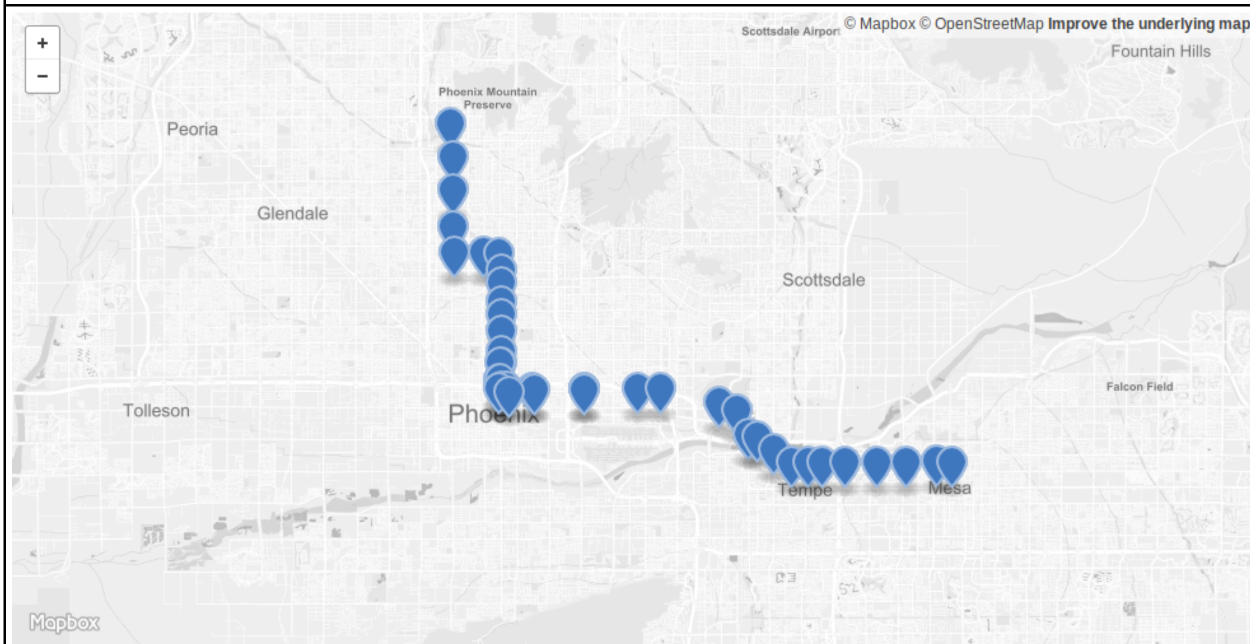
In [366]:
```
# imports
import pandas as pd
import numpy as np
import datetime as dt

import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams['figure.figsize'] = (12, 8)

import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.sandbox.regression.predstd import wls_prediction_std

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

limit = 100000000
```

In [367]:
```
# read in data
sold = pd.read_csv('../CSV_backups/ALL-sales.csv',nrows=limit, index_col=['prop
erty_id','transaction_id']).drop_duplicates()
```

```
/home/ilya/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.
py:2717: DtypeWarning: Columns (12,13,14,16) have mixed types. Specify dtype op
tion on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Many investors generally assume that light rail construction will lift property values. We utilize a dataset of home sales in Phoenix, Arizona over 2008-2018 to study the effect of light rail operation on house property values. Valley Metro began construction in March 2005 and opened in December 2008 with 28 stations. It as since been extended to 35 stations. We evaluate the impact of proximity to a light rail station on median home prices over the past 10 years. Analysis finds that in the first six years of operation, light rail actually caused a decline in house valuations in the surrounding area, when compared to homes that were further away. It was only in 2015 and later on that the effect of light rail operation had a consistently positive impact on median home prices. We also note that the positive effect appears rather muted, with homes near rail station fetching 5.6% higher prices than homes farther away. Given the initial negative impact on prices, investors should be wary of over-bidding on properties near future train stops in anticipation of price gains in the future. For the last 9 years, homes near light rail stations appreciated at 1% higher annual rate than homes that were far away.

Map of Valley Metro Stations


We start with a basic data set consisting of transaction data consisting of `date_closed`, `price`, `sqft`, and `dist_to_lightrail_station`. Distance to the closest light rail station is measured in kilometers, as the crow flies. We also calculate the price per squarter foot as `price_per_foot`.

Example 1	Example 2
	

In [368]:
```
# only show properties that were actually sold and closed dates are after 12/31
/2004 (1460 days since Y2K)
df = sold[(sold.date_closed != 0) & (sold.date_closed < 10000 )] \
        [["address", "date_closed","price","sqft","dist_to_lightrail_station"]]
df.rename(columns = {'date_closed':'date'}, inplace = True)

# convert days since Y2K to a nice looking date
df['date'] = df['date'].apply(lambda x: dt.date(2000, 1, 1) + dt.timedelta(days
=x)) \
                       .astype("datetime64[ns]")

df = df[df.date >= dt.date(2008,12,27)]

df['ppf'] = (df.price / df.sqft)
df.head(6)
```

Out[368]:

		address	date	price	sqft	dist_to_lightrail_station	ppf
property_id	**transaction_id**						
346200	**23951313**	8942 N 15th Ln, Phoenix, AZ 85021	2014-10-24	400000	2388	0.700000	167.5041
9020277	**23951289**	4350 W Shaw Butte Dr, Glendale, AZ 85304	2015-05-19	320000	2120	5.905930	150.9433
336902	**23951266**	2125 W State Ave, Phoenix, AZ 85021	2018-03-13	285000	1723	0.844038	165.4091
990354	**23951257**	1455 W Remington Dr, Chandler, AZ 85286	2017-12-05	367000	2286	13.006200	160.5424
9000471	**23951250**	11774 E Mercer Ln, Scottsdale, AZ 85259	2018-01-13	369000	1502	17.024700	245.6724
9035951	**23951029**	2351 W Del Oro Cir, Mesa, AZ 85202	2017-11-30	182500	1721	1.402180	106.0429

The dataset consists of 181,785 transactions dating back to the opening day of the light rail line. For this basic experiment, we will only study the effect of proximity to a light rail station on the total price of the house and the price per square foot.

In [369]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 181404 entries, (346200, 23951313) to (2579, 5359)
Data columns (total 6 columns):
address                      181404 non-null object
date                         181404 non-null datetime64[ns]
price                        181404 non-null int64
sqft                         181404 non-null int64
dist_to_lightrail_station    181404 non-null float64
ppf                          181404 non-null float64
dtypes: datetime64[ns](1), float64(2), int64(2), object(1)
memory usage: 15.0+ MB
```

The average home in our data set sold for $176k. There is a general filter that only includes homes between $50-400k, and between 500-10000 square feet. The dataset does not include any foreclosures or land-only transactions, but it has not been rigorously cleaned for something like the sale of a burned down house or sale of unpermitted buildings, resulting in some large variation in the price per footage. Most homes within 7km of a light rail station, with some faily long tails. This is expected - light rail goes through central areas of Phoenix, where there is highest population density and lots of existing homes. Price per foot follows a lognormal distribution, with quite a few high outliers but centered around \$102/sq ft. Square footage looks mostly like a normal distribution but there are some mansions of 3000+ ft while relatively few tiny houses.

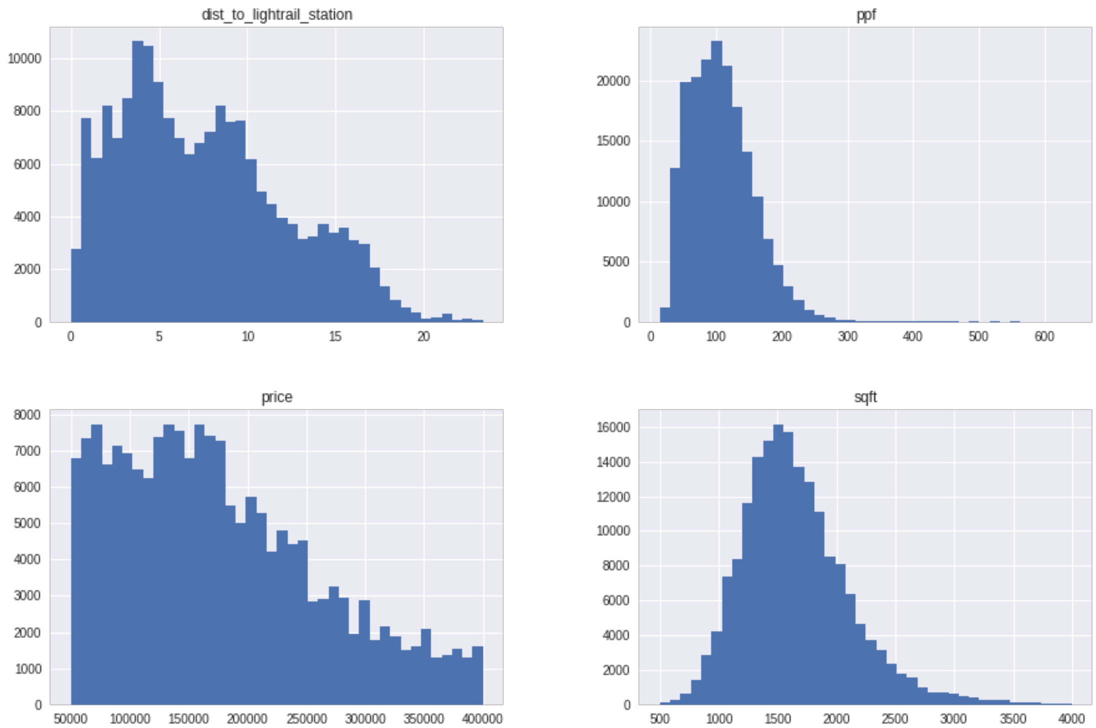
In [370]:
```
df.describe(include=['datetime64','int64','float64'])
```

