[PAA submission]

# Psychopathological Selection in Status Attainment

# : A Life Course Perspective

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Using the National Child Development Study and a Generalized Linear Mixed Model, we have explored psychological selection effects in social class mobility over the life course up until midlife. We find that (1) those selection effects are operating throughout life course; (2) that psychopathological selection effects are most pronounced at the time when people start their own job careers ; (3) that there is no sufficient evidence to support differential selection effects of psychological syndromes by class of origin across the life course except one interaction effect only at age 23. Only at age 23, upper class compared to middle class is more likely to experience downward mobility as psychopathological symptoms get worse. However, there is no evidence to give precedence to drift hypothesis over residue hypothesis and vise versa. These results can be interpreted as those two mechanisms are all operating throughout one's life.

## 1 Introduction

Regarding a time-invariant observation of disproportionate distribution of mental illness in socially disadvantaged groups, social selection versus social causation debate comprises one of classic subjects in mental health literature (Cockerham 2006; Dohrenwend et al. 1992; Turner & Wagenfeld 1967; Muntaner, Eaton & Diala 2000). Social causation argument refers to the theoretical standpoint in which socially disadvantaged groups are more likely to be exposed to adverse environments so that they are more likely to be mentally ill. On the other hand, social selection argument refers to theoretical position in which mentally ill people are more likely to drift downward in social stratification ladder or they are more likely to be unable to ascend to higher strata. Usually, out of these two selection hypotheses, the first is called “drift” hypothesis and the second is called “residue” hypothesis (Cockerham 2006).

Often these debates assumed incompatibility of two theories, partly because studies on this subject have been practiced in a retrospective study design. In a retrospective study whose representative is a case-control study, as widely implemented before the Epidemiologic Catchment Area Program, it is hard to perceive simultaneous causal processes with satisfactory precision. Then, no wonder that many social scientists have strived to find evidence supporting social causation theory, especially when we take it into account that social causation theory is thought to be more attractive than social selection theory in enhancing social equality.

However, we don’t see those two causal mechanism incompatible. Moreover, more accurate understandings on social selection process can promote concrete policy making efforts. For example, if we observe strong selection effects on status attainment in their 20's, it means we should make our efforts to prevent additional onsets of mental disorders and to mitigate psychopathological symptoms for those who already contract with mental disorders. Another example can be recent development in this debate into disorder-specific causal relationship (Dohrenwend et al. 1992; Eaton, Muntaner, Bovasso, & Smith 2001). By identifying which psychiatric problems are more related with social selection theory or social causality theory, they not only enhanced understandings on the inverse relationship but also suggested more flexible policy plans.

Based on these discussions, we investigate social selection mechanisms influencing status attainment. However, our study goes beyond traditional research on social selection in two aspects: (1) we test different selection effects by social class of origin. In many cases, it has been assumed that same type or amount of psychological symptoms would result in the same outcomes in social selection literature (Fox 1990). By examining interaction effects of psychiatric problems with class of origin, we can test differential selection mechanisms. (2) we study selection mechanisms over the life course, which includes both intergenerational mobility and intragenerational mobility. Most of studies on social selection have been confined either in intergenerational mobility or in intragenerational mobility. By combining two processes, we can evaluate relative strength and differential effects by stages in life course.

Recent development in statistical techniques and accumulation of longitudinal data open up new possibility to take a look at social selection process over the life course. Especially advance in categorical data analyses incorporating longitudinal data such as Generalized Linear Mixed Models (GLMMs) makes it possible to utilize longitudinal data without loss of significant amount of information (Agresti 2002). To attain our goals, we utilize a GLMM model and the National Child Development Study tracing a cohort from birth in 1958 up until now.

## 2 Research and Theories

Having set out contours of our study in this paper, we give an overview on what has been debated, what is still being debated and what has been settled in related literature to provide a more detailed background underlying our study.

### *A. Social Causation Versus Social Selection.*

Inverse relationship between psychological disorders and social statuses was well recognized before the turn of the 20$^{th}$ century (Dohrenwend et al. 1992). However, first systematic investigation on this inverse associations can be found in the Faris and Dunham's classical study in Chicago area (Cockerham 2006; Faris & Dunham1939). After that study, series of investigations has flourished in the mental health literature. This inverse relationship is one of consistent findings across all generations, if we are allowed to adopt generational distinction suggested by Dohrenwend and Dohrenwend (1982) followed by Dohrenwend (1998) in studies of distribution of psychological disorders in general population.

Two conceptually different theories have come up with and have been competing for explanation of this inverse relationship: social causation and social selection (Cockerham 2006; Dohrenwend et al. 1992; Turner & Wagenfeld 1967; Muntaner, Eaton & Diala 2000). Social causation theory argues that people in lower social class are more exposed to adverse environments to mental health so that they are more likely to contract with psychiatric disorders or more likely to be unable to get out of those disorders once onset of disorders is triggered (Eaton, Muntaner, Bovaso, & Smith 2001). On the other hand, social selection theory argues that psychological problems influence negatively to social mobility so that we frequently observe the inverse relationship between psychiatric disorders and social class. Social selection consists of two distinctive standpoints: (1) mentally ill people are more likely to drift downward in social stratification ladder, which is often called drift hypothesis; (2) people suffering mental disorders are more likely to be unable to ascend to higher social strata, which is often referred to as residue hypothesis (Cockerham 2006). Even though residue hypothesis is called selection effects in some studies, we reserve social selection to indicate general term including those two effects and residue effects to refer to the specific mechanism.

Even though these debates have contributed to our understanding on etiology of mental disorders and their social consequences, they often turned into a unfruitful tug-of-war, precisely because in many cases, they all focused on revealing causal mechanisms based on already observed mental outcomes. In other words, it becomes too difficult to determine which are main causes or moderating causes if we try to decide causal relationship interpolate causal mechanisms after observing inverse relationship. And more important, those study designs have failed to elicit clear message on social policies.

In addition, even though two theories are complementary in nature, they have been treated as though incompatible, partly because study designs have been restricted to retrospective frameworks. Under a retrospective design, it's very hard to investigate two causal processes simultaneously so that many researchers have concentrated on emphasizing one mechanism over the other.

From prospective study design, we find possibilities to fully appreciate those two theories relatively free of confounding of two causal mechanisms. Here, we investigate social selection mechanisms over the life course as a first endeavor to understand the social inequality in mental health, deferring study to scrutinize social causality mechanisms to the future work. By concentrating social selection mechanisms only, we expect to understand selection processes to more detailed extent. To do so, we incorporate two new features neglected in previous literature: (1) rigorous investigation on interaction effects of psychopathological symptoms with class of origin will be included; (2) life course perspective will be employed to cover entire life of individuals up until age 42. We will discuss these points more in remaining part of this section.

### *B. Class of Origin*

Even though class of origin is put into our model for controlling purpose, propensity of social fluidity or mobility per se is another interest of our current study. On the one hand, class of destination is not independent of class of origin (Kurz & Muller 1987; Featherman & Hauser 1978). Thus, we will get biased estimates if we are fail to account for class of origin. On the other hand, our model provide unique opportunity to take a look at intergenerational as well as intragenerational mobility in unified framework by comparing effects of one origin class with effects of another origin class. However, our model has a couple of distinctive features from conventional models: that is, we focus downward mobility rather than upward mobility because our main interest is to estimate psychological selection effects. Another difference is ordinality assumption of social statuses or social classes (Szreter 1993). Even though social class and social status are conceived as separate conceptual entities in vigorous research projects, we use those terms interchangeably for a convenience purpose.

Another interesting question is how psychopathological symptoms interact with class of origin in influencing social mobility. As well known in health literature in general and mental health literature in particular, relatively advantaged groups are less likely to fall victim of mortality and morbidity (Williams and Collins 1995; Kessler et al. 2005). These differentials originated from social positions apply not just to onset of morbidity but also to resilience of morbidity. In this context, we can hypothesize that the lower one's class of origin is, the lower one's class of destination is with psychological problems held constant.

Another important test we include in this study is whether these relationship would vary according to temporal stages in one's life. For instance, we ask whether effects of a origin class would change when we observe it at age 23 compared to at age 33. How about at age 42? Thus, we work in a life course perspective.

### *C. Control Variable: Gender.*

As is well known in mobility literature, gender is very important explanatory variable in explaining social mobility (Kurz and Muller 1987). Thus we include gender as a control variable. However, we are interested in observing temporal changes of gender inequality in status mobility. Then, gender and time interactions will be discussed in life course perspective.

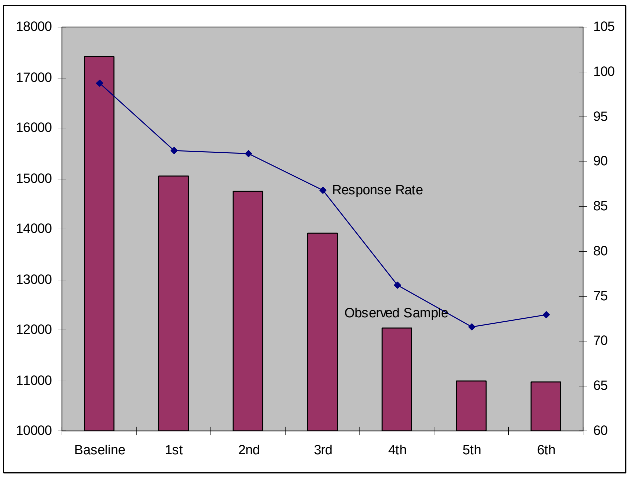
# 3 Data, Measurements and Statistical Models

## *A. Data.*

For examination of hypotheses discussed above, we use the National Child Development Study (NCDS) published by Economic and Social Data Service (ESDS) in Britain. The NCDS is an ongoing longitudinal study following whole members of a cohort who were born in a specific week of March 1958 in Great Britain. As implied by the name of its baseline survey, the Perinatal Mortality Survey (PMS), originally, the NCDS was devised to investigate the social and obstetric factors associated with stillbirth and death in early infancy (Shepherd 1995; Dodgeon, Elliott, Johnson, and Sheperd 2006). Up until now, 7 follow-up surveys have been undertaken excluding the baseline survey with the last one having been held in 2004, at cohort age 46.

There are total 18,558 persons who had taken part in at least one survey of the NCDS including 17,415 initial respondents. Immigrants who were born in the same week as the study cohort had been included to study sample up until the third follow-up in 1974. Like any other longitudinal studies, the NCDS also suffers from increase of attrition and nonresponse rate but remains one of few longitudinal surveys that holds great retention rate (Plewis, Calderwodd, Hawkes and Nathan 2004). For more information on attrition and response rates, we present Figure 1 below.

**Figure 1 Number of Observed Samples and Response Rates by Each Survey in the NCDS**




Source: Plewis, Calderwodd, Hawkes and Nathan 2004.

Note: Each bar stands for number of observed sample indexed by left side and points connected represent changes of response rates indexed by right side.

From Figure 1 above, it is evident that there is increasing number of unobserved cohort members. Nevertheless, we note that response rate is above 70% even in the sixth follow-up survey.

Out of those 7 surveys, we use 4 surveys which can be assumed to be spaced evenly in time line: the second follow-up at age 11 in 1969, the fourth follow-up at age 23 in 1981, the fifth follow-up at age 33 in 1991, and the sixth follow-up at age 42 in 2000. However, it should immediately be noted that the second follow-up survey provide only explanatory variables. Thus our main response variable comes from three surveys.

To catch more realistic pictures on life course of psychological selection effects, the first thing to consider is to find data which have been gathered in equally spaced time interval because conspicuous fluctuation in observation points in time could be confounded by time effects. If cases were observed in five year interval in one case and in 15 year interval in the other, for instance, we would be less confident in stating that any significant changes in both intervals are due to life course effects because our cases had been exposed to the risk for longer period.

As previous discussion strongly suggests, we have a lot of missing data in our final data set. Then complete data set strategy is adopted in analyses for this paper. Even though we have some evidence indicating our cases are not distributed as missing at random (Plewis, Calderwodd, Hawkes and Nathan 2004), other treatment for missing data will be deferred for further analyses. After deleting any cases with missing data, our data set ends up consisting of 5,802 cases who have all information in every follow-up.

### *B. Measurements.*

Our models are based on four core observed measures: class status in social stratification, psychological symptoms, sex, and each time point.

#### Class Status in Social Stratification

Class status in one stage of life course is our main outcome and proxies for class status are different from wave to wave. More specifically, National Vocational Qualification (NVQ: variable “hqual23”) strongly reflecting educational attainment represents class status at age 23. This variable compose of six categories: 1. No qualification; 2. CSE 2-5/NVQ1; 3. O Level/NVQ2; 4. A Level/NVQ3; 5. Higher qual/ NVQ4; 6. Degree/higher NVQ5, 6 (Smith 1991; for a brief discussion on this measure, see Makepeace et al. 2003).

At age 33 and 42, positions in occupational stratification are proxies for class statuses. In data sets published by ESDS included are measures on class statuses under the name of "social class" which is based on "professional model" of social structure ( Szreter 1993). This social class variable is derived from occupational position in each survey and classified according to schemes published by the General Register Office (GRO) that has devised those schemes to apply to the national census. This variable consists of six categories: I Professional; II Managerial; IIINM Skilled Non-Manual; IIIM Skilled Manual; IV Partly Skilled; V Unskilled. One of the nice features of this variable in our analysis is that this variable is hierarchically ordinal and strongly reflect educational requirements in each status level (Szreter 1993). Thus, it is no conceptual leap to compare status attainment represented by social class in age 33 with status attainment substituted with educational attainment in age 23. Needless to say is it that class status in age 42 is operationalized as social class in that survey. Those variables I used in this paper are: variable "n540033" for age 33 and variable "sc" for age 42.

For more meaningful analyses, we also put class status of approximately 10 year ago in the right hand equation. Then, educational attainment at age 23 and social class at age 33 are predictors for social class of age 33 and 42 respectively. However, we left one more response variable: class status superseded by educational attainment at age 23. For this outcome, social class of male head in the household at age 11 (variable "n1171") is inserted as a predictor. Therefore, our analyses incorporate transition of class statuses from childhood to early adulthood completing life course of status attainment up until middle aged adulthood.

As mentioned before, those proxy variables consist of six categories. However we recode these variables into ordinal variables with three categories such that each 2 adjacent categories are combined. We adopt this strategy because it turns out too expensive to stay 6 categories in computational terms and too many categories prevent succinctness in the right hand side of estimated equation. We put these ordinal status attainment variables into response variables in each stage of life course in addition to making them 2 dummy variables to be inserted into linear predictors. Due to our primary concerns about psychological selection effect, ordinal variables are coded as high value meaning lower classes. Lastly but not least, children with no male head at age 11 are coded as the lowest class.

**Psychopathological Symptoms**

The Bristol Social Adjustment Guide (BSAG) was implemented in the survey of 1969 when cohort were 11 years old. BSAG is a behavior check list evaluated by teacher. In 1969 survey, all items were subsumed under several syndromes including, but not limited to, withdrawal syndrome, depression syndrome and unforthcoming syndrome. However, in this analysis, we use total score for all syndromes (variable “n1008”) which ranges from zero to 70.

In 1981 and 1991 surveys, there consistently included the Malaise Inventory (MI) which is a self-completion measure on psychopathological symptoms. This was developed by Rutter and his colleagues based on items from the Cornell Medical Index

Health Questionnaire (Rutter, Tizard and Whitmore 1970; McGee, Williams and Silva 1986). MI consists of 24 items and studies on this measure have shown that this measure has good psychometric properties (McGee, Williams and Silva 1986; Rodgers, Pickles, Power, Collishaw and Maughan 1999)

Because these two measures are not identical in the theoretical ranges, we standardized to zero sample mean and unit sample variance before delete missing data. In these measures of psychopathological symptoms, bigger positive values represent more severe mental troubles.

**Gender and Time**

As discussed in literature review part, gender has proven to play an important role in status attainment. However, we are interested mainly in status demotion or drift so inclusion of gender variable in our analyses provide a great opportunity to take a look at what role gender plays in the dynamic of social stratification. It should be noted that we recode gender into dummy variable with female being zero and male one.

In our model, three time points are observed: at age 23 in 1981, at age 33 in 1991 and at age 42 in 2000. Each of these time points is referred to as time 1, time 2 and time 3 respectively and the last two time points are inserted into our model as indicator variables.

Race/ethnicity is not considered even though it has be proven to be a critical variable in status attainment precisely because the number of other races/ethnicities than European or Caucasian is negligible: all other races/ethnicities combined to be 285 out of 18,558 cohort members who took part in at least one interview.

### C. Statistical Models.

Currently we are interested in modeling each observation $y_{it}$ on status in social stratification in time $t$ of each individual $i$. If we treat individual cases as having randomly varying terms, say, as having random effects, Generalized Linear Mixed Model (GLMM) for repeated measures can be formulated as follows for link function g(·) (Agresti 2002).

**Equation 1**

$$g(\mu_{it}) = \mathbf{x}'_{it}\boldsymbol{\beta} + \mathbf{z}'_{it}\mathbf{u}_i$$

in which $\mathbf{x}_{it}$ refers to the design matrix, $\boldsymbol{\beta}$ denotes a column vector for fixed effect parameters, $\mathbf{u}_i$ signifies the vector of random effect values for an $i$ individual and $\mathbf{z}_{it}$ carries a column vector of explanatory variables. Here, $\mu_{it}$ represents conditional expectation of each observation $t$ of each individual $i$ conditioning on distribution of random effects $\mathbf{u}_i$. Formally, $\mu_{it} = E(Y_{it}|\mathbf{u}_i)$, where $y_{it}$ is observation $t$ in individual $i$.

