

SUPPLEMENTAL MATERIAL

Data S1.

Supplemental Methods

The JHS is a community-based prospective cohort study designed to examine the etiology of CVD and related risk factors among blacks.¹ CARDIA is a prospective cohort study designed to examine the development, determinants, and risk factors of clinical and subclinical CVD.² The IDH study was designed to compare strategies for diagnosing hypertension among a community-based sample.³ The MHT study was designed to evaluate the prevalence, predictors, and prognosis of masked hypertension.⁴

The Jackson Heart Study (JHS)

The JHS, a population-based prospective cohort study, was designed to evaluate the etiology of cardiovascular disease among African Americans. The JHS enrolled a total of 5,301 non-institutionalized African Americans ≥ 21 years old between 2000 and 2004 from the Atherosclerosis Risk in the Community site in Jackson, Mississippi, and a representative sample of urban and rural Jackson, Mississippi metropolitan tri-county (Hinds, Madison and Rankin counties) residents, volunteers, randomly contacted individuals and secondary family members. As part of an ancillary study, 1,148 JHS participants underwent 24-hour ABPM during their baseline examination. For the current analysis, we included 1,046 JHS participants who had ≥ 10 SBP and DBP valid readings while awake and ≥ 5 SBP and DBP valid readings while asleep. The JHS protocol was approved by the institutional review boards at the University of Mississippi Medical Center, Jackson State University, and Tougaloo College.

The Coronary Artery Risk Development in Young Adults (CARDIA) study

The CARDIA study was designed to examine the development and determinants of clinical and subclinical cardiovascular disease and its risk factors. The CARDIA study recruited 5,115 white and black men and women aged 18 to 30 years at four field centers in the United States (Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA) from 1985 to 1986.

Participants have completed nine study examinations including a baseline exam at year 0 and follow-up exams at 2, 5, 7, 10, 15, 20, 25 and 30 years following baseline. The details of these examinations are available on the CARDIA study website at www.cardia.dopm.uab.edu. As part of an ancillary study at the Year 30 Exam (2015-2016), 825 non-pregnant participants at the Birmingham and Chicago Field Centers underwent 24-hour ABPM. For the current analysis, we included 781 CARDIA participants who had ≥ 10 SBP and DBP valid readings while awake and ≥ 5 SBP and DBP valid readings while asleep. Institutional review boards at the coordinating center and each field center approved all aspects of the CARDIA study.

The Improving the Detection of Hypertension (IDH) Study

The IDH Study recruited adults, primarily from the upper Manhattan community surrounding Columbia University Medical Center, who did not have any of the following conditions: (1) clinic systolic blood pressure (SBP) ≥ 160 mm Hg or diastolic blood pressure (DBP) ≥ 105 mm Hg, (2) evidence of secondary hypertension, (3) current use of antihypertensive medications or other medications that are known to affect SBP or DBP (i.e. steroids, tricyclic antidepressants, etc.), (4) history of overt cardiovascular disease, chronic kidney failure, or organ transplantation, (5) current liver disease, adrenal disease, thyroid disease, rheumatologic disease, hematologic disease, or cancer (not in remission for at least 6 months), (6) currently pregnant, or (7) currently

diagnosed with dementia. The IDH study recruited 408 eligible participants, all of whom underwent 24-hour ABPM twice, between March 2011 and August 2013. For consistency with the other studies, we only used ABPM data from the first 24-hour monitoring period. For the current analysis, we included 395 IDH study participants with ≥ 10 SBP and DBP valid readings while awake and ≥ 5 SBP and DBP valid readings while asleep. The IDH study protocol was approved by Columbia University's institutional review board.

The Masked Hypertension (MHT) Study

The MHT study recruited adults who were employed and maintained > 20 work hours per week and worked on two or more consecutive days per week. Participants were recruited from Stony Brook University, University Hospital at Stony Brook, Columbia University Medical Center, and a private hedge fund management organization. Participants with any of the following conditions were not eligible for the MHT study: (1) screening systolic blood pressure (SBP) ≥ 160 mm Hg or diastolic blood pressure (DBP) ≥ 105 mm Hg, (2) evidence of secondary hypertension, (3) current use of antihypertensive medications or other medications that are known to affect BP (i.e. steroids, tricyclic antidepressants, etc.), (4) a history of overt cardiovascular disease or chronic renal failure, (5) current liver disease, adrenal disease, thyroid disease, rheumatologic disease, hematologic disease, or cancer (not in remission for at least 6 months), (6) currently pregnant, (7) currently engaged in active substance abuse, or (8) currently diagnosed with a serious mental health illness. The MHT Study enrolled 1,010 eligible participants between February 2005 and July 2012, and 893 of the enrolled participants underwent 24-hour ambulatory blood pressure monitoring (ABPM). For the current analysis, we included 772 participants with ≥ 10 SBP and DBP valid readings while awake and ≥ 5 SBP and DBP valid readings while asleep. The

institutional review boards at the participating research centers—Stony Brook University and Columbia University—approved the conduct of the MHT.