Out[370]:

	date	price	sqft	dist_to_lightrail_station	ppf
count	181404	181404.000000	181404.000000	181404.000000	181404.000000
unique	3400	NaN	NaN	NaN	NaN
top	2017-10-25 00:00:00	NaN	NaN	NaN	NaN
freq	1208	NaN	NaN	NaN	NaN
first	2008-12-27 00:00:00	NaN	NaN	NaN	NaN
last	2018-05-15 00:00:00	NaN	NaN	NaN	NaN
mean	NaN	175616.491158	1654.403674	7.562934	107.940965
std	NaN	86085.603240	461.070406	4.716722	48.918787
min	NaN	50000.000000	500.000000	0.000000	14.184997
25%	NaN	106611.000000	1338.000000	3.801110	70.267548
50%	NaN	160000.000000	1596.000000	6.906290	102.564103
75%	NaN	230000.000000	1900.000000	10.593325	137.636060
max	NaN	400000.000000	4000.000000	23.368200	641.666667

In [371]:
```
df.hist(bins=40,figsize=(15,10))
```

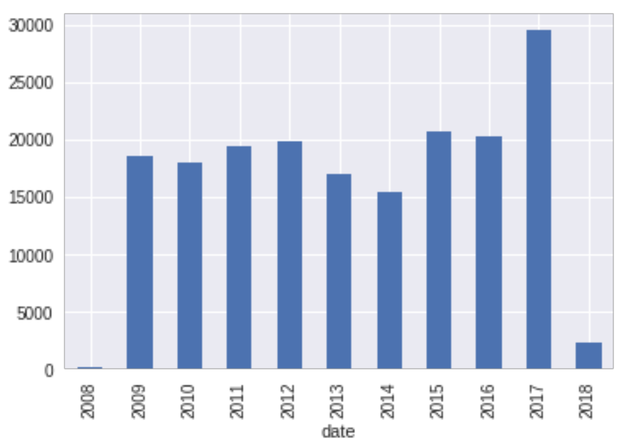
Out[371]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f9f56ac2048>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f9febb7ceb8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f9feba47240>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f9feb6a6e10>]], dty
pe=object)
```



In terms of transaction volume by year, the dataset starts on Dec 27, 2008 and goes through May 2018. 2008 only has a few transactions since we only care about sales that closed after the rail started operating and continue through today.

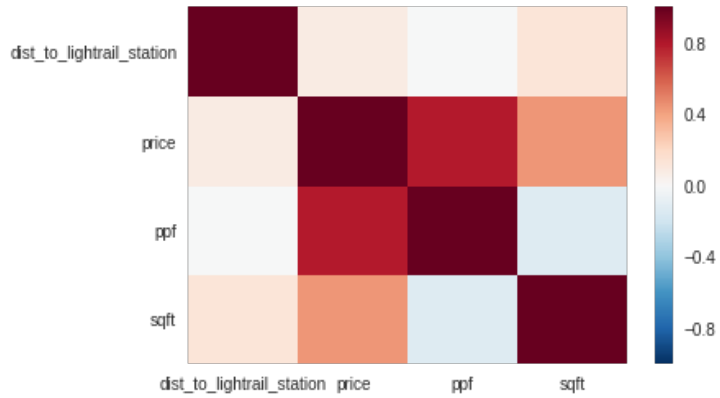
In [372]:
```
df.groupby(df["date"].dt.year).address.count().plot(kind="bar")
```

Out[372]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9febbbf1d0>
```



The correlation matrix shows high crosscorrelation between the PPF dependent variable with `price` and `sqft`.

