In [177]:
```
%load_ext sql
```

```
The sql extension is already loaded. To reload it, use:
  %reload_ext sql
```

In [178]:
```
%sql mysql://prod:nerd@52.2.153.189/rental_nerd
```

Out[178]: u'Connected: prod@rental_nerd'

In [179]:
```
result = %sql (SELECT \
properties.id as "property_id", \
property_transaction_logs.id as "transaction_log_id", \
properties.*, \
property_transaction_logs.* \
FROM \
properties, \
property_transactions, \
property_transaction_logs \
WHERE \
properties.id = property_transactions.property_id AND \
property_transactions.property_transaction_log_id = property_transaction_logs.id AND \
property_transactions.transaction_type = 'rental')

data = result.DataFrame()
```

```
560 rows affected.
```

In [180]:
```
result.csv(filename="SQLdump.csv")
```

Out[180]: CSV results (./files/SQLdump.csv)

In [181]:
```
# imports
import pandas as pd
import matplotlib.pyplot as plt
# follow the usual sklearn pattern: import, instantiate, fit
from sklearn.linear_model import LinearRegression
import numpy as np

# this allows plots to appear directly in the notebook
%matplotlib inline

# read data into a DataFrame
data.head()
```

Out[181]:

| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | id | price | tra |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 1 | 567 Vallejo Street #PH500 | San Francisco (North Beach) | 3 | 3 | 2081 | climbsf_renting | http://www.climbsf.com/for-rent/567-vallejo-st... | ... | 1 | 12000 | op |
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 2 | 3950 | op |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 3 | 5400 | op |
| **3** | 4 | 4 | 4 | 333 Fremont Street #705 | San Francisco (South Beach) | 1 | 1 | 0 | climbsf_renting | http://www.climbsf.com/for-rent/333-fremont-st... | ... | 4 | 3600 | op |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 5 | 3975 | op |

5 rows × 26 columns

In [182]:
```
import datetime

Date_final = [0.1] * len(data)

for x in range(0,len(data)):
    data
    if data["date_closed"][x] is not None :
        # print " row: "+ `x` + ": using date_rented"
        # data.ix['Date_final',x]
        Date_final[x] = data["date_closed"][x]

    elif data["date_listed"][x] is not None :
        # print " row: "+ `x` + ": using date_listed"
        Date_final[x] = data["date_listed"][x]
    else:
        Date_final[x] = data["date_closed"][2]
        print " row: "+ `x` + ": we are screwed"



data['Date'] = pd.to_datetime(Date_final)

data.head()
```

Out[182]:

| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | price | transa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 1 | 567 Vallejo Street #PH500 | San Francisco (North Beach) | 3 | 3 | 2081 | climbsf_renting | http://www.climbsf.com/for-rent/567-vallejo-st... | ... | 12000 | open |
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 3950 | open |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 5400 | open |
| **3** | 4 | 4 | 4 | 333 Fremont Street #705 | San Francisco (South Beach) | 1 | 1 | 0 | climbsf_renting | http://www.climbsf.com/for-rent/333-fremont-st... | ... | 3600 | open |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 3975 | open |

5 rows × 27 columns

In [183]:
```
# create neighborhoods from lat/long coordinates
import fiona
import shapely as shapely
from shapely.geometry import asShape
```

In [184]:
```
shaped_neighborhood = ['None'] * len(data)

with fiona.open('data/Realtor_Neighborhoods_4326/hoods_4326.shp') as fiona_collection:
    for hood in fiona_collection:
        print "checking for listings in: " + hood["properties"]["nbrhood"]
        # Use Shapely to create the polygon
        shape = asShape( hood['geometry'] )

        for row in range(0,len(data)):
            point = shapely.geometry.Point([data['longitude'][row], data['latitude'][row]]) # longitude, latitude

            if shape.contains(point):
                #print `row` + ": Found " + data.address[row] + " in hood " + hood["properties"]["nbrhood"]
                shaped_neighborhood[row] = hood["properties"]["nbrhood"]

data['shaped_neighborhood'] = shaped_neighborhood
data.head()
```

```
checking for listings in: Alamo Square
checking for listings in: Anza Vista
checking for listings in: Balboa Terrace
checking for listings in: Bayview
checking for listings in: Bernal Heights
checking for listings in: Buena Vista Park/Ashbury Heights
checking for listings in: Central Richmond
checking for listings in: Central Sunset
checking for listings in: Clarendon Heights
checking for listings in: Corona Heights
checking for listings in: Cow Hollow
checking for listings in: Crocker Amazon
checking for listings in: Diamond Heights
checking for listings in: Downtown
checking for listings in: Duboce Triangle
checking for listings in: Eureka Valley / Dolores Heights
checking for listings in: Excelsior
checking for listings in: Financial District/Barbary Coast
checking for listings in: Yerba Buena
checking for listings in: Forest Hill
checking for listings in: Forest Hills Extension
checking for listings in: Forest Knolls
checking for listings in: Glen Park
checking for listings in: Golden Gate Heights
checking for listings in: Golden Gate Park
checking for listings in: Haight Ashbury
checking for listings in: Hayes Valley
checking for listings in: Hunters Point
checking for listings in: Ingleside
checking for listings in: Ingleside Heights
checking for listings in: Ingleside Terrace
checking for listings in: Inner Mission
checking for listings in: Inner Parkside
checking for listings in: Inner Richmond
checking for listings in: Inner Sunset
checking for listings in: Jordan Park / Laurel Heights
checking for listings in: Lake Street
checking for listings in: Lake Shore
checking for listings in: Lakeside
checking for listings in: Lone Mountain
checking for listings in: Lower Pacific Heights
checking for listings in: Marina
checking for listings in: Merced Heights
checking for listings in: Merced Manor
checking for listings in: Midtown Terrace
checking for listings in: Miraloma Park
checking for listings in: Mission Bay
checking for listings in: Mission Dolores
checking for listings in: Mission Terrace
checking for listings in: Monterey Heights
checking for listings in: Mount Davidson Manor
checking for listings in: Noe Valley
checking for listings in: North Beach
checking for listings in: North Panhandle
checking for listings in: North Waterfront
checking for listings in: Oceanview
checking for listings in: Outer Mission
checking for listings in: Outer Parkside
checking for listings in: Outer Richmond
checking for listings in: Outer Sunset
checking for listings in: Pacific Heights
checking for listings in: Parkside
checking for listings in: Cole Valley/Parnassus Heights
checking for listings in: Pine Lake Park
checking for listings in: Portola
checking for listings in: Potrero Hill
checking for listings in: Presidio
checking for listings in: Presidio Heights
checking for listings in: Russian Hill
checking for listings in: Saint Francis Wood
checking for listings in: Sea Cliff
checking for listings in: Silver Terrace
checking for listings in: South Beach
checking for listings in: South of Market
checking for listings in: Stonestown
checking for listings in: Sunnyside
checking for listings in: Telegraph Hill
checking for listings in: Twin Peaks
checking for listings in: Van Ness/Civic Center
checking for listings in: Visitacion Valley
```

```
checking for listings in: West Portal
checking for listings in: Western Addition
checking for listings in: Westwood Highlands
checking for listings in: Westwood Park
checking for listings in: Lincoln Park
checking for listings in: Sherwood Forest
checking for listings in: Tenderloin
checking for listings in: Central Waterfront/Dogpatch
checking for listings in: Candlestick Point
checking for listings in: Bayview Heights
checking for listings in: Little Hollywood
checking for listings in: Nob Hill
```

