Entrepreneurship and Income Inequality

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Abstract: Entrepreneurship research highlights individual's entrepreneurship as a simultaneous source of enhanced income mobility for some, but a potential source of poverty for others. Research on inequality has furthered new types of models to decompose and problematize various sources of income inequality in modern economies, but attention to entrepreneurship as an increasingly prevalent occupational choice in these models remains scant. This paper seeks to bridge these two literatures by applying regression based decomposition of income among entrepreneurs and paid workers, distinguishing between self-employed (SE) and incorporated self-employed (ISE). We find that the proportion of self-employed in the workforce significantly increase income dispersion by way of widening the bottom-end of the distribution, while incorporated self-employed has only a marginal contribution to income dispersion in the top-end of the distribution.

1. Introduction

The latest decades have witnessed a rise in self-employment and small business ownership in most developed economies (Blanchflower, 2000; Steinmetz & Wright, 1989). Much of public policy has been directed towards increasing the supply of entrepreneurs, most often measured as the number of self-employed or the numbers of businesses in an economy (Shane, 2009). Parallel to this 'rise of the entrepreneurial economy' (Audretsch, 2009) scholars have noted a trend of accelerating income inequality and increasingly stratified unemployment (Atkinson, 2003; Autor, 2014; Goldthorpe, 2010). This type of stratification is also apparent in research on entrepreneurship which highlights self-employment as a simultaneous source of enhanced income mobility for some, but a potential source of poverty for a large fraction of the self-employed workforce (Åstebro, Chen, & Thompson, 2011).

This paper is motivated by these trends and addresses two orthogonal theoretical concerns in the literatures on entrepreneurship and economic inequality. First, while entrepreneurship constitutes a source of enhanced income mobility for some, the majority of entrepreneurs earn incomes lower than population average (Hamilton, 2000; Åstebro et al., 2011). Work that probes the relationship between entrepreneurship and overall workforce income inequality however remains scant in the previous literature (Van Praag & Versloot, 2007; Wright & Zahra, 2011). Second, recent inequality research has furthered new types of models to decompose and problematize various sources of income inequality in modern economies (e.g.

Cowell & Fiorio, 2011; Creedy & Hérault, 2011; Thewissen, Wang, & Van Vliet, 2013) but these models still lack attention to entrepreneurship as an increasingly common occupation.[1]

This paper seeks to bridge these literatures by developing and empirically testing a model of the relationship between entrepreneurship and income inequality. We start by discussing the different ways in which entrepreneurship can contribute to overall income inequality. We then develop an econometric model that lets us decompose aggregate measures of income dispersion into its individual micro-level sources. Our empirical analysis departs from a sub-group decomposition analysis of income inequality using the Generalized-entropy index (GE-index), where we distinguish between workers (W) self-employed entrepreneurs (SE), and incorporated self-employed (ISE) (e.g. Åstebro & Tåg, 2015; Özcan, 2011). These groups are likely to contribute to income inequality in differing ways. In tuning the GE-index to different segments of the income distribution, we are able to study inequality at different parts of the income distribution, and how they relate to SE and ISE. Our analysis also includes an integrated factor-source decomposition where we consider a number of explanatory variables to account for the inequality each of the groups respectively. This allows us to test how different explanatory variables relate to the within-group inequality, but also the extent to which the same group-specific explanatory variables individually relate to the total aggregate inequality (Cowell & Fiorio, 2011; Fields, 2003).

We find that on average, SE entrepreneurs exhibit lower incomes than W and this type of entrepreneurship consequently increases inequality by way of a widening of the bottom-end of the distribution. ISE entrepreneurs on the other hand exhibit higher incomes than workers, augmenting inequality from the top end of the income distribution by way of enhancing the total number of high income earners in society. The combined contribution of entrepreneurship on aggregate income inequality accounts for between 20 and 30% of overall inequality, depending on the inequality measure. This finding, together with the increasing rates of entrepreneurship as an occupational category highlighting the importance to also consider this increasingly prevalent occupation in models of income decomposition (e.g. Cowell & Fiorio, 2011).

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[1] At October 1st 2010, the minimum equity required when forming an incorporated business was lower from 100 000 SEK to 50 000 SEK.

To the best of our knowledge, this paper is the first to assess the effects of entrepreneurship for income inequality using state-of-the art decomposition techniques. It also represents a first attempt at addressing the joint theoretical concern in the literatures on entrepreneurship and economic inequality, namely how changes in the relative number of entrepreneurs and their within-group income dispersion affect aggregate income dynamics in modern economies. Our methodology leans heavily on the Cowell and Fiorio (2011), who shows how to decompose entropy-based inequality indexes using several sub-groups, in a regression framework. estimating inequality both between and within each sub-group. This helps explain each group's contribution to overall inequality, providing a clearer picture of the group dynamics that drive inequality at the population level. Further, we are able to pinpoint the significance of each explanatory factor and its contribution to subgroup inequality.

Our paper is structured as follows: In the next section we outline the theoretical background and previous literature. Section 3 outlines the empirical strategy and the regression based decomposition method used to analyse the link between entrepreneurship and income inequality. Section 4 details the data used in the analysis, followed by the results section. The paper concludes with a discussion about the implications for public policy.

2. Entrepreneurship, income dynamics and inequality

It has been noted in the empirical literature that much of the entrepreneurship in modern economies does not take the form of growing productive firms, but rather increasing rates of self-employment (Sanandaji & Leeson, 2013; Stam, 2013; Steinmetz & Wright, 1989). However, research has been scant on the possible consequences of this in terms of income dispersion.

A substantial number of studies have investigated income differentials between employees and the self-employed. By and large, this literature has concluded that entrepreneurship for the most part results in earnings lower than comparable salaried work. For example, the well-cited papers by Blau (1987), Borjas and Bronars (1989) and Evans and Leighton (1989) estimate earnings of the self-employed to be below those of workers, and - for the latter two studies - that the distribution of these earnings is considerably skewed downwards (i.e. skewed toward low-income earners). Similarly, in a paper addressing the same questions but instead comparing the returns to investment in U.S. non-publicly traded equity with public equity, Moskowitz and Vissing-Jorgensen (2002) identify a large public equity investment premium and similarly argue that entrepreneurship has overall poor returns.

More recent studies have furthered these findings, confirming that entrepreneurial earnings are below those of comparable salaried workers on average, but have added that the overall distribution of entrepreneurial earnings also comes with substantial 'fat' upward tails. Lin, Picot, and Yates (2000), using data from the Canadian Survey of Labor and Income Dynamics (SLID) 1993–1994, address earnings differences at different quantiles of the earnings distribution and the extent and cyclicality of entry and exit into and out of entrepreneurship. Their study shows that the mean income of the self-employed is about 20% lower than among comparable workers across the first four quantiles of the earnings distribution, but more than double that of employed workers in the top fifth quantile. Similarly, using monthly panel data on US male non-farm workers, 1983-1986, a well-cited study by Hamilton (2000) finds that most entrepreneurs persist in small businesses despite the fact that they have both lower initial earnings and lower earnings growth relative to employees. Estimating a median worker-entrepreneur earnings differential of around 35 percent across industries, and ruling out the possibility of entrepreneurs on average being lower-ability individuals, the study suggests non-pecuniary benefits to be a likely explanation of both entrepreneurial entry and persistence. However, Hamilton also finds support for the "superstar hypothesis" – that entrepreneurial income at the very top of the earnings distribution is highly skewed upwards because of a relatively small number very successful high-productivity individuals – and cautions that this pattern is not captured in his estimates of median income differentials.

This outcome is also in line with results from Åstebro et al. (2011) and Levine and Rubinstein (2013). In the first study, utilizing 1998–2004 panel data from the Korean Labor and Income Panel Study (KLIPS) to test their model of occupational choice, Åstebro et. al find that entrants into self-employment are drawn disproportionately from both tails of the earnings distribution. However, in contrast to the Hamilton (2000) study, Åstebro et. al also find that this reflects the distribution of ability in the workforce, where workers with above-average and below-average unobserved ability are more likely to engage in entrepreneurship. Levine and Rubinstein (2013) also provide evidence in line with this outcome. Using US data from the Current Population Survey, 1994–2010, which separates between salaried workers, the self-employed and incorporated entrepreneurs, they pinpoint determinants of the underlying sorting into these different types of employment, the differences in cognitive and non-cognitive traits as well as their subsequent earnings. Levine and Rubinstein argue that earlier findings suggesting that entrepreneurs earn below the median income of salaried workers essentially reflects the fact that incorporated entrepreneurs are much fewer than the self-employed, and that this latter group – that indeed do earn lower incomes – tend to dominate estimates of 'average outcomes' in earning equations comparing entrepreneurs to workers. In contrast, their results suggest that incorporated entrepreneurs have earnings of around 30% above salaried workers with comparable traits and skills, who in turn earn more than their self-employed counterparts. Similar to Åstebro et al. (2011), they also find that these outcomes to a significant degree reflect ability (non-cognitive traits and cognitive skills). Where some traits were common to both types of entrepreneurs (such as having been engaged in 'illicit activities' as teenagers and 'risky behaviour'), where the self-employed incorporated entrepreneurs on average scored higher in learning aptitude tests this did however not characterize the self-employed. [2]

Turning to studies that focus specifically of entrepreneurship and income inequality, we note a more scarce empirical literature which has tended to focus on the association between inequality within organizations and employees' transition to entrepreneurship. Rather than exploring possible links to workforce income dispersion per se, these studies have mostly focused on the conditions in which income dispersion within firms may represent a source of upward earnings mobility among individuals choosing to leave these firms for entrepreneurship (Carnahan, Agarwal, & Campbell, 2012; Sørensen & Sharkey, 2014). The few available macro oriented studies however indicate that the greater the number of small firms in an economy, the more unequal is the earnings distribution in that economy (Davis, 2013; Fields & Yoo, 2000). In terms of explanations for this pattern, the literature has mostly provided very broad structural patterns. For example, (Lippmann, Davis, & Aldrich, 2005), provide cross-country evidence on the relationship between workforce income inequality and the rate of entrepreneurship using Global Entrepreneurship Monitor (GEM) data. They find

[2] These results are also in line with work specifically focusing on necessity entrepreneurship. Necessity entrepreneurs are defined as those who have started their own firms "because they cannot find a suitable role in the world of work, creating a new business is their best available option" (Reynolds et al., 2005, p.217). Recent data from the Global Entrepreneurship Monitor suggest that between 3 and 30 percent of all entrepreneurs in OECD countries fit this last category, with high fluctuations over time (Singer, Amoros, & Moska, 2014). These necessity entrepreneurs have been shown to exhibit limited income mobility as well as low gains in individual productivity (Block & Wagner, 2010; Poschke, 2013).

that entrepreneurship rates are higher in countries with significant income inequality and discuss seven structural factors broadly associated with this pattern; level of economic development, government policies, foreign direct investment, service sector growth, increasing labor market flexibility, wealth transfer programs and variation in worker unionization.

To summarize, as for the literature on earnings differentials between salaried workers and entrepreneurs, rising levels of entrepreneurship has been suggested to potentially increase inequality by expanding the share of either top or bottom income earners in the workforce, or both. This possibility has however been indirectly inferred from equations of earning differentials between entrepreneurs and workers, and we do not know how entrepreneurship affects total inequality within the workforce taken as a whole. As for the literature using country comparisons to address the issue, this literature also suggest entrepreneurship as positively related to inequality, but is lacking in terms understanding of the dynamics involved, which parts of the income distribution that might be affected or how different types of entrepreneurship might affect the outcome.

Resolving this puzzle is vital if we are to provide any clear cut answer on the relationship between entrepreneurship and income inequality. This question forms the basis for our overall research question: *How does entrepreneurship affect overall workforce income inequality?*

3. Empirical strategy and method

To address the question of how entrepreneurship contribute to inequality, we distinguish self-between self-employed in a private business (SE) and self-employed in an incorporated business (ISE) to account for income both income trends observed among entrepreneurs. We also need to settle on an appropriate inequality measure. The most common inequality measure in the literature is the Gini coefficient (Akita, Lukman, & Yamada, 1999). Its attractiveness comes from its simplicity and emphasis on the middle income ranges. Since our study encompasses income levels both in the bottom and top of the income distribution, we require a more comprehensive measure that can be used to gauge the differential contribution of L, SE, and ISE on the overall income distribution. For this purpose we use the Generalized Entropy index (GE-Index). It has two important advantages relative the Gini-index. One, is that it can be decomposed into several sub-groups, which allows us to study inequality among in each group separately to assess how much each group accounts for aggregate inequality. Two, the GE-Index is defined as a function of a sensitivity parameter $\alpha \in (-\infty, \infty)$, which allows us to adjust the focus to specific parts of the income distribution. Thus, by choosing appropriate values on α when computing the contribution to overall inequality from each of the sub-groups, we can discern which part of the income distribution that is mostly affected by each group. The lower value on α, the more sensitive is the GE-index to dispersion in the lower parts of the income distribution, and conversely, the higher the level of α the more sensitive it is to dispersion in the upper parts (Cowell, 2000). We use the following subset of values of $\alpha \in \{-1, 0, 1{,}2\}$. Of particular interest is the relative contribution of SE and ISE to overall inequality when α is tuned to either the bottom or top parts of the income distribution (i.e. $\in \{-1, 2\}$), as compared to the middle parts of the income distribution ($\alpha \in \{0{,}1\}$).[3]

The formal definition of the GE index is as follows. Let $y = [y_1 \dots y_N]$ represent a vector of incomes for a total of N individuals that are active in the labor market. The sample analogue of the GE-index can then be defined on the income vector y as a function of α by

$$GE(y;\alpha) = \frac{1}{\alpha(\alpha-1)N} \sum_{i=1}^{N} \left[\left(\frac{y_i}{\mu(y)} \right)^{\alpha} - 1 \right], \qquad \alpha \in (-\infty, \infty) \cap \{0{,}1\}. \tag{1}$$

The sum is taken over the α-exponent of individual incomes y_i $(i = 1, \dots, N)$ weighted by the population's mean income $\mu(y)$.

For $\alpha = 2$, the $GE(y; 2)$ index reduces to half the squared coefficient of variation, that is $GE(y; 2) = \frac{\mathrm{var}(y)}{2\mu(y)}$, synonymous with the Hirschman-Herfindahl concentration index (Quintano, Castellano, & Regoli, 2005). If $\alpha \to 1$ or $\alpha \to 0$ in the limit, the GE-index is identical to the Theil index and the mean log deviation (MLD).[4] When $\alpha = -1$, the index

[3] With the possible exception for possibly $\alpha = -1$, this also constitutes the most popular values in similar studies that use the GE-Index, which focus on values of $\alpha \in \{0{,}1{,}2\}$. Since $\alpha = -1$ turns the focus to the bottom of the income distribution, we include it as one of our focus values given our research purpose.
[4] The corresponding formulas for MLD and Theil is found by using l'hopitals rule on the GE-index:

$$GE(y; 0\,) = \frac{1}{N} \sum_{i=1}^{N} \ln \frac{\mu(y)}{y_i}$$

$GE(y; -1)$ tunes even more to the bottom income ranges, as it contains the expected value of $1/y$.

3.1. Subgroup decomposition of the generalized entropy (GE) index

The additive property of the GE-index is crucial in evaluating the contributions from different subgroups for overall inequality.[5] Let's consider a total number of J subgroups ($J = 3$ throughout this study). The GE-index can then be divided into two parts, one between-group part, $GE_b(y; \alpha)$, and one within-group part $GE_w(y; \alpha)$, that adds up to $GE(y; \alpha)$, that is

$$GE(y; \alpha) = GE_b(y; \alpha) + GE_w(y; \alpha). \quad (2)$$

Here $GE_w(y; \alpha)$ is a weighted sum of the GE-index computed for each of the $j = 1, \ldots, J$ subgroups by

$$GE_w(y; \alpha) = \sum_{j=1}^{J} w_j GE(y_j; \alpha). \quad (3)$$

The weight is defined by $w_j = p_j r_j^{\alpha}$, with $p_j = N_j/N$ as a population weight and the mean-income ratio $r_j = \mu(Y_j)/\mu(Y)$ (Fiorio and Cowell, 2011). Substituting the components of the weight into expression (3) and using (1) yields the following expression of total within-group inequality:

$$GE_w(y; \alpha) = \frac{1}{\alpha^2 - \alpha} \sum_{j=1}^{J} \frac{N_j}{N} \left(\frac{\mu(Y_j)}{\mu(Y)} \right)^{\alpha} \frac{1}{N_j} \sum_{i=1}^{N_j} \left[\left(\frac{y_{ji}}{\mu(y_j)} \right)^{\alpha} - 1 \right]. \quad (4)$$

Expression (4) reflects the share of $GE(y; \alpha)$ that results from income dispersion within each of the separate subgroups combined. Using the identity in eq. (2), and the expression for $GE_w(y; \alpha)$ in eq. (4), the between part $GE_b(y; \alpha)$ can easily be backed out to

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$$GE(y; 0) = \frac{1}{N} \sum_{i=1}^{N} \ln \frac{\mu(y)}{y_i}.$$

[5] $GE(y; \alpha)$ is strictly decomposable indices because their between-group components measure the reduction in overall inequality when group means are equalized, keeping the within-group component constant.

$$GE_b(y;\alpha) = \frac{1}{\alpha^2 - \alpha} \sum_{j=1}^{J} \frac{N_j}{N} \left[\left(\frac{\mu(Y_j)}{\mu(Y)} \right)^{\alpha} - 1 \right]. \quad (5)$$

Expression (5) measures the 'residual inequality' once within-group inequality is accounted for.[6] It accounts for the differences in mean incomes across the sub/groups.[7] Thus while within-part accounts for the dispersion in incomes among individuals in the group, the between-part accounts for difference in the mean income in the group compared to the mean income in the population. Note that sub-group decomposition in (4) and (5) allows for an alternative decomposition by defining the contribution to $GE(y;\alpha)$ from individual group j by $\widetilde{GE}(y_j;\alpha)$,

$$\widetilde{GE}(y_j;\alpha) = \frac{p_j\left(r_j{}^{\alpha} - 1\right)}{\alpha^2 - \alpha} + w_j GE(y_j;\alpha), \quad (6)$$

The first term in expression (6) reflect group j's part for between income dispersion and the second term its within part. By summing both sides of the expression over the J groups we end up with population inequality $GE(y;\alpha)$. Whenever we distinguish between a particular group's contribution to between and within inequality, it is this expression we rely on, if not mentioned otherwise.

3.2. Factor source decomposition of subgroup within inequality

In this section we turn to factor-source decomposition of inequality that often accompanies an analysis of sub-group decomposition. This enables one to assess how different income factors contribute to inequality. Traditionally, a factor source regards the income from a particular sources, for instance salaried income, capital income or transfer payments. We rely

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[6] The between part in eq. (5) is written slightly different here compared to e.g. Fiorio and Cowell (2011), where the population weight is included within the square brackets as follows $\frac{1}{\alpha^2-\alpha}\left(\sum_{j=1}^{J}\left[\frac{N_j}{N}\left(\frac{\mu(Y_j)}{\mu(Y)}\right)^{\alpha}\right] - 1\right)$. Although the two expressions are equivalent, it is not clear in using the above expression how to calculate the contribution to aggregate inequality from one particular group's between part since it leave a 'residual term' of $\frac{-1}{\alpha^2-\alpha}$ that also needs to be distributed among the groups. Expression (5) takes care of this directly.

[7] Using the expression in footnote (4), similar expressions can be reached for the MLD and Theil index. We do not show separate derivations for these measures here. As long as $\alpha > 0$, it is apparent that for groups with lower mean income than the population average, the between-part contributes negatively to overall inequality. The converse is true for groups with mean income larger than the population average. For $\alpha < 0$ the relationship becomes the opposite.

extensively on the work of Fields (2003) and Fiorio and Cowell (2011) who develop a regression based framework that allows for a much wider set of possible sources that determines an individual's income and hence income inequality in a group or population. By applying a regression methodology to decomposition, this also establishes a direct link to research into the determinants of income using income regressions on the form given in eq. (12) below.

Let income for individuals ($i = 1, \dots, N$) in subgroup j ($j = 1, \dots, J$), be split into a sum of K different factor sources, here components:

$$y_{ji} = y_{1ji} + y_{2ji} + \cdots + y_{Kji}. \tag{7}$$

Provided that an inequality index denoted by $I(y_j)$ satisfies six basic assumptions laid out by Shorrocks (1982, see appendix 1), it can be decomposed into a sum of K inequality components, here denoted by $S_{kj}(y_{kj}, y_j)$ for $k = 1, \dots, K$:

$$I(y_j) = S_{1j}\left(y_{1j}, y_j\right) + S_{2j}\left(y_{2j}, y_j\right) + \cdots + S_{Kj}\left(y_{Kj}, y_j\right), \tag{8}$$

where y_{kj} refers to the kth income source for the jth group. In fact, provided the assumptions are fulfilled, this decomposition is invariant to the choice of inequality measure $I(y)$ (Shorrocks, 1982). To see this, define the share, i.e. the proportional contribution of S_{jk} to $I(y_j)$ by

$$s_{kj} \equiv \frac{S_{kj}(y_{kj}, y_j)}{I\left(y_j\right)}. \tag{9}$$

Since $s_{1j} + s_{2j} + \cdots + s_{Kj} = 1$ by construction, multiplying through with $I(y_j)$ shows that s_{jk} becomes a "loading" of the factor k to the inequality $I(y_j)$ given by,

$$I(y_j) = s_{1j}I(y_j) + s_{2j}I(y_j) + \cdots + s_{Kj}I(y_j) \tag{10}$$

For this class of inequality measures (the GE-index among them) the function s_{kj} can be furthermore written in terms of the covariance between the income component y_{kj} and total income y_j divided by the variance of y_j. Thus

$$s_{jk} = \frac{\sigma(y_{kj}, y_j)}{\sigma^2(y_j)}. \tag{11}$$

This result comes from Shorrocks (1982), and is key, first realized by Fields (2003), to connect standard regression analysis with the *a priori* inequality decomposition methods.

3.2. Combining factor source decomposition with Mincer-type regression

Following Fields (2003), we consider a linear model of income for some individual i in group j by,

$$y_{ji} = b_{0j} + \sum_{k=1}^{K-1} b_{kj} x_{kji} + u_{ji}, \tag{12}$$

that includes a number of (potentially endogenous) explanatory variables and an error term. Because of the linearity of regression equation in (7), it has the same form as the expression in equation (7), which means that a factor source decomposition of y_j can be accomplished by mapping $b_{kj}x_{kji}$ to y_{kj} in eq. (7).While the result in Fields (2003) are with respect to the full population, we keep with the sub-group indexation j as in Fiorio and Cowell (2011). By expanding the covariance we can see better how different parts of the regression equation contributes to $I\left(y_j\right)$,

$$s_{kj} = b_{kj}^2 \frac{\sigma^2(x_{kj})}{\sigma^2\left(y_j\right)} + b_{kj} \sum_{r \neq k}^{K-1} b_{rj}\, \rho(x_{rj}, x_{kj}) \frac{\sigma(x_{rj})\sigma(x_{kj})}{\sigma^2\left(y_j\right)} + b_{kj}\rho(u_j, x_{kj}) \frac{\sigma(u_j)\sigma(x_{kj})}{\sigma^2\left(y_j\right)}, \tag{13}$$

$$s_{Kj} = \frac{\sigma^2(u_j)}{\sigma^2\left(y_j\right)} + \sum_{k=1}^{K-1} b_{kj}\, \rho(u_j, x_{kj}) \frac{\sigma(u_j)\sigma(x_{kj})}{\sigma^2\left(y_j\right)} \tag{14}$$

Starting with s_{kj}, the first term gives the direct contribution of $b_{kj}x_{kj}$, the second represents the contribution should x_{kj} be correlated with x_{rj} for $r \neq k$ other explanatory variables (multicollinearity), whereas the third term represents the variation due to endogeneity, i.e. should the x_{kj} term be correlated with the residual term u_j.

As for the s_{Kj} share, which represents the contribution to inequality from the unobserved part of equation (12) in terms of the residual's direct contribution, and the variation resulting from any endogenous explanatory variables.

Since all direct contributions are squared, a necessary condition for s_k to be negative is that x_k is either correlated with at least one x_r ($r \neq k$ and hence multicolinear) or that x_k is correlated with the error term and hence endogenous (Fiorio and Cowell, 2011). On the other hand, if all assumptions in OLS are satisfied, s_{kj} and s_{Kj} are reduced to their respective first terms, $s_{kj} = b_{kj}^2\sigma^2(x_{kj})/\sigma^2\left(y_j\right)$ and $s_{Kj} = \sigma^2(u_j)/\sigma^2\left(y_j\right)$.

To find the point estimates of s_{kj} and s_{Kj}, we simply run the appropriate regression on (no-log) income and collect the estimates. These are combine with information about covariance and correlation matrix, which is readily available, to form $\hat{s}_k$ and $\hat{s}_K$.

When it comes to the standard deviations of the estimates $\hat{s}_k$ and $\hat{s}_K$, Fiorio and Cowell (2011) suggests a bootstrapping procedure from the difficulty of computing analytical standard errors. Since the computation outlined in this section involves numerous separate computations, and in our case almost 2.5 million observations, bootstrapping becomes very time consuming. Fortunately, using a result in Bigotta, Krishnakumar, and Rani (2015, p.5, theorem 2) we can compute asymptotic standard error for s_k based on the square root of the k^th diagonal elements in the following covariance matrix $\hat{\Sigma}(s_{kj})$:

$$\hat{\Sigma} = \frac{1}{N}\hat{\sigma}^2(u)\frac{\left(I_K \otimes \hat{\beta}^T X^T X\right) L (X^T X)^{-1} L^T \left(I_K \otimes \hat{\beta}^T X^T X\right)}{\left(\hat{\beta}^T X^T X \hat{\beta} + \hat{\sigma}^2(u)\right)^2}. \tag{15}$$

Here we dispense with the j sub-group indexation, but $\hat{\Sigma}$ should here be understood to correspond to the regression of a particular sub-group. I_K is a $K \times K$ identity matrix; $\otimes$, the Kronecker product; and L, a $K^2 \times K$ selection matrix $L = [l_1 \quad \cdots \quad l_K]^T$, where l_k is a $K \times K$ matrix of zeros and 1 on the k^th diagonal entry. To calculate the 95% confidence interval for the k^th factor, we use the k^th diagonal element of $\hat{\Sigma}$ to form asymptotical standard errors with the formula:

$$s_k = \left[\hat{s}_k \pm 1.96\sqrt{\hat{\Sigma}_{kk}}\right].$$

3.4. Combining sub-group decomposition with factor-source decomposition

This section takes is based on Fiorio and Cowell (2011) which presents a unifying framework including both sub-group decomposition (Section 3.2) and factor-source decomposition

(Section 3.3). From the fact that $\mu(y_j) = \sum_{k=1}^{K-1} b_{kj}\mu(x_{kj})$, the inequality contribution from group j given by eq. (6) can be written as

$$\widetilde{GE}(y_j;\alpha) = \frac{p_j}{\alpha^2-\alpha}\left(\left[\frac{\sum_{k=1}^{K-1} b_{kj}\mu(x_{kj})}{\sum_{k=1}^{K-1} b_{kj}\mu(x_k)}\right]^{\alpha} - 1\right) + w_j \sum_{k=1}^{K} GE(y_j;\alpha)s_k. \qquad (16)$$

The term in the nominator refers to the parameters from a regression restricted to the individuals in sub-group j, whereas the denominator gives the parameters from a regression on the full population. Except for the population shares that are calculated directly from the data, all information regarding the subgroup-factor-source decomposition are provided by regressing income on the set of explanatory variables in equation (18).

4. Data and descriptive statistics

4.1. Data

The empirical test for our model is based on microdata from Sweden for the years 2005 and 2013. The Swedish economy is traditionally characterized by one of the worlds' lowest rates of income inequality. However the growth in inequality between 1985 and the early 2010s was the largest among all OECD countries, increasing by roughly one-third (OECD, 2015). During the same period the country has been characterized by increasing rates of entrepreneurship in the form of self-employment and newly registered firms, making Sweden an interesting case to probe the role of entrepreneurship for income inequality.

Our paper relies on data from LISA database which includes all individuals residing in Sweden aged 16 and older. The database is drawn from governmental registers and maintained for research purposes by Statistics Sweden. The data contains a wealth of demographic and income information and is generated from a number of sources, including individual tax statements, birthplace registries, and school records. This offers information on employment, industrial and occupational structures, and also tracks flows in the labor market. While information on income dates back to 1990, the database does not include necessary data on entrepreneurial income and occupational data until more recently. In our analysis we therefore focus on two cross-sections, 2005 and 2013, the first and last years for which the LISA database includes comprehensive data on income and occupation. These two data points represent a full economic cycle and also allow us to include detailed data on disposable income that accounts for capital losses and income from active businesses, both available from 2005. Using the methodology described in the previous section, we can hereby account for both the *level* of inequality for each of these years, but also for any increase or decrease that occurs over the nine year period.

We sampled all individuals in the active work force between 25 and 65 years of age in the respective years for which labor market data is available. We also exclude individuals that are not associated with an employing organization such as sailors and seasonal workers. The sample that enters into the analysis comprise 3,530,060 individuals in 2005 and 3,678,212 individuals in 2013, representing the active Swedish workforce in the relevant age range.

This rich data further enables us to distinguish between two types of entrepreneurs. We differentiate between individuals that are self-employed (SE) in a private business from individuals that are self-employed in an incorporated firm (ISE) (Blanchflower, 2000). Consistent with government classifications, we define an entrepreneur as an individual who’s main source of income comes from a company in which he or she has a majority ownership stake and works full time (Folta, Delmar, & Wennberg, 2010).

To classify an individual into one of the three categories of workers, self-employed entrepreneurs or incorporated self-employed entrepreneurs we use information from three different sources. First, from where an individual derives the majority of her income. To compensate for the fact that business income is lower in terms of the ours spent working compared to workers, the reported business income is weighted by a factor of 1.6 in the classification.

Even though an individual may earn the majority of her income as an entrepreneur, it does not preclude that she has some alternative employment on the side. These so called “combinators” are expunged from the category of SE and ISE to ensure that the income reported from correspond to business related income to as large extent as possible. In deciding whether or not to drop these combinators from the data or not, we ended up placing them in the category of workers. Last, we also have further information from RAMS about whether the entrepreneur consider herself as active, in the sense that she works at least 600 hours a year in her own business. Unless she reports that she is actively doing business individuals are put into the workers category.

This rather strict definition of what constitutes entrepreneurship may reduce the count of people in the SE and ISE category, but at least we can be fairly certain that they are full time entrepreneurs. We include two different income variables in our models: *Market income* refers to the sum of gross wage income + net income from an active business + capital income. The reason for using all three variables is that while SE entrepreneurs receive 100% of their earnings in the form of 'net income from an active business', ISE entrepreneurs receive their earnings both as 'gross wage income' (from their own business) and 'capital income' (Alstadsæter & Jacob, 2015; Edmark & Gordon, 2013). We base all analyses on entrepreneurs' Market Income.

Disposable income is measured by Statistics Sweden by equalized disposable income, awarding different members of the household with potentially different consumption weights. For each member of a family, his or hers personal disposable income is multiplied with an individual consumption weight, as calculated by Statistics Sweden, then divided by the family's total consumption weight. Disposable income contains factor incomes such as gross wage and business related income (net deficit) and net capital profits, as well as taxable (and non-taxable) transfers such as rehabilitation compensation, pensions, and child allowance, (e.g. housing benefits, social security, and study allowance). We use disposable income in a series of robustness tests (Appendix 2) to ascertain that our results are not tainted by the potential problem of tax evasion among entrepreneurs (Engström & Holmlund, 2009).

The analysis of income inequality abstracts from the top 1 % highest income earners, which skew the distribution of both market and disposable income. Although the recent literature has directed a significant interest at top income earners(see e.g. Quadrini, 1999; Roine & Waldenström, 2008), including these into the regression analysis presents a challenge since they clearly violates the normality assumption. Since standard log-linear transformations that are estimated in Mincer type equations only allows for the decomposition of log income and not income in levels that we analyze in this paper, we have chosen to drop the individuals with highest 1% in market income and disposable income in either period. In addition to the two entrepreneurship variables, other explanatory variables included in the regression are *age* and *age squared, job tenure* and *job tenure square, job changes* and *years of education* (e.g. Folta et al., 2010; Yamauchi, 2001; Åstebro et al., 2011). All individuals living in Sweden receive a personal identification number based on their date of birth. We used this information to calculate individual's age (in years) as well the squared term. Job tenure and job changes were computed from LISA by measured by the number of years of experience at a focal workplace and number of workplace switches since 1990.[8] Years of education is the most common operationalization of general human capital in the entrepreneurship and inequality literatures (Arum & Müller, 2004; Cowell & Fiorio, 2011; Van Praag, van Witteloostuijn, & van der Sluis, 2013). The variable was created from educational codes, included for all individuals in the LISA register. The educational codes are based on the International Standard Classification (ISCED 97) that reports the length of the highest attained education.

Further, we also control for the number of *children living at home*, *marital status,* individuals' *sex*, and individuals' *occupation* (1 digit-level, based on the Swedish Standard Classification of Occupations 1996 (SSYK) comparable to the International Standard Classification of Occupations (ISCO-88).

We also control for *local labor market* (75 geographical regions) and *industry* (at the two digit NACE level) of the workplace where an individual works. Descriptive statistics for the complete sample as well as our two groups of entrepreneurs are presented below in Table 1.

[8] To account for the potential bias arising from the left censoring of the job tenure variable, in unreported robustness tests we replicated the results from the factors source regression analyses in Tables 5 and 6 with an additional dummy variable taking the value 1 for those individuals with the maximum years of job tenure (Wennberg et al., 2010). These results – available upon request – were consistent with the ones reported here.

Table 1. Descriptive statistics: Total workforce, and SE and ISE sub-groups.

	2005				*2013*			
Variables:	*Mean (1)*	*Sd. (2)*	*Min (3)*	*Max (4)*	*Mean (5)*	*Sd. (6)*	*Min (7)*	*Max (8)*
Number of Workers (W)								
Market income	2,324.541	1,176.23	0.909	7,915.223	2,682.033	1,347.201	0.812	9,275.121
Age	43.958	10.86	25	64	44.108	10.924	25	64
Age squared (demeaned)	132.852	134.611	0.033	520.699	134.77	141.971	0.001	530.632
Job tenure	6.307	5.291	0	15	7.599	7.097	0	23
Job changes	1.94	1.692	0	14	2.746	2.174	0	20
Children living at home	0.976	1.093	0	12	1.005	1.083	0	14
Gender (1=Men)	0.499	0.5	0	1	0.498	0.5	0	1
Marital status (1=Married/cohabitant)	0.486	0.5	0	1	0.466	0.499	0	1
Years of education	12.312	2.295	9	20	12.713	2.299	9	20
Obs.	3,312,618 (93.84% of the work force)				3,464,330 (94.19% of the work force)			
Self-employed (SE)								
Market income	1,564.278	1,265.852	0.909	7,911.586	1,702.328	1,351.855	0.812	9,270.25
Age	47.856	10.427	25	64	48.097	10.538	25	64
Age squared (demeaned)	108.723	108.631	0.033	520.699	111.043	115.558	0.001	530.632
Job tenure	6.462	5.29	0	15	8.83	6.875	0	23
Job changes	1.751	1.601	0	12	2.488	2.075	0	18
Children living at home	0.986	1.141	0	12	0.986	1.114	0	11
Gender (1=Men)	0.685	0.465	0	1	0.66	0.474	0	1
Marital status (1=Married/cohabitant)	0.557	0.497	0	1	0.519	0.5	0	1
Years of education	11.384	2.051	9	20	11.752	2.105	9	20
Obs.	140,401 (3.98% of the work force)				124,666 (3.39% of the work force)			
Incorporated entrepreneurs (ISE)								
Market income	2,824.959	1,413.357	0.909	7,914.313	3,330.515	1,683.662	0.812	9,275.121
Age	47.111	9.74	25	64	47.156	9.421	25	64
Age squared (demeaned)	95.358	98.171	0.033	520.699	89.529	101.375	0.001	530.632
Job tenure	8.248	5.072	0	15	8.863	7.062	0	23
Job changes	1.744	1.592	0	13	3.048	2.193	0	16
Children living at home	1.059	1.104	0	10	1.141	1.09	0	10
Gender (1=Men)	0.791	0.407	0	1	0.785	0.411	0	1
Marital status (1=Married/cohabitant)	0.613	0.487	0	1	0.578	0.494	0	1
Years of education	11.888	2.208	9	20	12.325	2.227	9	20
Obs.	77,041 (2.18% of the work force)				89,216 (2.43% of the work force)			

4.2. Descriptive statistics

4.2.1 Inequality

Table 1 shows descriptive statistics for three sub-groups of the population, namely workers (W), self-employed entrepreneurs (SE) and the incorporated entrepreneurs (ISE) for all variables in the years 2005 and 2013. The share of SE entrepreneurs to total workforce decreases from 3.5 to 5.6%, whereas and the share of ISE increases from 2.18 to 2.43%, respectively from 2005 to 2013. Most variables display fairly moderate changes across the two time periods, which is to be expected when working with large sample sizes. There are however some noteworthy differences, in particular looking at the average share of married/cohabiting individuals and the years of schooling. While the share of married and cohabiting individuals has decreased over the period in all groups, the sample average years of education has increased. This observations seem to hold for all groups.[9]

Both SE and ISE are predominately men with a higher average age of around 48 and 47 respectively compared to workers with an average age of 44. Table 1 also indicates average years of education increased somewhat for all groups from 2005 to 2013, however the group of SE entrepreneurs exhibit somewhat lower level of education than the worker as well as the ISE entrepreneurs in both periods (Robinson & Sexton, 1994).

Turning our attention to descriptive statistics of aggregate inequality developments, Figure 1 shows Lorentz curves for market income inequality in 2005 and 2013, followed by Table 2 that displays a set of common inequality measures. The Lorentz curves show a slight inward shift between the two years, indicating that the overall dispersion of market income becomes less unequal over the period.

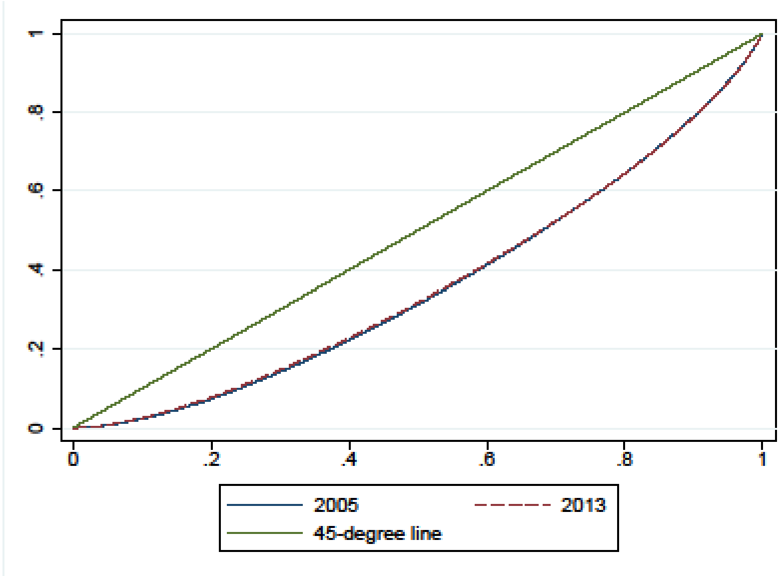


Figure 2. Lorentz curve for workforce market income, 2005 and 2013

[9] The fact that average job tenure displays an increase from 2005 to 2013 is mainly due to the fact that the tenure variable is left-censored in 1990, which means that the maximum tenure allowed in 2005 is 15 years compared to 23 years in 2013.

While the outward change in overall income inequality appears small in Figure 1, the inequality statistics in Table 2 reveals this change to be non-negligible. The table shows different measures of income inequality in the years 2005 and 2013 for the separate sub-groups of workers (W), self-employed (SE), and incorporated entrepreneurs (ISE). Specifically, we show income percentile ratios and the generalized entropy index (GE-index) at various percentiles and parts of the income distribution, together with the Gini index.

Table 2. Income inequality statistics of market income

	2005			*2013*		
	W	*SE*	*ISE*	*W*	*SE*	*ISE*
Inequality measure:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
p90/p10	3.857	15.328	3.804	3.635	15.225	3.976
p90/p50	1.692	2.453	1.821	1.712	2.331	1.828
p50/ p10	2.279	6.249	2.089	2.124	6.531	2.175
p75/p25	1.741	3.728	1.811	1.697	3.6	1.917
GE(-1)	0.642	3.602	0.294	0.53	5.088	0.306
GE(0)	0.159	0.464	0.139	0.147	0.47	0.145
GE(1)	0.125	0.313	0.121	0.121	0.304	0.125
GE(2)	0.128	0.327	0.125	0.126	0.315	0.128
Gini	0.277			0.271		

Note: All inequality measures are computed as raw figures for each of the subgroups, without weights that accounts for their contribution to the aggregate income inequality. The subgroups are created such that W + *SE* + *ISE* = *workforce* (population), where the SE and ISE groups corresponds to the number of individuals presented in Table 1, while W here corresponds to W = workforce - SE – ISE.

Table 2 also contains the equivalent measures of inequality in market income for workers (W) in column (1) and (4), for SE entrepreneurs in columns 2 and 5 and for ISE entrepreneurs in columns 3 and 6. Beginning with workers, we actually see a slight decrees in inequality over the period almost across all inequality measures. The decrease may be slight, by nevertheless present. The exception is the percentile ratio p90/p50 that displayed a slight increase of 1.2 %.

Among SE entrepreneurs, we see somewhat disparate developments across different income distributions, with decreasing inequality registered the p90/p10, p90/p50 and p75/p25 ratios but increasing inequality for the p50/p10. This would suggest some form of contraction of top incomes, whereas bottom incomes became more dispersed. As for the different GE-indices, they suggest the same development of shifting inequality from the top to the bottom. At the extremes, GE(-1) increased by 41.26%, compared to GE(2) merely showed a decrease of 3.7%.

Among the ISE entrepreneurs, change in income inequality is strictly positive, across all indices. The magnitude appears to be around 3 to 4 % for most indicators. The largest increase, however, is found in the middle income ranges with a p75/25 of 5.9%, whereas the smallest increase seem to occur for p90/50 of less than 1 percent.

5. RESULTS

5.1. Sub-group decomposition of the GE-index

To investigate what lies behind the increasing levels inequality presented in Table 2, we use the decomposability of the GE-index to disaggregate the inequality $GE(y;\alpha)$ into between and within parts for the various sub-groups (L, SE, and ISE). Instead of reporting the contributions in terms of inequality points, we calculate the percentage contributions for each of the terms in $\widetilde{GE}(y_j;\alpha)$ (eq. 16), which facilitates interpretation. Dividing both sides of $\widetilde{GE}(y_j;\alpha)$ with the aggregate inequality $GE(y;\alpha)$, we define $\Lambda\left(y_j;\alpha\right)$ as:

$$\Lambda\left(y_j;\alpha\right) \equiv \frac{\widetilde{GE}\left(y_j;\alpha\right)}{GE(y;\alpha)} = \underbrace{\frac{p_j\left({r_j}^{\alpha}-1\right)}{GE(y;\alpha)(\alpha^2-\alpha)}}_{\Lambda_b\left(y_j;\alpha\right)} + \underbrace{\frac{w_j GE\left(y_j;\alpha\right)}{GE(y;\alpha)}}_{\Lambda_w\left(y_j;\alpha\right)}. \tag{17}$$

The term $\Lambda_b(y_j;\alpha)$ here represents the contribution in percentage points to aggregate inequality from group j's between part and where $\Lambda_w(y_j;\alpha)$ represents the group's contribution from its within part. The total contribution from a specific group is given by $\Lambda(y_j;\alpha)$. These calculations are presented for market income in Table 3 below, corresponding to the rows *Between*, *Within* and *Total*. The tables show separate calculations for each of the inequality indexes *GE(-1)*, *GE(0)*, *GE(1)*, and *GE(2)* with index values for the different subgroups presented in the first row. Columns (1-4) uses income data from the year 2005, and columns (5-8) from the year 2013.

It is informative to calculate the contributions when between and within parts are summed across the groups. By taking the sum over all J groups, the equation takes the following identity:

$$\sum_{j=1}^{J} \Lambda\left(y_j;\alpha\right) = \sum_{j=1}^{J} \left[\Lambda_b\left(y_j;\alpha\right) + \Lambda_w\left(y_j;\alpha\right)\right] = 1. \tag{18}$$

By the rules of decomposition, summing all contributions amounts to 1 (100%). In table 3 this represents the sum of the entries in the row for *Total*, presented in the column for *Total*. The sums across the groups' between and within contributions are calculated using the terms $\sum_{j=1}^{J} \Lambda_b\left(y_j;\alpha\right)$ and $\sum_{j=1}^{J} \Lambda_w\left(y_j;\alpha\right)$, presented in the column *Total* as they sum the corresponding rows for *Between* and *Within.*

Table 3: Sub-group decomposition in percentage points of $GE(y;\alpha)$ for market income, 2005 and 2013

	2005				*2013*			
	W (1)	*SE* (2)	*ISE* (3)	*Total* (4)	*W* (5)	*SE* (6)	*ISE* (7)	*Total* (8)
GE(-1)	0.642	3.602	0.294	0.817	0.53	5.088	0.306	0.776
Between: $\Lambda_b(y_j;\alpha)$	-0.477	1.152	-0.246	0.43	-0.396	1.235	-0.313	0.527
Within: $\Lambda_w(y_j;\alpha)$	73.1	25.829	0.641	99.57	63.903	34.804	0.766	99.473
Total: $\Lambda(y_j;\alpha)$	72.623	26.982	0.395	100	63.507	36.039	0.454	100
GE(0)	0.159	0.464	0.139	0.174	0.147	0.47	0.145	0.161
Between: $\Lambda_b(y_j;\alpha)$	-4.495	8.853	-2.547	1.811	-3.818	9.416	-3.355	2.243
Within: $\Lambda_w(y_j;\alpha)$	85.862	10.587	1.741	98.189	85.697	9.875	2.185	97.757
Total: $\Lambda(y_j;\alpha)$	81.367	19.44	-0.807	100	81.88	19.291	-1.17	100
GE(1)	0.125	0.313	0.121	0.133	0.121	0.304	0.125	0.128
Between: $\Lambda_b(y_j;\alpha)$	5.924	-7.852	4.08	2.152	4.836	-7.571	5.278	2.543
Within: $\Lambda_w(y_j;\alpha)$	89.093	6.328	2.426	97.848	89.368	5.129	2.96	97.457
Total: $\Lambda(y_j;\alpha)$	95.017	-1.523	6.506	100	94.204	-2.442	8.238	100
GE(2)	0.128	0.327	0.125	0.135	0.126	0.315	0.128	0.133
Between: $\Lambda_b(y_j;\alpha)$	5.854	-7.954	4.059	1.959	4.675	-7.565	5.144	2.254
Within: $\Lambda_w(y_j;\alpha)$	90.555	4.445	3.041	98.041	90.804	3.29	3.652	97.746
Total: $\Lambda(y_j;\alpha)$	96.409	-3.509	7.1	100	95.479	-4.275	8.796	100

Note: The table shows the percentage contribution (1=100%) of the between and within inequality component from the sub-groups workers (W), self-employed (SE), and incorporated entrepreneurs (ISE). Separate contributions are calculated for the various GE-indices with $\alpha = \{-1,0,1,2\}$. The inequality levels for each of the subgroups are calculated using eq. (16) with the appropriate weights. These inequality levels differs from those presented in Table 2 that comprise raw calculations based on equation (1) applied to the restricted sample.

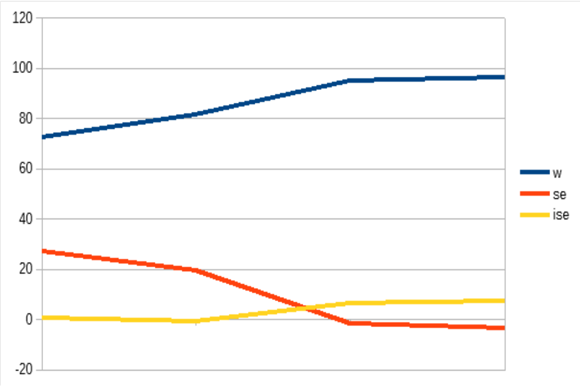
Looking at GE(-1), the total contribution to inequality from W, SE and ISE in terms of percent corresponds to 72.62%, 26.98% and 0.40%. Hence the majority of inequality when emphasizing the bottom parts of the income distribution comes from W. But considering their relatively small size of merely 3.98% (Table 1), the contribution is sizable. At GE(-1) it is the within group of each group that account for almost all of inequality.

Turning the sensitivity parameter to higher levels of the income distribution, we see that entrepreneurs as a group, i.e. SE and ISE, explains a decreasing share of total inequality. Beginning at 27.4 for GE(-1), it shrinks to 18.63% with GE(0), 4.98% with GE(1), and finally 3.6% with GE(2). As we gradually increase α, there are two interesting tendencies that stands out. The first is that the between inequality term plays a more prominent role, which leads to the second property of a reversal between SE and ISE in terms of their total contribution to inequality. Although, their combined effect decreases with larger α, ISE account for a larger share than SE for GE(1) and GE(2). At these measures the SE registers a total contribution of roughly -7.9%. whereas ISE registers a contribution with a size of 4%. The negative contribution of SE comes from the fact that the negative contribution from between inequality exeeds the amount of within inequality.

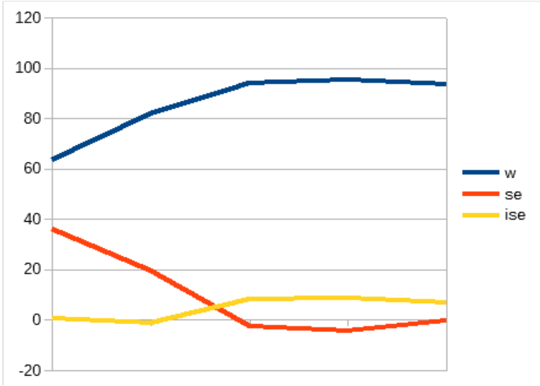
With one exception the same pattern is observed when we do the same decomposition for 2013, and that is the increasing share of SE when the GE(-1) index is used. This is a substantial change, indicating that the relative contribution of entrepreneurship compared to workers for total workforce inequality ($\Lambda(y;-1)$) increased from 2005 to 2013 by almost 10% from the bottom part of the income distribution. This change is also almost completely driven by changes in the within-inequality part and suggest a sizable shift in the low-income part of the market income distribution from 2005 to 2013.

We can illustrate the changing income dynamics of the sub-groups by plotting the total percentage contribution to aggregate income inequality for increasing values of α. This is shown in Figures 2 and 3 (market income inequality, 2005 and 2013, respectively). In the figures, workers' contributions to overall income inequality is represented by the drawn line, SE by the dashed line, and ISE by the dotted line. From Figures 2 and 3 it can be seen that the downward shift for workers with GE(-1) corresponds to an upward shift for the group of SE, while the contribution from ISE to inequality at low income levels remains largely unchanged..

Figure 2. Proportional contribution to overall inequality in market income from workers, self-employed and incorporated entrepreneurs



(i) Market income 2005



(ii) Market income 2013

5.2. Regression estimates from factor sources of income inequality

The final step in our analysis concerns estimating the income equation based on the same sample and variables as in the decomposition analysis. Our regression model is based on equation (12) when y_{it} = *market income*. We run separate regressions for each of the three sub-groups ($j = 1, \dots, 3$) of workers (L, $j = 1$), self-employed (SE, $j = 2$), and incorporated entrepreneurs (IES, j = 3). To shed light upon recent trends of increasing inequality, the model is estimated for the two cross-sections, presented in column (1) to (3) in Table 5 for 2005 and in Table 6 for 2013. We use the type of OLS model specified by Fiorio and Cowell (2011) where each table shows both individual-level coefficients and aggregate results for each coefficient's proportional contribution to income inequality s_{kj} in column (4) to (6), and should not be interpreted causally. These estimates give the percentage contribution to the inequality $GE(y_j; \alpha)$ of the combined "price" and "quantity" effect $\hat{b}_{kj}\mu(x_{kj})$, where $\hat{b}_{kj}$ is the estimated marginal effect and $\mu(x_{kj})$ the mean of explanatory variable x_{kj} ($k = 1, \dots, K$). In addition to the explanatory variables outlined in Section 4, each regression is fitted with three sets of dummy variables that capture fixed effects at the regional (75 local labor market areas), industry (10 categories for two-digit NACE level) and individuals' occupational types (113 categories for ISCO-88) within the respective sub-groups. In presenting the contribution of these fixed effects, individual contributions from the respective set are added up to yield a singular value.

In decomposing inequality to its various components $\hat{b}_{kj}\mu(x_{kj})$, the regression approach is limited by the amount of variance in income explained by the regression run for each subgroup. Thus, for a given subgroup j, adding up the contributions of all explanatory variables (s_{kj}) amounts to the R-square of each respective regression. The unexplained part of the model$(1 - R^2)$ equals the proportional contribution of s_{Kj}, computed for the residual in equation (14). These estimates are provided in the bottom row of each Table and shows how much of the variance in income inequality that cannot be attributed to the factor sources investigated.

Importantly, s_{kj} represents the raw contribution to inequality computed for a particular subgroup. Since each group varies in size, this means that s_{kj} needs to be reweighted to assess the contribution to aggregate inequality, $\Lambda(y_j;\alpha)$.[10] Focusing on the within-group inequality component shown to account for most of aggregate inequality, s_{kj} is then scaled by:

$$w_j \frac{GE(y_j;0)}{GE(y;0)}, \quad (19)$$

where w_j is the weight function defined in connection to expression (3). The different weight schemes computed for $GE(y_j;\alpha)$ with sensitivity parameters $\alpha = \{-1,0,1,2\}$ are presented in Table 4.

Table 4: Inequality weights (w_j) for the GE-index.

	2005			*2013*		
GE-index	*Workers*	*SE*	*ISE*	*Workers*	*SE*	*ISE*
GE(-1)	0.931	0.059	0.018	0.936	0.053	0.019
GE(0)	0.938	0.04	0.022	0.942	0.034	0.024
GE(1)	0.946	0.027	0.027	0.948	0.022	0.03
GE(2)	0.954	0.018	0.033	0.954	0.014	0.038

The aggregate inequality variancess_{kj} applies to all inequality indices, not solely to the various GE-indices, provided the basic assumptions in Shorrocks (1982) are satisfied (see Appendix 1). In order to investigate the contribution to aggregate inequality of a particular explanatory

[10] In terms of percentage points, we showed in Table 3 that within-group inequality contributed 97.8% and 97.5% of aggregate inequality for all $\alpha = 1$ in 2005 respective 2013. For differences values of α the within-share is even higher.

variable in a specific subgroup, one needs to specify a given index in order to define the scaling function.

5.1. Regression models of income inequality in 2005

Beginning with inequality the year 2005, Table 5 shows separate regression models of the main contributors to within-group inequality for the three groups: W, SE and ISE. Columns 1-3 display Mincer-type estimates (OLS) regressing our explanatory variables on individuals' market income, while columns 4-6 shows the effects of the same explanatory variables for overall income inequality in each specific group. Almost all variables are found statistically significant in the regressions, which is not unsurprising given the large number of observations. Regardless of subgroup, three variables stand out as the major contributors to inequality. These are Years of education, Gender (1=Male), and Age. Years of education shows large marginal effect in the individual-level estimates 84.810 for workers (W), which corresponds to a 8 481 SEK(€913) higher yearly income for each additional year of education. Among SE and ISE entrepreneurs, each additional year translates into a higher income of 3 562 SEK(€384) and 10 473 SEK(€1 129), respectively. Although ISE showed the largest marginal effect of education, inspecting the proportional contributions of education for overall income inequality in each groups (Columns 4-6), we observe another pattern, namely, that Education contributes the most to inequality among workers with 4.46%, whereas for SE only 0.338% for SE entrepreneurs, and with 3.92% for the group of ISE entrepreneurs. As much as these results inform us about the contribution to the inequality of $G(y_i, \alpha)$, it remains to compute their estimated contribution to aggregate inequality, that is to $G(y, \alpha)$.

Table 5: Regression results for market income 2005 and percentage contribution to $GE(y_j;\alpha)$

	Regression estimates			$100 \times s_{kj}$		
	W	*SE*	*ISE*	*W*	*SE*	*ISE*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Age	7.640***	-7.212***	-0.826	1.051	-0.11	-0.032
	(0.072)	(0.399)	(0.657)	(0.000)	(0.000)	(0.000)
Age square	-0.961***	-0.884***	-1.123***	1.847	0.793	0.74
	(0.005)	(0.031)	(0.053)	(0.000)	(0.000)	(0.000)
Job tenure	22.898***	46.661***	25.176***	0.873	2.82	0.42
	(0.137)	(0.832)	(1.411)	(0.000)	(0.000)	(0.000)
Job changes	15.930***	50.886***	20.317***	0.067	0.141	0.002
	(0.421)	(2.546)	(4.340)	(0.000)	(0.000)	(0.000)
No. children	-51.475***	16.953***	-1.476	0.192	0.048	-0.003
	(0.528)	(3.187)	(5.109)	(0.000)	(0.000)	(0.000)
Gender	502.631***	333.634***	488.670***	6.481	2.085	1.716
	(1.386)	(8.536)	(12.387)	(0.000)	(0.000)	(0.000)
Marital Status	11.796***	97.789***	75.365***	0.041	0.068	0.141
	(1.097)	(7.000)	(10.718)	(0.000)	(0.000)	(0.000)
Years of education	84.810***	35.623***	104.731***	4.459	0.376	3.917
	(0.362)	(1.897)	(2.863)	(0.000)	(0.000)	(0.000)
Immigrant	-160.862***	-375.107***	-365.642***	0.171	0.76	0.185
	(2.637)	(11.314)	(37.006)	(0.000)	(0.000)	(0.000)
Constant	1153.008***	778.969***	870.616**	0.000	0.000	0.000
	(14.227)	(35.246)	(340.141)	(0.000)	(0.000)	(0.000)
Reg. f.e.	Yes	Yes	Yes	1.007	0.304	0.676
Ind. f.e.	Yes	Yes	Yes	4.875	6.013	6.153
Occ. f.e.	Yes	No	No	21.26	-	-
Obs.	3 312 618	140 401	77 041			
R-sq.	0.423	0.133	0.139			
Res. (=1-R-sq)				57.677	86.702	86.086

To gauge the contribution of each explanatory variable for overall income inequality we compute their estimated contribution based on the Theil index of $G(y,1)$ with weights from Table 4 and the GE-index values from Table 3. In 2005, the scaling factor amounts to 0.89 for W $(0.946 \times 0.125/0.133)$, 0.06 for SE $(0.027 \times 0.313/0.133)$, and 0.02 for ISE entrepreneurs $(0.027 \times 0.121/0.133)$. Once multiplied with the weight, we find that education among workers accounts for 3.96% of $\Lambda_w(y;1)$, 0.02% for SE entrepreneurs, and for 0.1% for ISE.[11] Although, education among SE and ISE accounts for a sizable portion of

[11] The reason for $\Lambda_w(y;1)$ instead of $\Lambda(y;1)$, is that we focus on the decomposition of within-group inequality. Strictly speaking since $b_{kj}\mu(x_{kj})$ is also contained in $\Lambda_b(y;1)$, the decomposition results in the regression analysis does only account for the contribution of $b_{kj}\mu(x_{kj})$ to $\Lambda(y;1)$ via $\Lambda_w(y;1)$. Given the

that groups within-inequality, the contribution of differences in education level within these groups to aggregate income inequality naturally drops because of these groups being comparatively small compared to W. What is more, to know the total contribution of an explanatory variable to aggregate inequality, we can simply add the weighted contributions of that variable from all groups. For Years of education, this amounts to 4.08% (out of 100%).

Turning to the gender variable that takes the value of 1 if the individual is male and 0 otherwise, we find the largest marginal effect for all groups. Among workers it appears that men on average earn 50 263 SEK (€ 5 028) more than the average woman.[12] The gender income difference is smaller for SE of 33 363 SEK (€ 3 595), as with ISE with a difference of 48 867 SEK (€5 266). The proportional contributions of gender to within- group inequality is even more pronounced for workers, with 6.48% for W compared to the 2.09% for SE and 1.72% for ISE. Rescaled as contributions to aggregate within-inequality $\Lambda_w(y;1)$, the gender composition of each group contributes with 5.76% from W, 0.13% from SE, and 0.04% from ISE. We can also add these last percentage-point contributions to get the total workforce inequality contribution attributable to gender differences in income. Doing this, we find that gender accounts for 5.93% out of total aggregate inequality.[13]

Table 5 also shows that while age is positively associated with incomes for both W and ISE it is negatively associated for SE (Yamauchi, 2001). Using the scaling factor we see that the total contribution of Age to income inequality in each group amounts to 0.94% for W, −0.01% for SE, and −0.00% for ISE. From adding the scaled contributions we get the total contribution from Age-squared to $\Lambda_w(y;1)$, which amounts to 0.93%.

Before comparing the same results for the regression in the 2013 sample, it is worth mentioning the fixed effects, and the model fit. Among the fixed effects included in we see in columns 4-6 of Table 5 that the occupational fixed effects accounts for the highest share of inequality in each sub-group. The variance in income across occupations accounts for 21.26% for W and if scaled it amounts to 22.22% of $\Lambda_w(y;1)$.

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comparatively small contribution of $\Lambda_b(y;1)$ to $\Lambda(y;1)$, however, the impact from any particular $b_{kj}\mu(x_{kj})$ on $\Lambda_b(y;1)$ is almost negligible and therefore left out when presenting the results.

[12] The large gender income gap may be partly attributed to women more often working part-time.

[13] Strictly speaking, the total contribution of 4.99% from Gender refers to the aggregate within inequality of $\Lambda_w(y;1) =$ 98.3%, and not to the 100% that corresponds to $\Lambda(y;1)$.

An important reason for why we find larger contributions in the group of workers can be seen from the R2 value, which shows that the empirical model explains 42% of the variance in income for W. High R2 values are common in mincer-type earnings equations (Robinson & Sexton, 1994). For the SE and ISE entrepreneurs however, R2 amounts to 13.3%, and 13.9%, partly reflecting the no inclusion of occupational fixed effects for the entrepreneurial groups. This means that the residual contribution to within group inequality as captured by the error term in the model, is comparatively large for entrepreneurs. One reason for this difference is empirical in that the higher variance in market income among these groups compared to workers leads to lower explanatory power in OLS models. Another reason may be theoretical in that income among entrepreneurs is known to be more affected by unobserved ability than among workers (Åstebro et al., 2011)

The contribution of the error term for overall income inequality within groups is presented in the bottom row in columns (4) to (6), and accounts for 57.7% for the inequality within W, which for SE amounts to 86.7%, and for ISE 86.1%. Since the residual enters the model just as any other explanatory variable we can also compute the total contribution to aggregate inequality $\Lambda_w(y;1)$ from u_{ji} in expression (12), which amounts to 60%.

5.2. Changes in inequality over time, 2005 – 2013

By repeating the empirical analysis for a later period we are able to investigate changes in the determinants of inequality between the two time periods. Table 6 presents identical models to those of Table 5 but for the 2013 sample. To begin with, we observe that Years of education, Gender, and Age all still play a significant role in accounting for inequality in 2013. Continuing with the Theil index, the scaling factors for 2013 amounts to 0.90 for W $(0.95 \times 0.12/0.13)$, 0.05 for SE $(0.02 \times 0.304/0.13)$, and 0.03 for ISE $(0.03 \times 0.13/0.13)$. Going forward we focus on the scaled contribution to the inequality aggregate when discussing differences in 2013 compared to 2005.

Starting with education, in W it accounts for 3,38% of aggregate inequality, compared to Years of education among SE and ISE that contributes by 0.004% and 0,07%. As a total, considering the effect from education across all groups it accounts for 3.38% of aggregate inequality. Since education accounted for 4.08% in 2005, the results for 2013 suggest that education as a means to explain the development of income inequality has declined.

A similar development seems to have occurred if we consider the age and gender variable, which appears to be lesser correlates of income inequality in 2013 compared to 2005. The percentage contribution from the gender variables 3.59% for W, 0.09% for SE, and 0.03% for ISE, which adds up to 3.71% in total. For Age, we have 1.56 for W, -0.01% for SE and -0.01% for ISE, which together amount to 1.54%.

One explanation to this particular development can be located at the bottom row of Table 6. For each of the groups, we see that the part of the variance in income that is not explained by the model has increased, which directly impacts the size of the estimates for the partial contributions s_{kj}.

Table 6. Regression results for market income 2013 and contribution to $GE(Y_j;0)$

	Regression estimates			$100 \times s_{kj}$		
	W	*SE*	*ISE*	*W*	*SE*	*ISE*
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Age	11.660***	-11.596***	-5.932***	1.736	-0.204	-0.223
	(0.080)	(0.462)	(0.731)	(0.000	(0.006)	(0.008)
Age square	-0.952***	-0.806***	-1.608***	2.096	0.684	1.101
	(0.005)	(0.035)	(0.058)	(0.000)	(0.001)	(0.001)
Job tenure	20.027***	40.156***	35.948***	1.157	2.686	1.384
	(0.114)	(0.731)	(1.039)	(0.000)	(0.003)	(0.002)
Job changes	13.271***	44.339***	9.633***	0.156	0.336	0.001
	(0.358)	(2.115)	(3.162)	(0.000)	(0.002)	(0.002)
No. children	-42.097***	24.039***	13.295**	0.01	0.079	0.035
	(0.597)	(3.728)	(5.670)	(0.000)	(0.001)	(0.002)
Gender	453.313***	309.497***	486.060***	4.009	1.662	1.146
	(1.506)	(9.795)	(14.138)	(0.000)	(0.003)	(0.003)
Marital Status	27.663***	83.136***	100.675***	0.107	0.061	0.188
	(1.224)	(7.889)	(11.474)	(0.000)	(0.001)	(0.002)
Years of education	86.578***	24.837***	92.213***	3.686	0.074	2.451
	(0.389)	(2.081)	(3.156)	(0.000)	(0.006)	(0.009)
Immigrant	-136.289***	-304.619***	-368.599***	0.208	0.617	0.237
	(2.301)	(12.192)	(29.902)	(0.000)	(0.000)	(0.000)
Constant	1347.316***	1277.275***	2297.892**	0.000	0.000	0.000
	(15.939)	(40.870)	(1097.735)	(0.000)	(0.000)	(0.000)
Reg. f.e.	Yes	Yes	Yes	1.116	0.598	0.845
Ind. f.e.	Yes	Yes	Yes	5.733	4.754	6.912
Occ. f.e.	Yes	No	No	21.392	-	-
Obs.	3464330	124666	89216			
R-sq.	0.414	0.113	0.141			
Res. (=100-R^2*100)				58.594	88.652	85.921

4. Summary and Discussion.

We have outlined an approach which seeks to problematize and probe the ways in which entrepreneurship may contribute to income inequality. We develop an econometric model to decompose aggregate changes in income dispersion based on a generalized-entropy index distinguishing between self-employed (SE) and incorporated entrepreneurs (ISE) using detailed microdata for Sweden in 2005 and 2013. Sweden represents a setting traditionally characterized by low income inequality but where inequality has recently increased rapidly, providing an interesting case to probe the role of entrepreneurship for income inequality. At the same time, the rate of necessity entrepreneurs in Sweden remains low (Singer et al., 2014), meaning that our results are of limited risk of being severely affected by workers being forced into entrepreneurship due to lack of alternative employment opportunities. By tuning the GE-index to different segments of the income distribution, we find across a range of specifications that the self-employed entrepreneurs seem to increases workforce inequality by way of a widening of the bottom-end of the distribution. Incorporated entrepreneurs more modestly increases workforce inequality by increasing the total number of high income earners in society. The aggregate effects of both types of entrepreneurship for overall workforce income inequality are similar in magnitude to more conventional factors such as relative educational group size, suggesting that entrepreneurship do not represent an exclusive explanation for the rising income inequality in contemporary economies. This finding is of value for entrepreneurship research discussing the role of entrepreneurship for economic development (Lippmann et al., 2005; Praag & Versloot, 2007; Shane, 2009).

To the best of our knowledge, this paper is the first to assess the effects of entrepreneurship for income inequality using state-of-the art decomposition techniques. By decomposing entropy-based inequality indexes by several sub-groups and estimating inequality both between and within each sub-group, our model provides a clearer picture of the group dynamics that drive inequality at the population level. Further, we are able to pinpoint the significance of each explanatory factor and its contribution to subgroup inequality. Self-employed (SE) and incorporated entrepreneurs (ISE) do contribution to workforce income inequality but in different ways, and the relative importance of entrepreneurship for overall income inequality seems to have increased. This suggests that inequality scholars could benefit from including entrepreneurship in their analyses of workforce inequality in various settings.

Our model and results also comes with limitations that could be extended and probed by future research efforts. Specifically, after the abolition of wealth taxation in Sweden in 2005, the microdata do not include measures of wealth. Future research could expand on our model by examining wealth inequality instead of income inequality, as prior studies suggest that entrepreneurship is a key element to understand wealth concentration (Buera, 2009; Quadrini, 1999). Further, the decomposition techniques utilized do not lend themselves to causal interpretations in that they are driven by both within-workforce shifts in occupational categories and changes in income dispersion within those categories. Future research could benefit from using regulatory changes or other quasi experimental settings to gauge causal relationship between rates of entrepreneurship and levels of income inequality (Kerr & Nanda, 2009).

Appendix 1: The Shorrocks' assumption for income decomposition

Shorrock's (1982) six assumptions for computing inequality measures has for long been central in the literature (Bigotta et al., 2015). The six assumptions posits inequality as a function $I(\boldsymbol{y})$ and are listed below:

ASSUMPTION 1: (i) $I(\boldsymbol{y})$ is continuous and symmetric. (ii) $I(\boldsymbol{y}) = 0$ iff $\boldsymbol{y} = \mu\boldsymbol{e}$, for $\boldsymbol{e} = (\mathbf{1}, \dots, \mathbf{1})$, where μ is the mean income.

ASSUMPTION 2: (i) $S_k(\boldsymbol{y}^{\mathbf{1}}, \dots, \boldsymbol{y}^{\boldsymbol{K}}; K)$ is continuous in $\boldsymbol{y}^{\boldsymbol{k}}$. (ii) That $S_{\boldsymbol{\pi}_{\boldsymbol{k}}}(\boldsymbol{y}^{\mathbf{1}}, \dots, \boldsymbol{y}^{\boldsymbol{K}}; K) = S_k(\boldsymbol{Y}^{\boldsymbol{\pi}_1}, \dots, \boldsymbol{Y}^{\boldsymbol{\pi}_K}; K)$, where $\boldsymbol{\pi}_{\mathbf{1}}, \dots, \boldsymbol{\pi}_{\boldsymbol{K}}$ is some permutation of $1, \dots, K$.

ASSUMPTION 3: That $S_1(\boldsymbol{y}^{\mathbf{1}}, \dots, \boldsymbol{y}^{\boldsymbol{K}}; K) = S_1(\boldsymbol{y}^{\mathbf{1}}, \boldsymbol{y} - \boldsymbol{y}^{\mathbf{1}}; 2) = S(\boldsymbol{y}^{\mathbf{1}}, \boldsymbol{y})$, which means independence of the level of disaggregation.

ASSUMPTION 4: That decomposition is consistent, hence $\sum_k S_k(\boldsymbol{y}^{\mathbf{1}}, \dots, \boldsymbol{y}^{\boldsymbol{K}}; K) = \sum_k S(\boldsymbol{y}^{\boldsymbol{k}}, \boldsymbol{y}) = I(\boldsymbol{y})$.

ASSUMPTION 5: (i) Of population symmetry, that $\boldsymbol{P}$ is some n by n permutation matrix. $S(\boldsymbol{y}^{\boldsymbol{k}}\boldsymbol{P}, \boldsymbol{y}\boldsymbol{P}) = S(\boldsymbol{y}^{\boldsymbol{k}}, \boldsymbol{y})$. (ii) And normalization for equal factor distribution, which means that $S(\mu^{\boldsymbol{k}}\boldsymbol{e}, \boldsymbol{y}) = 0, \forall \mu_k$.

ASSUMPTION 6: That for all permutation matrices, $S(\boldsymbol{y}^{\mathbf{1}}, \boldsymbol{y}^{\mathbf{1}} + \boldsymbol{y}^{\mathbf{1}}\boldsymbol{P}) = S(\boldsymbol{y}^{\mathbf{1}}\boldsymbol{P}, \boldsymbol{y}^{\mathbf{1}} + \boldsymbol{y}^{\mathbf{1}}\boldsymbol{P})$.

Appendix 2: Robustness tests for disposable income

In this section we present the corresponding tables, figures and results for disposable income in place of market income.

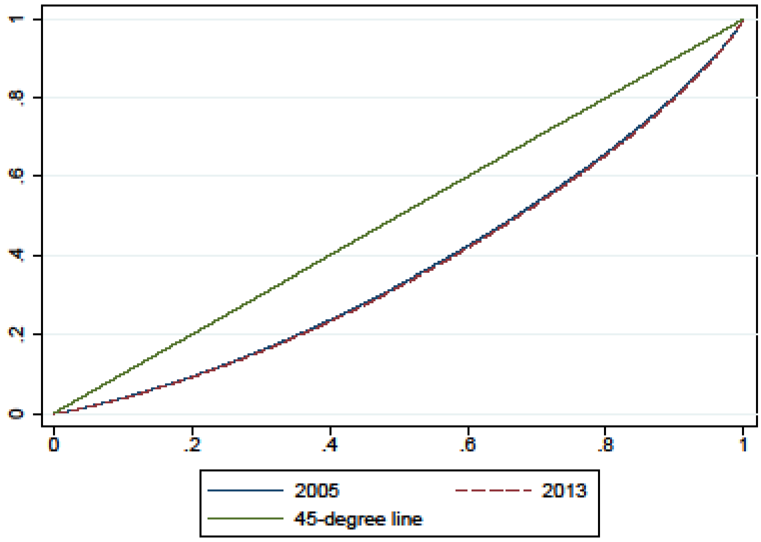


Figure A.1. Lorentz curve for workforce disposable income, 2005 and 2013

Table A1. Descriptive statistics: Disposable income among entrepreneurs

	2005				2013			
Variables:	*Mean* (1)	*Sd.* (2)	*Min* (3)	*Max* (4)	*Mean* (5)	*Sd.* (6)	*Min* (7)	*Max* (8)
Number of Workers (W)								
Market income	1493.661	672.915	0.909	4693.129	1842.711	859.643	0.812	6071.121
Obs.	3346001				3509346			
Self-employed (SE)								
Market income	1186.328	717.269	0.909	4693.129	1444.678	910.184	0.812	6071.121
Obs.	159966				150800			
Incorporated entrepreneurs (ISE)								
Market income	1789.158	836.433	5.455	4693.129	2326.387	1121.46	4.871	6071.121
Obs.	77087				89168			

Table A2 Income inequality statistics (disposable income)

	2005			*2013*		
	Pop.	*SE*	*ISE*	*Pop.*	*SE.*	*ISE*
Inequality measure:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Disposable Income						
p90/p10	3.197	4.949	3.538	3.278	5.466	3.7
p90/p50	1.682	2.051	1.779	1.714	2.093	1.832
p50/ p10	1.9	2.414	1.989	1.913	2.611	2.019
p75/p25	1.86	2.285	1.909	1.884	2.383	1.984
GE(-1)	0.125	0.591	0.144	0.137	1.034	0.151
GE(0)	0.1	0.202	0.112	0.106	0.233	0.12
GE(1)	0.096	0.171	0.105	0.102	0.187	0.112
GE(2)	0.101	0.183	0.109	0.109	0.198	0.116
Gini	0.249			0.257		

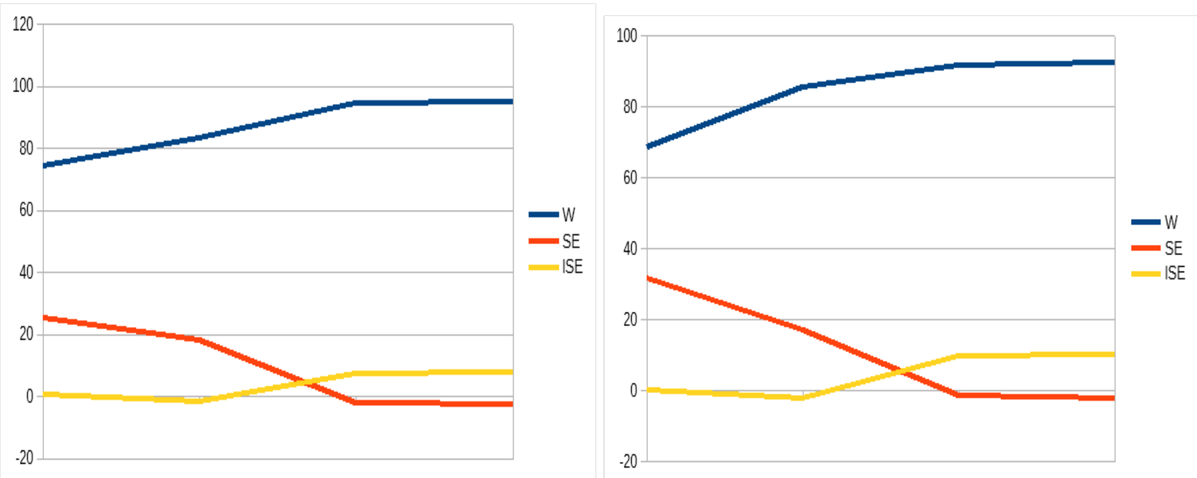
In Tables A3 and Figure A1 we present the same decomposition as in Table 3 and Figure 2 in the main paper, but for disposable income instead of market income. The results are qualitatively similar to those for market income. Workers accounts for roughly 80% of aggregate inequality. Looking at Figure 3 (i) and (ii) we see that the inequality-group dynamics between SE and ISE largely remains for disposable income over the period. SE (ISE) stands for most of workers' residual contribution when inequality is computed with emphasis on the lower (upper) tail of the disposable income distribution

Table A3 (akin to Table 3): Sub-group decomposition in percentage points of $GE(y;\alpha)$ for disposable income, 2005 and 2013.

	2005				*2013*			
	W (1)	*SE* (2)	*ISE* (3)	*Total* (4)	*W* (5)	*SE* (6)	*ISE* (7)	*Total* (8)
GE(-1)	0.125	0.591	0.144	0.154	0.137	1.034	0.151	0.776
Between: $\Lambda_b(y_j;\alpha)$	-1.497	3.671	-1.184	0.99	-0.616	2.946	-1.342	0.527
Within: $\Lambda_w(y_j;\alpha)$	75.828	21.512	1.67	99.01	69.015	28.474	1.522	99.473
Total: $\Lambda(y_j;\alpha)$	74.331	25.183	0.486	100	68.4	31.42	0.18	100
GE(0)	0.1	0.202	0.112	0.106	0.106	0.233	0.12	0.161
Between: $\Lambda_b(y_j;\alpha)$	-4.355	9.497	-3.765	1.377	-2.022	8.549	-4.942	2.243
Within: $\Lambda_w(y_j;\alpha)$	87.835	8.508	2.28	98.623	87.647	8.255	2.513	97.757
Total: $\Lambda(y_j;\alpha)$	83.48	18.005	-1.485	100	85.625	16.804	-2.429	100
GE(1)	0.096	0.171	0.105	0.1	0.102	0.187	0.112	0.128
Between: $\Lambda_b(y_j;\alpha)$	4.635	-8.028	4.8	1.407	2.155	-7.144	6.65	2.543
Within: $\Lambda_w(y_j;\alpha)$	89.767	6.104	2.722	98.593	89.624	5.554	3.16	97.457
Total: $\Lambda(y_j;\alpha)$	94.402	-1.925	7.522	100	91.78	-1.59	9.81	100
GE(2)	0.101	0.183	0.109	0.106	0.109	0.198	0.116	0.133
Between: $\Lambda_b(y_j;\alpha)$	5.854	-7.954	4.059	1.959	4.675	-7.565	5.144	2.254
Within: $\Lambda_w(y_j;\alpha)$	90.555	4.445	3.041	98.041	90.804	3.29	3.652	97.746
Total: $\Lambda(y_j;\alpha)$	96.409	-3.509	7.1	100	95.479	-4.275	8.796	100

Note: The table shows the percentage contribution (1=100%) of the between and within inequality component from the sub-groups workers, SE, and ISE. Separate contributions are calculated for the various GE-indices with $\alpha = \{-1,0,1,2\}$. The inequality levels for each of the subgroups are calculated using eq. (16) with the appropriate weights. These inequality levels differs from those presented in Table 2 that comprise raw calculations based on equation (1) applied to the restricted sample.

Figure A1 (akin to Figure 2). Proportional contribution to overall inequality in disposable income from workers, self-employed and incorporated entrepreneurs



(i) Disposable income 2005 (ii) Disposable income 2013

The next three tables replicates tables 4-6 in the main paper using disposable income instead of market income. Again, we use the method of Fiorio and Cowell (2011) to decompose within group inequality $\Lambda_w(y_j;\alpha)$ to a number of explanatory variables (factor sources).

Table A4: Inequality weights (w_j) for the GE-index.

	Workers	SE	ISE	Workers	SE	ISE
Disposable income, 2005				**Disposable income, 2013**		
GE(-1)	0.929	0.056	0.018	0.934	0.051	0.019
GE(0)	0.934	0.045	0.022	0.936	0.04	0.024
GE(1)	0.938	0.036	0.026	0.938	0.032	0.03
GE(2)	0.943	0.028	0.031	0.941	0.025	0.038
GE(3)	0.948	0.023	0.038	0.943	0.02	0.048

Table A5: Regression results for disposable income 2005 and contribution to $GE(Y_j;0)$

	Regression estimates disp. inc.			% contrib. to $GE(y_j;\alpha)$ ($s_k \times 100$)		
Variable	Workers	Self-emp.	Inc. emp.	Workers	Self-emp.	Inc. emp.
Age	11.901***	12.641***	13.694***	4.576	4.669	4.264
	(0.044)	(0.212)	(0.376)	(0.000)	(0.002)	(0.005)
Age square	-0.109***	0.181***	-0.088***	0.13	-0.016	0.003
	(0.003)	(0.017)	(0.031)	(0.000)	(0.000)	(0.001)
Job tenure	6.202***	11.260***	11.392***	0.277	0.888	0.736
	(0.081)	(0.424)	(0.783)	(0.000)	(0.001)	(0.002)
Job Changes	13.958***	31.502***	15.766***	0.088	0.063	-0.189
	(0.236)	(1.274)	(2.361)	(0.000)	(0.000)	(0.001)
Children living at home	-202.706***	-85.785***	-211.268***	12.502	2.9	8.992
	(0.309)	(1.544)	(2.789)	(0.000)	(0.000)	(0.001)
Gender	264.791***	220.129***	342.141***	5.446	2.312	2.245
	(0.787)	(4.303)	(7.164)	(0.000)	(0.001)	(0.002)
Marital Status	-78.738***	97.844***	-18.195***	0.337	0.374	0.007
	(0.654)	(3.602)	(5.956)	(0.000)	(0.000)	(0.001)
Years of education	31.583***	24.226***	47.948***	1.6	0.479	1.946
	(0.204)	(0.972)	(1.600)	(0.000)	(0.002)	(0.005)
Imigrant	-96.247***	-207.135***	-191.386***	0.207	1.058	0.188
	(1.430)	(5.721)	(20.291)	(0.000)	(0.000)	(0.000)
Constant	920.204***	16.917	538.702***	-	-	-
	(8.025)	(18.416)	(196.975)	-	-	-
Reg. f.e.	yes	yes	yes	1.166	0.428	0.748

Ind. f.e.	yes	yes	yes	2.624	3.961	3.459
Occ. f.e.	yes	yes	yes	9.044	-	-
Obs.	3346001	159966	77087			
R-sq.	0.38	0.171	0.224			
Res. (=1-R-sq)				62.003	82.884	77.601

Table A6: Regression results for disposable income 2013 and contribution to $GE(\log Y_j;0)$

	Regression estimates disp inc.			% contrib. to $GE(y_j;\alpha)$, ($s_k \times 100$)		
Variable	Workers	Self-emp.	Inc. emp.	Workers	Self-emp.	Inc. emp.
Age	15.154***	11.616***	15.993***	4.685	3.035	3.33
	(0.056)	(0.278)	(0.480)	(0.000)	(0.002)	(0.005)
Age square	-0.094***	0.223***	-0.293***	0.142	-0.07	0.062
	(0.004)	(0.021)	(0.038)	(0.000)	(0.000)	(0.001)
Job tenure	7.311***	15.956***	15.904***	0.54	1.773	1.258
	(0.078)	(0.438)	(0.673)	(0.000)	(0.001)	(0.001)
Job Changes	14.670***	32.862***	15.318***	0.222	0.352	-0.098
	(0.231)	(1.239)	(1.987)	(0.000)	(0.001)	(0.001)
Nr. children	-239.937***	-93.317***	-261.534***	9.876	1.946	7.094
	(0.393)	(2.048)	(3.527)	(0.000)	(0.000)	(0.001)
Gender	298.296***	225.840***	427.118***	4.137	1.71	1.86
	(0.971)	(5.599)	(9.069)	(0.000)	(0.001)	(0.002)
Marital Status	-75.802***	131.779***	-15.537**	0.191	0.352	0.01
	(0.831)	(4.676)	(7.267)	(0.000)	(0.001)	(0.001)
Years of education	34.685***	20.820***	49.692***	1.166	0.149	1.393
	(0.249)	(1.225)	(2.035)	(0.000)	(0.002)	(0.005)
Imigrant	-122.704***	-255.266***	-212.346***	0.341	1.239	0.227
	(1.465)	(6.905)	(18.421)	(0.000)	(0.000)	(0.000)
Constant	1119.658***	326.949***	962.651***	-	-	-
	(10.164)	(24.326)	(228.985)			
Reg. f.e.	yes	yes	yes	1.612	0.809	1.46
Ind. f.e.	yes	yes	yes	3.316	3.1	4.325
Occ. f.e.	yes	yes	yes	9.242	-	-
Obs.	3509346	150800	89168			
R-sq.	0.355	0.144	0.209			
Res. (=1-R-sq)				64.53	85.605	79.077

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