Further, assuming an independent single random effect from a normal distribution with standard deviation $\sigma$ unknown, that is, assuming $\mathbf{z}_{it} = 1$ and $u_i \sim N(0, \sigma^2)$, Equation 1 can be rewritten as:

**Equation 2**

$$g(\mu_{it}) = \mathbf{x}'_{it}\boldsymbol{\beta} + u_i$$

which is usually called a random intercept model (Agresti 2002).

Our response variable has been measured as having ordinal property so that cumulative logit link is reasonable choice. Thus, our model can be transformed into:

**Equation 3**

$$\text{logit}[P(Y_{it} \leq j | u_i] = \alpha_j - [\mathbf{x}'_{it}\boldsymbol{\beta} + u_i]$$

where $j$ refers to the cut-offs of cumulative logits of the possible outcomes for $y_{it}$, thus j=1,…., C-1 in which C refers to the number of categories in the response variable and $\alpha$ denotes each intercept. Note that in our specification, linear predictor terms is included as negative form because we want to interpret regression coefficients having the same direction with the response variable. In other words, under the specification of Equation 3, positive coefficients mean positive association between Y and covariates. As is well-known, however, Equation 3 implies proportional odds structure (McCullagh 1980; Agresti 2002; Peterson and Harrell 1990; Hedeker and Mermelstein 1998; Hedeker, Mermelstein and Weeks 1999). That is, the log cumulative odds ratio is proportional to difference of values in a $\beta$ predictor (see Agresti 2002, p 276).

### D. Fitting Softwares.

To fit aforementioned models, we use statistical packages STATA and SAS. STATA is used mainly for extracting and making final data set from original data sets provided by ESDS. SAS is for fitting two models assuming proportional odds model expressed as Equation 3. Model fitting using "PROC NLMIXED" command in SAS turns out too time consuming. For instance, it took more than 2 hours when we fitted proportional GLMM incorporating life course parameters. User can specify initial value of each parameter so we input all zero value in all starting values except threshold and standard deviation of random effect which were set to 1. SAS employs maximum likelihood approach accompanied by adaptive Gaussian quadrature integration method. SAS performs statistical significance test of each estimate using t-test.

# 4 Outcomes and Interpretations

## A. Descriptive Statistics.

Table 1 below shows descriptive statistics in our final data set.

After deleting cases with any missing value, we end up with the total number of cases 5,802. Of these cases, 48.2% are female and the remaining 51.8% are male. From the numbers in parenthesis representing percentage in each column at specific age, some trends can be pointed out. Marginal distributions suggest 1) that weak drift from upper class to middle class occurred when measurement of class status changed from father's or male head's occupational status to his/her own educational attainment, 2) that overall upward mobility can be observed after age 23, 3) that this upward mobility can be attributed mainly to rise of middle class but noticeable ascent also appeared in lower class.

However, these trends were refracted by the medium of gender though we can find same trends within each gender. Nevertheless, we skip this differential patterns because gender is treated as a control variable in this paper.

**Table 1 Descriptive Statistics**

| Social Classes | | Gender | | | | Total | |
|---|---|---|---|---|---|---|---|
| | | Female | | Male | | | |
| | | Num. | Perc. | Num. | Perc. | Num. | Perc. |
| Age 11 | Upper | 706 | (25.2) | 805 | (26.8) | 1,511 | (26.0) |
| | Middle | 1,450 | (51.8) | 1,557 | (51.8) | 3,007 | (51.8) |
| | Lower | 641 | (22.9) | 643 | (21.4) | 1,284 | (22.1) |
| Age 23 | Upper | 613 | (21.9) | 613 | (20.4) | 1,226 | (21.1) |
| | Middle | 1,495 | (53.5) | 1,786 | (59.4) | 3,281 | (56.5) |
| | Lower | 689 | (24.6) | 606 | (20.2) | 1,295 | (22.3) |
| Age 33 | Upper | 962 | (34.4) | 1,302 | (43.3) | 2,264 | (39.0) |
| | Middle | 1,241 | (44.4) | 1,319 | (43.9) | 2,560 | (44.1) |
| | Lower | 594 | (21.2) | 384 | (12.8) | 978 | (16.9) |
| Age 42 | Upper | 1,088 | (38.9) | 1,469 | (48.9) | 2,557 | (44.1) |
| | Middle | 1,163 | (41.6) | 1,248 | (41.5) | 2,411 | (41.6) |
| | Lower | 546 | (19.5) | 288 | (9.6) | 834 | (14.4) |
| Total | | 2,797 | (100.0) | 3,005 | (100.0) | 5,802 | (100.0) |

| Variable | Obs | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Psy.. Symp. At age 11 | 5802 | -0.166 | -0.500 | 0.870 | -0.945 | 5.397 |
| Psy. Symp. at age 23 | 5802 | -0.096 | -0.479 | 0.902 | -0.815 | 5.568 |
| Psy. Symp. at age 33 | 5802 | -0.128 | -0.439 | 0.859 | -0.990 | 5.347 |

Note: Numbers in parenthesis are percentage in each column at specific age.

From the last three rows, we see descriptive statistics of psychopathological symptoms. Taking a look at mean column, we find that overall improvement occurred at age 23 but mental health deteriorated afterwards. Columns of median, minimum and maximum values indicate skewness of these measures to the right tail as is always the case in this kind of checklist measure. Nevertheless, there is no sign of asymmetric skewness in one particular measure in a certain age, which implies that it is safe to compare those three measures across ages.

We want to recall you that psychometric measures were standardized into zero sample mean and one unit standard deviation before sifting cases with missing value(s) when you take a look at standard deviation column. In this view point, you may find that the column suggests disproportional deletion of cases with bigger values in those measures because standard deviation decreased below one, which invokes further study about treatment on missing data. However, our analyses are restricted to this data set in this paper deferring those tasks to future agenda.

Table 2 below is devised to convey concisely what we want to model in this paper. For this table, we categorized continuous psychological symptoms into equally-spaced three levels, in this case, after selection of final data set. It is the three-way contingency table of social classes by social classes and degree of psychological sufferings. For example, all rows under the heading of age 11 show which class status one was destined after 10 year later, exactly speaking, after 12 years later for the outcome social classes was measured at age 23.

**Table 2 Association of Social Classes with Social Classes and Psychopathological Symptoms 10 Years Ago**

| Social Classes | | No Symptoms Upper | No Symptoms Middle | No Symptoms Lower | Mild Upper | Mild Middle | Mild Lower | Severe Upper | Severe Middle | Severe Lower |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Psychopathological Symptoms and Social Classes after 10 year later | | | | | | | | |
| Age 11 | Upper | 298 | 358 | 29 | 157 | 260 | 49 | 82 | 226 | 52 |
| | | (43.5) | (52.3) | (4.2) | (33.7) | (55.8) | (10.5) | (22.8) | (62.8) | (14.4) |
| | Middle | 271 | 685 | 162 | 173 | 590 | 231 | 99 | 486 | 310 |
| | | (24.2) | (61.3) | (14.5) | (17.4) | (59.4) | (23.2) | (11.1) | (54.3) | (34.6) |
| | Lower | 69 | 256 | 97 | 48 | 209 | 121 | 29 | 211 | 244 |
| | | (16.4) | (60.7) | (23.0) | (12.7) | (55.3) | (32.0) | (6.0) | (43.6) | (50.4) |
| Age 23 | Upper | 406 | 84 | 17 | 348 | 68 | 22 | 213 | 49 | 19 |
| | | (80.1) | (16.6) | (3.4) | (79.5) | (15.5) | (5.0) | (75.8) | (17.4) | (6.8) |
| | Middle | 427 | 554 | 139 | 380 | 634 | 143 | 305 | 544 | 155 |
| | | (38.1) | (49.5) | (12.4) | (32.8) | (54.8) | (12.4) | (30.4) | (54.2) | (15.4) |
| | Lower | 60 | 167 | 110 | 52 | 213 | 136 | 73 | 247 | 237 |
| | | (17.8) | (49.6) | (32.6) | (13.0) | (53.1) | (33.9) | (13.1) | (44.3) | (42.5) |
| Age 33 | Upper | 742 | 148 | 28 | 670 | 124 | 39 | 393 | 90 | 30 |
| | | (80.8) | (16.1) | (3.1) | (80.4) | (14.9) | (4.7) | (76.6) | (17.5) | (5.8) |
| | Middle | 225 | 644 | 108 | 230 | 534 | 117 | 150 | 479 | 73 |
| | | (23.0) | (65.9) | (11.1) | (26.1) | (60.6) | (13.3) | (21.4) | (68.2) | (10.4) |
| | Lower | 46 | 140 | 136 | 60 | 128 | 169 | 41 | 124 | 134 |
| | | (14.3) | (43.5) | (42.2) | (16.8) | (35.9) | (47.3) | (13.7) | (41.5) | (44.8) |

Note: Numbers in parenthesis show percentage in each row of each level of psychopathological symptoms.

Table 2 above reveals some answers to two core questions driving this paper: 1) if class status of origin is held constant, what effects does psychological pathology exert to status mobility on entire life span as well as on local fluctuation?; 2) Conversely, if psychological pathology is held constant, what effects do class status of origin exert to status mobility on global levels as well as local levels in terms of life course?

As to the first question, we contrast the three columns of no symptoms with the three columns of mild symptoms and the three columns of severe symptoms. In that case, we find that significant force of psychopathological drift is under operation, especially when respondents went through childhood and adolescence. For instance, let us compare those cells crossing three rows of age 11 and three columns of no symptoms and those cells crossing the same rows and three columns of severe symptoms. In upper class at age 11, 43.5% of cohort members remained in upper class when they experienced no symptoms while only 22.8 % of those who underwent severe symptoms remained in same class after 10 years later. Contrasts in other columns only strengthen our conclusion.

However, we find significant attenuation of this psychopathological effect at the turn of the middle life. For instance, examination of three rows of age 33 reveals that there is relatively high percentage of people remaining in upper class in face of severe psychological syndromes. Likewise, contrast between rows in a column will reveal effects of social status of origin, psychopathological symptoms being constant. Table for this purpose is not made because we will estimate those effects through modeling approach using GLMM in the next section.

### *B. Model Estimation.*

Here, two model will be examined: a base model and a life course model. In mathematical terms, the former can be written as Equation 3 where linear predictors can be written as Equation 4 as follows.

**Equation 4**

$$\mathbf{x}'_{it}\boldsymbol{\beta} = \beta_0 + \beta_1 * T2 + \beta_2 * T3 + \beta_3 * G_i \; + \beta_4 * MC_{it} \; + \beta_5 * LC_{it} \; + \beta_6 * PSY_{it}$$
$$+ \beta_7 * MC_{it} * PSY_{it} + \beta_8 * LC_{it} * PSY_{it}$$

where $T2$ contrasts time 2 (age 33=1) with time 1 (age 23=0), $T3$ distinguishes time 3 (age 42=1) from time 1 (age 23=0), $G_i$ represent gender (male=1, female=0), $MC_{it}$ denotes middle class status 10 years ago, $LC_{it}$ marks lower class status 10 years ago, $PSY_{it}$ means levels of psychopathological symptoms which is inserted as a continuous variable and remaining two terms are interaction effects between social classes and psychological sufferings. Note that gender variable doesn't carry t subscript because this is time-invariant variable. However, most of other variables are time-varying variables so that those time-varying terms have the subscript t.

Table 3 presents estimate outputs of two models: base model and life course model.

We find positive Time 2 effect, which means that overall level of social classes was degraded at age 33 compared to that at age 23. However, we see that there is no significant difference between overall level of social classes at age 42 from that at age 23. These facts suggest that people usually attain lower social classes at the period when people start their own job careers than the social classes predicted by education level but they recover the same social classes as predicted by education attainment in their 40's.

Next, we find statistically significant negative effect of gender. Let us recall you that we recoded gender such that male equals unity and female equals zero. Therefore, negative coefficient indicates that male is more likely to be in better position in social stratification compared to female.

**Table 3 Model Estimates**

| | Base Model | | | Life Course Model | | |
|---|---|---|---|---|---|---|
| | Est. | SE | P-value | Est. | SE | P-value |
| Int | -0.238 | 0.058 | <.0001 | -1.115 | 0.061 | <.0001 |
| Time 2 | 1.023 | 0.043 | <.0001 | 1.928 | 0.086 | <.0001 |
| Time 3 | 0.029 | 0.042 | 0.48 | 0.103 | 0.099 | 0.298 |
| Gender | -0.398 | 0.045 | <.0001 | -0.337 | 0.056 | <.0001 |
| Gen*T2 | | | | 0.132 | 0.076 | 0.084 |
| Gen*T3 | | | | -0.159 | 0.078 | 0.041 |
| MC | 1.288 | 0.054 | <.0001 | 2.286 | 0.066 | <.0001 |
| MC*T2 | | | | -1.399 | 0.091 | <.0001 |
| MC*T3 | | | | -0.277 | 0.105 | 0.009 |
| LC | 1.892 | 0.077 | <.0001 | 3.561 | 0.086 | <.0001 |
| LC*T2 | | | | -2.164 | 0.113 | <.0001 |
| LC*T3 | | | | -0.278 | 0.125 | 0.026 |
| Psy | 0.322 | 0.046 | <.0001 | 0.197 | 0.063 | 0.002 |
| Psy*T2 | | | | 0.349 | 0.090 | <.0001 |
| Psy*T3 | | | | -0.074 | 0.116 | 0.521 |
| MC*Psy | -0.05 | 0.053 | 0.352 | -0.171 | 0.076 | 0.024 |
| LC*Psy | -0.03 | 0.061 | 0.617 | -0.146 | 0.092 | 0.114 |
| MC*Psy*T2 | | | | 0.173 | 0.107 | 0.106 |
| MC*Psy*T3 | | | | 0.198 | 0.129 | 0.126 |
| LC*Psy*T2 | | | | 0.170 | 0.127 | 0.181 |
| LC*Psy*T3 | | | | 0.170 | 0.143 | 0.235 |
| $\sigma$ | 1.154 | 0.05 | <.0001 | 0.000 | 0.093 | 1.000 |
| $\alpha_2$ | 3.148 | 0.045 | <.0001 | 2.678 | 0.027 | <.0001 |
| -2LL | 30,815 | | | 30,427 | | |

Note: MC means Middle Class 10 years ago, LC means Lower Class 10 years ago, and Psy means Psychopathological symptoms 10 years ago. $\sigma$ means standard deviation of random effect and $\alpha_2$ means the random intercept.

Middle class compared to upper class is more likely to be in a lower social tier. Also lower class compared to upper class is more likely to be in a lower class. Statistical test indicates that there is significant difference between middle class and lower class the latter being more likely to end up in a lower social tier (data not shown)[i]. This is an established fact in social science requiring no further comments.

Psychopathological symptoms turn out to be a significant player in social mobility. Statistically significant positive coefficient of psychopathological symptoms indicates that persons showing more problematic mental syndromes are more likely to end up in a lower social tier. Our interested parameters representing differential selection effects of mental problems by class statuses, that is, interaction effects of mental problems with social classes turn out to be non-significant. These outputs can be interpreted as, if level of psychopathological symptoms is constant, neither middle class nor lower class, compared to upper class, is more likely to end up in a lower social tier. In a theoretical vein, these results suggest that there is no strong evidence on drift hypothesis or residue hypothesis. If drift hypothesis were right, we would observe statistically significant negative coefficient either on Psy*MC term or on Psy*LC term. On the other hand, if residue hypothesis were the case, we would find statistically significant positive coefficient either on Psy*LC or on the term subtracting the coefficient of Psy*MC term from Psy*LC term. Statistical insignificance of these coefficients point out absence of strong evidence to support superiority of either of two theoretical standpoints. However, as we discussed already, it should not forget that the main effect of psychopathological symptoms is outstanding, which indicates presence of social selection effect of psychological problems. In conclusion, we have evidence on psychological selection effects though we don’t have strong evidence giving precedence either drift argument or residue argument.

The formulation we have explored up until now is unsatisfactory in one respect: the model presumes the same effects of predictors across life course. In other words, the model assumes that psychological problems, for example, have the same effects whether they are observed in transition from age 11 to age 23, from age 23 to age 33, or from age 33 to age 42. Then, we proceed to relax the assumption of identical effects of each predictor over the life course. Main tasks in this part is to include various interaction effects of linear predictors with time points and to compare with one another. First, we specify our linear predictors as :

**Equation 5**

$$\begin{aligned}\mathbf{x}'_{it}\boldsymbol{\beta} = {} & \beta_0 + \beta_1{*}T2 + \beta_2{*}T3 + \beta_3{*}G_i + \beta_4{*}G_i{*}T2 + \beta_5{*}G_i{*}T3 \\ & + \beta_6{*}MC_{it} + \beta_7{*}MC_{it}{*}T2 + \beta_8{*}MC_{it}{*}T3 \\ & + \beta_9{*}LC_{it} + \beta_{10}{*}LC_{it}{*}T2 + \beta_{11}{*}LC_{it}{*}T3 \\ & + \beta_{12}{*}PSY_{it} + \beta_{13}{*}PSY_{it}{*}T2 + \beta_{14}{*}PSY_{it}{*}T3 \\ & + \beta_{15}{*}MC_{it}{*}PSY_{it} + \beta_{16}{*}MC_{it}{*}PSY_{it}{*}T2 + \beta_{17}{*}MC_{it}{*}PSY_{it}{*}T3 \\ & + \beta_{18}{*}LC_{it}{*}PSY_{it} + \beta_{19}{*}LC_{it}{*}PSY_{it}{*}T2 + \beta_{20}{*}LC_{it}{*}PSY_{it}{*}T3\end{aligned}$$

For a detailed account for each term, refer to Equation 4 and its adjunct explanation.

As is the case in the base model, we start with outputs regarding gender difference. Relative advantage of being a male hold true without significant change in intensity of inequality at age 33 compared at age 23 as the coefficients of interaction effects of gender with Time 2 suggest. However, at age 42 compared to at age 23, the coefficient is marginally significant. If we compare coefficient at age 33 with that at age 42, namely Gen*T3-Gen*T2, and test its statistical significance, we get result of statistically significant negative coefficient. This result, interestingly enough, reveals exacerbated inequalities of gender in social class mobility in their 40's compared to in their 30's. Thus we conclude that gender inequalities in status attainment are most pronounced in their 40's.

Next, we turn to effects of class of origin on 10-year-later class location. We see that both interaction term of middle class with Time 2 and interaction term of middle class with Time 3 are negative and statistically significant. Another test shows that MC*T3-MC*T2 term is positive and statistically significant. We detect same trends in the coefficients contrasting lower class with upper class Putting together, these analyses literally mean inequalities deriving from 10-years-earlier class location shrink in their 30's but expand again in their 40's even though the level of inequalities in their 40's is significantly lower than the period when intergenerational mobility takes place.

However, these investigations only deal with comparison of middle class and lower class with upper class. Therefore, one of interesting investigations would be to examine how these inequalities originating from class location work between middle class and lower class over the life course. If we take a look at LC*T2-MC*T2, which tests whether there is a change between inequalities at age 33 and those at age 23 , we get statistically significant negative coefficient. But we have the statistically insignificant negative coefficient when we test LC*T3-MC*T3 term, which amounts to test whether there is a change between inequalities at age 42 and those at age 23. Lastly, we also perform a statistical test probing difference in coefficient at age 42 from that at age 33. We find the coefficient positive and statistically significant. These results suggest that in a lower social tier, inequalities stemming from class of origin actually attenuate at age 33 but get exacerbated at age 42 beyond the previous level of at age 23. On balance, we synthesize these arguments with those presented in previous paragraph: Our sample shows that social inequalities generated by class mobility are most outstanding in intergeneration transition in a upper class boundary while those inequalities are most outstanding in their 40's in a lower class boundary.

Among those interaction terms devised to detect life course effects of psychological problems and differential psychopathological selection effects by social classes, only the interaction effect with Time 2 turns out to be statistically significant. If we undertake a statistical test on the term contrasting Time 3 with Time 2, say Psy*T3-Psy*T2, we get statistically significant negative coefficient. These results show that psychological syndromes have the most critical impact on class mobility in the period from at age 23 to at age 33. No wonder this period overlap with the job-seeking period. Because other coefficients testing differential class effects are not statistically significant, we don't have any evidence supporting the argument that psychological problems are operating asymmetrically across origin class statuses.

Nonetheless, we see a very intriguing finding in the life course model: change of MC*Psy term into a statistically significant negative term. What does this mean? We interpret this result as indicating buffering effects of belong to middle class compared to upper class only in the intergenerational class reshuffling period. That is, only at age 23, middle class is less likely to experience downward mobility or stay the same class than upper class as psychological problems get heightened. In other words, only at age 23, upper class compared to lower class is more likely to experience downward mobility as psychopathological symptoms get worse.

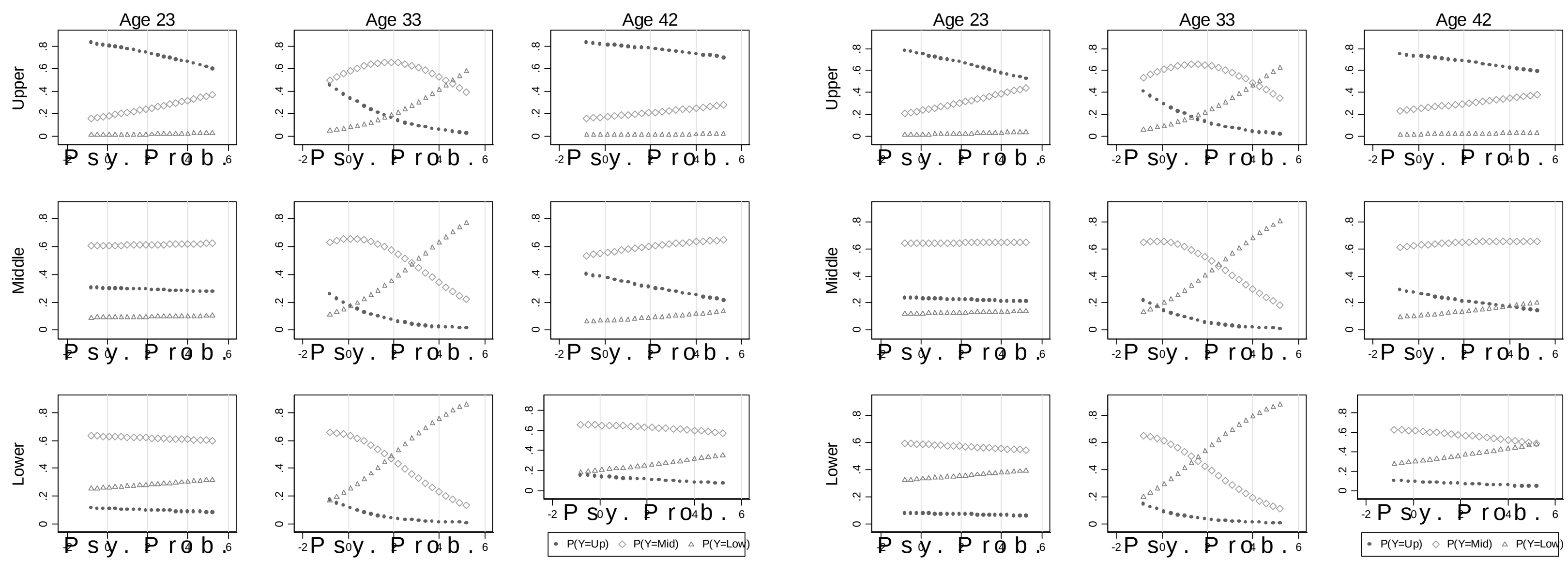
Figure 2 illustrates graphically these selection effects over the life course. These graphs were constructed from Table 3 after setting random effects ($u_i$ term in Equation 3) to be zero. Thus these graphs can be interpreted as showing mean probabilities of people who have random effects of zero. Y-axis denotes conditional probability that people move to a certain social class 10 years after they show a certain level of psychopathological symptoms (=X-axis). X-value ranges from maximum to minimum value of our sample. Rows of each panel represent class of origin 10 years ago. In all graphs, solid circles carry the probability to belong to upper class, hollow diamonds show the probability to belong to middle class, and hollow triangles represent the probability to belong to lower class. Columns show age of the cohort when the class destinations were observed. Panel A presents probability of male members and Panel B shows female's probability.

From these graphs, we can reiterate all the findings discussed so far. Among those findings, we want to briefly mention three things that are most pronounced in these graphs. (1) Social class of origin exert diehard influence on 10-year-later class locations; (2) Over the life course, selection effects of psychological problems on status attainment can be found regardless of origin classes; (3) we find most outstanding selection effects at age 33.

**Figure 2 Predicted Probabilities to Belong to Each Social Class**

Panel A. Male

Panel B. Female




Note: Each row represents class of origin and each column shows age of the cohort when the class destinations were observed.

We can perform the likelihood ratio $\chi^2$ test to evaluate the base model versus the life course model (Agresti 2002). In this case, $\chi^2$ statistic equals 30,815-30,427=388 with degree of freedom 23-11=12, resulting in p-value of less than 0.001. Thus we conclude that the life course model explain our data better. Lastly, we evaluate intraclass correlation using standard deviation of random effects, that is, $\sigma$ term. The estimated intraclass correlation can be written as $\sigma^2_{Estimate} /(\sigma^2_{Estimate} + \sigma^2_{latent})$ where $\sigma^2_{Estimate})$ means estimated variance of random effects and $\sigma^2_{latent}$ means the variance of latent continuous variable which equals $\pi_2 / 3$ in the logistic distribution (Hedeker & Mermelstein 1998). Using the estimates from SAS, intraclass correlation is 0.288 and 0.000 for the base model and for the life course model respectively. These estimates indicate that time-series measures of social classes are moderately correlated within individuals in the base model but are not correlated in the life course model.

# 5 Conclusion and Future Research

Using NCDS data, we have explored untapped dimensions in the previous literature related to social class mobility. Our findings in these analyses can be summarized as: There are overall downward class mobility at age 33 compared to at age 23 but this overall class level rebound at age 42 to the level of at age 23. As consistent with previous research, males are in more advantageous situation than females because they are less likely to experience downward mobility or stay in a lower social tier. Within the life course perspective, these gender inequalities are most pronounced at their 40’s. We also find that social class are finely structured that previous class location is a strong predictor of 10-years-later class location. As expected, the better class one is placed, the less likely one falls into a lower social tier. However, we also find interesting interaction effects of class locations with time points: our sample shows that social inequalities generated by class mobility are most outstanding in intergeneration transition in a upper class boundary while those inequalities are most outstanding in their 40’s in a lower class boundary.

As to our main interested area, that is, selection effects of psychological problems on downward mobility, we find those selection effects are operating throughout life course. It is interesting to note that psychopathological selection effects are most pronounced at the time when people start their own job careers. However, there is no evidence to give precedence to drift hypothesis over residue hypothesis and vise versa. These results can be interpreted as those two mechanisms are all operating throughout one’s life. In addition, we find no sufficient evidence to support differential selection effects of psychological syndromes by 10-year-earlier class statuses across the life course except one interaction effect only at age 23. Only at age 23, upper class compared to lower class is more likely to experience downward mobility as psychopathological symptoms get worse.

However, our findings should not be taken as a definitive work on psychopathological selection effects due to innate limitations to our data and methodology. More than anything else, measurement on response variables is not consistent throughout our study period. Our measurement on social classes experience a series of changes; father's job (at age 11)-educational attainment (at age 23)-one's own job (at age 33)-one's own job (at age 42). Even though we have some evidence to support our measurement (Szreter 1993), we need to be more cautious interpreting our results. In the same vein, we also point out that our main predictor, that is, psychopathological symptoms also is not identical throughout our study period.

Another possible source of biases include data limitations. Our data only report experiences of one cohort born in a specific week of 1958 in Great Britain. Thus, our results have weakness to be generalized temporarily and geographically. Also potential compounding of age effects by period effects should be kept in mind (Glenn 2005). Especially, we remind you of the tumultuous labor market in late 1980's and early 1990's in Britain when our cohort was at their late 20's and early 30's. Inadvertent biases due to sample selection both in the process of making complete data set in particular and in the attrition process underlying in all longitudinal data in general should be counted in when evaluating our results.

Nonetheless, these limitations don't mean worthlessness of our efforts at all. Rather, they suggest which way our work should develop. Our works will continue to analyze our data set and expand to another British longitudinal data. Also different statistical model will be experimented to find more powerful explanations on one's life course. Studies on psychological well-being can benefit from our works in that our study show how one's life can be affected by psychological status. Also status attainment and mobility studies can be enriched by our new findings on downward mobility and gender differences. More than anything else, emphasis on and its results from life course perspective can provide invaluable compass to the policy makers, sociologists and social scientists.

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[i] There are two ways in SAS to perform the statistical significance test of LC-MC term. First, you can specify “ESTIMATE” option when you file “PROC NLMIXED” command. Then the significance test result will be included in the outputs. Second, you can request asymptotic covariance matrix by specifying “COV” option in “PROC NLMIXED” command. Then using the following equations, you can perform t-test.

**Equation**

$$t(n-1, 1-\frac{1}{2}\alpha) = \frac{Estimate(LC) - Estimate(MC)}{\text{Standard Error}(LC - MC)}$$

where,

$$\begin{aligned}\text{Standard Error(LC - MC)} &= \sqrt{Var(LC) + Var(MC) - 2Cov(LC, MC)} \\ &= \sqrt{\text{SE(LC)}^2 + \text{SE(MC)}^2 - 2Cov(LC, MC)}\end{aligned}$$

Degree of freedom of this test is 5,801 because the number of our sample is 5,802. Either way, the results should be identical.