January 2014

Group Based Trajectories Of Blood Pressure Components From Adulthood To Elderly In Chinese Workers

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A Thesis Presented to

Yale School of Public Health

In Candidacy for the Degree of

Master of Public Health

2014

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ABSTRACT

Objective: The study aimed to identify trajectories of systolic blood pressure (SBP), diastolic blood pressure (DBP), and pulse pressure (PP) in Chinese adult workers from ages 18 to 81 years.

Methods: Analysis was conducted with a longitudinal data from Qingdao Port Health and Nutrition Examination Survey. This is a prospective study of employees of China's Qingdao Port Company that was initiated in 1999 and has been collecting annual measure of blood pressure. For our analysis, we focused on the cohort from 2000 to 2011. A group-based trajectory modeling was adopted to identify patterns of blood pressure over the lifespan. The dual model was used to jointly estimate the trajectories of two distinct, but related longitudinal outcome series.

Results: Five trajectory patterns were identified from dual trajectory model of systolic blood pressure and pulse pressure, and diastolic blood pressure and pulse pressure. Systolic blood pressure kept increasing over time whereas diastolic blood pressure gradually increased then decreased in older ages. Pulse pressure began to increase in middle age and rose more steeply subsequently. In the dual model, the posterior probability of being assigned to a distinct group for one outcome was influenced by the membership in the group of the other outcome that was modeled simultaneously. The most interesting finding was that the group membership assignment in single trajectory model remained the same in dual trajectory model only for systolic blood pressure.

Conclusion: Classifying individuals into unobserved latent trajectory groups allow us to gain a better understanding of the determinants of blood pressure patterns and lead to more personalized treatment and prevention plans among Chinese adult workers.

INTRODUCTION

Hypertension is a major risk factor for cardiovascular complications such as stroke, coronary heart disease (CHD), and heart failure. Considerable uncertainty exists in relative importance of various components of blood pressure (BP) in predicting cardiovascular disease risk. It was a widely accepted notion that all types of blood pressure increase with age. However, studies such as Framingham Heart Study in 1948 showed that there are differences in trends of diastolic and systolic blood pressure throughout life (Franklin et al. 1997). Systolic blood pressure increases almost linearly with age and continues to rise in to the 80s for women and into the 70s for men. In contrast, diastolic pressure increases steeply then decreases sharply after the age of 55 for men and 60 for women. In addition, pulse pressure, defined as the difference in SBP and DBP, begins to increase in middle age and rises more steeply thereafter (Kannel 1999).

Subsequent studies focused on identifying relative importance of different components of blood pressure as predictors for CHD risk (Pastor-Barriuso 2003). While these studies provide summary data for cohorts, they may obscure potential heterogeneity existing at the individual level. Summarizing the data with the average trend of blood pressure over age would fail to capture important information on some individuals who may diverge from the mean. Classifying groups of individuals who may experience distinctive trend of blood pressure over age can be useful in understanding biological, medical, behavioral, and environmental factors that may influence certain patterns of blood pressure trend.

In recent years, group-based modeling has become increasingly popular method in longitudinal research. Group-based modeling is a subject-centered and group-based analytic approach where it assumes that the study population consists of finite number of subgroups, or latent classes with distinctive patterns of change (Jones & Nagin 2007). In order to identify subgroups of individuals who may share similar patterns of blood pressure change over their lifespan, we employed a Latent Class Growth Modeling (LCGM) approach. In this paper, we illustrate the application of the group-based trajectory modeling first developed by Nagin in 1993 (Jones & Nagin 2001). We used the blood pressure data from Qingdao Port Health and Nutrition Examination Survey, which is a prospective study of employees of China's Qingdao Port Company that was initiated in 1999.

This paper aims to show that there are distinctive patterns of blood pressure changes over age. Our analysis focuses on three components of blood pressure measurements: systolic blood pressure (SBP), diastolic blood pressure (DBP), and pulse pressure (PP = SBP – DBP). We employed both univariate and dual group-based trajectory method to analyze each blood pressure components separately and jointly. The dual model is used to jointly estimate the trajectories of two distinct, but related longitudinal outcome series (Nagin & Tremblay 2001). Specifically, the linkage between systolic blood pressure and pulse pressure and diastolic blood pressure and pulse pressure are studied separately.

METHODS

Study Population

A cohort (2000–2011) of 25825 participants aged 18 to 81 years (20574 men, 5251 women) in Qingdao Port Health Study (QPHS) were recruited in this study. The personal lifestyle, height, weight, waist circumference, resting heart rate, blood pressure, fasting blood glucose, total cholesterol, triglycerides and plasma uric acid were collected annually in a comprehensive health checkup program. The Qingdao Port Health Study cohort was established in 2000 to evaluate potential risk factors for chronic diseases. The study participants consisted of all the employees aged 18 years or more from Qingdao Port Company, which is one of the largest ports in China for international trade and ocean shipping. A total of 11262 people (Men: 8711, Women: 2551) participated in the study at baseline (2000) and more participants were recruited in later years. Information on lifestyle variables, socio-economic status, physical examinations and biomedical variables were collected from each participant annually from 2000 to 2012. A self-administered questionnaire was used to collect information about demographics and lifestyle. Fro our analyses, covariates at baseline included age, sex, height, weight, waist circumference, and blood pressure (BP) at baseline. It is important to note that for the analyses of this paper, only a portion of the data was available on the additional measurements from questionnaires or check-ups and thus have not been explored in detail.

Group-Based Trajectory Model

Unlike the conventional random effects growth curve modeling which uses multivariate normal method, group-based trajectory modeling is a semi-parametric statistical method called "finite mixture modeling." It uses a multinomial modeling strategy to approximate continuous population distribution with discrete distributions. It identifies latent classes that exist within the study population (Nagin 2005). Group-based model identifies homogeneous clusters of individuals and allows heterogeneity only at the group level (Delucchi et al. 2004). This approach is distinct from Growth Mixture modeling where heterogeneity of growth is allowed both at the individual and group levels (Xie et al. 2010). The dual trajectory model is an extension of univariate group-based model (Jones & Nagin 2007; Nagin & Tremblay 2001). The univariate trajectory model handles a single longitudinal outcome whereas the dual model jointly estimates the trajectories of two related outcome series (Xie et al. 2010).