Candidate Modeling Algorithms

The modeling algorithms we included as candidates to create predictive equations included (1) logistic regression using forward variable selection, (2) logistic regression using backwards variable selection, (3) generalized logistic regression using forward variable selection, (4) penalized logistic regression with a lasso penalty, (5) penalized logistic regression with a ridge penalty, (6) random forests, and (7) gradient boosted decision trees.^{5,6} Generalized additive logistic regression incorporates non-linear effects into the framework of logistic regression by simultaneously fitting locally weighted smoothing curves and linear regression coefficients using a back-fitting algorithm. This algorithm is described in detail by the authors of the generalized additive model.⁶ Forward variable selection incorporates variables into a statistical model one by one and the variable added at each step is the one that optimizes some model goodness-of-fit criteria. Additionally, forward variable selection for the generalized additive logistic regression model incorporates non-linear effects for continuous variables in the model by comparing the model's goodness-of-fit with and without a non-linear effect for each continuous predictor variable. We used Akaike's information criteria to evaluate model goodness-of-fit and guide decisions to include additional terms into the predictive model. To avoid over-fitting, we implemented a maximum of 15 steps in the forward variable selection algorithms. Penalized logistic regression minimizes the usual deviance of the model, with a constraint on the sum of the absolute values (lasso penalty) or squared values (ridge penalty) of the regression coefficients. Random forests and gradient boosted decision trees are each ensemble learning

techniques based on classification and regression trees. Trees in the random forest can be fit in parallel and are de-correlated from each other, whereas gradient boosted trees are fit sequentially and each new tree attempts to correct the errors of the previous trees.

Development and internal validation of predictive equations

We applied resampling to develop and internally validate predictive equations using the derivation dataset. Optimistic estimates of generalization error occur when the same data set that is used to develop a predictive equation is also used to evaluate the accuracy of the equation. We applied the following procedure to avoid optimistic errors: (1) Using the derivation dataset, split the data randomly into a training and test set. Note that validation dataset is not used. (2) Apply each candidate modeling algorithm to the training dataset, separately, to develop one predictive equation for each candidate modeling algorithm. A modeling algorithm is the collection of steps that are applied to translate data into a predictive equation. (3) Apply each predictive equation to the test set, separately, to compute one set of predictions using each equation. (4) Evaluate each set of predicted probabilities based on their similarity to the observed outcomes in the test set by computing the calibration error, concordance error, and scaled Brier score for each set of predictions. (5) Repeat steps 1-4 at least 100 times. We used 250 replications of steps 1-4 to achieve stabilized distributions of concordance error, calibration error, and scaled Brier scores.

Validation of predictive equations

It is recommended that prediction equations are validated in an external sample. Three commonly used metrics that assess different aspects of a prediction equation are calibration, discrimination, and net reclassification improvement (NRI).⁷⁻¹¹ Calibration estimates the

accuracy of a prediction equation for estimating the absolute probability of the outcome while discrimination assesses whether an equation will assign higher predicted probability to those with, versus their counterparts without, the outcome.¹² An equation with good calibration but poor discrimination or good discrimination but poor calibration may not be useful. The NRI estimates how well a prediction equation classifies a population when a given probability cut-point is applied. The NRI statistics (i.e., positive NRI and negative NRI) are each based on a comparison between a current prediction equation and a new prediction equation. Positive NRI is the proportion of people with the outcome who have a higher predicted probability using a new equation versus an existing equation. Analogously, the negative NRI is the proportion of people without the outcome who have a lower predicted probability using a new equation versus an existing equation. Overall continuous NRI is the sum of its positive and negative components. Categorical NRI statistics have similar interpretations to their continuous counterparts.

Supplemental results

Exploratory analyses

The predictive equation for non-dipping diastolic blood pressure included age, race/ethnicity, waist circumference, alcohol use, high density lipoprotein-cholesterol, and log of the albumin-to-creatinine ratio as predictors (**Table S10**). In the validation data, there was no evidence of miscalibration overall for the non-dipping diastolic blood pressure predictive equations (**Table S11**). However, Hosmer and Lemeshow's goodness of fit test indicated miscalibration for these predictive equations among participants not taking antihypertensive medication. The value of Youden's index for these predictive equations exceeded those of ambulatory blood pressure screening methods based on clinic blood pressure (**Table S12**). However, screening for

ambulatory blood pressure monitoring with antihypertensive medication use provided a similar value for Youden's index in comparison to the predictive equations for non-dipping diastolic blood pressure. Categorical and continuous net reclassification indices also indicated that the predictive equation for non-dipping diastolic blood pressure improved upon screening methods based on clinic blood pressure (**Table S13**).

Table S1. Description of candidate variables in the Jackson Heart, Coronary Artery Risk Development in Young Adults, Improving the Detection of Hypertension, and Masked Hypertension studies.

Variable	Units or Categories	Description			
		JHS	CARDIA	MHT	IDH
Age	Years	Self-reported at baseline interview.	Collected by questionnaire at baseline and verified at the Year 2 exam.	Collected by questionnaire	
Race	Black or white				
Sex	Male or female				
Education	Years of formal education		Collected by questionnaire at Year 30 exam.		
Family Income	Above or below \$25,000 / year				
Current Smoker	Yes or no	Participants were asked the following questions:			
		(1) Have you smoked more than 400 cigarettes in your lifetime?	(1) Have you ever used any tobacco product such as cigarettes, cigars, tobacco pipe, chewing tobacco,	(1) Have you ever smoked cigarettes regularly for at least 3 months? By "regularly" we mean 5 or more	

			snuff, e-cigarettes (e.g., electronic cigarettes, vape pens, e-hookahs, etc.), nicotine chewing gum, or a nicotine patch?	cigarettes per week
		(2) Do you now smoke cigarettes?	(2) Have you ever smoked cigarettes regularly for at least three months?" ("Regularly" meant at least 5 cigarettes per week almost every week.)	(2) Do you currently smoke cigarettes?
		(3) How long has it been since you last smoked cigarettes?	(a) Do you still smoke cigarettes regularly? If response was "No", then participants were asked about time since they smoked cigarettes	(3) When did you stop smoking cigarettes regularly?

			regularly. (b) Have you started smoking regularly in the last three months?	
		Participants who were currently smoking or had quit less than 1 year ago were given a value of ‘Yes’ for this variable.		
Antihypertensive Medication Use	Yes or no	Defined as Yes if participant’s self-reported antihypertensive medication use at baseline interview.	Defined as Yes if participant’s self-reported antihypertensive medication use during Year 30 exam.	NONE, antihypertensive medication use was an exclusion criterion
Alcohol Consumption	Yes or No	Participants were asked: “Did you drink any alcoholic beverages in the past year?” at baseline interview	Participants were asked: “During the past 12 months, on average, how many days per week, month, or year did you drink any alcoholic beverage?”	Participants were asked "Did you drink any alcoholic beverages in the past year?"

			by questionnaire during Year 30 exam.	
		Participants who indicated consumption of alcohol in the past year had a value of ‘Yes’ for this variable and ‘No’ otherwise.		
Sleep Duration	Hours	Participants provided sleep diaries indicating when they went to sleep and when they woke up. Sleep duration was defined using these sleep diaries.	Participants wore actigraphy watches (Actiwatch, Philips-Respironics, Bend, OR) that monitored movement and indicated when participants were awake and asleep. Sleep duration was defined using the actigraphy data supplemented with self-reported sleep/wake times from a sleep diary.	
Clinic systolic and diastolic Blood Pressure	mm Hg	After participants had sat quietly for at least 5 minutes in an upright position with their back and arms supported, feet flat on the floor, legs uncrossed, and an appropriate-sized cuff was fitted, trained staff conducted blood pressure measurements using their right arm. Cuff	After participants had sat quietly for at least 5 minutes in an upright position with their back and arms supported, feet	

		<p>size was determined from an arm circumference measurement.</p>		<p>flat on the floor, legs uncrossed, and an appropriate-sized cuff was fitted, trained staff conducted blood pressure measurements using their left arm. Cuff size was determined from an arm circumference measurement.</p>
		<p>One to two minutes elapsed between the measurements. Two measurements were taken and averaged for</p>	<p>Three blood pressure measurements, each separated by at least 30 seconds, were recorded. The second and third BP measurements were averaged for</p>	<p>One to two minutes elapsed between the measurements. Three blood pressure measurements were obtained</p>

		analysis. A random-zero sphygmomanometer (Hawksley and Sons, Ltd) was used and blood pressure values were later calibrated using an Omron device.	analysis. An automated oscillometric device (Omron model® HEM907XL) was used to conduct blood pressure measurements.	using a mercury sphygmomanometer and averaged for analysis.
Diabetes	Yes or no	Participants with fasting (≥ 8 hours) glucose ≥ 126 mg/dL or HbA1c $\geq 6.5\%$ or taking anti-diabetes medication were given a value of 'Yes' for this variable.	Participants with fasting (≥ 8 hours) glucose ≥ 126 mg/dL or current use of antidiabetes medication were given a value of 'Yes' for this variable.	Participants with 1) self-reported diagnosis, 2) fasting (≥ 8 hours) glucose ≥ 126 mg/dL, 3) HbA1c $\geq 6.5\%$ or 4) taking anti-diabetes medication were given a value of 'Yes' for this variable.

Estimated glomerular filtration rate	< 60 or \geq 60 ml/min/1.73 m ²	Calculated using the Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) equation.		
High density lipoproteins	mg/dL	Measured by trained staff using blood samples after an overnight fast. Serum samples were sent on dry ice via overnight express to the testing laboratory	Measured by trained staff and quantified by precipitation with dextran sulfate-magnesium chloride	Enzymatic colorimetric test using cholesterol esterase and cholesterol oxidase coupled with PEG on a Roche modular test or Hitachi system
Low density lipoproteins	mg/dL	(Atherotech in Birmingham,	Measured by trained staff and calculated using the Friedewald equation.	
Total cholesterol	mg/dL	AL), where they were kept at -70°C until measurement.	Measured by trained staff and quantified using cholesterol in lipoprotein fractions performed by in vitro enzymatic tests using Roche reagents on a Roche	Enzymatic colorimetric test using cholesterol esterase and cholesterol oxidase on a Roche modular

			Double Modular P Analytical Automated Analyzer.	test or Hitachi system
Albuminuria	Urine albumin to urine creatinine ratio >30 or ≤ 30 mg/g	Urinary albumin and creatinine were quantified from a 24-hour urine collection or from a spot urine sample using the nephelometric immunoassay and enzymatic methods, respectively	Measured by trained staff using spot urine samples. Urinary albumin and creatinine were quantified using the nephelometric immunoassay and enzymatic methods.	Urinary albumin and creatinine were quantified using the nephelometric immunoassay and enzymatic methods, respectively from an overnight urine collection (sleep onset up to and including first morning void).
Height	cm	Measured by trained staff using a standardized protocol		
Weight	kg			
Waist Circumference	cm			

Neck Circumference	cm	
Body Mass Index	kg/m ²	Computed as weight in kilograms divided by height in meters squared

Table S2. Characteristics of participants in the Coronary Artery Risk Development In young Adults (CARDIA) study stratified by inclusion in the current analysis.

Characteristic*	Included in current analysis			P-value
	Overall (N = 5114)	No (N = 4327)	Yes (N = 787)	
Age, years	54.8 (3.63)	54.8 (3.62)	54.6 (3.68)	0.251
Male	45.5	46.5	40.2	0.001
Smoking Habits				0.154
Never	62.8	62.6	63.3	
Former	23.2	23.9	21.1	
Current	14.0	13.5	15.5	
Waist circumference, cm	96.2 (16.3)	95.9 (16.6)	97.2 (15.4)	0.039
Weight, lbs	194.1 (48.3)	193.2 (49.0)	196.7 (45.7)	0.069
Height, cm	169.9 (9.41)	170.2 (9.42)	168.9 (9.32)	< 0.001
Albumin-to-creatinine ratio, mg/g	27.2 (200.0)	26.0 (201.1)	30.8 (196.7)	0.552
Albuminuria [†]	8.34	8.16	8.91	0.557
eGFR < 60 ml/min/1.73 m ²	3.14	2.89	3.95	0.170
Blood glucose, mg/dL	102.6 (31.8)	101.9 (29.6)	104.9 (37.8)	0.040
Diabetes	14.3	13.4	17.3	0.006
HDL, mg/dL	59.8 (18.9)	60.0 (18.9)	59.3 (18.9)	0.415
LDL, mg/dL	110.3 (33.2)	109.8 (33.1)	111.7 (33.6)	0.168
Total cholesterol, mg/dL	191.3 (38.1)	191.0 (37.9)	192.2 (38.7)	0.420
Blood pressure, mm Hg				
Clinic systolic	120.8 (16.7)	120.5 (16.5)	121.8 (17.4)	0.069
Clinic diastolic	74.1 (11.1)	73.9 (11.1)	74.5 (11.0)	0.157

*Table values are presented as mean (standard deviation) or percent.

[†]Albuminuria: urinary albumin to urinary creatinine ratio \geq 30 mg/g.

eGFR = estimated glomerular filtration rate

Table S3. Characteristics of participants in the Jackson Heart Study (JHS) stratified by inclusion in the current analysis.

Characteristic*	Overall (N = 5306)	Included in current analysis		P-value
		No (N = 4243)	Yes (N = 1063)	
Age, years	54.8 (12.9)	53.9 (13.1)	58.7 (11.0)	< 0.001
Male	36.5	37.7	32.1	< 0.001
Smoking Habits				< 0.001
Never	67.6	67.7	67.2	
Former	19.3	18.5	22.7	
Current	13.1	13.8	10.1	
Waist circumference, cm	100.7 (16.2)	100.8 (16.3)	100.2 (15.7)	0.274
Weight, lbs	199.5 (47.2)	200.8 (47.9)	194.5 (43.5)	< 0.001
Height, cm	168.9 (9.28)	169.1 (9.32)	168.2 (9.10)	0.003
Albumin-to-creatinine ratio, mg/g	12.5 (125.4)	6.07 (111.0)	31.7 (159.2)	< 0.001
Albuminuria [†]	3.48	1.26	10.1	< 0.001
eGFR < 60 ml/min/1.73 m ²	6.22	6.22	6.20	> 0.999
Blood glucose, mg/dL	100.0 (33.4)	99.5 (34.1)	102.1 (30.2)	0.022
Diabetes	23.7	22.9	26.8	0.010
HDL-cholesterol, mg/dL	51.8 (14.6)	51.2 (14.5)	53.9 (15.0)	< 0.001
LDL-cholesterol, mg/dL	126.6 (36.6)	126.8 (36.8)	125.9 (35.8)	0.460
Total cholesterol, mg/dL	199.3 (40.1)	198.8 (40.2)	201.3 (39.8)	0.074
Blood pressure, mm Hg				
Clinic systolic	127.5 (16.9)	127.4 (17.2)	127.6 (15.8)	0.710
Clinic diastolic	75.7 (8.77)	76.0 (8.82)	74.3 (8.47)	< 0.001

*Table values are presented as mean (standard deviation) or percent.

[†]Albuminuria: urinary albumin to urinary creatinine ratio \geq 30 mg/g.

eGFR = estimated glomerular filtration rate; HDL = high density lipoprotein; LDL = low density lipoprotein

Table S4. Age, sex, and prevalence of nocturnal blood pressure phenotypes stratified by study.

Study	Number of participants	Age, years		% Women	Prevalence, %	
		Mean +/- SD	Range		NHTN	NDSBP
CARDIA	787	54.6 +/- 3.7	47.0 - 60.0	59.8	41.2	32.3
JHS	1063	58.7 +/- 11.0	21.0 - 84.0	67.9	57.1	72.8
IDH	395	41.2 +/- 13.2	18.3 - 81.8	60.0	26.8	33.7
MHT	772	45.1 +/- 10.4	21.3 - 81.3	59.3	18.7	24.7

CARDIA = Coronary Artery Risk Development in Young Adults, IDH = Improving Detection of Hypertension, JHS = Jackson Heart Study, MHT = Masked Hypertension, NDSBP = non-dipping systolic blood pressure, NHT = nocturnal hypertension, SD = standard deviation, % = percent

Table S5. Bootstrapped means of performance metrics and overall ranks of competing modeling algorithms for prediction of nocturnal hypertension and non-dipping systolic blood pressure.

Modeling Algorithm	Concordance Error (95% CI)	Hosmer-Lemeshow χ^2 Statistic (95% CI)	Scaled Brier Score (95% CI)	Mean Rank
	<i>Prediction of nocturnal hypertension</i>			
Generalized additive regression	16.9 (16.7, 17.1)	12.2 (11.5, 12.9)	31.3 (30.8, 31.7)	1.3
Forward stepwise regression	17.1 (16.9, 17.3)	13.7 (12.9, 14.4)	30.7 (30.3, 31.2)	3.0
Random forest	17.3 (17.0, 17.5)	10.8 (10.3, 11.4)	30.2 (29.8, 30.6)	3.3
Backward stepwise regression	17.2 (16.9, 17.4)	13.2 (12.5, 13.9)	30.6 (30.2, 31.1)	3.3
Lasso penalized regression	17.1 (16.8, 17.3)	17.9 (17.1, 18.8)	29.7 (29.3, 30.0)	4.3
Gradient boosted decision trees	17.4 (17.2, 17.6)	16.9 (15.1, 18.6)	29.1 (28.5, 29.6)	6.3
Ridge penalized regression	17.3 (17.0, 17.5)	19.0 (18.2, 19.8)	29.2 (28.9, 29.6)	6.3
<i>Prediction of non-dipping systolic blood pressure</i>				

Generalized additive regression	27.3 (27.1, 27.6)	12.8 (12.0, 13.5)	15.0 (14.6, 15.3)	1.7
Random forest	27.4 (27.1, 27.6)	11.8 (11.2, 12.5)	14.7 (14.4, 15.1)	2.0
Backward stepwise regression	27.9 (27.6, 28.1)	13.4 (12.6, 14.1)	14.3 (13.9, 14.7)	4.0
Forward stepwise regression	27.9 (27.7, 28.2)	12.9 (12.1, 13.6)	14.2 (13.8, 14.6)	4.3
Ridge penalized regression	27.8 (27.5, 28.1)	17.7 (16.8, 18.6)	13.3 (13.1, 13.5)	5.0
Gradient boosted decision trees	27.1 (26.9, 27.4)	25.9 (23.9, 27.9)	12.2 (11.7, 12.7)	5.0
Lasso penalized regression	28.1 (27.8, 28.3)	16.7 (15.9, 17.6)	13.1 (12.9, 13.4)	6.0

Table values were computed using the derivation data.

For clarity, concordance error, Brier scores, and calibration error were multiplied by 100.

Mean ranks were determined by taking the average of the order of the modeling algorithms from best (i.e., 1st) to worst (i.e., 7th) for concordance, calibration, and scaled Brier scores, separately.

Concordance error was measured one minus the concordance (C) statistic.

For concordance error and the Hosmer-Lemeshow X² Statistic, lower values indicate better fit. For the scaled Brier score, higher values indicate better fit.

CI = confidence interval.

Table S6. Proportions of bootstrap replicates where candidate variables were selected for inclusion in predictive equations for nocturnal hypertension.

Variable	Nocturnal hypertension
<i>Included in predictive equations</i>	
Race/ethnicity	100.0
Clinic SBP	100.0
Albumin-to-creatinine ratio	99.9
Age	98.3
Height	75.6
Neck circumference	64.8
Smoking status	57.0
High density lipoprotein-cholesterol	53.1
Clinic DBP	40.1
<i>Not included in predictive equations</i>	
Blood glucose	45.9
Sex	45.0
eGFR	27.0
Alcohol use	24.1
eGFR < 60 ml/min/1.73 m ²	23.4
Low density lipoprotein-cholesterol	10.2
High school graduate	10.0
Body mass index	7.4
Waist circumference	6.8
Antihypertensive medication use	5.4
Diabetes	5.4
Total cholesterol	5.1

eGFR = estimated glomerular filtration rate; DBP = diastolic blood pressure; SBP = systolic blood pressure

Table S7. Proportions of bootstrap replicates where candidate variables were selected for inclusion in predictive equations for non-dipping systolic blood pressure.

Variable	Non-dipping systolic blood pressure
<i>Included in predictive equations</i>	
Race/ethnicity	100.0
Alcohol use	98.9
Age	91.5
High density lipoprotein-cholesterol	89.8
Albumin-to-creatinine ratio	86.3
Sex	75.8
Waist circumference	57.9
Height	27.5
<i>Not included in predictive equations</i>	
Blood glucose	32.9
Smoking status	29.4
Clinic DBP	28.0
Neck circumference	25.6
Low density lipoprotein-cholesterol	24.0
Antihypertensive medication use	21.5
Body mass index	20.2
Total cholesterol	17.6
eGFR < 60 ml/min/1.73 m ²	15.8
Clinic SBP	13.7
Diabetes	11.1
eGFR	11.5
High school graduate	10.0

eGFR = estimated glomerular filtration rate; DBP = diastolic blood pressure; SBP = systolic blood pressure

Table S8. Calibration and discrimination of predictive equations for nocturnal hypertension and non-dipping systolic blood pressure overall and in sub-groups determined by race, sex, and antihypertensive medication use.

	Prevalence, %		P-value from Hosmer and Lemeshow's goodness of fit test		Concordance Statistic (95% Confidence Interval)	
	NHT	NDSBP	NHT	NDSBP	NHT	NDSBP
Race						
Non-white, N = 318 (62.8%)	46.2	57.2	0.310	0.158	0.82 (0.78, 0.87)	0.70 (0.64, 0.75)
White, N = 188 (37.2%)	20.2	22.9	0.143	0.560	0.81 (0.72, 0.89)	0.53 (0.43, 0.63)
Sex						
Female, N = 315 (62.3%)	30.2	43.8	0.152	0.925	0.83 (0.78, 0.87)	0.76 (0.71, 0.82)
Male, N = 191 (37.7%)	47.1	45.5	0.983	0.209	0.84 (0.79, 0.90)	0.69 (0.61, 0.77)
Antihypertensive medication use						
No, N = 346 (68.4%)	27.2	35.5	0.381	0.557	0.83 (0.78, 0.88)	0.66 (0.60, 0.73)
Yes, N = 160 (31.6%)	56.9	63.7	0.799	0.307	0.79 (0.72, 0.86)	0.76 (0.68, 0.84)
High school graduate						
Yes, N = 462 (91.3%)	34.0	42.9	0.382	0.558	0.84 (0.80, 0.88)	0.73 (0.68, 0.77)
No, N = 44 (8.7%)	63.6	61.4	0.395	0.344	0.73 (0.58, 0.89)	0.76 (0.61, 0.91)
All participants in validation data						
Overall, N = 506 (100.0%)	36.6	44.5	0.423	0.465	0.84 (0.80, 0.87)	0.73 (0.69, 0.78)

Table values were computed using the validation data.

NDSBP = non-dipping systolic blood pressure, NHT = nocturnal hypertension

Table S9. Predictive equations for nocturnal hypertension and non-dipping systolic blood pressure.

Equation	Formula
<p>Nocturnal hypertension</p>	<p>Linear predictor = $-33.055454 + 0.032777*(\text{age in years}) + 0.031443*(\text{neck circumference in cm}) + 1.014224*(1 \text{ if black, } 0 \text{ otherwise}) + 0.254249*(1 \text{ if asian, } 0 \text{ otherwise}) + 0.956609*(1 \text{ if other race, } 0 \text{ otherwise}) - 0.321403*(1 \text{ if former smoker, } 0 \text{ otherwise}) - 0.457890*(1 \text{ if never smoked, } 0 \text{ otherwise}) + 0.349868*(\text{height in cm}) - 0.000964*(\text{height in cm})^2 - 0.118164*(\text{clinic SBP in mm Hg}) + 0.001829*(\text{clinic SBP in mm Hg})^2 - 0.000006*(\text{clinic SBP in mm Hg})^3 - 0.132077*(\text{clinic DBP in mm Hg}) + 0.000990*(\text{clinic DBP in mm Hg})^2 - 0.008802*(\text{HDL in mg/dL}) + 0.321093*\log(\text{ACR} + 1)$</p> <p>Predicted probability = $\exp(\text{linear predictor}) / (1 + \exp(\text{linear predictor}))$</p>
<p>Non-dipping systolic blood pressure</p>	<p>Linear predictor = $-13.284558 + 0.027831*(\text{age in years}) - 0.001952*(\text{age in years})^2 + 0.000024*(\text{age in years})^3 - 0.611072*(1 \text{ if male, } 0 \text{ otherwise}) + 1.099851*(1 \text{ if black, } 0 \text{ otherwise}) + 0.182960*(1 \text{ if asian, } 0 \text{ otherwise}) + 0.470218*(1 \text{ if other race, } 0 \text{ otherwise}) - 0.437195*(1 \text{ if drinks alcohol, } 0 \text{ otherwise}) + 0.145586*(\text{height in cm}) - 0.000382*(\text{height in cm})^2 + 0.010166*(\text{waist circumference in cm}) - 0.011492*(\text{HDL in mg/dL}) - 1.061997*\log(\text{ACR} + 1) + 0.346205*\log(\text{ACR} + 1)^2 - 0.026371*\log(\text{ACR} + 1)^3$</p>

	$\text{Predicted probability} = \exp(\text{linear predictor}) / (1 + \exp(\text{linear predictor}))$
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$\exp(x)$ represents application of the exponential function to x .

The predictive equations shown here apply polynomials to model non-linear effects. These polynomials are approximately equal to the non-parametric smoothing functions used by the predictive equations developed in the current analysis.

ACR = albumin-to-creatinine ratio; DBP = diastolic blood pressure; HDL = high density lipoproteins; SBP = systolic blood pressure.

Table S10. Odds ratios for variables selected for inclusion in the predictive equations for non-dipping diastolic blood pressure.

Variable	Non-dipping Diastolic Blood Pressure
Age, 12 years	1.48 (1.31, 1.67)
Race/ethnicity	
White	1 (ref)
Black	2.76 (2.12, 3.60)
Asian	0.23 (0.03, 1.67)
Other race	1.30 (0.76, 2.23)
Waist circumference, 16 cm	1.17 (1.04, 1.32)*
Alcohol use	0.81 (0.66, 1.01)
HDL-cholesterol, 17 mg/dL	0.82 (0.73, 0.93)
Log(1+ACR), g/24hr	1.22 (1.10, 1.35)

Table values were computed using the derivation data.

* This is a non-linear variable in the predictive equation. The odds ratio is presented using the mean as a reference value.

The odds ratios for the following predictor variables are presented for a one standard deviation higher level of the exposure value: age, waist circumference, and high-density lipoprotein-cholesterol.

ACR = albumin-to-creatinine ratio; DBP = diastolic blood pressure; SBP = systolic blood pressure.

Table S11. Calibration and discrimination of predictive equations for non-dipping diastolic blood pressure overall and in sub-groups determined by race, sex, and antihypertensive medication use.

	P-value from Hosmer and Lemeshow's goodness of fit test	Concordance Statistic (95% Confidence Interval)
Race		
Non-white, N = 318 (62.8%)	0.912	0.70 (0.63, 0.76)
White, N = 188 (37.2%)	0.637	0.66 (0.53, 0.79)
Sex		
Female, N = 315 (62.3%)	0.973	0.72 (0.65, 0.78)
Male, N = 191 (37.7%)	0.135	0.73 (0.64, 0.82)
Antihypertensive medication use		
No, N = 346 (68.4%)	0.042	0.65 (0.56, 0.73)
Yes, N = 160 (31.6%)	0.644	0.69 (0.60, 0.77)
High school graduate		
Yes, N = 462 (91.3%)	0.526	0.72 (0.66, 0.78)
No, N = 44 (8.7%)	0.810	0.70 (0.53, 0.87)
All participants in validation data		
Overall, N = 506 (100.0%)	0.640	0.72 (0.67, 0.78)

Table values were computed in the validation data.

Table S12. Test characteristics of the predictive equations for non-dipping diastolic blood pressure versus alternative screening methods for identifying adults with a high probability of non-dipping diastolic blood pressure.

	Methods of identifying who should undergo 24-hour ambulatory blood pressure monitoring.							
	Predictive equation for non-dipping diastolic blood pressure probability cut-points				Systolic/Diastolic blood pressure cut-points, mm Hg			Currently using anti-hypertensive medication
	1	2	3	4	I	II	III	IV
Classification cut-point	≥0.36	≥0.19	≥0.44	≥0.19	≥120/70	≥130/80	≥140/90	Yes
Percent screened	21.5	51.2	9.68	52.2	78.5	42.1	14.6	31.6
Sensitivity	0.45	0.76	0.25	0.76	0.81	0.47	0.24	0.55
Specificity	0.86	0.56	0.95	0.55	0.22	0.60	0.88	0.76
Positive Predictive Value	0.49	0.35	0.59	0.34	0.24	0.26	0.38	0.41
Negative Predictive Value	0.84	0.89	0.81	0.88	0.80	0.79	0.79	0.85
Youden's Index	1.30	1.33	1.19	1.31	1.04	1.07	1.12	1.31

Table values were computed using the validation data.

Participants with values \geq classification cut-point values are recommended to undergo 24-hour ambulatory blood pressure monitoring.

The following probability cut points of the predictive equation for non-dipping diastolic blood pressure were chosen based on the derivation data:

1. Closest number of predicted and observed cases with nocturnal hypertension and non-dipping systolic blood pressure.
2. The maximum specificity with a sensitivity ≥ 0.80 ;
3. The maximum negative predictive value with a positive predictive value ≥ 0.60 ,
4. The maximum sum of sensitivity and specificity.

Notably, cut-point 3 in our main analysis was selected as the maximum negative predictive value with a positive predictive value ≥ 0.60 . However, the distribution of predicted probabilities from the predictive equations for non-dipping diastolic blood pressure could only meet the adjusted criteria used above, i.e., maximum negative predictive value with a positive predictive value ≥ 0.60 .

Table S13. Net reclassification improvement and integrated discriminative improvement using a predictive equation for non-dipping diastolic blood pressure versus screening methods based on clinic blood pressure and antihypertensive medication use.

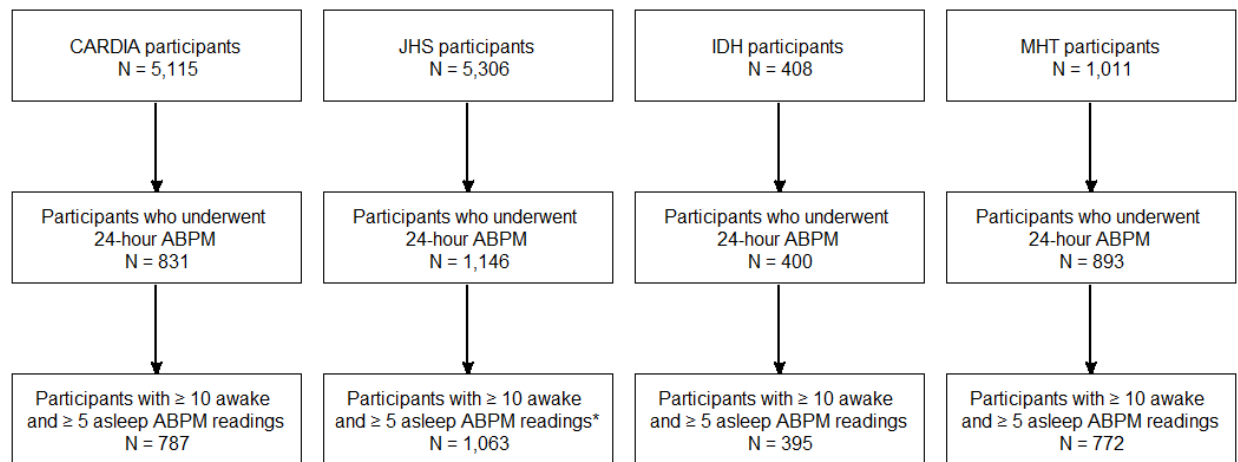
Methods of identifying who should undergo 24-hour ambulatory blood pressure monitoring	Reclassification improvement using predictive equations (95% confidence interval) for non-dipping diastolic blood pressure
Overall categorical net reclassification index*	
Clinic SBP/DBP \geq 120/70 mm Hg	0.28 (0.17, 0.40)
Clinic SBP/DBP \geq 130/80 mm Hg	0.24 (0.12, 0.38)
Clinic SBP/DBP \geq 140/90 mm Hg	0.20 (0.09, 0.30)
Antihypertensive medication use	0.01 (-0.09, 0.11)
Negative categorical net reclassification index	
Clinic SBP/DBP \geq 120/70 mm Hg	0.33 (0.27, 0.39)
Clinic SBP/DBP \geq 130/80 mm Hg	-0.04 (-0.11, 0.02)
Clinic SBP/DBP \geq 140/90 mm Hg	-0.33 (-0.39, -0.28)
Antihypertensive medication use	-0.20 (-0.25, -0.16)
Positive categorical net reclassification index	
Clinic SBP/DBP \geq 120/70 mm Hg	-0.05 (-0.15, 0.05)
Clinic SBP/DBP \geq 130/80 mm Hg	0.29 (0.18, 0.40)
Clinic SBP/DBP \geq 140/90 mm Hg	0.53 (0.42, 0.62)
Antihypertensive medication use	0.21 (0.12, 0.30)
Continuous net reclassification index	
Models using SBP, DBP and antihypertensive medication use [†]	0.42 (0.21, 0.62)
Integrated discriminative improvement index	
Models using SBP, DBP and antihypertensive medication use [†]	0.04 (0.02, 0.06)

Table values were computed using the validation data.

* For categorical net reclassification indices, the probability cut-points maximizing Youden's index for the predictive equations (0.19) was used. This cut-point was chosen assuming that it would provide better overall classification characteristics than the other three cut-points.

† Predicted probabilities were obtained from equations formed for non-dipping diastolic blood pressure using logistic regression in the derivation data set with clinic systolic and diastolic blood pressure and antihypertensive medication use as independent variables.

Figure S1. Inclusion cascade of participants from four studies that contributed data to the current analysis.

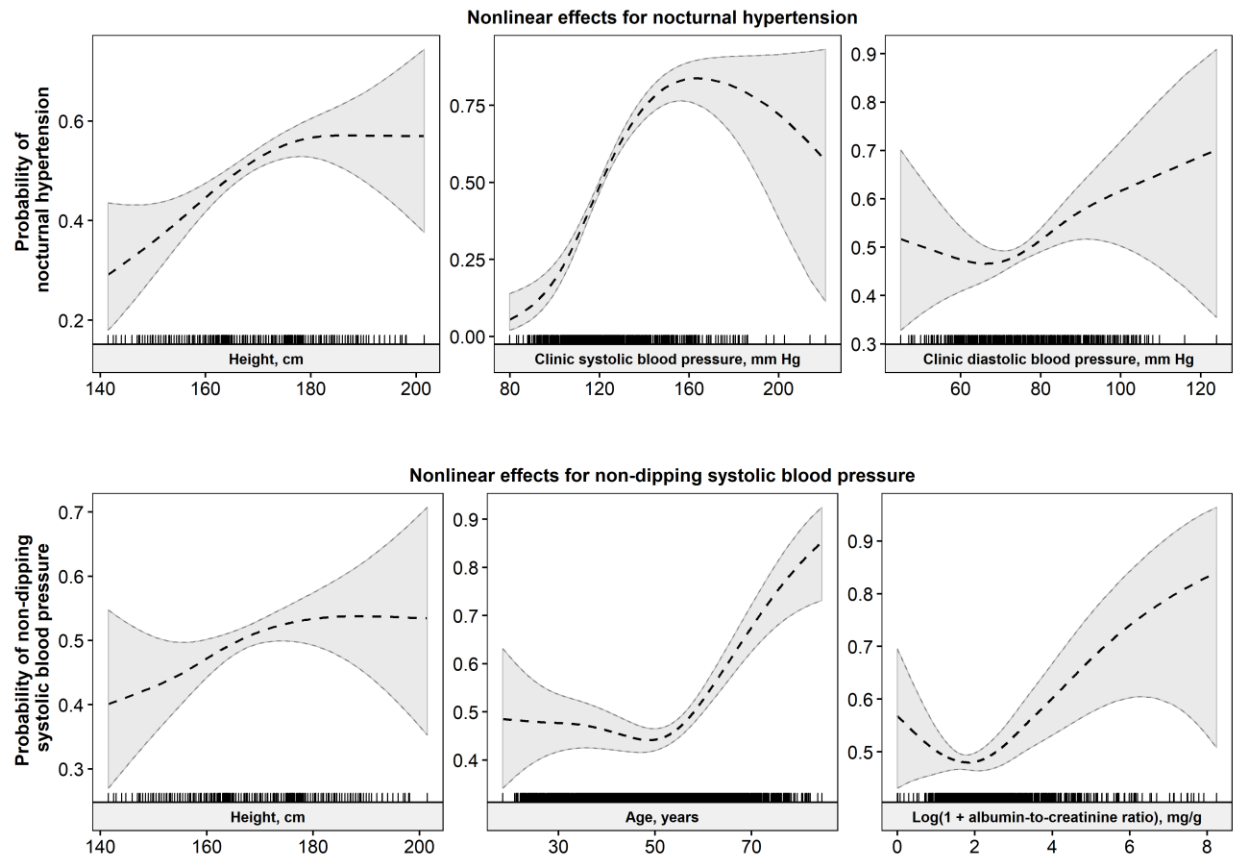


*For participants in the Jackson Heart Study who provided valid sleep diaries, we included those with ≥ 10 awake and ≥ 5 asleep blood pressure readings during self-reported awake and asleep periods. For Jackson Heart Study participants who did not provide valid sleep diaries, we included those with ≥ 10 daytime (10AM-8PM) and ≥ 5 nighttime (12AM-6AM) blood pressure readings.

ABPM = ambulatory blood pressure monitoring; CARDIA = Coronary Artery Risk

Development in Young Adults; IDH = Improving Detection of Hypertension; JHS = Jackson Heart Study; MHT = Masked Hypertension Study

Figure S2. Predicted probability of nocturnal hypertension (top panels) and non-dipping systolic blood pressure (bottom panels) according to non-linear variables in the predictive equations.



Results are based on the derivation data.

Tick marks in the bottom of each panel indicate the distribution of observed values for a given variable.

Black curves are the predicted probability of nocturnal hypertension and non-dipping BP, relative to the given predictor variable, holding other predictors in the equation fixed.

Gray areas drawn around black curves are 95% confidence intervals for the predicted probability.

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