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Measuring the Role of Self-Employment in Earnings Inequality

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Introduction[*]

An extensive literature has chronicled the increase in wage inequality in the United States since the 1970s.[1] These studies have generally focused only on wage and salary workers because data on self-employed workers are limited and measurement of their labor income is difficult. However, earnings inequality is generally found to be greater among self-employed workers than wage and salary workers. As a consequence, studies that exclude self-employed workers may provide an incomplete picture of the levels and changes in wage inequality in the United States.

This paper uses data from the Survey of Consumer Finances (SCF) to examine wage inequality among self-employed workers and its effects on overall wage inequality. Existing evidence on this question comes primarily from European countries, and only two previous studies of which we are aware (Sullivan and Smeeding (1997) and Green, Hamilton, and Paarsch (1995)) have examined it in the American context. The detailed data available in the SCF on the components of self-employment income and the characteristics of self-employed workers allow us to examine two key questions about the extent of inequality among these workers.

The first question is a measurement question. The labor income of wage and salary workers is fairly straightforward to measure. In contrast, self-employed workers can choose how much income to pay themselves and how much to retain in the business. Tax considerations may also particularly affect reporting of self-employment income. Thus, we construct various measures of self-employed earnings and examine how sensitive the results regarding the relative levels of inequality in the self-employed sector compared to the wage/salary sector are to these different measures.

[*] The views expressed in this paper are the authors' alone and are not necessarily those of the Board of Governors or its staff. We thank colleagues at the Federal Reserve Board for helpful discussions and suggestions.

[1] See, for example, Juhn, Murphy, and Pierce (1993), DiNardo, Fortin, and Lemieux (1996), Eckstein and Nagypál (2004), Autor, Katz, and Kearney (2005), and Lemieux (2006).

The second is a policy question, namely the sources of these differences in inequality. Specifically, we examine the extent to which the less equal distribution of self-employed earnings that we observe is due to differences in: i) the characteristics of workers employed in each sector; ii) the returns to these characteristics across sectors, and; iii) the variability of earnings within each group of workers. We use the decomposition techniques outlined in Machado and Mata (2005) and Autor, Katz, and Kearney (2005) to distinguish between these explanations.

We show that earnings inequality is greater among the self-employed. This finding is robust to the choice of measure of self-employment income. We find that differences in the characteristics of workers employed in each sector do little to explain this difference in inequality. Differences in the returns to observed characteristics generally explain between 20 and 40 percent of the higher inequality among self-employed workers. Thus, the majority of the disparity in earnings inequality is attributed to differences in residual inequality, i.e., earnings dispersion that remains after controlling for the skills and characteristics of workers and for the labor market prices of these attributes.

Understanding why earnings inequality is greater among self-employed workers is potentially important given the array of non-profit and government programs that aim to promote entrepreneurship among disadvantaged and unemployed workers (OECD (2000), Fairlie (2005)). In particular, the greater volatility of self-employment income (including the risk of losses, which wage and salary workers do not face directly) raises the possibility that these workers would have greater or more stable earnings if they were able to obtain a wage or salary position. Our finding that most of the differences in earnings inequality are due to residual dispersion suggests that, in targeting these programs, it may be important to consider both the higher degree of income volatility and the greater role played by unobservables (e.g., risk preferences, social connections, and "luck") in self-employment earnings.

Prior Literature

This paper contributes to the growing literature on self-employment in the U.S. as well as other countries. Despite increased research interest in entrepreneurship, however, relatively little is known about earnings inequality among the self-employed and its effect on the overall distribution of labor income, particularly for the United States.[2] Sullivan and Smeeding (1997) compare the distribution of self-employment earnings across nineteen countries and examine the sensitivity of the p90/p10 ratio to the inclusion of self-employed income for six countries. They find that including self-employment earnings generally increases this measure and the resulting changes in the ratio are substantial enough to alter the ordering of inequality across countries.[3] Further, they show that U.S. households with only self-employment income are over-represented in the bottom decile of the overall income distribution, whereas those with both self-employment and wage/salary income are disproportionately concentrated in the top quartile. A similar pattern holds across several countries they consider.

The studies of Jenkins (1995) and Quintano, Castellano and Regoli (2005) provide further evidence regarding the contribution of self-employment income to overall inequality. Jenkins examines an array of possible explanations for the trends in income inequality in the U.K. between the 1970s and mid-1980s and concludes that growth in the dispersion of self-employment income was a primary factor underlying the marked increase in overall inequality

[2] We recently learned of and requested the Green, Hamilton, and Paarsch (1995) study of income inequality among self-employed workers in the U.S..

[3] For samples both of full-year/full-time workers and of all workers, the p90/p10 ratio rose when self-employed workers were included for Australia, Canada, Sweden, and the United States and held about steady for Germany. For the Netherlands, the ratio fell when the self-employed were included in the calculation for full-time/full-year workers and increased slightly for the sample of all workers.

between 1981 and 1986. Similarly, Quintano, Castellano and Regoli find that inequality in self-employment income rose in Italy between 1998 and 2002. Consequently, the share of aggregate inequality accounted for by self-employment earnings also increased, though offsetting changes in the distribution of property income led to a decline in overall inequality over this period.

Finally, Parker (1997) offers suggestive evidence that higher income inequality among the self-employed might reflect, in part, greater variation in the characteristics of self-employed workers compared to the variation in employees' characteristics. Specifically, Parker finds that the increase in self-employed income inequality in the U.K. between 1976 and 1991 was likely the result of increased heterogeneity among self-employed workers rather than a change in returns to self-employment brought about by increased self-employment rates.[4]

As noted above, one potential explanation for the limited research on self-employment is the difficulty of measuring and obtaining data on earnings for self-employed workers. Numerous authors have noted that the self-employed have much more flexibility in reporting earnings, both through tax avoidance strategies (legal and illegal) and through the timing of the realization of earnings.[5] Two recent studies that investigate these measurement problems are Hamilton (2000) and Moore (2004).

Using data from the Survey of Income Program Participation (SIPP), Hamilton constructs two alternative measures to the usual net income measure, which is often influenced by tax considerations and so may understate true profits. As alternative measures, he considers how much the business owner withdrew in salary and a measure that adds an estimate of the year-to-

[4] Parker (1999) finds that demographic characteristics explain a greater share of both levels and changes in earnings inequality for wage/salary workers than for self-employed workers. Consequently, he concludes that it is difficult to identify the key dimensions of the increase in heterogeneity among the self-employed.