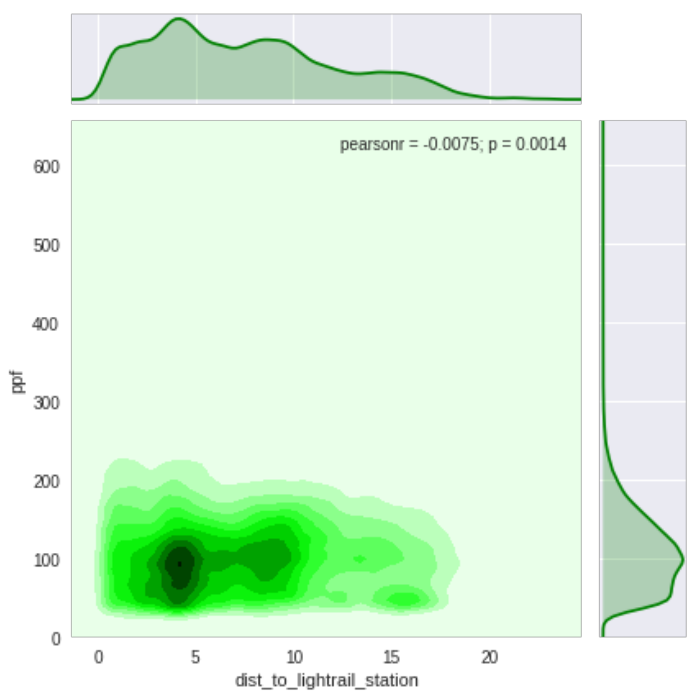
In [373]:
```
# Calculate and plot
numerical = list(set(df.columns) - set(['address','date']))

corr_matrix = df[numerical].corr()
sns.heatmap(corr_matrix);
```



The density function of price per foot and distance shows two clusters - one at around 5km away from a transit station and at average price of $90/ft and a second, smaller one at 8km away and $100/ft. Homes don't necessarily gain value as they get closer to a train station, but the extreme outliers that are very far away sell for lower valuations. Also homes that sell for $200+/ft appear to be all within 5km of a train station.

In [374]:
```
sns.jointplot('dist_to_lightrail_station', 'ppf', data=df, kind="kde", color="g
")
```

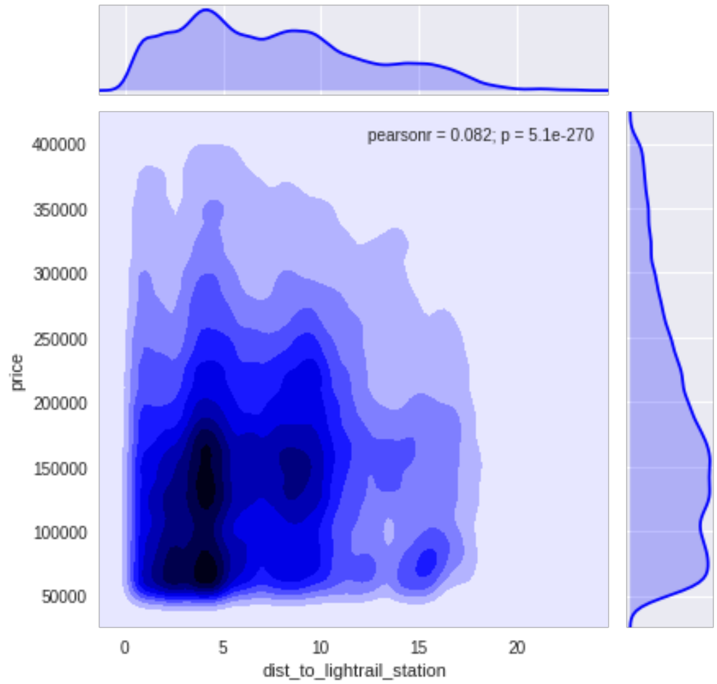
Out[374]: <seaborn.axisgrid.JointGrid at 0x7f9feb8e0be0>



Initially I had assumed that light rail would attract a less affluent resident, and that the most expensive homes would be farther away from the transit stops. Homes between $50-100k do tend to cluster relatively closely to train stations, while homes in the $200k+ range peak a bit farther away.

In [375]:
```
sns.jointplot('dist_to_lightrail_station', 'price', data=df, kind="kde", color=
"b")
```