Statistical Theory

Let Y_i represent the longitudinal sequence of measurements on an individual i over T periods.

$$Y_i = \{y_{i1}, y_{i2}, y_{i3}, \dots, y_{1T}\}$$

Let and $P(Y_i)$ denote the likelihood of observing the above sequence such that

$$P(Y_i) = \sum_j \pi_j P^j(Y_i),$$

where $P^j(Y_i)$ is the probability of Y_i given membership in group j, and π_j is the probability of membership in group j. We determine the form of $P(Y_i)$ based on the type of the data. Conditional on group membership j, the random variables, $y_{it}, t = 1,2 \dots T$, are assumed to be independent. Hence, $P^j(Y_i) = \prod_{t=1}^{T} p^{jt}(y_{it})$.

The group membership probabilities, $\pi_j, j = 1 \dots J$, are estimated by a multinomial logit function:

$$\pi_j = e^{\theta j} / \sum_1^J e^{\theta j} \quad ,$$

where θ_1 is normalized to zero. This indirect estimation ensures that the group membership probability is between 0 and 1.

The likelihood function then is defined as,

$$L = \prod_{i=1}^{N} P(Y_i)$$

For our analysis, $p^{jt}(y_{it})$ is assumed to follow the censored normal distribution (CNORM). Since our response variable was continuous, the CNORM model was considered. The link between age and blood pressure measurements were established via a latent variable, which is the group indicator. We assumed a third-order polynomial relationship between predicted outcome $y_{it}^{(*j)}$, for each trajectory group:

$$y_{it}^{(*j)} = \beta_0^{(j)} + \beta_1^{(j)} Age_{it} + \beta_2^{(j)} Age_{it}^2 + \beta_3^{(j)} Age_{it}^3 + \varepsilon_{it},$$

The above equation determines the shape of the trajectory for blood pressure measurement (Y) for a given trajectory (j) at a specific time (t) for subject i. Further, ε_{it} is a disturbance that is assumed to be normally distributed with a mean of zero and a constant standard deviation. Denote $\boldsymbol{\beta}^{(j)}$ as the vector of the trajectory specific estimated coefficients for the model for a specific group j (Nagin & Tremblay 2001).

Posterior Probability

The estimated parameter coefficients provide direct information regarding group membership probabilities. Posterior probabilities are used to assign each individual membership to the trajectory that matches his or her profile of change.

We use the *maximum-probability assignment rule* to assign each individual membership to the trajectory to which the subject has the highest posterior membership probability.

$$\hat{p}(group\ j \mid data_i) = \hat{p}(data_i \mid group\ j)\, \hat{\pi}_j \Big/ \sum_j \hat{p}(data_i \mid group\ j)\, \hat{\pi}_j$$

Further, we can calculate the average of the posterior probabilities of group membership for each trajectory to evaluate the reliability of each trajectory. Trajectory groups with average posterior probabilities greater than 0.70 to 0.80 indicate that the trajectories are able to group individuals with similar patterns of change and discriminate between individuals with dissimilar patterns of change (Andruff et al. 2009).

Dual Trajectory Model

In the dual trajectory model, let, $Y^{(1)}$ and $Y^{(2)}$ denote the two longitudinal series of measurements for each individual i. Here, $Y^{(1)}$ is measured over T_1 periods and $Y^{(2)}$ is measured over T_2 periods. The index i representing each individual has been suppressed for notational convenience. The joint trajectory model is an extension of the univariate model. In the joint trajectory model, we estimate the trajectory groups that combine the parameters for each behavior (Nagin & Tremblay 2001).

Here, we need to consider three sets of parameters, $\pi_m, \boldsymbol{\alpha}^{(m)}, \boldsymbol{\beta}^{(m)}$, where m indexes the combined trajectory. Define π_m as the proportion of the population in each combined group, and $\boldsymbol{\alpha}^{(m)}$and $\boldsymbol{\beta}^{(m)}$ are vectors of parameters specifying the shape of group m's trajectory for behaviors $Y^{(1)}$ and $Y^{(2)}$, respectively. We continue to assume conditional independence given group membership. Hence the joint probability distribution is the product of the two independent probability distributions:

$$p\left(y_{it}^{(1)}, y_{it}^{(2)} \,\middle|\, \alpha_{it}^{(m)}, \beta_{it}^{(m)}\right) = f\left(y_{it}^{(1)} \middle| \alpha_{it}^{(m)}\right) h(y_{it}^{(2)} | \beta_{it}^{(m)})$$

where $\alpha_{it}^{(m)}$ and $\beta_{it}^{(m)}$ designate the parameters that determine the probability distribution for $y_{it}^{(1)}$ and $y_{it}^{(2)}$, $f(*)$ and $h(*)$, respectively. For our data, we assume censored normal probability distributions for $f(*)$ and $h(*)$.

For each class m, we assume the parameter governing $Y^{(1)}$ for individual i at time t is given by

$$\alpha_{it}^{(m)} = \alpha_0^{(m)} + \alpha_1^{(m)} t + \alpha_2^{(m)} t^2 + \alpha_3^{(m)} t^3,$$

Likewise, the parameter governing the probability distribution for Y^2 is given by

$$\beta_{it}^{(m)} = \beta_0^{(m)} + \beta_1^{(m)} t + \beta_2^{(m)} t^2 + \beta_3^{(m)} t^3$$

If $Y_i^{(1)}$ and $Y_i^{(2)}$ are each individual's longitudinal sequence of measurement of $y_{it}^{(1)}$ and $y_{it}^{(2)}$, conditional on group membership m, we assume that $y_{it}^{(1)}$ and $y_{it}^{(2)}$ are independently distributed over time. Then,

$$P\left(Y_i^{(1)}, Y_i^{(2)} \,\middle|\, m\right) = \prod_t f\left(y_{it}^{(2)} \,\middle|\, \propto_{it}^{(m)}\right) h\left(y_{it}^{(2)} \,\middle|\, \beta_{it}^{(m)}\right).$$

Also, the unconditional likelihood of $Y_i^{(1)}$ and $Y_i^{(2)}$ is obtained by summing over the M conditional likelihood functions and weigh each by the probability of membership in class m, which is π_m:

$$P\left(Y_i^{(1)}, Y_i^{(2)}\right) = \sum_m \pi_m \, P\left(Y_i^{(2)}, Y_i^{(1)}\right)$$

The likelihood function used to estimate the model parameters, α and β, is the product of $P\left(Y_i^{(1)}, Y_i^{(2)}\right)$ over the $I = 1,2 \ldots N$ individuals (Brame et. al 2000):

$$L = \prod_{i=1}^{N} P(Y_i^{(1)}, Y_i^{(2)})$$

For our analysis, we are interested in linking systolic blood pressure ($Y^{(1)}$) and pulse pressure ($Y^{(2)}$). Likewise, we are also interested in the linkage between diastolic blood pressure ($Y^{(1)}$) and pulse pressure ($Y^{(2)}$). Let m index the combined M trajectory groups associated with Y^1 and Y^2. Let π_m be the probability of membership in each of the combined trajectories. SAS PROC TRAJ provides an output which estimates π_m for $m = 1,2 \dots M$. The estimates of the coefficient from the model define the shape of the trajectory for each group m (Jones & Nagin 2007).

Model Selection

In order to determine the optimal number of groups to include in the model, we used the Bayesian Information Criterion (BIC) to make a comparison between the models. BIC is calculated as

$$BIC = \log(L) - 0.5 * \log(n) * (k),$$

where L is the model's maximized likelihood, n is the sample size, and k is the number of parameters in the model.

Based on Nagin's recommendation, model selection was based on the two univariate model searches. If we apply the BIC model selection criterion to the joint model, we would have to consider $N^1 * N^2$ joint models. Instead, if we base our searches on the two univariate model spaces, the number of models to consider reduces to $N^1 + N^2$ (Nagin 2001).

In addition to BIC values, we used Bayes Factor as a guide to compare model fit and selected the most parsimonious model. The decision was also based on the relative size of each resulting profile to ensure that no cluster had less than approximately 5% of the total sample (Delucchi et.al 2004). "The Bayes factor (B_{10}) gives the posterior odds that the alternative hypothesis is correct when the prior probability that the alternative hypothesis is correct equals one-half" (Nagin 2001). As shown by Kass and Raftery (1995), we used the BIC log Bayes factor approximation,

$$2log_e(B_{10}) \approx 2(\Delta BIC) = 2(BIC_{K+1} - BIC_K),$$

where ΔBIC is the BIC of the alternative (more complex) model minus the BIC of the null (simpler) model. The log form of the Bayes factor can be interpreted as the degree of evidence favoring the alternative model (Nagin 2001).

RESULTS

First, we fit single group-based models for SBP, DBP, and PP separately for men and women. Table 2 shows the BIC values corresponding to the number of trajectory groups considered for model selection. The three tables show BIC values from fitting univariate trajectory models for SBP, DBP, and PP separately. We notice that BIC score continues to improve (becomes less negative) as more groups are added to the model. Further the BIC values plateau after five groups or more for all blood pressure measurements. We can also compare the fit of the alternative model that has greater number of groups with the null model with a fewer number of groups. The log form of Bayes factor indicates the degree of evidence favoring an alternative model. We observe that for all blood pressure components, the log of Bayes factor decreases then becomes stable after five groups for both genders. One exception is found for the PP univariate model for females, where we have a negative value of the log Bayes factor. This results from the non-convergence issue when fitting a four groups model.

Using BIC and Bayes factor as guides to compare model fit, we selected the most parsimonious model. It seems most appropriate to stop at five groups since "addition of a new group results in splitting of a large group into two smaller groups with parallel trajectories" (Nagin 2001). Also, the relative size of each resulting profile was considered to ensure that no group had less than approximately 5% of the total sample. The smallest group size was around 3.7% of the sample with other groups consisting of more than approximately 10% of the sample. As a result, the five-group model for DBP, SBP, and PP best fit the data for both genders.

Figure 1 presents the results from fitting single trajectory models for each blood pressure component. Figure 1a shows that DBP rises until the third decade, becomes steady through the fifth decade, and then slowly decreases afterwards for both genders. We notice that group 5 with the highest baseline DBP experiences the most rapid increase in DBP until the third decade, but its rate of decreasing trend becomes similar to that of the other groups after the fifth decade. We also note that for males, the group with the second highest DBP values has an unusually steep decrease DBP after the 6^{th} decade.

Figure 1b presents the trajectories of SBP after fitting a single model. All five groups show steadily increasing trend in SBP for men and women. Also, the gaps in differences between the groups become wider as the subjects grow older. Gender differences in the trends are more visible for SBP compared to DBP. The SBP measures are higher for males than females for young adults, but over time the differences are less detectable. At older ages, females reach equally high SBP levels as males.

Next, Figure 1c illustrates the PP trajectories after fitting a single model. We see that for all groups, PP gradually increases until the sixth decade and increases very rapidly in the older ages. For females, the groups have very similar baseline PP values, but the gap in their differences becomes wider as they age. Furthermore, females experience more of a linear increasing trend in PP over time whereas males exhibit more fluctuations in PP over their lifespan. For males, it is more evident that PP decreases until their mid 30s then increases very steeply onwards.

After fitting the single group-based models, we examined the dual trajectory models. We have three outputs from dual models: estimate of the shapes of the group's joint blood pressure trajectories, estimate of the proportion of population following each joint trajectory, and estimate of the probability that each individual belongs to each of the groups (posterior probability of group membership). First, Table 3 shows the proportion of sample assigned to each group and the average posterior probability for each dual model. The smallest group size is 3.8%, but other four groups share larger proportion of the sample. It is interesting to see that not one group consists of more than 50% of the sample which suggests that the model is able detect some heterogeneity among individuals. In addition, the average posterior probability ranges from 0.7 to 0.9 indicating that the trajectories able to group individuals with similar patterns of change and also distinguish between dissimilar patterns of change.

Next, we examined the shapes of group trajectories from fitting the dual models. Figure 2a depicts the trajectories for women when considering DBP jointly with PP. We see that the group with the highest baseline DBP experiences a rapid drop from the fifth decade. We observe that higher the baseline DBP in the young adults, earlier the occurrence of decline in DBP. The trajectories for PP in a joint model with DBP illustrates that the group with the highest baseline PP has steadily increasing trend until the fifth decade then very sharp increase from the sixth decade. This coincides with the pattern shown in joint DBP trajectories where we see a sharp drop in their older ages. The two groups with the lowest DBP values over time have linearly increasing trend for PP whereas the groups with higher DBP values show steeper increase in PP after the fifth decade.

When modeling PP with SBP in a joint model, the group order agrees with each other. The group with the highest SBP trend also exhibits the highest PP trend over time. Likewise, the group with the lowest SBP trend is also the group with the lowest PP trend with a very flat slope. Individuals who have higher SBP measures over time have steeper increase in PP after the 6^{th} decade.

Based on Figures 2 and 3, there are some notable gender differences in the trends of blood pressure over time for males versus females. From Figure 2, we observe that the male groups have highly variable DBP values at young ages and this variability between the groups persists until the elderly. For females (Figure 3), the groups share similar DBP values at youth, but their differences become bigger over time. For SBP, males have on average, higher SBP measures in the 20s. The SBP levels are similar between the two genders in the elderly. In the dual models for PP, we again notice that individuals with higher SBP or DBP values as young adults experience a much sharp increase in PP in older ages. As seen in the single model for PP (Figure 1c), the trends of PP over time for male groups in the dual model have more curvature compared to females.

Tables 4 and 5 show cross tabulations of group memberships between single and dual models for men and women separately. For example, Table 4 displays the cross tabulation between single SBP model and dual model between SBP and PP for men. Among the individuals who are assigned to the first group (the lowest SBP group), about 92% of them are re-assigned to the first group in the dual model. Following the numbers on the diagonal of this table shows that most of the individuals who are assigned to a particular group in a single SBP model remains in the same group in the dual model (row percentages greater than 70). On the other hand, Table 4b shows a different result when comparing group membership from single PP model and dual model of SBP and PP. Here, we notice that the percentages in the diagonal are all around 50 or 60 with the exception of the fifth group. Among those who are assigned to the first PP group in a single model, about 64% of the individuals are allocated to the first group and 34% of them to the second group. For the first four groups, smaller proportions of the individuals in each group from a single model are assigned to the same corresponding group in the dual model. This result is also shown for the cross tabulations between single DBP model against the dual DBP-PP model and single PP model against the dual DBP-PP model. Hence we see that SBP is the only blood pressure component that has stable group membership in both single and dual models. This finding is consistent for both men and women.

DISCUSSION

Advantages of Group-Based Trajectory Model

To date, some studies have examined the trend of blood pressure and their effects on predicting cardiovascular outcome. However many of the analytic methods used are based on a priori categorization of subgroups of individuals. For instance, Framingham Heart Study in 1997 conducted an analysis by clustering subjects into pre-defined groups based on the clinical definition of normal to hypertensive blood pressure levels. Specifically, the participants were divided into four groups according to their systolic blood pressure (group 1, <120 mm Hg; group2, 120 to 139 mm Hg; group3, 140 to 159 mm Hg; group 4, ≥ 160 mm Hg). These groups were categorized as optimal, normal and high normal, stage 1 systolic hypertension, and stages 2, 3, and 4 systolic hypertension. The first two groups were classified as normotensive and the two latter groups as hypertensive groups. Regression models were fitted on blood pressure against age within individual subjects. Then slope and curvature estimates were compared among the four groups using the ANOVA procedure (Franklin et al. 1997).

The results from our analyses closely resemble the trends of blood pressure over age found in the Framingham Heart Study. While their method helped determine trends of blood pressure over age, the analyses of group-averaged data may have overlooked potential heterogeneity in blood pressure change among individuals in those subgroups. Hence, using the group-based trajectory method enables us to capture differences that may exist among the individuals within groups and identify unseen latent class of individuals who share the similar pattern (Nagin & Tremblay 2001). Also, latent trajectory model is an advantageous analytic approach because it does not rely on a priori categorization of trajectories. It removes subjectivity regarding which class or group an individual belongs to (Nagin 1999, 2005).

Clinical Implications

Overall, our dual trajectory analyses demonstrate that SBP and PP and DBP and PP are linked over age. Changes across time in one group of SBP coincide with shifts in the PP group. Indeed, we observe that those who are at the highest SBP group are also in the highest PP group. Similarly, those who are at the highest DBP group who experience a steep decline at old ages exhibit sharper increase in PP. All five trajectories maintain their relative positions throughout the period for two joint models. Exception is observed for DBP in both genders where the curves intersect. Due to such precipitous decline for groups in high DBP values, the relative standing in PP trajectories for those groups change. Nonetheless, the overall results provide strong evidence of continuity, in terms of relative standing of the trajectories of blood pressure (Brame et al. 2001).

The distinctive patterns observed for SBP, DBP, and PP for our data coincides with the results from the Framingham Heart Study. As the subjects grow older, SBP increases and DBP decreases resulting in a widened pulse pressure. A study done by Benetos et al. showed that subjects who experienced increase in SBP and decrease in DBP simultaneously had the highest risk for cardiovascular mortality after adjusting for age and other risk factors (Benetos et al. 2000). These studies suggest that increasing PP due to combined effect of increasing SBP and decreasing DBP is more harmful than other causes of increasing PP, such as heightened stroke volume (Franklin et.al 1997).

Franklin et al. proposes that the rise in SBP and DBP during young adults stage is mainly due to increase in peripheral vascular resistance. Also, the late fall in in DBP and sharp increase in PP after the 5^{th} or 6^{th} decade of age can be explained by increased large artery stiffness. Lastly, the linear increasing trend observed for SBP with aging is primarily due to increased peripheral vascular resistance during the early years and to increased large artery stiffness during the late years. It seems that for individuals in high SBP groups, large artery stiffening dominates as a hemodynamic factor over increasing vascular resistance (Franklin et al. 1997). This agrees with our finding where high SBP groups exhibit steeper decline in DBP and sharper increase in PP with aging.

Conclusion

In this study, we were able to detect heterogeneity that may exist in general relationship by identifying five groups with distinctive patterns of BP trends over lifespan. Single and dual group based trajectory modeling approach is useful to obtain a more accurate risk profile of individuals. The trends observed for each BP component are in accordance with the results from the Framingham Heart Study. Compared to the FHS, our data consists of subjects who are 18 or older. One of the limitations in their study was that the minimum age was 30 years at entry to the study. Therefore, the results could not be applied to young adults. While the subjects in FHS comprised of more than 99% Caucasians who were mostly middle-class subjects, our study extends the analysis to Asians and working class group. Results from this data can be useful for future studies to examine if there are differences in distinctive blood pressure trajectories among different populations.

Several limitations exist in our study. First, each individual contributed at most 11 repeated measurements of blood pressure over time, whereas Framing Heart Study had over 30 years of data on subjects. We compiled 11 repeated measurements from each individual and generated a longitudinal sequence of blood pressure components from ages 18 to 81 years old. Closer look at the age distribution for men and women indicates that men are generally younger than women. This may be because younger males tend to dominate in labor intense occupations compared to females. These differences in age distribution may call for stratified analysis at different age categories rather than compiling all the data together.

Secondly, our data is not a complete data with many missing measurements for some of the characteristics of individuals. The most available data exists for age, sex, and blood pressure measurements. Thus it was difficult to assess whether there are any significant differences between the trajectory groups in terms of disease related or individual level covariates. Also, the observed differences in blood pressure patterns with aging may have been due to the risk factors not adjusted for in the analysis. However, our intent of this study was to identify age-related blood pressure changes in the population-based cohort. Future analysis could consider additional risk factors and include them as time-invariant and time varying covariates.

Despite some of these limitations, our results may have important clinical consequences for risk stratification. To date, many studies have focused on identifying single predictor of risk of cardiovascular related diseases among systolic, diastolic, or pulse pressure (Pastor-Barriuso et al. 2003). The results from our study suggest that SBP may be the most stable blood pressure component when grouping individuals into different trajectory groups. Using single and dual group based models allows us to cross validate group membership. The cross tabulations of single versus the dual models show that grouping is stable only for SBP compared to DBP or PP. Rather than considering blood pressure components simultaneously, SBP alone may be sufficient to stratify individuals into unseen latent trajectory groups. Next steps would be to examine potential risk factors and cardiovascular related outcomes that may be associated with these trajectory groups. Further development of group-based method would help enhance accuracy in classification of such individuals and contribute to targeted intervention for at risk population.

TABLES & FIGURES

Table 1. Baseline Characteristics of Participants in the Qingdao Port Health and Nutrition Examination Survey *

Characteristic	**Men (n = 20574)**	**Women (n = 5251)**	**All (n = 25825)**
Age, *years*	36.78 ± 12.83	39.23 ± 12.75	37.28 ± 12.85
Missing(%)	0	0	0
Systolic Blood Pressure, *mm Hg*	123.13 ± 16.61	115.02 ± 18.52	121.49 ± 17.32
Missing (%)	0.18	0.90	0.33
Diastolic Blood Pressure, *mm Hg*	80.43 ± 11.57	74.25 ± 10.99	79.18 ± 11.72
Missing (%)	0.18	0.90	0.33
Pulse Pressure, *mm Hg*	42.69 ± 11.00	40.78 ± 11.69	42.31 ± 11.17
Missing (%)	0.18	0.90	0.33
Weight, *kg*	72.59 ± 13.22	60.75 ± 9.86	70.22 ± 13.48
Missing(%)	0.52	2.44	0.91
Height, *cm*	172.48 ± 7.21	160.95 ± 9.41	170.17 ± 8.98
Missing (%)	0.53	2.40	0.91
Waist Circumference, *cm*	83.85 ± 11.09	74.31 ± 10.29	81.94 ± 11.58
Missing (%)	0.58	2.93	1.06

* Values with plus/minus signs are means ± SDs.

Table 2. BIC and Bayes Factor Values for Different Number of Groups for Univariate Trajectory Models (SBP, DBP, PP) for Men and Women*

	Men (n = 20754)			**Women (n = 5251)**		
Number of Groups for **SBP**	BIC	Null Model	$2log_e(B_{10})$	BIC	Null Model	$2log_e(B_{10})$
1	-533120.9			-145073.8		
2	-510257.8	1		-138546.8	1	
3	-502789.1	2	45726.2	-136300.0	2	13054.0
4	-499368.7	3	14937.4	-135402.4	3	4493.6
5	-498045.7	4	6840.8	-135037.9	4	1795.2
6	-497223.9	5	2646	-134856.6	5	729.0
7	-496992.0	6	1643.6	-134837.1	6	362.6

	Men (n = 20754)			**Women (n = 5251)**		
Number of Groups for **DBP**	BIC	Null Model	$2log_e(B_{10})$	BIC	Null Model	$2log_e(B_{10})$
1	-483252.1			-129421.5		
2	-463668.5	1		-123917.4	1	
3	-457378.1	2	39167.2	-122217.4	2	11008.2
4	-454908.4	3	12580.8	-121606.1	3	3400.0
5	-453888.3	4	4939.4	-121427.3	4	1222.6
6	-453747.2	5	2040.2	-121331.9	5	357.6
7	-453255.1	6	282.2	-121290.7	6	190.8

	Men (n = 20754)			**Women (n = 5251)**		
Number of Groups for **PP**	BIC	Null Model	$2log_e(B_{10})$	BIC	Null Model	$2log_e(B_{10})$
1	-482866.5			-131028.2		
2	-472067.6	1		-127695.6	1	
3	-469003.7	2	21597.8	-126683.7	2	6665.2
4	-467946.1	3	6127.8	-127627.4	3	2023.8
5	-467528.7	4	2115.2	-126174.6	4	-1887.4
6	-467320.8	5	834.8	-126090.9	5	2905.6
7	-467322.8	6	415.8	-126084.6	6	167.4

* Null Model is the model with K-1 Groups

Table 3a. Average Posterior Probability of Group Assignment for Women

Joint Model of DBP and PP for Women

Group	Number of Subjects (%)	Average Posterior Probability (%)
1	1314 (25.02)	82.77
2	1056 (20.11)	76.82
3	2210 (42.09)	71.35
4	471 (8.97)	83.99
5	200 (3.81)	88.06

Joint Model of SBP and PP for Women

Group	Number of Subjects (%)	Average Posterior Probability (%)
1	1923 (36.62)	73.73
2	1631 (31.06)	75.57
3	743 (14.15)	84.59
4	737 (14.04)	83.42
5	217 (4.13)	90.38

Table 3b. Average Posterior Probability of Group Assignment for Men

Joint Model of DBP and PP for Men

Group	Number of Subjects (%)	Average Posterior Probability (%)
1	6224 (30.25)	81.52
2	1992 (9.68)	76.60
3	8700 (42.29)	75.35
4	2791 (13.57)	81.50
5	867 (4.21)	87.07

Joint Model of SBP and PP for Men

Group	Number of Subjects (%)	Average Posterior Probability (%)
1	8244 (40.07)	75.15
2	5361 (26.06)	74.99
3	3447 (16.75)	84.14
4	2700 (13.12)	78.70
5	822 (4.00)	86.91

Table 4a. Cross Tabulation of Membership for Single SBP Model versus Dual SBP-PP Model for **Men**

Single SBP Group Membership	Dual SBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	2913 92.21	246 7.79	0 0.00	0 0.00	0 0.00	3159
2nd Group	534 5.82	7621 83.00	1002 10.91	25 0.27	0 0.00	9182
3rd Group	0 0.00	377 7.11	4163 78.53	737 13.90	24 0.45	5301
4th Group	0 0.00	0 0.00	196 8.37	1871 79.89	275 11.74	2342
5th Group	0 0.00	0 0.00	0 0.00	67 11.36	523 88.64	590
Total	3447	8244	5361	2700	822	20574

*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest SBP, 5th Group = Highest SBP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 4b. Cross Tabulation of Membership for Single PP Model versus Dual SBP-PP Model for **Men**

Single PP Group Membership	Dual SBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	2223 64.53	1164 33.79	57 1.65	1 0.03	0 0.00	3445
2nd Group	1219 10.89	6614 59.09	2965 26.49	372 3.32	23 0.21	11193
3rd Group	5 0.11	466 10.22	2282 50.05	1679 36.83	127 2.79	4559
4th Group	0 0.00	0 0.00	57 5.02	634 55.81	445 39.17	1136
5th Group	0 0.00	0 0.00	0 0.00	14 5.81	227 94.19	241
Total	3447	8244	5361	2700	822	20574

*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest PP, 5th Group = Highest PP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 4c. Cross Tabulation of Membership for Single DBP Model versus Dual DBP-PP Model for **Men**

Single DBP Group Mebership	Dual DBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	3294 94.66	0 0.00	177 5.09	0 0.00	9 0.26	3480
2nd Group	2920 32.07	5242 57.57	920 10.10	3 0.03	21 0.23	9106
3rd Group	5 0.09	3373 62.34	832 15.38	1131 20.90	70 1.29	5411
4th Group	5 0.24	78 3.78	63 3.05	1508 73.10	409 19.83	2063
5th Group	0 0.00	7 1.36	0 0.00	149 28.99	358 69.65	514
Total	6224	8700	1992	2791	867	20574

*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest DBP, 5th Group = Highest DBP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 4d. Cross Tabulation of Membership for Single PP Model versus Dual DBP-PP Model for **Men**

Single PP Group Membership	Dual DBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	1693 49.14	1573 45.66	177 5.14	0 0.00	2 0.06	3445
2nd Group	3650 32.61	5919 52.88	1499 13.39	28 0.25	97 0.87	11193
3rd Group	837 18.36	1207 26.48	1076 23.60	1148 25.18	291 6.38	4559
4th Group	37 3.26	1 0.09	39 3.43	677 59.60	382 33.63	1136
5th Group	7 2.90	0 0.00	0 0.00	139 57.68	95 39.42	241
Total	6224	8700	2791	1992	867	20574

*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest PP, 5th Group = Highest PP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 5a. Cross Tabulation of Membership for Single SBP Model versus Dual SBP-PP Model for **Women**

Single SBP Group Membership	Dual SBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	580 96.51	21 3.49	0 0.00	0 0.00	0 0.00	601
2nd Group	163 8.32	1694 86.43	103 5.26	0 0.00	0 0.00	1960
3rd Group	0 0.00	208 12.27	1386 81.77	94 5.55	7 0.41	1695
4th Group	0 0.00	0 0.00	142 18.96	586 78.24	21 2.80	749
5th Group	0 0.00	0 0.00	0 0.00	57 23.17	189 76.83	246
Total	743	1923	1631	737	217	5251

*Groups are labeled by the relative position of the trajectory groups in the plots
(1^{st} Group = lowest SBP, 5^{th} Group = Highest SBP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 5b. Cross Tabulation of Membership for Single PP Model versus Dual SBP-PP Model for **Women**

Single PP Group Membership	Dual SBP-PP Group Membership					
	1st Group	2nd Group	3rd Group	4th Group	5th Group	Total
1st Group	278 79.66	70 20.06	1 0.29	0 0.00	0 0.00	349
2nd Group	459 18.90	1527 62.87	427 17.58	16 0.66	0 0.00	2429
3rd Group	6 0.32	324 17.18	1133 60.07	387 20.52	36 1.91	1886
4th Group	0 0.00	2 0.41	70 14.31	329 67.28	88 18.00	489
5th Group	0 0.00	0 0.00	0 0.00	5 5.10	93 94.90	98
Total	743	1923	1631	737	217	5251

*Groups are labeled by the relative position of the trajectory groups in the plots
(1^{st} Group = lowest PP, 5^{th} Group = Highest PP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 5c. Cross Tabulation of Membership for Single DBP Model versus Dual DBP-PP Model for **Women**

Single DBP Group Membership	**Dual DBP-PP Group Membership**					
	1st Group	**2nd Group**	**3rd Group**	**4th Group**	**5th Group**	**Total**
1st Group	980 95.61	28 2.73	12 1.17	0 0.00	5 0.49	1025
2nd Group	332 14.89	1750 78.48	132 5.92	0 0.00	16 0.72	2230
3rd Group	2 0.15	384 29.74	837 64.83	27 2.09	41 3.18	1291
4th Group	0 0.00	43 8.22	75 14.34	331 63.29	74 14.15	523
5th Group	0 0.00	5 2.75	0 0.00	113 62.09	64 35.16	182
Total	1314	2210	1056	471	200	5251

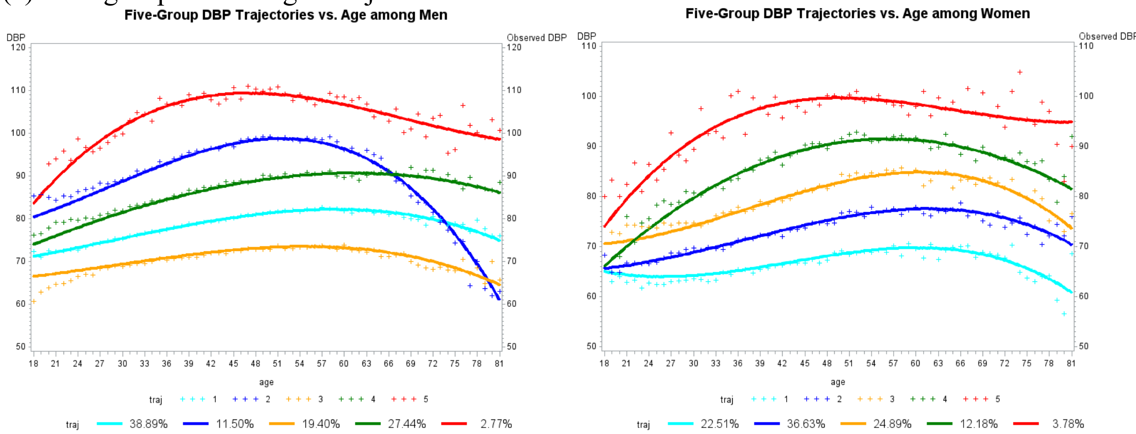
*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest DBP, 5th Group = Highest DBP)
*Within each cell, first row is the number of subjects and second row is the row percentages

Table 5d. Cross Tabulation of Membership for Single PP Model versus Dual DBP-PP Model for **Women**

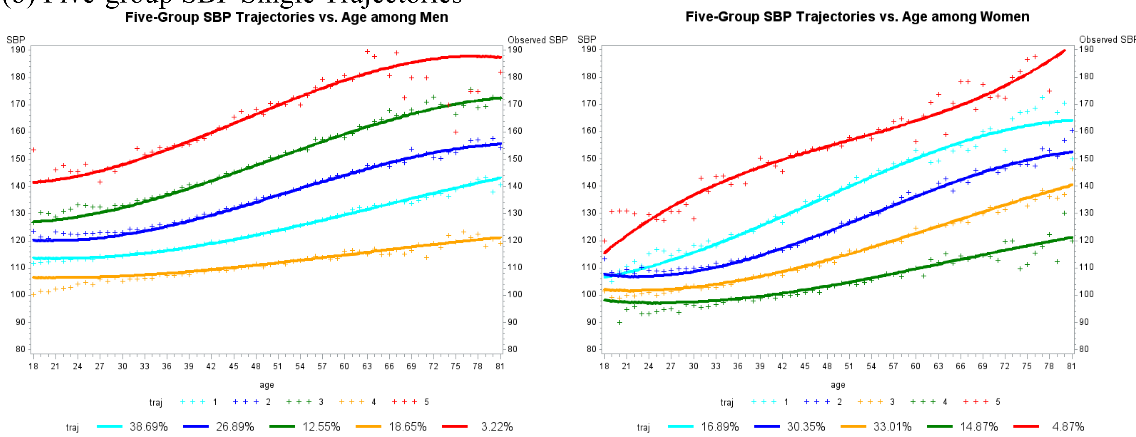
Single PP Group Membership	**Dual DBP-PP Group Membership**					
	1st Group	**2nd Group**	**3rd Group**	**4th Group**	**5th Group**	**Total**
1st Group	225 64.47	119 34.10	4 1.15	1 0.29	0 0.00	349
2nd Group	826 34.01	1243 51.17	122 5.02	238 9.80	0 0.00	2429
3rd Group	241 12.78	762 40.40	241 12.78	622 32.98	20 1.06	1886
4th Group	21 4.29	72 14.72	104 21.27	193 39.47	99 20.25	489
5th Group	1 1.02	14 14.29	0 0.00	2 2.04	81 82.65	98
Total	1314	2210	471	1056	200	5251

*Groups are labeled by the relative position of the trajectory groups in the plots
(1st Group = lowest PP, 5th Group = Highest PP)
*Within each cell, first row is the number of subjects and second row is the row percentages

(a) Five-group DBP Single Trajectories



(b) Five-group SBP Single Trajectories



(c) Five-group PP Single Trajectories

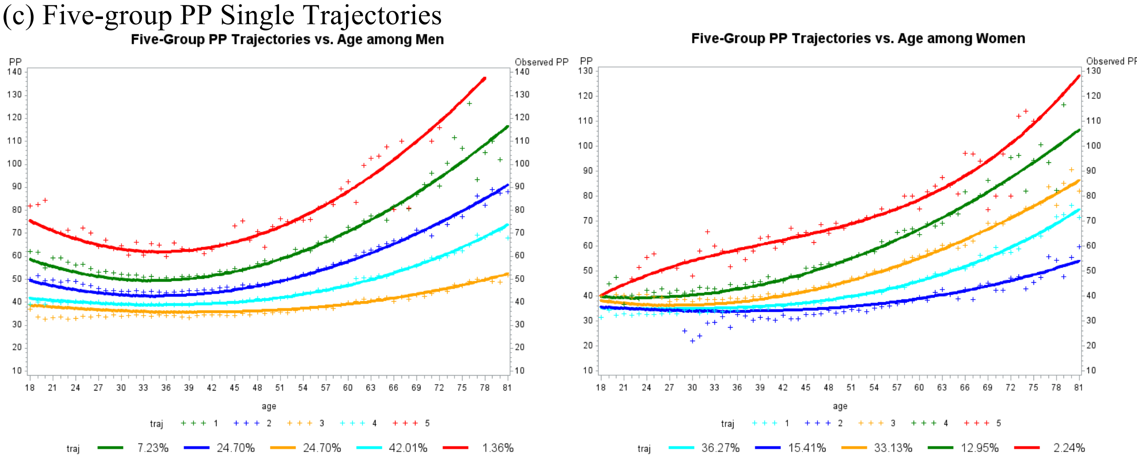
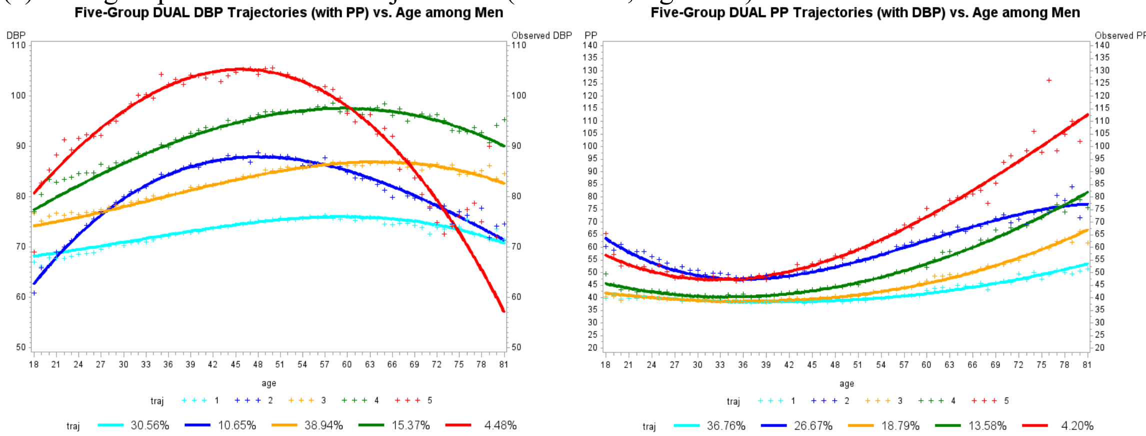


Figure 1. Five-Group Single Trajectories for Men and Women (a) DBP (b) SBP (c) PP

(a) Five-group DBP-PP Dual Trajectories (left: DBP, right: PP)



(b) Five-group SBP-PP Dual Trajectories (left: SBP, right: PP)

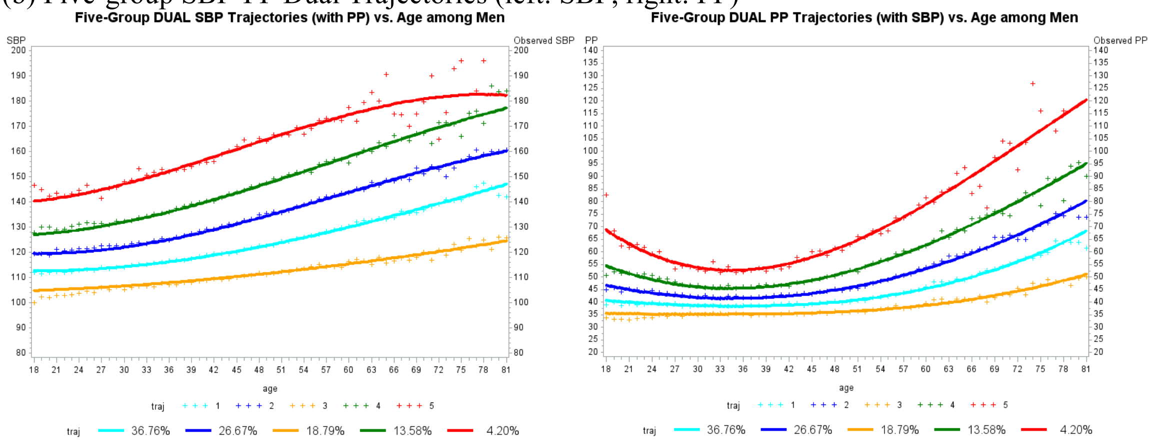
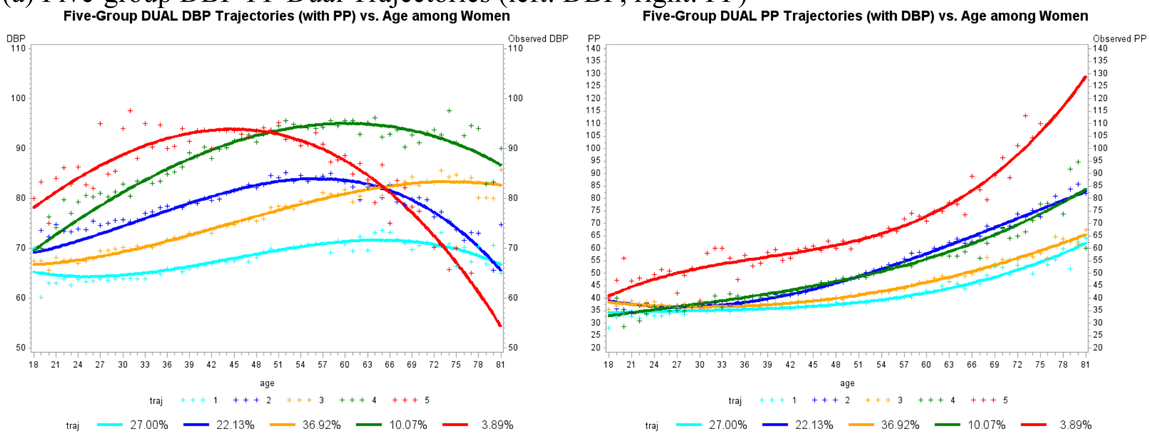


Figure 2. Five-group Dual Trajectories for Men (a) DBP and PP (b) SBP and PP

(a) Five-group DBP-PP Dual Trajectories (left: DBP, right: PP)



(b) Five-group SBP-PP Dual Trajectories (left: SBP, right: PP)

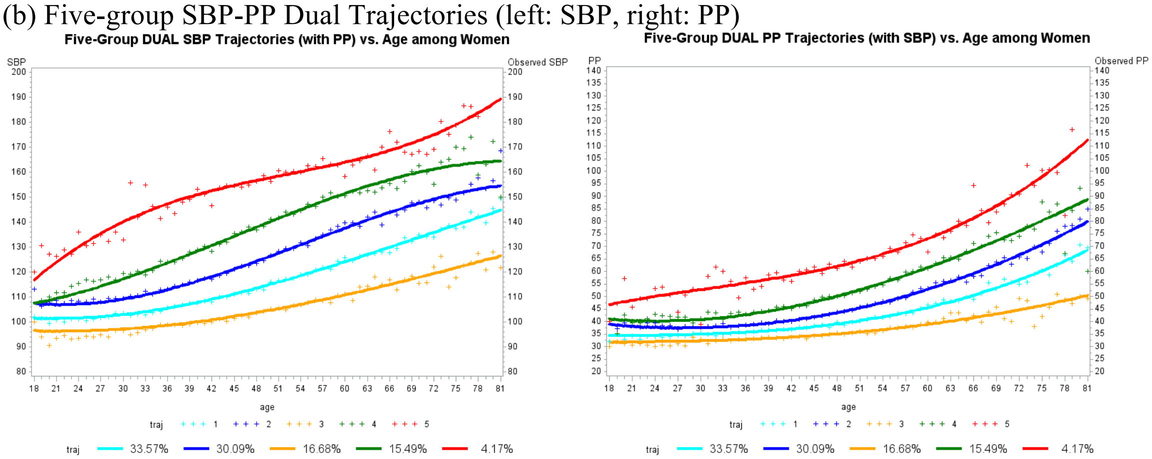


Figure 3. Five-group Dual Trajectories for Women (a) DBP and PP (b) SBP and PP

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