PAPERS on Economics & Evolution

# 1020

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by

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The *Papers on Economics and Evolution* are edited by the Evolutionary Economics Group, MPI Jena. For editorial correspondence, please contact: evopapers@econ.mpg.de

ISSN 1430-4716



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# Life satisfaction and self-employment: A matching approach☆

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**Abstract**

Despite lower incomes, the self-employed consistently report higher satisfaction with their jobs. But are self-employed individuals also happier, more satisfied with their lives as a whole? High job satisfaction might cause them to neglect other important domains of life, such that the fulfilling job crowds out other pleasures, leaving the individual on the whole not happier than others. Moreover, self-employment is often chosen to escape unemployment, not for the associated autonomy that seems to account for the high job satisfaction. We apply matching estimators that allow us to better take into account the above-mentioned considerations and construct an appropriate control group. Using the BHPS data set that comprises a large nationally representative sample of the British populace, we find that individuals who move from regular employment into self-employment experience an increase in life satisfaction (up to two years later), while individuals moving from unemployment to self-employment are not more satisfied than their counterparts moving from unemployment to regular employment. We argue that these groups correspond to "opportunity" and "necessity" entrepreneurship, respectively. These findings are robust with regard to different measures of subjective well-being as well as choice of matching variables, and also robustness exercises involving "simulated confounders".

*Key words:* self-employment, happiness, matching estimators, unemployment, BHPS, necessity entrepreneurship
JEL-classification: J24, J28, C21

☆No individuals were mistreated during our matching procedures. We are grateful to Rob Byrne, Jan Fagerberg, Steffen Künn, Ben Martin, Maria Savona, Josh Siepel, Jagannadha Pawan Tamvada, Dagmara Wechowska, Ulrich Witt and seminar participants at SPRU (University of Sussex), and also to Bram Timmermans for some interesting suggestions, comments etm. The authors are grateful for having been granted access to the BHPS data set, which was made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-Social Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here. Errors are ours.

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*December 21, 2010*

## 1. Introduction

Self-employment is something highly valued by individuals for the self-determination and autonomy it entails (Benz and Frey, 2008a). Being one's own boss has been shown to increase individuals' satisfaction with their job, despite drawbacks such as initially often decreased incomes through self-employment (Hamilton, 2000). But are self-employed individuals happier in a broad sense not only related to their job? Does their attraction to self-employment possibly crowd out other pleasures of life, leading to overall unhappy "workaholics"? And how happy are self-employed that are forced to go into self-employment to escape unemployment? These are questions that have only incompletely been addressed in the literature so far (e.g., Andersson, 2008).

The aim of our paper is thus to assess the satisfaction of the self-employed with their life in general. Our contribution to the literature is fivefold. First, we focus our analysis on the *satisfaction with life* of the self-employed. Most of the previous literature on the other hand has focused on the relationship between self-employment and the narrower concept of *job satisfaction*. By making life satisfaction the dependent variable, which implicitly considers the trade-off between total income and job satisfaction, we are more interested in the more global well-being of the self-employed (it is a broader indicator of "total utility").

Second, we use a large, nationally-representative dataset with a relatively large panel dimension, where annual responses are recorded for the period 1996-2006. This in itself is a useful contribution because early work on the topic has often focused on small samples (Brockhaus, 1980; Cromie and Hayes, 1991), and even in more recent work the data analyzed is often merely cross-sectional data (Hyytinen and Ruuskanen, 2007; Block and Koellinger, 2009) or data with a limited panel dimension (Bradley and Roberts, 2004; Andersson, 2008).

Third, we apply an appropriate empirical methodology for obtaining estimates of the causal impact of self-employment on satisfaction, in a context where a comparison of the treatment group to the control group is not trivial. In recent work, Schjoedt and Shaver (2007) cast doubt on previous results on the basis of difference-of-means tests relating group averages for self-employed versus employed individuals (without controlling for other influences). We argue that this methodology is flawed, because self-employed individuals differ from other individuals in many ways (see our Table 1), and these differences between the different employment categories must be controlled for. Multivariate regressions can be a useful tool here, and have been widely used in the related literature, but also present drawbacks compared to the matching estimators applied in this paper. Although the researcher is presumably interested in comparing individuals that have the same values for all covariates, multivariate regression modelling obscures information on the distribution of covariates in the treatment versus control groups. Unless there is substantial overlap in the two covariate distributions, multivariate regression estimates rely heavily on extrapolation, and can therefore be misleading (Imbens, 2004; Ichino et al., 2008, p. 312-13). Matching estimators are preferable because more care is taken to establish an appropriate control group. Another advantage of matching methods is that they require no assumptions on functional forms (Hussinger, 2008, p. 730). To our knowledge, however, matching estimators have so far not been used in the present context.

Fourth, we distinguish between opportunity and necessity entrepreneurship in our analysis of self-employment and life satisfaction. This distinction stands to be one of the most important causes for heterogeneity in the group of self-employed, since the former are going into self-employment voluntarily to pursue entrepreneurial opportunities, while the latter are forced into self-employment to escape unemployment. As important as this distinction *a priori* seems, few studies account for it when analysing the impact of self-employment on individuals' satisfaction (but see, e.g., Block and Koellinger, 2009).

A fifth feature of our paper is that we focus on the years of transition into self-employment. Most previous studies into job satisfaction and the self-employment decision have tended to pool together new entrants into self-employment and senior self-employed individuals, implicitly grouping together individuals who have spent greatly different periods of time in self-employment, an approach which has recently been criticized (Bradley and Roberts, 2004). In this paper, we focus on the periods of transition into self-employment, thereby focusing on nascent entrepreneurship (as opposed to individuals who have been self-employed for many years).[1]

The paper is structured as follows. Section 2 gives the literature background on different employment types (*inter alia* self-employment) and their effects on happiness. Section 3 introduces our matching estimators in more technical detail. We then present our data set in Section 4 and discuss the results of our matching methodology in Section 5. The robustness of our findings is explored in a variety of ways. Section 6 concludes.

## 2. Literature review

Work is an important facet of human life and it has strong effects on individuals' satisfaction with life or happiness (which we will use synonymously here). This relationship is especially strong and clear for unemployment, which makes individuals unhappier than can explained by only the effect of loss of income. Effects are consistently negative across a wide range of studies (e.g., Clark and Oswald, 1994; Di Tella et al., 2001; Helliwell, 2003). Moreover, males are more strongly affected by unemployment and there seems to be only incomplete adaptation to continued unemployment for them (Clark, 2003; Lucas et al., 2004). These effects are robust in panel studies that control for selection effects, i.e. the relationship is not due to unhappy individuals that self-select into unemployment (Winkelmann and Winkelmann, 1998; Lucas et al., 2004; Oswald and Powdthavee, 2008).

On the other hand, the relationship between self-employment and happiness is less clear.[2] We have "rather robust finding[s] across the nations on which data are available" that self-employment is related to higher *job satisfaction* (Blanchflower, 2004), this being the case e.g. in the US (Blanchflower and Oswald, 1998; Kawaguchi, 2008) and for other OECD countries (Blanchflower, 2000; Blanchflower et al., 2001). In contrast to this finding, however, one must also take into account the robust finding that the returns to self-employment are lower,

[1] Our focus on nascent entrepreneurship bears similarities to some previous work (Bradley and Roberts, 2004; Schjoedt and Shaver, 2007; Fuchs-Schundeln, 2009); see also Andersson (2008) who focuses on changes between two cross-sections (1991 and 2000).