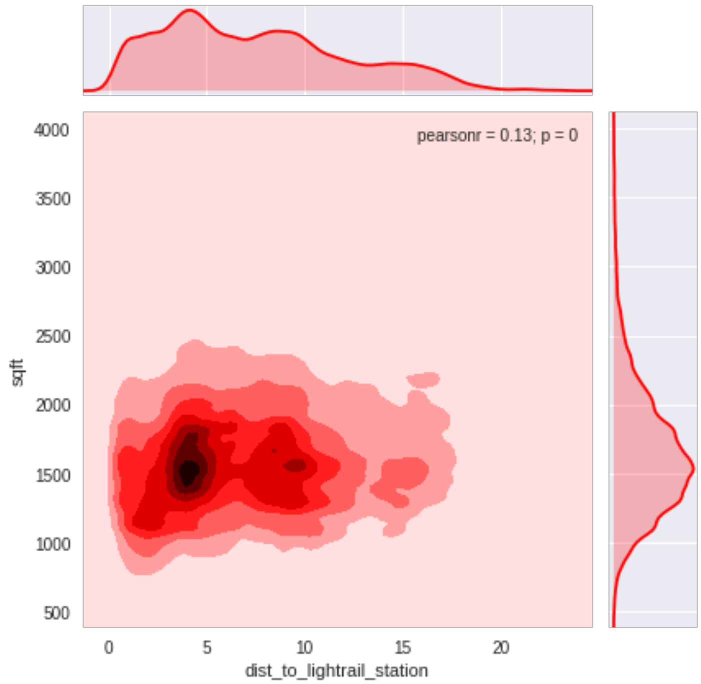
Out[375]: <seaborn.axisgrid.JointGrid at 0x7f9feb971828>



Home sizes are normally distributed, with a slight preference for the smaller sized homes in close proximity to light rail stations.

In [376]:
```
sns.jointplot('dist_to_lightrail_station', 'sqft', data=df, kind="kde", color="
r")
```

Out[376]: <seaborn.axisgrid.JointGrid at 0x7f9f5e5734e0>

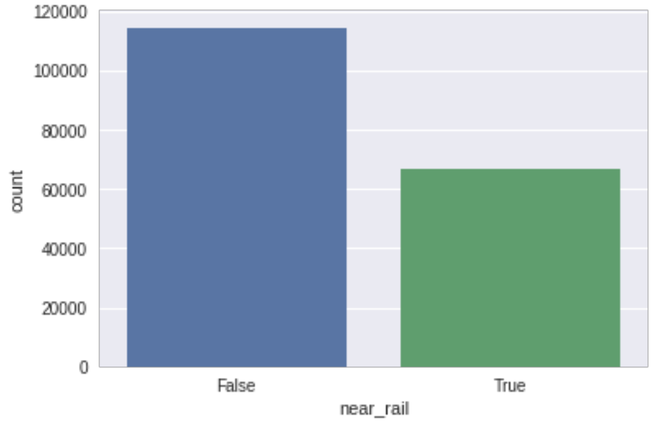


Phoenix house values peaked in 2007, then declined through 2011, and have grown at very high rates since 2011. So using average price per foot metrics across the entire data set would be very misleading and we need to adjust for the general appreciation trend in the data. Creating a dummy variable to track homes that are less than 5km from a light rail station (should be either walkable or very short drive to the station) we notice that they have appreciated at a higher rate than homes that are farther away from the light rail line.

In [377]:
```
# create dummy variables for years and for being near a light rail station
df["year"] = df.date.dt.year
df['near_rail'] = df['dist_to_lightrail_station'] < 5
```

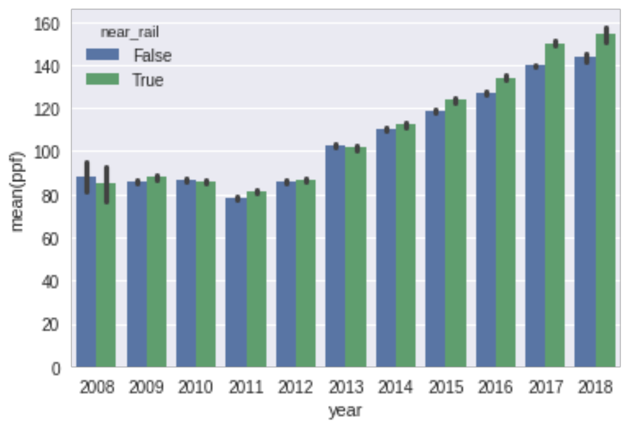
In [378]:
```
sns.countplot(x='near_rail', data=df)
```

Out[378]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f57bdff60>



In [379]:
```
sns.barplot(x="year", y="ppf", hue="near_rail", data=df)
```

Out[379]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9f5ea65ac8>



Let's start with a simple model that tries to predict price per square foot just from the total square footage and distance to light rail station. Larger homes sell for lower price per foot. Distance to light rail is actually a negative predictor of value, with every kilometer separation from station increasing price by $0.33/ft. If true, this would be a bad news for every transit project in the country.

In [380]:
```
price_model = ols("price ~ sqft + sqft:dist_to_lightrail_station", data=df).fit
()
# summarize our model
price_model.summary()
```

Out[380]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.198
Model:	OLS	**Adj. R-squared:**	0.198
Method:	Least Squares	**F-statistic:**	2.242e+04
Date:	Mon, 28 May 2018	**Prob (F-statistic):**	0.00
Time:	16:11:58	**Log-Likelihood:**	-2.2987e+06
No. Observations:	181404	**AIC:**	4.597e+06
Df Residuals:	181401	**BIC:**	4.597e+06
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.966e+04	678.523	58.447	0.000	3.83e+04	4.1e+04
sqft	79.5241	0.449	177.172	0.000	78.644	80.404
sqft:dist_to_lightrail_station	0.3434	0.022	15.512	0.000	0.300	0.387

Omnibus:	5318.670	**Durbin-Watson:**	1.280
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5748.402
Skew:	0.430	**Prob(JB):**	0.00
Kurtosis:	2.860	**Cond. No.**	5.97e+04

In [381]:
```
price_model = ols("price ~ sqft + sqft:near_rail", data=df).fit()
# summarize our model
price_model.summary()
```

Out[381]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.198
Model:	OLS	**Adj. R-squared:**	0.198
Method:	Least Squares	**F-statistic:**	2.239e+04
Date:	Mon, 28 May 2018	**Prob (F-statistic):**	0.00
Time:	16:11:58	**Log-Likelihood:**	-2.2987e+06
No. Observations:	181404	**AIC:**	4.597e+06
Df Residuals:	181401	**BIC:**	4.597e+06
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	3.93e+04	677.009	58.056	0.000	3.8e+04	4.06e+04
sqft	83.4809	0.395	211.427	0.000	82.707	84.255
sqft:near_rail[T.True]	-3.0654	0.223	-13.749	0.000	-3.502	-2.628

Omnibus:	5464.543	**Durbin-Watson:**	1.280
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5928.104
Skew:	0.438	**Prob(JB):**	0.00
Kurtosis:	2.868	**Cond. No.**	6.88e+03

Earlier, we observed that prices seemed to go up faster in areas that are located close to train stations. Adding years to the regressions shows that 1) prices per foot have risen steadily from the 2011 trough and 2) impact of being near the light rail station inverted from a negative factor in 2008-2014 and is now a positive factor to valuation.

In [382]:
```
price_model = ols("price ~ sqft:C(year) + sqft:C(year):near_rail-1", data=df).f
it()
# summarize our model
price_model.summary()
```

Out[382]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.877
Model:	OLS	**Adj. R-squared:**	0.877
Method:	Least Squares	**F-statistic:**	5.857e+04
Date:	Mon, 28 May 2018	**Prob (F-statistic):**	0.00
Time:	16:12:01	**Log-Likelihood:**	-2.2778e+06
No. Observations:	181404	**AIC:**	4.556e+06
Df Residuals:	181382	**BIC:**	4.556e+06
Df Model:	22		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
sqft:C(year)[2008]	87.4179	3.624	24.124	0.000	80.316	94.520
sqft:C(year)[2009]	84.1891	0.369	228.042	0.000	83.466	84.913
sqft:C(year)[2010]	84.9438	0.372	228.477	0.000	84.215	85.673
sqft:C(year)[2011]	78.3275	0.347	225.588	0.000	77.647	79.008
sqft:C(year)[2012]	86.3730	0.349	247.588	0.000	85.689	87.057
sqft:C(year)[2013]	102.4858	0.391	262.229	0.000	101.720	103.252
sqft:C(year)[2014]	109.5162	0.417	262.524	0.000	108.699	110.334
sqft:C(year)[2015]	116.3843	0.358	324.656	0.000	115.682	117.087
sqft:C(year)[2016]	123.5840	0.338	365.198	0.000	122.921	124.247
sqft:C(year)[2017]	133.9002	0.272	491.554	0.000	133.366	134.434
sqft:C(year)[2018]	136.4423	0.977	139.697	0.000	134.528	138.357
sqft:C(year)[2008]:near_rail[T.True]	-3.1717	5.948	-0.533	0.594	-14.831	8.487
sqft:C(year)[2009]:near_rail[T.True]	-1.9993	0.620	-3.223	0.001	-3.215	-0.783
sqft:C(year)[2010]:near_rail[T.True]	-4.4177	0.620	-7.124	0.000	-5.633	-3.202
sqft:C(year)[2011]:near_rail[T.True]	-0.6459	0.587	-1.100	0.271	-1.796	0.505
sqft:C(year)[2012]:near_rail[T.True]	-1.2496	0.587	-2.129	0.033	-2.400	-0.099
sqft:C(year)[2013]:near_rail[T.True]	-4.3218	0.637	-6.782	0.000	-5.571	-3.073
sqft:C(year)[2014]:near_rail[T.True]	-1.7037	0.668	-2.551	0.011	-3.012	-0.395
sqft:C(year)[2015]:near_rail[T.True]	1.5910	0.577	2.757	0.006	0.460	2.722
sqft:C(year)[2016]:near_rail[T.True]	4.5578	0.602	7.570	0.000	3.378	5.738
sqft:C(year)[2017]:near_rail[T.True]	8.0311	0.531	15.135	0.000	6.991	9.071
sqft:C(year)[2018]:near_rail[T.True]	7.7449	1.838	4.213	0.000	4.142	11.348

Omnibus:	8150.129	**Durbin-Watson:**	1.342
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9783.969

We can also run the model with the exact distance to a light rail station (instead of just the boolean variable), but it appears that it does not increase explanatory power. The boolean variable does just fine.

In [383]:
```
price_model2 = ols("price ~ sqft:C(year) + sqft:C(year):dist_to_lightrail_stati
on-1", data=df).fit()
# summarize our model
price_model2.summary()
```

Out[383]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.876
Model:	OLS	**Adj. R-squared:**	0.876
Method:	Least Squares	**F-statistic:**	5.851e+04
Date:	Mon, 28 May 2018	**Prob (F-statistic):**	0.00
Time:	16:12:03	**Log-Likelihood:**	-2.2779e+06
No. Observations:	181404	**AIC:**	4.556e+06
Df Residuals:	181382	**BIC:**	4.556e+06
Df Model:	22		
Covariance Type:	nonrobust		

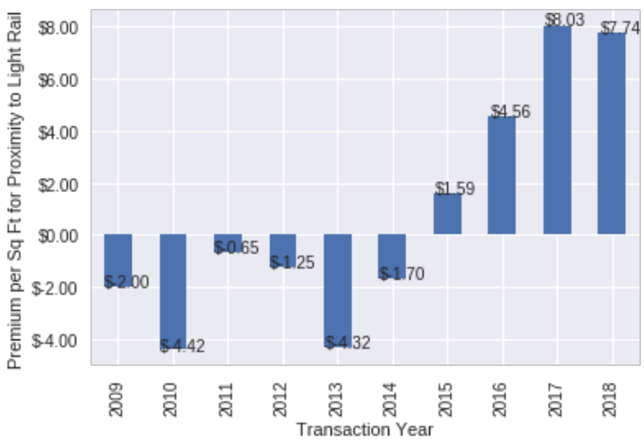
	coef	std err	t	P>|t|	[0.025	0.975]
sqft:C(year)[2008]	82.4369	5.429	15.185	0.000	71.797	93.077
sqft:C(year)[2009]	85.5927	0.563	151.933	0.000	84.489	86.697
sqft:C(year)[2010]	80.9463	0.564	143.646	0.000	79.842	82.051
sqft:C(year)[2011]	76.6374	0.533	143.726	0.000	75.592	77.683
sqft:C(year)[2012]	83.9288	0.536	156.661	0.000	82.879	84.979
sqft:C(year)[2013]	98.4879	0.584	168.729	0.000	97.344	99.632
sqft:C(year)[2014]	108.6845	0.606	179.292	0.000	107.496	109.873
sqft:C(year)[2015]	120.0164	0.528	227.158	0.000	118.981	121.052
sqft:C(year)[2016]	126.9022	0.553	229.668	0.000	125.819	127.985
sqft:C(year)[2017]	140.1586	0.489	286.343	0.000	139.199	141.118
sqft:C(year)[2018]	143.8902	1.702	84.547	0.000	140.555	147.226
sqft:C(year)[2008]:dist_to_lightrail_station	0.4577	0.554	0.826	0.409	-0.628	1.544
sqft:C(year)[2009]:dist_to_lightrail_station	-0.2631	0.060	-4.410	0.000	-0.380	-0.146
sqft:C(year)[2010]:dist_to_lightrail_station	0.3112	0.062	5.036	0.000	0.190	0.432
sqft:C(year)[2011]:dist_to_lightrail_station	0.1882	0.058	3.227	0.001	0.074	0.302
sqft:C(year)[2012]:dist_to_lightrail_station	0.2619	0.060	4.389	0.000	0.145	0.379
sqft:C(year)[2013]:dist_to_lightrail_station	0.3213	0.067	4.789	0.000	0.190	0.453
sqft:C(year)[2014]:dist_to_lightrail_station	0.0231	0.071	0.326	0.744	-0.116	0.162
sqft:C(year)[2015]:dist_to_lightrail_station	-0.4159	0.062	-6.746	0.000	-0.537	-0.295
sqft:C(year)[2016]:dist_to_lightrail_station	-0.2294	0.058	-3.943	0.000	-0.343	-0.115
sqft:C(year)[2017]:dist_to_lightrail_station	-0.4648	0.048	-9.633	0.000	-0.559	-0.370
sqft:C(year)[2018]:dist_to_lightrail_station	-0.6029	0.170	-3.538	0.000	-0.937	-0.269

Omnibus:	8206.203	**Durbin-Watson:**	1.342
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9850.646

We summarize the premium by year with some charts below.

In [384]:
```
import re
prem = price_model.params[-10:].rename(lambda x: re.findall("\[(\d{4})\]",x)[0]
)
ax = prem.plot(kind="bar")
for p in ax.patches:
    b = p.get_bbox()
    val = "${:3.2f}".format(b.y1 + b.y0)
    ax.annotate(val, (p.get_x() * 1.005, p.get_height() * 1.005))

# manipulate
vals = ax.get_yticks()
ax.set_yticklabels(['${:3.2f}'.format(x) for x in vals])
ax.set_ylabel("Premium per Sq Ft for Proximity to Light Rail")
ax.set_xlabel("Transaction Year")
```

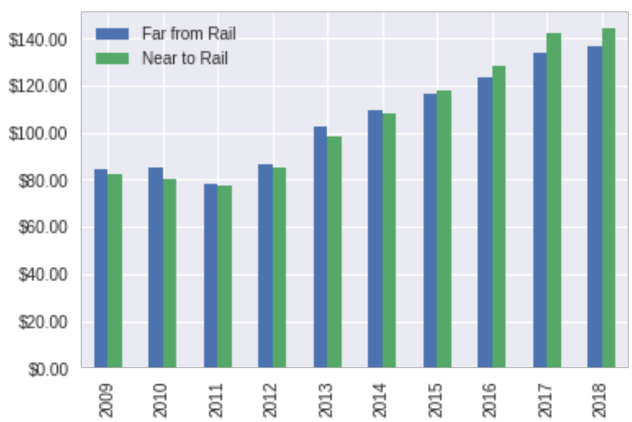
Out[384]: <matplotlib.text.Text at 0x7f9f71b60eb8>



In [385]:
```
far_from_rail = price_model.params[-21:-11].rename(lambda x: re.findall("\[(\d{
4})\]",x)[0]).rename("Far from Rail")
near_to_rail = (far_from_rail + prem).rename("Near to Rail")
output = pd.concat([far_from_rail, near_to_rail], axis=1)
print(output)
ax = output.plot(kind="bar")
vals = ax.get_yticks()
ax.set_yticklabels(['${:3.2f}'.format(x) for x in vals])
```

```
      Far from Rail  Near to Rail
2009      84.189119     82.189807
2010      84.943821     80.526147
2011      78.327532     77.681597
2012      86.372985     85.123428
2013     102.485847     98.164056
2014     109.516159    107.812473
2015     116.384348    117.975318
2016     123.584016    128.141814
2017     133.900187    141.931290
2018     136.442337    144.187244
```

Out[385]:
```
[<matplotlib.text.Text at 0x7f9f56d60240>,
 <matplotlib.text.Text at 0x7f9f56d67748>,
 <matplotlib.text.Text at 0x7f9f57793908>,
 <matplotlib.text.Text at 0x7f9f5779e7b8>,
 <matplotlib.text.Text at 0x7f9f56d54518>,
 <matplotlib.text.Text at 0x7f9f56d674e0>,
 <matplotlib.text.Text at 0x7f9f56c47ac8>,
 <matplotlib.text.Text at 0x7f9f57793b00>,
 <matplotlib.text.Text at 0x7f9f57789518>]
```



Based on this data, we can calculate the average apprerciation experienced by a home near the rail station and one farther away over the past 9 years. Homes near light rail stations appreciated at 1% higher rate than homes farther away.

In [386]:

```
def CAGR(first, last, periods):
    return (last/first)**(1/periods)-1
print('Price per foot CAGR of homes far from light rail stations {:.2%} '.forma
t(CAGR(output['Far from Rail']['2009'], output['Far from Rail']['2018'], 2018-2
009)))
print('Price per foot CAGR of homes near to light rail stations {:.2%} '.format
(CAGR(output['Near to Rail']['2009'], output['Near to Rail']['2018'], 2018-2009
)))
```

```
Price per foot CAGR of homes far from light rail stations 5.51%
Price per foot CAGR of homes near to light rail stations 6.44%
```

In [ ]: