```
!pip install ISLP
```

```
Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl (
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21.1/21.1 MB 34.2 MB/s eta 0:00:0
Downloading torchmetrics-1.6.1-py3-none-any.whl (927 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 927.3/927.3 kB 48.8 MB/s eta 0:00
Downloading formulaic-1.1.1-py3-none-any.whl (115 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 115.7/115.7 kB 8.5 MB/s eta 0:00:(
Downloading lightning_utilities-0.12.0-py3-none-any.whl (28 kB)
Downloading interface_meta-1.3.0-py3-none-any.whl (14 kB)
Building wheels for collected packages: autograd-gamma
  Building wheel for autograd-gamma (setup.py) ... done
  Created wheel for autograd-gamma: filename=autograd_gamma-0.5.0-py3-none-any
  Stored in directory: /root/.cache/pip/wheels/8b/67/f4/2caaae2146198dcb824f3
Successfully built autograd-gamma
Installing collected packages: scipy, nvidia-nvjitlink-cu12, nvidia-curand-cu1
  Attempting uninstall: scipy
    Found existing installation: scipy 1.13.1
    Uninstalling scipy-1.13.1:
      Successfully uninstalled scipy-1.13.1
  Attempting uninstall: nvidia-nvjitlink-cu12
    Found existing installation: nvidia-nvjitlink-cu12 12.5.82
    Uninstalling nvidia-nvjitlink-cu12-12.5.82:
      Successfully uninstalled nvidia-nvjitlink-cu12-12.5.82
  Attempting uninstall: nvidia-curand-cu12
    Found existing installation: nvidia-curand-cu12 10.3.6.82
    Uninstalling nvidia-curand-cu12-10.3.6.82:
      Successfully uninstalled nvidia-curand-cu12-10.3.6.82
  Attempting uninstall: nvidia-cufft-cu12
    Found existing installation: nvidia-cufft-cu12 11.2.3.61
    Uninstalling nvidia-cufft-cu12-11.2.3.61:
      Successfully uninstalled nvidia-cufft-cu12-11.2.3.61
  Attempting uninstall: nvidia-cuda-runtime-cu12
    Found existing installation: nvidia-cuda-runtime-cu12 12.5.82
    Uninstalling nvidia-cuda-runtime-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-runtime-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-nvrtc-cu12
    Found existing installation: nvidia-cuda-nvrtc-cu12 12.5.82
    Uninstalling nvidia-cuda-nvrtc-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-nvrtc-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-cupti-cu12
    Found existing installation: nvidia-cuda-cupti-cu12 12.5.82
    Uninstalling nvidia-cuda-cupti-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-cupti-cu12-12.5.82
  Attempting uninstall: nvidia-cublas-cu12
    Found existing installation: nvidia-cublas-cu12 12.5.3.2
    Uninstalling nvidia-cublas-cu12-12.5.3.2:
      Successfully uninstalled nvidia-cublas-cu12-12.5.3.2
```

```
      Attempting uninstall: nvidia-cusparse-cu12
        Found existing installation: nvidia-cusparse-cu12 12.5.1.3
        Uninstalling nvidia-cusparse-cu12-12.5.1.3:
          Successfully uninstalled nvidia-cusparse-cu12-12.5.1.3
      Attempting uninstall: nvidia-cudnn-cu12
        Found existing installation: nvidia-cudnn-cu12 9.3.0.75
        Uninstalling nvidia-cudnn-cu12-9.3.0.75:
          Successfully uninstalled nvidia-cudnn-cu12-9.3.0.75
      Attempting uninstall: nvidia-cusolver-cu12
        Found existing installation: nvidia-cusolver-cu12 11.6.3.83
        Uninstalling nvidia-cusolver-cu12-11.6.3.83:
          Successfully uninstalled nvidia-cusolver-cu12-11.6.3.83
    Successfully installed ISLP-0.4.0 autograd-gamma-0.5.0 formulaic-1.1.1 interfa
```

```
import numpy as np , pandas as pd
from matplotlib .pyplot import subplots
import statsmodels .api as sm
from ISLP import load_data
from ISLP.models import (summarize ,poly, ModelSpec as MS)
from statsmodels .stats.anova import anova_lm
```

```
from pygam import (s as s_gam ,
l as l_gam ,
f as f_gam ,
LinearGAM ,
LogisticGAM )
from ISLP. transforms import (BSpline ,
NaturalSpline )
from ISLP.models import bs , ns
from ISLP.pygam import (approx_lam ,
degrees_of_freedom ,
plot as plot_gam ,
anova as anova_gam )
```

```
Wage = load_data ('Wage')
y = Wage['wage']
age = Wage['age']
```

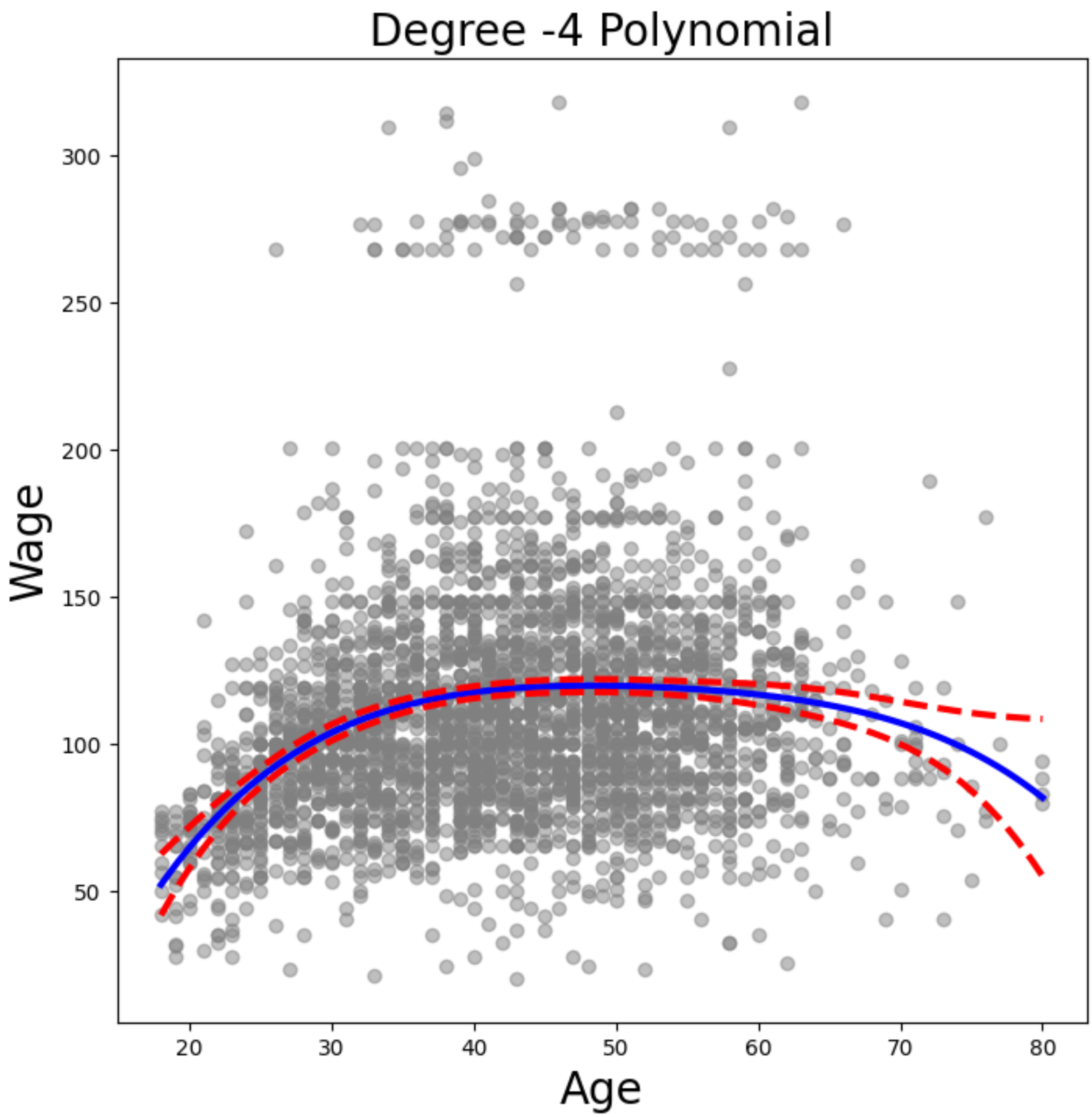
```
poly_age = MS([poly('age', degree =4) ]).fit(Wage)
M = sm.OLS(y, poly_age . transform (Wage)).fit ()
summarize (M)
```

	coef	std err	t	P>|t|
intercept	111.7036	0.729	153.283	0.000
poly(age, degree=4)[0]	447.0679	39.915	11.201	0.000
poly(age, degree=4)[1]	-478.3158	39.915	-11.983	0.000
poly(age, degree=4)[2]	125.5217	39.915	3.145	0.002
poly(age, degree=4)[3]	-77.9112	39.915	-1.952	0.051

```
age_grid = np. linspace (age.min (),
age.max (), 100)
age_df = pd. DataFrame ({'age': age_grid })
```

```
def plot_wage_fit (age_df ,basis , title):
  X = basis.transform(Wage)
  Xnew = basis. transform (age_df)
  M = sm.OLS(y, X).fit ()
  preds = M. get_prediction (Xnew)
  bands = preds.conf_int (alpha =0.05)
  fig, ax = subplots (figsize =(8 ,8))
  ax.scatter(age ,y,facecolor ='gray', alpha =0.5)
  for val , ls in zip([preds.predicted_mean ,bands [:,0],bands[: ,1]], ['b','r--','
    ax.plot(age_df.values , val , ls , linewidth =3)
    ax.set_title (title , fontsize =20)
    ax.set_xlabel ('Age', fontsize =20)
    ax.set_ylabel ('Wage', fontsize =20);
  return ax
```

```
plot_wage_fit(age_df , poly_age , 'Degree -4 Polynomial'); #fitted curve as well as
```



```
models = [MS([ poly('age', degree=d)])
for d in range (1, 6)]
Xs = [model.fit_transform (Wage) for model in models]
anova_lm (*[ sm.OLS(y, X_).fit ()
for X_ in Xs])
```

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
0	2998.0	5.022216e+06	0.0	NaN	NaN	NaN
1	2997.0	4.793430e+06	1.0	228786.010128	143.593107	2.363850e-32
2	2996.0	4.777674e+06	1.0	15755.693664	9.888756	1.679202e-03
3	2995.0	4.771604e+06	1.0	6070.152124	3.809813	5.104620e-02
4	2994.0	4.770322e+06	1.0	1282.563017	0.804976	3.696820e-01

```
summarize (M)
```

	coef	std err	t	P>|t|
intercept	111.7036	0.729	153.283	0.000
poly(age, degree=4)[0]	447.0679	39.915	11.201	0.000
poly(age, degree=4)[1]	-478.3158	39.915	-11.983	0.000
poly(age, degree=4)[2]	125.5217	39.915	3.145	0.002
poly(age, degree=4)[3]	-77.9112	39.915	-1.952	0.051

```
models = [MS(['education', poly('age', degree=d)])
for d in range (1, 4)]
XEs = [model. fit_transform (Wage)
for model in models]
anova_lm (*[ sm.OLS(y, X_).fit () for X_ in XEs ])
```

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
0	2997.0	3.902335e+06	0.0	NaN	NaN	NaN
1	2996.0	3.759472e+06	1.0	142862.701185	113.991883	3.838075e-26
2	2995.0	3.753546e+06	1.0	5926.207070	4.728593	2.974318e-02

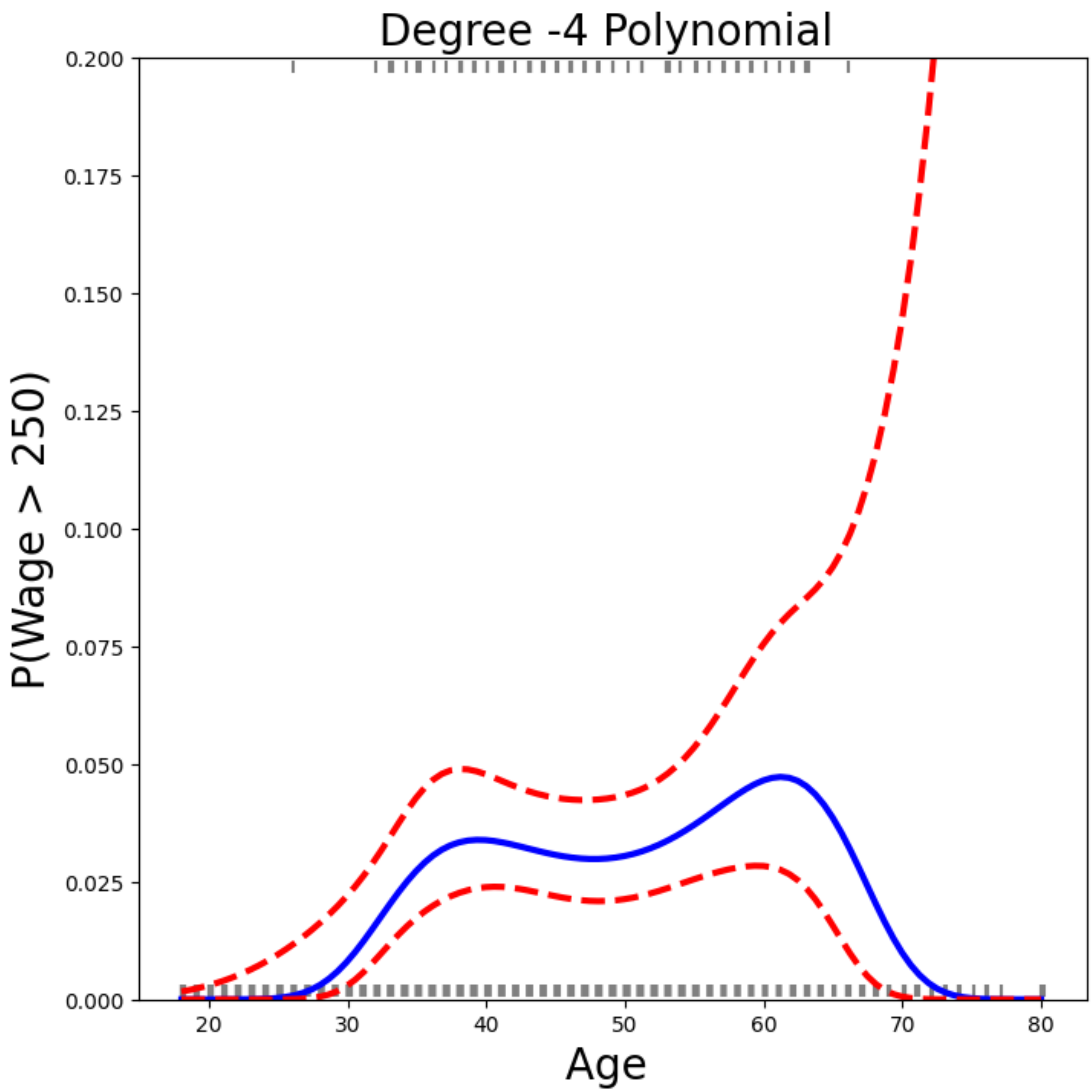
```
X = poly_age.transform (Wage)
high_earn = Wage['high_earn'] = y > 250 # shorthand
glm = sm.GLM(y > 250,
X,
family=sm. families.Binomial())
B = glm.fit()
summarize (B)
```

	coef	std err	z	P>|z|
intercept	-4.3012	0.345	-12.457	0.000
poly(age, degree=4)[0]	71.9642	26.133	2.754	0.006
poly(age, degree=4)[1]	-85.7729	35.929	-2.387	0.017
poly(age, degree=4)[2]	34.1626	19.697	1.734	0.083
poly(age, degree=4)[3]	-47.4008	24.105	-1.966	0.049

```
newX = poly_age.transform(age_df)
preds = B.get_prediction(newX)
bands = preds.conf_int(alpha =0.05)
```

```
fig , ax = subplots (figsize =(8 ,8))
rng = np.random. default_rng (0)
ax.scatter(age + 0.2 * rng.uniform(size=y.shape[0]) ,
np.where(high_earn, 0.198, 0.002) ,
fc='gray',
marker='|')
```

```
for val , ls in zip ([ preds.predicted_mean ,
bands [:,0],
bands [: ,1]] ,
['b','r--','r--']):
  ax.plot(age_df.values , val , ls , linewidth =3)
ax. set_title ('Degree -4 Polynomial ', fontsize =20)
ax. set_xlabel ('Age ', fontsize =20)
ax. set_ylim ([0 ,0.2])
ax. set_ylabel ('P(Wage > 250)', fontsize =20);
```


Degree -4 Polynomial
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
P(Wage > 250)
20
30
40
50
60
70
80
Age

```
cut_age = pd.qcut(age, 4)
summarize(sm.OLS(y, pd. get_dummies (cut_age)).fit())
```

	coef	std err	t	P>|t|
(17.999, 33.75]	94.1584	1.478	63.692	0.0
(33.75, 42.0]	116.6608	1.470	79.385	0.0
(42.0, 51.0]	119.1887	1.416	84.147	0.0
(51.0, 80.0]	116.5717	1.559	74.751	0.0

```
bs_ = BSpline(internal_knots =[25 ,40 ,60] , intercept=True).fit(age)
bs_age = bs_.transform (age)
bs_age.shape
```

```
(3000, 7)
```

```
bs_age = MS([bs('age', internal_knots =[25,40,60]) ])
Xbs = bs_age.fit_transform (Wage)
M = sm.OLS(y, Xbs).fit ()
summarize (M)
```

	coef	std err	t	P>|t|
intercept	60.4937	9.460	6.394	0.000
bs(age, internal_knots=[25, 40, 60])[0]	3.9805	12.538	0.317	0.751
bs(age, internal_knots=[25, 40, 60])[1]	44.6310	9.626	4.636	0.000
bs(age, internal_knots=[25, 40, 60])[2]	62.8388	10.755	5.843	0.000
bs(age, internal_knots=[25, 40, 60])[3]	55.9908	10.706	5.230	0.000
bs(age, internal_knots=[25, 40, 60])[4]	50.6881	14.402	3.520	0.000
bs(age, internal_knots=[25, 40, 60])[5]	16.6061	19.126	0.868	0.385

```
bs_age = MS([bs('age',
internal_knots =[25 ,40 ,60] ,
name='bs(age)')])
Xbs = bs_age. fit_transform(Wage)
M = sm.OLS(y, Xbs).fit ()
summarize (M)
```

	coef	std err	t	P>|t|
intercept	60.4937	9.460	6.394	0.000
bs(age)[0]	3.9805	12.538	0.317	0.751
bs(age)[1]	44.6310	9.626	4.636	0.000
bs(age)[2]	62.8388	10.755	5.843	0.000
bs(age)[3]	55.9908	10.706	5.230	0.000
bs(age)[4]	50.6881	14.402	3.520	0.000
bs(age)[5]	16.6061	19.126	0.868	0.385

```
BSpline(df =6).fit(age). internal_knots_
```

```
array([33.75, 42.  , 51.  ])
```

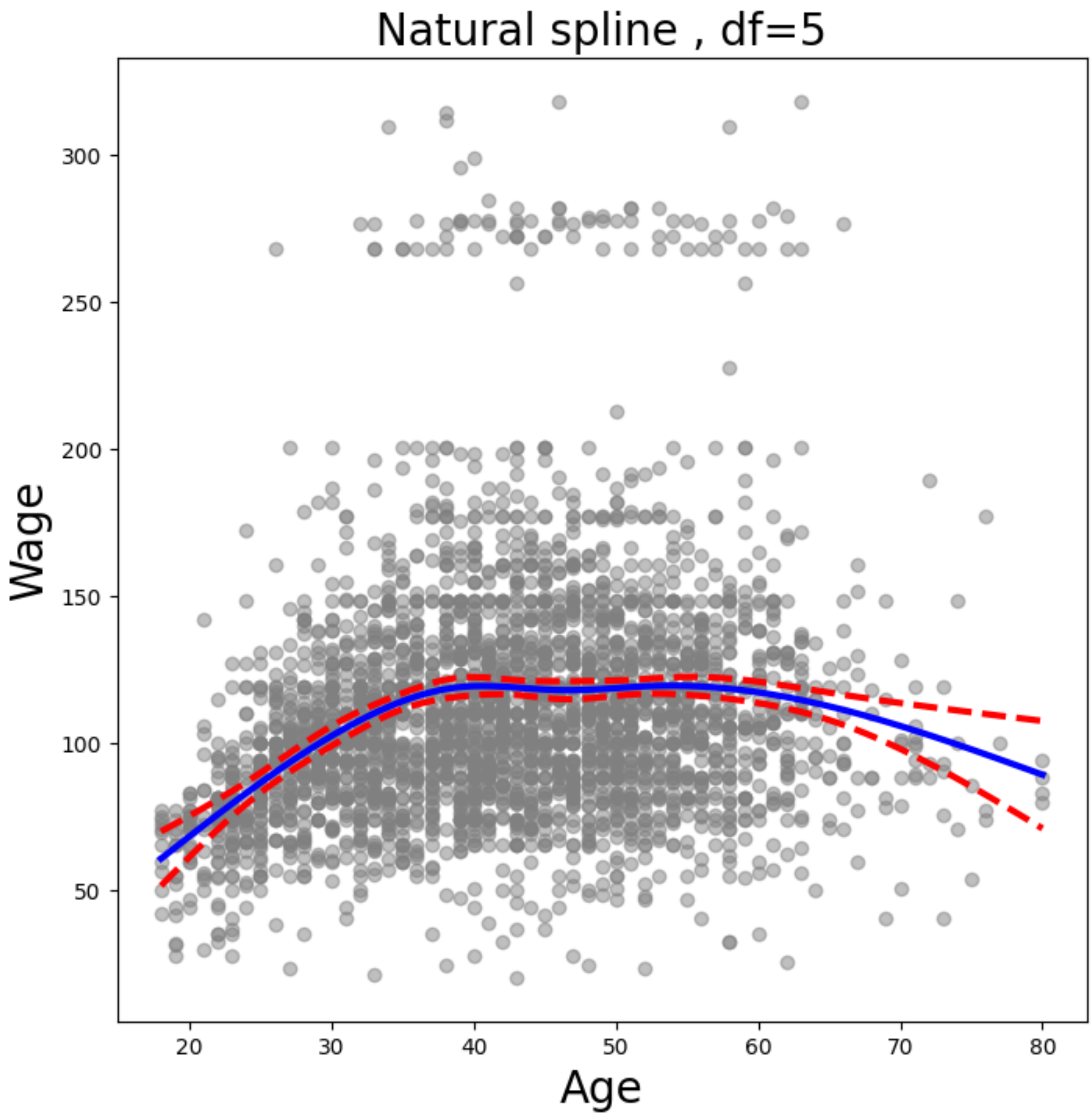
```
bs_age0 = MS([bs('age',
df=3,
degree =0)]).fit(Wage)
Xbs0 = bs_age0.transform(Wage)
summarize (sm.OLS(y, Xbs0).fit ())
```

	coef	std err	t	P>|t|
intercept	94.1584	1.478	63.687	0.0
bs(age, df=3, degree=0)[0]	22.3490	2.152	10.388	0.0
bs(age, df=3, degree=0)[1]	24.8076	2.044	12.137	0.0
bs(age, df=3, degree=0)[2]	22.7814	2.087	10.917	0.0

```
ns_age = MS([ns('age', df =5)]).fit(Wage)
M_ns = sm.OLS(y, ns_age. transform (Wage)).fit()
summarize(M_ns)
```

	coef	std err	t	P>|t|
intercept	60.4752	4.708	12.844	0.000
ns(age, df=5)[0]	61.5267	4.709	13.065	0.000
ns(age, df=5)[1]	55.6912	5.717	9.741	0.000
ns(age, df=5)[2]	46.8184	4.948	9.463	0.000
ns(age, df=5)[3]	83.2036	11.918	6.982	0.000
ns(age, df=5)[4]	6.8770	9.484	0.725	0.468

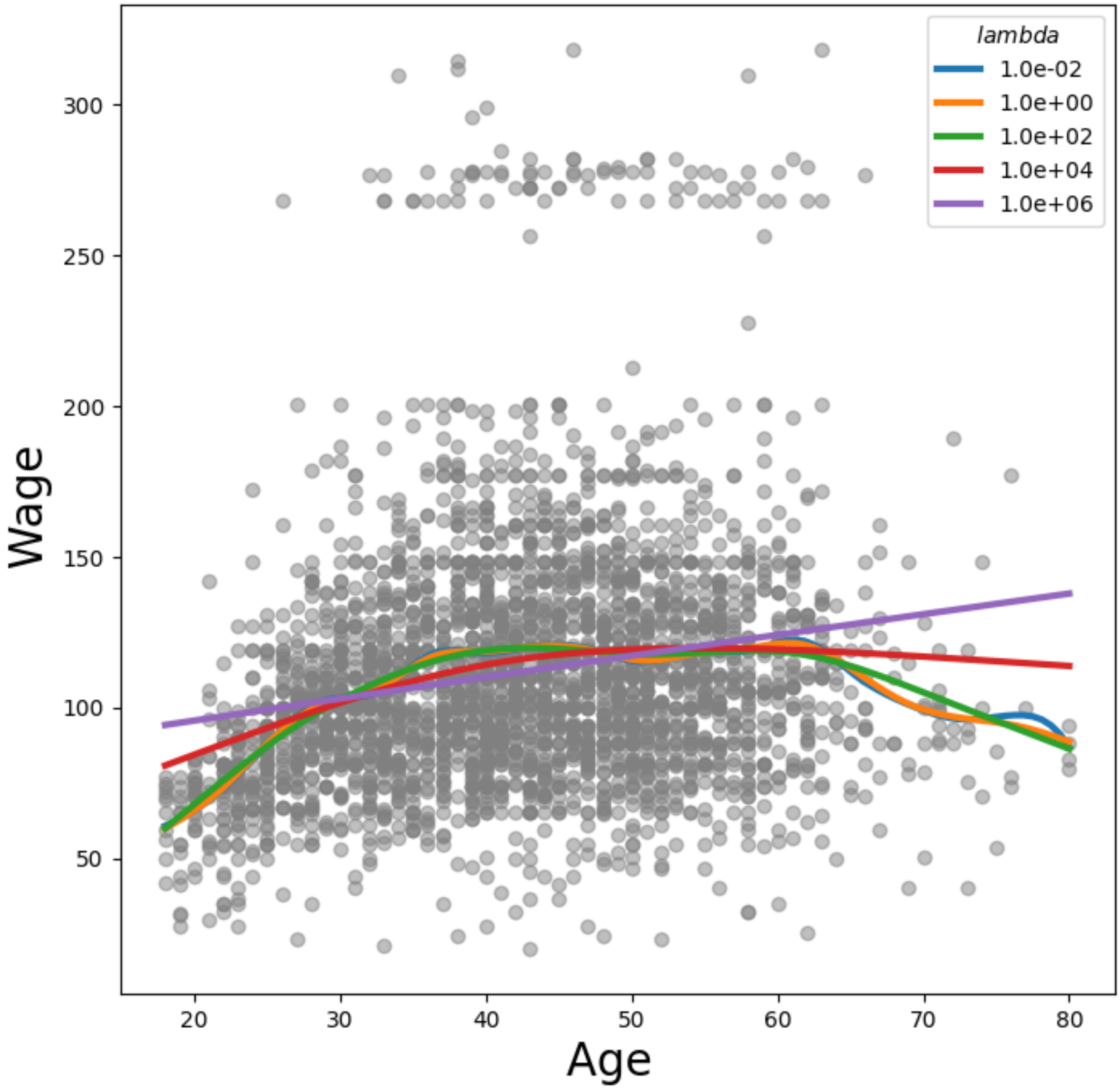
```
plot_wage_fit (age_df ,
ns_age ,
'Natural spline , df=5');
```



```
X_age = np.asarray(age).reshape (( -1 ,1))
gam = LinearGAM (s_gam (0, lam =0.6))
gam.fit(X_age , y)
```

```
LinearGAM(callbacks=[Deviance(), Diffs()], fit_intercept=True,
   max_iter=100, scale=None, terms=s(0) + intercept, tol=0.0001,
   verbose=False)
```

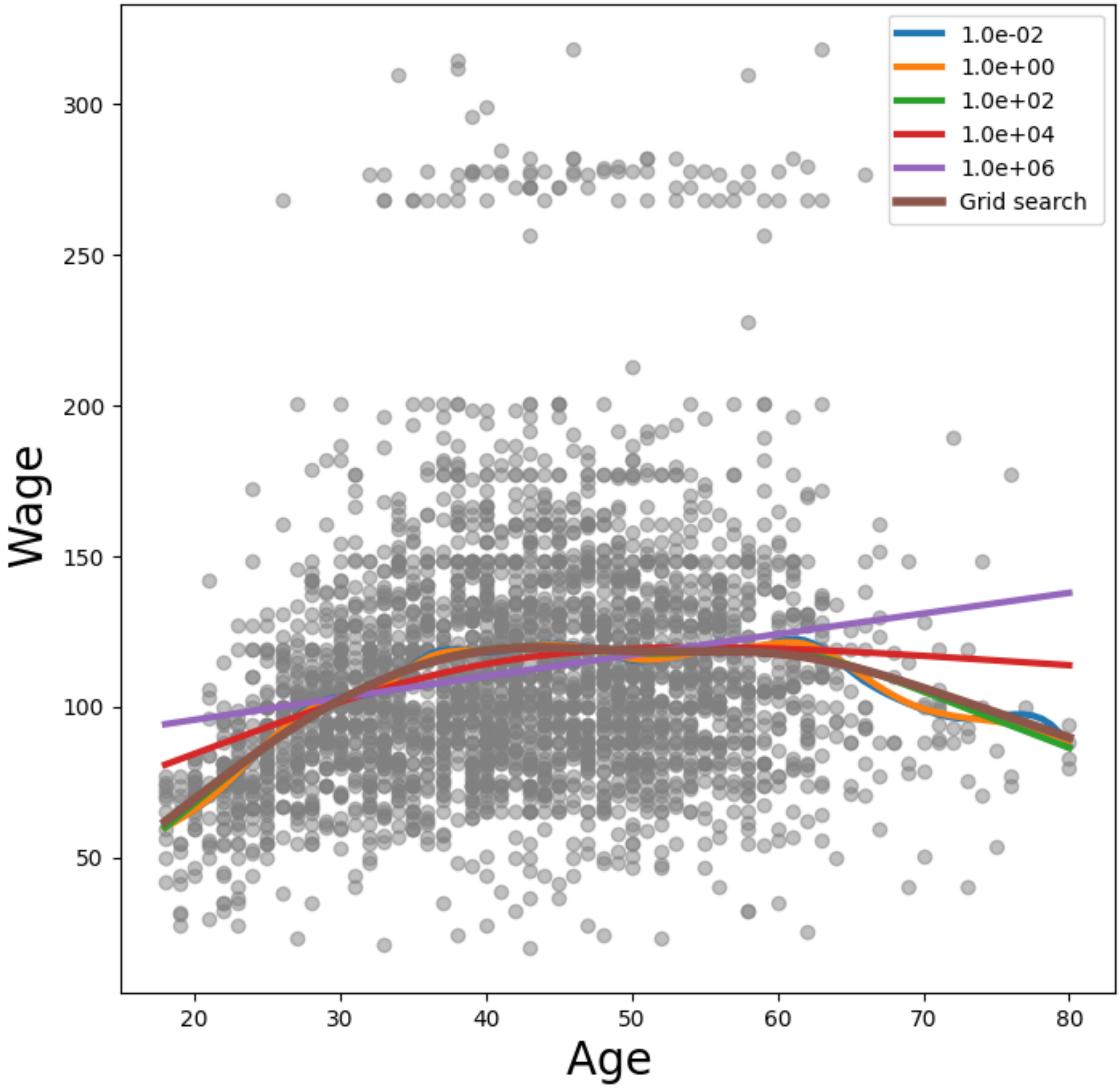
```
fig , ax = subplots (figsize =(8 ,8))
ax.scatter(age , y, facecolor ='gray', alpha =0.5)
for lam in np. logspace (-2, 6, 5):
  gam = LinearGAM (s_gam (0, lam=lam)).fit(X_age , y)
  ax.plot(age_grid ,
  gam.predict( age_grid), label='{:.1e}'.format(lam), linewidth =3)
ax. set_xlabel ('Age ', fontsize =20)
ax. set_ylabel ('Wage ', fontsize =20);
ax.legend(title='$\ lambda$ ');
```




```
gam_opt = gam. gridsearch (X_age , y)
ax.plot(age_grid ,
gam_opt.predict( age_grid ),
label='Grid search ',
linewidth =4)
ax.legend ()
```

```
fig
```

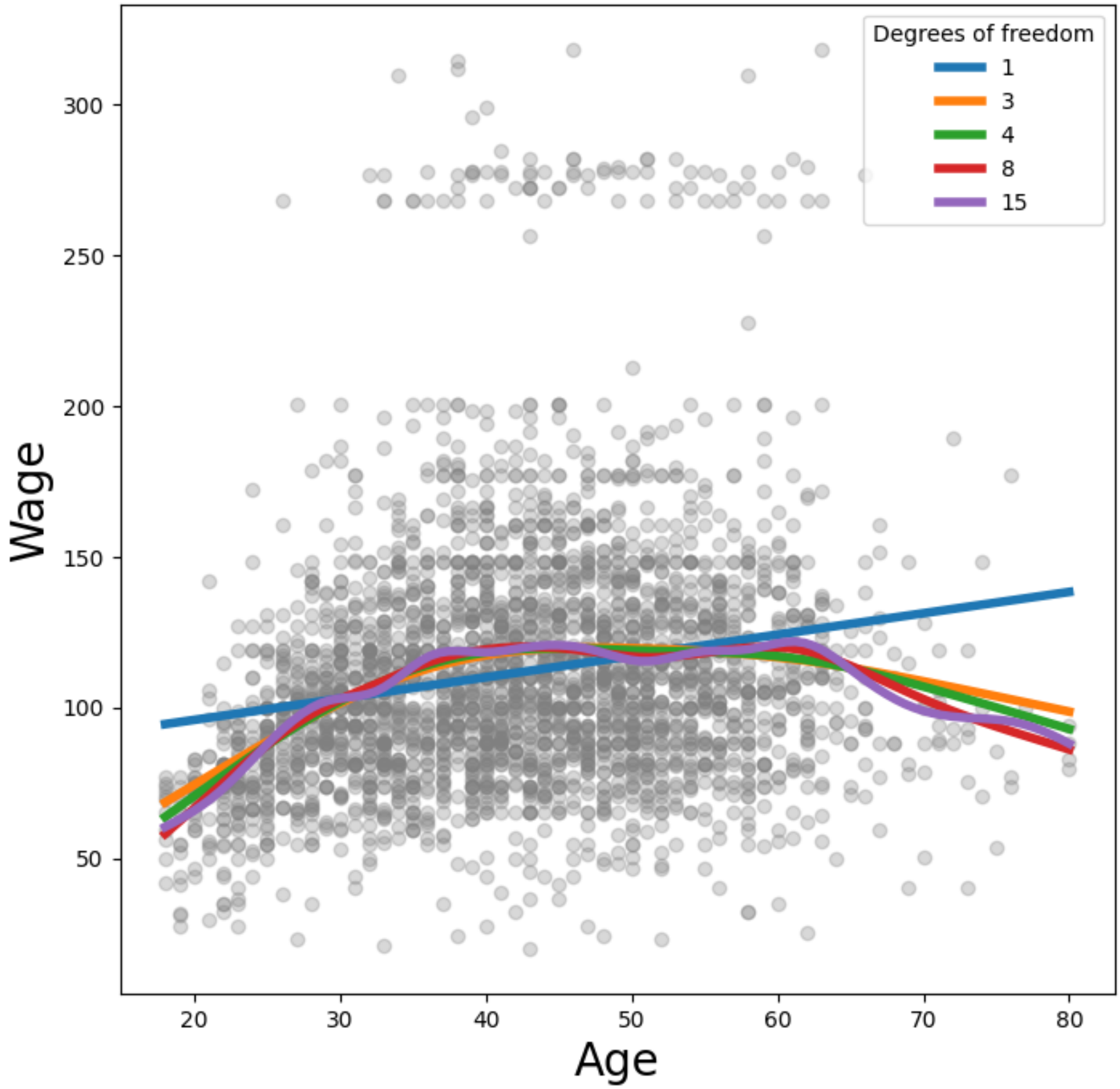
```
100% (11 of 11) |########################| Elapsed Time: 0:00:00 Time:  0:00:0
```



```
age_term = gam.terms [0]
lam_4 = approx_lam (X_age , age_term , 4)
age_term .lam = lam_4
degrees_of_freedom (X_age , age_term )
```

```
4.000000100003869
```

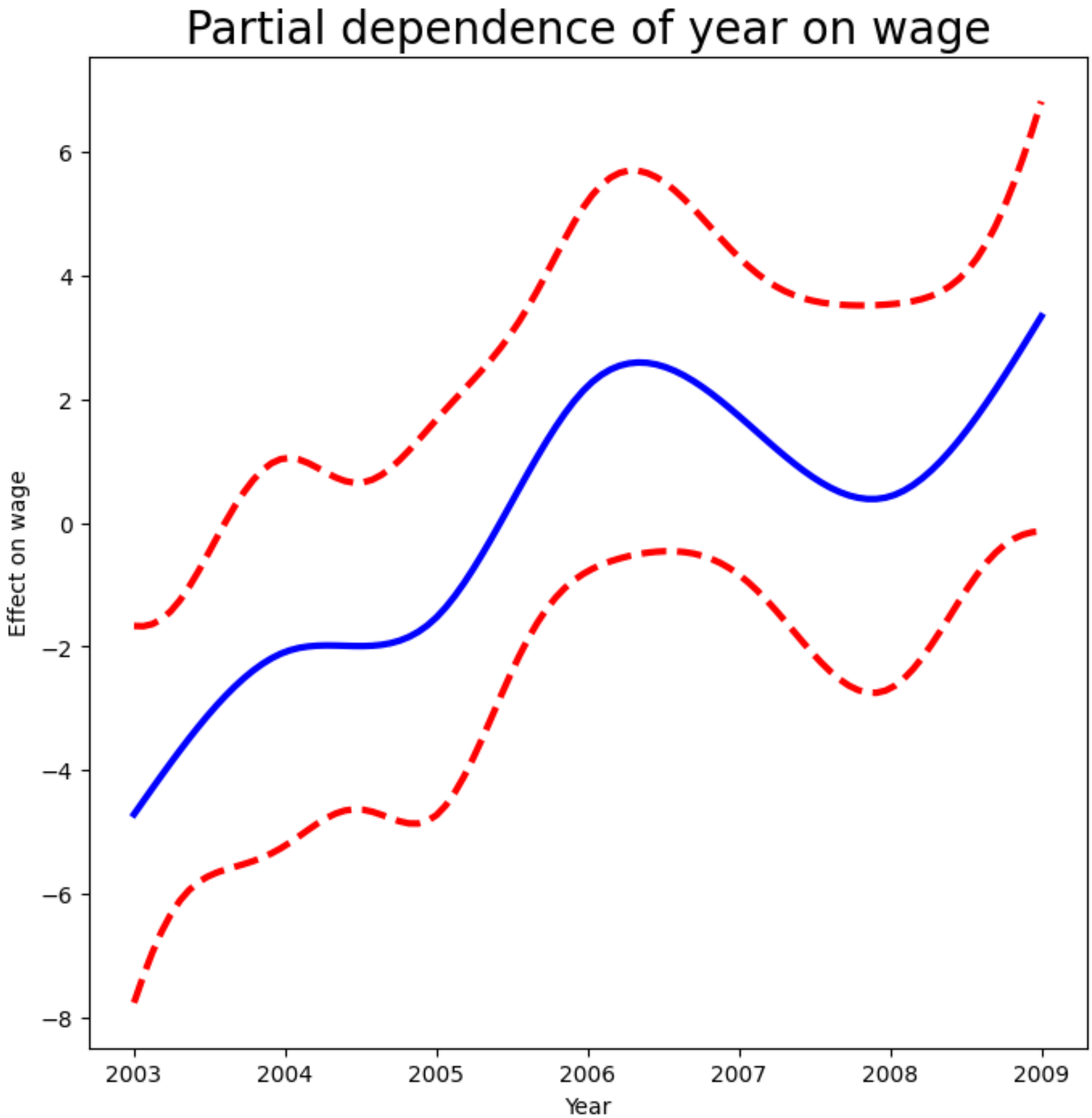
```
fig , ax = subplots (figsize =(8 ,8))
ax.scatter(X_age, y ,facecolor ='gray', alpha =0.3)
for df in [1 ,3 ,4 ,8 ,15]:
  lam = approx_lam (X_age, age_term , df +1)
  age_term .lam = lam
  gam.fit(X_age , y)
  ax.plot(age_grid , gam.predict( age_grid), label='{:d}'.format(df), linewidth =
ax. set_xlabel ('Age', fontsize =20)
ax. set_ylabel ('Wage', fontsize =20);
ax.legend(title='Degrees of freedom');
```


Degrees of freedom
1
3
4
8
15
Wage
300
250
200
150
100
50
20
30
40
50
60
70
80
Age

```
ns_age = NaturalSpline (df =4).fit(age)
ns_year = NaturalSpline (df =5).fit(Wage['year'])
Xs = [ns_age. transform (age),
ns_year. transform (Wage['year']),
pd. get_dummies (Wage['education']).values]
X_bh = np.hstack(Xs)
gam_bh = sm.OLS(y, X_bh).fit ()


age_grid = np. linspace (age.min (),
age.max (),
100)
X_age_bh = X_bh.copy () [:100]
X_age_bh [:] = X_bh [:]. mean (0)[None ,:]
X_age_bh [: ,:4] = ns_age. transform ( age_grid )
preds = gam_bh. get_prediction ( X_age_bh )
bounds_age = preds. conf_int (alpha =0.05)
partial_age = preds. predicted_mean
center = partial_age .mean ()
partial_age -= center
bounds_age -= center
fig , ax = subplots (figsize =(8 ,8))
ax.plot(age_grid , partial_age , 'b', linewidth =3)
ax.plot(age_grid , bounds_age [:,0], 'r--', linewidth =3)
ax.plot(age_grid , bounds_age [:,1], 'r--', linewidth =3)
ax. set_xlabel ('Age')
ax. set_ylabel ('Effect on wage ')
ax. set_title ('Partial dependence of age on wage ', fontsize =20);
```

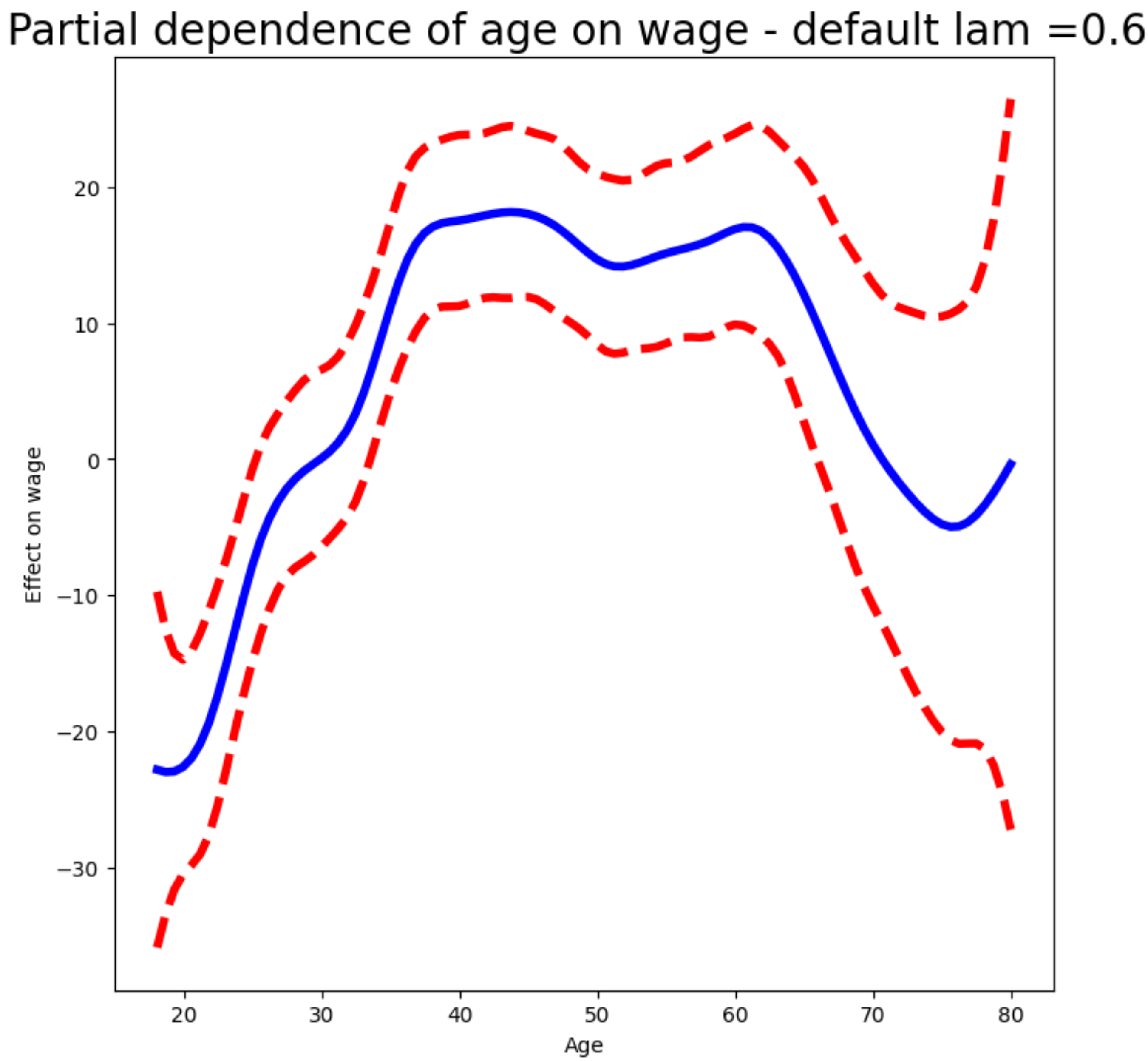

```
year_grid = np. linspace (2003 , 2009 , 100)
year_grid = np. linspace (Wage['year']. min (),
Wage['year']. max (), 100)
X_year_bh = X_bh.copy () [:100]
X_year_bh [:] = X_bh [:]. mean (0)[None ,:]
```

```
X_year_bh [: ,4:9] = ns_year. transform ( year_grid )
preds = gam_bh. get_prediction ( X_year_bh )
bounds_year = preds. conf_int (alpha =0.05)
partial_year = preds. predicted_mean
center = partial_year .mean ()
partial_year -= center
bounds_year -= center
fig , ax = subplots (figsize =(8 ,8))
ax.plot(year_grid , partial_year , 'b', linewidth =3)
ax.plot(year_grid , bounds_year [:,0], 'r--', linewidth =3)
ax.plot(year_grid , bounds_year [:,1], 'r--', linewidth =3)
ax. set_xlabel ('Year')
ax. set_ylabel ('Effect on wage')
ax. set_title ('Partial dependence of year on wage', fontsize =20);
```


Partial dependence of year on wage
Effect on wage
Year
6
4
2
0
−2
−4
−6
−8
2003
2004
2005
2006
2007
2008
2009

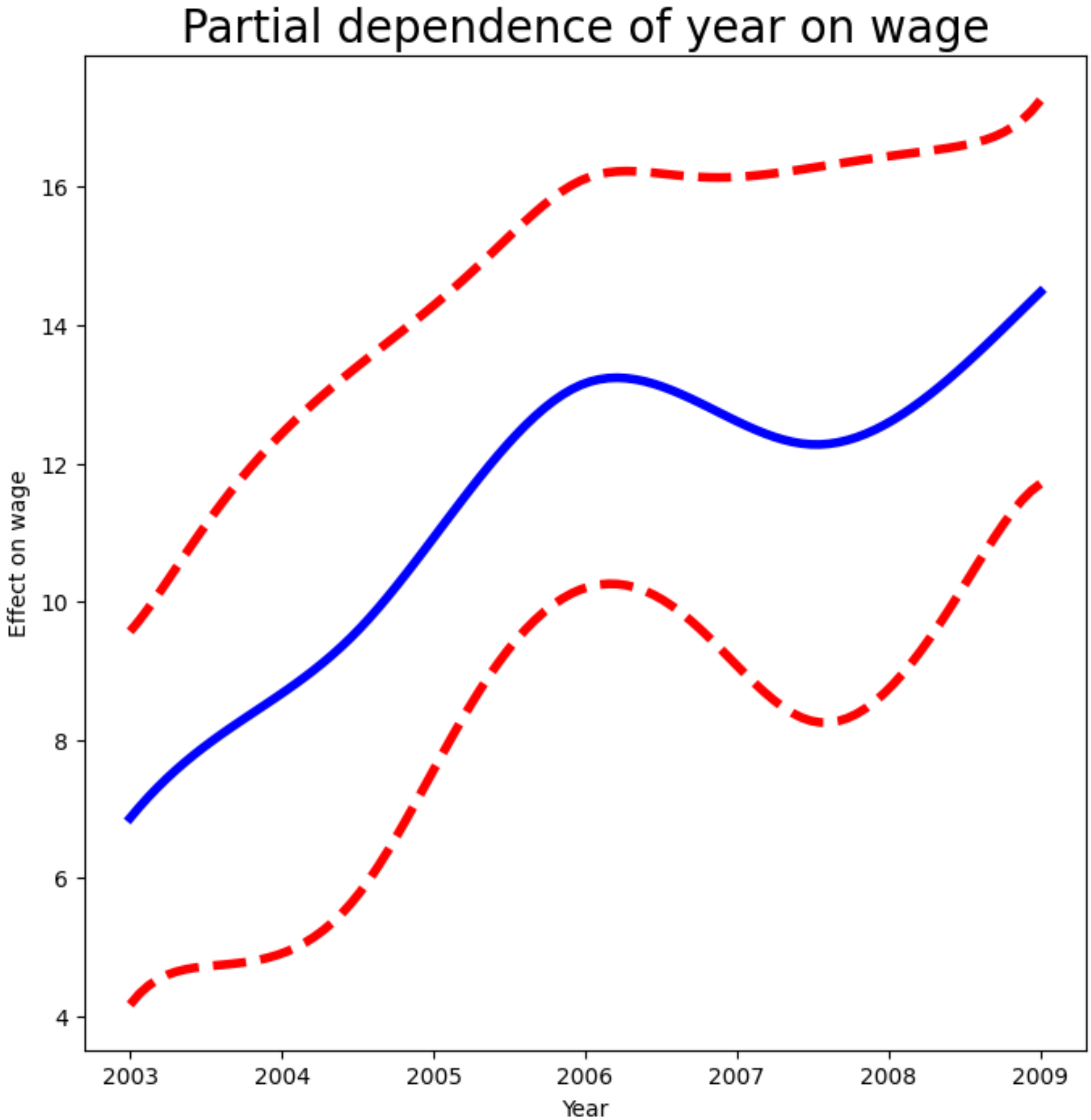
```
gam_full = LinearGAM(s_gam (0) +
s_gam (1, n_splines =7) +
f_gam (2, lam =0))
Xgam = np. column_stack ([age ,
Wage['year'],
Wage['education']. cat.codes ])
gam_full = gam_full .fit(Xgam , y)
```

```
fig , ax = subplots (figsize =(8 ,8))
plot_gam (gam_full , 0, ax=ax)
ax. set_xlabel ('Age')
ax. set_ylabel ('Effect on wage')
ax. set_title ('Partial dependence of age on wage - default lam =0.6 ',
fontsize =20);
```


Partial dependence of age on wage - default lam =0.6
Effect on wage
Age
20
10
0
−10
−20
−30
20
30
40
50
60
70
80

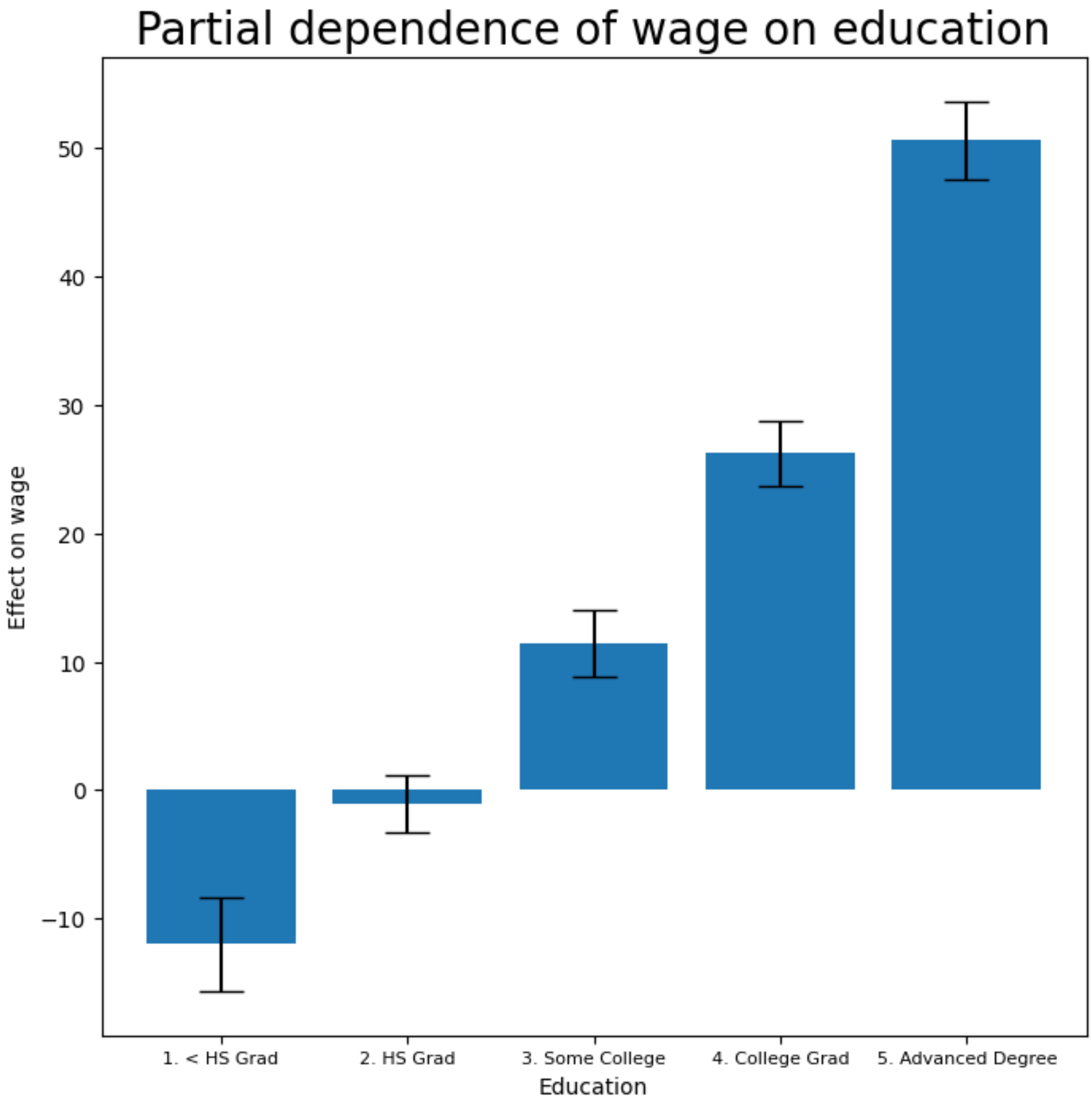
```
age_term = gam_full .terms [0]
age_term .lam = approx_lam (Xgam , age_term , df =4+1)
year_term = gam_full .terms [1]
year_term .lam = approx_lam (Xgam , year_term , df =4+1)
gam_full = gam_full .fit(Xgam , y)


fig , ax = subplots (figsize =(8 ,8))
plot_gam (gam_full ,
1,
ax=ax)
ax. set_xlabel ('Year')
ax. set_ylabel ('Effect on wage')
ax. set_title ('Partial dependence of year on wage', fontsize =20)
```

```
Text(0.5, 1.0, 'Partial dependence of year on wage')
```




```
fig , ax = subplots (figsize =(8, 8))
ax = plot_gam (gam_full , 2)
ax. set_xlabel ('Education')
ax. set_ylabel ('Effect on wage')
```

```
ax. set_title ('Partial dependence of wage on education',
fontsize =20);
ax. set_xticklabels (Wage['education']. cat.categories , fontsize =8);
```



```
gam_0 = LinearGAM (age_term + f_gam (2, lam =0))
gam_0.fit(Xgam , y)
gam_linear = LinearGAM (age_term +
l_gam (1, lam =0) +
f_gam (2, lam =0))
gam_linear .fit(Xgam , y)
```

```
LinearGAM(callbacks=[Deviance(), Diffs()], fit_intercept=True,
   max_iter=100, scale=None, terms=s(0) + l(1) + f(2) + intercept,
   tol=0.0001, verbose=False)
```

```
anova_gam (gam_0 , gam_linear , gam_full )
```

	deviance	df	deviance_diff	df_diff	F	pvalue
0	3.714362e+06	2991.004005	NaN	NaN	NaN	NaN
1	3.696746e+06	2990.005190	17616.542840	0.998815	14.265131	0.002314
2	3.693143e+06	2987.007254	3602.893655	2.997936	0.972007	0.435579

```
gam_0 = LinearGAM ( year_term +
f_gam (2, lam =0))
gam_linear = LinearGAM (l_gam (0, lam =0) +
year_term +
f_gam (2, lam =0))
gam_0.fit(Xgam , y)
gam_linear .fit(Xgam , y)
anova_gam (gam_0 , gam_linear , gam_full )
```

	deviance	df	deviance_diff	df_diff	F	pvalue
0	3.975443e+06	2991.000589	NaN	NaN	NaN	NaN
1	3.850247e+06	2990.000704	125196.137317	0.999884	101.270106	1.681120e-07
2	3.693143e+06	2987.007254	157103.978302	2.993450	42.447812	5.669414e-07

```
gam_full.summary ()
```

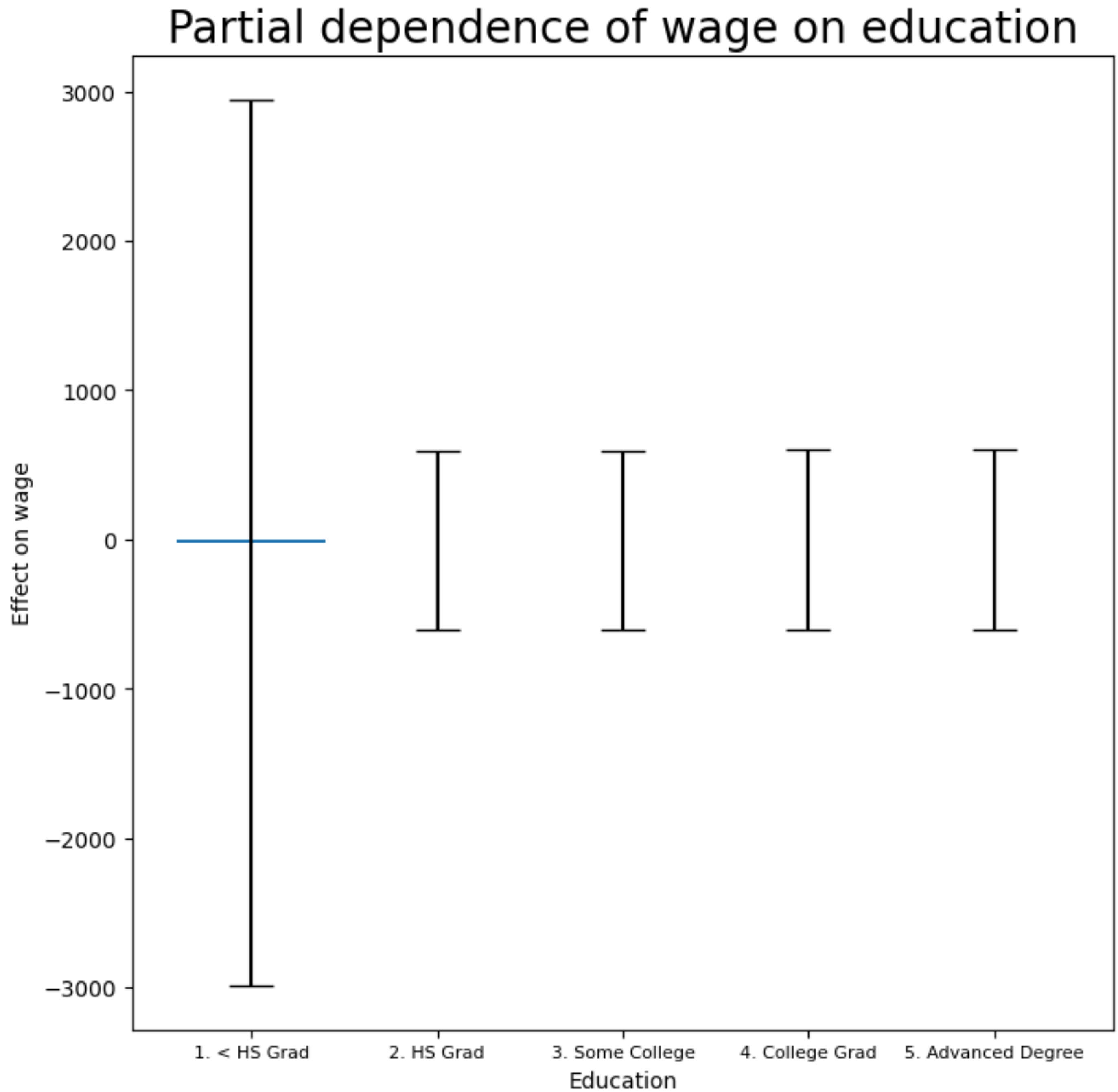
```
LinearGAM
=============================================== ==================================
Distribution:                        NormalDist Effective DoF:
Link Function:                     IdentityLink Log Likelihood:
Number of Samples:                         3000 AIC:
                                                AICc:
                                                GCV:
                                                Scale:
                                                Pseudo R-Squared:
==================================================================================
Feature Function                  Lambda               Rank         EDoF
================================= ==================== ============ =========
s(0)                              [465.0491]           20           5.1
s(1)                              [2.1564]             7            4.0
f(2)                              [0]                  5            4.0
intercept                                              1            0.0
==================================================================================
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a mode
         which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized
         known smoothing parameters, but when smoothing parameters have been e
         are typically lower than they should be, meaning that the tests reje
<ipython-input-154-891b9639a411>:1: UserWarning: KNOWN BUG: p-values computed

Please do not make inferences based on these values!

Collaborate on a solution, and stay up to date at:
github.com/dswah/pyGAM/issues/163

  gam_full.summary ()
```

```
Yhat = gam_full.predict(Xgam)
```

```
#  logistic regression model
gam_logit = LogisticGAM ( age_term +
l_gam (1, lam =0) +
f_gam (2, lam =0))
gam_logit.fit(Xgam , high_earn)
```

```
LogisticGAM(callbacks=[Deviance(), Diffs(), Accuracy()],
    fit_intercept=True, max_iter=100,
    terms=s(0) + l(1) + f(2) + intercept, tol=0.0001, verbose=False)
```

```
#  Partial dependence of wage on education
fig , ax = subplots (figsize =(8, 8))
ax = plot_gam (gam_logit , 2)
ax. set_xlabel ('Education')
ax. set_ylabel ('Effect on wage')
ax. set_title ('Partial dependence of wage on education',
fontsize =20);
ax. set_xticklabels(Wage['education'].cat.categories , fontsize =8);
```


Partial dependence of wage on education
3000
2000
1000
0
−1000
−2000
−3000
Effect on wage
1. < HS Grad
2. HS Grad
3. Some College
4. College Grad
5. Advanced Degree
Education

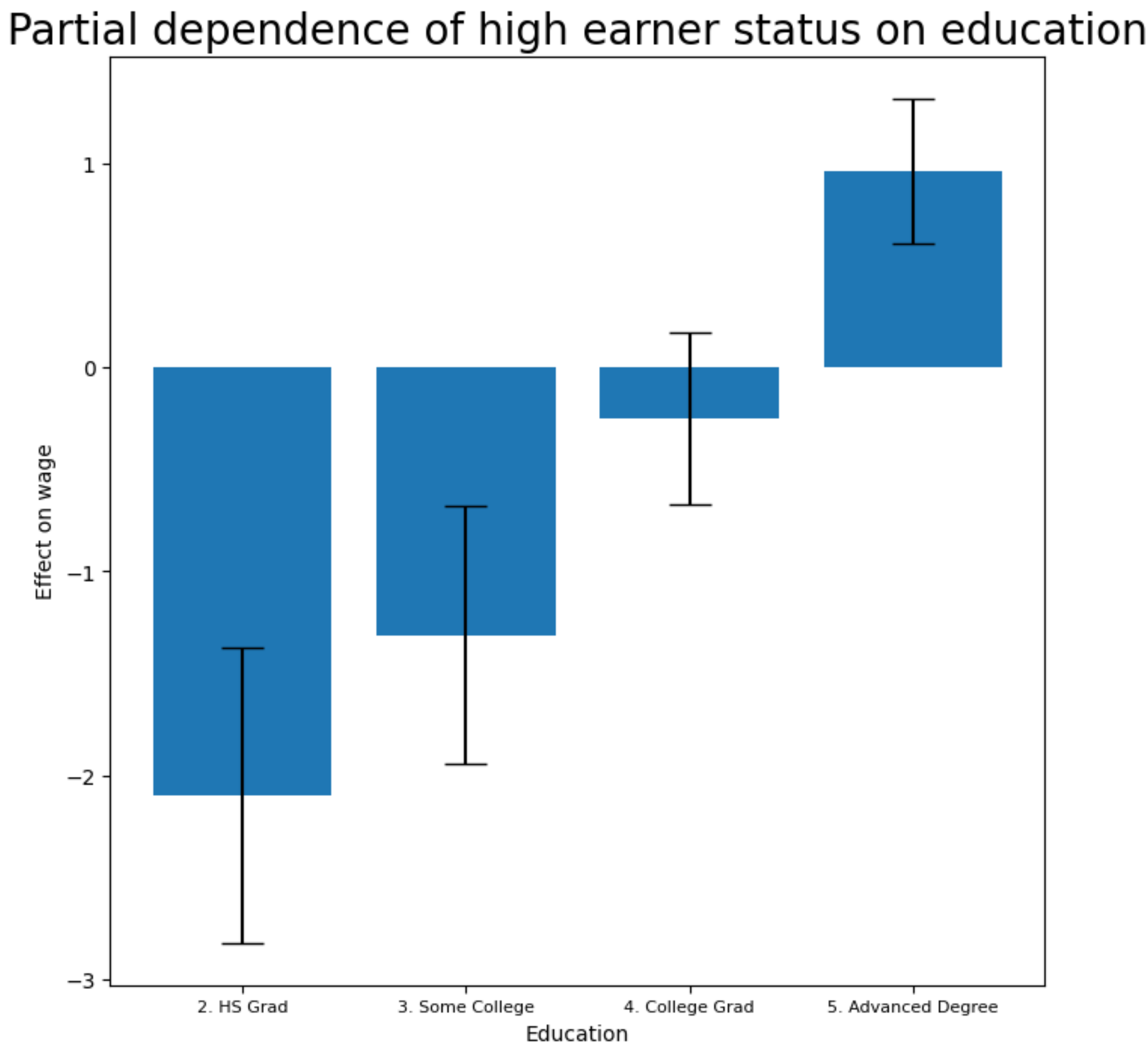
```
pd.crosstab(Wage['high_earn'], Wage['education'])
```

education high_earn	1. < HS Grad	2. HS Grad	3. Some College	4. College Grad	5. Advanced Degree
False	268	966	643	663	381
True	0	5	7	22	45

```
only_hs = Wage['education'] == '1. < HS Grad'
Wage_ = Wage.loc[~only_hs]
Xgam_ = np.column_stack ([ Wage_['age'],
Wage_['year'],
Wage_['education']. cat.codes -1])
high_earn_ = Wage_['high_earn']


# logistic regression model
gam_logit_ = LogisticGAM (age_term +
year_term +
f_gam (2, lam =0))
gam_logit_ .fit(Xgam_ , high_earn_ )
```

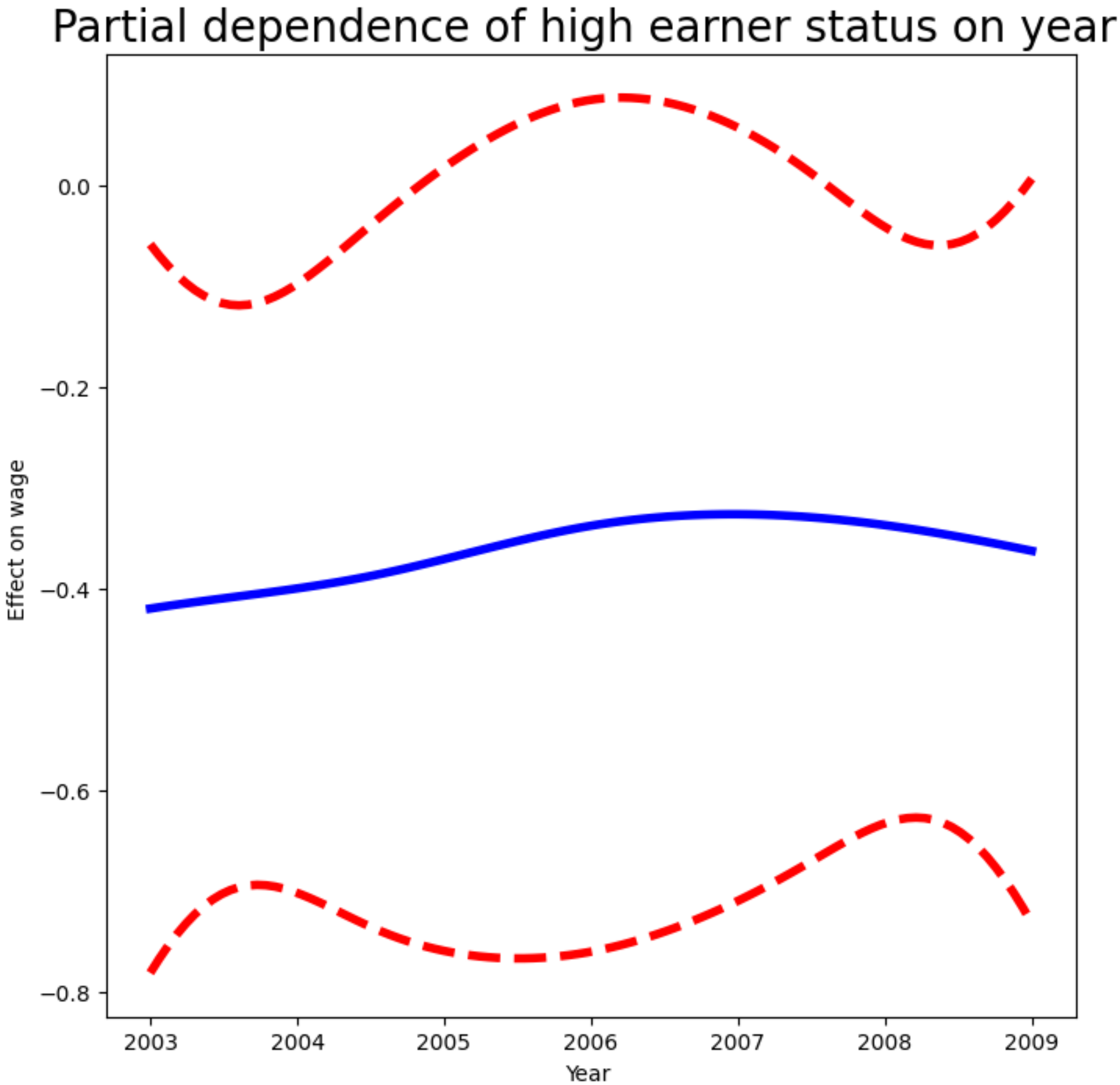
```
LogisticGAM(callbacks=[Deviance(), Diffs(), Accuracy()],
   fit_intercept=True, max_iter=100,
   terms=s(0) + s(1) + f(2) + intercept, tol=0.0001, verbose=False)
```

```
# Partial dependence of high earner status on education
fig , ax = subplots (figsize =(8, 8))
ax = plot_gam (gam_logit_ , 2)
ax. set_xlabel ('Education')
ax. set_ylabel ('Effect on wage')
ax. set_title ('Partial dependence of high earner status on education', fontsize =
ax. set_xticklabels (Wage['education']. cat. categories [1:] ,
fontsize =8);
```



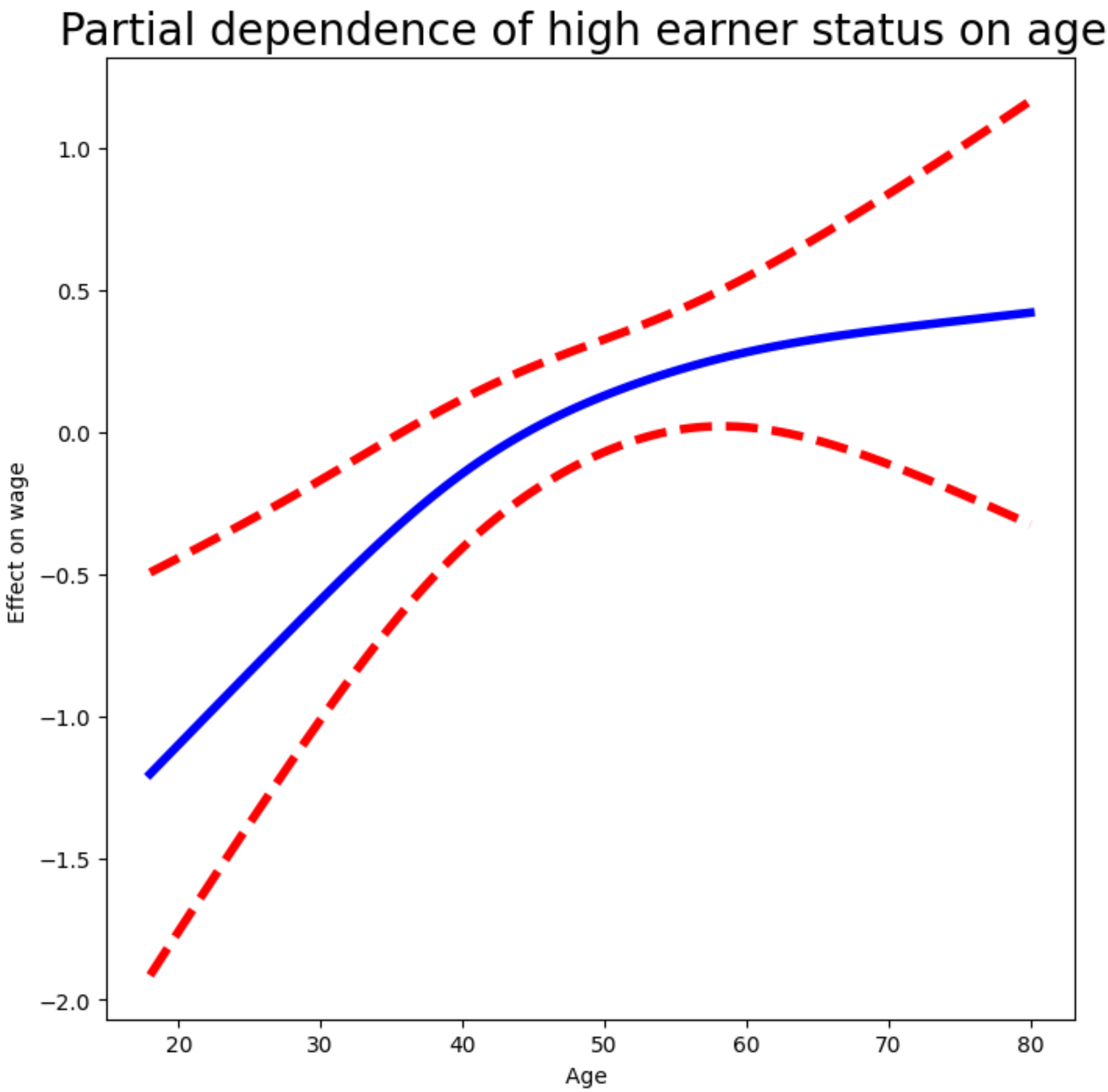

```
# grpah shows Partial dependence of high earner status on year
fig , ax = subplots (figsize =(8, 8))
ax = plot_gam (gam_logit_ , 1)
ax. set_xlabel ('Year ')
ax. set_ylabel ('Effect on wage ')
```

```
ax. set_title ('Partial dependence of high earner status on year ',
fontsize =20);
```



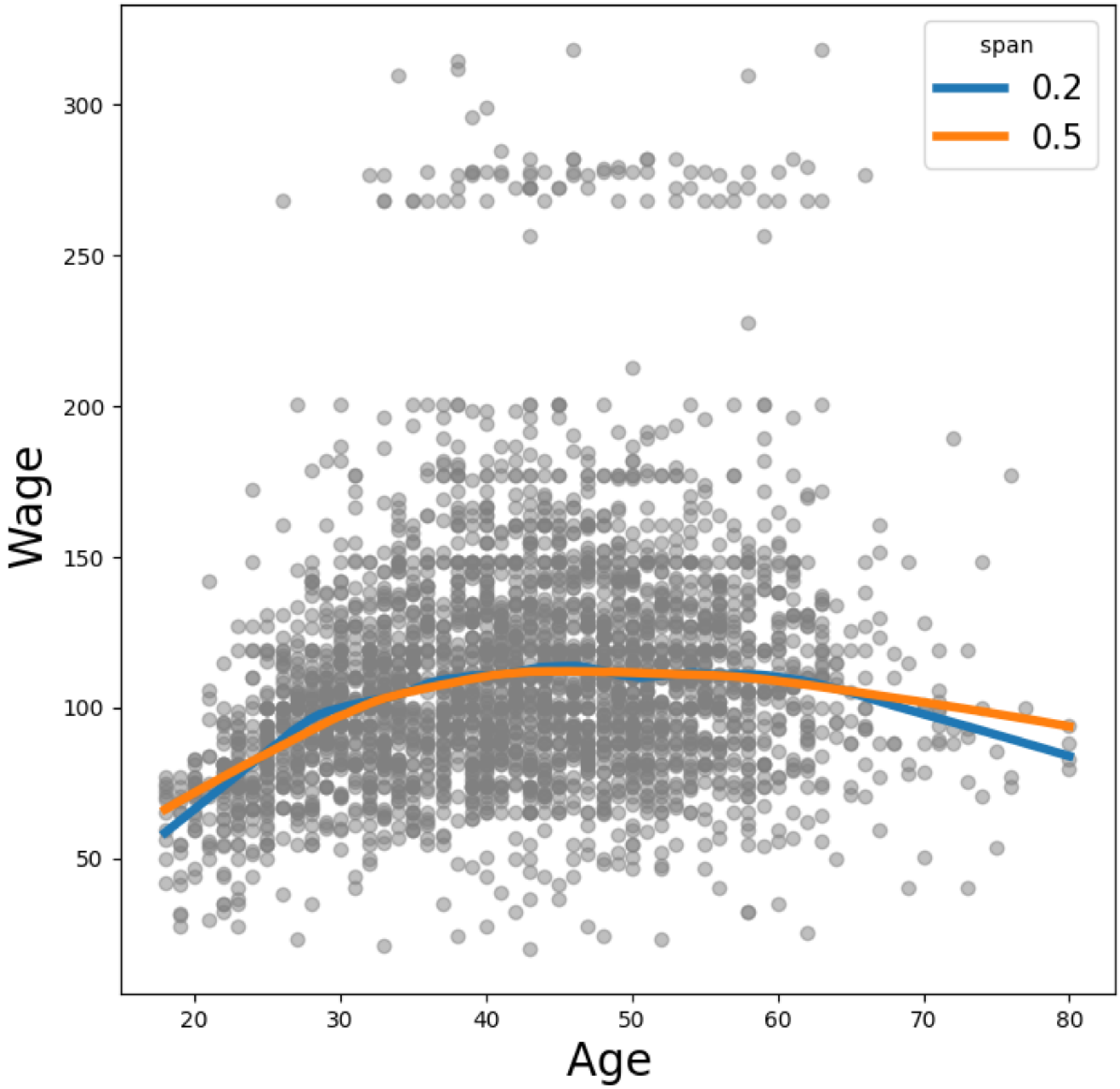

```
# graph shows Partial dependence of high earner status on age
fig , ax = subplots (figsize =(8, 8))
ax = plot_gam (gam_logit_ , 0)
```

```
ax. set_xlabel ('Age ')
ax. set_ylabel ('Effect on wage ')
ax. set_title ('Partial dependence of high earner status on age ',
fontsize =20);
```




```
# The graph shows that using a span of 0.5 is better than 0.2
```

```
lowess = sm. nonparametric .lowess
fig , ax = subplots (figsize =(8 ,8))
ax.scatter(age , y, facecolor ='gray', alpha =0.5)
for span in [0.2 , 0.5]:
  fitted = lowess(y,age , frac=span , xvals=age_grid )
  ax.plot(age_grid ,fitted , label='{:.1f}'.format(span), linewidth =4)
ax. set_xlabel ('Age ', fontsize =20)
ax. set_ylabel ('Wage ', fontsize =20);
ax.legend(title='span ', fontsize =15);
```


span
0.2
0.5
Wage
300
250
200
150
100
50
20
30
40
50
60
70
80
Age