[5] A 1976 IRS study cited by Long (1982) revealed that only 64 percent of possible self-employment income was reported, compared to 98 percent of wage/salary income. A more recent study by Slemrod, Blumenthal, and Christian (2001) cites the 1988 IRS Taxpayer Compliance Measurement Program, which reports that 99.5% of wage and salary income is reported, but that only 41.4% of Schedule C income is reported. See also Sullivan and Smeeding (1997).

year change in the equity value of the business to the owner's salary. Hamilton finds that net income is the lower bound on self-employment earnings, and that the median employee wage is larger than the median for all the self-employed earnings measures. A similar result is found for mean earnings, except for the self-employed earnings measure that incorporates the change in the equity value of the business.

The study by Moore (2004) is similar in spirit to Hamilton but uses data from the Survey of Consumer Finances (SCF) and a slightly different equity-adjusted earnings measure for the self-employed. Moore finds that the measure of self-employed earnings matters in the comparisons of both the median and mean earnings of the two groups. For median earnings, the employee wage significantly exceeds only the net income measure, and for mean earnings all of the self-employed measures are significantly larger than the employee wage. An important conclusion of both Hamilton and Moore is that alternative measures of self-employed earnings provide a useful means of addressing measurement and reporting issues.

Data

The data used in this paper are from the 2004 Survey of Consumer Finances (SCF). The Board of Governors of the Federal Reserve System conducts this survey of household assets and liabilities on a triennial basis. Besides collecting information on assets and liabilities, the SCF collects information on household demographics, income, relationships with financial institutions, attitudes toward risk and credit, current and past employment, and pensions. The sample size for the 2004 SCF is 4,522 households.[6]

The SCF uses a dual frame sample design to provide adequate representation of the financial position of all households in the United States. One part of the sample is a standard

[6] For more details on the 2004 SCF, see Bucks, Kennickell, and Moore (2006).

multi-stage national area probability sample (Tourangeau et al., 1993), while the second component of the sample draws on statistical records derived from tax returns to oversample households that are likely to be wealthy (Kennickell, 2001). This dual frame design provides the SCF with efficient representation of both widely held assets, such as cars and houses, and narrowly held assets, such as private businesses and bonds. The oversample of households likely to have higher wealth also means that the unweighted number of self-employed households in the SCF is larger than would be obtained via simple random sampling.

Wealth data from the SCF are widely regarded as the most comprehensive microdata available for the United States. Non-response adjusted sample weights constructed for the SCF yield estimates that are representative of U.S. households (Kennickell and Woodburn, 1999; Kennickell, 1999). Missing values in the SCF are imputed using a multiple imputation technique (Kennickell 1998).

While most of the data collected in the SCF are at the household level, information on employment is collected separately for the household head and the spouse/partner. The employment data in the SCF provide information on the current main job, any second jobs, and the longest prior job held by the household head or spouse/partner. In this study, we limit the sample to male household heads aged 25-64 who are currently working. Self-employment status is determined by the question asking whether the household head works for himself or someone else on their current main job; the self-employment rate in our sample is 18.3 percent.[7]

[7] This definition includes individuals who indicate being partners, potentially in a large firm; in our sample, 4.4 percent of self-employed workers report being partners. For a discussion of alternative definitions of self-employment using SCF data, see Moore (2004). For comparison, Hipple (2004) reports a self-employment rate among men aged 25 or older of 15.5 percent using the 2003 Current Population Survey.

Individuals who work for someone else on their main job but report being self-employed on a second job, are not classified as self-employed.[8]

The SCF also asks detailed questions about businesses in which the household has an active or non-active management role. Because these questions are asked separately from the employment questions, it is possible for an individual to report being self-employed and to report not owning any actively managed businesses. Indeed, 36 percent of self-employed workers in our sample do not report owning a business. While this may seem troubling, there are reasons why this might occur. First, some occupations, such as accountancy, consulting, and computer programming, do not necessarily require a large investment in tangible capital or it may be difficult to separate the personal and business use of capital. In comparison to self-employed workers with a business, self-employed workers who do not report owning a business are more likely to be in technical/sales or production/craft/repair occupations, and they are less likely to work in manufacturing or wholesale/retail trade industries. Second, individuals just starting self-employment may not have accrued substantial business assets; excluding the non-business-owning self-employed would potentially bias the sample towards more established self-employed. Further evidence that the self-employed workers that do not report owning a business are actually engaged in entrepreneurial activities is that 50 percent of this group report filing a Schedule C tax form in the preceding year.

Earnings Measures

Measuring earnings for employees is straightforward—we construct annual and hourly earnings measures using the wage and salary data in the SCF for the current main job. Measuring the earnings of the self-employed is more difficult because of the greater potential

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[8] Of household heads who are employees on their main current job, only 3.7 percent report being self-employed on a second job. Roughly 10 percent of both employees and self-employed workers report holding a second job.

degree of misreporting and the flexibility the self-employed have in reporting their earnings. We use the detailed information in the SCF data to construct three measures of self-employment earnings. Start with the simple accounting identity for self-employed earnings in equation (1) (from Hamilton, 2000).

$$\text{(1)} \qquad \text{Revenue}_{\text{it}} - \text{Expenses}_{\text{it}} = \text{Salary}_{\text{it}} + \text{Retained earnings}_{\text{it}}$$

In equation (1), for a self-employed individual net profit is represented by the left-hand side of equation (1); this is the measure is usually reported in surveys like the Current Population Survey. However, because net profit is generally the basis for determining tax liability, tax considerations may cause this value to be underreported. Some of those tax considerations include illegal acts such as overstating expenses, but others are due to the structure of the tax code. For example, certain depreciation methods allow business owners to immediately deduct a large fraction of new capital investments. Our first measure of self-employment earnings from the SCF is a measure of net profit (NI), specifically the individual's share (if he or she is not the sole owner) of net income from all actively managed businesses that the individual works in.

While most data sets only contain information on net profit, the SCF contains information on the right-hand side variables in equation (1). Self-employed individuals are asked how much they received in salary or wages before taxes and how much they received from retained earnings; we will call this second measure the salary or wages of the self-employed individual. Of course, self-employed individuals may report a low salary if they are currently investing in their business.

Although the SCF does not ask about the value of retained earnings, we can approximate the year-to-year equity change in business by taking the difference between the current equity value and the original cost basis, divided by the age of the business. We then subtract from this measure an opportunity cost of capital, which is the average equity amount multiplied by the interest rate on a ten-year Treasury bill.[9] Any reported salary is then added to the adjusted equity value to yield our third measure, the equity-adjusted salary (EAS).

There are a few technical issues with constructing the three self-employment earnings measures. The first issue is that for the non-business-owning self-employed, we do not have a measure of net income or a measure of the value of the business. For these individuals we set the (missing) values of net income and EAS to be equal to the value of their wages, if their wages are greater than zero. Setting the EAS measure equal to wages explicitly recognizes that the non-business-owning self-employed have no business equity, making them no different from a self-employed worker that owned a business with zero equity value. The rationale for setting net income equal to wages for the non-business-owning self-employed is that the business had to produce at least enough income to cover the owner's salary.[10] We also apply this rule to the business-owning self-employed who report zero net income but positive wages.

Studies of earnings and earnings inequality generally examine log earnings. Because self-employment incomes may be zero or negative, for which the logarithm would be undefined, we instead utilize the inverse hyperbolic sine (IHS) to transform earnings measures for much of our analysis. The inverse hyperbolic sine is symmetric: it takes an approximately linear form about the origin and approximates log(x) in its right tail and -log(-x) in its left tail.[11] Like the logarithm, the inverse hyperbolic sine mutes the effects of outliers in estimation.

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[9] The average interest rate on the ten-year Treasury bill in 2004 was 4.27%.

[10] As noted earlier, about 50 percent of the non-business owning self-employed filed a Schedule C tax form in the year preceding the survey. While Schedule C income should be captured in the income questions asked in the SCF, only 40 percent of non-business owning self-employed who filed a Schedule C report business income in the income questions sequence. For all Schedule C filers, only 60 percent report business income.

[11] The inverse hyperbolic sine of x is $\theta^{-1}\sinh^{-1}(\theta x) = \theta^{-1}\ln(\theta x + (\theta^2 x^2 + 1)^{½})$, where θ is a scaling parameter that can be estimated via maximum likelihood. For more details on the inverse hyperbolic sine see Burbidge, Magee, and Robb (1988) and Pence (2006). Kennickell and Sunden (1997) also employ the IHS transformation. These studies each set θ =0.0001, which we also use for the annual earnings measures; our ML estimate of θ when rounded to four

Basic Results

Table 1 shows the distribution of selected demographic characteristics for wage/salary and self-employed workers. Consistent with other studies, we find that older workers are more likely to be self-employed; about 63 percent of the self-employed in our sample are 45 or older compared to about 42 percent of employees. This difference in ages is also reflected in the distribution of current job tenure and work experience. Roughly 25 percent of the self-employed have been in their current job for over 20 years, twice the share among employees. Even more strikingly, about 66 percent of the self-employed have worked full-time for over 20 years.

As is well documented, minorities are less likely to be self-employed. In terms of occupations, about 66 percent of the self-employed are in manager/professional or technical/sales occupations, whereas only about 50 percent of employees are in those occupations. The self-employed are also much less likely to be in service or operator/laborer occupations. While the self-employed are slightly more likely to have an advanced degree, the remainder of the education distribution for employees and the self-employed is fairly similar.

Figure 1 shows the densities of annual wages for employees as well as annual wages, net income, and equity-adjusted salary for self-employed workers. The employee wage distribution has the usual, unimodal shape. In contrast, all three self-employed earnings measures have a sizeable mass at zero. In addition, the distributions for the self-employed earnings measures exhibit much more dispersion and longer and fatter right tails than the employee wage distribution. The net income and EAS measures also have very long left tails due to the self-employed who report losses; about 5 percent of the self-employed have negative net income and about 1 percent have negative EAS values. The wage and EAS distributions track each other

decimal points was also 0.0001 and our conclusions are robust to alternative values. For the hourly earnings, we estimate θ=0.2.

fairly closely, which is not surprising since the EAS measure is simply wages augmented by the change in the equity value of the business.

The first three columns of Table 2 provide further evidence of the differences in the earnings of the two groups. Median wages and median EAS for the self-employed are very similar to the median wages for wage/salary workers, however median net income is notably lower. At the mean, all three self-employed measures are substantially larger than the employee wage, with net income and EAS about twice as large as the employee wage. The ratio of the 75th to 25th percentile reveals that the interquartile ranges for the self-employed earnings measures are at least twice as large as for employee wages.

The substantial differences in the earnings distributions of the two groups are also evident in the two inequality measures shown in Table 2. While there are many different inequality measures to choose from, we are limited in our choice by the presence of zero and negative values in the data. The last column of Table 2 shows that the fraction of zero or negative values in the data are minimal for employees, but about 10 percent of the self-employed fall into this category.[12] As noted in Jenkins and Jäntti (2005) and Amiel, Cowell, and Polovin (1996), many of the standard inequality indices are undefined when the data contain negative or zero values. Therefore, we use the Gini coefficient and a generalized entropy measure (GE(2)), both of which are estimable when values are not strictly positive.[13] The Gini coefficient is well-defined for zero and negative values because it is based on a summation of absolute differences between

[12] In the analysis below, we examine the sensitivity of our results to excluding workers with zero earnings. For employees, 95 percent of those with zero reported earnings have worked in their current job for less than one year. In contrast, 16 percent of self-employed workers with zero earnings have job tenure of less than a year. Only 8 percent of business-owning self-employed workers that report zero net income have tenure less than one year.

[13] The Gini coefficient for an unweighted sample of incomes y of size N with mean μ is $G = \frac{1}{2N^2\mu}\sum_{i,j} | y_i - y_j |$.

The class of generalized entropy measures with parameter θ is given by $GE(\theta) = \frac{1}{\theta(\theta-1)}\left[\sum_i \frac{1}{N}\left(\frac{y_i}{\mu}\right)^{\theta} - 1\right]$.

pairs of values. However, one caveat with the Gini is that the presence of negative values can lead to estimates greater than one. Since generalized entropy inequality measures involve evaluation of the power function y_i^θ, they are only well-defined for negative values of y if θ is an integer greater than one. Thus, we choose θ=2, which makes the measure equivalent to half the square of the coefficient of variation. An important limitation of the GE(2) is its sensitivity to large values in the right tail.[14]

As shown in the fourth column of Table 2, the Gini coefficient for annual wages for all workers is .506 and the GE(2) measure is 6.2. When we calculate the indices for the two groups separately, the results are striking. The Gini coefficient for employee wages is .424, while the Gini for self-employed earnings is as much as .801 (for the net income measure). The values of the GE(2) exhibit a similar pattern, with the employee wage GE(2) about one-quarter the size of the GE(2) for the self-employed earnings measures.[15]

Comparing the results in Table 2 to other studies is difficult given the lack of U.S. studies. However, Parker (1997) reports Gini coefficients for U.K. self-employed income in the range of .61 to .69, and GE(2) measures between 1.12 and 3.35. While the largest of Parker's Gini coefficients are close to our Gini coefficients for self-employed earnings, our GE(2) measures are much larger. Parker (1999) reports the GE(2) measure for both employees and the self-employed in the U.K. While the levels of the GE(2) measures are different from our estimates, the ratio of the GE(2) for employees to the GE(2) for the self-employed is similar (about one-quarter).

[14] This sensitivity is mitigated by the use of the IHS transform in the subsequent analysis. We report the value of the inequality indices based on the untransformed values in Table 2 for ease of comparison with other studies.
[15] A decomposition of the GE(2) measure into within- and between-group inequality reveals that within-group inequality accounts for about 99 percent of total inequality.

Decomposing Differences in Inequality Across Sectors

The differences in inequality documented in Table 2 could be due to several factors. The first of these is differences in the composition of the workforce: consistent with Parker (1997), higher earnings inequality among the self-employed may be due in part to greater dispersion in the skills and characteristics of the self-employed. In addition, as emphasized by Lemieux (2002, 2006), differences in characteristics could further contribute to the observed disparity in inequality if self-employed workers are over-represented among demographic groups—such as older and more-educated workers—with relatively high within-group, or residual wage dispersion. Greater inequality among the self-employed may also reflect differences in returns, i.e., the relationship between workers' characteristics and earnings in each sector. Finally, self-employment income may be more dispersed even after controlling for these differences.

We use the approach of Machado and Mata (2005) and the extension proposed by Autor, Katz, and Kearney (2005) (AKK) to decompose the differences in inequality between the self-employed and wage/salary earnings into shares attributable to differences in the characteristics of self-employed workers versus wage/salary workers ("composition"), in the returns to these characteristics in each sector ("returns"), and remaining earnings variability ("residual"). The technique uses quantile regression to generate counterfactual earnings distributions—and levels of inequality—that would be observed, for example, if only the composition of workers differed between the two sectors while the returns and residual dispersion were identical. Comparing the actual and counterfactual distributions provides a straightforward method of isolating the contributions of each of the three factors to differences in overall inequality.

The starting point for the Machado-Mata method is the conditional quantile function, $Q_\theta(y \mid x)$, which gives the θ^{th} quantile of the distribution of earnings conditional on covariates

x.[16] Modeling the conditional quantile function for each $\theta \in (0,1)$ as $Q_\theta(y \mid x) = x'\beta(\theta)$, we can simulate a sample from the distribution of earnings conditional on a given vector of characteristics x by repeatedly drawing random quantiles $\tilde{\theta}$ from a uniform(0,1) distribution, estimating the corresponding quantile regression coefficient $\widehat{\beta}(\tilde{\theta})$, and calculating $\tilde{y} = x'\widehat{\beta}(\tilde{\theta})$. Similarly, to generate a sample from the unconditional earnings distribution, Machado and Mata propose randomly sampling vectors of covariates $\tilde{x}$ and pairing each vector with a random quantile regression coefficient vector $\widehat{\beta}(\tilde{\theta})$. This resampling procedure is numerically equivalent to integrating over both the distribution of covariates and the conditional quantile function. Drawing on other work, Autor, Katz, and Kearney (2005) argue that multiplying the matrix of covariates by a matrix of estimated quantile regression coefficients yields more precise estimates of the distribution than the Machado-Mata resampling method; we follow the AKK approach in this paper.

These steps are readily modified to generate counterfactual earnings distributions (albeit under the strong partial equilibrium assumption that changes in aggregate quantities of skills do not affect skill prices). For example, we can estimate the distribution of the counterfactual earnings of currently self-employed workers if the returns to observed characteristics were identical in the self-employed and wage/salary sectors by pairing the matrix of covariates among self-employed workers with the matrix of quantile regression coefficients $\widehat{\beta}_{ws}(\tilde{\theta})$ estimated over the sample of employees.

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[16] This discussion and notation draws on Autor, Katz, and Kearney (2005), who also show that the Machado-Mata approach nests the decompositions of Juhn, Murphy, and Pierce (1993) and DiNardo, Fortin, and Lemieux (1996). The decomposition approach of Biewen and Jenkins (2005), based on fitting parametric income distributions whose parameters depend on covariates, is also similar to the Machado-Mata method in that they are able to distinguish between differences in characteristics and differences in the relationship between characteristics and poverty status in explaining poverty rates in the U.S., Germany, and Great Britain.

Autor, Katz and Kearney (2005) extend the Machado-Mata approach to further distinguish between the effects of the returns to labor market characteristics in each sector and the level of residual dispersion in earnings that remains after controlling for observable characteristics and their prices. Specifically, AKK use the median regression coefficients $\widehat{\beta}^m \equiv \widehat{\beta}(.5)$ in each sector as a measure of the typical returns to observed characteristics within a given sector, analogous to the OLS coefficients in the standard Oaxaca-Blinder decomposition. To measure residual dispersion, AKK subtract the median regression coefficient vector from each of the quantile regression coefficient vectors $\beta(\theta)$, yielding $\widehat{\beta}^r(\theta) \equiv \widehat{\beta}(\theta) - \widehat{\beta}^m$ for each $\theta \in (0,1)$. Just as the set of coefficients $\widehat{\beta}(\theta)$ characterize the conditional distribution of earnings, the resulting matrix of differenced coefficient vectors $\widehat{\beta}^r(\theta)$ measure the expected dispersion of earnings conditional on *x* and holding the conditional median at zero.

Let $g_j(x)$ denote the distribution of characteristics *x* in sector *j*={ws, se} (wage/salary and self-employed, respectively). Extending this notation to the vector of prices and matrix of "residual" quantile regression coefficients, we can estimate both observed and counterfactual distributions through different combinations of $g_j(x)$, $\widehat{\beta}_j^m(\theta)$ and $\widehat{\beta}_j^r(\theta)$. To generate observations from an estimate of the actual distribution of earnings for employees, for instance, we multiply the matrix of wage/salary covariates $g_{ws}(x)$ by the matrix constructed by adding $\widehat{\beta}_{ws}^m$ to each vector of $\widehat{\beta}_{ws}^r(\theta)$. We write the resulting distribution as $f(g_{ws}(x), \widehat{\beta}_{ws}^m, \widehat{\beta}_{ws}^r(\theta))$. The counterfactual distribution,, $f(g_{se}(x), \widehat{\beta}_{ws}^m, \widehat{\beta}_{ws}^r(\theta))$, of earnings of self-employed workers if they were to be employed in the wage/salary sector is generated identically, except the matrix $g_{se}(x)$ is multiplied by the combined matrix of quantile regression coefficients.

We decompose differences in earnings inequality for self-employed workers relative to employees by comparing values for a given inequality measure *I* across a sequence of distributions. In our discussion, we focus on the following sequence of distributions and corresponding definitions of the contribution of each factor:

(2a) *Difference in composition* $= I[f(g_{se}(x), \widehat{\beta}^m_{se}, \widehat{\beta}^r_{se}(\theta))] - I[f(g_{ws}(x), \widehat{\beta}^m_{se}, \widehat{\beta}^r_{se}(\theta))]$

(2b) *Difference in returns* $= I[f(g_{ws}(x), \widehat{\beta}^m_{se}, \widehat{\beta}^r_{se}(\theta))] - I[f(g_{ws}(x), \widehat{\beta}^m_{ws}, \widehat{\beta}^r_{se}(\theta))]$

(2c) *Difference in residual dispersion* $= I[f(g_{ws}(x), \widehat{\beta}^m_{ws}, \widehat{\beta}^r_{se}(\theta))] - I[f(g_{ws}(x), \widehat{\beta}^m_{ws}, \widehat{\beta}^r_{ws}(\theta))]$

Performing the steps of the decomposition in this order, the contribution of differences in the workers' characteristics is measured in (2a) by the difference in the values of the respective inequality measure *I* when the characteristics used in estimation are varied from the self-employment covariates to those of employees, holding returns and residual inequality at their values in the self-employment sector. In contrast, in the final step (shown in equation (2c)) the contribution of residual differences in inequality is defined as the difference in a given inequality measure when residual inequality is varied and the characteristics and returns are held constant at their values for wage/salary workers. As with any decomposition, the ordering of factors is arbitrary, and the discussion below also considers an alternative ordering.[17]

In practice, we implement the Machado-Mata/AKK procedure by estimating a series of 499 quantile regressions with $\theta = 0.002$, 0.004, . . ., 0.998 for each of the earnings measures and separately for wage/salary and self-employed workers. The regressions include a cubic in years worked full-time interacted with highest degree obtained (high school, college, post-baccalaureate), a cubic in current job tenure, and dummies for the education, race, and occupation categories shown in Table 1.

[17] In a future draft, we intend to use the Shapley-value decomposition proposed by Shorrocks (1999).

Discussion of Decomposition Results

Table 3 presents the results of the decompositions for the different earnings measures. In addition to the GE(2) and Gini inequality indices, we also show results for the ratios of various percentiles.[18] The top row in each panel shows the value of each inequality measure for the estimated earnings distribution among wage/salary workers, $f(g_{ws}(x), \hat{\beta}_{ws}^{m}, \hat{\beta}_{ws}^{r}(\theta))$, i.e. the distribution generated using the Machado-Mata technique to replicate the observed distribution. Inequality indices based on the estimated distribution of self-employed earnings are presented in the second row of each panel. The difference between the actual and estimated values of the indices in each sector and for each of the self-employed earnings measures in Table 3 are generally small.[19] Subsequent rows in each panel show, for each inequality measure, the fraction of the difference in inequality attributable to differences in composition, labor market returns, and residual inequality based on the decomposition shown in equations (2a) through (2c).

Decomposition results for the first earnings measure, annual earnings or wages, are presented in the top panel of Table 3. Figure 2 additionally illustrates the decomposition of the differences in these earnings distributions. The result of the decompositions for earnings reveals that the composition effect is small and, in fact, adds to disparities in inequality for most of the measures. The effect of the change in composition is represented visually by the shift from the dark solid line in Figure 2 to the dashed line. Returns to observed characteristics, captured by the difference between the dotted and the dashed densities in Figure 2, account for roughly one-

[18] Values for the GE(2), Gini coefficient, and the p75/p25 ratio in Table 3 differ from those in Table 2 because the earnings measures in regressions have been transformed by the IHS. The levels of each inequality measure are comparable across the annual earnings measures since the same value of θ is used for each.

[19] For the Gini coefficient and GE(2) these differences never exceed 5 percent. For employees the differences in the percentile ratios are 1 percent or less whereas the p75/p25 and p50/p25 ratios for self-employed workers differ by +/- 7–9 percent for annual wages, net income and EAS. The notable exception is the Gini coefficient for the self-employed net income measure for households who reported owning a business (see Appendix Table 1, lower panel), for which the actual and predicted values differ by 22 percent (0.274 versus 0.335).

quarter of the difference in earnings inequality as measured by the Gini and GE(2) and for nearly 40 percent of the difference in the p50/p25 ratio. While this latter finding might suggest that returns play a larger role in explaining inequality among lower-income workers, this conclusion is not robust to reversing the order of decomposition (shown in Appendix Table 2). Regardless of the order of decomposition, the largest share of the difference in the levels of inequality across sectors is explained by residual earnings dispersion for all five inequality measures. The effect of assuming this lower level of earnings variation is apparent from a comparison of the dotted and solid thin lines in Figure 2, labeled “Actual WS”.

To examine the sensitivity of our results, we also decompose log annual earnings for the subset of workers with positive earnings in the top panel of Appendix Table 1. The most notable difference between the decomposition of earnings inequality between the two samples is the positive contribution of compositional differences for the narrower alternative sample using the primary order of decomposition. However, when using the alternative order of decomposition (Appendix Table 2), the share of the difference in inequality accounted for by compositional differences is negative regardless of whether individuals with zero earnings are excluded. Overall, both samples and sequences of decompositions attribute roughly 70–80 percent of the difference in the Gini, GE(2), and p50/p25 ratio between the two sectors to differences in residual earnings dispersion, with somewhat smaller “residual” shares for the p75/p25 and p75/p50 ratios.

Results for the hourly earnings measure in the second panel of Table 3 are broadly similar to those for the annual earnings, suggesting that differences inequality across the two sectors are not due to differences in the hours or weeks worked across the two sectors. As was the case for annual earnings, about 80 percent of the differences in the Gini coefficient and in the

GE(2) are attributed to residual earnings dispersion. In contrast to the other earnings measures shown in Table 3, returns explain a slightly higher fraction of the p75/p50 ratio than they do of the p50/p25 ratio.

Results for the net income measure show the composition effect again slightly exacerbates the estimated difference in inequality, and differences in residual earnings dispersion account for 65–80 percent of the difference in the Gini and GE(2); the estimated share for the percentile ratios, while always greater than 50 percent, are more sensitive to the order of decomposition. The lower panel of Appendix Table 1, which excludes self-employed workers who do not own a business, shows that this restriction substantially shifts the decomposition of the Gini coefficient, while the percentile ratios are fairly similar across the two samples.

For equity-adjusted salary, the share of the difference in inequality attributed to residual variation in earnings rises further, and conversely the percentage accounted for by returns falls to roughly 10–20 percent in Table 3. While the "returns" share is higher when the order of decomposition is reversed, looking across earnings measures in Appendix Table 2, the "residual" share remains comparatively high for most inequality indices.

Taken together, the decompositions show that the differences in the characteristics of employees and self-employed workers shown in Table 1 are not primary a factor in explaining the differences in inequality between the two groups. Differences in the returns to these characteristics do explain a substantial fraction of the inequality between the two groups, suggesting that returns to human capital and to risk-taking may accrue more directly to the self-employed than to employees. Overall, with few exceptions, residual inequality explains the largest share of inequality for each earnings and inequality measure. This might be taken as evidence that many of the usual human capital variables that have strong predictive power for employee wages are less important for self-employed earnings. One potential solution to this issue is to add variables to the earnings regression that may better predict self-employed earnings, such as a measure of risk tolerance or previous self-employment experience.

Conclusion

The results from this paper show that earnings inequality is substantially greater among the self-employed than employees, regardless of the measure of self-employed earnings or the measure of inequality used. Although the self-employed are a relatively small group, omitting them from analyses of earnings inequality therefore likely understates overall inequality. Of course, measurement and reporting issues continue to be a problem with self-employed earnings, and not all data sets contain enough information to compute the alternative measures constructed in this paper.

Decompositions of the earnings distributions reveal that differences in characteristics between the two groups explain little of the disparities in inequality. Although the returns to characteristics are important in explaining the differences in inequality, the most influential factor is unexplained, residual earnings dispersion. This finding highlights the limited role that observable characteristics play in determining self-employed earnings.

We plan to extend our analysis in a few directions. First, we recognize that it is difficult to draw conclusions from these findings without a measure of their statistical significance. The SCF provides bootstrap replicate weights drawn in accordance with the sample design for this purpose, but the Machado-Mata technique is computationally intensive. The analytical standard errors derived by Albrecht, van Vuuren, and Vroman (2006) may provide a feasible alternative.

Further, given the large component attributed to residual differences in inequality and evidence that year-to-year volatility in earnings is greater for the self-employed (see, e.g., Saks and Shore (2005)), we intend to additionally consider differences in wealth inequality, which may be less affected by temporal variation in earnings. Further, we plan to expand the set of regressors used in the models to include variables that may have more predict power for the self-employed, such as measures of risk tolerance and previous self-employment experience. Finally, we have begun to examine other years of the SCF to assess the robustness of our current findings and to investigate how changes in self-employment may have contributed to shifts in aggregate earnings inequality over time.

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Figure 1

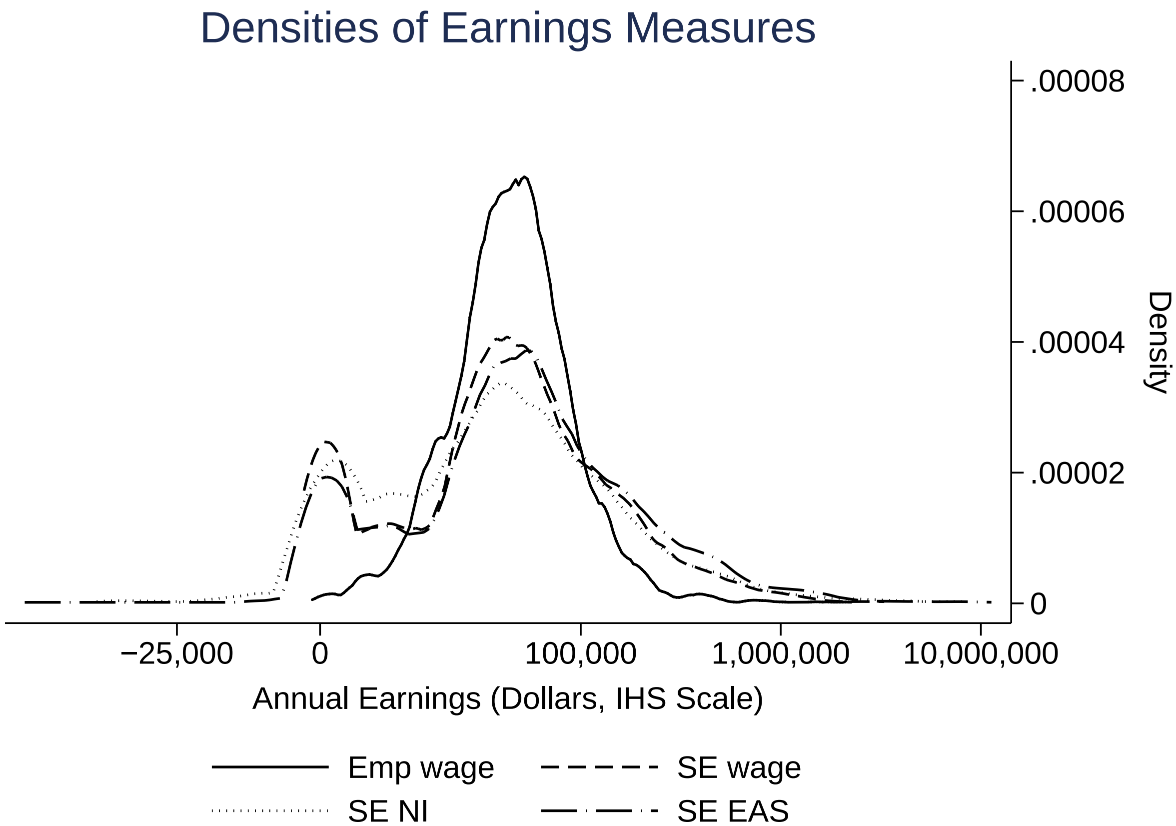
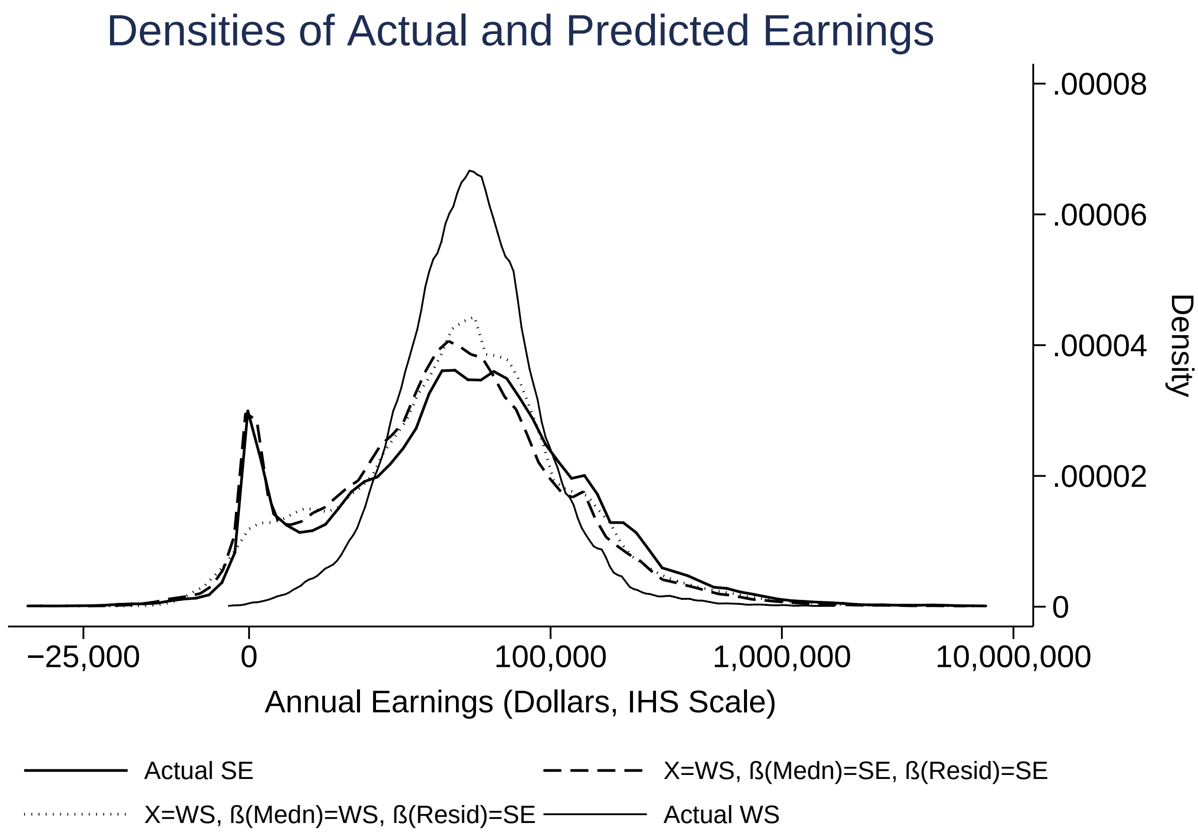

Densities of Earnings Measures
.00008
.00006
.00004
.00002
0
Density
−25,000
0
100,000
1,000,000
10,000,000
Annual Earnings (Dollars, IHS Scale)
Emp wage
SE wage
SE NI
SE EAS

Figure 2


Densities of Actual and Predicted Earnings
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.00006
.00004
.00002
0
Density
−25,000
0
100,000
1,000,000
10,000,000
Annual Earnings (Dollars, IHS Scale)
Actual SE
X=WS, ß(Medn)=SE, ß(Resid)=SE
X=WS, ß(Medn)=WS, ß(Resid)=SE
Actual WS

Table 1
Characteristics of Employees (WS) and Self-Employed (SE) Workers
2004 SCF (Percent)

	WS	SE		WS	SE
Age			*Race*		
25–34	26.8	12.7	White	73.2	83.3
35–44	31.0	24.4	Black	9.6	7.0
45–54	27.1	39.3	Hispanic	12.3	6.3
55–64	15.1	23.6	Other	4.8	3.4
Current Job Tenure			*Occupation*		
<=5	50.9	30.9	Manager/Professional	37.6	54.4
6–10	19.9	21.9	Technical/Sales	12.8	12.2
11–15	9.3	12.3	Services	10.6	6.1
16–20	8.0	9.9	Prod/Craft/Repair	23.3	19.0
21–30	8.9	16.7	Operators/Laborers	14.6	5.0
>30	3.1	8.4	Farm/Forest/Fish	1.1	3.3
Years Full-Time			*Education*		
<=5	4.9	3.1	No HS degree	9.2	9.7
6–10	16.1	6.1	HS degree	29.2	28.9
11–15	13.8	9.8	Some college	17.3	16.2
16–20	17.6	15.3	College degree	31.0	29.0
21–30	29.2	32.8	Advanced degree	13.4	16.2
31-40	15.1	26.3			
>40	3.4	6.6			

Table 2
Employee and Self-Employed Earnings and Earnings Inequality Measures
2004 SCF

	Median	Mean	p75/25	Gini	GE(2)	Pct <= 0
All workers						
Wages	44.7	68.2	2.5	0.506	6.2	2.1
Employees						
Wages	45.0	60.4	2.3	0.424	2.5	0.1
Self-employed						
Wages	42.0	103.1	4.7	0.703	10.9	10.9
Net income	35.9	117.6	8.3	0.801	12.9	11.8
EAS	47.2	137.9	5.0	0.735	10.7	8.4

Note: Mean and median values are in thousands of 2004 dollars.

Table 3
Decomposition of Differences in Earnings Inequality of Self-Employed versus Employees
2004 SCF

	GE(2)	Gini	p75/p25	p75/p50	p50/p25
			Earnings		
Employees	0.049	0.172	1.47	1.19	1.24
Self-Employed	0.194	0.345	2.30	1.35	1.70
Composition (X)	-5.4%	-3.9%	-3.4%	3.7%	-6.4%
Returns ($ß^m$)	26.8%	22.2%	37.7%	28.7%	38.3%
Residual ($ß^r$)	78.6%	81.6%	65.7%	67.7%	68.1%
			Hourly Earnings		
Employees	0.044	0.163	1.46	1.19	1.23
Self-Employed	0.177	0.332	2.11	1.36	1.56
Composition (X)	-10.2%	-7.4%	-5.2%	-1.8%	-6.7%
Returns ($ß^m$)	30.4%	24.2%	38.2%	39.9%	33.7%
Residual ($ß^r$)	79.8%	83.2%	67.0%	61.9%	73.0%
			Net Income		
Employees	0.049	0.172	1.47	1.19	1.24
Self-Employed	0.259	0.401	2.90	1.44	2.01
Composition (X)	-7.2%	-4.1%	-11.2%	-5.5%	-11.5%
Returns ($ß^m$)	41.5%	33.0%	59.7%	44.7%	59.2%
Residual ($ß^r$)	65.6%	71.1%	51.5%	60.9%	52.2%
			Equity-Adjusted Salary		
Employees	0.049	0.172	1.47	1.19	1.24
Self-Employed	0.183	0.335	2.20	1.35	1.64
Composition (X)	-6.6%	-3.3%	3.3%	10.2%	-0.7%
Returns ($ß^m$)	12.5%	11.0%	17.9%	12.7%	19.3%
Residual ($ß^r$)	94.1%	92.2%	78.8%	77.1%	81.4%

Note: Earnings measures are transformed using the inverse hyperbolic sine, with θ=0.0001 for the annual earnings measures and θ=0.2 for hourly earnings.

Appendix Table 1
Decomposition of Differences in Earnings Inequality of Self-Employed versus Employees
Alternative Earnings Measures, 2004 SCF

	GE(2)	Gini	p75/p25	p75/p50	p50/p25
			Earnings>0		
Employees	0.0025	0.0379	1.08	1.04	1.04
Self-Employed	0.0065	0.0626	1.14	1.06	1.07
Composition (X)	4.2%	3.5%	3.8%	9.1%	3.9%
Returns ($ß^m$)	18.8%	16.8%	24.5%	27.3%	19.6%
Residual ($ß^r$)	77.0%	79.7%	71.7%	63.6%	76.4%
			Net Income If Reported Owning a Business		
Employees	0.049	0.172	1.47	1.19	1.24
Self-Employed	0.335	0.427	3.06	1.48	2.07
Composition (X)	-54.5%	-17.7%	-12.1%	-5.9%	-13.0%
Returns ($ß^m$)	51.7%	33.7%	57.3%	40.5%	57.5%
Residual ($ß^r$)	102.8%	84.0%	54.8%	65.4%	55.5%

Note: Earnings for those with positive earnings are transformed using the logarithm. Net income for self-employed workers who additionally report owning a business are transformed using the inverse hyperbolic sine, with θ=0.0001.

Appendix Table 2
Alternative Decomposition of Differences in Earnings Inequality of Self-Employed versus Employees, 2004 SCF (Percent)

	GE(2)	Gini	p75/p25	p75/p50	p50/p25
			Earnings		
Residual ($ß^r$)	78.7%	72.5%	76.5%	55.5%	82.0%
Returns ($ß^m$)	24.1%	32.7%	29.0%	52.4%	23.2%
Composition (X)	-2.8%	-5.2%	-5.5%	-7.9%	-5.2%
			Hourly Earnings		
Residual ($ß^r$)	78.7%	71.4%	67.2%	54.2%	71.0%
Returns ($ß^m$)	23.7%	32.2%	36.9%	48.8%	33.9%
Composition (X)	-2.3%	-3.6%	-4.1%	-3.0%	-4.9%
			Net Income		
Residual ($ß^r$)	80.1%	72.5%	81.8%	70.4%	82.9%
Returns ($ß^m$)	21.8%	31.4%	21.5%	34.8%	20.2%
Composition (X)	-1.9%	-3.9%	-3.2%	-5.1%	-3.1%
			Equity-Adjusted Salary		
Residual ($ß^r$)	83.3%	77.8%	80.0%	64.3%	84.3%
Returns ($ß^m$)	19.7%	27.7%	26.3%	43.9%	21.8%
Composition (X)	-3.0%	-5.5%	-6.3%	-8.3%	-6.0%
			Earnings>0		
Residual ($ß^r$)	71.6%	65.7%	54.7%	36.4%	69.8%
Returns ($ß^m$)	28.9%	36.4%	50.9%	68.2%	33.9%
Composition (X)	-0.5%	-2.1%	-5.7%	-4.5%	-3.7%
			Net Income If Reported Owning a Business		
Residual ($ß^r$)	85.1%	74.9%	84.7%	75.1%	85.4%
Returns ($ß^m$)	17.1%	30.6%	19.4%	31.8%	18.7%
Composition (X)	-2.2%	-5.5%	-4.1%	-6.9%	-4.1%

Note: Earnings measures are transformed using the inverse hyperbolic sine, with θ=0.0001 for the annual earnings measures and θ=0.2 for hourly earnings. Earnings for those with positive earnings are transformed using the logarithm. Percentages are the fraction of the overall difference in each inequality measure, shown in the top two rows of each panel of Table 3 and Appendix Table 1.