Out[184]:

| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | transaction_s |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 1 | 567 Vallejo Street #PH500 | San Francisco (North Beach) | 3 | 3 | 2081 | climbsf_renting | http://www.climbsf.com/for-rent/567-vallejo-st... | ... | open |
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | open |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | open |
| **3** | 4 | 4 | 4 | 333 Fremont Street #705 | San Francisco (South Beach) | 1 | 1 | 0 | climbsf_renting | http://www.climbsf.com/for-rent/333-fremont-st... | ... | open |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | open |

5 rows × 28 columns

In [185]:

```
# filter out any outliers, defined as rent >$10k or >2,500 sq ft, or not in SF

print "Entries before filter: " + `len(data)`
data = data[(data.shaped_neighborhood != 'None') & (data.sqft <= 2500) & (data.price <= 8000) & (data.price != 0) & (data.
bedrooms <= 4) & (data.bathrooms <= 3) & (data.sqft != 0)]

# filter out listings over one month old


print "Entries after filter: " + `len(data)`
```

```
Entries before filter: 560
Entries after filter: 304
```

In [186]:
```
# create year dummy variables (because date isn't very intuitive variable)
data["Year"] = pd.DatetimeIndex(data["Date"]).to_period('Y')

# create dummy variables using get_dummies, then exclude the first dummy column
year_dummies = pd.get_dummies(data.Year, prefix='Year').iloc[:, :-1]

# print out baseline neighborhood
base_area = pd.get_dummies(data.shaped_neighborhood, prefix='neighborhood').iloc[:, 0:1].columns[0]
print('Base neighborhood: %s' % base_area)

# create dummy variables using get_dummies, then exclude the first dummy column
area_dummies = pd.get_dummies(data.shaped_neighborhood, prefix='neighborhood').iloc[:, 1:]

# concatenate the dummy variable columns onto the original DataFrame (axis=0 means rows, axis=1 means columns)
data = pd.concat([data, area_dummies, year_dummies], axis=1)

data.head()
```

```
Base neighborhood: neighborhood_Alamo Square
```

Out[186]:

| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | neighborho Hill |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 0 |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 0 |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 0 |
| **7** | 8 | 8 | 8 | 1160 Mission Street #1112 | San Francisco (SOMA) | 1 | 1 | 664 | climbsf_renting | http://www.climbsf.com/for-rent/1160-mission-s... | ... | 0 |
| **11** | 12 | 12 | 12 | 655 26th Avenue | San Francisco (Central Richmond) | 2 | 1 | 1300 | climbsf_renting | http://www.climbsf.com/for-rent/655-26th-ave/ | ... | 0 |

5 rows × 83 columns

In [187]:
```
# FACTORING BY YEAR AND NEIGHBORHOOD
# Thesis: Neighborhoods influence valuations as a multiplier, rather than a constant.
# a square foot in SOMA is worth more than a square foot in Portrero by X%
# New model will look like this:
#      Price = B_1 x (SOMA Coeff * Year Coeff * Sqft) + intercept
#      $3,900 = B_1 x (1.20% * 1.15% * 2,023 sqft) + intercept
# where B_1 represents the price per square foot in base year and base neighborhood
# I will ignore intercepts for now FIXME
# calculate the coefficients for the following matrix and save them for later regressions
#                  SOMA    Mission    Portrero    Intercept
#  Price/SQFT      $1.23    $0.59       $0.88        $_.__

# create Price per square foot

price_per_foot = data.price / data.sqft
price_per_foot.name = 'price_per_foot'
data = pd.concat([data, price_per_foot], axis=1)

data.head()
```

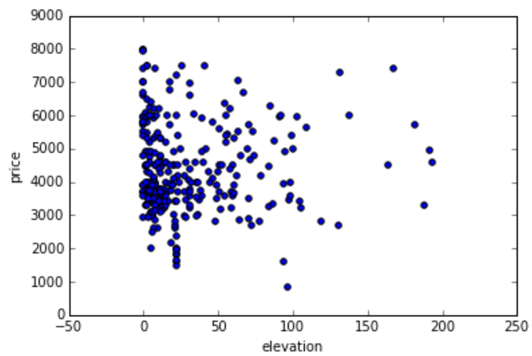
Out[187]:

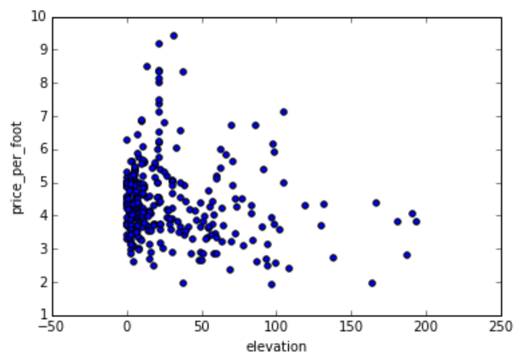
| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | neighborho Ness/Civic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 0 |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 0 |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 0 |
| **7** | 8 | 8 | 8 | 1160 Mission Street #1112 | San Francisco (SOMA) | 1 | 1 | 664 | climbsf_renting | http://www.climbsf.com/for-rent/1160-mission-s... | ... | 0 |
| **11** | 12 | 12 | 12 | 655 26th Avenue | San Francisco (Central Richmond) | 2 | 1 | 1300 | climbsf_renting | http://www.climbsf.com/for-rent/655-26th-ave/ | ... | 0 |

5 rows × 84 columns

In [188]:
```
# visualize the relationship between the features and the response using scatterplots
data.plot(kind='scatter', x='elevation', y='price')
data.plot(kind='scatter', x='elevation', y='price_per_foot')
```

Out[188]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x112475f10>
```




In [189]:
```
class ListTable(list):
    """ Overridden list class which takes a 2-dimensional list of
        the form [[1,2,3],[4,5,6]], and renders an HTML Table in
        IPython Notebook. """

    def _repr_html_(self):
        html = ["<table>"]
        for row in self:
            html.append("<tr>")

            for col in row:
                html.append("<td>{0}</td>".format(col))

            html.append("</tr>")
        html.append("</table>")
        return ''.join(html)
```

In [190]:
```
feature_cols = area_dummies.columns

X = data[feature_cols]
y = data.price_per_foot

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))

# print raw results
print("Base area is %s: $%.2f" % (base_area, lm.intercept_))

zip(feature_cols,lm.coef_)

table = ListTable()

dtype = [('Neighborhood', 'S100'), ('$ per square', float)]

# round to pennies
round_coef = map(round,lm.coef_,[2]*len(lm.coef_))
x = np.array(zip(feature_cols, round_coef),dtype=dtype)
x.T
x = np.sort(x,axis=0,order='$ per square')

table.append(['Neighborhood','$ per square (+/-)'])
for i in x:
    table.append(i)

table
```

```
Residual sum of squares: 0.82
Variance score: 0.44
Base area is neighborhood_Alamo Square: $4.17
```

Out[190]:

| Neighborhood | $ per square (+/-) |
|---|---|
| neighborhood_Mount Davidson Manor | -1.75 |
| neighborhood_Ingleside | -1.7 |
| neighborhood_Visitacion Valley | -1.6 |
| neighborhood_Portola | -1.52 |
| neighborhood_Glen Park | -1.44 |
| neighborhood_Bernal Heights | -1.38 |
| neighborhood_Diamond Heights | -1.36 |
| neighborhood_Silver Terrace | -1.33 |
| neighborhood_Lake Shore | -1.3 |
| neighborhood_Central Richmond | -1.05 |
| neighborhood_Anza Vista | -1.03 |
| neighborhood_Bayview | -0.94 |
| neighborhood_Excelsior | -0.94 |
| neighborhood_Cole Valley/Parnassus Heights | -0.79 |
| neighborhood_Downtown | -0.78 |
| neighborhood_Outer Parkside | -0.64 |
| neighborhood_Outer Richmond | -0.57 |
| neighborhood_Buena Vista Park/Ashbury Heights | -0.47 |
| neighborhood_Western Addition | -0.4 |
| neighborhood_Forest Hills Extension | -0.37 |
| neighborhood_Golden Gate Heights | -0.33 |
| neighborhood_Mission Bay | -0.32 |

| | |
|---|---|
| neighborhood_Oceanview | -0.21 |
| neighborhood_Central Waterfront/Dogpatch | -0.13 |
| neighborhood_Van Ness/Civic Center | -0.13 |
| neighborhood_North Panhandle | -0.12 |
| neighborhood_Miraloma Park | -0.1 |
| neighborhood_South of Market | -0.08 |
| neighborhood_Telegraph Hill | -0.02 |
| neighborhood_Inner Richmond | -0.0 |
| neighborhood_Potrero Hill | 0.07 |
| neighborhood_Marina | 0.1 |
| neighborhood_Noe Valley | 0.18 |
| neighborhood_South Beach | 0.19 |
| neighborhood_Lower Pacific Heights | 0.2 |
| neighborhood_Lone Mountain | 0.34 |
| neighborhood_Yerba Buena | 0.48 |
| neighborhood_Eureka Valley / Dolores Heights | 0.5 |
| neighborhood_Pacific Heights | 0.5 |
| neighborhood_Inner Mission | 0.6 |
| neighborhood_Nob Hill | 0.64 |
| neighborhood_Duboce Triangle | 1.04 |
| neighborhood_Russian Hill | 1.05 |
| neighborhood_North Waterfront | 1.07 |
| neighborhood_Mission Dolores | 1.22 |
| neighborhood_Inner Sunset | 1.69 |
| neighborhood_North Beach | 2.46 |
| neighborhood_Hayes Valley | 2.64 |
| neighborhood_Financial District/Barbary Coast | 4.17 |

In [191]:

```
full_price = [lm.intercept_] * len(lm.coef_)
full_price += lm.coef_

area_price_per_foot = dict(zip(feature_cols,full_price))
area_price_per_foot[base_area] = lm.intercept_

dtype = [('Neighborhood', 'S100'), ('$ per sqft', float)]

# round to pennies
round_coef = map(round,full_price,[2]*len(full_price))
x = np.array(zip(feature_cols, full_price),dtype=dtype)
x.T
x = np.sort(x,axis=0,order='$ per sqft')

table = ListTable()

table.append(['Neighborhood','$ per sqft'])
for i in x:
    table.append(i)

table
```

Out[191]:

| Neighborhood | $ per sqft |
|---|---|
| neighborhood_Mount Davidson Manor | 2.41970021413 |
| neighborhood_Ingleside | 2.46875 |
| neighborhood_Visitacion Valley | 2.56314257913 |
| neighborhood_Portola | 2.64285714286 |
| neighborhood_Glen Park | 2.72727272727 |

| | |
|---|---|
| neighborhood_Bernal Heights | 2.78200061463 |
| neighborhood_Diamond Heights | 2.8085106383 |
| neighborhood_Silver Terrace | 2.83464566929 |
| neighborhood_Lake Shore | 2.86666666667 |
| neighborhood_Central Richmond | 3.11732711733 |
| neighborhood_Anza Vista | 3.13581037796 |
| neighborhood_Excelsior | 3.22222222222 |
| neighborhood_Bayview | 3.22391991699 |
| neighborhood_Cole Valley/Parnassus Heights | 3.3732856291 |
| neighborhood_Downtown | 3.38847472785 |
| neighborhood_Outer Parkside | 3.52669238052 |
| neighborhood_Outer Richmond | 3.59375 |
| neighborhood_Buena Vista Park/Ashbury Heights | 3.69863013699 |
| neighborhood_Western Addition | 3.76897132069 |
| neighborhood_Forest Hills Extension | 3.8 |
| neighborhood_Golden Gate Heights | 3.83333333333 |
| neighborhood_Mission Bay | 3.85094171788 |
| neighborhood_Oceanview | 3.95238095238 |
| neighborhood_Van Ness/Civic Center | 4.03577014404 |
| neighborhood_Central Waterfront/Dogpatch | 4.04075057006 |
| neighborhood_North Panhandle | 4.04545454545 |
| neighborhood_Miraloma Park | 4.07072368421 |
| neighborhood_South of Market | 4.08636554466 |
| neighborhood_Telegraph Hill | 4.14764859845 |
| neighborhood_Inner Richmond | 4.16363636364 |
| neighborhood_Potrero Hill | 4.2321829593 |
| neighborhood_Marina | 4.27103404056 |
| neighborhood_Noe Valley | 4.35031959807 |
| neighborhood_South Beach | 4.35394300952 |
| neighborhood_Lower Pacific Heights | 4.36170254619 |
| neighborhood_Lone Mountain | 4.50186409772 |
| neighborhood_Yerba Buena | 4.64558173282 |
| neighborhood_Pacific Heights | 4.66270219935 |
| neighborhood_Eureka Valley / Dolores Heights | 4.66682988664 |
| neighborhood_Inner Mission | 4.76632367548 |
| neighborhood_Nob Hill | 4.80566691815 |
| neighborhood_Duboce Triangle | 5.20254134584 |
| neighborhood_Russian Hill | 5.22053967721 |
| neighborhood_North Waterfront | 5.24109014675 |
| neighborhood_Mission Dolores | 5.38924963925 |
| neighborhood_Inner Sunset | 5.85714285714 |
| neighborhood_North Beach | 6.62254901961 |
| neighborhood_Hayes Valley | 6.80851715243 |
| neighborhood_Financial District/Barbary Coast | 8.33333333333 |

In [192]:
```
# calculate the multipliers for each neighborhood relative to base area
# SOMA_mult = SOMA_per_foot / Base_per_foot

area_mults = [lm.intercept_] * len(lm.coef_)
area_mults = full_price / area_mults - [1]*len(lm.coef_)


dtype = [('Neighborhood', 'S100'), ('Multiplier', float)]

# round to pennies
round_coef = map(round,area_mults,[2]*len(area_mults))
x = np.array(zip(feature_cols, area_mults),dtype=dtype)
x.T
x = np.sort(x,axis=0,order='Multiplier')

table = ListTable()

table.append(['Neighborhood','Multiplier'])
table.append([base_area,0])
for i in x:
    table.append(i)

table
```

Out[192]:

| Neighborhood | Multiplier |
|---|---|
| neighborhood_Alamo Square | 0 |
| neighborhood_Mount Davidson Manor | -0.419271948608 |
| neighborhood_Ingleside | -0.4075 |
| neighborhood_Visitacion Valley | -0.384845781009 |
| neighborhood_Portola | -0.365714285714 |
| neighborhood_Glen Park | -0.345454545455 |
| neighborhood_Bernal Heights | -0.332319852489 |
| neighborhood_Diamond Heights | -0.325957446809 |
| neighborhood_Silver Terrace | -0.31968503937 |
| neighborhood_Lake Shore | -0.312 |
| neighborhood_Central Richmond | -0.251841491841 |
| neighborhood_Anza Vista | -0.247405509289 |
| neighborhood_Excelsior | -0.226666666667 |
| neighborhood_Bayview | -0.226259219923 |
| neighborhood_Cole Valley/Parnassus Heights | -0.190411449016 |
| neighborhood_Downtown | -0.186766065317 |
| neighborhood_Outer Parkside | -0.153593828675 |
| neighborhood_Outer Richmond | -0.1375 |
| neighborhood_Buena Vista Park/Ashbury Heights | -0.112328767123 |
| neighborhood_Western Addition | -0.0954468830351 |
| neighborhood_Forest Hills Extension | -0.088 |
| neighborhood_Golden Gate Heights | -0.08 |
| neighborhood_Mission Bay | -0.0757739877095 |
| neighborhood_Oceanview | -0.0514285714286 |
| neighborhood_Van Ness/Civic Center | -0.0314151654308 |
| neighborhood_Central Waterfront/Dogpatch | -0.0302198631857 |
| neighborhood_North Panhandle | -0.0290909090909 |
| neighborhood_Miraloma Park | -0.0230263157895 |
| neighborhood_South of Market | -0.0192722692805 |
| neighborhood_Telegraph Hill | -0.00456433637285 |
| neighborhood_Inner Richmond | -0.000727272727277 |

| | |
|---|---|
| neighborhood_Potrero Hill | 0.0157239102317 |
| neighborhood_Marina | 0.0250481697352 |
| neighborhood_Noe Valley | 0.0440767035374 |
| neighborhood_South Beach | 0.0449463222858 |
| neighborhood_Lower Pacific Heights | 0.0468086110849 |
| neighborhood_Lone Mountain | 0.0804473834535 |
| neighborhood_Yerba Buena | 0.114939615876 |
| neighborhood_Pacific Heights | 0.119048527843 |
| neighborhood_Eureka Valley / Dolores Heights | 0.120039172793 |
| neighborhood_Inner Mission | 0.143917682115 |
| neighborhood_Nob Hill | 0.153360060357 |
| neighborhood_Duboce Triangle | 0.248609923 |
| neighborhood_Russian Hill | 0.252929522531 |
| neighborhood_North Waterfront | 0.25786163522 |
| neighborhood_Mission Dolores | 0.29341991342 |
| neighborhood_Inner Sunset | 0.405714285714 |
| neighborhood_North Beach | 0.589411764706 |
| neighborhood_Hayes Valley | 0.634044116583 |
| neighborhood_Financial District/Barbary Coast | 1.0 |

In [193]:
```
# calculate the adjusted Sqft (Sqft * Area_mult) for the dataset and add it as a new column to data

# for each property, multiplier is sum of array [area_dummies] x [area_mults]

t = data[area_dummies.columns] * area_mults
t = t.T.sum()

t.name = 'area_multiplier'
t = t + 1
data = pd.concat([data, t], axis=1)

adj_sqft = data.sqft * t
adj_sqft.name = 'area_adj_sqft'
data = pd.concat([data, adj_sqft], axis=1)

data.head()
```

Out[193]:

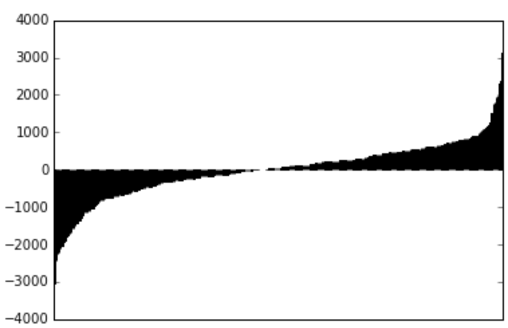
| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | neighborho Addition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 0 |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 0 |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 0 |
| **7** | 8 | 8 | 8 | 1160 Mission Street #1112 | San Francisco (SOMA) | 1 | 1 | 664 | climbsf_renting | http://www.climbsf.com/for-rent/1160-mission-s... | ... | 0 |
| **11** | 12 | 12 | 12 | 655 26th Avenue | San Francisco (Central Richmond) | 2 | 1 | 1300 | climbsf_renting | http://www.climbsf.com/for-rent/655-26th-ave/ | ... | 0 |

5 rows × 86 columns

In [194]:
```
# run the regression based on area_adj_sqft rather than sqft

# create X and y
feature_cols = [data.area_adj_sqft.name]

X = data[feature_cols]
y = data.price

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
print("Intercept: %.2f" % lm.intercept_)

# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))
zip(feature_cols, lm.coef_)

# calculate predictions for the data set and plot errors
predictions = lm.predict(X)
errors = predictions-y
errors.name = 'Error'

# visualize the relationship between the features and the response using scatterplots
errors.sort()
errors.plot(kind='bar').get_xaxis().set_ticks([])
```

```
Intercept: 1581.13
Residual sum of squares: 587671.58
Variance score: 0.67
```

Out[194]: []



In [195]:
```
feature_cols = year_dummies.columns

X = data[feature_cols]
y = data.price_per_foot

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))

# print raw results
print lm.intercept_

zip(feature_cols,lm.coef_)
```

```
Residual sum of squares: 1.32
Variance score: 0.11
4.79633313103
```

Out[195]:
```
[(u'Year_1969', -1.9410031817959141),
 (u'Year_2011', -0.62577229712902971),
 (u'Year_2012', -1.3700383103173595),
 (u'Year_2013', -0.98855679368271021),
 (u'Year_2014', -0.60179239513716498)]
```

In [196]:
```
full_price = [lm.intercept_] * len(lm.coef_)
full_price += lm.coef_

year_price_per_foot = dict(zip(feature_cols,full_price))
year_price_per_foot[base_area] = lm.intercept_

print year_price_per_foot
```

```
{u'Year_1969': 2.8553299492385782, u'neighborhood_Alamo Square': 4.7963331310344923, u'Year_2012': 3.4262948207171329, u'Y
ear_2013': 3.8077763373517821, u'Year_2011': 4.1705608339054629, u'Year_2014': 4.194540735897327}
```

In [197]:
```
# calculate the multipliers for each year relative to base year
# 2014_mult = 2014_per_foot / 2015_per_foot

year_mults = [lm.intercept_] * len(lm.coef_)
year_mults = full_price / year_mults - [1]*len(lm.coef_)

zip(feature_cols, year_mults)
```

Out[197]:
```
[(u'Year_1969', -0.40468481416287083),
 (u'Year_2011', -0.13046889780861826),
 (u'Year_2012', -0.28564285942787804),
 (u'Year_2013', -0.2061067833854765),
 (u'Year_2014', -0.12546926551937987)]
```

In [198]:
```
# calculate the adjusted Sqft (Sqft * Year_mult) for the dataset and add it as a new column to data

# for each property, multiplier is sum of array [year_dummies] x [year_mults]

t = data[year_dummies.columns] * year_mults
t = t.T.sum()

t.name = 'year_multiplier'
t = t + 1
data = pd.concat([data, t], axis=1)

year_adj_sqft = data.area_adj_sqft * t
year_adj_sqft.name = 'adj_sqft'
data = pd.concat([data, year_adj_sqft], axis=1)

data.head()
```

Out[198]:

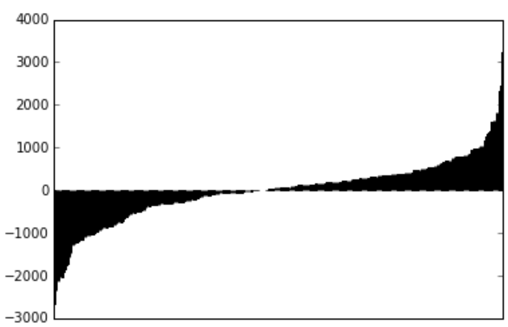
| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | Year_1969 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 0 |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 0 |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 0 |
| **7** | 8 | 8 | 8 | 1160 Mission Street #1112 | San Francisco (SOMA) | 1 | 1 | 664 | climbsf_renting | http://www.climbsf.com/for-rent/1160-mission-s... | ... | 0 |
| **11** | 12 | 12 | 12 | 655 26th Avenue | San Francisco (Central Richmond) | 2 | 1 | 1300 | climbsf_renting | http://www.climbsf.com/for-rent/655-26th-ave/ | ... | 0 |

5 rows × 88 columns

In [199]:
```
# run the regression based on year_and_area_adj_sqft rather than area_adj_sqft

# create X and y
feature_cols = ['adj_sqft']

X = data[feature_cols]
y = data.price

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
print lm.intercept_
# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))
print zip(feature_cols, lm.coef_)

# calculate predictions for the data set and plot errors
predictions = lm.predict(X)
errors = predictions-y
errors.name = 'Error'

# visualize the relationship between the features and the response using scatterplots
errors.sort(inplace=True)
errors.plot(kind='bar').get_xaxis().set_ticks([])

errors.tail(10)
```

```
1510.45714164
Residual sum of squares: 547156.69
Variance score: 0.69
[('adj_sqft', 2.8457143729597223)]
```

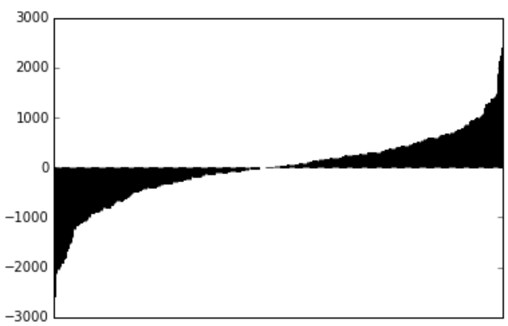
Out[199]:
```
326    1351.485576
243    1371.524527
328    1609.231682
236    1624.388449
108    1636.430154
66     1807.945788
427    1820.489102
294    2338.071426
60     2435.630745
455    3240.446932
Name: Error, dtype: float64
```



In [200]:
```
# create X and y
feature_cols = ['adj_sqft', 'bedrooms', 'bathrooms']

X = data[feature_cols]
y = data.price

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
print("Intercept: %.2f" % lm.intercept_)
# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))
print zip(feature_cols, lm.coef_)

# calculate predictions for the data set and plot errors
predictions = lm.predict(X)
errors = predictions-y
errors.name = 'Error'

# visualize the relationship between the features and the response using scatterplots
errors.sort()
errors.plot(kind='bar').get_xaxis().set_ticks([])
```

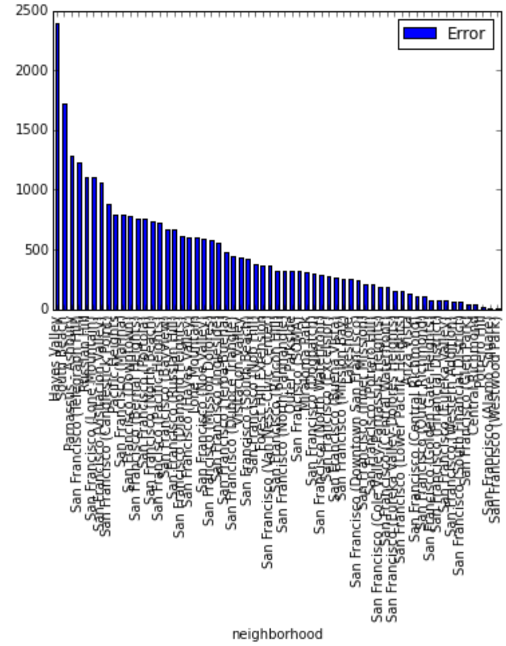
```
Intercept: 1229.39
Residual sum of squares: 489125.54
Variance score: 0.73
[('adj_sqft', 2.323433447134625), ('bedrooms', 194.36513659462096), ('bathrooms', 341.12870661669922)]
```

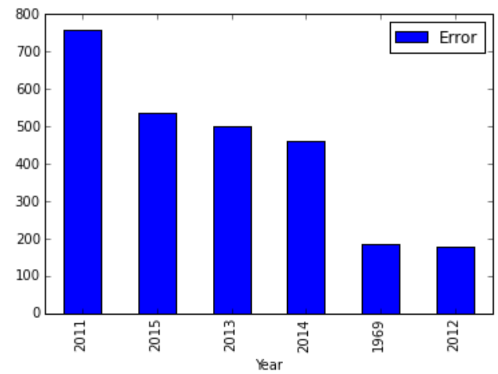
Out[200]: []

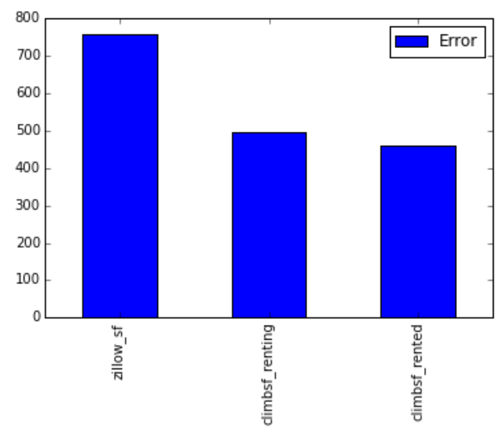


In [201]:
```
# show errors by neighborhood to see if there are any neighborhoods with funky differences

hooderrors = data[['neighborhood']]

errors = predictions-y
errors.name = 'Error'

hooderrors = pd.concat([hooderrors,errors.abs()],axis=1)

hood_group = hooderrors.groupby('neighborhood')

import numpy
def median(lst):
    return numpy.median(numpy.array(lst))

error_avg = hood_group.median()
error_avg.sort(columns='Error',ascending=False).plot(kind='bar')

# show errors by year to see if there are any years with funky differences

yearerrors = data[['Year']]

yearerrors = pd.concat([yearerrors,errors.abs()],axis=1)

year_group = yearerrors.groupby('Year')
error_avg = year_group.mean()
error_avg.sort(columns='Error',ascending=False).plot(kind='bar')

# show errors by source to see if there are any sources have noisy data

srcerrors = data[['source']]

srcerrors = pd.concat([srcerrors,errors.abs()],axis=1)

src_group = srcerrors.groupby('source')
error_avg = src_group.mean()
error_avg.sort(columns='Error',ascending=False).plot(kind='bar')
```

```
Out[201]: <matplotlib.axes._subplots.AxesSubplot at 0x106660ed0>
```



In [202]:
```
import csv

table = ListTable()

dtype = [('Effect', 'S100'), ('Coefficient', float)]

# round to pennies
round_coef = map(round,lm.coef_,[6]*len(lm.coef_))
x = np.array(zip(feature_cols, round_coef),dtype=dtype)
x.T
print zip(feature_cols, lm.coef_)
#x = np.sort(x,axis=0,order='Coefficient')

with open('model_features_v1.csv', 'wb') as csvfile:
    modelwriter = csv.writer(csvfile, delimiter=',', quotechar='|', quoting=csv.QUOTE_MINIMAL)

    header = ['Effect','Coefficient']
    table.append(header)
    modelwriter.writerow(header)
    for i in x:
        table.append(i)
        modelwriter.writerow(i)


    table.append(['base_rent', lm.intercept_])


    modelwriter.writerow(['base_rent',lm.intercept_])

table
```

```
[('adj_sqft', 2.323433447134625), ('bedrooms', 194.36513659462096), ('bathrooms', 341.12870661669922)]
```

Out[202]:

| Effect | Coefficient |
|---|---|
| adj_sqft | 2.323433 |
| bedrooms | 194.365137 |
| bathrooms | 341.128707 |
| base_rent | 1229.39138178 |

In [203]:
```
table = ListTable()

dtype = [('Effect', 'S100'), ('Coefficient', float)]

# round to pennies
round_coef = map(round,(area_mults + [1]*len(area_mults)),[6]*len(area_mults))
x = np.array(zip(area_dummies.columns, round_coef),dtype=dtype)
x.T
x = np.sort(x,axis=0,order='Coefficient')

with open('model_hoods_v1.csv', 'wb') as csvfile:
    hoodwriter = csv.writer(csvfile, delimiter=',', quotechar='|', quoting=csv.QUOTE_MINIMAL)

    header = ['Neighborhood','Multiplier']
    table.append(header)
    hoodwriter.writerow(header)

    for i in x:
        table.append(i)
        hoodwriter.writerow(i)

    lastrow = [base_area, 1]
    table.append(lastrow)
    hoodwriter.writerow(lastrow)


table
```

Out[203]:

| Neighborhood | Multiplier |
|---|---|
| neighborhood_Mount Davidson Manor | 0.580728 |
| neighborhood_Ingleside | 0.5925 |
| neighborhood_Visitacion Valley | 0.615154 |
| neighborhood_Portola | 0.634286 |

| | |
|---|---|
| neighborhood_Glen Park | 0.654545 |
| neighborhood_Bernal Heights | 0.66768 |
| neighborhood_Diamond Heights | 0.674043 |
| neighborhood_Silver Terrace | 0.680315 |
| neighborhood_Lake Shore | 0.688 |
| neighborhood_Central Richmond | 0.748159 |
| neighborhood_Anza Vista | 0.752594 |
| neighborhood_Excelsior | 0.773333 |
| neighborhood_Bayview | 0.773741 |
| neighborhood_Cole Valley/Parnassus Heights | 0.809589 |
| neighborhood_Downtown | 0.813234 |
| neighborhood_Outer Parkside | 0.846406 |
| neighborhood_Outer Richmond | 0.8625 |
| neighborhood_Buena Vista Park/Ashbury Heights | 0.887671 |
| neighborhood_Western Addition | 0.904553 |
| neighborhood_Forest Hills Extension | 0.912 |
| neighborhood_Golden Gate Heights | 0.92 |
| neighborhood_Mission Bay | 0.924226 |
| neighborhood_Oceanview | 0.948571 |
| neighborhood_Van Ness/Civic Center | 0.968585 |
| neighborhood_Central Waterfront/Dogpatch | 0.96978 |
| neighborhood_North Panhandle | 0.970909 |
| neighborhood_Miraloma Park | 0.976974 |
| neighborhood_South of Market | 0.980728 |
| neighborhood_Telegraph Hill | 0.995436 |
| neighborhood_Inner Richmond | 0.999273 |
| neighborhood_Potrero Hill | 1.015724 |
| neighborhood_Marina | 1.025048 |
| neighborhood_Noe Valley | 1.044077 |
| neighborhood_South Beach | 1.044946 |
| neighborhood_Lower Pacific Heights | 1.046809 |
| neighborhood_Lone Mountain | 1.080447 |
| neighborhood_Yerba Buena | 1.11494 |
| neighborhood_Pacific Heights | 1.119049 |
| neighborhood_Eureka Valley / Dolores Heights | 1.120039 |
| neighborhood_Inner Mission | 1.143918 |
| neighborhood_Nob Hill | 1.15336 |
| neighborhood_Duboce Triangle | 1.24861 |
| neighborhood_Russian Hill | 1.25293 |
| neighborhood_North Waterfront | 1.257862 |
| neighborhood_Mission Dolores | 1.29342 |
| neighborhood_Inner Sunset | 1.405714 |
| neighborhood_North Beach | 1.589412 |
| neighborhood_Hayes Valley | 1.634044 |
| neighborhood_Financial District/Barbary Coast | 2.0 |
| neighborhood_Alamo Square | 1 |

In [204]:
```
# show negative errors meaning we expected rents to be higher

error = predictions-y
error.name = 'error'

data = pd.concat([data,error,pd.DataFrame(predictions,columns=['predicted_price'])],axis=1)

data.head()
```

Out[204]:

| | property_id | transaction_log_id | id | address | neighborhood | bedrooms | bathrooms | sqft | source | origin_url | ... | Year_2012 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN |
| **1** | 2 | 2 | 2 | 252 Granada Avenue | San Francisco (Ingleside) | 2 | 2 | 1600 | climbsf_renting | http://www.climbsf.com/for-rent/252-granada-ave/ | ... | 0 |
| **2** | 3 | 3 | 3 | 460 Valley Street | San Francisco (Noe Valley) | 2 | 2 | 1446 | climbsf_renting | http://www.climbsf.com/for-rent/460-valley-st/ | ... | 0 |
| **3** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | ... | NaN |
| **4** | 5 | 5 | 5 | 420 Mission Bay Boulevard North #121 | San Francisco (Mission Bay) | 1 | 1 | 980 | climbsf_renting | http://www.climbsf.com/for-rent/420-mission-ba... | ... | 0 |

5 rows × 90 columns

In [205]:
```
# filter out overshoot error
overshoot = data[(data.error <= -500)]
columns = data.columns - ['error','latitude', 'longitude', 'address', 'origin_url','price','neighborhood']
overshoot = data.drop(columns,1)
overshoot.sort('error',ascending=True,inplace=True)
overshoot.head(30)
```

Out[205]:

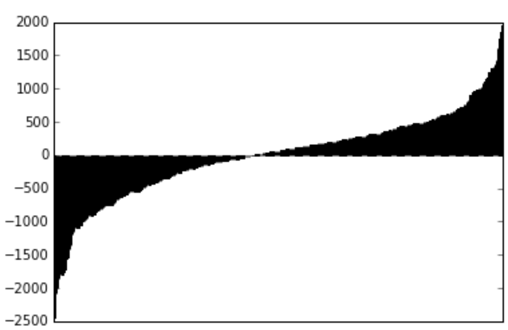
| | address | neighborhood | origin_url | latitude | longitude | price | error |
|---|---|---|---|---|---|---|---|
| **546** | 301 Main St UNIT 35A, San Francisco, CA 94105 | South Beach | http://www.zillow.com/homedetails/301-Main-St-... | 37.7894 | -122.391 | 7950 | -2571.090349 |
| **233** | 338 Spear Street #39E | San Francisco (South Beach) | http://www.climbsf.com/for-rent/338-spear-st-39e/ | 37.7894 | -122.391 | 7975 | -2121.288504 |
| **273** | 301 Mission Street #29F | San Francisco (South Beach) | http://www.climbsf.com/for-rent/301-mission-st... | 37.7905 | -122.396 | 7975 | -2047.617280 |
| **517** | 20th St San Francisco, CA 94110 | None | http://www.zillow.com/homedetails/20th-St-San-... | 37.7588 | -122.416 | 6200 | -2043.079832 |
| **434** | 748 Bay St, San Francisco, CA 94109 | Russian Hill | http://www.zillow.com/homedetails/748-Bay-St-S... | 37.8049 | -122.419 | 7500 | -1982.857244 |
| **158** | 338 Spear Street #39A | San Francisco (South Beach) | http://www.climbsf.com/for-rent/338-spear-st-39a/ | 37.7894 | -122.391 | 6700 | -1893.917532 |
| **382** | 480 Mission Bay Boulevard North #PH1606 | San Francisco (Mission Bay) | http://www.climbsf.com/for-rent/480-mission-ba... | 37.7731 | -122.393 | 7500 | -1815.353787 |
| **89** | 88 King Street #904 | San Francisco (South Beach) | http://www.climbsf.com/for-rent/88-king-st-904/ | 37.7807 | -122.389 | 6250 | -1808.208257 |
| **299** | 401 Harrison Street #3803 | San Francisco (Rincon Hill) | http://www.climbsf.com/for-rent/401-harrison-s... | 37.7864 | -122.392 | 7225 | -1673.712059 |
| **232** | 2560 Vallejo Street | San Francisco (Pacific Heights) | http://www.climbsf.com/for-rent/2560-vallejo-st/ | 37.7950 | -122.439 | 7050 | -1599.302373 |
| **525** | 20th St San Francisco, CA 94114 | None | http://www.zillow.com/homedetails/20th-St-San-... | 37.7578 | -122.432 | 5700 | -1528.763634 |
| **381** | 301 Main Street #35F | San Francisco (South Beach) | http://www.climbsf.com/for-rent/301-main-st-35f/ | 37.7894 | -122.391 | 7000 | -1487.557871 |
| **457** | Lombard St San Francisco, CA 94133 | None | http://www.zillow.com/homedetails/Lombard-St-S... | 37.8021 | -122.419 | 6700 | -1392.986525 |
| **357** | 296 Francisco Street | San Francisco (Telegraph | http://www.climbsf.com/for-rent/296- | 37.8053 | -122.410 | 5475 | -1232.987894 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Hill) | francisco-st/ | | | | |
| **459** | Tehama St San Francisco, CA 94103 | None | http://www.zillow.com/homedetails/Tehama-St-Sa... | 37.7793 | -122.407 | 6000 | -1225.930548 |
| **203** | 461 2nd St. #557T | San Francisco (South Beach) | http://www.climbsf.com/for-rent/461-2nd-st-557t/ | 37.7838 | -122.394 | 6750 | -1137.802049 |
| **293** | 425 1st Street #3402 | San Francisco (Rincon Hill) | http://www.climbsf.com/for-rent/425-1st-st-3402/ | 37.7858 | -122.392 | 6600 | -1121.547956 |
| **119** | 1837 Jefferson Street | San Francisco (Marina) | http://www.climbsf.com/for-rent/1837-jefferson... | 37.8045 | -122.443 | 6200 | -1098.241906 |
| **408** | Van Ness Ave San Francisco, CA 94102 | None | http://www.zillow.com/homedetails/Van-Ness-Ave... | 37.7767 | -122.419 | 4500 | -1097.671345 |
| **113** | 301 Mission Street #701 | San Francisco (SOMA) | http://www.climbsf.com/for-rent/301-mission-st... | 37.7905 | -122.396 | 7400 | -1079.024926 |
| **204** | 1839 Jefferson Street | San Francisco (Marina) | http://www.climbsf.com/for-rent/1839-jefferson... | 37.8048 | -122.443 | 6400 | -1058.718792 |
| **411** | Vallejo St San Francisco, CA 94133 | None | http://www.zillow.com/homedetails/Vallejo-St-S... | 37.7985 | -122.410 | 4000 | -1056.922032 |
| **405** | Vallejo St San Francisco, CA 94123 | None | http://www.zillow.com/homedetails/Vallejo-St-S... | 37.7952 | -122.435 | 4200 | -1037.812684 |
| **134** | 301 Main Street #25E | San Francisco (South Beach) | http://www.climbsf.com/for-rent/301-main-st-25e/ | 37.7894 | -122.391 | 5800 | -994.196530 |
| **283** | 234 Grand View Avenue | San Francisco (Noe Valley) | http://www.climbsf.com/for-rent/234-grand-view... | 37.7545 | -122.441 | 7300 | -977.321123 |
| **282** | 301 Main Street #5C | San Francisco (South Beach) | http://www.climbsf.com/for-rent/301-main-st-5c/ | 37.7894 | -122.391 | 7000 | -920.251919 |
| **109** | 229 Brannan Street #12J | San Francisco (South Beach) | http://www.climbsf.com/for-rent/229-brannan-st... | 37.7826 | -122.390 | 5950 | -902.984513 |
| **123** | 480 Mission Bay Boulevard North #1608 | San Francisco (Mission Bay) | http://www.climbsf.com/for-rent/480-mission-ba... | 37.7711 | -122.389 | 5475 | -883.385142 |
| **430** | 501 Beale St, San Francisco, CA 94105 | South Beach | http://www.zillow.com/homedetails/501-Beale-St... | 37.7863 | -122.389 | 6000 | -883.299578 |
| **406** | San Bruno Ave San Francisco, CA 94107 | None | http://www.zillow.com/homedetails/San-Bruno-Av... | 37.7621 | -122.405 | 4900 | -876.886047 |

In [206]:
```
data = data[(data.sqft <= 2500) & (data.price <= 8000) & (data.price != 0) & (data.bedrooms <= 4) & (data.bathrooms <= 3)
& (data.sqft != 0)]



# add squared square footage to the table
squared = data.adj_sqft ** 2
squared.name = 'sqft_squared'

squared_beds = data.bedrooms ** 2
squared_beds.name = 'beds_squared'

data = pd.concat([data, squared, squared_beds], axis=1)
#data = pd.concat([data, squared_beds], axis=1)



# create X and y
feature_cols = ['adj_sqft', 'bedrooms', 'bathrooms','sqft_squared','beds_squared']

X = data[feature_cols]
y = data.price

# instantiate, fit
lm = LinearRegression()
lm.fit(X, y)

# print coefficients
print("Intercept: %.2f" % lm.intercept_)
# The mean square error
print("Residual sum of squares: %.2f"
      % np.mean((lm.predict(X) - y) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % lm.score(X, y))
print zip(feature_cols, lm.coef_)

# calculate predictions for the data set and plot errors
predictions = lm.predict(X)
errors = predictions-y
errors.name = 'Error'

# visualize the relationship between the features and the response using scatterplots
errors.sort()
errors.plot(kind='bar').get_xaxis().set_ticks([])
```

```
Intercept: 96.06
Residual sum of squares: 434859.13
Variance score: 0.76
[('adj_sqft', 5.0230290888950986), ('bedrooms', 13.092104186543915), ('bathrooms', 257.0417615635385), ('sqft_squared', -0
.0010601887998804621), ('beds_squared', 21.146936417757299)]
```

Out[206]: []



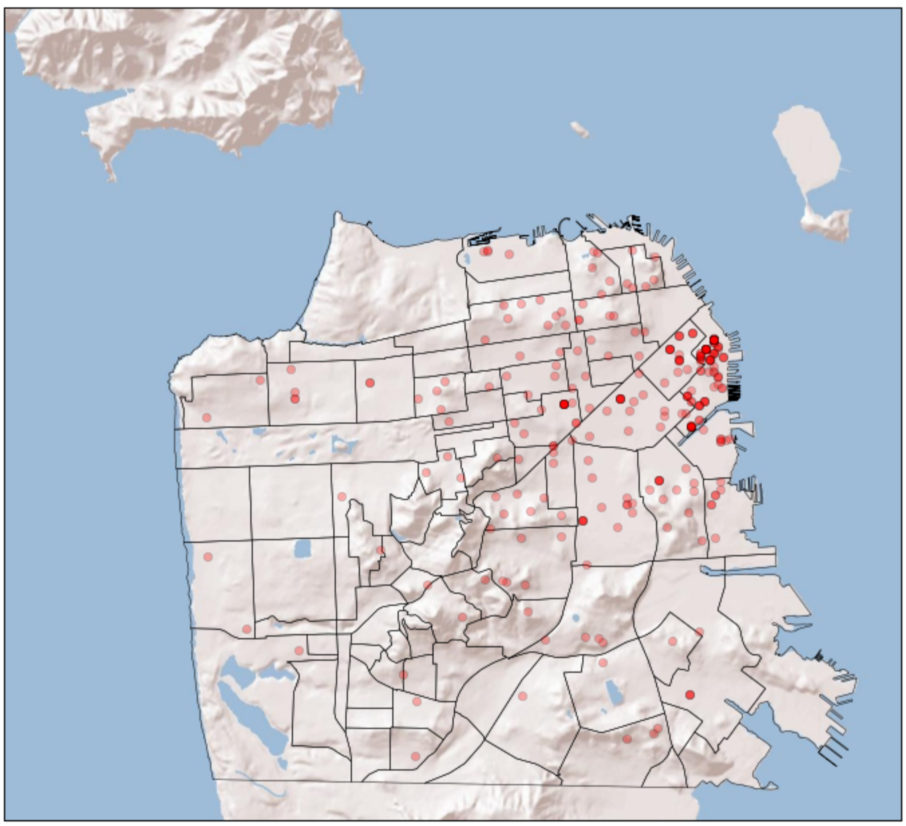
In [207]:
```
import statsmodels.formula.api as sm
result = sm.ols(formula="price ~ adj_sqft + bedrooms + bathrooms + elevation", data=data).fit()
print result.params
print result.summary()
```

```
Intercept    1310.572163
adj_sqft        2.296425
bedrooms      254.244471
bathrooms     301.255818
elevation      -3.063361
dtype: float64
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.731
Model:                            OLS   Adj. R-squared:                  0.727
Method:                 Least Squares   F-statistic:                     202.3
Date:                Sun, 16 Aug 2015   Prob (F-statistic):           1.29e-83
Time:                        12:52:28   Log-Likelihood:                -2411.4
No. Observations:                 303   AIC:                             4833.
Df Residuals:                     298   BIC:                             4851.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
Intercept   1310.5722    129.624     10.111      0.000      1055.477  1565.667
adj_sqft       2.2964      0.138     16.680      0.000         2.025     2.567
bedrooms     254.2445     73.359      3.466      0.001       109.877   398.612
bathrooms    301.2558     97.168      3.100      0.002       110.034   492.477
elevation     -3.0634      1.162     -2.636      0.009        -5.351    -0.776
==============================================================================
Omnibus:                       17.314   Durbin-Watson:                   1.860
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               30.199
Skew:                           0.341   Prob(JB):                     2.77e-07
Kurtosis:                       4.388   Cond. No.                     3.87e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.87e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [208]:
```
from mpl_toolkits.basemap import Basemap
import fiona
```

In [209]:
```
plt.figure(figsize=(12,12))


# Create the Basemap
event_map = Basemap(projection='merc',
                    resolution='h', epsg=2227,
                    lat_0 = 37.7, lon_0=-122.4, # Map center
                    llcrnrlon=-122.55, llcrnrlat=37.7, # Lower left corner
                    urcrnrlon=-122.35, urcrnrlat=37.85) # Upper right corner

# Draw important features
event_map.arcgisimage(service='World_Shaded_Relief', xpixels = 1500, verbose= True)

# add neighborhoods
event_map.readshapefile(
    'data/Realtor_Neighborhoods_4326/hoods_4326', 'SF', color='black', zorder=2)

# create array storing lats and longs
listing_coords = zip(data.latitude,data.longitude)

# Draw the points on the map:
for longitude, latitude in listing_coords:
    x, y = event_map(latitude, longitude) # Convert lat, long to y,x
    event_map.plot(x,y, 'ro', alpha=0.3)
```

```
http://server.arcgisonline.com/ArcGIS/rest/services/World_Shaded_Relief/MapServer/export?bbox=5968621.97922,2083843.65958,
6027551.68158,2137245.61137&bboxSR=2227&imageSR=2227&size=1500,1359&dpi=96&format=png32&f=image
```



In [ ]:

In [ ]: