STA108 Project 1

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Introduction

We will be analyzing the county demographic information for 440 of the most populous counties in the United States. We will be studying the relationships between different variables, checking for correlation where necessary. We will particularly focus on the relationship between the number of active physicians in a specific region and three variables, total population, number of hospital beds, and total personal income, to see how well these variables can predict Y, the number of active physicians. Eventually, we will do some work with the residuals of these variables as well. Then, we will look into the linear regression model between per capita income and the percentage of individuals in a county having at least a bachelor's degree, checking for marginal differences among different geographic regions in the United States. We will use built-in R functions such as abline() and ggplot() for data visualization and create other functions manually to interpret the data.

```
CDI <- read.table("./Datasets/CDI.txt")
CDI
```

```
##      V1              V2 V3    V4      V5   V6   V7    V8    V9    V10
## 1     1     Los_Angeles CA  4060 8863164 32.1  9.7 23677 27700 688936
## 2     2            Cook IL   946 5105067 29.2 12.4 15153 21550 436936
## 3     3          Harris TX  1729 2818199 31.3  7.1  7553 12449 253526
## 4     4       San_Diego CA  4205 2498016 33.5 10.9  5905  6179 173821
## 5     5          Orange CA   790 2410556 32.6  9.2  6062  6369 144524
## 6     6           Kings NY    71 2300664 28.3 12.4  4861  8942 680966
## 7     7        Maricopa AZ  9204 2122101 29.2 12.5  4320  6104 177593
## 8     8           Wayne MI   614 2111687 27.4 12.5  3823  9490 193978
## 9     9            Dade FL  1945 1937094 27.1 13.9  6274  8840 244725
## 10   10          Dallas TX   880 1852810 32.6  8.2  4718  6934 214258
## 11   11    Philadelphia PA   135 1585577 29.1 15.2  6641 10494 109148
## 12   12            King WA  2126 1507319 30.1 11.1  5280  4009 124959
## 13   13     Santa_Clara CA  1291 1497577 32.6  8.7  4101  3342  77009
## 14   14  San_Bernardino CA 20062 1418380 30.1  8.8  2463  3349  83110
## 15   15        Cuyahoga OH   458 1412140 26.3 15.6  5620  8132  73150
## 16   16       Middlesex MA   824 1398468 31.7 12.5  5158  4152  35825
## 17   17       Allegheny PA   730 1336449 26.2 17.4  5281  8436  50186
## 18   18         Suffolk NY   911 1321864 27.9 10.8  3021  3904  66723
## 19   19          Nassau NY   287 1287348 25.7 14.2  6147  5200  43203
## 20   20         Alameda CA   738 1279182 30.8 10.6  3169  3284 107338
## 21   21         Broward FL  1209 1255488 25.3 20.7  2456  5543 107386
## 22   22           Bexar TX  1247 1185394 29.5  9.9  3062  4086 133098
## 23   23       Riverside CA  7208 1170413 27.9 13.2  1385  2435  95494
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## 24   24               Tarrant TX   864 1170103 32.2  8.3  1677  3672 132495
## 25   25               Oakland MI   873 1083592 27.6 10.9  4020  3254  50964
## 26   26            Sacramento CA   966 1041219 29.7 10.6  2464  2855  84305
## 27   27              Hennepin MN   557 1032431 31.6 11.3  3706  5395  71753
## 28   28             St._Louis MO   508  993529 26.1 13.1  1194  1056  42595
## 29   29                  Erie NY  1045  968532 27.3 15.2  2748  4632  55306
## 30   30              Franklin OH   540  961437 33.5  9.6  2675  4011  82680
## 31   31             Milwaukee WI   242  959275 29.3 13.6  2774  4141  73681
## 32   32           Westchester NY   433  874866 26.3 14.4  4577  3540  37118
## 33   33              Hamilton OH   407  866228 28.0 13.3  3164  4683  57208
## 34   34            Palm_Beach FL  1974  863518 23.3 24.4  1833  3164  76142
## 35   35              Hartford CT   736  851783 28.3 14.1  2851  2940  51926
## 36   36              Pinellas FL   280  851659 22.4 26.0  1620  4458  62344
## 37   37              Honolulu HI   600  836231 30.6 11.0  2025  2174  51032
## 38   38          Hillsborough FL  1051  834054 29.4 12.2  2012  3068  89895
## 39   39             Fairfield CT   626  827645 26.7 13.3  2417  2494  44374
## 40   40                Shelby TN   755  826330 29.4 10.4  2489  4918  67032
## 41   41                Bergen NJ   234  825380 25.4 15.3  3226  2279  28521
## 42   42        Fairfax_County VA   396  818584 29.2  6.5  1694   135  30202
## 43   43             New_Haven CT   606  804219 28.7 14.7  3161  2486  52903
## 44   44          Contra_Costa CA   720  803732 26.5 10.9  1761  1781  51243
## 45   45                Marion IN   396  797159 30.6 11.7  2936  4654  61004
## 46   46                DuPage IL   334  781666 29.0  8.7  2157  1842  29708
## 47   47                 Essex NJ   126  778206 28.6 12.7  2811  4841  75595
## 48   48            Montgomery MD   495  757027 28.6 10.2  4635  1507  34754
## 49   49                 Clark NV  7911  741459 29.0 10.5   969  2011  52786
## 50   50        Baltimore_City MD    81  736014 30.0 13.7  5444  6203  87355
## 51   51       Prince_George's MD   486  729268 33.7  6.9  1253  1322  54469
## 52   52             Salt_Lake UT   737  725956 27.8  8.5  2094  2076  58610
## 53   53         San_Francisco CA    47  723959 32.2 14.5  4761  3640  71234
## 54   54                Macomb MI   480  717400 28.2 12.3   705  1202  41048
## 55   55                Monroe NY   659  713968 29.0 12.5  2438  3077  43780
## 56   56             Worcester MA  1513  709705 29.2 13.7  1902  2205   7099
## 57   57             Baltimore MD   599  692134 27.8 14.0  1269   641  46789
## 58   58            Montgomery PA   483  678111 26.1 15.0  3237  2425  20335
## 59   59                Orange FL   908  677491 33.2 10.6  1367  2929  52577
## 60   60                 Duval FL   774  672971 30.7 10.7  1538  2623  68586
## 61   61             Middlesex NJ   311  671780 31.6 11.8  1637  1880  30548
## 62   62                 Essex MA   498  670080 27.3 14.1  1185  2009  34312
## 63   63               Ventura CA  1846  669016 28.8  9.4  1168  1372  30235
## 64   64                Fresno CA  5963  667490 28.3 10.4  1188  1681  62004
## 65   65                  Pima AZ  9187  666880 28.9 13.7  1841  2016  57051
## 66   66             Jefferson KY   385  664937 27.0 13.4  2171  3559  32419
## 67   67               Suffolk MA    59  663906 39.2 12.1  5674  6154  68808
## 68   68             Jefferson AL  1113  651525 26.7 14.0  2532  4602  55604
## 69   69             San_Mateo CA   449  649623 28.4 12.3  1814  1642  30473
## 70   70                Fulton GA   529  648951 31.6 10.0  3368  5757  93025
## 71   71               Jackson MO   605  633232 28.1 13.1  1695  3762  61760
## 72   72               Norfolk MA   400  616087 28.8 14.1  2758  1903  14830
## 73   73  District_of_Columbia DC    61  606900 33.6 12.8  3674  4262  64393
## 74   74              Oklahoma OK   709  599611 28.4 12.1  1922  3487  57045
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## 75   75           Providence RI  413  596270 29.9 15.8  1862  2360  34627
## 76   76              El_Paso TX 1013  591610 29.5  8.1   795  1650  54002
## 77   77               Pierce WA 1676  586203 29.5 10.5   915  1226  41980
## 78   78            Multnomah OR  435  583887 28.4 13.6  2571  3009  58216
## 79   79               Travis TX  989  576407 38.0  7.3  1254  1392  60961
## 80   80           Montgomery OH  462  573809 28.1 12.6  1313  3068  36665
## 81   81             Monmouth NJ  472  553124 25.6 12.7  1300  1904  22302
## 82   82               Hudson NJ   47  553099 31.5 12.7  1036  2443  40581
## 83   83             Delaware PA  184  547651 27.6 15.5  1374  1588  18924
## 84   84              De_Kalb GA  268  545837 32.6  8.5  1036   922  56950
## 85   85                 Kern CA 8142  543477 28.3  9.7   682  1194  36318
## 86   86                Bucks PA  608  541174 26.6 10.9   879  1435  16894
## 87   87                 Lake IL  448  516418 28.9  8.4  1093  1499  22349
## 88   88               Summit OH  413  514990 26.8 13.8  1216  2226  26228
## 89   89          Mecklenburg NC  527  511433 32.0  9.4  1114  2021  57999
## 90   90             Davidson TN  502  510784 32.1 11.6  2293  3847  45237
## 91   91              Bristol MA  556  506325 27.6 14.4   572  1306  22023
## 92   92                Tulsa OK  570  503341 28.2 11.5  1158  2512  39496
## 93   93               Camden NJ  222  502824 27.5 12.2  1255  2041  34814
## 94   94                 Kent MI  856  500631 29.6 10.8  1007  1460  31553
## 95   95              Orleans LA  181  496938 28.3 13.0  2500  4018  54238
## 96   96                Union NJ  103  493819 26.8 15.0  1362  2541  30299
## 97   97               Ramsey MN  156  485765 31.0 12.2  1512  1140  30574
## 98   98          San_Joaquin CA 1399  480628 27.7 11.1   666  1051  41179
## 99   99           Bernalillo NM 1166  480577 29.2 10.5  1585  1726  41280
## 100 100                 Lake IN  497  475594 25.5 12.3   707  2413  29926
## 101 101             Onondaga NY  780  468973 29.4 13.0  1534  1668  23249
## 102 102               Denver CO  153  467610 30.3 13.8  2867  3652  37466
## 103 103            Snohomish WA 2090  465642 28.1  9.5   502   672  20323
## 104 104                Lucas OH  340  462361 27.8 13.0  1391  3021  38194
## 105 105              Hampden MA  619  456310 27.8 14.8   904  1665  24247
## 106 106              Passaic NJ  185  453060 28.9 12.9   831  1912  26434
## 107 107            Jefferson LA  306  448306 28.1 10.2  1237  1648  41625
## 108 108                 Cobb GA  340  447745 31.7  6.3   622   983  27582
## 109 109           New_Castle DE  426  441946 30.6 11.4  1038  1488  27717
## 110 110            Jefferson CO  772  438430 26.9  8.0   551   298  23453
## 111 111             Plymouth MA  661  435276 27.1 11.6   576   813  14846
## 112 112                Ocean NJ  636  433203 22.4 23.2   513  1475  17379
## 113 113              Genesee MI  640  430459 27.2 10.2   692  1830  33136
## 114 114         Anne_Arundel MD  416  427239 29.6  8.8   616   617  21826
## 115 115                 Wake NC  834  423380 34.5  7.8   761  1199  26006
## 116 116            Lancaster PA  949  422822 27.2 13.1   574  1241  13086
## 117 117               Morris NJ  469  421353 26.7 10.6  1147  1599  12147
## 118 118              Douglas NE  331  416444 29.0 11.4  1603  2889  26006
## 119 119                 Polk FL 1875  405382 23.9 18.6   559  1288  37290
## 120 120             Sedgwick KS 1000  403662 28.5 11.4   930  1840  34071
## 121 121              Brevard FL 1019  398978 26.2 16.6   563  1085  23686
## 122 122              El_Paso CO 2127  397014 31.7  8.0   548  1026  25234
## 123 123       St._Louis_City MO   62  396685 28.7 16.6  4189  7814  64103
## 124 124           Burlington NJ  805  395066 28.8 10.7   719  1150  13034
## 125 125         VA_Beach_City VA  248  393069 35.3  5.9   679   530  23412
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## 126 126            Arapahoe CO  803  391511 28.3  7.4   583   742  27587
## 127 127             Sonoma CA 1576  388222 25.8 13.4   840   798  18556
## 128 128            Hidalgo TX 1569  383545 26.4 10.1   311   860  26712
## 129 129   East_Baton_Rouge LA  456  380105 31.5  9.2   841  1876  41592
## 130 130             Mobile AL 1233  378643 26.7 11.8   850  1898  30409
## 131 131            Chester PA  756  376396 27.1 10.9   594   920   9491
## 132 132            Volusia FL 1106  370712 24.3 22.8   495  1349  25736
## 133 133         Stanislaus CA 1495  370522 27.4 10.8   558  1306  25461
## 134 134       Westmoreland PA 1023  370321 23.3 17.1   522  1306   7445
## 135 135      Santa_Barbara CA 2739  369608 32.8 12.3   875  1031  18313
## 136 136              Stark OH  576  367585 24.9 14.4   595  1537  17466
## 137 137               Dane WI 1202  367085 35.6  9.3  1603  1382  20344
## 138 138            Spokane WA 1764  361364 27.0 13.2   852  1346  20042
## 139 139               Will IL  837  357313 27.4  8.6   298   746  16432
## 140 140           Monterey CA 3322  355660 32.6  9.8   515   602  17870
## 141 141            Johnson KS  477  355054 27.5  9.4  1173   925  15238
## 142 142           Gwinnett GA  433  352910 32.6  4.7   271   439  17119
## 143 143            Pulaski AR  771  349660 28.5 11.5  1510  2785  42404
## 144 144           Guilford NC  650  347420 30.4 11.9   676  1188  28212
## 145 145             Solano CA  828  340421 29.7  8.2   481   503  21756
## 146 146               York PA  905  339574 26.6 13.1   460   951  11292
## 147 147              Berks PA  859  336523 26.1 15.6   567  1041  12827
## 148 148       Hillsborough NH  877  336073 30.0 10.3   587  1050  12843
## 149 149               Knox TN  509  335749 30.0 12.7   984  2178  22422
## 150 150                Lee FL  804  335113 21.5 24.7   509  1202  18442
## 151 151            Luzerne PA  891  328149 24.1 19.7   594  1495   4982
## 152 152             Mercer NJ  226  325824 29.2 13.0   994  1724  20153
## 153 153         Greenville SC  792  320167 28.2 11.9   650  1358  20504
## 154 154               Kane IL  521  317471 27.8  9.3   473  1263  16721
## 155 155             Tulare CA 4824  311921 26.3 10.8   358   656  19489
## 156 156         Washington OR  724  311554 27.6 10.1   353   294  12630
## 157 157             Orange NY  816  307647 28.0 10.4   479   986  10975
## 158 158           Waukesha WI  556  304715 24.4  9.8   687   677   8935
## 159 159              Allen IN  657  300836 27.4 11.4   552  1268  19842
## 160 160         Charleston SC  917  295039 34.1 10.1  1357  1956  28190
## 161 161             Albany NY  524  292594 30.4 14.7  1257  1246  15077
## 162 162             Butler OH  467  291479 29.9 10.2   308   878  13850
## 163 163             Nueces TX  836  291145 27.3 10.1   584  1406  28606
## 164 164             Lehigh PA  347  291130 26.3 15.4   637  1305  12254
## 165 165           Seminole FL  308  287529 27.9 10.3   357   352  17518
## 166 166           Richland SC  757  285720 34.7  9.5   999  1207  24101
## 167 167           Hamilton TN  543  285536 26.3 13.5   738  1573  23532
## 168 168          Washtenaw MI  710  282937 39.5  7.5  2188  1730  19367
## 169 169               Lane OR 4554  282912 27.4 13.1   497   654  16091
## 170 170             Ingham MI  559  281912 37.4  8.7   729  1438  17337
## 171 171              Pasco FL  745  281131 18.4 32.3   308   941  12509
## 172 172          Clackamas OR 1868  278850 23.1 11.5   462   345  12855
## 173 173           Sarasota FL  572  277776 18.2 32.1   631  1363  19801
## 174 174               Erie PA  802  275572 27.5 13.8   468  1417   9936
## 175 175             Dakota MN  570  275227 30.6  6.4   201   283  10953
## 176 176         Cumberland NC  653  274566 37.4  6.2   291   586  25247
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## 177 177                 Denton TX   889  273525 36.9  5.0   216   458  20372
## 178 178                 Lorain OH   493  271126 26.4 11.6   291   941   9864
## 179 179                Forsyth NC   410  265878 29.2 12.3  1194  1609  21554
## 180 180               Rockland NY   174  265475 25.5 10.1   931   745   7194
## 181 181                  Adams CO  1192  265038 29.6  7.6   439   318  19369
## 182 182               Mahoning OH   415  264806 23.5 17.1   601  1473  13181
## 183 183                 Collin TX   848  264036 29.8  5.3   282   571  17625
## 184 184                   Utah UT  1998  263590 33.9  7.0   291   544  10605
## 185 185              St._Clair IL   664  262852 26.8 12.7   329  1088  14563
## 186 186               Escambia FL   664  262798 29.2 11.9   522  1584  14380
## 187 187            Norfolk_City VA    54  261229 41.7 10.5  1101  1471  25194
## 188 188                Cameron TX   906  260120 25.9 10.6   270   825  18842
## 189 189               Dutchess NY   802  259462 29.0 11.4   535   741   9087
## 190 190             New_London CT   666  254957 31.2 11.9   486   515   7807
## 191 191                 Washoe NV  6343  254667 29.5 10.3   603   990  18831
## 192 192                  Hinds MS   869  254441 29.5 11.2  1076  2118  28841
## 193 193              Winnebago IL   514  252913 26.5 12.7   521   910  19674
## 194 194                 Oneida NY  1213  250836 27.7 15.5   437   905   9234
## 195 195                Madison IL   725  249238 26.2 13.9   275  1120  10666
## 196 196                  Caddo LA   882  248253 25.2 13.3   898  1868  22091
## 197 197            Northampton PA   374  247105 26.9 15.0   459   933   6452
## 198 198              St._Joseph IN   457  247052 28.2 14.1   417   927  10637
## 199 199             Rockingham NH   695  245845 29.0  9.2   343   514   7295
## 200 200             Cumberland ME   836  243135 29.1 13.0   732  1104  13816
## 201 201               Somerset NJ   305  240279 28.6 10.8   783   374   8308
## 202 202              Jefferson TX   904  239397 25.8 14.0   449  1724  21677
## 203 203                Madison AL   805  238912 31.4  8.9   399   933   6635
## 204 204                  Clark WA   628  238053 25.3 10.6   256   299  10706
## 205 205                Dauphin PA   525  237813 26.8 14.3   824  1425  11563
## 206 206                  Marin CA   520  230096 24.7 12.3  1001   488   9460
## 207 207             Gloucester NJ   325  230082 28.0 10.8   199   339   9746
## 208 208             Santa_Cruz CA   446  229734 29.9 11.3   429   390  13707
## 209 209                 Marion OR  1185  228483 25.7 14.3   376   498  14825
## 210 210               Trumbull OH   616  227813 23.9 14.4   225   925   7315
## 211 211            Spartanburg SC   811  226800 27.0 12.6   375   832  17198
## 212 212              Fort_Bend TX   875  225421 26.8  4.9   231   301   9433
## 213 213                Fayette KY   285  225366 34.9  9.9  1248  1851  17378
## 214 214                Boulder CO   743  225339 34.2  7.6   452   387  14124
## 215 215               Atlantic NJ   561  224327 29.0 14.5   379   990  25167
## 216 216              Kalamazoo MI   562  223411 32.4 10.6   614   793  15306
## 217 217                Lubbock TX   900  222636 34.1  9.8   655  1562  14509
## 218 218                Niagara NY   523  220756 25.8 15.1   239   893   9437
## 219 219             Lackawanna PA   459  219039 24.3 19.8   429  1136   4368
## 220 220              Galveston TX   399  217399 26.9 10.5   950  1592  18586
## 221 221         San_Luis_Obispo CA  3305  217162 31.4 14.1   424   522   8103
## 222 222                Chatham GA   440  216935 28.5 12.8   494  1112  18732
## 223 223 Prince_William_County VA   338  215686 32.3  3.0   196   153   9001
## 224 224                   Lake OH   228  215499 26.4 12.0   233   359   5481
## 225 225              Lancaster NE   839  213641 33.9 10.8   389   778  16414
## 226 226             St._Charles MO   561  212907 29.0  6.9   172   613   7785
## 227 227                 Broome NY   707  212160 28.6 15.0   460   816   7435
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## 228 228             Saginaw MI  809 211946 25.5 12.0  335 1193 16190
## 229 229             Manatee FL  741 211707 21.0 28.1  322  855 16916
## 230 230          Montgomery AL  790 209085 28.4 11.6  419 1102 17388
## 231 231              Greene MO  675 207949 31.0 13.3  490 1785 13551
## 232 232             Kanawha WV  903 207619 23.9 15.7  569 1342 10246
## 233 233                 Ada ID 1055 205775 27.6 10.4  367  557  9701
## 234 234          Washington PA  857 204584 23.7 17.5  236  687  4526
## 235 235           St._Louis MN 6226 198213 24.3 16.9  406 1391  7518
## 236 236          Cumberland PA  550 195257 28.6 13.4  375  733  5247
## 237 237              Marion FL 1579 194833 21.6 22.1  235  451 14860
## 238 238               Brown WI  529 194594 29.6 10.8  289  632  8101
## 239 239                Leon FL  667 192493 38.5  8.2  413  823 23363
## 240 240            Brazoria TX 1387 191707 28.7  7.8  156  318  8692
## 241 241                Bell TX 1059 191088 34.6  8.8  513  572 10865
## 242 242              Kitsap WA  396 189731 27.7 10.7  233  244  8996
## 243 243            Richmond GA  324 189719 31.1 10.0 1032 1787 17918
## 244 244            McLennan TX 1042 189123 30.0 13.6  301  560 16486
## 245 245              Yakima WA 4296 188823 25.1 13.0  231  518 15139
## 246 246               Davis UT  305 187941 26.2  6.1  166  248  6279
## 247 247              Ottawa MI  566 187768 28.9  9.8  163  313  6140
## 248 248              Howard MD  252 187328 29.8  6.1  695  208  9057
## 249 249          Barnstable MA  396 186605 22.1 22.0  336  384  7441
## 250 250             Larimer CO 2601 186136 32.1  9.6  278  409  8921
## 251 251              Beaver PA  435 186093 23.6 16.9  197  616  4088
## 252 252             McHenry IL  604 183241 26.3  9.4  160  371  4854
## 253 253              Peoria IL  620 182827 26.0 14.2  581 1219 12483
## 254 254          Montgomery TX 1044 182201 25.5  8.6  125  340  9469
## 255 255             Harford MD  440 182132 28.8  8.3  247  333  6735
## 256 256               Butte CA 1640 182120 28.2 17.3  327  625  8939
## 257 257             Clayton GA  143 182052 32.4  5.8  191  346 15419
## 258 258              Durham NC  291 181835 33.7 10.7 1944 1496 15477
## 259 259             Alachua FL  874 181596 40.1  9.3 1180 1096 18218
## 260 260            Saratoga NY  812 181276 28.4 10.3  215  221  5281
## 261 261            Muscogee GA  216 179278 30.6 10.8  360 1168 11454
## 262 262              Merced CA 1929 178403 28.2  9.2  185  337  8587
## 263 263            Sangamon IL  868 178386 25.8 13.8  600 1330 11929
## 264 264              Gaston NC  357 175093 27.3 12.1  142  368 11865
## 265 265              Racine WI  333 175034 26.0 12.0  234  532 11110
## 266 266            Buncombe NC  656 174821 24.8 16.1  469  725  9512
## 267 267           Cleveland OK  536 174253 33.9  6.7  217  319 12194
## 268 268          Litchfield CT  920 174092 25.4 14.1  278  411  3593
## 269 269           Champaign IL  997 173025 41.6  8.8  382  805 11508
## 270 270              Placer CA 1404 172796 23.5 12.0  329  322  8904
## 271 271           Jefferson MO  657 171380 28.5  8.3   61  230  3128
## 272 272    Arlington_County VA   26 170936 37.6 11.3  615  781 12526
## 273 273   Newport_News_City VA   68 170045 33.9  9.3  354  836 11776
## 274 274           Calcasieu LA 1071 168134 26.6 10.9  248  845  6399
## 275 275           Lexington SC  701 167611 27.8  8.9  145  259  9814
## 276 276            Harrison MS  581 165365 30.0 10.8  313  764  7043
## 277 277              Ulster NY 1127 165304 27.8 13.0  258  413  4701
## 278 278         Vanderburgh IN  235 165058 27.0 15.7  411 1376  8405
```

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## 279 279          Lafayette LA  270 164762 31.1  8.3  361 1018 10599
## 280 280               York ME  991 164587 26.4 12.6  172  404  6027
## 281 281            Cambria PA  688 163029 23.0 18.7  301  892  3187
## 282 282          Wyandotte KS  151 161993 27.4 13.0  494 1019 18902
## 283 283            Berrien MI  571 161378 25.2 13.7  199  688 12229
## 284 284           Thurston WA  727 161238 25.3 11.7  283  500  7882
## 285 285               Kent RI  170 161135 26.2 15.1  264  359  7302
## 286 286            Shawnee KS  550 160976 26.2 13.1  451  661 13845
## 287 287           Muskegon MI  509 158983 25.8 13.0  182  660 12181
## 288 288              Weber UT  576 158330 26.0 11.1  266  573  9191
## 289 289            Elkhart IN  464 156198 26.8 11.2  164  478  7573
## 290 290         Rensselaer NY  654 154429 29.8 13.2  213  616  5297
## 291 291               Clay MO  397 153411 28.3 10.4  108  693 11085
## 292 292         Schuylkill PA  779 152585 22.9 20.0  147  634  2119
## 293 293               Lake FL  953 152104 19.0 27.5  167  664  7099
## 294 294            Collier FL 2026 152099 22.4 22.8  282  431  9426
## 295 295             Butler PA  789 152013 27.0 13.5  127  261  3420
## 296 296    Chesapeake_City VA  341 151976 28.6  8.4  212  210  8427
## 297 297              Smith TX  929 151309 26.2 13.7  349  795 11712
## 298 298         Tuscaloosa AL 1325 150522 33.3 11.4  299  731 12377
## 299 299          Frederick MD  663 150208 28.7  9.4  172  241  4939
## 300 300           Clermont OH  452 150187 28.1  8.7   82  151  5114
## 301 301          St._Lucie FL  573 150171 22.9 21.0  176  425  9842
## 302 302               Bibb GA  250 149967 27.5 12.9  438 1010 12701
## 303 303             Onslow NC  767 149838 49.7  4.4  104  133  7505
## 304 304            Jackson MI  707 149756 27.1 12.3  127  573  8630
## 305 305        Schenectady NY  206 149285 26.1 16.5  403  721  6364
## 306 306        Rock_Island IL  427 148723 24.9 15.0  209  769  7154
## 307 307              Clark OH  400 147548 25.3 13.8  173  463 10131
## 308 308             Shasta CA 3786 147036 22.8 14.1  267  468  7336
## 309 309          Penobscot ME 3396 146601 30.0 11.5  268  598  4749
## 310 310          Hampshire MA  529 146568 38.2 11.6  348  236  2547
## 311 311            Jackson OR 2785 146389 22.1 16.2  263  522  7170
## 312 312         Washington MN  392 145896 26.5  6.6  113   92  5365
## 313 313          St._Clair MI  725 145607 25.9 12.3  143  431  6568
## 314 314            Fayette PA  790 145351 22.9 18.0  124  409  3612
## 315 315           Anderson SC  718 145196 25.5 13.6  199  456  7525
## 316 316        St._Tammany LA  854 144508 24.2  8.9  282  512  4447
## 317 317              Horry SC 1134 144053 28.2 12.7  175  505 12459
## 318 318           Okaloosa FL  936 143776 30.8  9.3  178  482  5153
## 319 319           Sullivan TN  413 143596 24.6 14.3  377  982  6236
## 320 320          Middlesex CT  369 143196 28.4 13.1  340  235  3409
## 321 321            Portage OH  492 142585 33.6  9.4  101  285  2769
## 322 322           Ouachita LA  611 142191 28.3 11.2  268 1043 10605
## 323 323             Kenton KY  163 142031 28.3 11.5  263  733  6925
## 324 324         Chautauqua NY 1062 141895 25.7 15.7  164  653  5178
## 325 325               Yolo CA 1012 141092 36.5  9.6  339  168 10650
## 326 326          Outagamie WI  640 140510 28.2 11.1  228  511  4860
## 327 327          Winnebago WI  439 140320 30.3 12.8  242  528  6170
## 328 328         Williamson TX 1124 139551 29.1  7.6   88  185  5724
## 329 329               Rock WI  721 139510 26.2 12.6  171  491  7643
```

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## 330 330        Berkshire MA  931  139352 26.0 16.9   375   598   3862
## 331 331       Cumberland NJ  489  138053 26.7 13.5   181   534   9071
## 332 332           Greene OH  415  136731 28.5  9.8   134   210   5221
## 333 333          Calhoun MI  709  135982 25.1 13.3   172   566   9810
## 334 334         Dona_Ana NM 3807  135510 31.4  8.8   171   240   8850
## 335 335     Hampton_City VA   52  133793 33.0  9.6   163   251   8376
## 336 336           Monroe MI  551  133600 26.1 10.4    83   182   6726
## 337 337             Webb TX 3357  133239 28.5  7.9   107   382  12202
## 338 338             Weld CO 3993  131821 29.6 10.2   172   281   7901
## 339 339       Chittenden VT  539  131761 35.8  8.1   696   573   4739
## 340 340          Rapides LA 1323  131556 26.8 12.0   246   768   6101
## 341 341             York SC  683  131497 28.7 10.6   121   276   9525
## 342 342           Sussex NJ  521  130943 26.3  8.9   133   261   3174
## 343 343          Madison IN  452  130669 25.5 14.0   140   655   5373
## 344 344       Tippecanoe IN  500  130598 42.3  9.5   232   635   6141
## 345 345            Blair PA  526  130542 23.7 17.0   213   654   3196
## 346 346           McLean IL 1184  129180 37.0 10.5   171   588   5949
## 347 347           Porter IN  418  128932 26.4  9.8   170   379   4014
## 348 348          Tolland CT  410  128699 33.9  9.0   164   173   1799
## 349 349          Licking OH  687  128300 26.2 11.8   101   192   1380
## 350 350          Kenosha WI  273  128181 27.5 12.6   140   334   6616
## 351 351          Whatcom WA 2120  127780 28.8 12.5   203   214   7070
## 352 352              Bay FL  764  126994 27.7 12.0   178   478   8634
## 353 353         Davidson NC  552  126677 26.9 12.0    78   221   5662
## 354 354         Richland OH  497  126137 25.0 12.9   144   463   7977
## 355 355        El_Dorado CA 1712  125995 23.0 11.8   147   163   5152
## 356 356        Minnehaha SD  809  123809 29.7 11.6   376   912   5625
## 357 357           Centre PA 1108  123786 45.0  9.0   178   270   4136
## 358 358         Tazewell IL  649  123692 23.9 13.2    98   297   3140
## 359 359          Carroll MD  449  123372 26.6 10.2   142   123   3430
## 360 360           Pueblo CO 2389  123051 24.1 15.2   259   555   8640
## 361 361          Wichita TX  628  122378 29.5 12.8   243   457  10727
## 362 362           Medina OH  422  122354 24.5  9.7   125   226    563
## 363 363           Brazos TX  586  121862 49.4  6.7   170   279   8203
## 364 364           Oswego NY  953  121771 29.8 10.7    79   269   3582
## 365 365         Franklin PA  772  121082 25.5 14.4   136   296   3155
## 366 366           Mercer PA  672  121003 24.5 17.2   150   653   2777
## 367 367            Aiken SC 1073  120940 26.7 11.4   128   191   6835
## 368 368           Hawaii HI 4028  120317 22.5 12.6   182   391   7226
## 369 369      New_Hanover NC  199  120284 29.0 12.5   297   554  11892
## 370 370        Merrimack NH  935  120005 27.7 12.1   237   368   3325
## 371 371         Delaware IN  393  119659 32.9 12.7   217   494   1064
## 372 372           Taylor TX  916  119655 30.7 12.0   204   467   6785
## 373 373         Humboldt CA 3573  119118 27.5 12.3   207   311   5737
## 374 374            Ector TX  901  118934 27.1  9.3   153   389  14643
## 375 375          Stearns MN 1345  118791 33.6 10.5   199   661   4101
## 376 376         Lycoming PA 1235  118710 25.4 15.1   232   668   3826
## 377 377       Rutherford TN  619  118570 33.1  8.4   133   215   6072
## 378 378          Catawba NC  400  118412 27.2 11.9   179   464   6830
## 379 379            Macon IL  581  117206 24.1 14.5   171   725   6103
## 380 380            Pinal AZ 5370  116379 24.4 13.7    61   309   6275
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## 381 381          Calhoun AL  609 116034 28.8 12.4  133  486 4901
## 382 382         Kennebec ME  868 115904 26.1 13.4  241  497 4184
## 383 383       Livingston MI  568 115645 25.3  8.2   68   93 3760
## 384 384         Marathon WI 1545 115400 25.9 12.7  172  254 3655
## 385 385          Jackson MS  727 115243 25.9  9.4  170  346 4777
## 386 386         Florence SC  799 114344 26.2 11.2  211  731 8421
## 387 387          Lebanon PA  362 113744 25.3 15.0  162  196 2919
## 388 388      Yellowstone MT 2635 113419 25.6 12.4  262  554 3879
## 389 389       Washington AR  950 113409 32.0 11.2  208  651 6122
## 390 390             Wood OH  617 113269 34.5 10.2  128  124 3759
## 391 391           Benton WA 1703 112560 25.1 10.1  142  278 6249
## 392 392            Boone MO  685 112379 40.9  8.4  746 1023 5456
## 393 393      St._Lawrence NY 2686 111974 31.2 12.1  132  378 3851
## 394 394              Bay MI  444 111723 25.4 13.4  101  415 4849
## 395 395         Comanche OK 1069 111486 34.5  8.7  127  347 5979
## 396 396   Alexandria_City VA   15 111183 38.3 10.3  652  662 8537
## 397 397             Kent DE  591 110993 29.7 10.3  123  193 5846
## 398 398        Charlotte FL  694 110975 16.6 33.8  183  632 3741
## 399 399        Jefferson NY 1272 110943 32.7 10.9  124  336 3064
## 400 400             Napa CA  754 110765 24.5 16.5  345 1019 5056
## 401 401            Rowan NC  511 110605 26.0 15.2  114  244 5233
## 402 402       Washington RI  333 110006 31.0 12.3  162  241 3838
## 403 403            Allen OH  405 109755 26.2 13.4  168  560 4734
## 404 404         Imperial CA 4175 109303 25.5 10.2   82  221 8042
## 405 405           Monroe IN  394 108978 45.8  8.6  172  285 1657
## 406 406         Hamilton IN  398 108936 25.1  8.2  257  122 1699
## 407 407       Columbiana OH  533 108276 23.4 14.9   80  485  898
## 408 408         Alamance NC  431 108213 27.3 14.8  132  340 4152
## 409 409             Pitt NC  652 107924 35.4  9.9  496  583 4603
## 410 410        Hunterdon NJ  430 107776 25.6  9.5  184  182 2068
## 411 411          Osceola FL 1322 107728 27.1 13.9   98  291 9665
## 412 412          Yavapai AZ 8124 107714 18.3 23.8  114  159 3952
## 413 413         La_Porte IN  598 107066 26.0 13.1  149  519 6021
## 414 414         La_Salle IL 1135 106913 23.8 17.2  104  504 2982
## 415 415             Yuma AZ 5514 106895 27.4 13.8  118  197 5414
## 416 416          Midland TX  900 106611 26.8  9.0  139  333 7546
## 417 417         Randolph NC  788 106546 27.1 12.2   69  145 2940
## 418 418          Olmsted MN  653 106470 29.3 10.0 1814 1437 4310
## 419 419             Vigo IN  403 106107 30.2 15.1  179  576 3435
## 420 420             Clay FL  601 105986 26.3  8.5  164  277 4560
## 421 421      Androscoggin ME  470 105259 27.9 13.4  198  527 4020
## 422 422          Robeson NC  949 105179 26.7 10.7   83  281 4318
## 423 423            Gregg TX  274 104948 26.4 13.3  166  420 9181
## 424 424            Wayne NC  553 104666 29.7 10.2  113  263 4682
## 425 425        Strafford NH  369 104233 34.8 10.7  139  237 3651
## 426 426        Sheboygan WI  514 103877 25.4 14.6  114  421 4433
## 427 427        Fairfield OH  506 103461 25.2 11.3   86  195  625
## 428 428           Sumner TN  529 103281 25.5 10.2   96  259 3285
## 429 429             Cass ND 1766 102874 34.4  9.8  343  643 3401
## 430 430           Sumter SC  666 102637 31.6  9.4   88  214 7138
## 431 431            Sarpy NE  241 102583 30.4  4.8   39  160 2689
```

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## 432 432              Windham CT   513  102525 28.5 12.5   123   254   1397
## 433 433                Kings CA  1390  101469 33.7  7.7    82   180   4449
## 434 434                Wayne OH   555  101461 26.3 11.6    84   155   2377
## 435 435              Charles MD   461  101154 29.9  6.5    67   104   5279
## 436 436             Hernando FL   478  101115 16.4 30.7    98   290   4414
## 437 437               Martin FL   556  100900 20.4 27.5   193   277   5081
## 438 438           Montgomery TN   539  100498 35.7  7.9    87   188   6537
## 439 439                 Maui HI  1159  100374 26.2 11.3   192   182   7130
## 440 440               Morgan AL   582  100043 26.3 11.7   122   464   4693
##       V11  V12  V13  V14   V15    V16 V17
## 1    70.0 22.3 11.6  8.0 20786 184230   4
## 2    73.4 22.8 11.1  7.2 21729 110928   2
## 3    74.9 25.4 12.5  5.7 19517  55003   3
## 4    81.9 25.3  8.1  6.1 19588  48931   4
## 5    81.2 27.8  5.2  4.8 24400  58818   4
## 6    63.7 16.6 19.5  9.5 16803  38658   1
## 7    81.5 22.1  8.8  4.9 18042  38287   4
## 8    70.0 13.7 16.9 10.0 17461  36872   2
## 9    65.0 18.8 14.2  8.7 17823  34525   3
## 10   77.1 26.3 10.4  6.1 21001  38911   3
## 11   64.3 15.2 16.1  8.0 16721  26512   1
## 12   88.2 32.8  5.0  4.6 23779  35843   4
## 13   82.0 32.6  5.0  5.5 25193  37728   4
## 14   75.4 14.9 10.3  8.0 16399  23260   4
## 15   74.0 20.1 11.0  5.5 21086  29776   2
## 16   84.3 35.4  4.2  7.3 25312  35398   1
## 17   79.0 22.6  8.7  5.3 20681  27639   1
## 18   82.2 23.0  3.3  7.0 24262  32071   1
## 19   84.2 30.0  2.5  5.1 31679  40782   1
## 20   81.4 28.8  8.1  5.3 22148  28331   4
## 21   76.8 18.8  7.1  7.4 22355  28066   3
## 22   72.7 19.7 16.2  6.7 15508  18383   3
## 23   74.1 14.6  8.4 10.7 17185  20114   4
## 24   79.9 24.0  8.2  6.6 18825  22027   3
## 25   84.6 30.2  4.4  7.3 26884  29131   2
## 26   82.2 23.0  9.8  6.3 18934  19714   4
## 27   88.2 31.6  6.4  4.3 23705  24474   2
## 28   82.3 29.2  4.0  5.1 24219  24062   2
## 29   76.4 20.0  9.4  6.8 18305  17729   1
## 30   81.0 26.6  9.1  4.2 19040  18306   2
## 31   76.3 19.3 12.6  4.9 18431  17680   2
## 32   81.0 35.3  4.7  5.4 33330  29159   1
## 33   75.6 23.7 10.3  4.5 20580  17827   2
## 34   78.8 22.1  6.2  8.4 26798  23141   3
## 35   77.7 25.8  6.0  6.9 24875  21188   1
## 36   78.1 18.5  6.2  6.2 21610  18404   3
## 37   81.2 24.6  5.4  2.3 21307  17818   4
## 38   75.6 20.2  9.5  6.0 16876  14075   3
## 39   81.0 34.2  4.5  5.9 32342  26768   1
## 40   75.1 20.8 14.7  5.4 18430  15229   3
## 41   81.6 31.7  2.7  5.2 32230  26602   1
```

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## 42  91.4 49.0  2.2  3.2 28999  23738   3
## 43  77.5 24.2  6.0  7.3 22197  17851   1
## 44  86.5 31.6  5.5  5.6 25523  20514   4
## 45  76.8 21.4  9.3  5.0 19148  15264   2
## 46  88.6 36.0  1.7  4.8 26772  20927   2
## 47  70.1 24.0 11.3  7.9 24523  19084   1
## 48  90.6 49.9  2.7  3.3 30081  22772   3
## 49  77.3 13.8  7.5  5.8 18625  13810   4
## 50  60.7 15.5 17.8  9.4 17263  12706   3
## 51  83.2 25.5  3.7  5.0 19568  14270   3
## 52  85.3 23.8  7.7  4.5 15399  11179   4
## 53  78.0 35.0  9.7  5.6 28532  20656   4
## 54  76.9 13.5  4.0  9.4 20924  15011   2
## 55  80.1 26.3  7.7  4.4 21641  15451   1
## 56  77.4 22.2  6.3 10.2 19895  14120   1
## 57  78.4 25.0  3.8  5.7 23470  16244   3
## 58  83.8 32.1  2.2  5.0 28462  19300   1
## 59  78.8 21.2  7.8  6.6 17879  12113   3
## 60  76.9 18.4  9.8  6.6 17662  11886   3
## 61  79.4 26.5  3.4  5.7 24896  16725   1
## 62  80.2 25.9  7.5  9.0 22834  15301   1
## 63  79.4 23.0  5.0  7.0 21420  14330   4
## 64  66.2 16.9 16.8 12.6 16365  10923   4
## 65  80.5 23.3 12.0  3.9 15191  10131   4
## 66  74.1 19.3 10.9  6.3 19140  12727   3
## 67  75.4 27.7 14.4  8.7 23150  15369   1
## 68  73.8 19.9 12.7  5.3 18624  12134   3
## 69  84.1 31.3  4.3  4.2 28819  18721   4
## 70  77.8 31.6 15.4  5.3 22819  14808   3
## 71  79.5 20.0  9.8  6.5 18611  11785   2
## 72  88.0 34.4  3.1  7.5 26909  16578   1
## 73  73.1 33.3 13.3  7.7 23603  14325   3
## 74  79.1 22.6 11.3  6.0 17741  10638   3
## 75  67.0 18.3  8.9  9.0 17866  10653   1
## 76  63.7 15.2 22.4 10.8 11545   6830   3
## 77  83.2 17.5  8.7  6.4 16194   9493   4
## 78  82.9 23.7  8.9  5.1 19215  11219   4
## 79  83.4 34.7 10.2  4.8 18340  10571   3
## 80  77.8 20.0  9.8  5.7 18410  10564   2
## 81  82.8 28.4  3.4  5.8 27391  15151   1
## 82  64.1 19.7 12.4  9.0 18463  10212   1
## 83  81.4 24.8  5.0  5.3 23658  12956   1
## 84  83.9 32.7  7.2  4.4 21005  11465   3
## 85  67.6 13.3 13.7 11.8 15881   8631   4
## 86  82.9 24.8  2.9  6.7 22548  12202   1
## 87  84.7 32.0  3.7  4.6 27378  14138   2
## 88  78.3 19.7  9.5  6.0 18583   9570   2
## 89  81.6 28.3  7.2  4.8 20942  10710   3
## 90  75.9 24.4 10.0  4.6 19505   9963   3
## 91  65.0 15.9  7.4 12.3 18521   9378   1
## 92  81.7 23.7 10.0  6.1 19295   9712   3
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## 93  75.5 21.0  8.0  6.9 19930  10021   1
## 94  80.3 20.7  6.9  7.5 18674   9349   2
## 95  68.1 22.4 27.3  6.1 16578   8238   3
## 96  75.2 25.0  5.3  6.9 26248  12962   1
## 97  85.0 28.8  8.1  4.3 20303   9862   2
## 98  68.6 13.2 12.0 12.0 15453   7427   4
## 99  82.1 26.7 10.9  5.2 17518   8419   4
## 100 73.5 12.8 11.7  7.1 16327   7765   2
## 101 80.7 24.4  7.1  5.6 19401   9099   1
## 102 79.2 29.0 13.1  5.4 22156  10360   4
## 103 85.7 19.3  4.9  5.6 18545   8635   4
## 104 76.2 17.0 12.0  8.8 17815   8237   2
## 105 73.6 17.6 10.9  9.6 19073   8703   1
## 106 68.8 18.7  7.6  8.1 21973   9955   1
## 107 76.0 18.8 11.4  5.6 17101   7666   3
## 108 85.8 33.0  3.8  4.1 21933   9820   3
## 109 80.6 25.2  5.0  6.2 22284   9848   1
## 110 89.8 30.7  4.1  4.1 20997   9206   4
## 111 83.8 22.2  5.3 10.4 21500   9358   1
## 112 74.9 15.3  4.3  7.4 20974   9086   1
## 113 76.8 12.8 14.0 12.6 16829   7244   2
## 114 81.1 24.6  3.0  5.0 22797   9740   3
## 115 85.4 35.3  5.5  3.5 20658   8746   3
## 116 70.5 16.7  5.3  5.3 18878   7982   1
## 117 87.0 36.7  1.8  5.1 31520  13281   1
## 118 84.5 24.9  8.1  2.9 19629   8174   2
## 119 68.0 12.9  9.4 10.1 14835   6014   3
## 120 82.4 22.2  8.3  4.5 19276   7781   2
## 121 82.3 20.4  6.3  7.1 17668   7049   3
## 122 88.3 25.8  8.1  6.1 16807   6673   4
## 123 62.8 15.3 20.6  9.0 18113   7185   2
## 124 81.9 23.6  3.1  5.6 23008   9090   1
## 125 88.0 25.5  4.3  5.4 17697   6956   3
## 126 91.5 35.2  4.4  3.9 22507   8812   4
## 127 84.4 24.5  5.2  5.7 22055   8562   4
## 128 46.6 11.5 36.3 17.6  8899   3413   3
## 129 80.5 27.5 15.1  5.4 17881   6797   3
## 130 70.1 15.5 17.5  7.2 14389   5448   3
## 131 84.9 34.7  3.0  4.6 24732   9309   1
## 132 75.4 14.8  7.9  6.9 15648   5801   3
## 133 68.4 13.0 11.4 14.3 15238   5646   4
## 134 77.7 15.4  8.6  6.9 17069   6321   1
## 135 80.0 26.6  7.4  6.0 21902   8095   4
## 136 76.0 14.3  8.9  6.9 16898   6211   2
## 137 88.9 34.2  4.8  3.1 20087   7374   2
## 138 84.4 20.6  9.8  6.2 16365   5914   4
## 139 80.4 18.0  4.5  7.4 18787   6713   2
## 140 72.9 21.5  8.5 10.9 19465   6923   4
## 141 92.9 40.5  2.5  3.3 26156   9287   2
## 142 86.7 29.6  2.9  4.0 19861   7009   3
## 143 79.0 23.5 10.5  5.8 18225   6373   3
```

```
## 144 76.1 24.8  7.3  5.4 20349   7070   3
## 145 82.7 18.7  6.0  7.0 17268   5878   4
## 146 72.8 13.9  4.3  6.2 19502   6622   1
## 147 70.0 15.1  5.2  6.7 19655   6614   1
## 148 82.2 26.4  4.0  7.5 22581   7589   1
## 149 74.6 23.9 10.2  4.6 17382   5836   3
## 150 76.9 16.4  6.1  6.4 18877   6326   3
## 151 72.0 13.1  8.3  8.8 16405   5383   1
## 152 77.1 29.5  5.3  5.5 26026   8480   1
## 153 71.6 21.0  7.8  4.9 17874   5723   3
## 154 77.7 21.4  5.0  7.5 21684   6884   2
## 155 60.2 11.8 18.0 17.1 14710   4588   4
## 156 88.2 29.8  4.8  4.4 19932   6210   4
## 157 77.2 19.5  6.4  6.7 19788   6088   1
## 158 88.0 27.1  2.2  4.1 23004   7010   2
## 159 81.2 19.0  5.6  5.9 19123   5753   2
## 160 75.5 22.4 13.8  4.9 16015   4725   3
## 161 80.9 28.3  6.0  4.5 21003   6145   1
## 162 76.0 18.7  7.6  6.6 16750   4882   2
## 163 68.9 17.0 17.2  7.7 15124   4403   3
## 164 74.6 19.6  4.9  6.6 19785   5760   1
## 165 84.6 26.3  5.3  6.1 17885   5142   3
## 166 79.4 28.0 10.1  4.6 17137   4896   3
## 167 72.5 19.7 10.2  5.9 18242   5209   3
## 168 87.2 41.9  6.4  6.0 22782   6446   2
## 169 83.0 22.2  9.4  6.5 15701   4442   4
## 170 83.9 29.2 11.0  6.9 17458   4922   2
## 171 66.9  9.1  7.9  8.3 13944   3920   3
## 172 85.7 23.6  4.7  4.2 19942   5561   4
## 173 81.3 21.9  4.6  5.1 24948   6930   3
## 174 77.5 16.2  9.5  7.1 16331   4500   1
## 175 90.7 27.6  3.3  4.7 21123   5814   2
## 176 80.3 16.6 12.1  6.4 12923   3548   3
## 177 86.8 32.3  4.5  5.6 17801   4869   3
## 178 75.3 12.3  9.1  9.5 16006   4340   2
## 179 77.6 24.1  7.8  4.4 20645   5489   3
## 180 83.3 33.0  4.1  5.3 26757   7103   1
## 181 78.8 13.0  8.8  5.0 16116   4271   4
## 182 74.6 14.0 12.8  6.7 16256   4305   2
## 183 88.3 39.1  3.9  5.9 22303   5889   3
## 184 87.9 26.2 10.6  4.3 11467   3023   4
## 185 72.6 14.7 13.9  8.4 16190   4256   2
## 186 76.2 18.2 13.3  5.8 15392   4045   3
## 187 72.7 16.8 15.1  6.4 16412   4287   3
## 188 50.0 12.0 33.7 12.5  9728   2530   3
## 189 79.8 24.8  3.6  5.1 22173   5753   1
## 190 80.9 21.8  4.7  6.8 20259   5165   1
## 191 82.5 20.7  6.3  5.0 21327   5431   4
## 192 75.2 26.4 16.7  6.3 16215   4126   3
## 193 76.3 16.7  7.7  7.9 18376   4648   2
## 194 75.1 16.7  8.8  6.7 16477   4133   1
```

```
## 195 75.8 14.4  8.5  7.9 17980   4481   2
## 196 73.4 18.2 19.1  7.1 16337   4056   3
## 197 73.1 16.7  4.9  6.8 18336   4531   1
## 198 76.1 19.2  7.1  5.7 17211   4252   2
## 199 86.2 25.9  3.2  8.0 21770   5352   1
## 200 85.0 27.6  5.7  5.7 21362   5194   1
## 201 86.3 38.3  1.4  4.1 33180   7972   1
## 202 74.4 15.5 15.5  6.7 17418   4170   3
## 203 80.2 30.1  8.4  5.2 18990   4537   3
## 204 83.9 16.8  7.0  6.6 16790   3997   4
## 205 77.6 18.6  7.2  5.5 18348   4363   1
## 206 91.9 44.0  3.0  4.0 37541   8638   4
## 207 77.5 18.1  4.7  7.1 18523   4262   1
## 208 81.9 29.7  6.2  8.0 22025   5060   4
## 209 78.7 17.5  9.4  5.7 16022   3661   4
## 210 75.2 11.4  9.4  7.9 16144   3678   2
## 211 63.0 14.3  8.8  5.5 15776   3578   3
## 212 80.9 30.2  6.9  3.8 18301   4125   3
## 213 80.2 30.6 10.2  3.8 19320   4354   3
## 214 91.3 42.1  5.6  3.5 21421   4827   4
## 215 72.9 16.4  6.4  8.3 24035   5392   1
## 216 83.4 27.1  8.9  5.9 18288   4086   2
## 217 74.2 23.4 13.2  5.6 15443   3438   3
## 218 75.8 13.6  8.6  8.3 16647   3675   1
## 219 73.3 14.8  7.8  7.9 16963   3716   1
## 220 75.8 19.3 12.5  7.0 17744   3858   3
## 221 83.3 22.9  6.8  5.8 17221   3740   4
## 222 73.7 18.6 13.6  4.3 17776   3856   3
## 223 87.8 27.6  2.3  4.3 20543   4431   3
## 224 81.1 17.5  3.6  5.7 19692   4244   2
## 225 88.1 27.6  6.0  2.2 17816   3806   2
## 226 83.3 21.2  3.5  6.4 18753   3993   2
## 227 78.9 20.7  6.5  5.9 18058   3831   1
## 228 74.8 13.0 14.7  8.8 16904   3583   2
## 229 75.6 15.5  6.8  5.8 17997   3810   3
## 230 75.3 24.2 14.1  5.9 17469   3653   3
## 231 78.9 20.7  9.2  4.8 16630   3458   2
## 232 72.4 17.6 12.3  7.5 17192   3569   3
## 233 87.2 24.9  6.2  4.1 18786   3866   4
## 234 73.2 13.6  9.7  7.0 16625   3401   1
## 235 80.3 17.3  9.7  6.5 15419   3056   2
## 236 81.0 22.9  2.8  4.6 19254   3759   1
## 237 69.6 11.5 10.8  8.6 13802   2689   3
## 238 82.6 17.7  6.7  4.6 18490   3598   2
## 239 84.9 37.1  9.4  3.9 16422   3161   3
## 240 75.5 15.1  7.7  5.6 17951   3441   3
## 241 79.1 17.2 12.2  6.7 13536   2587   3
## 242 86.6 19.8  7.5  5.2 17009   3227   4
## 243 70.9 17.3 14.8  4.9 15941   3024   3
## 244 71.6 16.6 13.9  6.4 14925   2823   3
## 245 66.1 13.7 15.6 11.6 15374   2903   4
```

```
## 246 89.9 23.5  5.5  4.5 13394   2517   4
## 247 79.8 18.7  3.8  6.5 18360   3447   2
## 248 91.1 46.9  2.2  4.1 27546   5160   3
## 249 88.4 28.1  5.8 11.1 23267   4342   1
## 250 88.6 32.3  6.6  4.1 17140   3190   4
## 251 74.9 11.9 10.8  9.7 15162   2822   1
## 252 84.5 21.0  2.5  7.1 21855   4005   2
## 253 77.9 19.5 11.3  7.2 18342   3353   2
## 254 75.5 19.4  9.4  5.5 17084   3113   3
## 255 81.6 21.5  4.1  6.7 20941   3814   3
## 256 77.6 19.5 12.2  9.4 15051   2741   4
## 257 77.2 14.7  7.3  5.8 16171   2944   3
## 258 78.9 33.4  8.7  3.6 19238   3498   3
## 259 82.7 34.6 14.4  4.2 16058   2916   3
## 260 83.0 25.2  4.4  5.9 18857   3418   1
## 261 71.5 16.6 14.9  4.6 15505   2780   3
## 262 63.1 12.0 15.4 14.6 13961   2491   4
## 263 81.8 22.4  7.2  4.8 19601   3497   2
## 264 60.9 10.8  8.2  6.2 16319   2857   3
## 265 76.4 16.5  7.9  6.5 18426   3225   2
## 266 74.5 19.1  8.2  4.9 16934   2960   3
## 267 83.9 25.9  7.0  4.8 14443   2517   3
## 268 80.9 25.0  2.4  7.0 25161   4380   1
## 269 87.5 34.1  8.0  4.5 16957   2934   2
## 270 85.1 22.7  5.3  6.8 20168   3485   4
## 271 71.6  9.0  6.0  8.7 15896   2724   2
## 272 87.5 52.3  4.3  3.6 30242   5169   3
## 273 79.3 18.4 12.2  6.5 15327   2606   3
## 274 70.3 14.7 15.5  7.8 14968   2517   3
## 275 77.3 21.0  6.3  4.1 18126   3038   3
## 276 74.7 16.3 15.4  6.7 13691   2264   3
## 277 76.6 21.6  5.6  5.9 18824   3112   1
## 278 75.2 16.0  9.1  5.7 18093   2986   2
## 279 73.3 22.5 16.2  5.0 16868   2779   3
## 280 79.5 19.0  4.7  6.9 17908   2947   1
## 281 71.2 10.8 11.2  9.2 14473   2360   1
## 282 69.9 10.3 13.9  7.4 14134   2290   2
## 283 74.7 16.7 11.6  9.1 16232   2619   2
## 284 86.5 24.7  7.1  5.9 17312   2791   4
## 285 76.8 20.5  3.7  8.6 20086   3237   1
## 286 84.4 22.3  7.4  4.7 19558   3148   2
## 287 74.2 11.1 12.4 12.0 14767   2348   2
## 288 82.5 18.0  7.8  5.7 15301   2423   4
## 289 72.8 14.2  5.3  6.4 16770   2619   2
## 290 77.7 19.5  6.6  6.3 17774   2745   1
## 291 84.7 20.0  4.2  5.7 18395   2822   2
## 292 68.4  8.1  7.7  9.7 15853   2419   1
## 293 70.6 12.7  7.9  8.9 17496   2661   3
## 294 79.0 22.3  6.4  7.5 25589   3892   3
## 295 78.6 15.6  7.1  6.8 17251   2622   1
## 296 77.1 16.9  7.0  6.1 16924   2572   3
```

```
## 297 75.7 19.8 12.6  6.6 17511   2650   3
## 298 69.6 20.0 13.5  5.4 15113   2275   3
## 299 80.4 22.0  3.5  6.0 19954   2997   3
## 300 72.8 14.5  7.4  6.0 16231   2438   2
## 301 71.7 13.1  8.5 13.8 14137   2123   3
## 302 68.2 17.0 15.9  4.1 17548   2632   3
## 303 83.0 13.4  9.8  5.6 10190   1527   3
## 304 77.7 12.9  9.4  9.9 15750   2359   2
## 305 80.7 23.0  5.7  5.6 20679   3087   1
## 306 77.4 15.0 10.2  7.5 17818   2650   2
## 307 73.4 12.2 10.4  6.5 16676   2461   2
## 308 78.4 13.7 11.0 10.3 16277   2393   4
## 309 79.1 17.7  9.5  8.0 15521   2275   1
## 310 83.0 31.9  5.7  7.7 17853   2617   1
## 311 80.1 17.6  9.7  7.6 15582   2281   4
## 312 90.0 26.2  3.6  4.6 20682   3017   2
## 313 74.8 10.7  9.2 11.8 17480   2545   2
## 314 67.8  9.3 17.6  9.4 14051   2042   1
## 315 64.0 12.9  8.6  6.6 14205   2063   3
## 316 76.9 23.1 11.1  6.2 17129   2475   3
## 317 74.3 16.0 11.6  7.7 14693   2117   3
## 318 83.8 21.0  7.8  6.7 15803   2272   3
## 319 66.8 15.6 10.4  4.4 15747   2261   3
## 320 82.6 28.2  2.6  5.8 24132   3456   1
## 321 79.3 17.6  7.6  6.0 16031   2286   2
## 322 71.6 18.9 19.6  6.4 13869   1972   3
## 323 74.4 17.0  8.2  5.4 16935   2405   3
## 324 74.4 14.2  9.9  7.7 15197   2156   1
## 325 79.1 30.3  9.8  7.2 19727   2783   4
## 326 81.5 16.7  4.6  4.9 17182   2414   2
## 327 80.6 18.2  5.3  4.8 17645   2476   2
## 328 81.4 24.6  7.6  3.8 14934   2084   3
## 329 78.2 13.3  7.8  9.7 16742   2336   2
## 330 77.9 20.9  6.3 10.1 20068   2797   1
## 331 63.4 10.8 10.2 10.7 16819   2322   1
## 332 82.4 26.0  7.1  5.2 18161   2483   2
## 333 76.8 13.8 11.0  8.5 15944   2168   2
## 334 70.4 21.9 20.7  7.4 11379   1542   4
## 335 79.7 19.1  8.8  6.8 14743   1973   3
## 336 74.1 10.5  6.9 11.1 17278   2308   2
## 337 47.8 11.1 33.1  9.8  8973   1196   3
## 338 74.9 18.4 10.6  4.5 15874   2093   4
## 339 86.7 34.0  5.0  4.4 19940   2627   1
## 340 69.0 14.6 18.6  7.1 14615   1923   3
## 341 67.5 16.9  7.6  5.5 16713   2198   3
## 342 85.1 24.9  2.5  6.8 24405   3196   1
## 343 73.5 11.7 10.3  7.5 16018   2093   2
## 344 85.2 30.7  6.8  3.2 15847   2070   2
## 345 75.0 10.5 11.0  9.0 14779   1929   1
## 346 84.7 29.0  5.9  4.6 18961   2449   2
## 347 82.4 18.5  4.6  4.5 17566   2265   2
```

```
## 348 84.7 29.2  2.7  5.9 21944   2824   1
## 349 76.4 13.0  8.3  6.3 16412   2106   2
## 350 75.1 12.7  7.6  6.4 17338   2222   2
## 351 83.2 22.0  7.4  6.3 16002   2045   4
## 352 74.7 15.7 11.2  8.0 14814   1881   3
## 353 64.2 10.0  7.3  5.9 15079   1910   3
## 354 73.5 11.6  8.4  9.4 16191   2042   2
## 355 85.9 20.8  5.8  6.1 19250   2425   4
## 356 83.1 21.3  5.4  2.5 18526   2294   2
## 357 83.6 32.3  6.2  6.1 15476   1916   1
## 358 78.6 13.6  7.1  7.4 18008   2227   2
## 359 78.5 19.6  2.5  5.7 22002   2714   3
## 360 73.9 14.0 16.7  7.0 14197   1747   4
## 361 75.1 16.5 12.5  6.8 17119   2095   3
## 362 82.4 18.0  4.1  5.8 18892   2312   2
## 363 79.8 35.8 14.9  3.6 12641   1540   3
## 364 74.7 12.9  8.1 10.0 14834   1806   1
## 365 69.4 12.4  5.7  6.7 16281   1971   1
## 366 75.1 13.6 10.1  7.2 15177   1836   1
## 367 70.7 17.2 11.0  4.9 17898   2165   3
## 368 77.7 18.5 10.9  4.0 16728   2013   4
## 369 78.1 21.2  9.9  5.9 17119   2059   3
## 370 83.2 25.4  3.6  7.1 20600   2472   1
## 371 74.5 16.5 10.3  6.1 15697   1878   2
## 372 75.4 20.7 11.2  5.9 16021   1917   3
## 373 80.5 20.0 12.8  8.8 16138   1922   4
## 374 66.9 11.4 16.6  6.6 14766   1756   3
## 375 78.3 17.5  7.3  5.4 14757   1753   2
## 376 74.5 12.3  8.4  8.0 15778   1873   1
## 377 73.9 18.7  7.6  5.4 15501   1838   3
## 378 66.7 14.2  4.8  6.4 17396   2060   3
## 379 76.2 14.8  9.8  8.9 18021   2112   2
## 380 65.5  8.2 18.7  7.9 11396   1326   4
## 381 67.4 14.2 11.7  7.3 13776   1598   3
## 382 78.9 18.1  7.3  6.8 17131   1986   1
## 383 85.6 19.6  3.0  8.1 21153   2446   2
## 384 75.9 13.5  5.5  5.9 16305   1882   2
## 385 74.4 14.4 14.0  7.1 13475   1553   3
## 386 64.3 14.8 15.9  5.9 14961   1711   3
## 387 70.0 11.8  5.2  5.9 16500   1877   1
## 388 83.7 21.5  9.0  5.3 17272   1959   4
## 389 73.2 20.0  9.8  3.7 14736   1671   3
## 390 83.8 21.9  5.0  6.6 17522   1985   2
## 391 83.9 23.3  8.9  6.8 17332   1951   4
## 392 84.8 36.5  9.3  3.2 17175   1930   2
## 393 73.1 15.1 12.8  9.8 12704   1423   1
## 394 74.0 11.0 10.2  9.2 16499   1843   2
## 395 81.1 18.4 13.3  6.6 13228   1475   3
## 396 86.9 48.5  4.7  4.6 31699   3524   3
## 397 73.1 15.0  8.7  7.6 14946   1659   1
## 398 75.7 13.4  5.2  7.2 16362   1816   3
```

```
## 399 76.4 13.6  9.5 11.0 15205   1687   1
## 400 80.7 22.3  4.6  5.9 22668   2511   4
## 401 66.0 11.7  6.8  5.4 15691   1736   3
## 402 82.8 29.1  3.7  6.7 19449   2140   1
## 403 76.1 11.4 10.4  7.3 16542   1816   2
## 404 53.2  9.7 20.8 21.3 14523   1587   4
## 405 82.1 32.9  9.5  3.7 14266   1555   2
## 406 88.7 36.2  2.6  2.8 25681   2798   2
## 407 71.8  8.5 13.0  6.7 12597   1364   2
## 408 67.9 14.6  6.0  4.5 17306   1873   3
## 409 71.0 21.9 15.5  5.5 15852   1711   3
## 410 85.9 34.6  1.8  4.1 30255   3261   1
## 411 73.7 11.2  6.9  6.7 16451   1772   3
## 412 78.9 17.7  9.8  5.4 13681   1474   4
## 413 73.9 11.7  7.8  5.8 16655   1783   2
## 414 73.1 10.5  8.7  9.6 16119   1723   2
## 415 64.9 12.7 15.4 17.8 11490   1228   4
## 416 76.8 26.4 11.5  5.4 19345   2062   3
## 417 62.0  9.1  6.5  4.8 14721   1568   3
## 418 88.0 29.5  4.5  3.3 20515   2184   2
## 419 76.0 18.1 10.7  5.0 15036   1595   2
## 420 81.2 17.9  5.4  5.9 16029   1699   3
## 421 71.8 12.6  8.7  9.7 16154   1700   1
## 422 57.0 11.0 20.7  8.9 10849   1141   3
## 423 75.8 17.7 13.4  8.2 16775   1761   3
## 424 71.2 12.7 11.9  7.3 13350   1397   3
## 425 79.8 21.7  5.1  6.5 17182   1791   1
## 426 77.4 13.8  4.5  5.6 18061   1876   2
## 427 78.8 15.5  6.8  6.3 16342   1691   2
## 428 70.6 14.4  7.0  6.8 16514   1706   3
## 429 87.1 26.5  7.3  2.5 16275   1674   2
## 430 69.8 15.0 16.9  9.4 11803   1211   3
## 431 91.0 25.4  3.5  2.6 16137   1655   2
## 432 71.1 16.8  6.0  9.2 18070   1853   1
## 433 65.6  9.0 15.0 12.8 13907   1411   4
## 434 73.6 13.9  8.4  5.9 16464   1670   2
## 435 81.0 16.2  3.7  4.9 19317   1954   3
## 436 70.5  9.7  7.9  8.2 13919   1407   3
## 437 79.7 20.3  5.0  9.8 27125   2737   3
## 438 77.9 16.5 10.8  8.0 13169   1323   3
## 439 77.0 17.8  5.7  3.2 18504   1857   4
## 440 69.4 15.5  9.4  7.1 16458   1647   3
```

```
CDI <- as.data.frame(CDI)
colnames(CDI) <- c("Identification number", "County", "State", "Land area", "Total
population", "Percent of population aged 18-34", "Percent of population 65 or older
", "Number of active physicians", "Number of hospital beds", "Total serious crimes"
, "Percent high school graduates", "Percent bachelor's degrees", "Percent below pov
erty level", "Percent unemployment", "Per capita income", "Total personal income",
"Geographic region")
dim(CDI)
```

```
## [1] 440  17
```

Part 1. *Fitting Regression Models*

Refer to the CDI data set in Appendix C.2. The number of active physicians in a CDI (*Y*) is expected to be related to total population, number of hospital beds, and total personal income. Assume that first-order regression model(1.1) is appropriate for each of the three predictor variables.

a. Regress the number of active physicians in turn on each of the three predictor variables. State the estimated regression functions.

```
Y <- CDI$`Number of active physicians`
X1 <- CDI$`Total population`
X2 <- CDI$`Number of hospital beds`
X3 <- CDI$`Total personal income`

beta1 <- function(x, y) {
  sum((y-mean(y))*(x-mean(x))) / sum((x-mean(x))^2)
}
beta0 <- function(x, y) {
  mean(y) - sum((y-mean(y))*(x-mean(x)))/sum((x-mean(x))^2) * mean(x)
}

beta1_1 <- beta1(X1, Y)
beta0_1 <- beta0(X1, Y)
reg1.43_1 <- lm(CDI$`Number of active physicians`~CDI$`Total population`)

beta1_2 <- beta1(X2, Y)
beta0_2 <- beta0(X2, Y)
beta1_2
```

```
## [1] 0.7431164
```

```
beta0_2
```

```
## [1] -95.93218
```

```
reg1.43_2 <- lm(`Number of active physicians` ~ `Number of hospital beds`, data = C
DI)

beta1_3 <- beta1(X3, Y)
beta1_3
```

```
## [1] 0.1317012
```

```
beta0_3 <- beta0(X3, Y)
beta0_3
```

```
## [1] -48.39485
```

```
reg1.43_3 <- lm(`Number of active physicians` ~ `Total personal income`, data = CDI
)
```

against total popl: y = -110.6348 + 0.002795425x

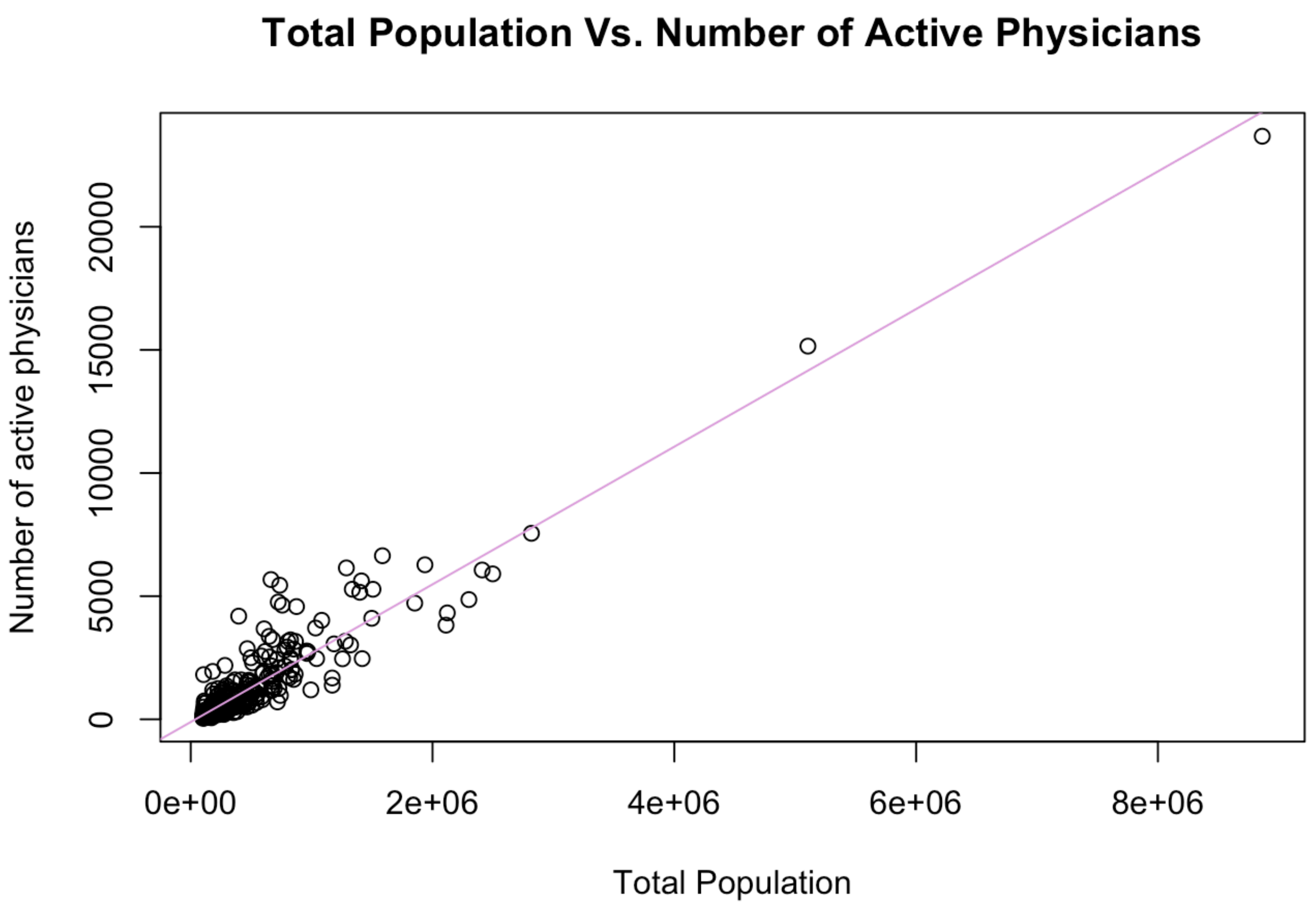
againt number of hospital beds: y = -95.93218 + 0.7431164x

against total personal income: y = -48.39485 + 0.1317012x

b. Plot the three estimated regression functions and data on separate graphs. Does a linear regression relation appear to provide a good fit for each of the three predictor variables?

total population against number of active physicians

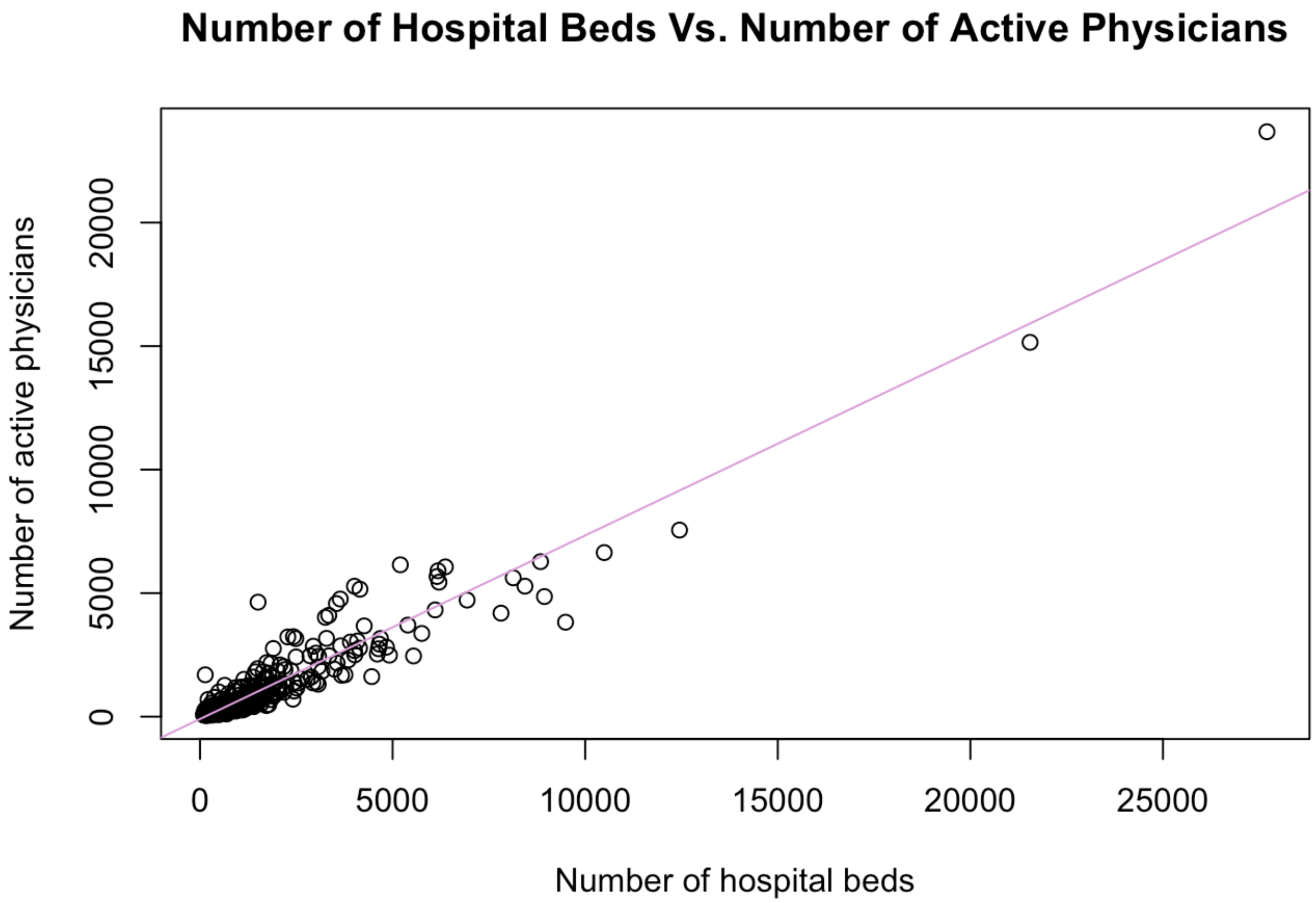
```
plot(X1, Y,
     xlab = "Total Population",
     ylab = "Number of active physicians",
     main = "Total Population Vs. Number of Active Physicians") +
  abline(reg1.43_1, col = "plum")
```




```
## integer(0)
```

number of hospital beds against number of active physicians

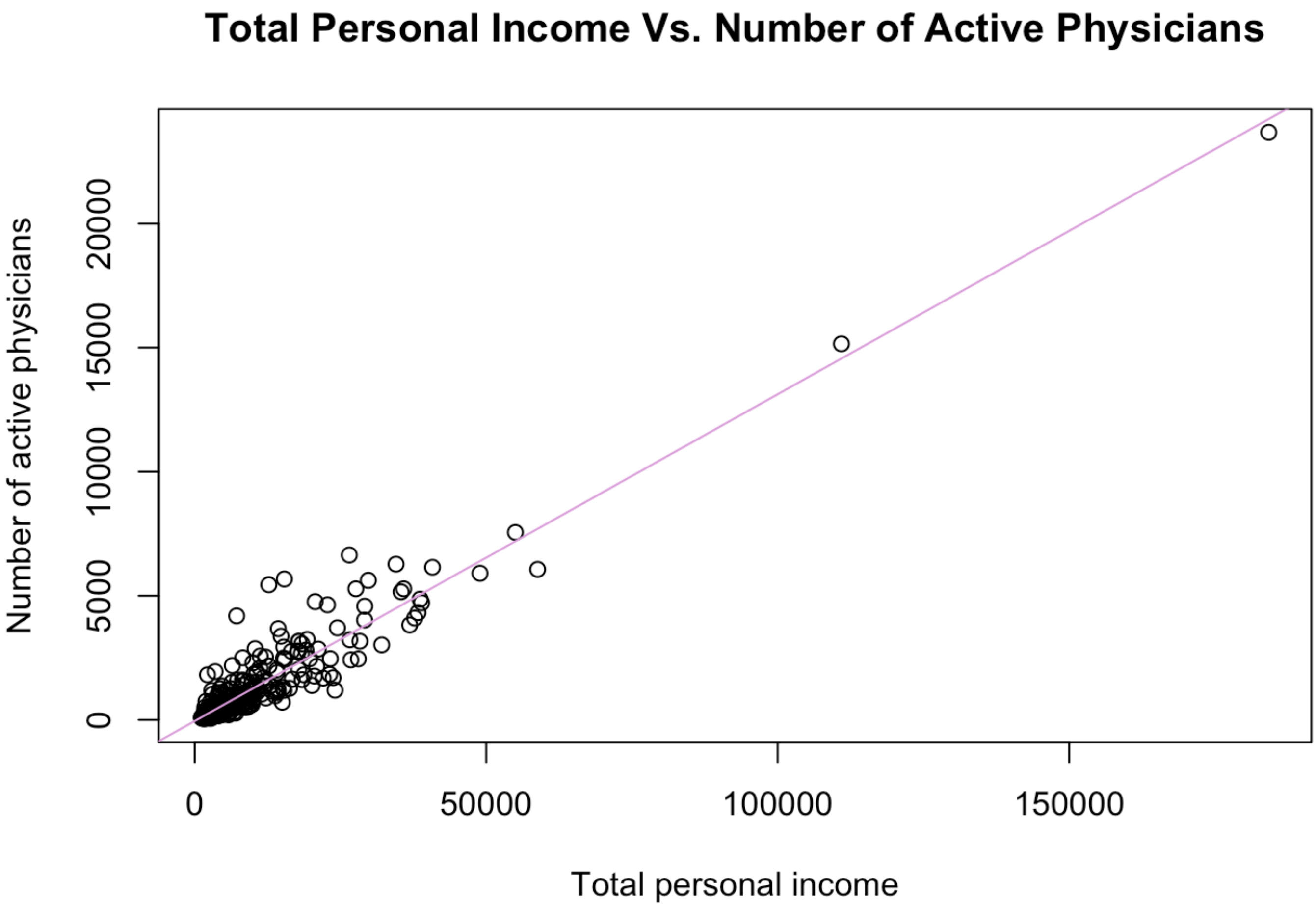
```
plot(X2, Y,
     xlab = "Number of hospital beds",
     ylab = "Number of active physicians",
     main = "Number of Hospital Beds Vs. Number of Active Physicians") +
  abline(reg1.43_2, col = "plum")
```




```
## integer(0)
```

total personal income against number of active physicians

```
plot(X3, Y,
     xlab = "Total personal income",
     ylab = "Number of active physicians",
     main = "Total Personal Income Vs. Number of Active Physicians") +
  abline(reg1.43_3, col = "plum")
```




```
## integer(0)
```

Yes, each linear function seems to fit well.

c. Calculate MSE for each of the three predictor variables. Which predictor variable leads to the smallest variability around the fitted regression line?

```
mse <- function(x, y) {
  linreg <- lm(y ~ x)
  n <- length(y)
  residual <- residuals(linreg)
  sum(residual^2) / (n-2)
}

mse(X1, Y)
```

```
## [1] 372203.5
```

```
mse(X2, Y)
```

```
## [1] 310191.9
```

```
mse(X3, Y)
```

```
## [1] 324539.4
```

Total population MSE = 372203.5 Number of hospital beds MSE = 310191.9 Total personal income MSE = 324539.4

The number of hospital beds leads to the least variation.

Part 2. *Measuring linear associations*

Refer to the **CDI** data set in Appendix C.2 and Project 1.43. Using R^2 as the criterion, which predictor variable accounts for the largest reduction in the variability in the number of active physicians?

Since R^2, the coefficient of determination measures the effect of X in reducing the variation in Y, the predictor variable with the greatest value of R^2 is the answer.

```
summary(reg1.43_1)
```

```
## 
## Call:
## lm(formula = CDI$`Number of active physicians` ~ CDI$`Total population`)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -1969.4  -209.2   -88.0    27.9  3928.7 
## 
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)    
## (Intercept)            -1.106e+02  3.475e+01  -3.184  0.00156 ** 
## CDI$`Total population`  2.795e-03  4.837e-05  57.793  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 610.1 on 438 degrees of freedom
## Multiple R-squared:  0.8841, Adjusted R-squared:  0.8838 
## F-statistic:  3340 on 1 and 438 DF,  p-value: < 2.2e-16
```

```
summary(reg1.43_2)
```

```
##
## Call:
## lm(formula = `Number of active physicians` ~ `Number of hospital beds`,
##     data = CDI)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3133.2  -216.8   -32.0    96.2  3611.1
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)              -95.93218   31.49396  -3.046  0.00246 **
## `Number of hospital beds`   0.74312    0.01161  63.995  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 556.9 on 438 degrees of freedom
## Multiple R-squared:  0.9034, Adjusted R-squared:  0.9032
## F-statistic:  4095 on 1 and 438 DF,  p-value: < 2.2e-16
```

```
summary(reg1.43_3)
```

```
##
## Call:
## lm(formula = `Number of active physicians` ~ `Total personal income`,
##     data = CDI)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1926.6  -194.5   -66.6    44.2  3819.0
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            -48.39485   31.83333   -1.52    0.129
## `Total personal income`   0.13170    0.00211   62.41   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 569.7 on 438 degrees of freedom
## Multiple R-squared:  0.8989, Adjusted R-squared:  0.8987
## F-statistic:  3895 on 1 and 438 DF,  p-value: < 2.2e-16
```

Total population R^2 = 0.8841 Number of hospital beds R^2 = 0.9034 Total personal income R^2 = 0.8989

R^^2 also indicates that the number of hospital beds is the best predictor variable for the number of active physicians in each county, i.e., it reduces the variability in teh number of active physicians the most.

Part 3. *Inference about regression parameters*

Refer to the **CDI** data set in Appendix C.2 and Project 1.44. Obtain a separate interval estimate of $\beta 1$ for each region. Use a 90-percent confidence coefficient in each case. Do the regression lines for the different regions appear to have similar slopes? // Also carry out ANOVA for each regression model and state the results of the F-tests.

```
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.1 ─
─
```

```
## ✓ ggplot2 3.3.5     ✓ purrr   0.3.4
## ✓ tibble  3.1.2     ✓ dplyr   1.0.7
## ✓ tidyr   1.1.4     ✓ stringr 1.4.0
## ✓ readr   1.4.0     ✓ forcats 0.5.1
```

```
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ─
─
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(dplyr)
CDI <- as.tibble(CDI)
```

```
## Warning: `as.tibble()` was deprecated in tibble 2.0.0.
## Please use `as_tibble()` instead.
## The signature and semantics have changed, see `?as_tibble`.
```

```
beta1_ci <- function(x, conf = 0.90) {
  se <- sd(x) / sqrt(length(x))
  alpha <- 1 - conf
  mean(x) + se * qnorm(c(alpha / 2, 1 - alpha / 2))
}

CDI %>%
  group_by(`Geographic region`) %>%
  summarise(
    mse = mse(`Percent bachelor's degrees`, `Per capita income`),
    se_squared = mse / sum((`Percent bachelor's degrees`-mean(`Percent bachelor's d
egrees`))^2
  ),
  n = length(`Per capita income`),
  alpha = 1 - 0.90,
  ci = beta1(`Percent bachelor's degrees`, `Per capita income`) + sqrt(se_squared)
* qt(c(alpha / 2, 1 - alpha / 2), n-2)
  )
```

```
## `summarise()` has grouped output by 'Geographic region'. You can override using
the `.groups` argument.
```

```
## # A tibble: 8 x 6
## # Groups:   Geographic region [4]
##   `Geographic region`      mse se_squared     n alpha    ci
##                  <int>    <dbl>      <dbl> <int> <dbl> <dbl>
## 1                    1 7335008.      1379.   103   0.1  461.
## 2                    1 7335008.      1379.   103   0.1  584.
## 3                    2 4411341.       741.   108   0.1  193.
## 4                    2 4411341.       741.   108   0.1  284.
## 5                    3 7474349.       736.   152   0.1  286.
## 6                    3 7474349.       736.   152   0.1  376.
## 7                    4 8214318.      2058.    77   0.1  365.
## 8                    4 8214318.      2058.    77   0.1  516.
```

```
CDI1 <- CDI %>%
  filter(`Geographic region` == 1) %>%
  summarise(
    `Per capita income 1` = `Per capita income`,
    `Percent bachelor's degrees 1` = `Percent bachelor's degrees`)

CDI2 <- CDI %>%
  filter(`Geographic region` == 2) %>%
  summarise(
    `Per capita income 2` = `Per capita income`,
    `Percent bachelor's degrees 2` = `Percent bachelor's degrees`)

CDI3 <- CDI %>%
  filter(`Geographic region` == 3) %>%
  summarise(
    `Per capita income 3` = `Per capita income`,
    `Percent bachelor's degrees 3` = `Percent bachelor's degrees`)

CDI4 <- CDI %>%
  filter(`Geographic region` == 4) %>%
  summarise(
    `Per capita income 4` = `Per capita income`,
    `Percent bachelor's degrees 4` = `Percent bachelor's degrees`)

region1 <- lm(CDI1$`Per capita income 1` ~ CDI1$`Percent bachelor's degrees 1`)
anova(region1)
```

```
## Analysis of Variance Table
##
## Response: CDI1$`Per capita income 1`
##                                      Df     Sum Sq    Mean Sq F value    Pr(>F)
## CDI1$`Percent bachelor's degrees 1`   1 1450517671 1450517671  197.75 < 2.2e-16
## Residuals                           101  740835765    7335008
##
## CDI1$`Percent bachelor's degrees 1` ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
region2 <- lm(CDI2$`Per capita income 2` ~ CDI2$`Percent bachelor's degrees 2`)
anova(region2)
```

```
## Analysis of Variance Table
##
## Response: CDI2$`Per capita income 2`
##                                    Df    Sum Sq   Mean Sq F value    Pr(>F)
## CDI2$`Percent bachelor's degrees 2`   1 338907694 338907694  76.826 3.344e-14
## Residuals                         106 467602149   4411341
##
## CDI2$`Percent bachelor's degrees 2` ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
region3 <- lm(CDI3$`Per capita income 3` ~ CDI3$`Percent bachelor's degrees 3`)
anova(region3)
```

```
## Analysis of Variance Table
##
## Response: CDI3$`Per capita income 3`
##                                    Df     Sum Sq    Mean Sq F value    Pr(>F)
## CDI3$`Percent bachelor's degrees 3`   1 1109873245 1109873245  148.49 < 2.2e-16
## Residuals                         150 1121152411    7474349
##
## CDI3$`Percent bachelor's degrees 3` ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
region4 <- lm(CDI4$`Per capita income 4` ~ CDI4$`Percent bachelor's degrees 4`)
anova(region4)
```

```
## Analysis of Variance Table
##
## Response: CDI4$`Per capita income 4`
##                                   Df    Sum Sq   Mean Sq F value    Pr(>F)
## CDI4$`Percent bachelor's degrees 4`  1 773745787 773745787  94.195 6.856e-15
## Residuals                         75 616073841   8214318
##
## CDI4$`Percent bachelor's degrees 4` ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

90% Confidence interval for Region 1 = (460.5177, 583.8000) ANOVA Result: F-value = 197.75, the p-value is less than 2.2*10^(-16). Since the p-value is approximately 0, the null hypothesis is rejected, i.e., there exists an association between per capita income and percent bachelor's degrees in region 1.

90% Confidence interval for Region 2 = (193.4858, 283.8530) ANOVA Result: F-value = 76.826, the p-value is 3.344*10^(-14). Since the p-value is approximately 0, the null hypothesis is rejected, i.e., there exists an association between per capita income and percent bachelor's degrees in region 2.

90% Confidence interval for Region 3 = (285.7076, 375.5158) ANOVA Result: F-value = 148.49, the p-value is less than 2.2*10^(-16). Since the p-value is approximately 0, the null hypothesis is rejected, i.e., there exists an association between per capita income and percent bachelor's degrees in region 3.

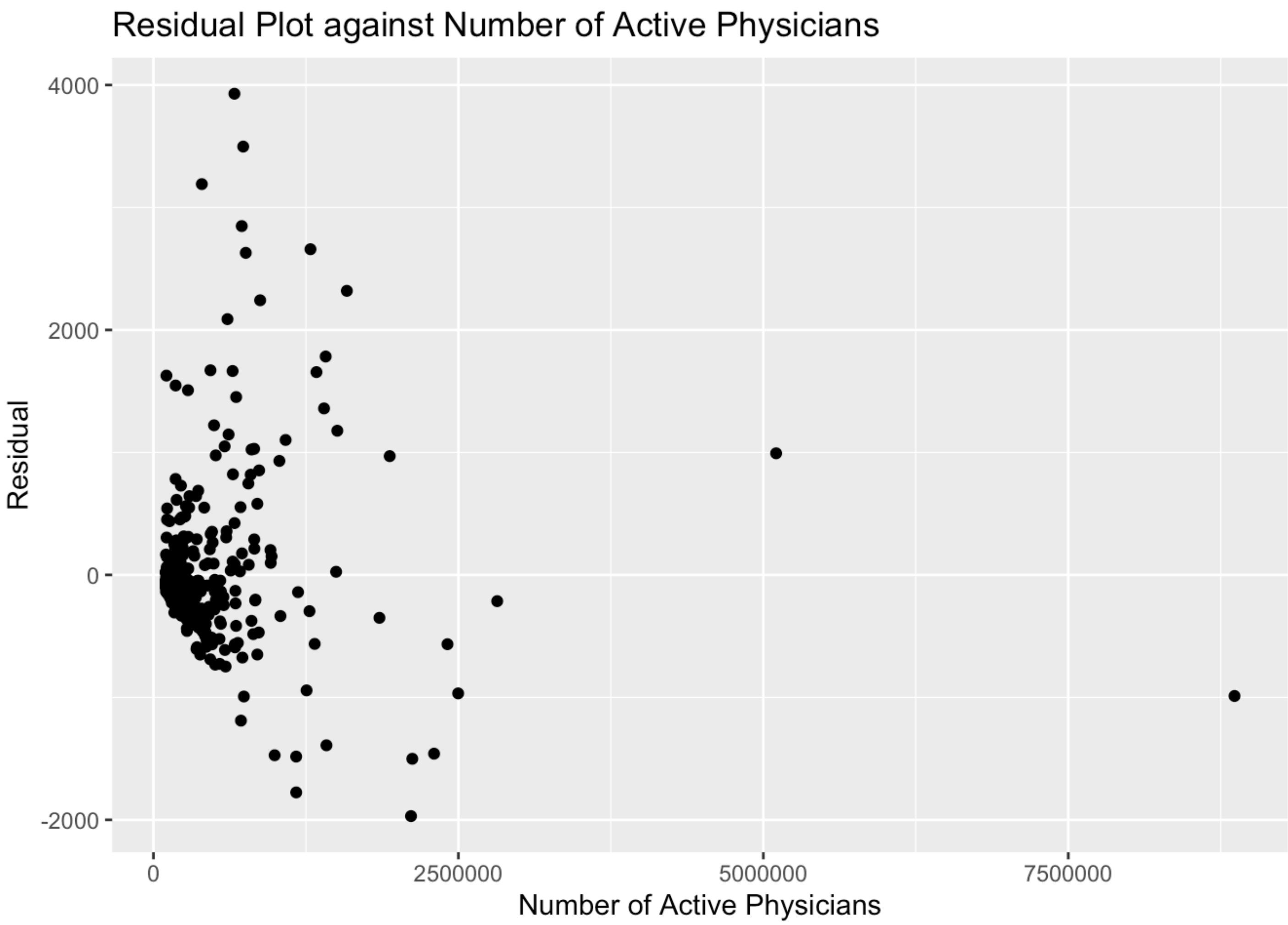
90% Confidence interval for Region 4 = (364.7585, 515.8729) ANOVA Result: F-value = 94.195, the p-value is less than 6.856*^(-15). Since the p-value is approximately 0, the null hypothesis is rejected, i.e., there exists an association between per capita income and percent bachelor's degrees in region 4.

The regression lines for the different regions appear to have different slopes.

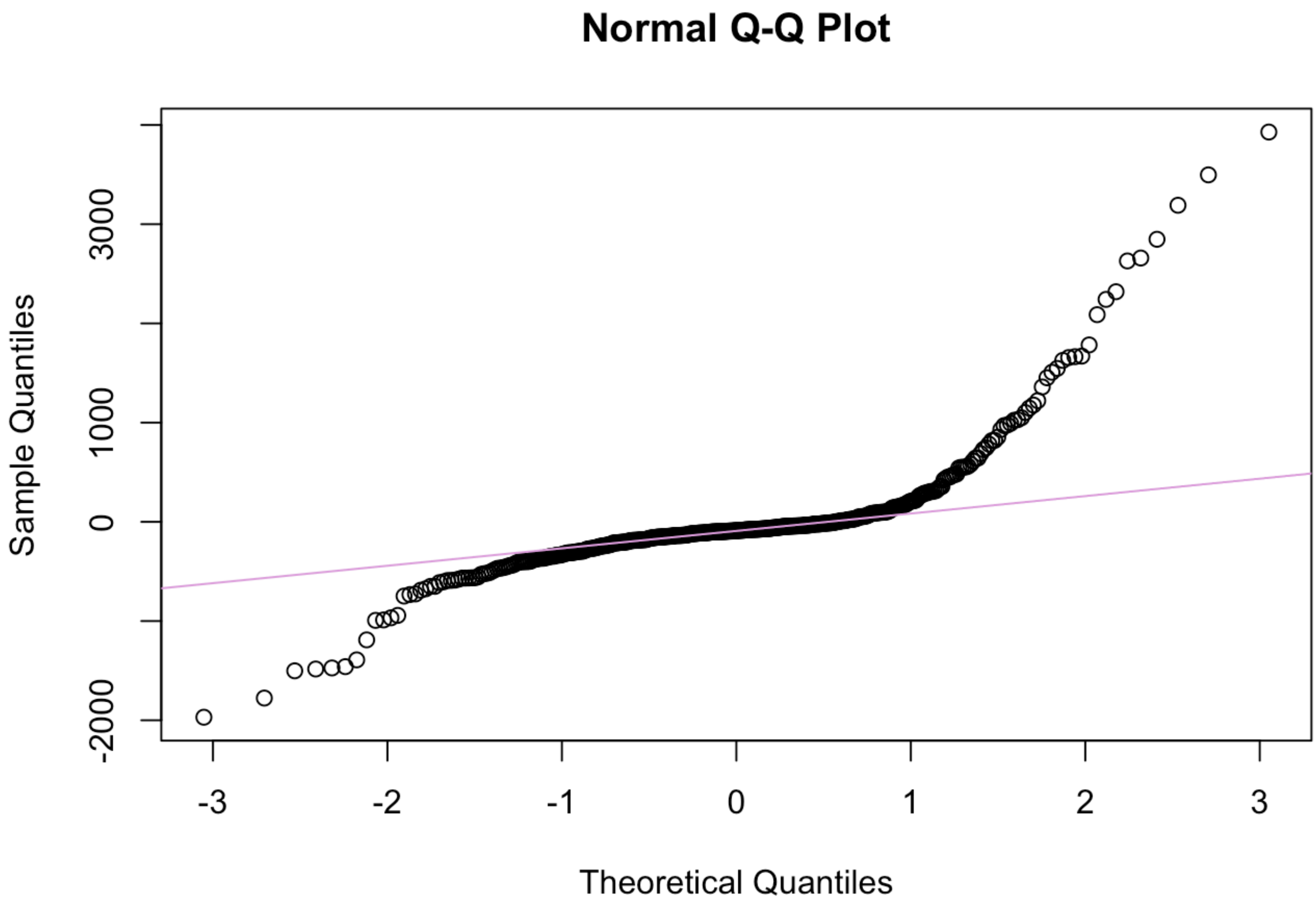
Part 4. *Regression diagnostics*

Refer to the **CDI** data set in Appendix C.2 and Project 1.43. For each of the three fitted regression models, obtain the residuals and prepare plot against X and a normal probability plot. Summarize your conclusions. Is linear regression model (2.1) more appropriate in one case than in the others?

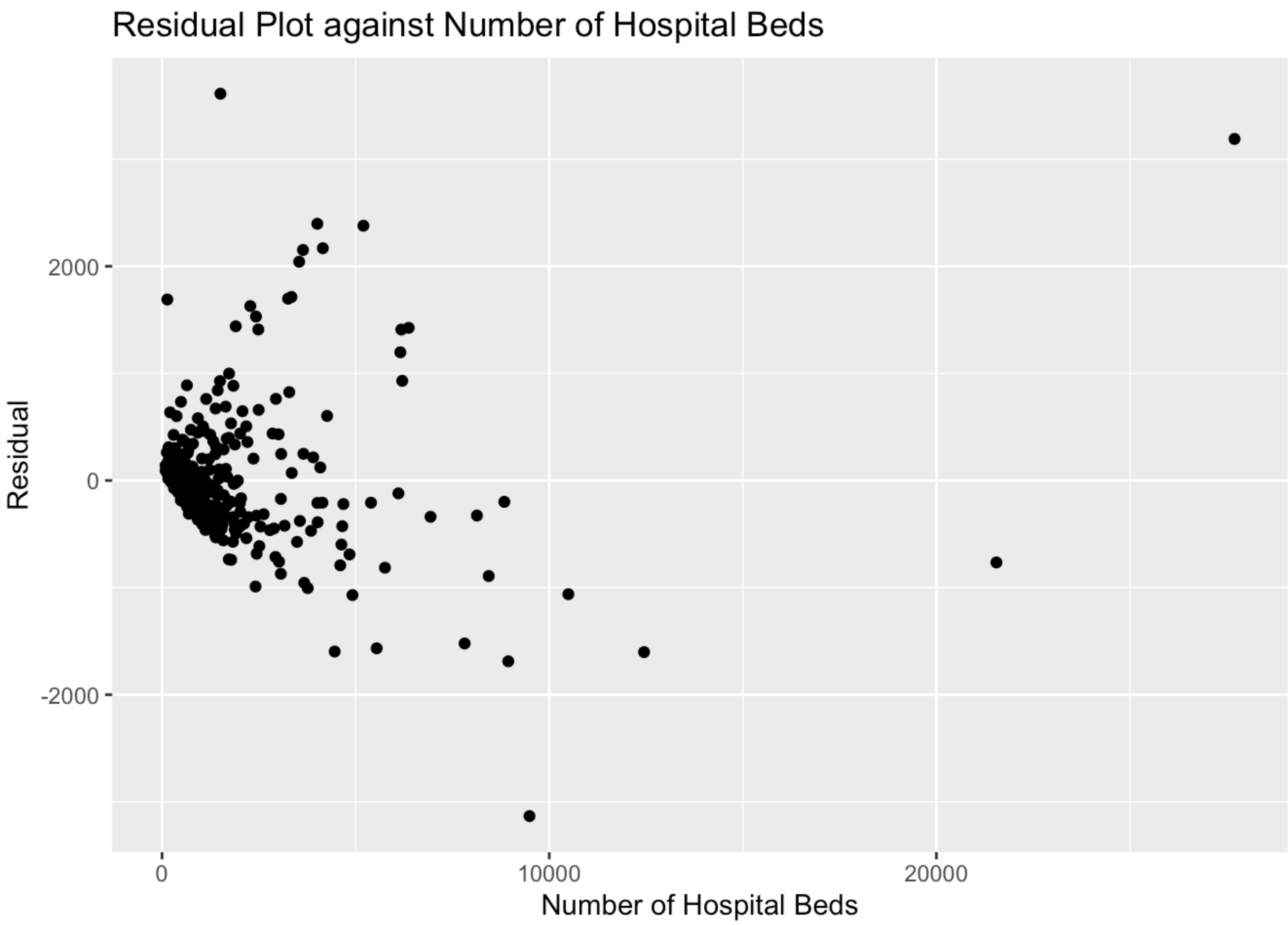
```
?qqnorm

dev1 <- residuals(reg1.43_1)
data1 <- data.frame(X1, dev1)
ggplot(data1, aes(x = X1, y = dev1)) +
  geom_point() +
  labs(
    title = "Residual Plot against Number of Active Physicians",
    x = "Number of Active Physicians",
    y = "Residual"
  )
```



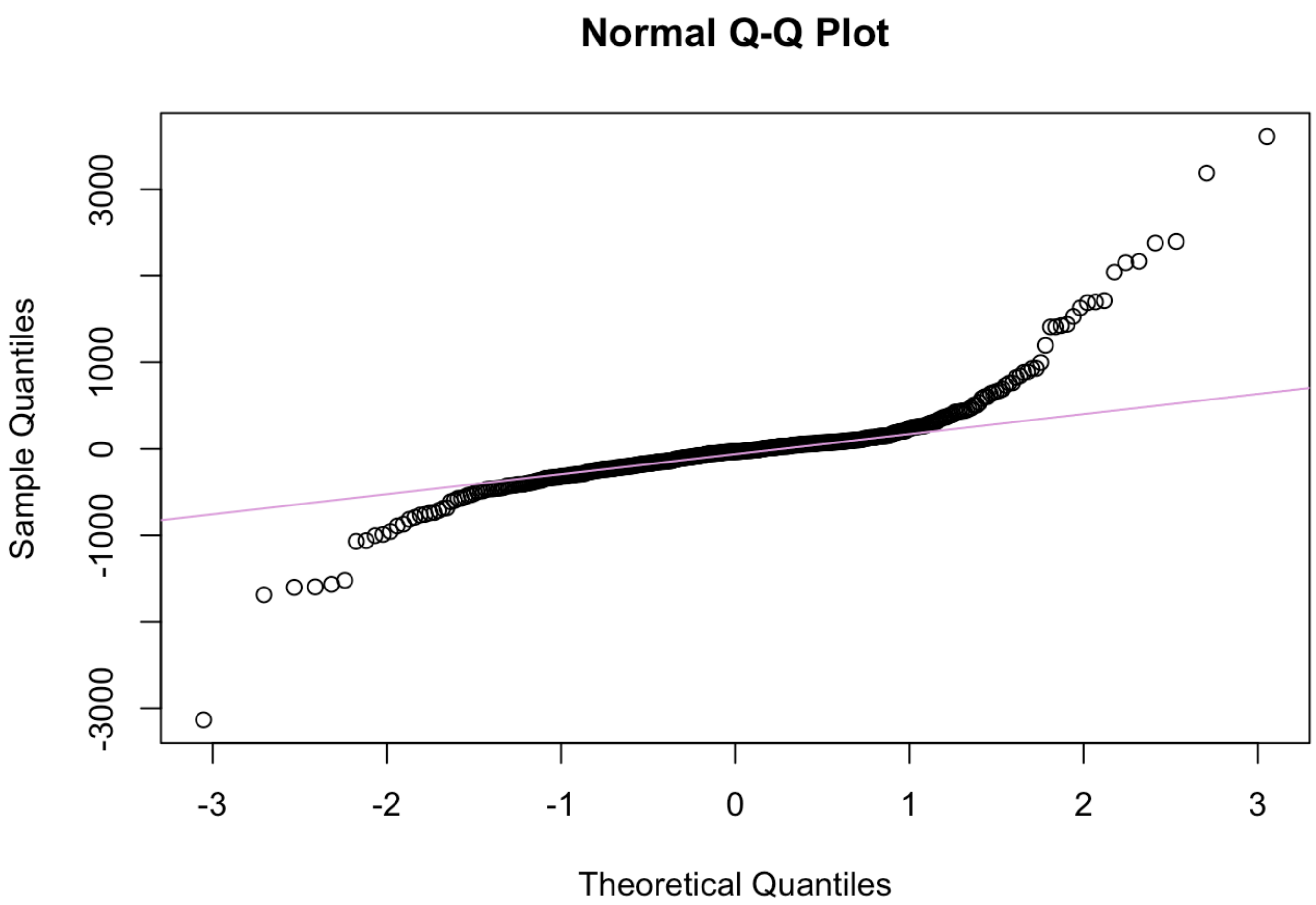

```
qqnorm(dev1)
qqline(dev1, col = "plum")
```



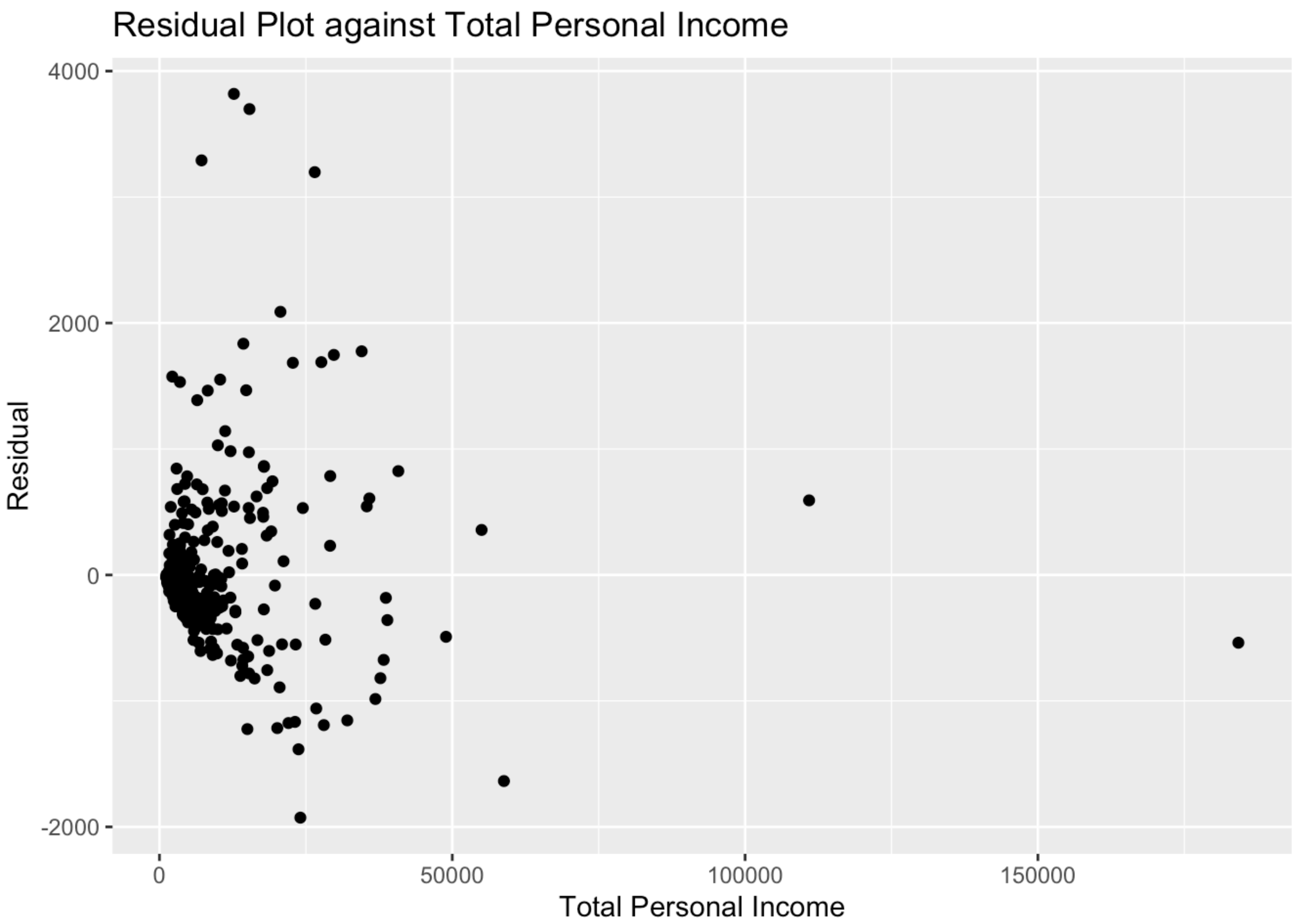

```
dev2 <- residuals(reg1.43_2)
data2 <- data.frame(X2, dev2)
ggplot(data2, aes(x = X2, y = dev2)) +
  geom_point() +
  labs(
    title = "Residual Plot against Number of Hospital Beds",
    x = "Number of Hospital Beds",
    y = "Residual"
  )
```



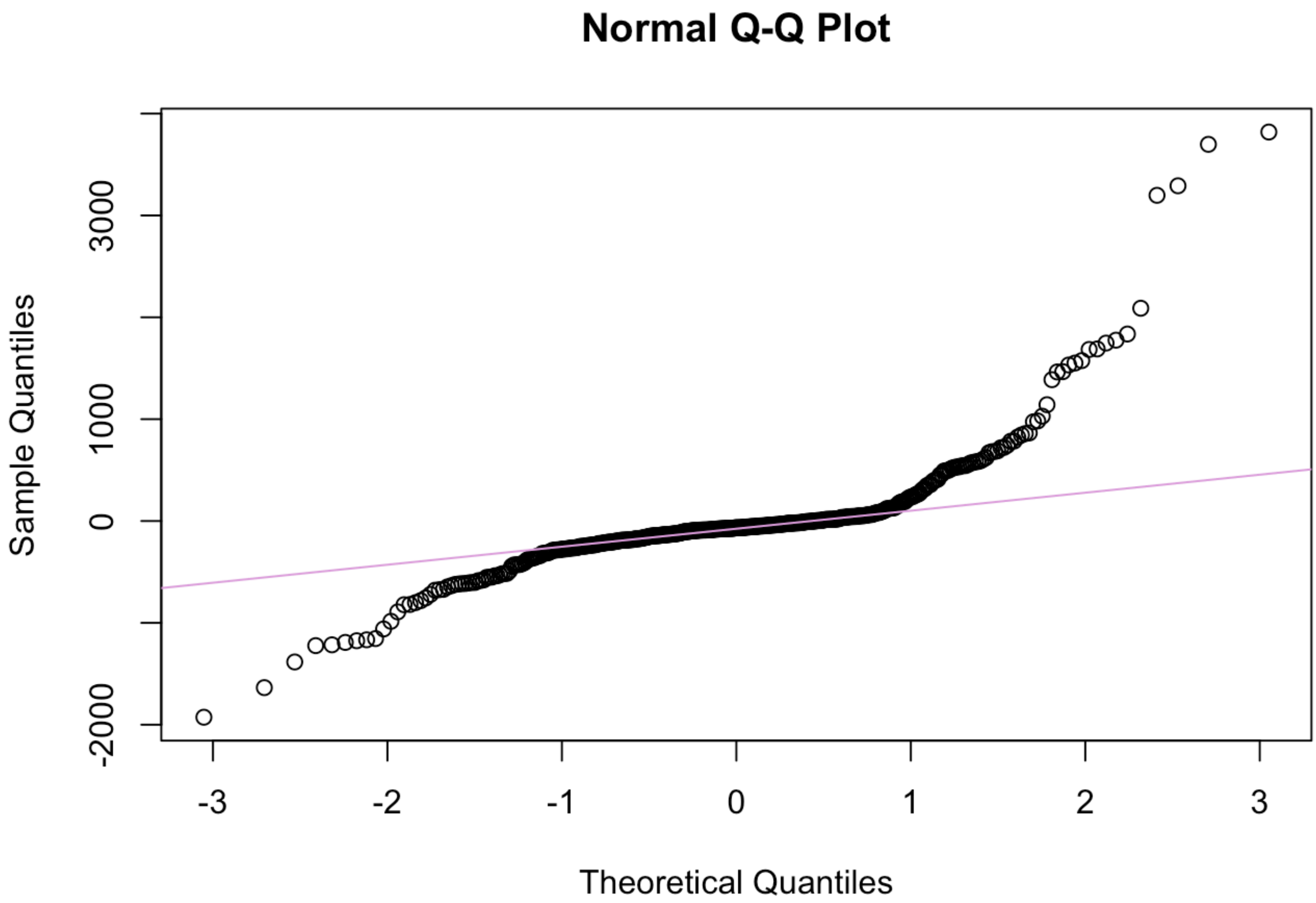

```
qqnorm(dev2)
qqline(dev2, col = "plum")
```




```
dev3 <- residuals(reg1.43_3)
data3 <- data.frame(X3, dev3)
ggplot(data3, aes(x = X3, y = dev3)) +
  geom_point() +
  labs(
    title = "Residual Plot against Total Personal Income",
    x = "Total Personal Income",
    y = "Residual"
  )
```




```
qqnorm(dev3)
qqline(dev3, col = "plum")
```



Conclusion: All three residual plots and three normal probability plots look similar - especially, the residual plots seem to not show any particular pattern except for that the residuals are clustered around the origin. Since all three normal probability plots look similar to each other, there does not seem to be a particular case in which linear regression model is the most appropriate. However, the second normality probability plot, which draws residuals against the number of hospital beds, would be the best among these three because the residual points are least distant from the straight line. This result coincides with the conclusion about the explanatory variable with the least variation.

Part 5. *Discussion*

Discuss the possible impact of observational data on your results. Are there anything else that you'd like to comment on? Any suggestions on how to improve the linear regression models?

Having a sizable amount of data improves the strength of our conclusions. Due to the quantity and the quality of the data that was gathered prior to this study, we were able to work towards various kinds of conclusions. In Part 1, we were able to conclude that all three predictor variables, total population, number of hospital beds, and total personal income, when regressed against the number of active physicians, have a linear association. In part 3, we were able to conclude that the regression lines for the different locations have different slopes, but the conclusions are all the same in that an association can be found between per capita income and percent bachelor's degrees. Lastly, in Part 4, we conclude that a linear regression may be most appropriate for the number of hospital beds data since their residuals are closest to the straight normal probability(QQ) plot. Also, it is worth noting that there are some sources for error. We cannot draw conclusions from this dataset on all counties in the United States, as this is a dataset of the most populous counties in the country. In other words, the dataset is not representative of the general population of the United States.