The American Dream Lives in Sweden: Trends in intergenerational absolute income mobility

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Abstract: Despite a sizeable literature on relative income mobility across generations, there is a dearth of studies of absolute mobility across generations, i.e. whether current generations earn more or less than their parents did at the same age, as well as how to explain the level of absolute mobility. We use individual micro data to study the trend in intergenerational absolute income mobility measured as the share of sons and daughters earning more than their fathers and mothers, respectively, for eleven Swedish birth cohorts between 1970 and 1980. We find that absolute mobility in Sweden significantly exceeds that of the United States and is largely on par with Canada. The rate of absolute mobility for women exceeds that of men throughout the study period, however the trend has been stronger for men. Using an augmented decomposition model which supplements standard models by accounting for differences in the income distribution of every birth cohort’s parent generation, we find that heterogeneity in the parent income distribution strongly determines how much economic growth contributes to absolute mobility across birth cohorts. If income inequality is high in the parent generation, more growth is required if children that move downward in the relative income distribution are to earn more than their parents.

Keywords: Absolute mobility, income decomposition, intergenerational income mobility, social mobility

JEL codes: D31, D63, J62, E24
1.0 Introduction

During the last two decades, research on intergenerational income mobility has expanded both within economics and other social sciences, complementing earlier inequality research by adding a time dimension to the concept of income inequality and thereby also allowing for the study of equality of opportunity. While sociologists have primarily attended to social mobility in terms of occupation, education or social class, economists have mostly focused on income mobility (Breen et al 2016). While some research has focused on mobility of income within a generation (intragenerational income mobility, see e.g. Aaberge et al 2002), the paper at hand focuses on income mobility across generations (intergenerational income mobility).1

Because parents’ income can be invested into their children’s education and other factors that can influence children’s future income, parents’ income will therefore well predict the future income of a child (Becker and Tomes 1979). A substantial literature consequently seeks to measure intergenerational income mobility and seeking to understand its mechanism (Solon 1999). In this line of research, children and their parent’s income are compared at the same age, commonly at age 30 or later (Richard 2009). A main distinction in the intergenerational income literature is that between absolute and relative mobility, where the former focuses on how income changes across generations in real terms and the latter focuses on mobility between the relative ranks in the income distribution. Intergenerational absolute mobility thus ignores individuals’ relative position in the contemporary income distribution and focuses only on how an individual’s real standard of living has changed compared to his or her parents. Relative mobility on the other hand, ignores change in an individual’s real standard of living, focusing instead on the income rank at adulthood of individuals in a birth cohort as compared to the income rank of his or her parents at the same age (Fields and Ok 1999).

While relative income mobility has been studied extensively, this is not true for absolute income mobility (see e.g. Jäntti and Jenkins (2015) for a recent overview). A partial explanation for the lack of attention to absolute income mobility is the high and relatively equally distributed economic growth enjoyed by most parts of the Western world during the post-war era. Under consistent growth, which is fairly equitable distributed, it can be justified to simply use aggregated growth rates as a proxy for intergenerational upward mobility in standards of living. As of late, however, it has increasingly come into question whether such a simplification is warranted. In the United States, stagnating median wage growth since the 1970 has given rise to the notion that recent generations earn less than their parent’s generation (Zingales 2014). Since the ‘prospect of upward mobility’ in society (Bénébou and Ok 2001 p.1) or to be ‘free to accomplish almost anything you

1 From here on we refer to the intergenerational form of income mobility when we use the term income mobility.
want with hard work’ (PEW 2009 poll) are both seen as important components in the idea of the American Dream, it has increasingly been questioned whether the promises of the American dream still hold up. In a recent paper, Chetty et al (2017) study this issue in United States by measuring the percentage in a birth cohort earning more than their parents, denoting this absolute mobility. By doing so for several birth cohorts in a sequel, it is possible to study the trend in the percentage of a cohort that earns more than their parents, which we in this paper refer to as ‘absolute income mobility’, or more straightforward ‘absolute mobility’.

Chetty et al (2017) showed using pooled cross sections that the percentage of US children earning more than their parents decreased sharply from the birth cohort of 1940, for which over 90 percent earned more than their parents, to the birth cohort of 1960, in which just under 60 percent of children earned more than their parents. The observed rate of absolute mobility was stable and even increased slightly for birth cohorts in the mid 1960s to early 1970, before declining again from just over 60 percent to about 50 percent for the 1980 birth cohort.

In Canada, a study using family income data (Ostrovsky 2017) shows a more optimistic picture as regards the trend in absolute mobility, although it should be noted that their data cover a shorter time span of birth cohorts, from 1970 to 1985. The results suggest that Canadian absolute mobility has been quite stable at around 60 percent from cohorts born 1970 to those born in 1985.

Berman (2019) uses aggregated data to approximate absolute mobility for several cohorts born before the first world war up until the 1980 for Sweden, United States and France, and for birth cohorts born after the second world war until the 1980s for Canada, Denmark, Germany, and United Kingdom. The trends in absolute mobility for all these countries take the shape of an inverted U-shaped curve, peaking at 90 percent earning more than their parents for the birth cohorts born in around the 1940s, decreasing to around 70 percent for children born in the 1980s in the Scandinavian countries, and to between 50 and 60 percent for Canada, Denmark, France, Germany, United States, United Kingdom.

Using counterfactual simulations, Chetty et al (2017) showed that two thirds of the decrease in absolute mobility during the second half of the 20th century in the US can be attributed to increasing income inequality, and a third due to declining economic growth. Yet, their counterfactual approach has two limitations: First, relative mobility is not considered in the counterfactual scenarios. As Berman (2018) has showed the extent that children move between the income rank positions in the income distribution compared to their parents has implications for the rate of absolute mobility. Second, counterfactual simulations focusing on growth and changes to the income distribution across time are not sufficient when decomposing absolute income measures. Heterogeneity in the initial income distribution also has a significant effect on the marginal effect of
growth on absolute income measures, a well-known fact in the literature on growth and absolute poverty, but to date largely overlooked in studies on absolute income mobility (Bourguignon 2003).

This paper seeks to (1) map the trends in absolute mobility in Sweden using detailed panel data on earnings across generations, and (2) to contribute a more precise theoretical and empirical understanding of the determinants of absolute mobility by decomposing the measured absolute mobility to its subcomponents. Performing this decomposition allows us to identify how much each of the three central explanatory factors of growth (average earning growth), income dispersion (income inequality) and exchange (relative income mobility) has contributed to the measured absolute mobility for Sweden. A similar decomposition strategy has previously been used for other mobility measures such as the absolute distance of log-incomes (Van Kerm et al 2004). To these three standard components in the literature, we introduce an additional explanatory factor to capture the effect of heterogeneity in the parent generations’ income distribution. This is done by separating the growth component into one component measuring the effect of growth on absolute mobility when assuming that the parent income distribution is homogeneous across all birth cohorts, and one component in which we measure the effect of growth when using the parent income distribution from the observed data. Performing this decomposition on as many as 11 child cohorts born from year 1970 to 1980 allows us to determine the relative importance of these components for each birth cohorts, as well which of them that is ultimately driving the trend in absolute mobility.

By performing the decomposition strategy on men and women separately, we are able to demonstrate the importance of our decomposition approach. While the mean earnings growth for women was stronger (likely due to women’s earnings converging to men’s), this still only translates to a slightly higher level of absolute mobility than for men. We show that this is due to lower earnings dispersion in the father generation compared to the mother generation, meaning that less mean earnings growth was needed to achieve high rates of absolute mobility for men than for women. Based on our augmented decomposition model and the results obtained, we conclude that this should have great implications for when comparing absolute mobility across time and countries.

2.0 Empirical strategy
The model set-up and empirical results from our analysis are presented in three steps: First, we examine how the trend in absolute mobility has changed in Sweden using a baseline estimation strategy. This estimation of the rate and trend in mobility constitute a fairly data driven analysis, described in detail in section 3.0. Second, these results are complemented with robustness checks to gauge how well the baseline approach measures absolute mobility. Third, to explain the measured
level and trend in absolute mobility, we decompose our estimate of absolute mobility to each of the three subcomponents that per definition make up any of the income mobility measures commonly used in the literature (Van Kerm et al 2004). To this we add an additional measure capturing heterogeneity of the parent income distribution. In the subsequent section 2.1, we first outline and discuss each of the expressions for computing and decomposing absolute mobility.

2.1 Computing absolute mobility

Our purpose is to study absolute mobility as measured by the share of children that receive a higher lifetime income than their parents. This can be expressed as:

\[
A(y^0, y^1) = \frac{1}{N} \sum_{i=1}^{N} D_i, \quad D_i = \begin{cases} 
1 & \text{if } y^1_i \geq y^0_i \\
0 & \text{if } y^1_i < y^0_i
\end{cases} \quad (1)
\]

Where \(A(y^0, y^1)\) expresses the ratio of children in income vector \(y^1 = \{y^1_1, y^1_2, y^1_3, \ldots y^1_N\}\) with a higher income than their parents expressed as an income vector \(y^0 = \{y^0_1, y^0_2, y^0_3, \ldots y^0_N\}\). For every child-parent pair \(i\) where child \(y^1_i\) earns more than his or her parent \(y^0_i\), the dummy variable \(D_i\) computes 1 and is 0 otherwise. These dichotomic values for all child-parent pairs are then summarized and divided by the number of child-parent pairs (N). Like in Chetty et al (2017), we use expression (1) for every birth cohort separately and then compare how the rate of absolute mobility changes over time by birth cohort.

2.2 Conceptualizing the mobility components

Having defined absolute mobility, we now outline the decomposition strategy. To explain the rate and trend in absolute mobility, a more detailed conceptualization of absolute mobility is necessary. Income mobility across a child-parent generation can occur in three different dimensions: (1) changes in the mean income, which we denote as the growth component, (2) changes in the shape of the income distribution, which we here denote as the dispersion component. These two are sometimes treated collectively as a single component denoted as the structure component (Markandya 1984; Ruiz-Castillo 2004), but similarly to Van Kerm (2004) we keep them as separated components, with the advantages of being able to draw inferences for the relative magnitude of each of these rather separate mechanisms. Finally, the last component, (3) the exchange component captures mobility between positions in the income rank order (relative mobility).
The decomposition seeks to gauge the marginal contribution to absolute mobility of each of these separate components. The decomposition is done by subsequently adding one component at a time using counterfactual simulations, the counterfactual being that all remaining components not yet added to the analysis are held constant. The marginal contribution of a component is thus defined as the change in absolute mobility when adding that specific component.

To illustrate and explain the intuition behind the three separate components of growth, dispersion and exchange, we use fictive income distributions for child- and parent generations as examples (previously done in Berman (2018)). Figure 1 below shows in grey the income distribution representing the income distribution of the parent’s generation of a child cohort, and the transparent distribution with blue frames represents the child cohort’s income distribution. In this example, every bin corresponds to one percentile in the distribution. Starting with the growth component, displayed in the upper section of Figure 1, the child income distribution is just a copy of the parent income distribution, but where we multiply all parent incomes by the cross generational growth rate (in this case, 1.5). As the upper section in Figure 1 shows, the shape of the income distribution is however unchanged. Thus, the purpose of the growth component is to capture the change in mean income across parent and child generations, and its implications for absolute mobility.

Figure 1. Illustration of the growth and dispersion component (inspired by Berman (2018)).

Next, we move to illustrate how changes in the distribution of incomes across generations affects absolute mobility, denoted as the dispersion component (Van Kerm 2014). The intuition behind this
component is illustrated at the bottom of Figure 1 using another hypothetical child income distribution where we increase the standard deviation of the child cohort’s income distribution. Again, each bin represents one percent of the income distribution. Compared to the parent income distribution where thinner bins are more concentrated around the mean of the distribution, the child distribution has wider bins less concentrated around the mean, but the mean income of both the parent and child distributions remains the same. Hence, while the growth component captures changes in mean income across parent- and child generations, the dispersion component captures changes in the shape of the distribution. In our hypothetical example, the income dispersion increases symmetrically from the mean, meaning that just as many moves upward as downward as a result of the increasing dispersion. However, increasing income dispersion can just as well result from just a small share of the population increasing their incomes while many are trailing behind. As Chetty et al (2017) notes, if all growth is captured by a single person, this will not generate any increase in absolute mobility.

Finally, the exchange component captures mobility in-between the ranks within the income distribution (Markandya 1984; Jäntti and Jenkins 2015). For intuition, we can think of the income distribution as a ladder where each step of the ladder represents a separate individual within the distribution. If there is no economic growth across generations, the ladder will neither move upward nor downward. If there are no changes in the dispersion component, the distance between the steps on the ladder remains the same across generations. This means that the relative positions of the steps are fixed and whether a child earns more or less than the parents will only be determined by upward or downward mobility in-between the steps. The purpose of the exchange component is thus to measure the effect that changes between the ranks within the income distribution across the parent and child generations has on absolute mobility. The specific interpretation of the exchange component is further discussed in detail in Section 2.4.

In addition to these three components, which are fairly standard in the literature, we argue that it is vital to also account for heterogeneity in the income distribution of the parental generation for measuring the effect that growth has on absolute mobility. To foreshadow our results, this additional component will be shown to exhibit a substantial effect on the marginal effect that growth has on both the rate and trend in absolute income.

2.3 The hitherto missing component: heterogeneity in parent income distribution across birth cohorts

In our analysis, the three standard mobility components for cross generational mobility described above is also supplemented with an additional component accounting for the shape of the parent
income distribution for different cohorts. The logic of this is straightforward: Consider two separate birth cohorts experiencing the same average income growth rate across generations, but no change in income dispersion. One could think this would always result in the same level of absolute mobility for the two cohorts. This is however not the case since the initial income distribution matters for the effect of growth on an absolute income measure, a stylized fact in the literature on growth and absolute poverty (see e.g. Ravallion and Huppi 1991; Datt and Ravallion 1992; Bourguignon 2003; Kalwij and Verschoor 2005). We apply this insight for absolute income mobility.

To illustrate this issue we show in Figure 2 two fictitious birth cohorts, one with low and another with high income dispersion in the parent generation (in the upper and lower section of Figure 2, respectively). In both cases, the child generation experiences identical average income growth compared to their parent’s generation, and the income distributions in terms of its shape are unchanged across the child and the parent generations. As illustrated, due to the fact that the income dispersion is higher for the parent generation in the lower part of Figure 2, the same increase in average income with income dispersion kept constant across generations results in the income distributions overlapping much more in the lower part of Figure 2, and consequently the probability of earning more than one’s parent is higher in the upper example of Figure 2. Thus, absolute mobility is higher when the parent income distribution is more compressed.

Figure 2. Illustration of the significance of heterogeneity of the parent distribution.

To make the issue of heterogeneity in parent income distribution across birth cohorts more intuitive, consider a country with very low income dispersion: In such a setting, it is of less importance if a
child’s parents are top earners but the child ends up receiving middle class incomes since with significant cross generational income growth, a mediocre paying job in the child’s generation can still yield higher real incomes than a high-incomes position a generation ago. In such a case, it is thus possible that the child experience upward absolute mobility (higher real incomes) but downward relative mobility (lower income rank in the income distribution). Consider instead a country with high income inequality in the parent distribution: In such a setting, the decline in incomes for someone who fails in getting a job about as good as their parents is much greater, which also means that mean income growth needs to be much higher to compensate for this in order to arrive at the same rate of absolute mobility. Heterogeneity in the parent income distribution therefore determines the effect that cross generational mean income growth has on absolute mobility.\(^2\)

When measuring the role of mean income growth in relation to absolute mobility, the growth component therefore has to be split into two separate sub-components where the first measures the effect that growth has on mobility when parent income distributions do not differ across birth cohorts (where we keep parent income distributions homogeneous across birth cohorts). By doing so, the effect that growth has on absolute mobility across cohorts will not be affected by heterogeneity in the parent income distributions, we denote this as the growth component using homogeneous parent income distributions. The second growth component then measures the effect that growth has on absolute mobility when using the factually observed parent income distributions, which we denote as the growth component using observed parent income distributions. The difference in absolute mobility between using homogeneous compared to observed income distributions therefore gives us info on how much absolute mobility we get from a certain level of growth.

### 2.4 Interpreting the exchange component

While section 2.2 briefly explained the exchange component, some elaboration is needed to derive an expression for how to decompose the exchange component’s marginal contribution to absolute mobility. To interpret how the exchange component relates to absolute mobility, we will relate our measurement for absolute mobility used in this paper with the rich literature of relative income mobility. The canonical measurement for relative mobility is that of intergenerational income elasticity, which is estimated using the following regression:

\[
\ln y^1_i = \alpha + \beta \ln y^0_i + \varepsilon \quad (2)
\]

\(^2\) Conversely, with negative income growth across generation, a higher level of income inequality in the parent generation actually increases absolute mobility compared to if income inequality in the parent generation was lower. This is because if the parent and child income distributions overlap more there is a chance to earn more than one’s parents with upward exchanges within income distribution while if the income distributions do not overlap at all, everyone would earn less than their parents.
where $y^1_i$ denotes a child income variable and $y^0_i$ denotes a parent income variable. The term $\beta$ is 
the correlation between children’s and parent’s income. Thus, $\beta$ measures to what degree relative income positions 
are inherited across generations, and therefore measures income immobility, and $1-\beta$ will consequently be a measure of income mobility. The parameter $\alpha$ captures the trend in average income across generations (Solon, 1999). Since both income variables are logged, we can interpret $\beta$ as the elasticity between parent income on child income. If $\beta=1$, it means that all relative positions in the income distribution will be inherited across a generation, and if $\beta=0$, it implies that the children’s relative positions are completely random in relation to the income of the parents.

One can easily make the mistake of assuming that relative mobility co-varies with absolute mobility. If there is substantial amount of mobility within the income rank order across generations, this indicates that individuals generally start with a level playing field and have great chances of increasing their incomes regardless of the income and wealth of one’s parents. However, on an aggregate level, relative mobility and absolute mobility in fact exhibit an inverted relationship (Berman 2018). To explain this, we can go back to the example of $\beta=1$ which implies that all positions in the income rank order are inherited. We can then (by definition) conclude that there is no relative mobility, and thus no upward exchanges in the income rank order. However, this also means that there are no downward exchanges either. It thus only takes non-negative income growth in order for absolute mobility to be 100 percent, indicating that everyone in the child generation is having a higher income than their parents.

Turning to the case of $\beta=0$ when relative mobility is very high, the expected absolute mobility is higher for individuals in the child cohort with parents at a lower rank in the income pecking order, and lower for individuals in the child cohort with parents higher in the income rank order. Because $\beta=0$ implies that there is no correlation between parent and child income, i.e. complete randomness as to where the children end up in the income distribution, this means that it is more likely for children in the bottom (top) of the income distribution to improve (worsen) their income rank. Because of this, we will have a substantial number of individuals born rich that will earn less that their parents because of downward relative mobility. The children born poor of course benefit if relative mobility is high since it increases the probability of upward mobility. However, these children would already have experienced upward mobility had they retained their parent’s relative income positions, given our assumption of some amount of income growth across generations. This implies that, given any rate of non-negative growth (proportionally distributed across the income distribution), aggregate absolute mobility is higher when relative mobility is lower (Berman 2018).
This interpretative insight of when $\beta=0$ gives us a reference point for measuring the contribution of the exchange component on absolute mobility compared to when holding the exchange component constant. We can define the marginal contribution of the exchange component on absolute mobility as the change in absolute mobility when moving from a counterfactual scenario where exchanges are completely random, i.e. $\beta=0$, to the actual exchanges taking place across the parent and child generation.\(^3\)

2.5 Decomposition sequence

In decomposition analysis, recall that the marginal contribution of a component on absolute mobility is defined as the change in absolute mobility when adding each respective component, while holding all other components constant. Such decompositions require a starting point to be used as a benchmark when subsequently measuring the contribution of each separate component. In our analysis, we choose this benchmark to be a counterfactual scenario of when the marginal contribution of all components is zero. That is, when the mean income across generations is unchanged (no growth component), the shape of the income distribution is unchanged (no dispersion component) and exchanges are completely random (i.e. $\beta=0$). In this counterfactual scenario, absolute mobility will be around 50 percent. To explain why, one can again use the analogy of the income distribution as a ladder where each step represents an individual in the income distribution. Our counterfactual scenario thus implies that absolute mobility is only determined by random up or downward movements between the steps. When using large population data, the probability of an individual attaining the same rank as their parent in the income distribution is very low, and because no position on the ladder can be left vacant, each upward movement will always have to be replaced by at least one downward movement. In a sufficiently large population, therefore, about half will move upward and about half will move down (attaining the value of 1 and 0 for the mobility dummy, respectively). The expected absolute mobility when removing all components is thus about 50 percent, which also makes this a suitable benchmark for the decomposition. The marginal contribution of the first added component will thus be calculated by subtracting 50 percent from the level of absolute mobility measured after adding the first component.

As Van Kerm (2004) notes, it matters in which sequence one introduces each component. This is even more so in the case when using a dichotomic mobility measure as the one used in this paper. Section 2.4 showed that the exchange component is sensitive to whether there is growth or not in the economy. If there is no growth or no change in the shape of the income distribution

\(^3\) A strength using this approach is that we also capture non-linearities of $\beta$, which has been shown to be the case of Sweden (Björklund et al 2012).
across generations, absolute mobility will be around 50% due to exchanges between the income ranks.\(^4\) This has two consequences for the decomposition. First, the exchange component only makes sense if added after the growth and dispersion components (and as previously noted, will initially be set to \(\beta=0\)). Second, the marginal effect of the exchange component depends on both the growth and dispersion components. If there is no cross generational change in the income distribution, absolute mobility will be around 50% both before and after the exchange component is added. We will therefore add the exchange component last.

The marginal contribution of the dispersion component to absolute mobility is also dependent on the cross generational growth and should therefore be added after the growth component. To see why, consider the example of a birth cohort in which the mean income growth across generation is being unequally distributed, but the whole income distribution is enjoying income growth to some extent.\(^5\) In this scenario, despite increasing income inequality, all percentiles within the child distribution will experience higher real incomes than in the parent generation. Thus, in this scenario, children need only keep the same rank position in the income order as their parents in order to enjoy upward absolute mobility.

If we assume another birth cohort for which the same exact change in relative incomes occurs as in the first example, but there is no mean income growth across generations,\(^6\) parts of the income distribution will now not only be worse off in relative but also in absolute terms. Consequently, and unlike in the first scenario, this would mean that children would be experiencing downward absolute mobility, even if they are not downward mobile in terms their attained rank in the income distribution. Two identical changes in the shape of the income distribution across generations thus generate different changes to absolute mobility because of different levels of mean income growth.

This is not necessarily a weakness of the decomposition strategy; the dispersion component is successfully capturing the change in absolute mobility caused by cross generational changes to the shape of income distribution. However, one should keep in mind that the dispersion component is not merely a function of the cross generational change in the income distribution, but also depends on the mean income growth since we add the dispersion component after the growth component.

2.6 Computing each step of the decomposition

Now that we have (1) conceptualized the components used in the decomposition analysis, (2) highlighted the importance of taking into account heterogeneity in the parent cohorts, (3)

\(^4\) As Hayek (2011 [1960]) noted, in a stagnant society “there will be about as many who will be descending as there will be those rising” (p. 95-96)

\(^5\) Implying a downward shift in the Lorenz curve.

\(^6\) That is, an identical shift in the Lorenz curve as in the first example.
identified the starting point of 50 percent as a base level for absolute mobility across generations, and (4) outlined the decomposition sequence, we can formulate the full decomposition strategy and how to compute each step. The decomposition seeks to estimate how much each of our four components contributes to absolute mobility, and how this has changed over time. The decomposition takes place in four steps where each step constitutes a counterfactual simulation of a parent and child income vector on the basis of which we calculate the level of absolute mobility. Adding one component at a time allows us to compare the level of absolute mobility before and after adding each specific component, and we define the measured difference in mobility as the marginal contribution of each of these components. To estimate the effect of the growth component, we first generate fictive parent income vectors which are set to be the same for all birth cohorts. Using these, we then generate child income vectors by multiplying our parent income vectors with the cross generational growth rate (defined as the ratio between the mean of the factual parent income vector and the mean of the factual child income vector). Since heterogeneity in the parent vectors across birth cohorts determines the effect on absolute mobility for a certain amount of cross generational economic growth, generating fictive parent vectors that are set to be identical for all birth cohorts can in a first step remove this effect. The first step thus gives us the marginal effect that average income growth has on absolute mobility under the assumption that parent and child income vectors are ‘homogeneous’ for all birth cohorts.

To compute this, we use a randomly generated fictive vector \( y^c \) that takes the form of a normal distribution \( N(\mu, \sigma^2) \) with the characteristics \( \mu = 15 \) and \( \sigma = 7.5 \). We apply the growth component by multiplying \( y^c \) with the mean income ratio of the observed parent vector and child vectors, where \( \mu^1 \) denotes the mean of the observed child vector \( y^1 \), and \( \mu^0 \) denotes the mean of the observed parent income vector \( y^0 \). The expression \( \frac{\mu^1}{\mu^0} \) thus gives us the cross generational mean income ratio. This vector is then compared to another randomly generated vector, \( y^b \), with the same specifics \( (\mu = 15 \text{ and } \sigma = 7.5) \), but which we do not multiply with the cross generational growth rate. Because both \( y^b \) and \( y^c \) will be the same for all birth cohorts, differences in absolute mobility across birth cohorts at this stage of the decomposition will only be determined by the mean income ratio across the child and parent income vectors, expressed as:

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7 ‘Income vector’ being a marginal income distribution where every integer is the income of an individual. We consistently use the term ‘income vectors’ in technical sections 2.6 and 2.7, but income distributions in other parts of the paper to ease interpretation.
\[
\overline{G}(y^B, y^A) = \frac{1}{N} \sum_{i=1}^{N} D_i, \quad D_i = \begin{cases} 
1 & \text{if } \left( \frac{\mu_1^i \cdot y^c_i}{y^A} \right) \geq y^B_i \\
0 & \text{if } \left( \frac{\mu_1^i \cdot y^c_i}{y^A} \right) < y^B_i 
\end{cases} 
\] 

(3)

where \(\overline{G}(y^B, y^A)\) is the share of children that earn more than their parents if we just apply the growth component. For every instance where \(y^A\) is equal or larger than \(y^B\) we get \(D_i = 1\), otherwise \(D_i = 0\). When summarizing all \(D_i\) and dividing with the number of child parent pairs \(N\), we get the counterfactual level of absolute mobility, \(\overline{G}(y^B, y^A)\).

In the second step of the decomposition we allow for heterogeneity in the parent income vector. We will therefore generate child income vectors by multiplying the observed parent income vectors with the cross generational growth rate, with a similar expression as that in the first step:

\[
\hat{G}(y^0, y^A) = \frac{1}{N} \sum_{i=1}^{N} D_i, \quad D_i = \begin{cases} 
1 & \text{if } \left( \frac{\mu_1^i \cdot y^D_i}{y^A} \right) \geq y^0_i \\
0 & \text{if } \left( \frac{\mu_1^i \cdot y^D_i}{y^A} \right) < y^0_i 
\end{cases} 
\] 

(4)

Where \(y^0\) is the observed parent vector. Hence, we use the observed income distributions for each birth cohort. Vector \(y^A\), as before, is a counterfactual child income vector constructed from multiplying \(y^D\), a replica of \(y^0\) but with all relative income positions randomly reordered. The dummy \(D_i\) captures the aggregated average of absolute mobility under the counterfactual scenario of applying the growth component to the observed parent vectors, denoted as \(\hat{G}(y^0, y^A)\). The expression \(\hat{G}(y^0, y^A)\) thus allows us to estimate the effect of growth on absolute mobility while also taking account of heterogeneity in the parent income distributions across birth cohorts. In both the first and second stage of the decomposition we leave the shape of the income distribution unchanged across generations. Comparing absolute mobility under the different assumptions
regarding the parent income distribution, these first two steps of the decomposition together allows us to isolate and estimate the growth component.

In the third stage we study the effect of the dispersion component by comparing the observed parent income vector $y^0$ to a replica of the observed child income vector, but all relative income positions randomly reordered, expressed as $y^A$. This allows us to study how the shape of the income distribution changes across generations:

$$D(y^0, y^A) = \frac{1}{N} \sum_{i=1}^{N} D_i, \quad D_i = \begin{cases} 1 \text{ if } y^A_i \geq y^0_i \\ 0 \text{ if } y^A_i < y^0_i \end{cases} \quad (5).$$

Until now we have assumed all relative income positions between parent and child, i.e. their positions in terms of income rank, as randomly generated ($\beta=0$). The fourth and final stage of the decomposition relaxes this assumption to examine the effect of the exchange component by using the observed cross generational exchanges of relative income positions. Because the exchange component is the only remaining component, we arrive at the measured level of absolute mobility $A(y^0, y^1)$. Absolute mobility when adding the exchange component, denoted as $E(y^0, y^1)$, can thus be expressed simply as $E(y^0, y^1) = A(y^0, y^1)$. As shown in the section 2.7 below, the marginal contribution of the exchange component is calculated as the residual between $A(y^0, y^1)$ and the absolute mobility obtained when we added the previous component (the dispersion component).

### 2.7 Measuring the marginal contribution of each component

The above steps outline how to compute the counterfactual level of absolute mobility by adding one component at the time, starting with the growth component, using homogeneous income vectors, and finishing with the exchange component. Our next step is to use the counterfactually generated levels of absolute mobility to calculate the marginal contribution of each component. The marginal contribution of a component is measured as the change in absolute mobility when adding that component. As noted, we use 50 percent absolute mobility as the starting point of the decomposition. To measure the marginal contribution of the first added component, i.e. the growth component when using homogeneous parent income vectors (denoted as $\Delta \tilde{G}$), we subtract 50% from the level of absolute mobility we arrive at when computing (3), i.e. the expression $\tilde{G}(y^B, y^A)$, : 

$$\Delta \tilde{G} = \tilde{G}(y^B, y^A) - 50\% \quad (6)$$
For the remaining components, the marginal contribution to absolute mobility is measured as the level of absolute mobility when adding each additional component, subtracted by the level of absolute mobility for the previous step in the decomposition. Moving to the marginal contribution of the growth component when using observed income vectors, we obtain the expression:

$$\Delta \bar{G} = \bar{G}(y^0, y^A) - \bar{G}(y^B, y^A)$$  \hspace{1cm} (7)

Thus, $\Delta \bar{G}$ measures the difference in absolute mobility when using homogeneous and observed parent income distributions. One could argue that while using homogeneous parent income distributions helped making the growth component comparable across birth cohorts, it also might make the interpretation of how much growth actually contributes to absolute mobility more difficult. However, one could simply add the growth component together into the combined growth component to get a sense of how much growth in total contributes to absolute mobility.

$$\Delta \bar{G} + \Delta \tilde{G}$$  \hspace{1cm} (8)

This gives the same value as if we skip the first step of when using homogeneous income distributions.\(^8\) The combined marginal contribution, and the subsequent steps in the decomposition are therefore not affected by the fact that we in the first step use an arbitrarily chosen income distribution on which we apply the cross generational mean income growth.

To calculate the marginal contribution of the dispersion component we use the expression:

$$\Delta D = D(y^0, y^A) - \bar{G}(y^0, y^A)$$  \hspace{1cm} (9),

where $\Delta D$ is the marginal contribution of the dispersion component. Finally, to calculate the marginal contribution of the exchange component, we use the formula:

$$\Delta E = E(y^0, y^1) - D(y^0, y^A)$$  \hspace{1cm} (10)

---

\(^8\) This can be showed by first rearranging the expression 7 into $\bar{G}(y^B, y^A) = \Delta \bar{G} + 50\%$, and then plug the right hand side into expression 8, which gives us $\Delta \tilde{G} = \bar{G}(y^0, y^A) - \Delta \bar{G} + 50\%$. We can then rearrange this into $\bar{G}(y^0, y^A) - 50\% = \Delta \bar{G} + \Delta \tilde{G}$. This shows that the combined marginal contribution of the growth components is the same as if we skipped the first step of the decomposition of using homogeneous income vectors, and thus if $\Delta \tilde{G}$ was the first step in the decomposition.
where $\Delta E$ is the marginal contribution of the exchange component. The final decomposition of the observed measured level of absolute mobility is therefore:

$$A(y^0, y^1) = 50\% + \Delta G + \Delta \hat{G} + \Delta D + \Delta E$$ (11)

3.0 Data

All data used for this paper are from Statistics Sweden, delivered through Microdata Online Access (MONA). Since we want to connect individuals within cohorts to their respective parents, we use the Swedish Multi-Generation Register (Flergenerationsregistret), covering all individuals registered as living in Sweden anytime since 1961 and who are born 1932 or later (Statistics Sweden 2011). Data on lifetime income comes from Statistics Sweden’s income and tax register (“Inkomst- och taxeringsregistret”) for the years 1968 and 1989, and from the “Longitudinal integration database for health insurance and labour market studies” (LISA) for the years 1990 to 2012.

Since we ultimately want to estimate the number of individuals within a birth cohort that are better off in terms of living standard as compared to their parents, we need to clarify what we mean by being “better off”. Income and living standards can be measured in a number of ways, e.g. at the individual or household level, before or after taxes and government transfers, including or excluding capital income. The combined datasets for the income and tax statistics 1968 - 1989 and LISA 1990-2012 make all these considerations possible, however, not for as long a time period as is required for an intergenerational analysis. The earliest high-quality measure available for the full population, which we use in the study, is ‘Gross total earnings, available from 1968. This measure is defined as individual level pre-tax earnings, including taxable benefits such as unemployment assistance and pensions. Incomes from abroad and non-taxable social benefits are however not available until later years and are therefore not included. Since we measure incomes as earnings, we will refer to earnings when referring directly to the empirical data. However, we will refer to incomes when using theoretical concepts retrieved from the methodology section or retrieved from previous literature.

Since we want to compare child cohorts and their parent’s lifetime income, we have to consider how to define lifetime income. Ideally, one would use actual lifetime income (Grätz och Kolk 2019). Working age is usually defined as being in-between late adolescence to retirement age, but is rarely used in estimation due to data limitations. Another approach – predominating in the literature on intergenerational mobility – is to pick a few years that work reasonably well as a proxy for lifetime income. The literature on relative income mobility suggests that life time income is often
under-estimated if we base this proxy estimate on income from individuals in their late twenties as compared to their late thirties (Solon 1999; Chetty 2017), and that the years on which we base this proxy should be chosen from a mid-career time span as opposed to early on. Using American data, Haider and Solon (2006) test empirically which ages that best correspond to lifetime income and conclude that it “would be fairly well founded if sons’ incomes were measured between the early thirties and mid-forties” (p. 1317). This study is replicated by Böhlmark and Lindquist (2006) on Swedish data, yielding similar results with current income for men at early to mid-thirties corresponding well to their subsequent lifetime income, and for women shortly before and shortly after that of men depending on birth cohort. On this basis, a suitable ideal proxy for lifetime income using Swedish data would thus be in the age span around 30-36.

Using such a wide age span as a basis for a lifetime income proxy, however, poses another challenge, since the older the age of proxy lifetime income we choose, the fewer the cohorts we are able to study.9 Because the main purpose of this study is to compare absolute mobility over time, and we therefore want to include as many birth cohorts as possible, we choose a somewhat shorter age span of 30 to 32 as proxy for lifetime income (i.e. the average of an individuals’ income at age 30, 31 and 32).10 Since we have income data until 2012, this allows for using 1980 as the last possible child cohort to include in the study.

The literature on relative income mobility has shown that choosing just a single year as proxy income is likely to bias the results since a single income year will be a more ‘noisy’ sample (Solon 1999). We therefore take an average of an individuals’ earnings at age 30, 31 and 32 to create our earnings variable.

We analyse men and women separately. However, because married women’s labour-force participation rates have generally been lower than men's, the literature on intergenerational income mobility has considered women’s earnings as a more unreliable proxy of their economic status (Chadwick and Solon 2002). Different approaches have therefore been used as whether to measure daughter’s economic background either as the father’s income (as is done by Dearden et al 1997; Peters 1992) or family income (as is done in e.g Chadwick and Solon 2002; Chetty et al 2014 and Chetty et al 2017). Österberg (2000) measures income mobility both comparing daughters’ earnings against mothers’, as well as daughters’ against fathers’. We therefore measure absolute mobility both comparing daughters’ earnings against mothers’, and alternatively as daughters’ earnings against fathers’. The decomposition is however best performed on daughter-mother pairs. This is because

---

9 If we for example choose 36 as the proxy for lifetime income, the last possible cohort we can study is 1976, since 2012 is the last year for which we have data on (2012 – 36 = 1976). If we change the lifetime proxy to 35, it would allow us to study 1977 as the last possible birth cohort (2012 – 35 = 1977).

10 In robustness tests reported in section 2.3, we alternatively define lifetime income as the mean earning at age 30 to 34 and 30 to 36. This did not radically affect any of the main results.
the decomposition rests on the assumption that if the components are constant across parent-child generation, the income distribution is unchanged and absolute mobility is 50 percent. However, if we decomposed daughter-father, this assumption will not hold as the father generation does not represent a fully comparable group one generation earlier.

Preferably, a consistent sample concerning parent’s age at childbirth should be used, however that would entail abandoning a population level approach. That is, we want to avoid using child cohorts that only include parents whom had children at a certain age, for example at age 18. This would be the case if we chose birth year 1956 as our first child cohort since a parent that had children at aged 19 (or older) would turn 30 in 1967 (or earlier), preceding the first year for which we have income data. Taking this into consideration, the parent age of birth span chosen is 18 to 32. This means that the first birth cohort studied will be those who are born in 1970.

Since we study daughters-mothers and sons-fathers separately, our age of birth restrictions will not cause attrition from large age differences between spouses. Even if we ensure that the sample is consistent across all birth cohorts regarding age of birth span, it is however possible that the distribution of parent age of birth might differ across cohorts. For simplicity in handling the data, adopted children have been excluded. Because nominal gross total earnings is used to measure earnings in the raw data, we also deflate the nominal prices to real prices using 2010 as base year.

Individuals with no taxable income will be counted as having zero income in the data. This would for example apply for students only living on untaxed benefits. Nybom (2011) solves this by removing observations that has not had a taxable income for at least 10 years. A similar solution is done in this paper by removing all zero-income for the studied lifetime income age span. This means that in the baseline model, all individuals that have zero-recorded incomes for all years between 30 to 32 years are removed.

3.1 Descriptive data:
Table 1 below displays descriptive data for key variables in the studied birth cohorts. The number of father-son pairs (shown in Table 1, column 2) and daughter-mother pairs (shown in Table 1, column 10) studied constitute more than half of all registered births in Sweden within a cohort (see Table A8 in the appendix). As the dataset includes over half of all individuals born each year, the estimated level of absolute mobility should well reflect the actual level of mobility as long as there are no

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11 When only including parents whose age of birth was between 18 to 32 in our analysis, the mean age of mothers giving birth to a daughter increases from 24.7 to 27.3 between the 1970 and the 1980 birth cohorts, and from 26.5 to 28.0 for fathers having a son.

12 To somewhat take this into consideration, as a robust test, we also measure mobility including individuals with zero earnings (see Appendix Figure 10 and 11).
biases in the data that cannot be accounted for. To address potential attrition bias following these limitations we perform a number of robustness tests, see appendix 7.2.

To provide a more intuitive understanding of the growth-, dispersion- and exchange components, we highlight separately how real mean earnings has developed over time, as well as report the Gini coefficients and intergenerational income elasticities for every birth cohort and their respective parent generation.

Starting with earnings growth, the mean yearly earnings (in 100s of Swedish SEK) for son birth cohorts increases continuously (column 3) for every birth cohort born 1970 to 1980, while the mean father earnings remains stagnant (column 4). The son-father mean earnings ratio thus increases from 1.16 to 1.41 between birth cohorts 1970 and 1980 (column 5). This means that the average earnings of sons was 16 percent higher between age 30 to 32 than their parents was at the same age for the 1970 birth cohorts, and 41 percent higher for the 1980 birth cohort. This increase of the cross generational growth is likely due to the fact that Swedish average real wages stagnated between 1979 and 1995, while increasing again thereafter (Aaberge 2018). This means that later birth cohorts enjoyed more years of increasing real wages (before turning 30) and fewer years of when real wages were stagnant, compared to earlier birth cohorts.

The mean yearly earnings for daughter birth cohorts increase continuously for every cohort from 1,707 to 2,101 hundred SEK for birth cohorts born 1970 to 1980. However, the trend among mothers also increased (contrary to the developments of fathers’ earnings that), from 982 to 1209 hundred SEK for the same birth cohorts (column 13). The mean income ratio (or cross generational income growth) for daughter-mother pairs is therefore stable throughout the time period, at or above 1.7. This means that daughters earned on average around 70 percent more at age 30 to 32 than their mothers did at the same age, in all birth cohorts. Since the cross generational earnings growth was higher for women than men cohorts, it implies that the growth component should contribute more to absolute mobility for all daughter cohorts compared to sons cohorts, but since the trend across cohorts was stable for all women cohorts while increasing for men, it implies a increasing trend in the growth component for men, while remaining stable for women.

Table 1 also shows values for the Gini coefficient to ease interpretation of the dispersion component. Columns 6 and 7 shows the Gini coefficient for sons and fathers respectively, revealing that earnings dispersion decreased somewhat, from 25.4 for the 1970 sons’ birth cohorts to 23.5 for the 1980 birth cohort, while remaining stable for their fathers. The Gini coefficient is however higher for all child cohorts compared to their fathers’ generations. A similar decline in the Gini coefficient for the corresponding male birth cohorts was also observed in Brandén (2017). For women, column 16 in Table 1 shows a decline in the Gini coefficient from 33.4 for the 1970
daughter birth cohort to 29.1 for the 1980 cohort. However, the decline is even sharper among mothers, decreasing from 40.3 to 28.9 between mothers for birth cohorts born 1970 and 1980 (column 17).

To ease interpretation of the exchange component, we report intergenerational earning elasticities, denoted as $\beta$ in Table 1, in column 9 for men and column 18 for women. As expected, the $\beta$-value is higher for men than women, but decreasing from 0.248 to 0.170 for men, and increasing from 0.019 to 0.067 for women. The increasing rate in relative mobility for men corresponds to findings in Brandén (2017) and the lower value for women is similar to those shown by Österberg (2000). These figures implies that the exchange component should have a larger positive marginal contribution to absolute mobility for men than women, all else being equal.
Table 1. Descriptive statistics per birth cohort. Yearly Earnings calculated as 100 SEK and inflation adjusted with 2010 as base year

<table>
<thead>
<tr>
<th>Cohort Birth Year</th>
<th>Number of observations</th>
<th>Sons' Mean Earnings</th>
<th>Fathers' Mean Earnings</th>
<th>Mean Sons' Fathers' Earnings Ratio</th>
<th>Median Sons' Fathers' Earnings Ratio</th>
<th>Sons' Gini Coefficient</th>
<th>Fathers' Gini Coefficient</th>
<th>Sons' relative mobility (ß)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td></td>
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<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
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<tr>
<td>1970</td>
<td>35,813</td>
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<td>1.18</td>
<td>25.4</td>
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<td>2,388</td>
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<td>18.7</td>
<td>0.226</td>
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<td>1.18</td>
<td>25.3</td>
<td>18.7</td>
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<td>1.24</td>
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<td>2,269</td>
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<td>1.31</td>
<td>23.8</td>
<td>18.3</td>
<td>0.207</td>
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<td>30,691</td>
<td>2,959</td>
<td>2,241</td>
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<td>1.34</td>
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<td>0.190</td>
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<td>1.37</td>
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<td>1.39</td>
<td>23.7</td>
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<td>23.5</td>
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<table>
<thead>
<tr>
<th>Cohort Birth Year</th>
<th>Number of observations</th>
<th>Daughters' Mean Earnings</th>
<th>Mothers' Mean Earnings</th>
<th>Mean Daughters' Mothers' Earnings Ratio</th>
<th>Median Daughters' Mothers' Earnings Ratio</th>
<th>Daughters' Gini Coefficient</th>
<th>Mothers' Gini Coefficient</th>
<th>Daughters' relative mobility (ß)</th>
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<tr>
<td>1970</td>
<td>33,540</td>
<td>1,707</td>
<td>982</td>
<td>1.74</td>
<td>1.77</td>
<td>33.4</td>
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<td>36,806</td>
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<td>998</td>
<td>1.74</td>
<td>1.76</td>
<td>33.2</td>
<td>39.6</td>
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<td>33.1</td>
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<td>1,059</td>
<td>1.72</td>
<td>1.71</td>
<td>32.4</td>
<td>36.6</td>
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<tr>
<td>1975</td>
<td>36,950</td>
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<td>1,077</td>
<td>1.74</td>
<td>1.73</td>
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<td>1,111</td>
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<td>34.1</td>
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<td>32.8</td>
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<td>30.1</td>
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<tr>
<td>1979</td>
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<td>1,184</td>
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<td>1.71</td>
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<tr>
<td>1980</td>
<td>26,954</td>
<td>2,101</td>
<td>1,209</td>
<td>1.74</td>
<td>1.71</td>
<td>29.1</td>
<td>28.9</td>
<td>0.067</td>
</tr>
</tbody>
</table>
4.0 Results

4.1 Absolute mobility in the benchmark model

Our goals are to (i) measure the level of absolute mobility in Sweden and how this level has evolved over time, and (ii) gauge what explain this level and trend using our decomposition strategy outlined above. We start by addressing the first of these two questions. The dashed line in Figure 3 shows the baseline estimates for intergenerational absolute mobility of men for all birth cohorts born from 1970 to 1980. Interestingly, absolute mobility increases from 64% to 77% for these birth cohorts. The dotted line in Figure 3 below shows the baseline estimates for absolute mobility of women, for which we can notice an upward trend from 72% to 77% earning more than their mothers. Recall that the expected level of absolute mobility when holding all components constant is 50%. The absolute mobility for the 1980 cohort of 77% for both men and women can from this point of view be regarded as rather high.

Despite the caveat that the income data does not automatically translate across countries, and the fact that our empirical strategy deviates somewhat from that of Chetty et al (2017), it is still noteworthy that these results suggest that absolute mobility in Sweden has been higher and the trend more positive, compared to the US where absolute mobility decreased markedly during the same time period (Chetty et al 2017).13

Noteworthy in Figure 3 is also that gender differences in absolute mobility has converged over time, with a slightly more positive trend for women than for men, resulting in absolute mobility being all but identical for men and women in the 1980 birth cohort. In our decomposition analysis, we address the underlying causes for these converging trends.

Since it could be argued that the earnings of mothers is an unreliable measurement for one’s economic status, the solid black line in Figure 3 also report absolute mobility for women when comparing daughters earnings to fathers (instead as compared to their mothers). Women’s absolute mobility measured in this way increases from 27% to 45% between the 1970 and 1980 cohorts. This highlight considerable progress of women in the labour market happen during the studied birth cohorts.

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13 One should note that absolute mobility for the US 1940s birth cohorts was over 90%, before the sharp decline in the 50s and 60s. This is substantially higher than for the Swedish 1970 birth cohorts in this paper. If Sweden had a similar decline in absolute mobility in the immediate post-war era as the US, or if Sweden had a more constant trend could unfortunately not be answered in this data. The simulations in Berman (2018) suggest that Sweden also experienced a similar inverted U-shaped curve as the US in absolute mobility. Still, bearing all this in mind, it seems that out of Sweden, Canada and the US, the last stands out in having this contrary sharp decline in absolute mobility for 1970 birth cohorts, while Sweden and Canada have had an increasing trend in absolute mobility.
Figure 3. Absolute mobility for men and women by birth cohort.

4.2 Decomposition results

The benchmark estimates in the previous section provided an overview of the level of absolute mobility for men and women in Sweden. In the next step we use our decomposition model to gauge how much each separate component has contributed to these observed levels.

Results are shown graphically in Figures 5A and 5B. The figure should be interpreted as follows: Since the starting point of the decomposition is an absolute mobility of 50 percent, we add up all components that have a positive contribution to mobility above the 50 percent absolute mobility line, while all components that have a negative contribution are placed below.\(^{14}\) The black squared dots show the measured level of absolute mobility from the benchmark model.\(^{15}\) Remember that the marginal contribution of a component should be interpreted as to what extent that component increases or decreases the percentage of a birth cohort earning more than their parents, with the marginal contribution measured as changes in percentage points.

\(^{14}\) Appendix Tables 3 and 4 show exact estimates for the mobility decomposition for men and women, respectively.

\(^{15}\) The decomposition can be calibrated against the estimated absolute mobility by adding all components; 

\[ A(y^6, y^7) = 50\% + \Delta \bar{G} + \Delta G + \Delta D + \Delta E \] 

(as shown in equation 12).
Figure 5. Per component marginal contribution to absolute mobility for men (A) and women (B).

Note: Since absolute mobility is expected to be 50 percent when all components are held constant across generations, we stack all the components that have a positive contribution to mobility over the 50 percent and the components that have a negative contribution to absolute mobility is added below the 50 percent line.
As seen in Figure 5, the growth component is highlighted as being the most important factor for absolute mobility, for both men and women. The growth component measures the change in absolute mobility from the benchmark level of 50 percent when we simulate an equally distributed earnings growth on the parent income distribution.\(^\text{16}\)

The blue coloured bars show the growth component when applying the cross generational mean earnings growth on homogeneous parent income distributions ($\Delta \bar{G}$), and the red bars on the observed income distributions ($\Delta \bar{G}$). Remember that estimates based on homogeneous parent income distributions means that the effect of growth on absolute mobility cannot be affected by heterogeneity in the parent income distributions. Thus, the different levels of $\Delta \bar{G}$ that we see in figure 5A and 5B across men and women, and across birth cohorts is only due to differences in the mean earnings growth across generations. For the 1970 male birth cohort in Figure 5A for which the mean earnings for sons is 16 percent higher than for their fathers, the marginal effect of the growth component using homogeneous parent income distributions ($\Delta \bar{G}$) is 9.1 percentage points. Since the earning dispersion for fathers of all birth cohorts is low, the level of absolute mobility increases by another 5.3 percentage points when applying the growth component when using the observed parent income distributions ($\Delta \bar{G}$). In other words, assuming homogeneous parent income distributions would cause us to underestimate the level of mobility by more than a third, highlighting the importance of taking cross-generational differences in income inequality into account when explaining differences in absolute income mobility across countries or time. If the difference between a high and a low paying job is lower in the father generation, less growth is needed for a relatively worse paying job in the father generation to be better payed in real terms a generation later.

For subsequent cohorts where the cross generational mean earnings growth is higher (42.5 percent for the 1980 birth cohort), the marginal contribution of the growth component is even more substantial: 18.8 percentage points in absolute mobility using homogeneous parent income distributions, and an additional 10.5 percentage points in absolute mobility when using the observed parent income distributions.

Women, in turn, exhibit stronger cross generational mean earnings growth of around 70 percent for all birth cohorts. This would suggest that the growth component should more important for explaining the level absolute mobility among women, compared to men. This is indeed what we see in the results of the decomposition models based on homogeneous income distributions,

\(^\text{16}\) Parent income distribution is measured in earnings, but we here use a terminology applicable for any income measure for the components in the decomposition. As earlier, we will use the term earnings when referring directly to the empirical data, but incomes when referring to theoretical concepts retrieved from the methodology section or from previous literature.
showed as blue bars in Figure 5B. The bars show a marginal contribution of growth for absolute mobility of around 27 percentage points for all daughter cohorts, substantially higher than for men. However, since earning dispersion is so high in the mothers’ earning distribution (especially for mothers to the 1970 daughter cohorts), the marginal effect of the growth component when using observed parent income distributions, shown as the red bars in Figure 5B, is in fact negative for all daughter birth cohorts. For example, for the 1970 daughter birth cohort, the marginal effect of the growth component when using observed parent income distributions is −9.2 percentage points, meaning that the growth component for this cohort increases absolute mobility by 18 percentage points in total $\Delta G + \Delta G = (27\% + (−9\%)) = 18\%$.\(^{17}\) Because the earning dispersion in the mother generations decreases continuously from the 1970 to the 1980 daughter birth cohorts (column 17 in Table 1), the negative contribution of the growth component when using observed income distributions diminishes. For the 1980 birth cohort, it is a mere −0.2 percentage points.

The dispersion component $(\Delta D)$ displayed as green bars in Figure 5A turns out to have a negative marginal effect on absolute mobility for all male cohorts. Remember that the dispersion component measures the effects on absolute mobility when moving from growth being equally distributed to how it actually is distributed. As noted in columns 6 and 7 of Table 1, the Gini coefficient for the 1970 (1980) birth cohort increased across generation to 25.4 (23.5) for sons compared to 18.7 (18.4) for their fathers. This increase in the Gini coefficient however only leads to a negative marginal effect of the dispersion component to absolute mobility of 2.3 (4.1) percentage points for the 1970 (1980) birth cohort. If all growth was captured by a single individual in the child distribution, absolute mobility would go all the way back to the benchmark level of 50%. Thus, while the potential marginal change of the dispersion component is vast, the result in this case suggest that moderate increasing income dispersion across generation only decreases absolute mobility by a few percent points.

For women we see that the dispersion component, displayed as green bars in Figure 5B, has a positive marginal contribution to absolute mobility of 3.9 percentage points for the 1970 birth cohort, and a negative contribution of -1.2 percentage points for the 1980 birth cohort. This is in line with the descriptive evidence in Table 1 where the Gini coefficient for the 1970 birth cohort was lower for daughters as compared to mothers.\(^{18}\) This means that rather than growth being distributed equally across generations, it has actually benefited the bottom parts of the earnings distribution more than the top parts. The positive effect of the dispersion component shows that this has positively contributed to absolute mobility: the number of daughters earning less than their

\(^{17}\) See equation 8 in section 2.7 for the interpretation of the combined growth component.

\(^{18}\) 0.334 among daughters and 0.403 among mothers.
mothers due a more equal distribution was fewer than the ones earning more than their mothers due a more equal distribution. In the 1980 birth cohort however, the Gini coefficient was almost unchanged across generations (from 28.9 for mothers to 29.1 for daughters), which of course means that the dispersion component only has a very small contribution to absolute mobility, at minus -1.2 percent.

Finally, the exchange component (Δ𝐸) is displayed as yellow bars in Figures 5A for men and in Figure 5B for women. Remember that the exchange component was measured as the change in absolute mobility when moving from exchanges being random (β=0), to the actual exchanges taking place across generations (which will be β>0). For men, the exchange component contributes 2.3 percentage points to absolute mobility for the 1970 birth cohort, and 1.8 percentage points for the 1980 birth cohort, while for women the equivalent number is 0.58 percent for the 1970 birth cohort, and 1.6 percentage points for the 1980 birth cohort. The marginal contribution being higher for men than women is in line with the descriptive evidence of relative mobility being higher for women than men (columns 9 and 18 Table 1). The results from estimating the exchange component thus confirms the conclusions in Berman’s (2018) simulations that relative mobility actually reduces absolute mobility when cross-generational growth is positive.\(^{19}\)

5.0. Concluding discussion

This paper examines intergenerational absolute mobility across generations using population data for all Swedish birth cohorts between 1970 and 1980, comparing their earnings in adult age and their parents’ earnings at the same age. Our results show that absolute mobility increases from 64 percent to 77 percent between cohorts born between 1970 to 1980 for men, and from 72 percent to 77 percent for women. In Sweden, absolute mobility has thus been slowly increasing for the cohorts for which earnings in adulthood are most recently available, and the rate of absolute mobility is also higher than what was recently documented for the US as well as for Canada for the corresponding birth cohorts.

Using a novel decomposition technique allows us to estimate how much of the rate and trend in absolute mobility is explained by the three components growth, dispersion and exchange. Furthermore, we demonstrate the importance of separating the growth component into two separate components. This is due to that the effect of mean income growth on the level of absolute

\(^{19}\) As discussed in section 2.4, this is due to when we move from β=0 to β>0, we will have less mobility in the income distribution, and thus less downward relative mobility. The children born poor would of course have benefited more from β=0 since that would have meant more upward relative mobility. However, since growth is positive, these children would have experienced upward mobility even if they just retained their parent’s relative income positions given that there has been income growth across generation.
mobility is not only a function of how much the mean income grows across generations. Importantly, it is also affected by the parent income distribution. If these two are not separated, two identical mean income growth rates could yield vastly different rates of absolute mobility unless differences in the parent income distributions are considered. This effect has previously been explored in research papers on growth and poverty reduction, but to our knowledge has not been previously accounted for in the literature on absolute mobility. If income inequality in the parent generation is high (low), more (less) growth is needed to ensure that those children that are downward mobile in relative terms compared to their parents still earn more than their parents in real terms.

Our empirically strategy exploits the fact that the mean earnings growth rate for the studied cohorts was higher for women than for men, but earnings dispersion was higher in the mother compared to the father generation due to fewer mothers working full time. This should lead to a given growth generating more absolute mobility for men than women, which is confirmed in the empirical results from the decomposition. For example, for the 1970 birth cohort, sons had on average only 16 percent higher real earnings than their fathers, while daughters had on average 71 percent higher real earnings than their mothers. If the mother and father income distributions were identical (homogeneous) we showed that these different cross generational growth rates should increase absolute mobility by 27 percent points for women and 9 percent. However, when taking into account the observed income distributions of mothers and fathers, this lowers the contribution of growth on absolute mobility to 21 percent for women, while increasing the contribution of growth on absolute mobility for men to 14 percent points. This shows the significance of the parent income distribution when decomposing how much growth contributes to absolute mobility. Future research should therefore take this into consideration when for example comparing absolute mobility across countries and time.

We also analyse the effect that the dispersion component, i.e the effect that cross generational changes of the income distribution, has on absolute mobility. This is done by measuring the change to absolute mobility when moving from when all growth is simulated to be distributed equally across the earnings distribution, to how it actually is distributed. The dispersion component showed that this would negatively contribute to absolute mobility for men, but positively for women. This was in line with the descriptive statistics showing that income dispersion increased across generation for men, but decreased for women. However, the effect is quite small, which suggest that the general trend of increasing income dispersion in Sweden since the 1980 has only to

20 For the last studied birth cohort (1980), the Gini coefficient was roughly the same for mothers and daughters, which meant only minor negative effect of the dispersion component.
a small degree affected absolute mobility negatively. However, if earnings dispersion increases for several generations, this will decrease absolute mobility not only through growth being less equally distributed (captured by the dispersion component) but also because the parent earnings distribution will be more dispersed, thus decreasing how much absolute mobility a given cross generational growth rate will generate (captured by heterogeneity in the parent income distribution). Future research should further study whether absolute mobility is more sensitive to cross generational changes in the income distribution or the parent income distribution.

Our decomposition analysis also suggests that the exchange component, i.e. the effect of individuals changing their relative position in the income distribution, has a small effect on aggregated absolute mobility (something that Berman (2019) has previously proven). Because lower levels of mobility in-between the ranks in the income distribution implies higher levels of absolute mobility, the small contribution of the exchange component that we observe in this study is partly due to the high rate of relative income mobility in Sweden. The small positive effect of lower relative mobility on absolute mobility is by far offset by the general positive contributions to economy and society that comes along with income mobility (see Hassler and Rodríguez Mora (2000)).

Finally, while it seems that the American Dream lives in Sweden, it is uncertain whether this will continue into the future, partly since per capita growth has stagnated, and partly due to increasing income dispersion. Because of the significance that the parent income distribution has on absolute mobility, the increasing income dispersion since the 1980 will likely come back and haunt future generation’s absolute mobility.

6.0 References


7.0 Appendix

7.1 Complementary tables

Table 2. Number of observations per birth cohort for men and women.

<table>
<thead>
<tr>
<th>Cohort Birthyear</th>
<th>All Men registered in Sweden by birth year</th>
<th>Among which included in dataset</th>
<th>Percentage of total included in dataset</th>
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<td>1970</td>
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### Table 3. Decomposing of absolute mobility for men.

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<tr>
<th>Cohort Birth Year</th>
<th>Cohort Absolute Mobility (A(y^0, y^1))</th>
<th>Absolute mobility when applying growth component with homogeneous parent distributions (\bar{G}(y^0, y^4))</th>
<th>Absolute mobility when applying growth component with observed parent distributions (\bar{G}(y^0, y^4))</th>
<th>Absolute mobility when applying dispersion component (D(y^c, y^1))</th>
<th>Absolute mobility when applying exchange component (E(y^0, y^1))</th>
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### Marginal effect per component for men

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<th>Cohort Birth Year</th>
<th>Marginal effect of Growth component with homogeneous parent distributions (\Delta \bar{G} = \bar{G}(y^0, y^4) - \bar{G}(y^0, y^4))</th>
<th>Marginal effect of growth component with observed parent distributions (\Delta \bar{G} = \bar{G}(y^0, y^4) - \bar{G}(y^0, y^4))</th>
<th>Marginal effect of Dispersion component (\Delta D = D(y^c, y^1) - \bar{G}(y^0, y^4))</th>
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Table 4. Decomposing of absolute mobility for women.

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<th>Absolute mobility when applying growth component with observed parent distributions $\bar{G}^*(y^0, y^1)$</th>
<th>Absolute mobility when applying dispersion component $D(y^c, y^1)$</th>
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Marginal effect per component for women

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<th>Marginal effect of growth component with observed parent distributions ($\Delta \bar{G} = \bar{G}(y^0, y^1) - \bar{G}(y^{b}, y^{a})$)</th>
<th>Marginal effect of Dispersion component ($\Delta D = D(y^c, y^1) - \bar{D}(y^b, y^a)$)</th>
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</table>
7.3 Robustness checks

To gauge if some of the restrictions in the dataset could bias the estimated level of absolute mobility, a number of robustness checks are conducted. As noted in the data description (section 3.0), when we either increase the age span serving as proxy for lifetime income, or increase the age of birth span, the number of cohorts possible to study decreases. Figure 4 shows the number of cohorts possible to study when adjusting for each of these circumstances.

First, to assess whether the relatively narrow age span of 30-32 could bias the estimated level of absolute mobility, we increase the age span from 30-32 (shown as the thin blue line) to 30-34 (shown as the dotted red line) and 30-36 (shown as the thick green line). The results for men are shown in Figure 6 below. When using the wider age span 30-36, absolute mobility increases marginally from 64.4 to 66.9 percent for the 1970 birth cohort, and from 73.1 to 76.7 for the 1980 birth cohort. The results for women (Figure 7) when using 30 to 36 as age span shows that absolute mobility increases from around 72.2 percent in our main estimates to 75.8 percent for the 1970 birth cohort, and from 75.9 to 83 percent for the 1980 birth cohort. It thus seems like the main models estimated underestimates absolute mobility by a few percentage points, especially for women. Since the trend and level does not deviate considerable, we can with fairly good precision use 30-32 as proxy for lifetime income, keeping in mind that this seems to yield fairly conservative estimates of absolute mobility.

We similarly estimate robustness checks to assess whether the estimated level of absolute mobility may be biased by the fact that we could only include child-parent pairs for parents aged between 18 and 32 at the time of the child’s birth Figures 8 and 9 show the estimated absolute mobility when we increase the parents’ age of birth span from 18-32 used in the main model (shown as thin blue lines in Figures 8 and 9) to 18-34 (dotted red lines) and 18-36 (thick green lines). The all
but uniform patterns of these lines suggests that only include child-parent pairs where parents are aged 18 and 32 at the time of the child’s birth yield consistent estimates to those also including older parents.

Next we examine whether the estimated level of absolute mobility is sensitive to the exclusion of individuals that did not have a taxable income for all three income years (i.e. having ‘zero income’). It is possible that cohort-specific differences in the unemployment rate or the number of students not having a taxable income could influence the results. Figures 10 (men) and 11 (women).

Again, we compare the estimated absolute mobility from the benchmark model shown as the blue dotted line with the estimated absolute mobility when keeping individuals with zero annual incomes shown as the red dashed line. For men, we see both the rate and the trend in absolute mobility are robust for when dropping zero income child-parent pairs. Absolute mobility decreases from to 64.4 to 62.1 percent when keeping zero incomes for the 1970 birth cohort, and from 76.9 to 72.6 for the 1980 birth cohort.

For women, we see that the trend is more stagnant instead of the slightly positive trend observed in the benchmark model when we remove individuals with no taxable income. Absolute mobility decreases from 71.9 to 72.3 when keeping zero incomes for the 1970 birth cohort but from 77.0 to 72.3 for the 1980 birth cohort. The trend in absolute mobility is therefore slightly biased upward if one would argue for keeping child-parent pairs for which either the parent of the child had zero incomes. On the other hand, remember that the trend in absolute mobility of the benchmark model is slightly biased downward as compared to when increasing the age span as proxy for lifetime income. The results suggest that the benchmark model can therefore generally be seen as robust, both for when adjusting the age span for lifetime income, as well as for age of birth and individuals with no taxable income.
Figure 6. Robustness check for controlling if the estimated absolute mobility for **men** is biased by the narrow age span of 30-32 used in the benchmark model.

![Graph showing mobility trends for men across different age spans.](image)

**Note:** We increase the age span from 30-32 used in the benchmark model (shown as the thin blue line) to 30-34 (shown as the dotted red line) and 30-36 (shown as the thick green line).

Figure 7. Robustness check for controlling if the estimated absolute mobility for **women** is biased by the narrow age span of 30-32 used in the benchmark model.

![Graph showing mobility trends for women across different age spans.](image)

**Note:** We increase the age span from 30-32 used in the benchmark model (shown as the thin blue line) to 30-34 (shown as the dotted red line) and 30-36 (shown as the thick green line).
Figure 8. Robustness check for controlling if the estimated absolute mobility for men is biased by the fact that we could only include son-father pairs for which the father’s age at son’s birth was between 18-32.

We increase the age of birth span of 18-32 used in the benchmark model (shown as the thin blue line) to 18-34 (shown as the dotted red line) and 18-36 (shown as the thick green line).

Figure 9. Robustness check for controlling if the estimated absolute mobility for women is biased by the fact that we could only include son-father pairs for which the father’s age at son’s birth was between 18-32.

We increase the age of birth span of 18-32 used in the benchmark model (shown as the thin blue line) to 18-34 (shown as the dotted red line) and 18-36 (shown as the thick green line).
Figure 10. Robustness checks for controlling if the estimated absolute mobility for \textit{men} is sensitive to the exclusion of individuals that did not have a taxable income for all three income years (having ‘zero income’).

Figure 11. Robustness checks for controlling if the estimated absolute mobility for \textit{women} is sensitive to the exclusion of individuals that did not have a taxable income for all three income years (having ‘zero income’).