[2] Van Praag and Versloot (2007, pp. 375-6) provide a brief overview over some contributions entrepreneurship has on the utility levels of entrepreneurs and their employees.

on average, than those obtained from employment (Hamilton, 2000).[3,4] The self-employed generally have lower pay than the employed, but this does not mean that the self-employed are not interested in financial rewards — in fact, it has been observed that financial success is the single most important variable associated with start-up satisfaction among a group of self-employed individuals (Block and Koellinger, 2009). In addition to lower pay, there is also evidence that the self-employed have longer working weeks than paid employees (Hyytinen and Ruuskanen, 2007). Interestingly enough, it has even been observed that, among the self-employed, the number of hours worked for the start-up business is *positively* correlated with start-up satisfaction (Block and Koellinger, 2009). Taken together, these results suggest that the self-employed derive utility from their job (known as "procedural utility", Benz and Frey, 2008a,b) that cannot simply be expressed in terms of the "output" (remuneration, hours worked) associated with their jobs.[5]

Self-employed individuals obtain satisfaction from leading an independent lifestyle and "being their own bosses". Hundley (2001) finds that the self-employed are more satisfied with their jobs mainly because of greater autonomy, but also because of more flexibility, skill utilization and, to some extent, higher (perceived) job security. Relatedly, empirical work has shown that employees have a lower job satisfaction in large firms compared to small firms (Idson, 1990; Benz and Frey, 2008a), and this can be explained to a large extent by "procedural" aspects of work such as the nature of the work tasks and the ability to use of one's own initiative (Benz and Frey, 2008a).[6]

Other researchers have found that self-employment can be associated with a dissatisfaction with previous circumstances. For example, Kawaguchi (2008) observes that job quitting tends to follow low job satisfaction. Noorderhaven et al. (2004) observe that the levels of "dissatisfaction with life" observed in a society are positively associated with self-employment rates.

Having a higher job satisfaction, however, does not necessarily translate into self-employed individuals being overall more satisfied with their lives as a whole. Life satisfaction in itself is a much more global evaluation of individual's actual state of being, being influenced not only by job satisfaction but a complex and interacting web of influences (Binder and Coad, 2010a,b). Since individuals might be able to compensate high achievement in some domains of life with low achievements otherwise, a high job satisfaction might be counterbalanced by lower satisfaction in the family domain, or social life more generally, or, as mentioned

[3]In addition, it has been shown that individuals in small businesses have fewer fringe benefits compared to their counterparts in large firms (Storey, 1994, Ch. 6).

[4]Interestingly enough, Cooper and Artz (1995, p. 452) observe that female entrepreneurs had a lower financial performance than their male counterparts, but that controlling for these differences in income level, the female entrepreneurs indicated marginally higher levels of satisfaction.

[5]Cooper and Artz (1995) found that entrepreneurs with initially high expectations for their business venture performance turned out to be more satisfied than other entrepreneurs, suggesting that these more satisfied individuals have some more optimistic personality traits that influence their subsequent job satisfaction. This finding does probably only pertain to those entrepreneurs that create their business out of opportunity, not to escape unemployment.

[6]The positive effect of being self-employed on job satisfaction diminishes markedly when taking into account the heterogeneity of the control group of the employed in terms of the size of the firm they are working in (Benz and Frey, 2008a, p. 374).

above, in the income domain (etc.). If the satisfying work the self-employed enjoy crowds out pleasures from other domains of life, the overall life satisfaction of the self-employed could actually be not as high as one might expect based on their job satisfaction assessment alone. And indeed, there is scant evidence so far on the relationship between happiness and self-employment (Andersson, 2008, p. 231): Blanchflower and Oswald (1998) report for cross-sectional data from the US that young self-employed are happier and in a similar vein Craig et al. (2007) provide some evidence for this relationship from Australian small businesses. Looking at European countries, Blanchflower (2004) fails to find overly strong effects of self-employment on life satisfaction (only for subgroups, self-employment is significantly related to life satisfaction; and strongly depending on the data set used).

The empirically weak association between happiness and self-employment, however, could also be explained by a different, methodological phenomenon: it could be due to the fact that the self-employed are a quite heterogeneous group (Santarelli and Vivarelli, 2007).[7] It has been argued that, while some individuals would gladly self-select into self-employment, others who are forced into self-employment might not appreciate the self-employed lifestyle (Fuchs-Schundeln, 2009). Vivarelli (1991) writes that entry into self-employment cannot be seen merely in terms of pull factors such as expected profits (as predicted by the traditional industrial economics perspective), but there are also important push factors such as previous unemployment. In other words, in the light of the terminology in Reynolds et al. (2005), we should distinguish between necessity entrepreneurship (such as the flight from unemployment) and opportunity entrepreneurship (such as the exploitation of new business opportunities). Block and Koellinger (2009) distinguish between necessity entrepreneurship and opportunity entrepreneurship, and observe that necessity entrepreneurs have a lower average satisfaction with their startup than opportunity entrepreneurs, and also that a long period of unemployment is negatively related to startup satisfaction.

If one does not make this distinction of types of self-employment, one thus might lump together widely different individuals in the regression exercise and thus not be able to find any robust relationship between life satisfaction and self-employment. In order to separate the two possible explanations for the scant empirical evidence for a positive relationship between the two variables, we thus differentiate between opportunity and necessity self-employment and use a regression methodology that is better suited to deal with this individual heterogeneity than regression techniques usually employed in this context. We now turn to an exposition of this matching technique.

## 3. Matching methodology

"How happy would I be if I had not chosen to be self-employed?" To answer this kind of question, one must consider a counterfactual. The main problem is that if an individual chooses to be self-employed, then there is no data on exactly what would have happened had they not chosen to be self-employed.

In the case of a randomized laboratory experiment, such as a clinical trial, an accurate counterfactual can be established by referring to a control group that was not exposed to

[7] Another source of heterogeneity might stem from distinguishing entrepreneurship from self-employment, of which we abstract here.

the treatment of interest. However, establishing a counterfactual is much harder when the researcher is not dealing with randomized experimental data but instead observational data. The problem is that individuals are prone to self-select into their preferred employment category, which implies that comparing individuals from different employment categories is prone to a selection bias (this is like "comparing apples with oranges"). Conventional regression analysis is not suitable to dealing with this kind of selection bias. The approach we take is to carefully match individuals from the treatment group with individuals from the control group, to obtain more accurate estimates of the counterfactual. By comparing the treatment group with the control group, we can thus identify the causal effect of the self-employment decision on happiness. We here understand "causal effect" as defined by Rubin (1974), viz. "the causal effect of one treatment, E, over another, C, for a particular unit and an interval of time from $t_i$ to $t_2$ is the difference between what would have happened at time $t_2$ if the unit had been exposed to E initiated at $t_i$ and what would have happened at $t_2$ if the unit had been exposed to C initiated at $t_i$" (p. 689).[8]

