4.67	0.000	-32.84383	-13.41797
age_2s	-12.4064	2.863662	-4.33	0.000	-18.01979	-6.79302
age_4s	11.7336	2.723068	4.31	0.000	6.395807	17.07139
age_5s	.4984968	4.169168	0.12	0.905	-7.673955	8.670949
age_6s	-6.625	5.738162	-1.15	0.248	-17.87301	4.623011
_cons	45.2764	1.818854	24.89	0.000	41.71106	48.84174

Model 1. Single families

OLS regression

Source	SS	df	MS
Model	174092.764	6	29015.4607
Residual	4934780.32	6199	796.060707
Total	5108873.09	6205	823.347798

Number of obs =	6206
F(6, 6199) =	36.45
Prob > F =	0.0000
R-squared =	0.0341
Adj R-squared =	0.0331
Root MSE =	28.215

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	2.047798	.9775453	2.09	0.036	.1314706	3.964126
age_1m	-5.32501	1.249324	-4.26	0.000	-7.774119	-2.875901
age_2m	-.9321385	1.116259	-0.84	0.404	-3.120394	1.256117
age_4m	6.096838	1.244037	4.90	0.000	3.658095	8.535582
age_5m	9.154444	1.421193	6.44	0.000	6.368414	11.94048
age_6m	8.779809	1.111174	7.90	0.000	6.601524	10.9581
_cons	8.173877	.8119998	10.07	0.000	6.582076	9.765678

.1 Quantile regression — Number of obs = 6206

Raw sum of deviations 15018.38 (about -.015)

Min sum of deviations 14869.92 — Pseudo R2 = 0.0099

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.125	.0315092	-3.97	0.000	-.1867691	-.0632309
age_1m	-.9	.0431807	-20.84	0.000	-.9846491	-.8153509
age_2m	-.325	.0346249	-9.39	0.000	-.3928768	-.2571232
age_4m	.005	.0351856	0.14	0.887	-.063976	.073976
age_5m	.0751	.0393964	1.91	0.057	-.0021306	.1523306
age_6m	.225	.0314238	7.16	0.000	.1633985	.2866015
_cons	.025	.0246302	1.02	0.310	-.0232836	.0732836

```
.25 Quantile regression                             Number of obs =      6206
  Raw sum of deviations 35619.36 (about .24420001)
  Min sum of deviations 35268.51                    Pseudo R2     =    0.0099

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |       -.25   .0956787    -2.61   0.009    -.4375634   -.0624366
      age_1m |      -.405    .137167    -2.95   0.003    -.6738949   -.1361051
      age_2m |       -.14   .1127346    -1.24   0.214    -.3609989    .0809989
      age_4m |        .18   .1162715     1.55   0.122    -.0479325    .4079325
      age_5m |         .4   .1283741     3.12   0.002     .1483422    .6516578
      age_6m |       1.28   .1009453    12.68   0.000     1.082112    1.477888
       _cons |        .37   .0800627     4.62   0.000     .2130494    .5269507
------------------------------------------------------------------------------

Median regression                                   Number of obs =      6206
  Raw sum of deviations 66718.79 (about 2.75)
  Min sum of deviations 63324.21                    Pseudo R2     =    0.0509

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |       -.25   .1549962    -1.61   0.107    -.5538464    .0538464
      age_1m |      -3.11   .2324273   -13.38   0.000    -3.565638   -2.654362
      age_2m |      -1.89   .1894279    -9.98   0.000    -2.261344   -1.518656
      age_4m |       1.82   .1921283     9.47   0.000     1.443362    2.196638
      age_5m |     3.1293   .2089033    14.98   0.000     2.719777    3.538823
      age_6m |       6.02    .165373    36.40   0.000     5.695812    6.344189
       _cons |       3.28   .1287388    25.48   0.000     3.027627    3.532373
------------------------------------------------------------------------------

.75 Quantile regression                             Number of obs =      6206
  Raw sum of deviations 81248.92 (about 12.1445)
  Min sum of deviations  74004.8                    Pseudo R2     =    0.0892

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |       1.21   .4184961     2.89   0.004     .3896024    2.030397
      age_1m |    -8.9725   .6296604   -14.25   0.000    -10.20685   -7.738147
      age_2m |    -4.5725   .5243312    -8.72   0.000    -5.600371   -3.544629
      age_4m |     5.6475   .5573582    10.13   0.000     4.554885    6.740115
      age_5m |    11.2175   .5785744    19.39   0.000     10.08329    12.35171
      age_6m |    10.8275    .465409    23.26   0.000     9.915136    11.73986
       _cons |     9.9725   .3513467    28.38   0.000     9.283739    10.66126
------------------------------------------------------------------------------


.9 Quantile regression                              Number of obs =      6206
  Raw sum of deviations 66923.46 (about 28.0287)
  Min sum of deviations 62024.53                    Pseudo R2     =    0.0732

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   5.667999   2.085519     2.72   0.007     1.579659     9.75634
      age_1m |    -15.952   2.933937    -5.44   0.000    -21.70353   -10.20047
      age_2m |  -5.102001   2.467847    -2.07   0.039    -9.939837   -.2641651
      age_4m |     10.298   2.862875     3.60   0.000     4.685771    15.91023
      age_5m |    24.3386   2.907145     8.37   0.000     18.63959    30.03761
      age_6m |      18.08   2.404546     7.52   0.000     13.36626    22.79374
       _cons |     21.502   1.803292    11.92   0.000     17.96692    25.03708
------------------------------------------------------------------------------
```

Model 2: Married families

OLS regression

```
      Source |       SS       df       MS              Number of obs =    9595
-------------+------------------------------           F( 12,  9582) =   21.72
       Model |  1286796.99    12  107233.082           Prob > F      =  0.0000
    Residual |  47302948.1  9582  4936.64664           R-squared     =  0.0265
-------------+------------------------------           Adj R-squared =  0.0253
       Total |  48589745.1  9594  5064.59715           Root MSE      =  70.261

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |  -1.252008   1.758158    -0.71   0.476     -4.69837    2.194353
      age_1m |  -8.486194   5.332579    -1.59   0.112    -18.93918    1.966788
      age_2m |  -7.606801   2.719194    -2.80   0.005      -12.937   -2.276606
      age_4m |   5.672185   2.575934     2.20   0.028     .6228084    10.72156
      age_5m |   11.54044   3.689313     3.13   0.002     4.308603    18.77227
      age_6m |   6.758808   4.753843     1.42   0.155    -2.559731    16.07735
      age_1s |  -9.542304   4.533025    -2.11   0.035    -18.42799   -.6566152
      age_2s |  -4.608717    2.65172    -1.74   0.082    -9.806649    .5892142
      age_4s |   9.754452   2.622656     3.72   0.000     4.613491    14.89541
      age_5s |   9.083061   3.805697     2.39   0.017      1.62309    16.54303
      age_6s |   5.236101   4.957017     1.06   0.291    -4.480701     14.9529
      fmsz27 |    1.26932   .6770258     1.87   0.061    -.0577941    2.596433
       _cons |   18.42381   3.042659     6.06   0.000     12.45955    24.38806
------------------------------------------------------------------------------

.1 Quantile regression                                 Number of obs =      9595
  Raw sum of deviations 51650.59 (about 1.005)
  Min sum of deviations 50701.16                       Pseudo R2     =    0.0184
------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |  -.7199583   .2122166    -3.39   0.001    -1.135948   -.3039689
      age_1m |  -1.300667   .5813541    -2.24   0.025    -2.440244   -.1610897
      age_2m |  -.6206667   .3137306    -1.98   0.048    -1.235645   -.0056883
      age_4m |   1.052875    .341437     3.08   0.002     .3835861    1.722164
      age_5m |   .8334833   .4631007     1.80   0.072    -.0742921    1.741259
      age_6m |   .9393496    .617229     1.52   0.128    -.2705497    2.149249
      age_1s |  -1.369717   .5240545    -2.61   0.009    -2.396974   -.3424589
      age_2s |   -.702875   .3203131    -2.19   0.028    -1.330756   -.0749936
      age_4s |   .3665166    .345955     1.06   0.289    -.3116283    1.044662
      age_5s |   2.040042   .4836905     4.22   0.000     1.091906    2.988177
      age_6s |    1.66065   .6575123     2.53   0.012      .371787    2.949513
      fmsz27 |   .0535417   .0863274     0.62   0.535    -.1156782    .2227616
       _cons |   1.492917   .4010867     3.72   0.000     .7067019    2.279132
------------------------------------------------------------------------------

.25 Quantile regression                                Number of obs =      9595
  Raw sum of deviations 120281.7 (about 4.8221998)
  Min sum of deviations 114861.9                       Pseudo R2     =    0.0451
------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |  -.3671999    .289464    -1.27   0.205    -.9346105    .2002107
      age_1m |    -1.6718   .8448648    -1.98   0.048    -3.327914   -.0156865
      age_2m |    -1.0571   .4494765    -2.35   0.019    -1.938169   -.1760313
      age_4m |     2.0854    .448289     4.65   0.000     1.206659    2.964141
      age_5m |     2.3253   .6151703     3.78   0.000     1.119437    3.531164
      age_6m |        2.1   .7767098     2.70   0.007     .5774842    3.622515
      age_1s |    -3.5121   .7431165    -4.73   0.000    -4.968766   -2.055434
      age_2s |    -2.0815    .437749    -4.76   0.000    -2.939581    -1.22342
      age_4s |      1.386   .4594645     3.02   0.003     .4853522    2.286647
      age_5s |     4.4859   .6267946     7.16   0.000      3.25725     5.71455
      age_6s |     3.9213   .8111071     4.83   0.000     2.331358    5.511241
      fmsz27 |      .2053   .1126227     1.82   0.068    -.0154642    .4260643
       _cons |     4.5181   .5124793     8.82   0.000     3.513532    5.522668
------------------------------------------------------------------------------
```

Median regression Number of obs = 9595
Raw sum of deviations 206408 (about 13.3461)
Min sum of deviations 191814.9 Pseudo R2 = 0.0707

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	.3650007	.4331749	0.84	0.399	-.4841137	1.214115
age_1m	-4.2046	1.227193	-3.43	0.001	-6.610157	-1.799043
age_2m	-2.311	.6763741	-3.42	0.001	-3.636837	-.9851639
age_4m	4.316699	.618971	6.97	0.000	3.103385	5.530013
age_5m	6.916798	.8779168	7.88	0.000	5.195896	8.637701
age_6m	3.7268	1.127225	3.31	0.001	1.5172	5.9364
age_1s	-6.6483	1.083541	-6.14	0.000	-8.77227	-4.52433
age_2s	-3.7347	.656137	-5.69	0.000	-5.020868	-2.448533
age_4s	4.255	.6354282	6.70	0.000	3.009426	5.500574
age_5s	6.435	.9126546	7.05	0.000	4.646004	8.223996
age_6s	5.789899	1.18113	4.90	0.000	3.474635	8.105163
fmsz27	.3249998	.1641113	1.98	0.048	.0033068	.6466927
_cons	10.5983	.7539369	14.06	0.000	9.120425	12.07618

.75 Quantile regression Number of obs = 9595
Raw sum of deviations 238098.9 (about 28.941)
Min sum of deviations 218560.5 Pseudo R2 = 0.0821

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	.485	.8678834	0.56	0.576	-1.216235	2.186235
age_1m	-9.135	2.471543	-3.70	0.000	-13.97975	-4.290253
age_2m	-5.315001	1.280729	-4.15	0.000	-7.825501	-2.8045
age_4m	8.450001	1.162072	7.27	0.000	6.172094	10.72791
age_5m	15.2165	1.711364	8.89	0.000	11.86186	18.57114
age_6m	9.096501	2.367737	3.84	0.000	4.455235	13.73777
age_1s	-10.97	2.091791	-5.24	0.000	-15.07035	-6.869646
age_2s	-5.959999	1.247435	-4.78	0.000	-8.405236	-3.514763
age_4s	7.715001	1.197329	6.44	0.000	5.367983	10.06202
age_5s	8.5985	1.796269	4.79	0.000	5.077433	12.11957
age_6s	6.241901	2.500755	2.50	0.013	1.339893	11.14391
fmsz27	.9750005	.3201876	3.05	0.002	.347365	1.602636
_cons	20.1	1.426218	14.09	0.000	17.30431	22.89569

.9 Quantile regression Number of obs = 9595
Raw sum of deviations 200718.2 (about 55.599998)
Min sum of deviations 184536.7 Pseudo R2 = 0.0806

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	.6600005	2.161932	0.31	0.760	-3.577843	4.897844
age_1m	-13.5424	6.81345	-1.99	0.047	-26.8982	-.1865944
age_2m	-9.854899	3.097778	-3.18	0.001	-15.9272	-3.782598
age_4m	18.0351	2.8062	6.43	0.000	12.53436	23.53585
age_5m	38.9321	4.310991	9.03	0.000	30.48165	47.38255
age_6m	29.9751	5.818078	5.15	0.000	18.57044	41.37977
age_1s	-21.9876	5.275879	-4.17	0.000	-32.32944	-11.64576
age_2s	-12.4001	3.018855	-4.11	0.000	-18.31769	-6.482506
age_4s	10.6625	2.901818	3.67	0.000	4.974321	16.35068
age_5s	3.389901	4.49572	0.75	0.451	-5.422661	12.20246
age_6s	-5.220099	6.15054	-0.85	0.396	-17.27646	6.836259
fmsz27	2.6525	.7717636	3.44	0.001	1.139681	4.16532
_cons	35.44	3.481675	10.18	0.000	28.61518	42.26482

model 2: Single families

OLS regression

Source	SS	df	MS
Model	177389.825	7	25341.4036
Residual	4931483.26	6198	795.65719
Total	5108873.09	6205	823.347798

Number of obs =	6206
F(7, 6198) =	31.85
Prob > F =	0.0000
R-squared =	0.0347
Adj R-squared =	0.0336
Root MSE =	28.207

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	2.138012	.9783018	2.19	0.029	.2202009	4.055823
age_1m	-5.80894	1.271431	-4.57	0.000	-8.301385	-3.316496
age_2m	-1.182487	1.122732	-1.05	0.292	-3.383431	1.018458
age_4m	5.722914	1.257213	4.55	0.000	3.25834	8.187488
age_5m	8.532543	1.453307	5.87	0.000	5.683558	11.38153
age_6m	8.128358	1.156069	7.03	0.000	5.862062	10.39465
lone_p	-2.390763	1.174454	-2.04	0.042	-4.6931	-.0884257
_cons	8.807636	.8694464	10.13	0.000	7.103219	10.51205

.1 Quantile regression Number of obs = 6206
Raw sum of deviations 15018.38 (about -.015)
Min sum of deviations 14869.82 Pseudo R2 = 0.0099

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.1381	.0319222	-4.33	0.000	-.2006786	-.0755213
age_1m	-.8834	.0431694	-20.46	0.000	-.968027	-.798773
age_2m	-.3215	.0340897	-9.43	0.000	-.3883276	-.2546724
age_4m	.0135	.0353861	0.38	0.703	-.0558691	.0828691
age_5m	.0786	.0405799	1.94	0.053	-.0009506	.1581506
age_6m	.2416	.033069	7.31	0.000	.1767732	.3064267
lone_p	.0186	.0282797	0.66	0.511	-.036838	.074038
_cons	.0215	.0257302	0.84	0.403	-.0289401	.0719401

.25 Quantile regression Number of obs = 6206
Raw sum of deviations 35619.36 (about .24420001)
Min sum of deviations 35267.01 Pseudo R2 = 0.0099

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.2575	.092296	-2.79	0.005	-.4384322	-.0765678
age_1m	-.4468	.1360222	-3.28	0.001	-.7134507	-.1801493
age_2m	-.1639	.110168	-1.49	0.137	-.3798675	.0520674
age_4m	.1682	.1154111	1.46	0.145	-.0580457	.3944457
age_5m	.3607	.1296404	2.78	0.005	.1065599	.6148401
age_6m	1.2407	.105281	11.78	0.000	1.034313	1.447087
lone_p	-.0843	.0956975	-0.88	0.378	-.2719002	.1033003
_cons	.4168	.0866703	4.81	0.000	.2468961	.5867039

Median regression Number of obs = 6206
Raw sum of deviations 66718.79 (about 2.75)
Min sum of deviations 63313.62 Pseudo R2 = 0.0510

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.205	.2044484	-1.00	0.316	-.6057897	.1957898
age_1m	-3.1451	.3090923	-10.18	0.000	-3.751028	-2.539172
age_2m	-1.9052	.2501821	-7.62	0.000	-2.395644	-1.414756
age_4m	1.7509	.2574658	6.80	0.000	1.246178	2.255622
age_5m	2.9942	.2849712	10.51	0.000	2.435557	3.552842
age_6m	5.9299	.2312539	25.64	0.000	5.476562	6.383238
lone_p	-.2981	.2208112	-1.35	0.177	-.7309665	.1347665
_cons	3.3701	.1857648	18.14	0.000	3.005937	3.734263

```
.75 Quantile regression                             Number of obs =      6206
  Raw sum of deviations 81248.92 (about 12.1445)
  Min sum of deviations 73910.34                    Pseudo R2     =    0.0903

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   1.349999    .400552     3.37   0.001     .5647782     2.13522
      age_1m |    -9.4558   .5927162   -15.95   0.000    -10.61773   -8.293871
      age_2m |  -5.276801   .4967071   -10.62   0.000    -6.250519   -4.303082
      age_4m |     4.9942   .5406991     9.24   0.000     3.934242    6.054157
      age_5m |    10.2442   .5743705    17.84   0.000     9.118235    11.37017
      age_6m |   9.994199   .4728504    21.14   0.000     9.067248    10.92115
      lone_p |    -1.3718   .4536663    -3.02   0.003    -2.261143    -.482457
       _cons |    10.8058   .3701344    29.19   0.000     10.08021    11.53139
------------------------------------------------------------------------------

.9 Quantile regression                              Number of obs =      6206
  Raw sum of deviations 66923.46 (about 28.0287)
  Min sum of deviations 61761.97                    Pseudo R2     =    0.0771

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   5.159401   1.635448     3.15   0.002     1.953357    8.365445
      age_1m |     -16.42   2.189873    -7.50   0.000    -20.71291   -12.12709
      age_2m |     -6.239   1.923366    -3.24   0.001    -10.00946   -2.468536
      age_4m |   9.604998   2.255098     4.26   0.000     5.184224    14.02577
      age_5m |     22.685   2.361764     9.61   0.000     18.05512    27.31488
      age_6m |    16.4945   1.990427     8.29   0.000     12.59257    20.39643
      lone_p |  -6.555599   1.735367    -3.78   0.000     -9.95752   -3.153678
       _cons |    23.1556    1.53919    15.04   0.000     20.13825    26.17295
------------------------------------------------------------------------------
```

Model 3. Married families

OLS regression

```
      Source |       SS       df       MS              Number of obs =    9595
-------------+------------------------------           F( 33,  9561) =   14.82
       Model |  2364079.64    33  71638.7768           Prob > F      =  0.0000
    Residual |  46225665.4  9561  4834.81492           R-squared     =  0.0487
-------------+------------------------------           Adj R-squared =  0.0454
       Total |  48589745.1  9594  5064.59715           Root MSE      =  69.533

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |  -3.028583   1.770768    -1.71   0.087    -6.499663    .4424966
      age_1m |  -6.913408   5.333866    -1.30   0.195    -17.36892    3.542101
      age_2m |   -8.31906   2.721797    -3.06   0.002    -13.65436   -2.983759
      age_4m |   5.155992   2.599865     1.98   0.047     .0597057    10.25228
      age_5m |   13.06048   3.793656     3.44   0.001     5.624112    20.49685
      age_6m |    9.79736    4.95974     1.98   0.048     .0752174     19.5195
      age_1s |  -7.019513   4.565563    -1.54   0.124    -15.96898    1.929958
      age_2s |  -4.801123   2.653793    -1.81   0.070    -10.00312    .4008734
      age_4s |   11.32402    2.63431     4.30   0.000     6.160217    16.48783
      age_5s |   13.25817   3.862315     3.43   0.001     5.687217    20.82913
      age_6s |   12.22906   5.049869     2.42   0.015     2.330247    22.12787
      fmsz27 |   1.557893   .6743649     2.31   0.021     .2359945    2.879791
     femal_m |    1.72221    5.25555     0.33   0.743    -8.579782     12.0242
      ed0_8m |  -7.543371   3.555323    -2.12   0.034    -14.51256   -.5741848
     ed9_13m |  -2.331468   2.957144    -0.79   0.430    -8.128099    3.465162
      ed_psm |  -.3419116   2.493164    -0.14   0.891    -5.229042    4.545219
       ed_um |   13.25476   3.231011     4.10   0.000     6.921293    19.58823
     ed_abum |    21.9878   3.757955     5.85   0.000     14.62141    29.35419
      ed0_8s |  -2.900782   6.819357    -0.43   0.671    -16.26817     10.4666
     ed9_13s |  -1.617007    5.34507    -0.30   0.762    -12.09448    8.860464
      ed_pss |  -.2054964   4.487763    -0.05   0.963    -9.002464    8.591471
       ed_us |   3.634291   5.436891     0.67   0.504    -7.023168    14.29175
     ed_abus |   4.941923   7.069264     0.70   0.485    -8.915334    18.79918
     ed_sx1m |  -12.12264   8.660346    -1.40   0.162    -29.09875    4.853477
     ed_sx2m |  -8.916497   6.635925    -1.34   0.179    -21.92432    4.091324
     ed_sx4m |   .0340322   5.172547     0.01   0.995    -10.10526    10.17332
     ed_sx5m |  -11.33357   6.157495    -1.84   0.066    -23.40356    .7364285
     ed_sx6m |  -10.20507   7.951173    -1.28   0.199    -25.79106    5.380916
     ed_sx1s |  -9.931271   7.587629    -1.31   0.191    -24.80463    4.942092
     ed_sx2s |  -4.721376   5.943287    -0.79   0.427    -16.37148    6.928727
     ed_sx4s |   1.464326   4.934252     0.30   0.767    -8.207855    11.13651
     ed_sx5s |   2.916632   6.156065     0.47   0.636    -9.150562    14.98383
     ed_sx6s |   1.820452    8.55965     0.21   0.832    -14.95828    18.59918
       _cons |   14.45514   3.776933     3.83   0.000     7.051546    21.85872
------------------------------------------------------------------------------
```

.1 Quantile regression Number of obs = 9595
Raw sum of deviations 51650.59 (about 1.005)
Min sum of deviations 49968.94 Pseudo R2 = 0.0326

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-1.468909	.2264972	-6.49	0.000	-1.912892	-1.024927
age_1m	-1.648764	.6142577	-2.68	0.007	-2.852839	-.4446883
age_2m	-.9157727	.3113916	-2.94	0.003	-1.526166	-.3053791
age_4m	1.053555	.3625818	2.91	0.004	.3428173	1.764292
age_5m	1.765027	.4975556	3.55	0.000	.7897127	2.740342
age_6m	2.609509	.6624828	3.94	0.000	1.310902	3.908116
age_1s	-1.468582	.548296	-2.68	0.007	-2.543358	-.3938053
age_2s	-.6313546	.3173089	-1.99	0.047	-1.253347	-.0093619
age_4s	.8504819	.3569964	2.38	0.017	.1506933	1.550271
age_5s	2.417009	.5046978	4.79	0.000	1.427695	3.406324
age_6s	2.149655	.6865228	3.13	0.002	.8039245	3.495385
fmsz27	.3402273	.0902906	3.77	0.000	.1632385	.5172161
femal_m	.1239273	.8156518	0.15	0.879	-1.474923	1.722778
ed0_8m	-.1404182	.4319988	-0.33	0.745	-.9872274	.7063911
ed9_13m	.028291	.364336	0.08	0.938	-.6858849	.7424669
ed_psm	.6347092	.3296496	1.93	0.054	-.011474	1.280892
ed_um	1.625836	.4215894	3.86	0.000	.7994319	2.452241
ed_abum	3.513709	.4936764	7.12	0.000	2.545999	4.48142
ed0_8s	-1.5717	.9306746	-1.69	0.091	-3.39602	.2526196
ed9_13s	-1.287255	.7957482	-1.62	0.106	-2.84709	.2725808
ed_pss	-.3802455	.6558305	-0.58	0.562	-1.665812	.9053214
ed_us	.6250091	.7862303	0.79	0.427	-.9161691	2.166187
ed_abus	-.2089272	.9197686	-0.23	0.820	-2.011869	1.594014
ed_sx1m	-1.663518	1.081478	-1.54	0.124	-3.783445	.4564083
ed_sx2m	-.8604729	.83275	-1.03	0.301	-2.49284	.7718937
ed_sx4m	.1931726	.6892421	0.28	0.779	-1.157888	1.544233
ed_sx5m	-1.568964	.8168955	-1.92	0.055	-3.170252	.0323246
ed_sx6m	-2.258218	1.058798	-2.13	0.033	-4.333687	-.1827498
ed_sx1s	-1.736882	1.027835	-1.69	0.091	-3.751656	.2778922
ed_sx2s	.1431907	.8722379	0.16	0.870	-1.566581	1.852962
ed_sx4s	.6357635	.7225509	0.88	0.379	-.7805895	2.052116
ed_sx5s	-.3108092	.8863183	-0.35	0.726	-2.048181	1.426563
ed_sx6s	-.556191	1.185252	-0.47	0.639	-2.879536	1.767154
_cons	.5548636	.5417574	1.02	0.306	-.5070957	1.616823

.25 Quantile regression   Number of obs =   9595
  Raw sum of deviations 120281.7 (about 4.8221998)
  Min sum of deviations 112097.8   Pseudo R2   =   0.0680

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-1.048617	.2210771	-4.74	0.000	-1.481975	-.6152588
age_1m	-1.927666	.6481078	-2.97	0.003	-3.198095	-.6572375
age_2m	-1.47195	.3525029	-4.18	0.000	-2.16293	-.7809694
age_4m	1.879767	.3455796	5.44	0.000	1.202358	2.557176
age_5m	4.1217	.4769762	8.64	0.000	3.186726	5.056675
age_6m	2.788368	.6247783	4.46	0.000	1.56367	4.013065
age_1s	-3.418184	.5926631	-5.77	0.000	-4.579929	-2.256438
age_2s	-2.226684	.3428949	-6.49	0.000	-2.89883	-1.554537
age_4s	2.001933	.3486973	5.74	0.000	1.318412	2.685454
age_5s	5.462499	.4781905	11.42	0.000	4.525145	6.399854
age_6s	7.147966	.6343621	11.27	0.000	5.904482	8.39145
fmsz27	.4483333	.0821686	5.46	0.000	.2872655	.6094012
femal_m	-.410017	.6878268	-0.60	0.551	-1.758304	.9382694
ed0_8m	-2.4399	.4195221	-5.82	0.000	-3.262252	-1.617548
ed9_13m	-.9219332	.3620493	-2.55	0.011	-1.631627	-.2122397
ed_psm	.6723666	.3089044	2.18	0.030	.0668484	1.277885
ed_um	2.6896	.4008467	6.71	0.000	1.903856	3.475345
ed_abum	5.185466	.4654031	11.14	0.000	4.273178	6.097755
ed0_8s	-4.329667	.810874	-5.34	0.000	-5.919152	-2.740182
ed9_13s	-1.681	.6849585	-2.45	0.014	-3.023664	-.3383362
ed_pss	-.41665	.5760625	-0.72	0.470	-1.545855	.7125548
ed_us	-1.366017	.705526	-1.94	0.053	-2.748997	.0169637
ed_abus	-1.66295	.9376445	-1.77	0.076	-3.500932	.1750325
ed_sx1m	-.0870324	1.012238	-0.09	0.931	-2.071235	1.89717
ed_sx2m	-.7906829	.8024753	-0.99	0.324	-2.363705	.7823388
ed_sx4m	-.067316	.6405674	-0.11	0.916	-1.322964	1.188332
ed_sx5m	-.7091831	.7720279	-0.92	0.358	-2.222521	.8041553
ed_sx6m	-1.711782	.9732564	-1.76	0.079	-3.619571	.1960065
ed_sx1s	-1.456733	.9111562	-1.60	0.110	-3.242793	.3293262
ed_sx2s	-.6906666	.7569896	-0.91	0.362	-2.174527	.7931935
ed_sx4s	.2829501	.6366661	0.44	0.657	-.9650504	1.530951
ed_sx5s	2.565084	.7951441	3.23	0.001	1.006432	4.123735
ed_sx6s	1.7729	1.142767	1.55	0.121	-.4671654	4.012965
_cons	4.1933	.4790205	8.75	0.000	3.254318	5.132282

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Median regression                                   Number of obs =      9595
  Raw sum of deviations   206408 (about 13.3461)
  Min sum of deviations 185212.6                    Pseudo R2     =    0.1027

------------------------------------------------------------------------------
      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   .2391866   .5314421     0.45   0.653    -.8025526    1.280926
      age_1m |  -2.881534   1.489722    -1.93   0.053    -5.801704    .0386371
      age_2m |  -2.120813    .822771    -2.58   0.010    -3.733619   -.5080079
      age_4m |   4.304106   .7599977     5.66   0.000     2.814349    5.793862
      age_5m |   6.271628   1.095574     5.72   0.000     4.124071    8.419186
      age_6m |    5.59934   1.442774     3.88   0.000     2.771197    8.427484
      age_1s |  -5.632726   1.324296    -4.25   0.000    -8.228626   -3.036826
      age_2s |  -3.890093   .7981176    -4.87   0.000    -5.454573   -2.325614
      age_4s |   5.063146   .7789306     6.50   0.000     3.536277    6.590015
      age_5s |   9.867559   1.135568     8.69   0.000     7.641605    12.09351
      age_6s |    9.86817    1.47697     6.68   0.000     6.972996    12.76334
      fmsz27 |   .6608134   .1986362     3.33   0.001     .2714444    1.050182
     femal_m |  -.4528921   1.563615    -0.29   0.772    -3.517909    2.612125
      ed0_8m |  -3.009446   1.021519    -2.95   0.003    -5.011839   -1.007053
     ed9_13m |  -1.147099   .8493131    -1.35   0.177    -2.811932    .5177352
      ed_psm |   1.408534   .7399232     1.90   0.057    -.0418728     2.85894
       ed_um |   6.238534    .943697     6.61   0.000     4.388688     8.08838
     ed_abum |   11.17899   1.099768    10.16   0.000     9.023217    13.33477
      ed0_8s |  -4.344885   1.986294    -2.19   0.029    -8.238443   -.4513266
     ed9_13s |  -1.828574   1.605043    -1.14   0.255    -4.974798     1.31765
      ed_pss |  -.3969465   1.361647    -0.29   0.771    -3.066063     2.27217
       ed_us |    .204173   1.669748     0.12   0.903    -3.068888    3.477234
     ed_abus |    .323267   2.257363     0.14   0.886    -4.101644    4.748178
     ed_sx1m |  -3.295251    2.52669    -1.30   0.192    -8.248099    1.657597
     ed_sx2m |  -1.203809   1.957527    -0.61   0.539    -5.040978     2.63336
     ed_sx4m |  -.7910679   1.533532    -0.52   0.606    -3.797117    2.214981
     ed_sx5m |  -3.510381   1.837925    -1.91   0.056    -7.113104    .0923421
     ed_sx6m |    .746631   2.498712     0.30   0.765    -4.151375    5.644637
     ed_sx1s |  -2.425553   2.213673    -1.10   0.273    -6.764822    1.913716
     ed_sx2s |    -2.3567   1.791566    -1.32   0.188    -5.868549    1.155149
     ed_sx4s |  -.0827007   1.491571    -0.06   0.956    -3.006497    2.841096
     ed_sx5s |   1.886548   1.868194     1.01   0.313    -1.775508    5.548603
     ed_sx6s |   3.523739   2.689222     1.31   0.190    -1.747706    8.795184
       _cons |   8.750746   1.127357     7.76   0.000     6.540886    10.96061
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.75 Quantile regression                             Number of obs =      9595
  Raw sum of deviations 238098.9 (about 28.941)
  Min sum of deviations 208452.4                    Pseudo R2     =    0.1245

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      wealth |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     imigrnt |   1.345572   .7796901     1.73   0.084     -.182786     2.87393
      age_1m |  -5.065064   2.256685    -2.24   0.025    -9.488646   -.6414823
      age_2m |  -4.843715   1.204525    -4.02   0.000    -7.204839   -2.482591
      age_4m |   6.962841   1.060237     6.57   0.000      4.88455    9.041131
      age_5m |   14.11863   1.563906     9.03   0.000     11.05304    17.18422
      age_6m |   9.488796   2.229681     4.26   0.000      5.11815    13.85944
      age_1s |  -8.496237   1.921012    -4.42   0.000    -12.26183   -4.730646
      age_2s |  -6.271829   1.176279    -5.33   0.000    -8.577586   -3.966072
      age_4s |   9.076319    1.09125     8.32   0.000     6.937239     11.2154
      age_5s |   11.63984   1.629121     7.14   0.000     8.446412    14.83326
      age_6s |   12.54426   2.290435     5.48   0.000     8.054525      17.034
      fmsz27 |   1.382159   .2779591     4.97   0.000     .8372998    1.927017
     femal_m |  -1.425987   2.174213    -0.66   0.512    -5.687905    2.835931
      ed0_8m |  -5.098573     1.5222    -3.35   0.001    -8.082409   -2.114738
     ed9_13m |  -2.235245   1.238172    -1.81   0.071    -4.662325    .1918345
      ed_psm |   .4462846   1.076953     0.41   0.679    -1.664772    2.557341
       ed_um |   9.301577   1.404003     6.63   0.000     6.549432    12.05372
     ed_abum |   25.34648   1.578104    16.06   0.000     22.25307     28.4399
      ed0_8s |  -3.519796   2.892381    -1.22   0.224    -9.189476    2.149885
     ed9_13s |  -1.619305    2.24735    -0.72   0.471    -6.024587    2.785978
      ed_pss |  -1.732237   1.985295    -0.87   0.383    -5.623835    2.159362
       ed_us |   1.768469   2.428436     0.73   0.466    -2.991781    6.528718
     ed_abus |   7.766419   2.975005     2.61   0.009     1.934778    13.59806
     ed_sx1m |  -11.53296   3.566675    -3.23   0.001     -18.5244   -4.541521
     ed_sx2m |  -2.064196   2.817678    -0.73   0.464    -7.587442     3.45905
     ed_sx4m |   .6344079   2.234519     0.28   0.776    -3.745722    5.014538
     ed_sx5m |  -7.009235   2.674768    -2.62   0.009    -12.25235   -1.766122
     ed_sx6m |  -12.90788   3.551634    -3.63   0.000    -19.86984   -5.945927
     ed_sx1s |  -6.756518   3.229367    -2.09   0.036    -13.08676   -.4262733
     ed_sx2s |  -4.897579   2.528013    -1.94   0.053    -9.853021    .0578621
     ed_sx4s |   .5991257    2.19149     0.27   0.785    -3.696659     4.89491
     ed_sx5s |   4.905931   2.731083     1.80   0.072     -.447571    10.25943
     ed_sx6s |   5.239484   3.660747     1.43   0.152    -1.936356    12.41532
       _cons |   17.42251   1.586679    10.98   0.000     14.31228    20.53274
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```

.9 Quantile regression   Number of obs =   9595
Raw sum of deviations 200718.2 (about 55.599998)
Min sum of deviations 173455.9   Pseudo R2   =   0.1358

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.3683978	1.68768	-0.22	0.827	-3.676608	2.939813
age_1m	-7.746803	4.970098	-1.56	0.119	-17.48925	1.995642
age_2m	-9.132994	2.484933	-3.68	0.000	-14.00399	-4.261998
age_4m	9.615798	2.099166	4.58	0.000	5.500987	13.73061
age_5m	34.60221	3.251929	10.64	0.000	28.22774	40.97668
age_6m	27.1281	4.296113	6.31	0.000	18.70681	35.54939
age_1s	-12.4855	3.939435	-3.17	0.002	-20.20762	-4.763367
age_2s	-9.239504	2.417842	-3.82	0.000	-13.97899	-4.500021
age_4s	16.86719	2.158997	7.81	0.000	12.6351	21.09929
age_5s	9.930202	3.303318	3.01	0.003	3.454998	16.40541
age_6s	5.184414	4.435765	1.17	0.243	-3.510626	13.87945
fmsz27	2.932505	.5846673	5.02	0.000	1.786433	4.078577
femal_m	-3.884625	4.288986	-0.91	0.365	-12.29195	4.522697
ed0_8m	-11.0045	3.235849	-3.40	0.001	-17.34745	-4.661546
ed9_13m	-5.832194	2.552641	-2.28	0.022	-10.83591	-.8284761
ed_psm	-2.137509	2.268009	-0.94	0.346	-6.583287	2.30827
ed_um	17.91299	3.004863	5.96	0.000	12.02282	23.80316
ed_abum	38.13041	3.272838	11.65	0.000	31.71495	44.54586
ed0_8s	3.961321	5.723303	0.69	0.489	-7.257566	15.18021
ed9_13s	3.504611	4.488261	0.78	0.435	-5.293333	12.30255
ed_pss	1.361777	4.156263	0.33	0.743	-6.785379	9.508933
ed_us	6.380887	5.005174	1.27	0.202	-3.430315	16.19209
ed_abus	15.68609	6.596424	2.38	0.017	2.755696	28.61647
ed_sx1m	-14.67498	7.153151	-2.05	0.040	-28.69667	-.6532884
ed_sx2m	-7.537489	5.6014	-1.35	0.178	-18.51742	3.442443
ed_sx4m	1.378445	4.492383	0.31	0.759	-7.427579	10.18447
ed_sx5m	-11.40987	5.298609	-2.15	0.031	-21.79627	-1.023473
ed_sx6m	1.830929	7.76012	0.24	0.813	-13.38055	17.04241
ed_sx1s	-16.27923	6.431123	-2.53	0.011	-28.88559	-3.672865
ed_sx2s	-12.31461	5.058619	-2.43	0.015	-22.23058	-2.398648
ed_sx4s	-1.639275	4.598618	-0.36	0.721	-10.65354	7.374991
ed_sx5s	5.493613	5.629813	0.98	0.329	-5.542015	16.52924
ed_sx6s	21.30861	8.102683	2.63	0.009	5.425629	37.19158
_cons	29.53499	3.434569	8.60	0.000	22.8025	36.26747

Model 3: Single families

OLS regression

Source	SS	df	MS
Model	386473.828	18	21470.7682
Residual	4722399.26	6187	763.277721
Total	5108873.09	6205	823.347798

Number of obs =	6206
F(18, 6187) =	28.13
Prob > F =	0.0000
R-squared =	0.0756
Adj R-squared =	0.0730
Root MSE =	27.627

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	1.241774	.9627768	1.29	0.197	-.6456027	3.129151
age_1m	-4.696066	1.252074	-3.75	0.000	-7.150566	-2.241566
age_2m	-1.734072	1.107456	-1.57	0.117	-3.905072	.4369268
age_4m	5.739514	1.235539	4.65	0.000	3.317427	8.1616
age_5m	11.39586	1.453811	7.84	0.000	8.545887	14.24584
age_6m	13.81462	1.245591	11.09	0.000	11.37283	16.25641
lone_p	.4143839	1.208417	0.34	0.732	-1.954534	2.783302
femal_m	-1.649115	1.938463	-0.85	0.395	-5.449176	2.150946
ed0_8m	-7.115401	2.189638	-3.25	0.001	-11.40785	-2.82295
ed9_13m	-2.854334	1.869095	-1.53	0.127	-6.518409	.8097411
ed_psm	.5190615	1.594598	0.33	0.745	-2.606904	3.645027
ed_um	3.955156	1.90972	2.07	0.038	.211441	7.698871
ed_abum	23.22687	2.589299	8.97	0.000	18.15095	28.3028
ed_sx1m	-3.611768	2.814161	-1.28	0.199	-9.128502	1.904965
ed_sx2m	-1.779847	2.563184	-0.69	0.487	-6.804579	3.244885
ed_sx4m	-1.227717	2.227144	-0.55	0.581	-5.593694	3.13826
ed_sx5m	2.272931	2.678421	0.85	0.396	-2.977705	7.523567
ed_sx6m	-9.379294	3.718524	-2.52	0.012	-16.66889	-2.089695
_cons	8.315637	1.519489	5.47	0.000	5.33691	11.29436

.1 Quantile regression — Number of obs = 6206

Raw sum of deviations 15018.38 (about -.015)

Min sum of deviations 14841.38 — Pseudo R2 = 0.0118

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.19035	.0421632	-4.51	0.000	-.2730046	-.1076954
age_1m	-.9099	.0633416	-14.36	0.000	-1.034072	-.7857284
age_2m	-.29285	.0481171	-6.09	0.000	-.3871763	-.1985237
age_4m	.0801	.0499086	1.60	0.109	-.0177382	.1779382
age_5m	.1818	.0574463	3.16	0.002	.0691854	.2944146
age_6m	.3556	.0521732	6.82	0.000	.2533224	.4578775
lone_p	.0137	.045854	0.30	0.765	-.0761897	.1035897
femal_m	.2062	.0761251	2.71	0.007	.0569683	.3554317
ed0_8m	-.2053	.0964094	-2.13	0.033	-.3942959	-.016304
ed9_13m	-.1233	.0751612	-1.64	0.101	-.270642	.024042
ed_psm	-.185	.0708969	-2.61	0.009	-.3239826	-.0460174
ed_um	-.12535	.0774405	-1.62	0.106	-.2771603	.0264603
ed_abum	.50225	.0971824	5.17	0.000	.3117388	.6927613
ed_sx1m	-.1369	.1143616	-1.20	0.231	-.3610885	.0872885
ed_sx2m	-.2366	.1021333	-2.32	0.021	-.4368168	-.0363832
ed_sx4m	-.0695	.0934076	-0.74	0.457	-.2526113	.1136113
ed_sx5m	.2363	.1072333	2.20	0.028	.0260855	.4465145
ed_sx6m	-.6101	.1389367	-4.39	0.000	-.8824642	-.3377358
_cons	.0682	.0632443	1.08	0.281	-.0557807	.1921807

.25 Quantile regression   Number of obs = 6206
Raw sum of deviations 35619.36 (about .24420001)
Min sum of deviations 35024.89   Pseudo R2 = 0.0167

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.4281667	.0811104	-5.28	0.000	-.5871711	-.2691622
age_1m	-.5168333	.1193128	-4.33	0.000	-.7507278	-.2829388
age_2m	-.1618334	.0967264	-1.67	0.094	-.3514507	.027784
age_4m	.3351	.1009783	3.32	0.001	.1371474	.5330527
age_5m	.6181667	.1145654	5.40	0.000	.3935788	.8427547
age_6m	1.608167	.0985345	16.32	0.000	1.415005	1.801328
lone_p	.0031667	.0910515	0.03	0.972	-.1753259	.1816593
femal_m	.1167334	.1511818	0.77	0.440	-.1796355	.4131022
ed0_8m	-.8534	.1705971	-5.00	0.000	-1.187829	-.5189705
ed9_13m	-.4332666	.1517149	-2.86	0.004	-.7306805	-.1358526
ed_psm	-.2050999	.1328095	-1.54	0.123	-.4654527	.0552528
ed_um	.0467334	.1782988	0.26	0.793	-.3027942	.396261
ed_abum	2.046733	.1985859	10.31	0.000	1.657436	2.436031
ed_sx1m	-.1184334	.2133187	-0.56	0.579	-.5366122	.2997454
ed_sx2m	-.0995001	.2010395	-0.49	0.621	-.4936073	.2946071
ed_sx4m	-.0049001	.1795989	-0.03	0.978	-.3569763	.3471762
ed_sx5m	.5155667	.2353318	2.19	0.029	.0542346	.9768988
ed_sx6m	-.7817334	.2805659	-2.79	0.005	-1.33174	-.2317268
_cons	.5751	.1253678	4.59	0.000	.3293355	.8208644

Median regression   Number of obs = 6206
Raw sum of deviations 66718.79 (about 2.75)
Min sum of deviations 62166.46   Pseudo R2 = 0.0682

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	-.5059999	.1532742	-3.30	0.001	-.8064706	-.2055293
age_1m	-3.055	.2305001	-13.25	0.000	-3.50686	-2.60314
age_2m	-2.13	.1860982	-11.45	0.000	-2.494817	-1.765183
age_4m	1.695	.192285	8.82	0.000	1.318054	2.071945
age_5m	3.845	.217207	17.70	0.000	3.419199	4.270801
age_6m	7.634	.1926481	39.63	0.000	7.256343	8.011657
lone_p	.3121999	.1764906	1.77	0.077	-.0337831	.6581829
femal_m	.0938002	.3020295	0.31	0.756	-.4982825	.6858829
ed0_8m	-3.6885	.3403379	-10.84	0.000	-4.355681	-3.021319
ed9_13m	-.655	.3113385	-2.10	0.035	-1.265332	-.0446682
ed_psm	.0200001	.2700963	0.07	0.941	-.5094824	.5494826
ed_um	1.9725	.3374776	5.84	0.000	1.310927	2.634073
ed_abum	6.855199	.3989561	17.18	0.000	6.073106	7.637292
ed_sx1m	-1.143301	.4231655	-2.70	0.007	-1.972852	-.3137493
ed_sx2m	-.8738002	.4061492	-2.15	0.031	-1.669994	-.0776066
ed_sx4m	-.6678003	.3564641	-1.87	0.061	-1.366594	.0309932
ed_sx5m	-.5463003	.4481023	-1.22	0.223	-1.424736	.3321358
ed_sx6m	-4.567199	.5617786	-8.13	0.000	-5.66848	-3.465918
_cons	3.71	.2500645	14.84	0.000	3.219787	4.200213

.75 Quantile regression Number of obs = 6206
Raw sum of deviations 81248.92 (about 12.1445)
Min sum of deviations 71648.52 Pseudo R2 = 0.1182

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	2.550001	.2691401	9.47	0.000	2.022393	3.077609
age_1m	-7.665498	.3978997	-19.26	0.000	-8.44552	-6.885477
age_2m	-5.450498	.3312576	-16.45	0.000	-6.099878	-4.801119
age_4m	4.618799	.3606453	12.81	0.000	3.911809	5.325789
age_5m	11.3095	.3945493	28.66	0.000	10.53605	12.08296
age_6m	13.1587	.3714826	35.42	0.000	12.43046	13.88693
lone_p	.0249998	.3249658	0.08	0.939	-.6120461	.6620457
femal_m	.7601013	.5457036	1.39	0.164	-.3096674	1.82987
ed0_8m	-5.471199	.60885	-8.99	0.000	-6.664756	-4.277642
ed9_13m	-2.2927	.5463236	-4.20	0.000	-3.363684	-1.221716
ed_psm	.9942997	.4704082	2.11	0.035	.0721363	1.916463
ed_um	4.8193	.5812571	8.29	0.000	3.679834	5.958765
ed_abum	17.7101	.7246001	24.44	0.000	16.28963	19.13057
ed_sx1m	-3.9887	.7758824	-5.14	0.000	-5.509699	-2.467701
ed_sx2m	-.9081015	.7364942	-1.23	0.218	-2.351886	.5356829
ed_sx4m	-3.400101	.6347959	-5.36	0.000	-4.644522	-2.155681
ed_sx5m	-.3901023	.7920087	-0.49	0.622	-1.942715	1.16251
ed_sx6m	-11.21	1.034088	-10.84	0.000	-13.23717	-9.182831
_cons	10.1312	.4424659	22.90	0.000	9.263812	10.99859

.9 Quantile regression Number of obs = 6206
Raw sum of deviations 66923.46 (about 28.0287)
Min sum of deviations 58785.28 Pseudo R2 = 0.1216

wealth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
imigrnt	5.021503	.7592353	6.61	0.000	3.533137	6.509868
age_1m	-11.845	1.014508	-11.68	0.000	-13.83379	-9.856212
age_2m	-6.795002	.8930657	-7.61	0.000	-8.545722	-5.044283
age_4m	6.8845	1.022141	6.74	0.000	4.880749	8.888251
age_5m	23.705	1.095374	21.64	0.000	21.55769	25.85231
age_6m	21.24	1.067323	19.90	0.000	19.14768	23.33232
lone_p	-.0955	.8917334	-0.11	0.915	-1.843607	1.652607
femal_m	-1.255004	1.667609	-0.75	0.452	-4.524097	2.01409
ed0_8m	-12.765	1.768964	-7.22	0.000	-16.23279	-9.297218
ed9_13m	-9.129502	1.532161	-5.96	0.000	-12.13307	-6.125935
ed_psm	-2.03	1.35076	-1.50	0.133	-4.677958	.6179577
ed_um	11.87	1.718796	6.91	0.000	8.500562	15.23944
ed_abum	19.525	2.082712	9.37	0.000	15.44216	23.60784
ed_sx1m	-4.744997	2.232101	-2.13	0.034	-9.12069	-.3693035
ed_sx2m	-2.720497	2.055796	-1.32	0.186	-6.75057	1.309577
ed_sx4m	-5.504999	1.864994	-2.95	0.003	-9.161035	-1.848962
ed_sx5m	-1.849495	2.309112	-0.80	0.423	-6.376157	2.677167
ed_sx6m	-5.408796	2.939209	-1.84	0.066	-11.17067	.3530753
_cons	25.225	1.302765	19.36	0.000	22.67113	27.77888