We are therefore interested in comparing the outcome (in our case: life satisfaction) $Y_i(0)$ for an individual $i$ from the control group, with the outcome $Y_i(1)$ for the same individual after undergoing the treatment of interest (in our case: going into self-employment):

$$\tau_i = Y_i(1) - Y_i(0) \tag{1}$$

However, the drawback is that we can never observe both $Y_i(0)$ and $Y_i(1)$ for the same individual (Imbens, 2004). One way of dealing with this problem is to estimate the (Population) Average Treatment Effect:

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)] \tag{2}$$

A drawback of this estimate, however, is that the treatment is not intended for everyone, and that individuals self-select into the treatment group. It would be better to estimate the Average Treatment effect for the Treated (ATT), which focuses explicitly on the subsample of individuals that are the most affected by the treatment (i.e. those individuals that actually did decide to be self-employed):

$$\tau_{ATT} = E(\tau|D=1) = E[Y(1)|D=1] - E[Y(0)|D=1] \tag{3}$$

where D is the treatment indicator, taking the value 1 if an individual underwent the treatment (i.e. choosing self-employment) and 0 otherwise. Unbiased estimates for $E[Y(1)|D=1]$ can be obtained by taking mean values of the outcome variable for self-employed individuals. Obtaining unbiased estimates for $E[Y(0)|D=1]$ will be more difficult, however, because we cannot observe the case of individuals who chose self-employment but are not self-employed. Since individuals that self-select into self-employment are expected to be different from individuals who do not, (i.e. $E[Y(0)|D=1] \neq E[Y(0)|D=0]$), it is not possible to calculate $\tau_{ATT}$ by simply comparing the outcomes of the self-employed with those of other individuals who are not self-employed.

[8] For a more detailed introduction to matching, see the surveys in Imbens (2004) and Caliendo and Kopeinig (2008).

To identify the parameter of interest, $\tau_{ATT}$, we need to make two further assumptions. The first assumption is called the "conditional independence assumption (CIA)", and is also known as "selection on observables" or "unconfoundedness". This assumption means that the potential outcome (life satisfaction) and participation in the treatment (i.e. choice to enter self-employment) are independent for individuals with the same set of exogenous characteristics (Almus and Czarnitzki, 2003). Under this assumption, we have:

$$Y(0), Y(1) \perp D | X \tag{4}$$

If this first assumption is correct, we can use the fact that $E[Y(0)|D = 1, X = x] = E[Y(0)|D = 0, X = x]$ to identify $\tau_{ATT}$. Under this CIA assumption, all individual characteristics ($X$) that influence both the treatment assignment and potential outcomes simultaneously must be observed by the econometrician. Unobserved variables are not allowed to influence treatment assignment and potential outcome.

The second assumption is known as "overlap", or also as "strong ignorability" or the "common support condition", and can be expressed as:

$$0 < P(D = 1|X) < 1 \tag{5}$$

This assumption ensures that those individuals with the same characteristics have a positive probability of being both participants (i.e. choosing self-employment) or nonparticipants (not choosing self-employment). If the overlap assumption does not hold, then the resulting estimates can be heavily biased (Heckman et al., 1996).

The first assumption, CIA, is a strong assumption, and it cannot be verified directly. There are ways in which the robustness of the matching estimator $\tau_{ATT}$ can be investigated, although unfortunately most previous work that applies matching estimators has not verified the robustness of the estimates in a satisfactory way (Caliendo and Kopeinig, 2008). We examine the robustness of our estimates in Section 5.3 using the procedure described in Ichino et al. (2008) and Nannicini (2007), which explores the sensitivity of the matching estimates to simulated confounding variables.

In contrast to the CIA assumption, the overlap assumption is relatively easy to verify, and in our dataset it is indeed verified.

We use two different matching procedures in this paper and begin our matching analysis by using the nearest-neighbour matching estimator outlined in Abadie et al. (2004), which finds the nearest neighbour from the control group for each of the dimensions of $X$. If we have many matching covariates $X$, however, it becomes prohibitively difficult to find good matches for individuals in all dimensions simultaneously. On the one hand, it has been argued that omitting important variables can seriously increase bias in the resulting estimates (Heckman et al., 1997; Dehejia and Wahba, 1999). On the other hand, however, including too many variables should also be avoided, because it becomes more difficult to find suitable matches, and the variance of the estimates increases. Caliendo and Kopeinig (2008, p. 39) write that "there are both reasons for and against including all of the reasonable covariates available", and suggest that the choice of matching covariates be undertaken with reference to theory and previous empirical findings.

One alternative to nearest neighbour matching, that does not suffer from dimensionality problems when a large number of matching covariates are considered, is propensity score matching, which matches individuals by collapsing the vector of individual characteristics into a scalar propensity score. This synthetic propensity score can then used as the single matching criterion (Almus and Czarnitzki, 2003). Matching according to a propensity score implies that there is a (data-driven) tradeoff between the different dimensions — one observation might be matched to another observation that scores higher in one dimension but this is compensated for by a lower score in another dimension. These sorts of compensation are not done in nearest neighbour matching.

Propensity score matching relies on the following corollary to Assumption 1:

$$Y(0), Y(1) \perp D | P(X) \tag{6}$$

where $P(X)$ is the propensity score given the observed covariates $X$. Using both types of matching analysis helps to ascertain the robustness of the chosen approach.

## 4. Data

For our analysis, we use a data set that is not primarily concerned with entrepreneurs but which offers a rich variety of employment status information for a representative sample of the British populace. The British Household Panel Survey (BHPS) is a longitudinal survey of private households in Great Britain that contains information on various areas of the respondents' lives, ranging from income to household consumption, education, health, but also social and political values.[9]

We are using unbalanced panel data from 1996 to 2006 (waves f to p) and have a total of $76,752$ observations after cleaning the panel: during the time period, two waves had to be deleted since not all of our variables have been asked in them, leaving us with a total of 9 waves. We will now discuss the indicators chosen for our analysis as well as characteristics according to which we later match our individuals. While our main analysis will focus on the matching methodology described in Section 3, a benchmark will be a set of preliminary regressions, where we analyze the impact of different job situations on life satisfaction, job satisfaction and mental well-being.

To examine an individual's life satisfaction, we use the BHPS's life satisfaction question. It covers the response to the question "How dissatisfied or satisfied are you with your life overall?" It is effectively tracking an individual's life satisfaction ordinally on a seven point Likert scale, ranging from "not satisfied at all" (1) to "completely satisfied" (7). Comparatively more studies on the BHPS center on the GHQ-12 measure of mental well-being, but recent work took up using the life satisfaction question too (Binder and Coad, 2010b; Clark and Georgellis, 2010; Powdthavee, 2009). Nevertheless, to explore the robustness of our findings, we also use the broader GHQ-12 "mental well-being" variable, which is more encompassing

[9] The survey is undertaken by the ESRC UK Longitudinal Studies Centre with the Institute for Social and Economic Research at the University of Essex, UK (BHPS, 2009). Its aim is to track social and economic change in a representative sample of the British population (for more information on the data set, see Taylor, 2009). The sample comprises about 15,000 individual interviews. Starting in 1991, up to now, there have been 17 waves of data collected with the aim of tracking the individuals of the first wave over time (there is a percentage of rotation as some individuals drop out of the sample over time and others are included, but attrition is quite low, see Taylor, 2009).

| | (1) employed mean | (2) self-employed mean | (3) unemployed mean |
|---|---|---|---|
| life satisfaction | 5.2449 | 5.3171 | 4.6258 |
| mental well-being | 26.2908 | 26.5934 | 24.0307 |
| log(income) | 10.1228 | 9.9603 | 9.5732 |
| health status | 4.0152 | 4.0555 | 3.6626 |
| d_married | 0.5850 | 0.6840 | 0.2915 |
| d_separated | 0.0228 | 0.0271 | 0.0390 |
| d_widowed | 0.0150 | 0.0123 | 0.0091 |
| d_divorced | 0.0834 | 0.0909 | 0.1178 |
| d_disabled | 0.0201 | 0.0229 | 0.0580 |
| gender | 1.4976 | 1.2601 | 1.4158 |
| age | 39.4423 | 45.0684 | 35.0702 |
| (age-mean age)$^2$ | 183.1217 | 140.8183 | 294.1427 |
| education | 3.6222 | 3.4488 | 2.7861 |
| Observations | 40859 | 5455 | 2309 |

Table 1: Summary statistics

as it also relates to mental health. It is an index from the 'General Health Questionnaire' of the BHPS, composed of the answers to 12 questions that assess happiness, mental distress (such as existence of depression or anguish), and well-being. This subjective assessment is measured on a Likert scale from 0 to 36, which we have recoded to values of one (lowest well-being) to 37 (highest scores in mental well-being).

Our main focus lies on analysing the effects of self-employment on life-satisfaction, but we also include a variable for job satisfaction in our preliminary regressions. Our variable for job satisfaction is based on the question "How dissatisfied or satisfied are you with your job (if in employment)?" and also ranges from "not satisfied at all" (1) to "completely satisfied" (7). Pairwise correlation between life satisfaction and job satisfaction in our sample is $\rho = 0.4762$ overall. It is higher for the self-employed ($\rho = 0.5460$) than for the employed ($\rho = 0.4793$).

Our main explanatory variable is the job status of individuals. A variety of job conditions are detailed in the BHPS, the three most important of which are being unemployed, employed and self-employed. Pooled over all sample years ($n = 76,752$), $40,859$ (53.24%) individuals have been in employment, $5,455$ (7.11%) were self-employed and $2,309$ (3.01%) were unemployed. The rest were either retired ($15,278$; 19.91%), in some form of schooling or studies ($3,839$; 5.00%), had maternity leave (361; 0.47%), were long-term sick ($3,095$; 4.03%) or in family care ($5,109$; 6.66%). 447 (0.58%) fell into none of these categories. Except for these different employment types, we control for some important individual characteristics in our analysis. The most prominent of our control variables are detailed in Table 1, where we have disaggregated them for the three most important employment categories.

Table 1 shows that the self-employed have higher life satisfaction scores, on average, than those in regular employment. They tend to be in better health, are more likely to be married, and are generally older than the employed. However, their expected income is lower than employed individuals. Our summary statistics are broadly similar to those reported elsewhere (see e.g. Andersson, 2008, Table 2).

| | life satisfaction | mental wb | d_employed | d_selfemployed | d_unemployed | log(income) | education | age | gender |
|---|---|---|---|---|---|---|---|---|---|
| life satisfaction | 1.0000 | | | | | | | | |
| mental wb | 0.5543*** | 1.0000 | | | | | | | |
| | (0.0000) | | | | | | | | |
| d_employed | 0.0037 | 0.0833*** | 1.0000 | | | | | | |
| | (0.3043) | (0.0000) | | | | | | | |
| d_selfemployed | 0.0168*** | 0.0371*** | -0.2951*** | 1.0000 | | | | | |
| | (0.0000) | (0.0000) | (0.0000) | | | | | | |
| d_unemployed | -0.0857*** | -0.0598*** | -0.1879*** | -0.0487*** | 1.0000 | | | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | | | |
| log(income) | 0.0793*** | 0.0795*** | 0.2953*** | 0.0020 | -0.1120*** | 1.0000 | | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.5886) | (0.0000) | | | | |
| education | -0.0165*** | 0.0593*** | 0.2870*** | 0.0470*** | -0.0367*** | 0.3110*** | 1.0000 | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | |
| age | 0.0898*** | -0.0347*** | -0.3616*** | -0.0066 | -0.1028*** | -0.0317*** | -0.3184*** | 1.0000 | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0690) | (0.0000) | (0.0000) | (0.0000) | | |
| gender | -0.0037 | -0.1314*** | -0.0691*** | -0.1496*** | -0.0403*** | -0.0616*** | -0.0636*** | 0.0196*** | 1.0000 |
| | (0.3033) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| Observations | 76752 | | | | | | | | |

P-values in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Table 2: Correlation matrix

One important control variable is an appropriate measure of income, for which we have decided to use net equivalised annual household income (in British Pound Sterling), before housing costs and deflated to price level of 2008, as provided and detailed by Levy and Jenkins (2008). As equivalence scales, we have opted for applying the widely accepted McClements scale (McClements, 1977). In accordance with consensus in the happiness literature, we use the *logarithm* of the income measure as a matching variable in our analysis, assuming that a given change in the proportion of income leads to the same proportional change in well-being (Easterlin, 2001, p. 468). A remark is in order on self-reports of income in the context of self-employment and entrepreneurship: it is quite well-known that self-reports of income are quite unreliable in the context of entrepreneurs and self-employed (e.g., Block and Koellinger, 2009; Blanchflower and Oswald, 1998), leading to biased estimates when controlling for income in standard regressions. A second problem lies in theoretical concerns whether one should control for income at all: "if the hypothesis is that the self-employed have higher job and life satisfaction but at the same time, they receive lower incomes, it is not certain that we want to control for income. Including income as a control variable in the fixed-effects models is even more problematic. Since becoming self-employed for the average individual means a decrease in income, it can be hard to disentangle the effect of becoming self-employed from the effect of receiving a lower income on the outcomes" (Andersson, 2008, p. 218).

Using a matching approach, we are immune to both kinds of problems since we are not regressing income on life satisfaction but using the variable to match individuals who report similar incomes. Our approach thus allows us to use the information contained in the income variable without having to fear that the negative effect of lower income on happiness is entangled with the positive effect of being self-employed.

To measure individuals' health, we focus on an individual's subjective assessment of health (during the last 12 months). This is ordinally scaled on a five point Likert scale, ranging from "excellent" (five) to "very poor" (one).[10] Subjective assessments of health seem to predict objective health quite well in some cases (e.g., regarding morbidity). Whether objective health is sufficiently well captured by subjective health assessments is still debated (Johnston et al., 2009). In order to account for more objective aspects of individual health, we also included a dummy variable to account for disability of an individual.

Besides income and health, our control variables also comprise the usual set of gender, age, and age$^2$ (we use the squared difference between age and mean-age instead of age$^2$ in order to avoid problems of multicollinearity), as well as some dummies regarding marital status (e.g., being married, being separated, divorced or widowed). We have also added a regional control variable, dummies for different ethnicities and years (which we do not report, however). Also included is an educational control variable, viz. an individual's highest level of education. This is measured ordinally, ranging from one ("none of these") to seven ("higher degree"), giving intermediate values to the middle education levels.[11] Of our sample, 53.00% were female. The mean age is 45.49 years (s.d. 17.85) with maximum age at 98 years and minimum age at 15 (younger individuals were not interviewed in the BHPS).

In Table 2, we report pairwise correlations between our variables. A look at these correlations offers first insights. Most of the correlations are highly significant, with the exception of life satisfaction and gender (not many studies report significant effects of gender on life satisfaction, see Dolan et al., 2008) as well as log(income) and the self-employment dummy. We find a negative association between life satisfaction and unemployment ($\rho = -0.0857$) and a less strong positive relationship between life satisfaction and self-employment ($\rho = 0.0168$). Education has a somewhat negative association with life satisfaction ($\rho = -0.0165$). A similar effect has been found by Binder and Coad (2010b) for the upper quantile of the life satisfaction distribution. Not surprising is that education correlates strongly ($\rho = 0.3110$) with log(income). On the other hand, quite interestingly, education also strongly correlates with being employed ($\rho = 0.2870$), but only slightly so with being self-employed ($\rho = 0.0470$). One could hypothesize that education is of much less importance for the self-employed (probably due to the majority of them not owning knowledge-intensive high-tech start-ups but low-tech businesses). Education is moreover slightly negatively associated with being unemployed ($\rho = -0.0367$). A last impression concerns the association of gender and self-employment, which is quite strongly negative ($\rho = -0.1496$), suggesting that comparatively fewer females are in self-employment (of the $5,455$ individuals in our sample in self-employment, only $1,419$ were female). This simple correlation exercise can but give a first impression of our data set, since it does not control for any confounding factors.

Figure 1 shows the cumulative density functions (cdf) for log income (left) and life satisfaction (right). Starting with the cdf for log income, we see that the self-employed earn less than the employed in most cases, while at the upper end of the distribution (starting at the $80^{th}$ percentile) a handful of "superstar" self-employed individuals earn more than their employed counterparts. Put differently, the income distribution for the employed does not

[10] We have reversed the numerical order of the Likert scale to consistently use higher values for better outcomes. The original coding in the BHPS codes a value of one to be excellent health and five to be very poor health.

[11] For more information see Taylor (2009), App. 2, pp. 18-9.

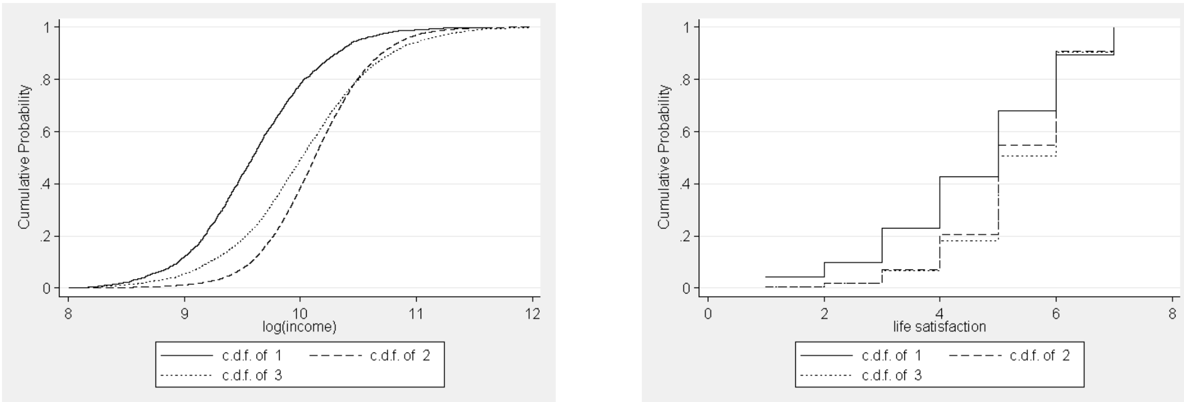


Figure 1: Cumulative density functions for log income (left) and life satisfaction (right) for the three employment categories: unemployed (1), employed (2) and self-employed (3).

stochastically dominate the income distribution of the self-employed. This finding is similar to results for US data in Hamilton (2000), but seem to be at odds with results on Indian data (Tamvada, 2010), where the distribution of per capita consumption for the employed stochastically dominates the corresponding distribution of the self-employed. It is important to note, however, that Tamvada (2010) splits the self-employed group into “solo entrepreneurs” and “employers”, something that we are unable to do in our dataset. These divergent findings may well be reconciled if we consider that the income distribution of employers stochastically dominates the income distribution those in paid employment, which in turn stochastically dominates the income distribution of solo entrepreneurs.

Concerning the life satisfaction distribution, the self-employed generally report higher life satisfaction, although we do not strictly observe that the life satisfaction distribution for the self-employed stochastically dominates the corresponding distribution for the employed because of a handful of very dissatisfied self-employed individuals.[12]

In Table 3 we depict a transition matrix where (pooled) mean changes in life satisfaction are correlated with changes in job status (for transition between employment “E”, unemployment “UE” and self-employment “SE” from period $t-1$ to $t$). We can clearly see that there are no big changes in life satisfaction exhibited if one’s employment status stays constant (the diagonal in the table). However, moving into unemployment from any type of (self-)employment is associated with a negative change in life satisfaction and leaving unemployment is also positively associated with an increase in life satisfaction. Interestingly enough, the effect of moving from employment to self-employment is larger than vice versa. The signs of change in well-being are comparable to the analysis by Clark (2003). As the pairwise correlation table, the transition matrix presented here can but offer a simple first overview over the data.

| Mean change in life satisfaction | | | |
|---|---|---|---|
| | $E_t$ | $UE_t$ | $SE_t$ |
| $E_{t-1}$ | -0.0087 | -0.3962 | 0.0820 |
| | (.0068) | ( .0651) | ( .0446) |
| obs | 23,439 | 419 | 512 |
| $UE_{t-1}$ | 0.4286 | 0.0109 | 0.4242 |
| | (.0591) | (.0689) | (.1871) |
| obs | 490 | 458 | 66 |
| $SE_{t-1}$ | 0.0169 | -0.3571 | -0.0039 |
| | (.05334) | ( .2151) | (.0190) |
| obs | 415 | 42 | 2,804 |

Standard errors in parentheses.

Table 3: Transition matrix: Mean change in life satisfaction and change in job status ("E", "S" and "U" denoting employment, self-employment and unemployment respectively) from $t-1$ to $t$

## 5. Analysis

We contribute to the literature by making use of recent developments in matching econometrics to create an accurate control group, and thus identify the causal effect of self-employment on happiness. Our dataset has comprehensive information on individual characteristics, which allows us to find a "perfect twin" for each self-employed individual, and thus recreate an appropriate control group in our analysis of how satisfied individuals are with self-employment (Almus and Czarnitzki, 2003).

### *5.1. Preliminary regressions*

As a first orientation, we want to present a standard regression analysis, where we regress the typical factors on life satisfaction and job satisfaction. In Table 4, we show two pooled ordered probit regressions (models (1) and (2)), where life satisfaction (1) and job satisfaction (2) are the dependent variables. While we clearly see a strong effect of being self-employed on job satisfaction, this effect is much smaller when taking life satisfaction as a dependent variable. The latter two columns (models (3) and (4)) now repeat this analysis within a fixed-effects (FE) regression framework, where we are not interested in the between-variance but the variance within individuals over time, controlling for time-invariant individual-specific components. Accounting for fixed effects in happiness regressions does substantively alter regression results, a fact happiness researchers become increasingly more aware of (Ferrer-i Carbonell and Frijters, 2004). Since happiness is in part determined by genes and stable personality traits (Lykken and Tellegen, 1996; Diener et al., 1999), accounting for fixed effects would seem to be the route to choose. Model (3) here depicts the FE-version of model (1) and model (4) is a robustness test where we use a broader mental well-being variable as

[12] We observe that 0.58% of the self-employed report a life satisfaction score of 1, compared to 0.50% of employed individuals.

| | (1) life satisfaction Ord. probit | (2) job satisfaction Ord. probit | (3) life satisfaction FE | (4) mental well-being FE |
|---|---|---|---|---|
| d_unemployed | -0.2716*** | -0.7025*** | -0.3269*** | -1.9826*** |
| | (-10.61) | (-8.40) | (-10.14) | (-12.90) |
| d_selfemployed | 0.0588*** | 0.3171*** | -0.0020 | -0.0354 |
| | (4.15) | (20.61) | (-0.08) | (-0.31) |
| d_retired | 0.2368*** | -0.2284** | 0.0292 | 0.1469 |
| | (13.04) | (-2.73) | (1.06) | (1.31) |
| d_studyschool | 0.0857*** | -0.2129*** | 0.0492 | -0.0325 |
| | (4.24) | (-7.29) | (1.59) | (-0.21) |
| d_maternityleave | 0.3855*** | -0.1681** | 0.2724*** | -0.2217 |
| | (7.52) | (-2.89) | (6.42) | (-0.95) |
| d_longtermsick | -0.2132*** | -0.4808*** | -0.3702*** | -2.0802*** |
| | (-8.19) | (-5.68) | (-8.43) | (-9.80) |
| d_familycare | 0.0094 | -0.1284* | -0.0574* | -0.4566*** |
| | (0.53) | (-2.09) | (-2.16) | (-3.58) |
| d_other | 0.0563 | 0.0734 | -0.0328 | -0.2485 |
| | (1.03) | (0.91) | (-0.54) | (-0.81) |
| log(income) | 0.0999*** | 0.0339*** | 0.0309** | -0.0028 |
| | (14.00) | (3.60) | (3.14) | (-0.06) |
| health status | 0.3826*** | 0.2342*** | 0.2130*** | 1.3505*** |
| | (75.57) | (37.27) | (31.33) | (39.45) |
| d_married | 0.1894*** | 0.1482*** | 0.0611* | -0.3526** |
| | (16.63) | (10.83) | (2.28) | (-2.62) |
| d_separated | -0.2556*** | -0.0002 | -0.1225* | -1.7689*** |
| | (-8.92) | (-0.01) | (-2.38) | (-6.52) |
| d_widowed | -0.0804*** | 0.0883 | -0.2166** | -1.5190*** |
| | (-3.54) | (1.90) | (-3.13) | (-5.67) |
| d_divorced | -0.1033*** | 0.0064 | 0.0475 | -0.0844 |
| | (-5.97) | (0.30) | (1.05) | (-0.38) |
| d_disabled | -0.1839*** | 0.0045 | -0.1530*** | -0.6140*** |
| | (-9.88) | (0.12) | (-6.11) | (-5.66) |
| gender | 0.0481*** | 0.1317*** | | |
| | (6.05) | (13.71) | | |
| age | 0.0039*** | 0.0089*** | -0.0124 | -0.0331 |
| | (9.67) | (16.22) | (-0.84) | (-0.54) |
| (age-mean age)$^2$ | 0.0004*** | 0.0006*** | 0.0000 | 0.0003 |
| | (20.06) | (18.93) | (0.33) | (1.28) |
| education | -0.0447*** | -0.0235*** | 0.0126 | 0.0600 |
| | (-18.37) | (-7.69) | (0.92) | (0.91) |
| Observations | 76752 | 49419 | 76752 | 76752 |
| (Pseudo-) $R^2$ | 0.0580 | 0.0215 | 0.0388 | 0.1217 |

$t$ statistics in parentheses
$^*$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 4: Ordered probit and fixed effects regressions for life satisfaction and job satisfaction

a dependent variable.[13] In line with the above discussed findings in the literature, we can observe that the small effect of self-employment on happiness disappears when controlling for individual-specific time-invariant effects in our regressions (see, similarly, Andersson, 2008). However, by removing time-invariant characteristics, we may be "throwing out the baby with the bathwater", and effectively we may be removing some effects of interest (in particular, slow-changing character traits) by "over-controlling". Also, fixed-effect regression suffers from other drawbacks of regression models discussed above (in particular, lack of a common support for treatment and control groups). In order to come to more reliable estimates of the effect of being self-employed on life satisfaction, we turn now to our matching estimates.

*5.2. Matching estimates*

Our main analysis centers around estimating the causal effect that going into self-employment has on an individual's life satisfaction. Figure 2 gives a graphical representation of our matching approach. In both cases, we restrict attention to individuals that are similar, along a number of dimensions, at time $t$. We then track these individuals over time and observe differences between the treatment group (those moving into self-employment) and the control group (their matched counterparts in regular employment). We are interested here in two different situations, which correspond to the distinction of opportunity versus necessity entrepreneurship. In the first case (Figure 2, left) all individuals start off in regular employment in $t$, and some individuals move into self-employment in $t + 1$. We suggest that this case corresponds to opportunity entrepreneurship. In the second case (Figure 2, left), all individuals start off as unemployed in $t$, and some move into self-employment while the control group moves into regular employment in $t + 1$. This case would correspond to necessity entrepreneurship, where individuals chose to become self-employed to escape unemployment.

Since we are also interested in the dynamics of well-being, we have chosen to examine whether there is a lagged effect of self-employment on life satisfaction, i.e. the possible impact of self-employment on life satisfaction at period $t + 2$. A robust finding emerging from the happiness literature is that individuals adapt to changes in their life circumstances. Hedonic adaptation, the hedonic dulling of repeated or constant affective stimuli (Frederick and Loewenstein, 1999) is highly domain-specific and varies with the concrete stimulus (for example, hedonic adaptation to marriage is faster and more complete than hedonic adaptation to repeated unemployment, see, e.g., Clark et al., 2008b). The yearly structure of our panel data set suggests to include a second year to check for hedonic adaptation but additional

[13] The rationale for model (4) lies in some econometric reservations one could have in our using an ordinal scaled life-satisfaction variable in a fixed effects OLS regression, thus implicitly treating life satisfaction as a cardinal variable. This is in part motivated by the absence of a commonly agreed-on method to account for fixed effects in an ordered probit framework. However, econometric research on happiness shows that there are no substantial differences between both approaches in terms of the results they generate (Ferrer-i Carbonell and Frijters, 2004) and a cardinal treatment of life satisfaction is common in the psychological literature on well-being. One reason for the robustness of the life satisfaction measure to being treated as cardinal could lie in the fact that individuals seem to convert ordinal response labels into similar numerical values such that these cardinal values equally divide up the response space (Van Praag, 1991; Clark et al., 2008). Nevertheless, model (4) with a 37-point scale alleviates the possible objection to using life satisfaction in an FE framework, since treating a 37-point scaled mental well-being construct as a cardinal variable seems much more uncontroversial.

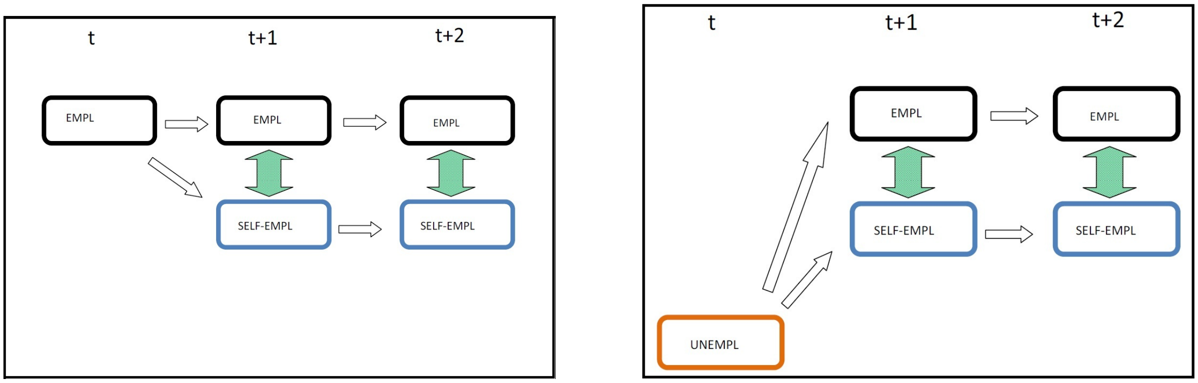


Figure 2: A graphical depiction of our matching approach. In both cases, we match individuals at time $t$ and observe these individuals at times $t+1$ and $t+2$, comparing those individuals that have moved into self-employment with comparable individuals who are in regular employment. In the first case (left) all individuals start out in regular employment, and the control group remains in regular employment. In the second case (right) all individuals start out unemployed, and the control group consists of those moving from unemployment to regular employment.

lags might be added in future work. Our dynamic approach, according to which we match individuals at time $t$ and observe them again at times $t+1$ and $t+2$, additionally takes into account the fact that failure to control for lagged outcome can lead to bias in matching estimators (see, e.g., González and Pazó, 2008).[14]

We are carrying out our analysis for two different types of matching, viz. nearest neighbour matching as well as propensity score matching. Both methods differ with respect to how individuals are matched. Nearest neighbour matching finds a match in many dimensions simultaneously while propensity score matching collapses all covariates into on composite variable (the "propensity score"). This difference has the consequence that adding too many covariates according to which one matches individuals in nearest neighbour matching results in a dimensionality problem, i.e. one is not likely to find good matches in each of the dimensions simultaneously. Therefore, for the nearest neighbour matching, we matched individuals according to a smaller number of criteria, namely: previous life satisfaction, log(income), gender, age, education, subjective health assessment as well as dummies for ethnicity and being married. Adding more criteria would have made it harder to get good matches in our context.

For the propensity score matching, we did not have pressing concerns of dimensionality (since the matching covariates are collapsed into a synthetic propensity score, and matching is performed with reference to the propensity score only). Therefore with propensity score matching, we matched individuals according to the above mentioned factors but added also the following list of covariates: year dummies, regional dummies for the different former Metropolitan counties and Inner and Outer London, dummies for being separated, divorced

[14]Cooper and Artz (1995) focus in their analysis on third year business because prospects can fluctuate and in the beginning, uncertain prospects might lower satisfaction. This initial uncertainty offers thus an additional reason for taking into account the intertemporal structure of life satisfaction following one's decision to go into self-employment.

| | | |
|---|---|---|
| E to SE vs. E to E | | |
| 1 lag | **0.172** | 15181 |
| SE | 0.062 | |
| $t$-stat | 2.76 | |
| 2 lags | **0.241** | 7896 |
| SE | 0.085 | |
| $t$-stat | 2.83 | |
| U to SE vs. U to E | | |
| 1 lag | -0.130 | 326 |
| SE | 0.210 | |
| $t$-stat | -0.62 | |
| 2 lags | -0.031 | 147 |
| SE | 0.317 | |
| $t$-stat | -0.10 | |

Table 5: Nearest neighbour matching estimates of the Sample Average Treatment Effect (SATE). 4 matches are selected for each treatment observation. SATE, Standard Errors and $z$-stats estimated following Abadie et al. (2004).

or widowed, a dummy for being disabled and a quadratic age term.[15]

Table 5 shows the nearest neighbour matching results ("E", "SE" and "UE" denoting employment, self-employment and unemployment respectively), while Table 6 shows the estimates obtained from a propensity score matching estimator. For both matching estimators, we can see significant positive effects on happiness of switching from employment to self-employment, compared to a matched sample of those who remain in employment. Our findings here complement results that have been reported for US data by Hundley (2001), who find that individuals going from employment into self-employment experience an increase in job satisfaction. With our matching approach, we are able to show that this increase in satisfaction is not related only to the job but to satisfaction with life as a whole.

Interestingly enough, both matching estimators show a larger effect at the second lag compared of the first, which suggests that the positive impact on well-being is not only not transitory, but it even increases with time. Individuals who move from employment to self-employment will appreciate this transition even more two years afterwards, once they have become more accustomed to the self-employed lifestyle. The causal effect self-employment has on life satisfaction is thus (at least in the first years) not only exempt from hedonic adaptation, it seems to show the opposite: an increasing antiadaptive effect.

It is important to point out, however, that there is a marked difference between this positive effect of self-employment on happiness for individuals who switch from employment (i.e. opportunity entrepreneurs) and those who become self-employed to escape unemployment. In all these cases, there is no significant difference between the well-being of individuals who switch from unemployment to self-employment, compared to those to switch from unem-

[15] We also wanted to match individuals according to industry in which they are employed (or had their last employment), but since data reporting definitions changed over the sample period we were prevented from doing this.

| | ATT | Controls | Treated |
|---|---|---|---|
| E to SE vs. E to E | | | |
| 1 lag | **0.155** | 23409 | 512 |
| SE | 0.049 | | |
| $t$-stat | 3.14 | | |
| 2 lags | **0.212** | 23409 | 512 |
| SE | 0.071 | | |
| $t$-stat | 2.97 | | |
| U to SE vs. U to E | | | |
| 1 lag | -0.225 | 490 | 66 |
| SE | 0.231 | | |
| $t$-stat | -0.98 | | |
| 2 lags | -0.166 | 490 | 66 |
| SE | 0.273 | | |
| $t$-stat | -0.61 | | |

Table 6: Propensity score matching estimates of the Average Treatment Effect on the Treated (ATT), obtained using the kernel option (using the "pscore" command in Stata 11, developed by Sascha Becker and Andrea Ichino). Analytical SEs cannot be computed; bootstrapped SEs are reported (100 bootstrap replications).

ployment to regular employment. In each case, the estimated effect is actually negatively signed, but far from significant (perhaps due to the lower number of observations). In the case of those leaving unemployment (i.e. when it comes to necessity entrepreneurship), self-employment has no advantage over a regular job in terms of individuals' life satisfaction.

### *5.3. Robustness of matching estimates*

While such a matching approach offers a robust way of identifying appropriate control and treatment groups, it can be quite sensitive to identification bias. In particular, problems might arise if the conditional independence assumption (CIA) is not valid. This aspect is often ignored in the literature on matching (Caliendo and Kopeinig, 2008). In order to account for this sensitivity, we conduct various robustness tests.

To begin with, we follow a simulation approach by Nannicini (2007) and Ichino et al. (2008) that allows us to identify the robustness of our estimation strategy with respect to simulated confounders that recreate violations of the CIA. The sensitivity analysis is reported in Table 7. As recommended by Nannicini (2007, p. 6), "the results of this simulation-based sensitivity analysis should be judged more on the basis of the distance between point estimates associated to different $p_{ij}$, rather than the significance level of the simulated ATTs." Our robustness analysis reveals that our results are generally robust with respect to simulated confounders such as gender and marriage status variables, but not to "strong confounders". However, it has been observed that the "strong confounder" configuration taken here (following Nannicini, 2007) is especially stringent, and although our results are not robust to the presence of a "strong confounder" they are nonetheless fairly robust.

A second robustness test we conducted was to repeat our analysis with mental well-being

| | UtoSE vs UtoE | | Fraction U=1 by t/o | | Outcome effect Γ | Selection effect Λ | ATT | SE |
|---|---|---|---|---|---|---|---|---|
| | $p_{11}$ | $p_{10}$ | $p_{01}$ | $p_{00}$ | | | | |
| E to SE: 1 lag | | | | | | | | |
| No confounder | | | | | | | 0.084 | 0.074 |
| Neutral confounder | 0.5 | 0.5 | 0.5 | 0.5 | 0.996 | 0.983 | 0.089 | 0.096 |
| Strong confounder | 0.8 | 0.8 | 0.6 | 0.3 | 3.489 | 5.22 | -0.021 | 0.094 |
| *confounder-like* | | | | | | | | |
| d_female | 0.33 | 0.34 | 0.5 | 0.48 | 1.048 | 0.541 | 0.097 | 0.092 |
| d_married | 0.67 | 0.62 | 0.63 | 0.57 | 1.289 | 1.235 | 0.083 | 0.092 |
| UE to SE: 1 lag | | | | | | | | |
| No confounder | | | | | | | . | . |
| Neutral confounder | 0.5 | 0.5 | 0.5 | 0.5 | 1.031 | 1.172 | -0.212 | 0.304 |
| Strong confounder | 0.8 | 0.8 | 0.6 | 0.3 | 10.19 | 2.07E+16 | -0.463 | 0.483 |
| *confounder-like* | | | | | | | | |
| d_female | 0.13 | 0.22 | 0.39 | 0.38 | 1.062 | 0.308 | -0.231 | 0.313 |
| d_married | 0.35 | 0.35 | 0.3 | 0.3 | 1.082 | 1.543 | -0.211 | 0.293 |
| E to SE: 2 lags | | | | | | | | |
| No confounder | | | | | | | 0.125 | 0.093 |
| Neutral confounder | 0.5 | 0.5 | 0.5 | 0.5 | 1.007 | 1.014 | 0.14 | 0.123 |
| Strong confounder | 0.8 | 0.8 | 0.6 | 0.3 | 3.542 | 3.962 | 0.012 | 0.135 |
| *confounder-like* | | | | | | | | |
| d_female | 0.34 | 0.33 | 0.49 | 0.48 | 1.055 | 0.541 | 0.166 | 0.125 |
| d_married | 0.65 | 0.62 | 0.6 | 0.58 | 1.089 | 1.267 | 0.157 | 0.13 |
| UE to SE: 2 lags | | | | | | | | |
| No confounder | | | | | | | | |
| Neutral confounder | 0.5 | 0.5 | 0.5 | 0.5 | 1.085 | 1.107 | -0.166 | 0.353 |
| Strong confounder | 0.8 | 0.8 | 0.6 | 0.3 | 1.50E+09 | 1.03E+07 | -0.746 | 0.539 |
| *confounder-like* | | | | | | | | |
| d_female | 0.19 | 0.15 | 0.43 | 0.32 | 2.231 | 0.281 | -0.106 | 0.373 |
| d_married | 0.35 | 0.35 | 0.34 | 0.18 | 3.772 | 1.327 | -0.132 | 0.36 |

Table 7: Robustness of treatment effect estimates. Sensitivity analysis investigating the effect of calibrated confounders using the simulated approach presented in Nannicini (2007).

as the dependent variable instead of life satisfaction. Mental well-being is a broader concept of well-being that includes more affective and mental health related aspects of human life (the correlation between life satisfaction and mental well-being is $\rho = 0.5543$). We thus repeated the matching analysis with mental well-being and obtained similar results, for both models, and for both lags, and for both matching techniques (nearest neighbour matching, and propensity score matching).[16] In other words, using mental well-being instead of life satisfaction we observed that individuals switching from regular employment were happier (at $t+1$ and $t+2$) than those who remained in regular employment. On the other hand, individuals who moved from unemployment into self-employment were not significantly different from those who moved from unemployment into regular employment.[17] Taken together, we are reasonably convinced of the soundness and robustness of our matching estimation strategy.

## 6. Conclusion

In previous studies, the self-employed were found to be more satisfied with their jobs than employed control groups. This finding has proven robust even though the self-employed often earn less and work more hours than individuals in regular employment. Explanations suggest that the autonomy enjoyed by "being one's own boss" more than compensates entrepreneurs for the hardships otherwise associated with self-employment. The present paper has investigated to which extend higher job satisfaction of the self-employed also translates into a more global assessment of well-being, namely their satisfaction with life in general. Few studies so far were able to present empirical evidence on higher life satisfaction of the

[16] The authors will provide the detailed results of this exercise on request.

[17] The coefficient was also always negative but not significant.

self-employed, either due to methodological difficulties since the self-employed are a very heterogeneous group, or due to a lack of a causal connection between the variables. Following the latter line of reasoning, self-employed individuals might not enjoy higher life satisfaction than the employed because their high job satisfaction could result in the self-employed focussing so strongly on their work that they crowd out other activities that contribute to high life satisfaction, such as social relations or health.

To account for these methodological difficulties and to explore the above-mentioned theoretical intuition, we have applied a matching methodology in order to better identify treatment and control groups and thus being able to examine the causal effect that a transition into self-employment has on life satisfaction. Since individuals go into self-employment for quite divergent reasons, we have broadly distinguished two motivations in our regressions: individuals going into self-employment to escape unemployment (necessity self-employment) differ from individuals who go into self-employment to exploit a business opportunity (opportunity self-employment). In our analysis we found that individuals moving from regular employment into self-employment (the case of "opportunity entrepreneurship") experience a positive and significant increase in life satisfaction, that actually increases from the first year of self-employment to the second. However, we also observed that individuals moving from unemployment to self-employment were not better off than those moving from unemployment to regular employment (the case of "necessity entrepreneurship"). Those moving from unemployment to self-employment actually had lower life satisfaction scores than the control group, but these differences were not statistically significant.

Further research might fruitfully centre on extending our findings from the British Household Panel Survey (BHPS) data set to other countries as well as extending the analysis to cover longer horizons in order to explore the longer term causal effects of self-employment on life satisfaction. This might be a worthwhile undertaking, considering that it has been observed that the self-employed not only have lower pay, but also that their pay increases at a lower rate over time (Hamilton, 2000).

*Date: December 21, 2010; ca. 7,400 words*

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