DATA 200 Final Project: Contraception

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This notebook contains all of the code for conducting our final project. It is organized into the following sections:

1. Exploratory Data Analysis (EDA)
2. Feature Engineering and Data Cleaning
3. Modeling (Logistic Regression and Random Forests)
   - 3a. Contraception use by no use, short term, long term
   - 3b. Contraception use by yes vs. no
   - 3c. Contraception use by short term vs. long term (for those on contraception)
4. Assessing Precision and Recall

In [1]:
```
# import libraries
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="white", context="talk")

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import re

colours_cafe = np.array(['#6B3231', '#DB565D', '#FACCAD', '#FF8A40'])
colours_cafe = sns.set_palette(sns.color_palette(colours_cafe))
```

In [2]:
```
# read in raw dataset
contra = pd.read_csv('contraceptive_for_students.csv')
this_dic = {1:0, 3:1, 2:2}
contra['contraceptive'] = contra['contraceptive'].map(this_dic)
```

In [3]:
```
# explore
contra.head(5)
```

Out[3]:

	wife_age	wife_education	husband_education	num_child	wife_religion	wife_work	husband_occupation	stand
0	24	2	3	3	1	1	2	
1	45	1	3	10	1	1	3	
2	43	2	3	7	1	1	3	
3	42	3	2	9	1	1	3	
4	36	3	3	8	1	1	3	

In [4]:
```
# split into train and test
contra_train, contra_test = train_test_split(contra, test_size=0.25, random_state
```

1. Exploratory Data Analysis

1a. Subset Verification

The hypothesis test below is verifying the representativeness of number of children within this subset of the full national survey. We are testing whether or not the mean "fertility rate" which is the number of children a woman has in her lifetime is truly 3.3 or not according to a Wilcoxon Signed-Rank test. The resulting p-value of 0.0004 provides evidence that our subset (the initial dataset without any cleaning) does not have a fertility rate that matches the stated average from the pamphlet.

In [5]:
```
np.mean(contra['num_child']), np.std(contra['num_child'])
```

Out[5]:
```
(3.2613713509843856, 2.3577481331234464)
```

In [6]:
```
from scipy.stats import wilcoxon
wilcoxon(contra['num_child'] - 3.3)
```

Out[6]:
```
WilcoxonResult(statistic=485783.0, pvalue=0.0004621540880216536)
```

1b. Summary Statistics

In [7]:
```
contra_train.apply([np.mean, np.median])
```

Out[7]:

	wife_age	wife_education	husband_education	num_child	wife_religion	wife_work	husband_occupation
mean	32.365942	2.942029	3.415761	3.218297	0.852355	0.749094	2.143116
median	31.000000	3.000000	4.000000	3.000000	1.000000	1.000000	2.000000

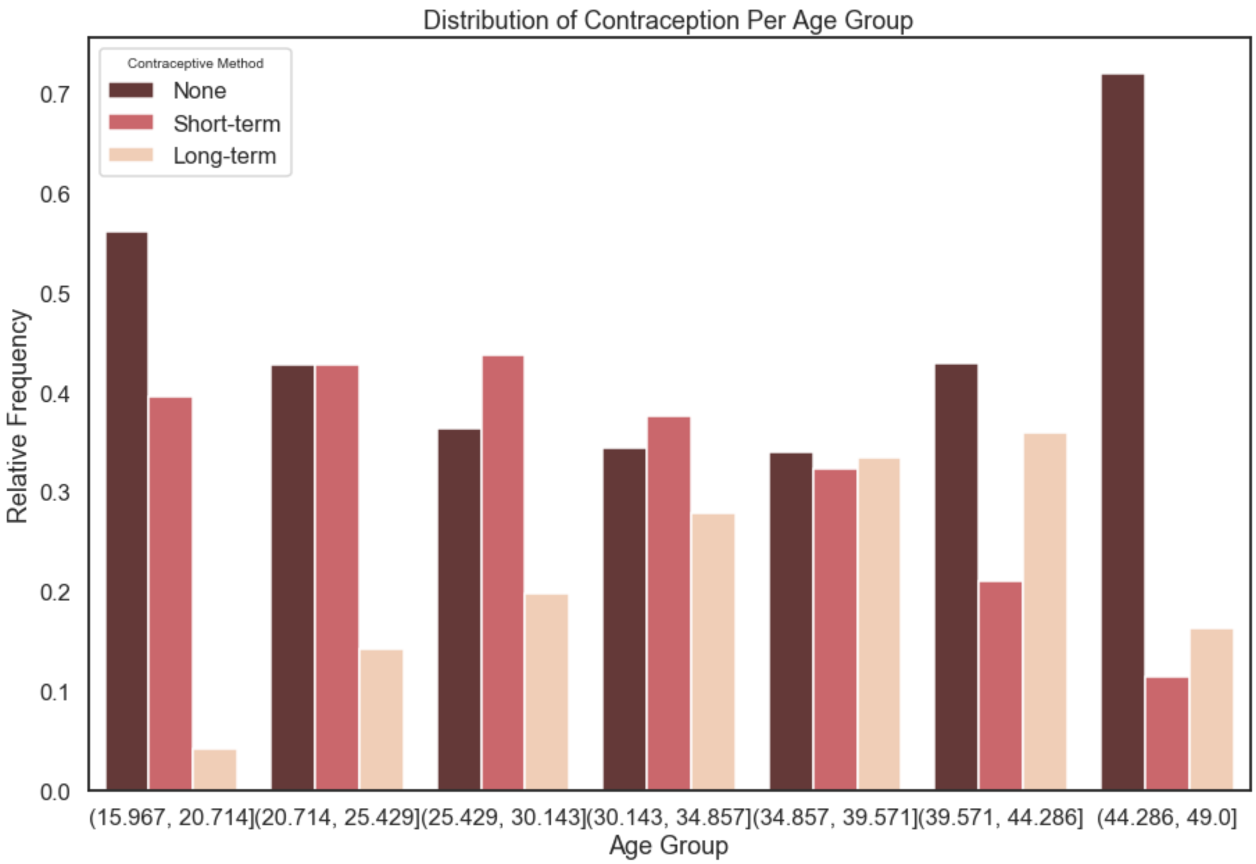
1c. Distribution of number of children per age group

Seven equally-spaced age groups were created based on the standardized wife age values. The barplots show that the relative frequencies between age groups differ. In the younger age groups, no contraception and short-term contraception are used at similar rates. In older age groups, more mass is distributed to the "None" contraception bar. Notably, the middle age group (-0.0199, 0.489] shows a relatively uniform spread between all three contraceptive options.

In [8]:
```
contra_train['age_bin'] = pd.cut(contra_train.wife_age, bins=7)
age_contra = contra_train.groupby(['age_bin', 'contraceptive'], as_index=False).s
age_contra = age_contra.rename({0:'count'}, axis=1)

num_in_bins = contra_train.groupby('age_bin', as_index=False).size()
age_contra['total'] = np.array(np.repeat(num_in_bins, len(contra_train['contracep
age_contra['freq'] = age_contra['count'] / age_contra['total']
```

```
/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy (http://pandas.pydata.org/pa
ndas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  """Entry point for launching an IPython kernel.
```

In [9]:
```
plt.figure(figsize=(15,10))
age_contra['contra_description'] = age_contra['contraceptive'].map({0:'None', 1:'
ax = sns.barplot(x='age_bin',
            y='freq',
            hue='contra_description',
            data=age_contra)


ax.set(ylabel='Relative Frequency', xlabel='Age Group', title='Distribution of Co
ax.legend(title='Contraceptive Method');
```

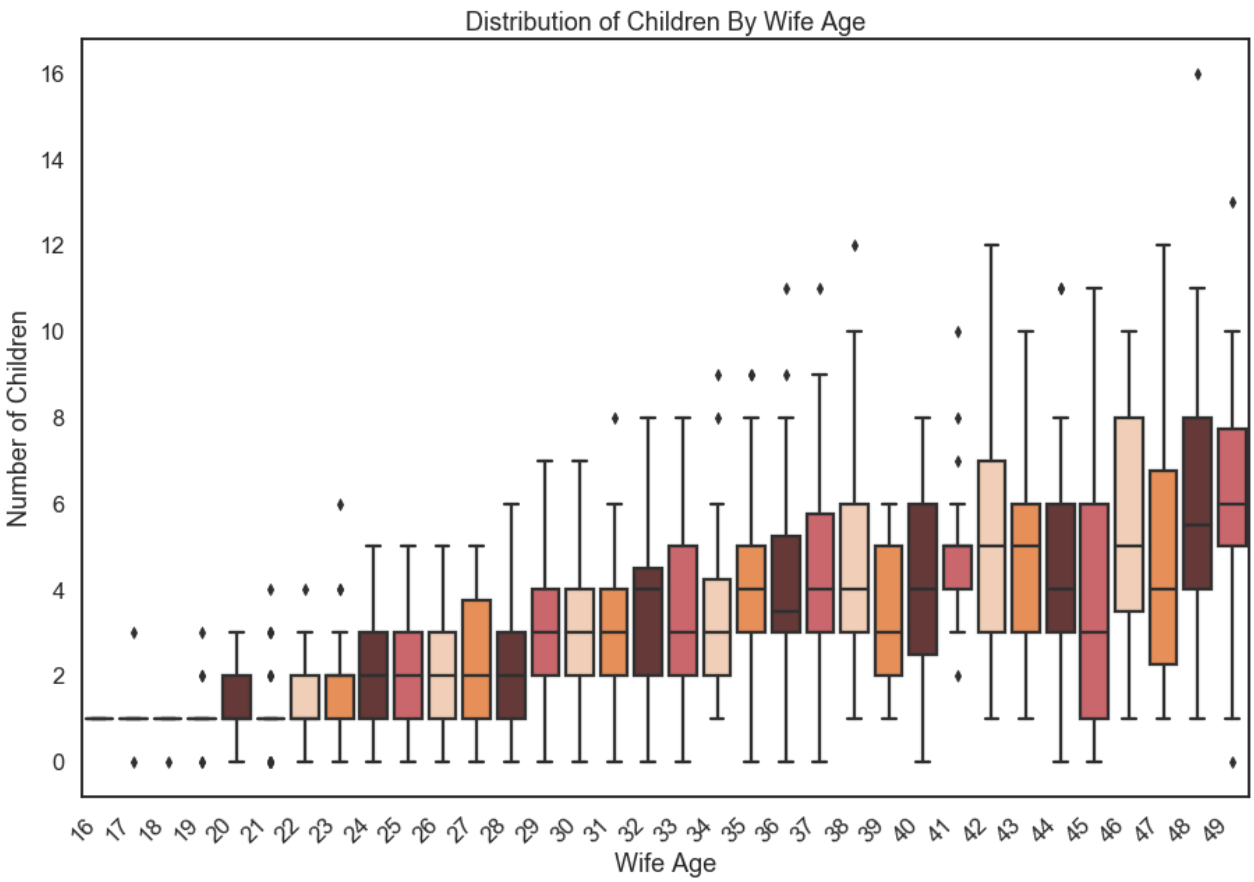


1d. Number of kids versus age

Below, we plot the distribution of number of children within each wife age group. Recall that the age groups are standardized and the minimum wife age in our dataset is 20 years. Clearly, women in older age groups have a larger range and more children on average. The R^2 value between number of children and wife age is approximately 0.268. The relationship here does not seem to be linear as expected due in part to natural limitations of fertility.

In [10]:

```
plt.figure(figsize=(15,10))
ax = sns.boxplot(x=round(contra_train['wife_age'], 3),
                 y='num_child',
                 data=contra_train,
                 palette=['#6B3231', '#DB565D', '#FACCAD', '#FF8A40'])

ax.set(ylabel='Number of Children',
       xlabel='Wife Age',
       title='Distribution of Children By Wife Age')

ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right',
    fontweight='light');
```



In [11]:

```
r_sq = np.corrcoef(x=contra_train['wife_age'], y=contra_train['num_child'])[0,1]*
print('The R^2 value between number of children and wife age is ' + str(r_sq) + '
```

```
The R^2 value between number of children and wife age is 0.3038711512413086.
```

1e. Calculating the Percent of Women Under the Age of 20

In order to include number of children per year as a feature, we need to filter out women under the age of 20 as we do not have summary statistics concerning their estimated year of marriage. As our calculations show, women under the age of 20 compose 2% of our sample and do not change the median age in our sampled women under the age of 20 compose 2% of our sample and do not change the median age in our sampled population. Thus, removing these records from our data will cause minimal changes in our sample characteristics.

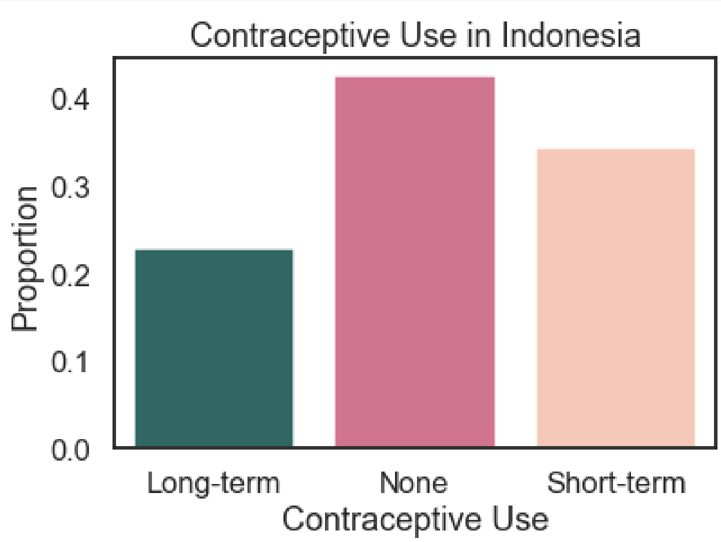
In [12]:
```
perc_of_women_under_20 = contra_train[contra_train["wife_age"] < 20].shape[0]/ co
women_over_20 = contra_train[contra_train["wife_age"] > 20]
median_age_wo_under_20 = women_over_20["wife_age"].median()

print("% of women under 20:", perc_of_women_under_20)
print("Median Age without women under 20:", median_age_wo_under_20)
```

```
% of women under 20: 0.023550724637681l6
Median Age without women under 20: 32.0
```

1f. Examining the Distribution of Contraception Use Across Women

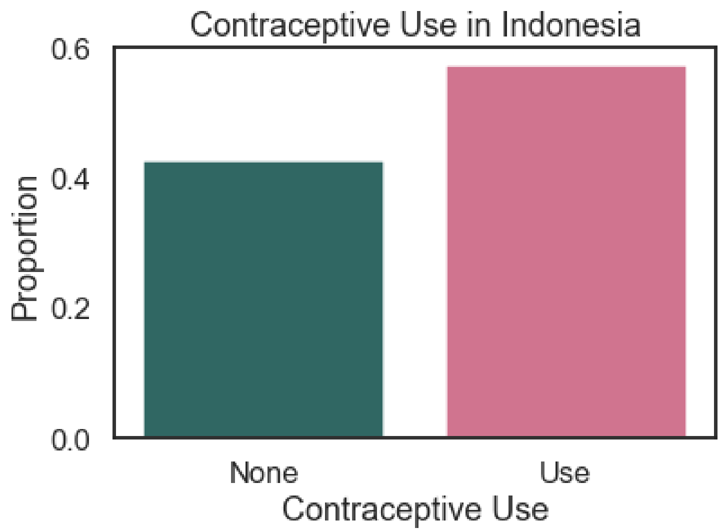
Additionally, we examined the distribution of contraception use among women as a skewness in our outcome variable may heavily impact our predictive ability. As noticed below, there is generally an uneven distribution among contraceptive types used. When we binarize use of contraceptive we lessen this uneven distribution of data for our outcome variable. These figures influenced our decision to compare predictive ability of the multinomial regression and the two-step binarized models.

In [13]:
```
contra_dist = contra_train.copy()

contra_dist.replace({"contraceptive": {0: "None", 1:"Short-term", 2:"Long-term"}}

ax = sns.barplot(x = (contra_dist.groupby('contraceptive')["contraceptive"].count
            y = (contra_dist.groupby('contraceptive')["contraceptive"].count()/co
           palette=['#27706B', '#DF6589', '#FFC3AF' ])
plt.title("Contraceptive Use in Indonesia")
plt.xlabel("Contraceptive Use")
plt.ylabel("Proportion");
```



In [14]:

```
contra_binary = contra_train.copy()
contra_binary.replace({"contraceptive": {0: "None", 1:"Use", 2:"Use"}}, inplace =

contra_binary.replace({"wife_education": {1: "Incomp Prim", 2:"Incomp Prim", 3:"C
                    inplace = True)

contra_binary.replace({"standard_living": {1: "Low", 2:"Middle", 3:"Middle", 4:"H
                    inplace = True)

use = sns.barplot(x = (contra_binary.groupby('contraceptive')["contraceptive"].co
            y = (contra_binary.groupby('contraceptive')["contraceptive"].count()/
           palette=['#27706B', '#DF6589'])
plt.title("Contraceptive Use in Indonesia")
plt.xlabel("Contraceptive Use")
plt.ylabel("Proportion");
```

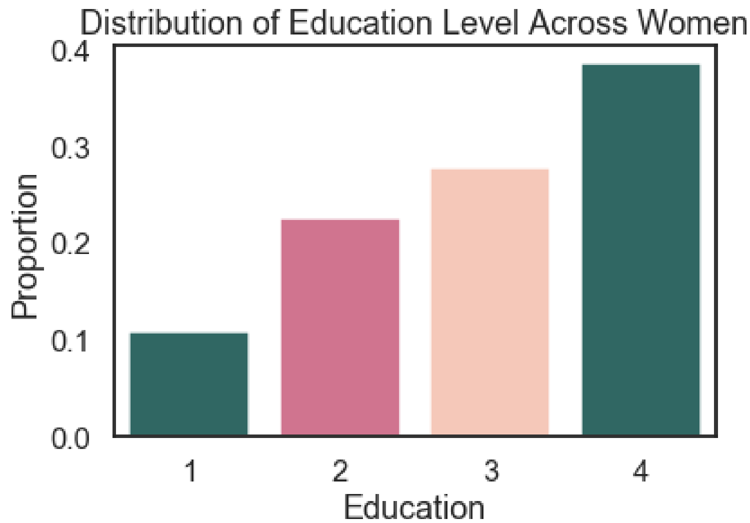


1g. Examining the Distribution of Standard of Living and Education

As above, we wanted to determine if there was an uneven representation of women in our data subset. Noticeably, our data contains uneven sampling largely containing women from higher standards of living and those that have completed a primary level of education.

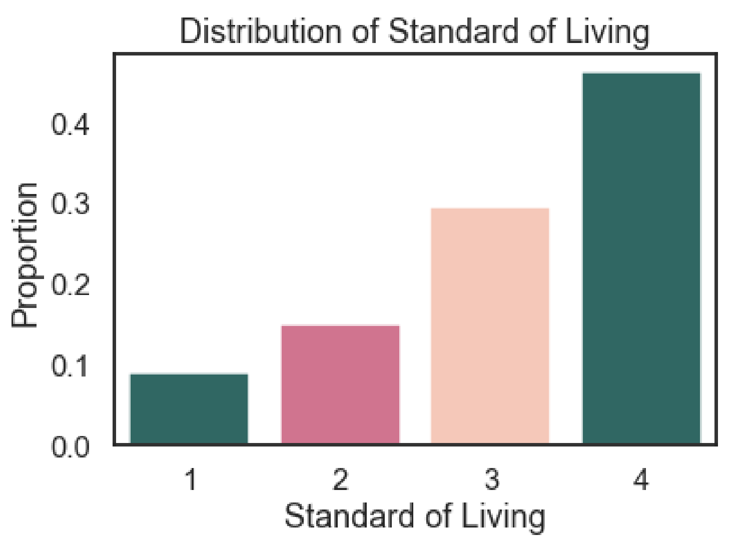
In [15]:

```
edu = sns.barplot(x = (contra_dist.groupby('wife_education')["wife_education"].co
            y = (contra_dist.groupby('wife_education')["wife_education"].count()/
           palette=['#27706B', '#DF6589', '#FFC3AF'])
plt.title("Distribution of Education Level Across Women")
plt.xlabel("Education")
plt.ylabel("Proportion");
```



In [16]:

```
stand_living = sns.barplot(x = (contra_dist.groupby('standard_living')["standard_
            y = (contra_dist.groupby('standard_living')["standard_living"].count(
           palette=['#27706B', '#DF6589', '#FFC3AF', '#27706B'])
plt.title("Distribution of Standard of Living")
plt.xlabel("Standard of Living")
plt.ylabel("Proportion");
```



In [17]:
```
(contra_dist.groupby('standard_living')["standard_living"].count()/contra_dist.sh
```
Out[17]:
```
Int64Index([1, 2, 3, 4], dtype='int64', name='standard_living')
```

2. Feature Engineering and Data Cleaning

2a. Creating Education Gap

The distributions of contraceptive method are not uniform per education gap group. When husbands are more educated than their wives, it seems that the "None" group is more frequent than the two contraceptive groups. When the husbands and wives are equally educated, the distribution of preferences is more uniform, however there are still more subjects within the "None" group than the other two. When the wife is more educated, short-term contraceptives are most popular.

In [18]:
```
contra_tmp = contra_train.copy()
```

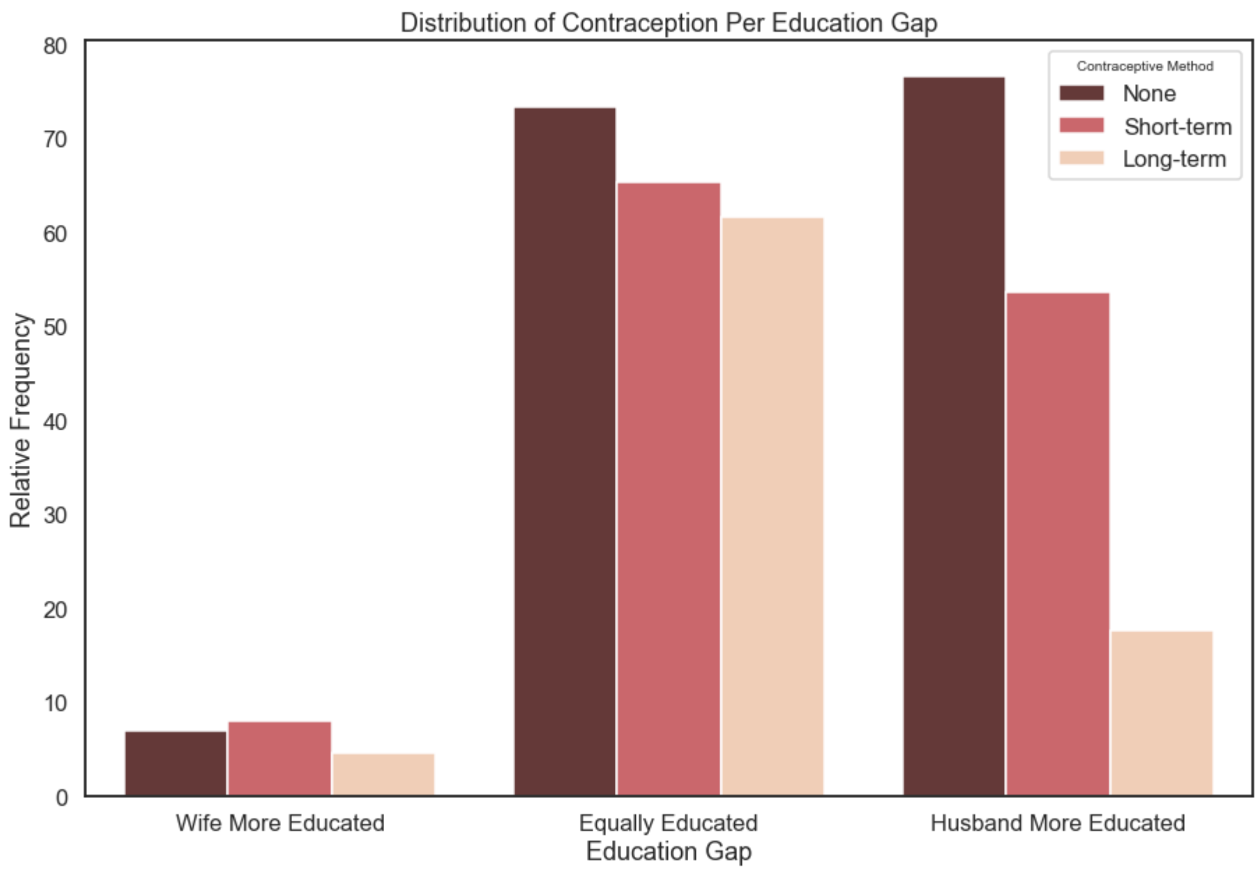
In [19]:
```
contra_tmp['education_gap'] = contra_tmp['husband_education'] - contra_tmp['wife_
gap_intervals = [-3, 0, 1, 4]
contra_tmp['education_gap_categorical'] = pd.cut(contra_tmp.education_gap, bins=g

contra_tmp.education_gap.value_counts().to_frame() / contra_tmp.shape[0]
```
Out[19]:

	education_gap
0	0.544384
1	0.283514
2	0.103261
-1	0.045290
3	0.015399
-2	0.007246
-3	0.000906

In [20]:
```
edugap_contra = contra_tmp.groupby(['education_gap_categorical', 'contraceptive']
edugap_contra = edugap_contra.rename({0:'count'}, axis=1)
num_in_bins = edugap_contra.groupby('education_gap_categorical', as_index=False).

edugap_contra['total'] = np.array(np.repeat(num_in_bins, len(contra_tmp['contrace
edugap_contra['freq'] = edugap_contra['count'] / edugap_contra['total']
```

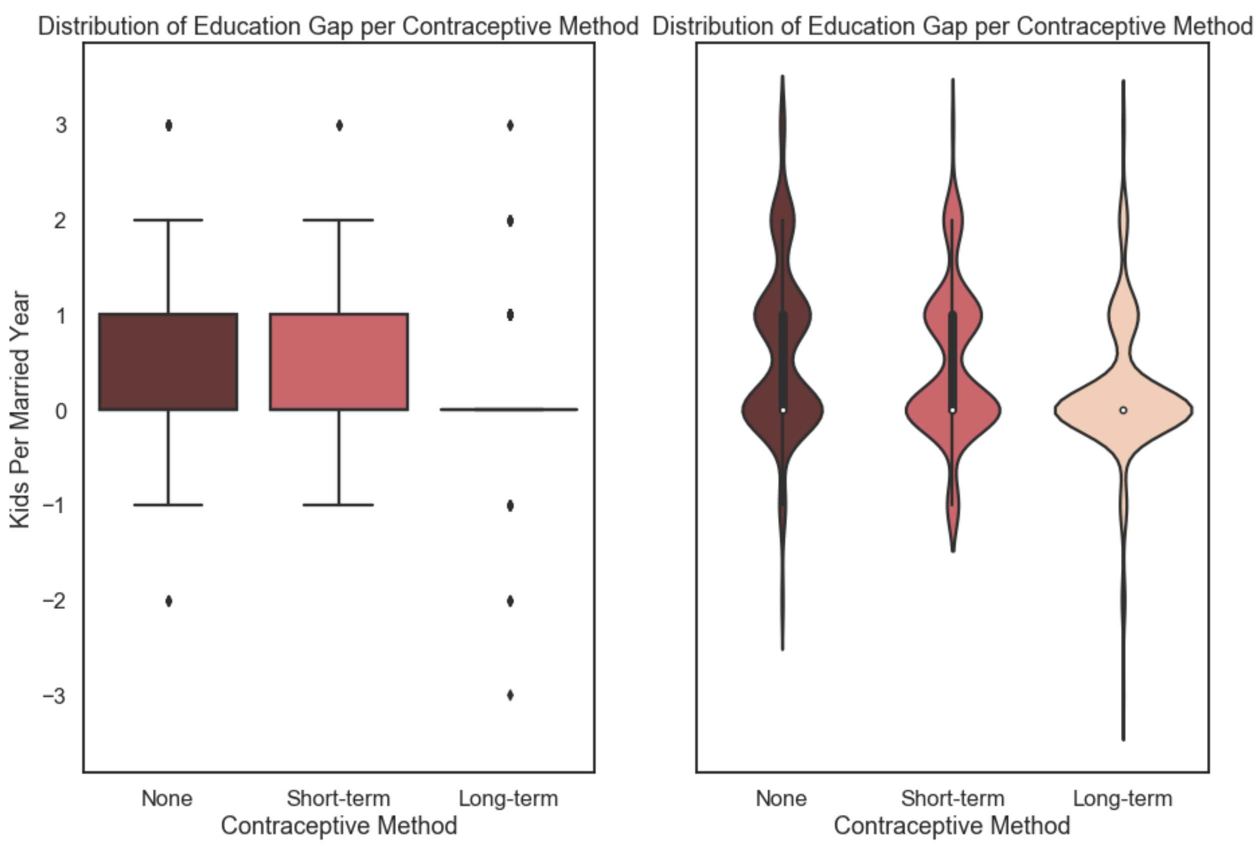
In [21]:

```
plt.figure(figsize=(15,10))
edugap_contra['contra_description'] = edugap_contra['contraceptive'].map({0:'None
edugap_contra['education_gap_categorical'] = edugap_contra['education_gap_categor

ax = sns.barplot(x='education_gap_categorical',
            y='freq',
            hue='contra_description',
            data=edugap_contra)


ax.set(ylabel='Relative Frequency', xlabel='Education Gap', title='Distribution c
ax.legend(title='Contraceptive Method');
```



In [22]:

```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15,10))

sns.boxplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Short-term', 2:'Long-
            y='education_gap',
            data=contra_tmp,
            order=['None', 'Short-term', 'Long-term'],
            ax=ax[0])

ax[0].set(ylabel='Kids Per Married Year',
          xlabel='Contraceptive Method',
          title='Distribution of Education Gap per Contraceptive Method');

sns.violinplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Short-term', 2:'Lo
               y='education_gap',
               data=contra_tmp,
               order=['None', 'Short-term', 'Long-term'],
               ax = ax[1])

ax[1].set(ylabel='',
       xlabel='Contraceptive Method',
       title='Distribution of Education Gap per Contraceptive Method')


plt.show()
```



2b. Creating Kids Per Married Year

We are interested in the relationship between our engineered feature, KPMY, and the existing covariates of wife age and number of children. We see that the scatteplot between wife age and number of children shows patterns that can be explained by the feature's calculation. That is, there is a minimum estimated number of married years per age group, therefore KPMY has a linear offset for each level of number of children. There are also outliers where some women had many children very quickly with a high KPMY. The R^2 value between these two variables is 0.060 which provides evidence for a nonlinear relationship.

In [23]:
```
# the following function cleans the lower bound and upper bound of the intervals
def cleanIntervals(age_intervals):
    '''
    Input:
        age_intervals: Array of intervals
    Output:
        lows: An array of lower bounds
        highs: An array of upper bounds
    '''

    lows  = []
    highs = []

    for ix in range(len(age_intervals)):
        lo_hi = [re.sub('\(|\]', '', k) for k in age_intervals[ix].split(',')]
        lows.append(lo_hi[0])
        highs.append(lo_hi[1])

    return(np.array(lows),
           np.array(highs))
```

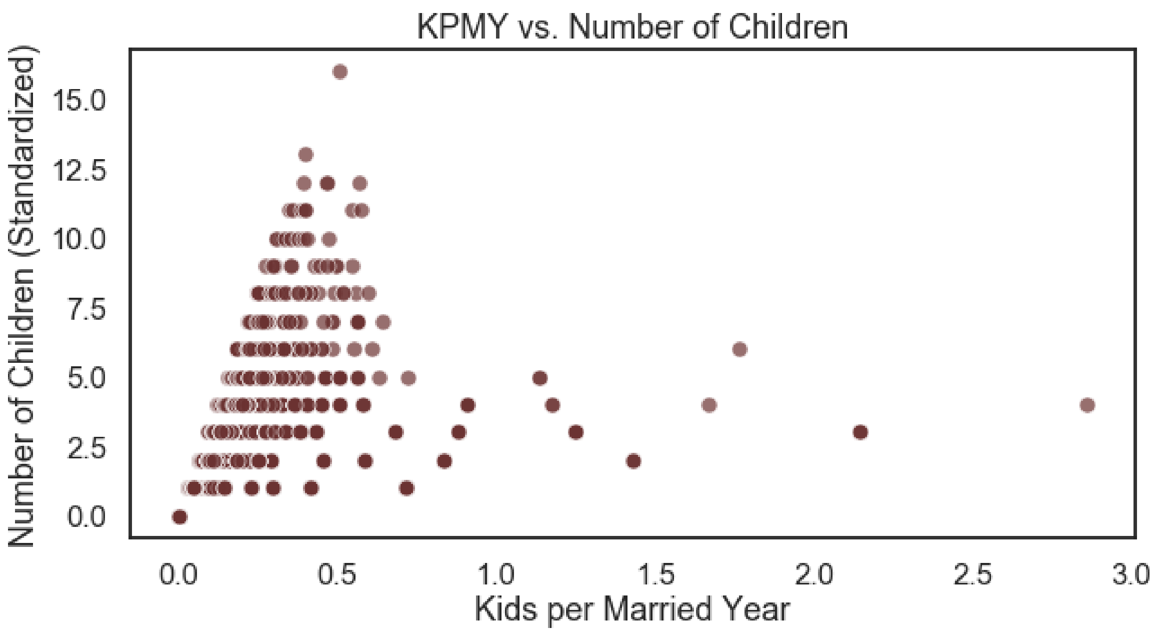
In [24]:
```
contra_tmp = contra_tmp[contra_tmp.wife_age > 20]
contra_tmp = contra_tmp.reset_index(drop=True)

### set age intervals to define median age married
age_intervals = pd.IntervalIndex.from_tuples([(20, 24), (24, 29), (29, 34), (34,3
age_interval_df = pd.DataFrame(age_intervals)
age_interval_df['median_marriage_age'] = [19.6, 18.1, 17.6, 16.8, 16.4, 16.5]
age_interval_df = age_interval_df.rename({0:'age_bin'}, axis=1)
age_interval_df['age_bin'] = age_interval_df['age_bin'].astype(str)
age_interval_df['age_bin_low'], age_interval_df['age_bin_high'] = cleanIntervals(
contra_tmp['age_bin'] = pd.cut(contra_tmp.wife_age, bins=age_intervals)

### fill the NA's
contra_tmp['age_bin'] = contra_tmp['age_bin'].cat.add_categories('None')
contra_tmp['age_bin'] = contra_tmp['age_bin'].fillna('None')
contra_tmp['age_bin'] = contra_tmp['age_bin'].astype(str)

contra_tmp['age_bin_low'], contra_tmp['age_bin_high'] = cleanIntervals(contra_tmp
contra_tmp = contra_tmp.merge(age_interval_df)

### create est_years_married: wife's age minus median marriage age for age group
contra_tmp['est_years_married'] = contra_tmp['wife_age'] - contra_tmp['median_mar

### create kids_per_year: amount of kids divided by number of est years married
contra_tmp['kids_per_year'] = contra_tmp['num_child'] / contra_tmp['est_years_mar
```

In [25]:
```
np.mean(contra_tmp['kids_per_year'])
```

Out[25]: 0.27422882816512245

In [26]:

```
plt.figure(figsize=(10,5))
ax = sns.scatterplot(x='kids_per_year',
                     y='num_child',
                     data=contra_tmp,
                     alpha=0.7)

ax.set(ylabel='Number of Children (Standardized)',
       xlabel='Kids per Married Year',
       title='KPMY vs. Number of Children');
```



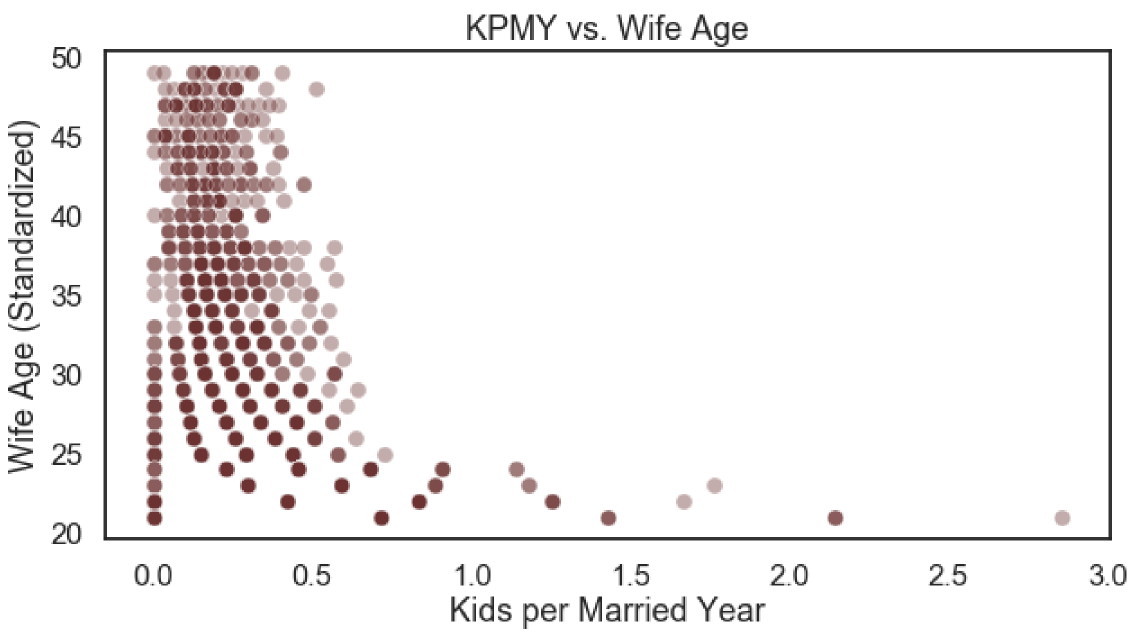
In [27]:

```
r_sq = np.corrcoef(x=contra_tmp['kids_per_year'], y=contra_tmp['num_child'])[0,1]
print('The R^2 value between KPMY and number of children is ' + str(r_sq) + '.')
```

```
The R^2 value between KPMY and number of children is 0.05866323547070084.
```

The plot below reflects the relationship between KPMY and wife age. The relationship between these two variables exhibits qualities of an exponential decay curve shifted across multiple starting points. The R^2 value between these two variables is 0.157 which provides evidence for a nonlinear relationship.

In [28]:
```
plt.figure(figsize=(10,5))
ax = sns.scatterplot(x='kids_per_year',
                     y='wife_age',
                     data=contra_tmp,
                     alpha=0.4)

ax.set(ylabel='Wife Age (Standardized)',
       xlabel='Kids per Married Year',
       title='KPMY vs. Wife Age');
```



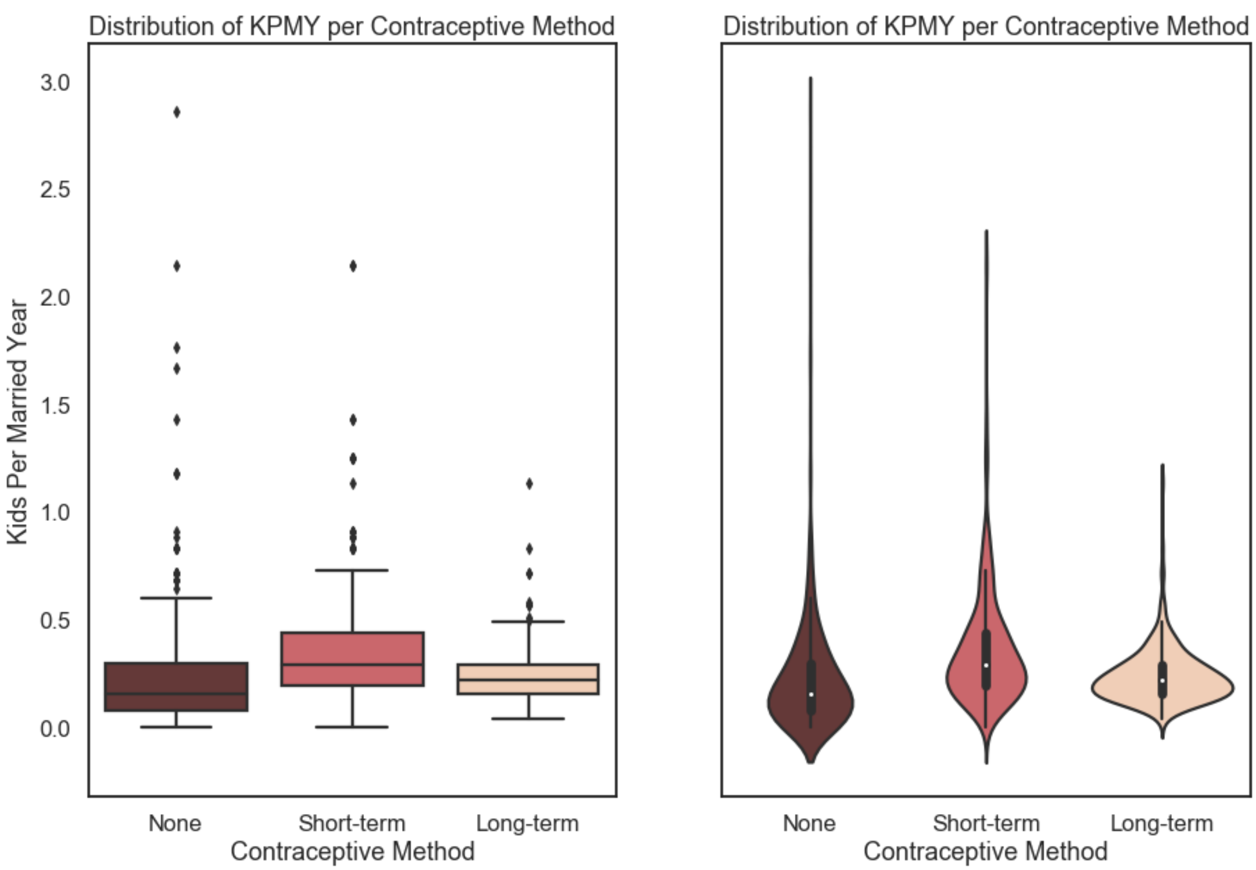
Since we are using KPMY as a covariate in multiclass prediction, we check below if there are significant differences in KPMY values across the three classes: no contraception, short-term, and long-term. We will use a Kruskal-Wallis test to determine to test the hypothesis of whether or not the three groups share the same KPMY distribution. The resulting p-value of 2.772e-25 leads us to conclude that there are distributional differences of KPMY between the three classes.

In [29]:
```
contra_tmp['contraceptive'].value_counts() / contra_tmp.shape[0]
```

Out[29]:
```
0    0.420455
1    0.342803
2    0.236742
Name: contraceptive, dtype: float64
```

In [30]:

```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15,10))

sns.boxplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Short-term', 2:'Long-
            y='kids_per_year',
            data=contra_tmp,
            order=['None', 'Short-term', 'Long-term'],
            ax = ax[0])

ax[0].set(ylabel='Kids Per Married Year',
          xlabel='Contraceptive Method',
          title='Distribution of KPMY per Contraceptive Method');

sns.violinplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Short-term', 2:'Lo
               y='kids_per_year',
               data=contra_tmp,
               order=['None', 'Short-term', 'Long-term'],
               ax = ax[1])

ax[1].set(ylabel='',
       xlabel='Contraceptive Method',
       title='Distribution of KPMY per Contraceptive Method')


plt.show()
```



In [31]:

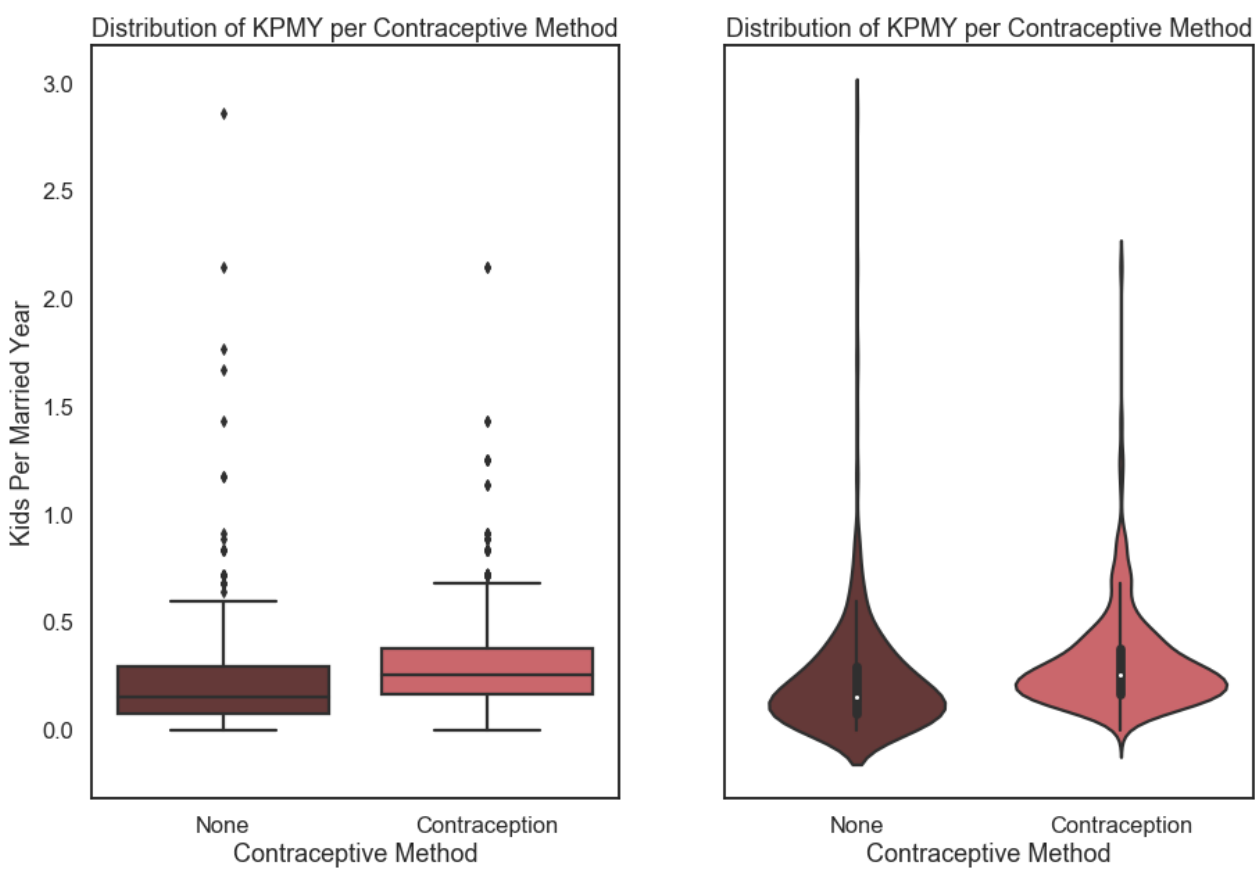
```
from scipy import stats
stats.kruskal(contra_tmp['kids_per_year'][contra_tmp['contraceptive'] == 0],
              contra_tmp['kids_per_year'][contra_tmp['contraceptive'] == 1],
              contra_tmp['kids_per_year'][contra_tmp['contraceptive'] == 2])
```

Out[31]:

```
KruskalResult(statistic=113.12097832014258, pvalue=2.7295538332042766e-25)
```

Since we are also interested in the binary prediction between women who use and do not use contraception in our dataset, we will test the hypothesis of whether KPMY is distributed the same between these binary groups. We will opt for a Mann-Whitney U test to circumvent distributional assumptions. We conclude that there are distributional differences for KPMY between the no contraception and the contraception groups (p-value=1.123e-20).

In [32]:
```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15,10))

sns.boxplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Contraception', 2:'Co
            y='kids_per_year',
            data=contra_tmp,
            ax = ax[0])

ax[0].set(ylabel='Kids Per Married Year',
          xlabel='Contraceptive Method',
          title='Distribution of KPMY per Contraceptive Method');

sns.violinplot(x=contra_tmp['contraceptive'].map({0:'None', 1:'Contraception', 2:
               y='kids_per_year',
               data=contra_tmp,
               ax = ax[1])

ax[1].set(ylabel='',
       xlabel='Contraceptive Method',
       title='Distribution of KPMY per Contraceptive Method')


plt.show()
```



In [33]:

```
from scipy import stats
stats.mannwhitneyu(x=contra_tmp['kids_per_year'][contra_tmp['contraceptive'] == 0
                      y=contra_tmp['kids_per_year'][contra_tmp['contraceptive'].isin
```

Out[33]:

```
MannwhitneyuResult(statistic=90613.5, pvalue=1.1145990835122907e-20)
```

2x. Function

We have written a wrapper function that preprocesses the raw data and outputs a train and test dataset that can be fed into the modeling code. We will use the following function without our preprocessing function:

The following is the complete processing function that takes in the raw contraception dataset and output the train and test data:

In [34]:

```
def preprocess(data):

    # 1. define Kids Per Married Year:

    ### drop those under 20
    data = data[data.wife_age > 20]
    data = data.reset_index(drop=True)

    ### set age intervals to define median age married
    age_intervals = pd.IntervalIndex.from_tuples([(20, 24), (24, 29), (29, 34), (
    age_interval_df = pd.DataFrame(age_intervals)
    age_interval_df['median_marriage_age'] = [19.6, 18.1, 17.6, 16.8, 16.4, 16.5]
    age_interval_df = age_interval_df.rename({0:'age_bin'}, axis=1)
    age_interval_df['age_bin'] = age_interval_df['age_bin'].astype(str)
    age_interval_df['age_bin_low'], age_interval_df['age_bin_high'] = cleanInterv
    data['age_bin'] = pd.cut(data.wife_age, bins=age_intervals)

    ### fill the NA's
    data['age_bin'] = data['age_bin'].cat.add_categories('None')
    data['age_bin'] = data['age_bin'].fillna('None')
    data['age_bin'] = data['age_bin'].astype(str)

    data['age_bin_low'], data['age_bin_high'] = cleanIntervals(data.age_bin)
    data = data.merge(age_interval_df)

    ### create est_years_married: wife's age minus median marriage age for age gr
    data['est_years_married'] = data['wife_age'] - data['median_marriage_age']

    ### create kids_per_year: amount of kids divided by number of est years marri
    data['kids_per_year'] = data['num_child'] / data['est_years_married']

    ### drop unnecessary age_bin feature
    data.drop(['age_bin'], axis=1, inplace=True)

    # 2. Education gap
    data['education_gap'] = data['husband_education'] - data['wife_education']
    gap_intervals = [-3, 0, 1, 4]
    data['education_gap_categorical'] = pd.cut(data.education_gap, bins=gap_inter

    # 3. Contraceptive Use
    this_dic = {0:0, 1:1, 2:1}
    data['contraceptive_use'] = data['contraceptive'].map(this_dic)

    # 4. Adjusted Standard of Living

    ### combine middle-low and middle-high into single category
    this_dic = {1: 1, 2:2, 3:2, 4:3}
    data['standard_living'] = data['standard_living'].map(this_dic)

    # 5. Adjusted Education Level

    ### separate wives' education level into 0 for not having completed primary s
    this_dic = {1:0, 2:0, 3:1, 4:1}
    data['wife_education'] = data['wife_education'].map(this_dic)

    # 6. One-hot Encoding Categorical Variables
    data = pd.get_dummies(data,
                          columns=['wife_education', 'husband_education', 'wife_rel
                                   'wife_work', 'husband_occupation', 'standard_liv
                                   'media_exposure', 'education_gap_categorical'],
                          drop_first=True)

    # 7. Scaling Continuous Variables
```

```
    continuous_vars = ['wife_age', 'num_child', 'kids_per_year', 'est_years_marri
    standardized_vars = pd.DataFrame(StandardScaler().fit_transform(data[continuo

    ### drop original, non-scaled variables
    data.drop(continuous_vars, axis=1, inplace=True)
    data = data.join(standardized_vars)

    # 8. return cleaned dataset
    return data
```

In [35]:

```
# apply function to the two datasets
contra_train_clean = preprocess(contra_train)
contra_test_clean = preprocess(contra_test)
```

In [36]:

```
# examine outputs
[contra.shape, contra_train_clean.shape, contra_test_clean.shape]
```

Out[36]:

```
[(1473, 10), (1056, 24), (353, 24)]
```

3. Modeling

We will predict and compare three outcomes of interest:

- Contraceptive method of (1) no use, (2) short term, (3) long term
- Contraceptive method of (1) no use vs. (2) use?
- Contraceptive method of (1) short-term vs. (2) long-term for those on contraception

Which of the three above has a better prediction accuracy? What are the pros and cons of each?

Additionally, by running logistic regression and Random Forests on each of the above, we hope to assess which model performs better and why.

3a. Predicting Contraceptive: No Use, Short Term, Long Term

i. Feature Selection and Data Preparation

Our first set of models will work on predicting all three outcomes. We will start by running our multinomial logistic regression model with all existing features in the dataset to evaluate initial performance. Afterwards, we will utilize a leave-one-out approach to determine which features help vs. hurt accuracy in order to pick the optimal combination.

Here is the ultimate set of features that we drop (see Part iii on details).

In [37]:

```
# training data
# remove the first 2 because they are the response
# remove age_bin because they were used for another variable
# remove education_gap because it was coded into a categorical variable
X_train = contra_train_clean.drop(['contraceptive', 'contraceptive_use', 'age_bir
                             'education_gap', 'wife_age', 'num_child'], axis = 1)
Y_train = contra_train_clean['contraceptive']

# test data
X_test = contra_test_clean.drop(['contraceptive', 'contraceptive_use', 'age_bin_l
                           'education_gap', 'wife_age', 'num_child'], axis = 1)
Y_test = contra_test_clean['contraceptive']
```

ii. Multinomial Logistic Regression

Here is the multinomial logistic regression without CV.

In [38]:
```python
from sklearn.linear_model import LogisticRegression

# fit multinomial model
multinomial_logit = LogisticRegression(multi_class='multinomial', solver='newton-
multinomial_logit.fit(X = X_train, y = Y_train)

# obtain accuracies (train and CV)
train_accuracy_lr = multinomial_logit.score(X = X_train, y = Y_train)
test_accuracy_lr  = multinomial_logit.score(X = X_test, y = Y_test)

# print accuracy
[train_accuracy_lr, test_accuracy_lr]
```

Out[38]: [0.5606060606060606, 0.46175637393767704]

In [39]:
```python
coef_df = pd.DataFrame(multinomial_logit.coef_).T
coef_df = coef_df.apply(np.exp)
coef_df.insert(0, 'covariate', X_train.columns)
coef_df = coef_df.sort_values(by=[0,1,2], ascending=False)
coef_df
```

Out[39]:

	covariate	0	1	2
0	median_marriage_age	2.091204	0.666310	0.717674
16	est_years_married	2.056530	0.548533	0.886466
14	education_gap_categorical_1	1.962771	0.964749	0.528100
13	education_gap_categorical_0	1.429635	0.752391	0.929675
5	wife_religion_1	1.414735	0.980726	0.720737
12	media_exposure_1	1.370073	0.749246	0.974164
7	husband_occupation_2	1.185907	1.421175	0.593337
8	husband_occupation_3	0.975531	1.435600	0.714045
6	wife_work_1	0.919098	1.081199	1.006311
2	husband_education_2	0.841769	2.706726	0.438897
9	husband_occupation_4	0.804463	1.038018	1.197537
1	wife_education_1	0.706955	1.134441	1.246885
10	standard_living_2	0.665096	1.097489	1.369984
15	kids_per_year	0.608747	1.362949	1.205269
3	husband_education_3	0.569813	2.801743	0.626382
11	standard_living_3	0.549502	1.194639	1.523331
4	husband_education_4	0.499897	2.515439	0.795253

Here is the multinomial logistic regression with CV=10.

In [40]:
```python
from sklearn.linear_model import LogisticRegressionCV

# fit multinomial CV model
multinomial_logit_cv = LogisticRegressionCV(cv=10, multi_class='multinomial', sol
multinomial_logit_cv.fit(X = X_train, y = Y_train)

# obtain CV accuracies
train_accuracy_cv = multinomial_logit_cv.score(X = X_train, y = Y_train)
test_accuracy_cv  = multinomial_logit_cv.score(X = X_test, y = Y_test)

# print
[train_accuracy_cv, test_accuracy_cv]
```

Out[40]: [0.5643939393939394, 0.45609065155807366]

In [41]:
```python
coef_df = pd.DataFrame(multinomial_logit_cv.coef_).T
coef_df = coef_df.apply(np.exp)
coef_df.insert(0, 'covariate', X_train.columns)
coef_df = coef_df.sort_values(by=[0,1,2], ascending=False)
coef_df
```

Out[41]:

	covariate	0	1	2
0	median_marriage_age	1.468973	0.833437	0.816796
16	est_years_married	1.456477	0.689613	0.995613
5	wife_religion_1	1.254527	0.971452	0.820538
14	education_gap_categorical_1	1.248821	1.097800	0.729418
12	media_exposure_1	1.243990	0.845580	0.950667
7	husband_occupation_2	1.136115	1.199838	0.733593
2	husband_education_2	1.116870	1.107355	0.808557
13	education_gap_categorical_0	0.983187	0.871383	1.167226
9	husband_occupation_4	0.979854	0.986620	1.034401
8	husband_occupation_3	0.975852	1.251364	0.818903
6	wife_work_1	0.952887	1.059641	0.990375
3	husband_education_3	0.902189	1.203680	0.920855
10	standard_living_2	0.896190	1.073288	1.039642
4	husband_education_4	0.806513	1.064344	1.164948
11	standard_living_3	0.758882	1.129077	1.167085
15	kids_per_year	0.695787	1.293721	1.110922
1	wife_education_1	0.682674	1.138014	1.287180

iii. Visualize Feature Selection vs. CV Error

To select features, we began with including all features in the model and removing, one by one, those that decreased training error. We have written a function that evaluates this for the first round (first feature removal) and subsequently, we plot this to more easily visualize the effect of feature removal.

In [42]:

```
# modified df
contra_df = contra_train_clean.drop(['contraceptive', 'contraceptive_use', 'age_b
                                     'age_bin_high', 'education_gap'], axis = 1)

# features we will remove one by one
quantitative_features = ['median_marriage_age', 'wife_education_1', 'wife_religio
                         'wife_work_1', 'media_exposure_1', 'wife_age', 'num_chil
                         'kids_per_year', 'est_years_married']

# to track accuracy for features
accuracy_train = {}
accuracy_cv_train = {}

# loop through feature removal
for i in range(len(quantitative_features)):

    # The name we are giving to the ith model
    name = quantitative_features[i]

    # subset dataframe
    X_train_i = contra_df.drop(quantitative_features[i], axis = 1)
    Y_train_i = contra_train_clean['contraceptive']

    # initialize models
    model = LogisticRegression(multi_class='multinomial', solver='newton-cg')
    model_cv = LogisticRegressionCV(cv=10, multi_class='multinomial', solver='new

    # fit models
    model.fit(X = X_train_i, y = Y_train_i)
    model_cv.fit(X = X_train_i, y = Y_train_i)
    train_model = model.score(X = X_train_i, y = Y_train_i)
    train_model_cv = model_cv.score(X = X_train_i, y = Y_train_i)

    # Saving the ith model
    accuracy_train[name] = train_model
    accuracy_cv_train[name] = train_model_cv
```

In [43]:

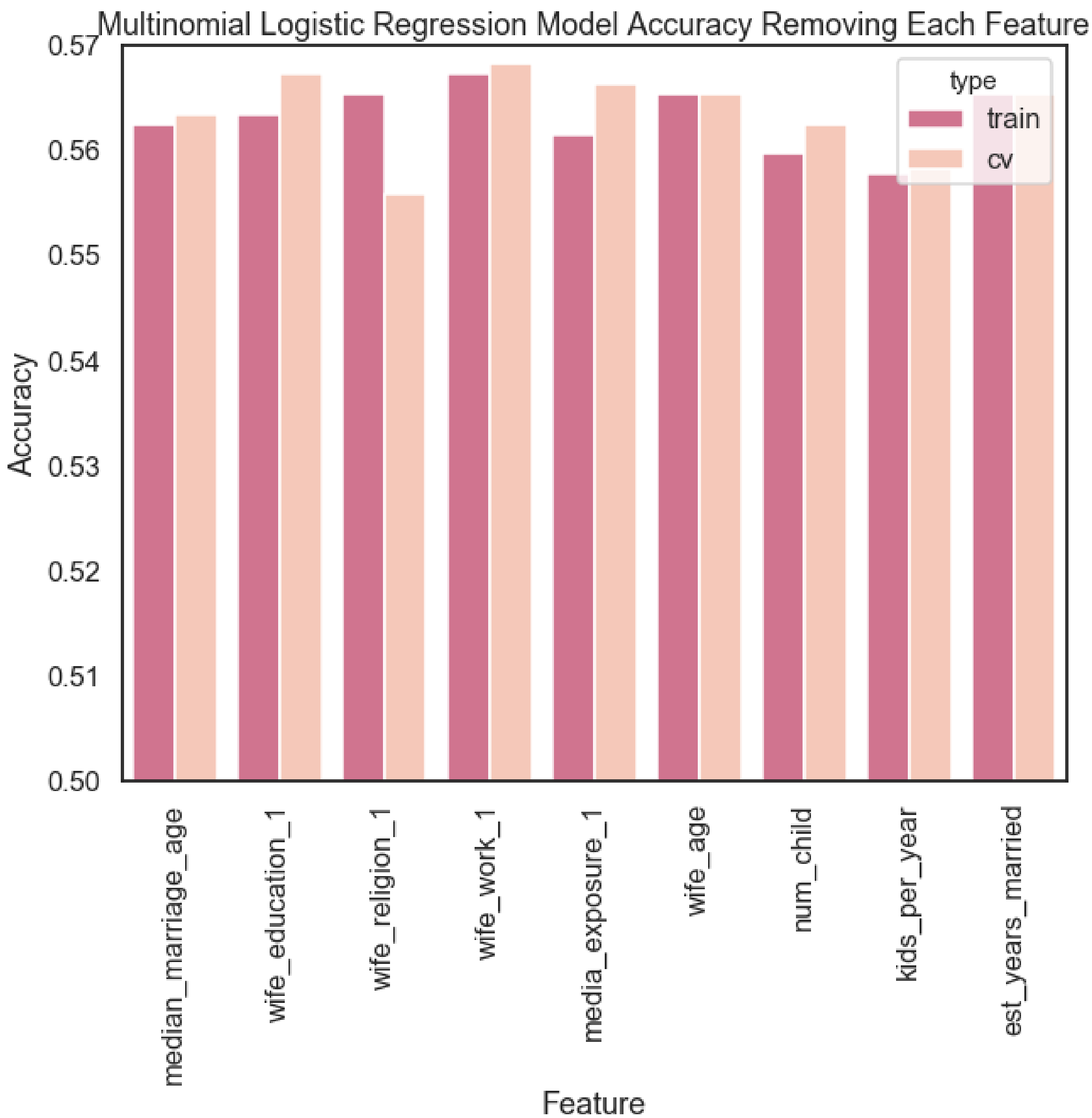
```
def visualize_errors(accuracy_train, accuracy_cv):

    # prepare train df for plotting
    accuracy_train_df = pd.DataFrame(accuracy_train.items(), columns = ['feature'
    accuracy_train_df['type'] = 'train'

    # prepare cv df for plotting
    accuracy_cv_df = pd.DataFrame(accuracy_cv.items(), columns = ['feature','accu
    accuracy_cv_df['type'] = 'cv'

    # combine datasets
    accuracy_df = pd.concat([accuracy_train_df, accuracy_cv_df])

    # generate plot
    plt.figure(figsize=(10,8))
    ax = sns.barplot(x = 'feature', y = 'accuracy', hue = 'type', data = accuracy
                     palette=['#DF6589', '#FFC3AF'])
    ax.set(xlabel='Feature',
           ylabel='Accuracy');
    ax.set_xticklabels(ax.get_xticklabels(), rotation = 90)

    # return plot
    return ax
```

In [44]:

```
# visualize
ax = visualize_errors(accuracy_train, accuracy_cv_train)
plt.ylim(0.5, 0.57)
ax.set(title = 'Multinomial Logistic Regression Model Accuracy Removing Each Feat
```

Out[44]:

```
[Text(0.5, 1.0, 'Multinomial Logistic Regression Model Accuracy Removing Each Featu
re')]
```



iv. Random Forests

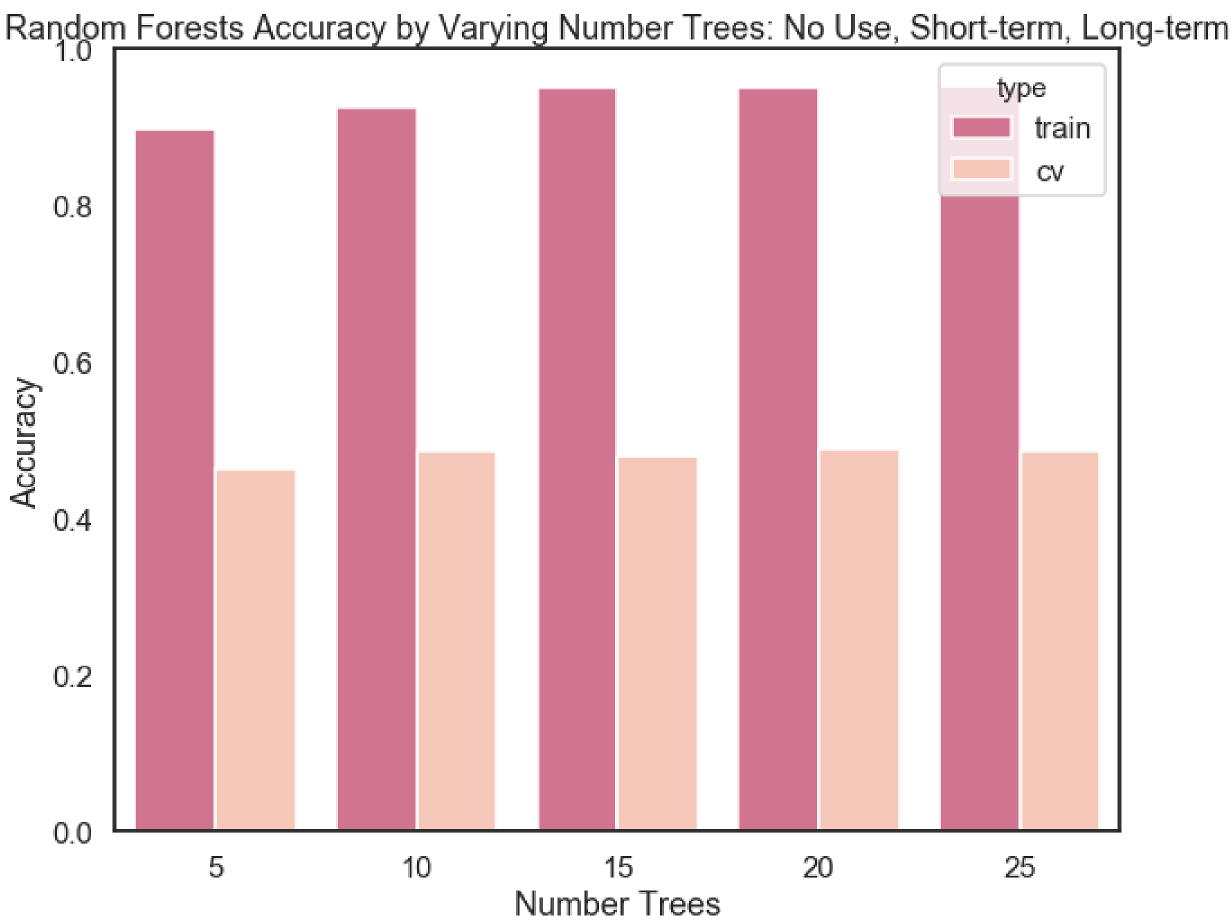
To fit a Random Forests model to the data, we will tune the number of trees using cross-validation, while allowing the Random Forests algorithm to tune the remaining features through its use of bagging. We visualize the training and cross-validated accuracies for a range of number trees to (1) confirm overfitting occurs when fitting on a single training set and (2) select the number of trees we will use.

In [45]:

```
from sklearn import ensemble
from sklearn.model_selection import cross_val_score

# to track accuracy for features
accuracy_train_rf = {}
accuracy_cv_rf = {}
n_trees = range(5, 30, 5)

# cross validate for n trees
for i in n_trees:

    # fit model
    random_forest = ensemble.RandomForestClassifier(n_estimators = i)
    random_forest.fit(X = X_train, y = Y_train)

    # obtain accuracy
    accuracy_train_rf[i] = random_forest.score(X = X_train, y = Y_train)
    accuracy_cv_rf[i] = cross_val_score(random_forest, X_train, Y_train, cv = 5).
```

In [46]:

```
# prepare train df for plotting
accuracy_train_df = pd.DataFrame(accuracy_train_rf.items(), columns = ['n_tree','
accuracy_train_df['type'] = 'train'
accuracy_train_df

# prepare cv df for plotting
accuracy_cv_df = pd.DataFrame(accuracy_cv_rf.items(), columns = ['n_tree','accura
accuracy_cv_df['type'] = 'cv'

# combine datasets
accuracy_df = pd.concat([accuracy_train_df, accuracy_cv_df])

# generate plot
plt.figure(figsize=(10,8))
ax = sns.barplot(x = 'n_tree', y = 'accuracy', hue = 'type', data = accuracy_df,
                palette=['#DF6589', '#FFC3AF'])
ax.set(xlabel='Number Trees',
       ylabel='Accuracy',
       title = 'Random Forests Accuracy by Varying Number Trees: No Use, Short-te
```



Finally, we fit the final training model with the selected number of trees.

In [47]:

```
# fit final model with n tree selected
random_forest = ensemble.RandomForestClassifier(n_estimators=25)
random_forest.fit(X = X_train, y = Y_train)

# obtain accuracies
train_accuracy_rf = random_forest.score(X = X_train, y = Y_train)
test_accuracy_rf = random_forest.score(X = X_test, y = Y_test)

# print
[train_accuracy_rf, test_accuracy_rf]
```

Out[47]:

```
[0.9545454545454546, 0.5184135977337111]
```

3b. Predicting Binary Contraceptive: No vs. Yes

We will repeat the above process on the binary outcomes (starting with use vs. no use).

i. Feature Selection and Data Preparation

Here are the features we have selected to use (see Part iii for details).

In [48]:

```
# training data
X_train_binary = contra_train_clean.drop(['contraceptive', 'contraceptive_use', '
                                    'education_gap', 'wife_age'], axis = 1)
Y_train_binary = contra_train_clean['contraceptive_use']

# test data
X_test_binary = contra_test_clean.drop(['contraceptive', 'contraceptive_use', 'ag
                                  'education_gap', 'wife_age'], axis = 1)
Y_test_binary = contra_test_clean['contraceptive_use']
```

ii. Binary Logistic Regression

Here is the binary logistic regression without CV.

In [49]:

```
# fit binomial logistic regression model
binary_logit = LogisticRegression(solver = 'newton-cg')
binary_logit.fit(X = X_train_binary, y = Y_train_binary)

# obtain accuracies
train_accuracy_lr_binary = binary_logit.score(X = X_train_binary, y = Y_train_bir
test_accuracy_lr_binary  = binary_logit.score(X = X_test_binary, y = Y_test_binar

# print
[train_accuracy_lr_binary, test_accuracy_lr_binary]
```

Out[49]:

```
[0.7111742424242424, 0.6770538243626062]
```

In [50]:

```
coef_df = pd.DataFrame(np.exp(binary_logit.coef_)).T
coef_df.insert(0, 'covariate', X_train_binary.columns)
coef_df = coef_df.sort_values(by=0, ascending=False)
coef_df
```

Out[50]:

	covariate	0
4	husband_education_4	2.634987
11	standard_living_3	2.198738
3	husband_education_3	2.166172
15	num_child	1.845273
1	wife_education_1	1.708828
10	standard_living_2	1.563410
16	kids_per_year	1.377807
2	husband_education_2	1.230336
9	husband_occupation_4	1.226588
6	wife_work_1	1.099829
8	husband_occupation_3	1.060621
7	husband_occupation_2	0.766700
13	education_gap_categorical_0	0.631620
12	media_exposure_1	0.583507
5	wife_religion_1	0.540628
0	median_marriage_age	0.456700
14	education_gap_categorical_1	0.420235
17	est_years_married	0.277349

In [51]:

```
# fit CV binomial model
binary_logit_cv = LogisticRegressionCV(cv = 10, solver = 'newton-cg')
binary_logit_cv.fit(X = X_train_binary, y = Y_train_binary)

# obtain accuracies
train_accuracy_cv_binary = binary_logit_cv.score(X = X_train_binary, y = Y_train_
test_accuracy_cv_binary  = binary_logit_cv.score(X = X_test_binary, y = Y_test_bi

# print
[train_accuracy_cv_binary, test_accuracy_cv_binary]
```

Out[51]: [0.7007575757575758, 0.6685552407932012]

In [52]:

```python
coef_df = pd.DataFrame(np.exp(binary_logit_cv.coef_)).T
coef_df.insert(0, 'covariate', X_train_binary.columns)
coef_df = coef_df.sort_values(by=0, ascending=False)
coef_df
```

Out[52]:

	covariate	0
1	wife_education_1	1.706125
15	num_child	1.550442
11	standard_living_3	1.421775
4	husband_education_4	1.374369
16	kids_per_year	1.299535
3	husband_education_3	1.140833
10	standard_living_2	1.089798
13	education_gap_categorical_0	1.060120
8	husband_occupation_3	1.051564
6	wife_work_1	1.046736
9	husband_occupation_4	1.003467
7	husband_occupation_2	0.836742
2	husband_education_2	0.833020
14	education_gap_categorical_1	0.772851
0	median_marriage_age	0.761498
12	media_exposure_1	0.734029
5	wife_religion_1	0.711845
17	est_years_married	0.538213

iii. Visualize Feature Selection vs. CV Error

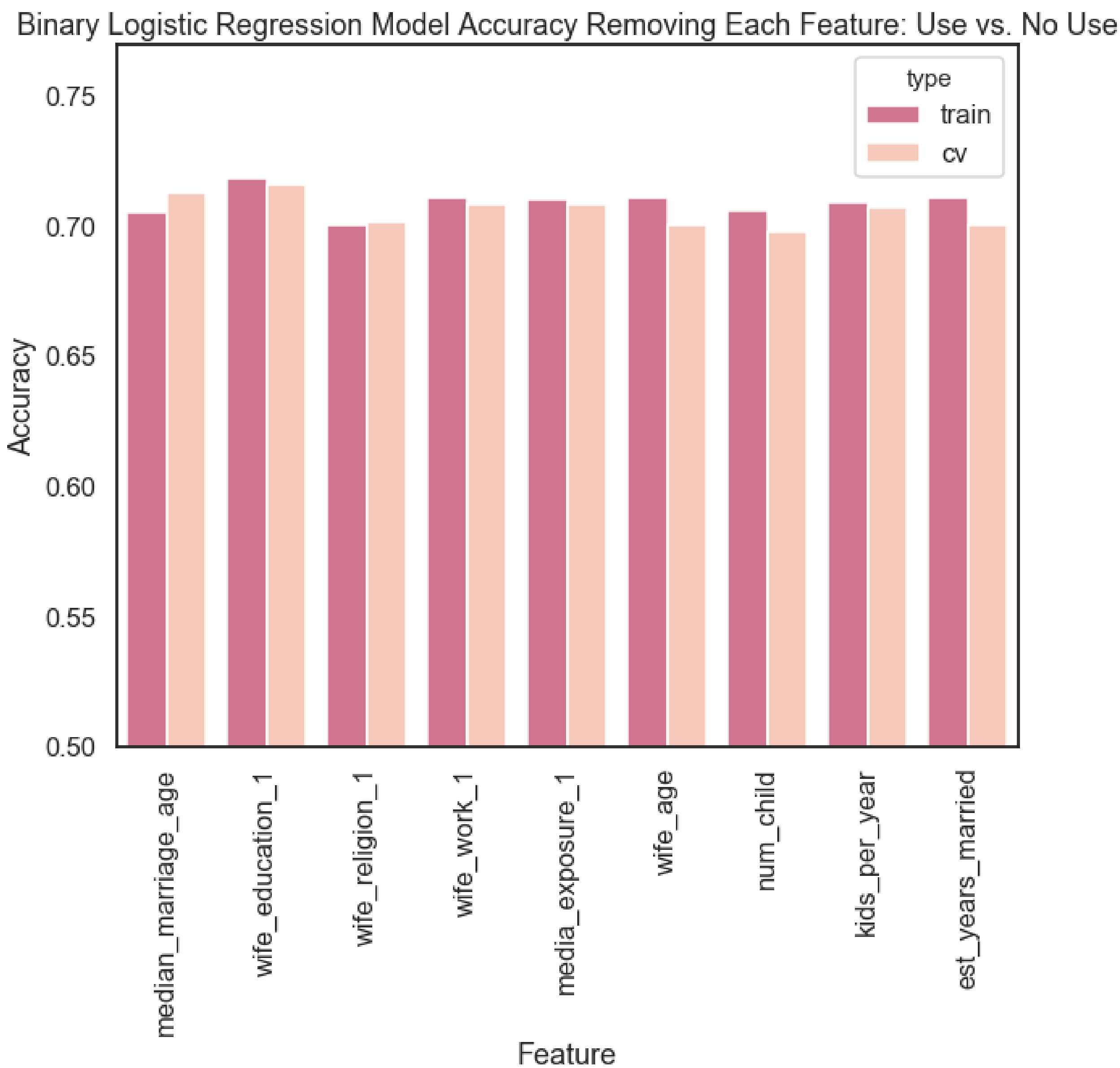
Here is how dropping features in the first round affected training and CV accuracy.

In [53]:

```
# modified df
contra_df = contra_train_clean.drop(['contraceptive', 'contraceptive_use', 'age_b
                                     'age_bin_high', 'education_gap'], axis = 1)

# features we will drop one by one
quantitative_features = ['median_marriage_age', 'wife_education_1', 'wife_religio
                         'wife_work_1', 'media_exposure_1', 'wife_age', 'num_chil
                         'kids_per_year', 'est_years_married']

# to track accuracy for features
accuracy_train = {}
accuracy_cv_train = {}

# loop through feature removal
for i in range(len(quantitative_features)):

    # The name we are giving to the ith model
    name = quantitative_features[i]

    # subset dataframe
    X_train_i = contra_df.drop(quantitative_features[i], axis = 1)
    Y_train_i = contra_train_clean['contraceptive_use']

    # initialize models
    model = LogisticRegression(solver = 'newton-cg')
    model_cv = LogisticRegressionCV(cv=10, solver='newton-cg')

    # fit models
    model.fit(X = X_train_i, y = Y_train_i)
    model_cv.fit(X = X_train_i, y = Y_train_i)
    train_model = model.score(X = X_train_i, y = Y_train_i)
    train_model_cv = model_cv.score(X = X_train_i, y = Y_train_i)

    # Saving the ith model
    accuracy_train[name] = train_model
    accuracy_cv_train[name] = train_model_cv
```

In [54]:
```
# visualize
ax = visualize_errors(accuracy_train, accuracy_cv_train)
plt.ylim(0.5, 0.77)
ax.set(title = 'Binary Logistic Regression Model Accuracy Removing Each Feature:
```

Out[54]:
```
[Text(0.5, 1.0, 'Binary Logistic Regression Model Accuracy Removing Each Feature: U
se vs. No Use')]
```



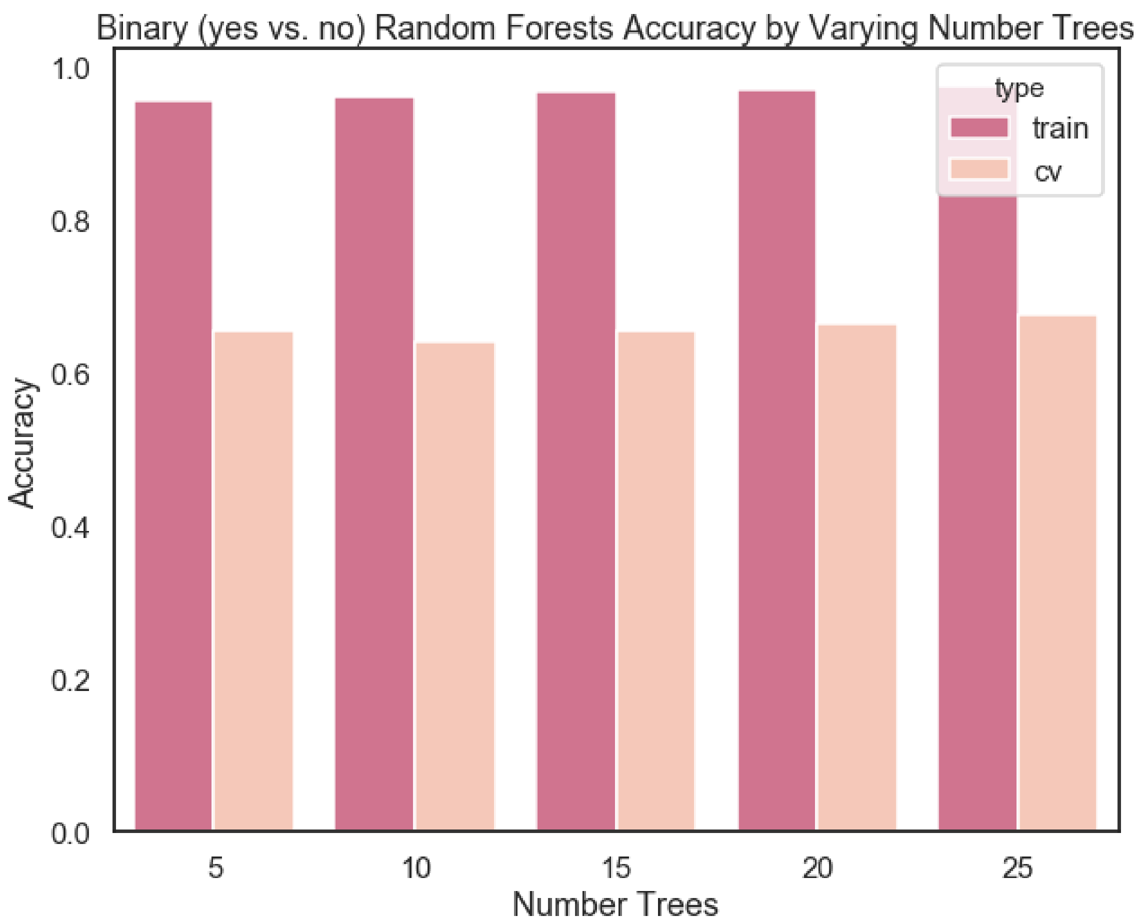
iv. Random Forests

By cross-validating number of trees, we end up with 25 trees to improve accuracy.

In [55]:

```
# to track accuracy for features
accuracy_train_rf = {}
accuracy_cv_rf = {}
n_trees = range(5, 30, 5)

# cross validate for n trees
for i in n_trees:

    # fit model
    random_forest = ensemble.RandomForestClassifier(n_estimators = i)
    random_forest.fit(X = X_train_binary, y = Y_train_binary)

    # obtain accuracy
    accuracy_train_rf[i] = random_forest.score(X = X_train_binary, y = Y_train_bi
    accuracy_cv_rf[i] = cross_val_score(random_forest, X_train_binary, Y_train_bi
```

In [56]:
```
# prepare train df for plotting
accuracy_train_df = pd.DataFrame(accuracy_train_rf.items(), columns = ['n_tree','
accuracy_train_df['type'] = 'train'
accuracy_train_df

# prepare cv df for plotting
accuracy_cv_df = pd.DataFrame(accuracy_cv_rf.items(), columns = ['n_tree','accura
accuracy_cv_df['type'] = 'cv'

# combine datasets
accuracy_df = pd.concat([accuracy_train_df, accuracy_cv_df])

# generate plot
plt.figure(figsize=(10,8))
ax = sns.barplot(x = 'n_tree', y = 'accuracy', hue = 'type', data = accuracy_df,
                palette=['#DF6589', '#FFC3AF'])
ax.set(xlabel='Number Trees',
       ylabel='Accuracy',
       title = 'Binary (yes vs. no) Random Forests Accuracy by Varying Number Tre
```



We fit the final model on the training and test datasets.

In [57]:
```
# fit model
binary_random_forest = ensemble.RandomForestClassifier(n_estimators = 25)
binary_random_forest.fit(X = X_train_binary, y = Y_train_binary)

# obtain accuracies
train_accuracy_rf_binary = binary_random_forest.score(X = X_train_binary, y = Y_t
test_accuracy_rf_binary  = binary_random_forest.score(X = X_test_binary, y = Y_te

# print
[train_accuracy_rf_binary, test_accuracy_rf_binary]
```

Out[57]:
```
[0.9734848484848485, 0.6968838526912181]
```

3c. Predicting Contraceptive of Those Who Use: Short-term vs. Long-term

This is our final round of running models on binary short-term vs. long-term outcome.

i. Feature Selection and Data Preparation

Here are the features we selected for this binary case:

In [58]:
```
# data preprocessing
contra_train_use = contra_train_clean[contra_train_clean['contraceptive_use'] ==
contra_test_use = contra_test_clean[contra_test_clean['contraceptive_use'] == 1]

# training data
X_train_use = contra_train_use.drop(['contraceptive', 'contraceptive_use', 'age_b
                                     'education_gap', 'wife_education_1', 'wife_w
Y_train_use = contra_train_use['contraceptive']

# test data
X_test_use = contra_test_use.drop(['contraceptive', 'contraceptive_use', 'age_bir
                                   'education_gap', 'wife_education_1', 'wife_wor
Y_test_use = contra_test_use['contraceptive']
```

ii. Logistic Regression

Here is the logistic regression without CV.

In [59]:
```
# fit model
binary_use_logit = LogisticRegression(solver = 'newton-cg')
binary_use_logit.fit(X = X_train_use, y = Y_train_use)

# obtain accuracies
train_accuracy_lr_use = binary_use_logit.score(X = X_train_use, y = Y_train_use)
test_accuracy_lr_use  = binary_use_logit.score(X = X_test_use, y = Y_test_use)

# print
[train_accuracy_lr_use, test_accuracy_lr_use]
```

Out[59]:
```
[0.6830065359477124, 0.5911330049261084]
```

In [60]:

```
coef_df = pd.DataFrame(np.exp(binary_use_logit.coef_)).T
coef_df.insert(0, 'covariate', X_train_use.columns)
coef_df = coef_df.sort_values(by=0, ascending=False)
coef_df
```

Out[60]:

	covariate	0
15	est_years_married	1.707865
10	media_exposure_1	1.409701
0	median_marriage_age	1.297509
11	education_gap_categorical_0	1.122332
13	num_child	1.096576
8	standard_living_2	1.084401
7	husband_occupation_4	1.040759
9	standard_living_3	1.036650
4	wife_religion_1	0.697196
14	kids_per_year	0.628148
12	education_gap_categorical_1	0.502310
6	husband_occupation_3	0.500167
5	husband_occupation_2	0.421524
3	husband_education_4	0.413834
2	husband_education_3	0.288582
1	husband_education_2	0.245464

Here is the logistic regression with CV=10.

In [61]:

```
# fit model
binary_use_logit_cv = LogisticRegressionCV(cv = 10, solver = 'newton-cg')
binary_use_logit_cv.fit(X = X_train_use, y = Y_train_use)

# obtain accuracies
train_accuracy_cv_use = binary_use_logit_cv.score(X = X_train_use, y = Y_train_us
test_accuracy_cv_use  = binary_use_logit_cv.score(X = X_test_use, y = Y_test_use)

# print
[train_accuracy_cv_use, test_accuracy_cv_use]
```

Out[61]: [0.6552287581699346, 0.6551724137931034]

In [62]:

```
coef_df = pd.DataFrame(np.exp(binary_use_logit_cv.coef_)).T
coef_df.insert(0, 'covariate', X_train_use.columns)
coef_df = coef_df.sort_values(by=0, ascending=False)
coef_df
```

Out[62]:

	covariate	0
15	est_years_married	1.162491
11	education_gap_categorical_0	1.125818
3	husband_education_4	1.079694
9	standard_living_3	1.053821
7	husband_occupation_4	1.005278
10	media_exposure_1	1.000902
13	num_child	0.995298
8	standard_living_2	0.969562
1	husband_education_2	0.957643
4	wife_religion_1	0.953854
2	husband_education_3	0.936045
5	husband_occupation_2	0.926837
6	husband_occupation_3	0.909959
0	median_marriage_age	0.883608
12	education_gap_categorical_1	0.883400
14	kids_per_year	0.849181

iii. Visualize Feature Selection vs. CV Error

Here is how accuracy changes when removing each feature in the first round.

In [63]:

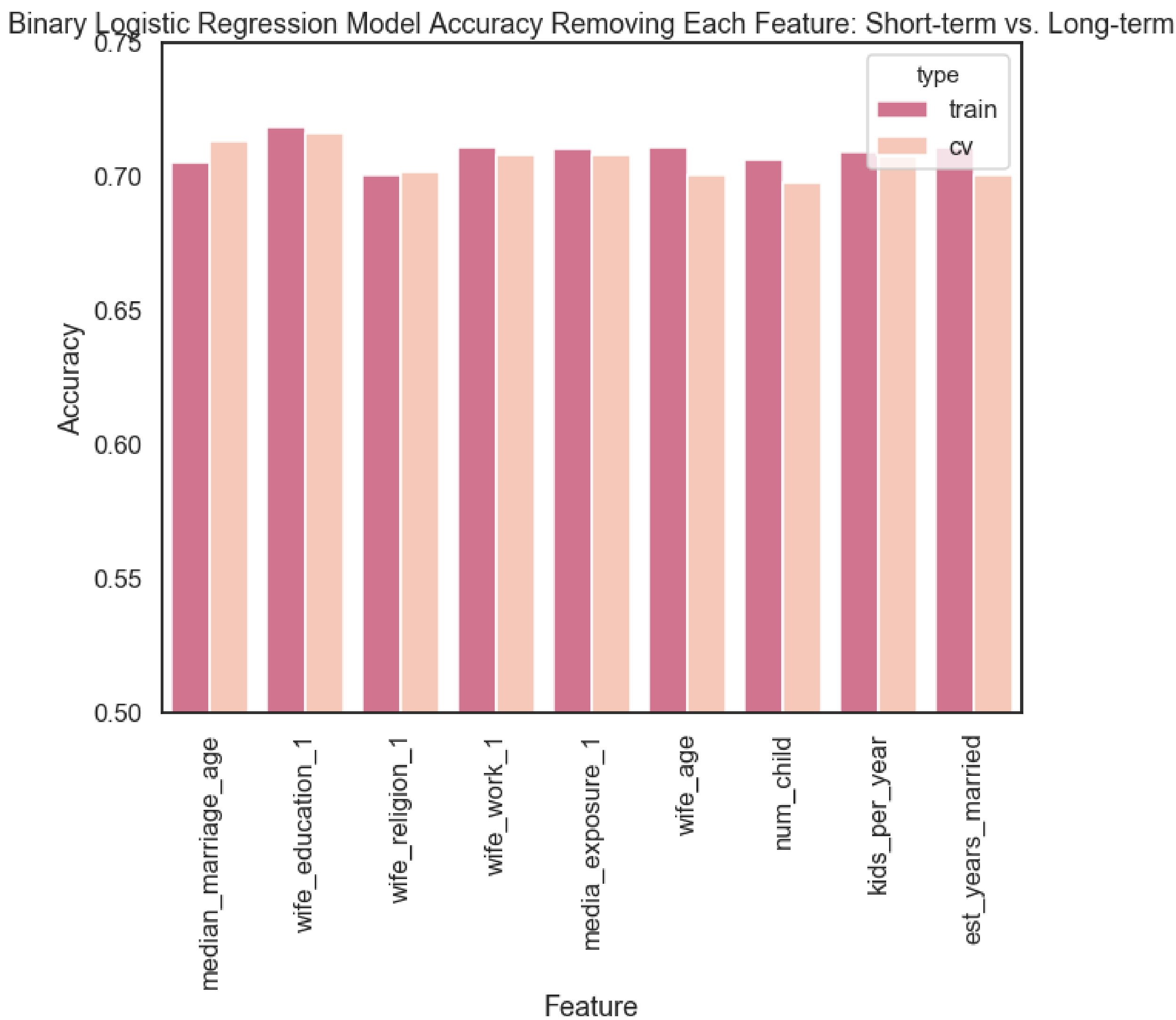
```python
# modified df
contra_df = contra_train_clean.drop(['contraceptive', 'contraceptive_use', 'age_b
                                     'age_bin_high', 'education_gap'], axis = 1)

# features we will drop one by one
quantitative_features = ['median_marriage_age', 'wife_education_1', 'wife_religio
                         'wife_work_1', 'media_exposure_1', 'wife_age', 'num_chil
                         'kids_per_year', 'est_years_married']

# to track accuracy for features
accuracy_train = {}
accuracy_cv_train = {}

# loop through feature removal
for i in range(len(quantitative_features)):

    # The name we are giving to the ith model
    name = quantitative_features[i]

    # subset dataframe
    X_train_i = contra_df.drop(quantitative_features[i], axis = 1)
    Y_train_i = contra_train_clean['contraceptive_use']

    # initialize models
    model = LogisticRegression(solver = 'newton-cg')
    model_cv = LogisticRegressionCV(cv=10, solver='newton-cg')

    # fit models
    model.fit(X = X_train_i, y = Y_train_i)
    model_cv.fit(X = X_train_i, y = Y_train_i)
    train_model = model.score(X = X_train_i, y = Y_train_i)
    train_model_cv = model_cv.score(X = X_train_i, y = Y_train_i)

    # Saving the ith model
    accuracy_train[name] = train_model
    accuracy_cv_train[name] = train_model_cv
```

In [64]:

```
# visualize
ax = visualize_errors(accuracy_train, accuracy_cv_train)
plt.ylim(0.5, 0.75)
ax.set(title = 'Binary Logistic Regression Model Accuracy Removing Each Feature:
```

Out[64]:

```
[Text(0.5, 1.0, 'Binary Logistic Regression Model Accuracy Removing Each Feature: S
hort-term vs. Long-term')]
```



iv. Random Forests

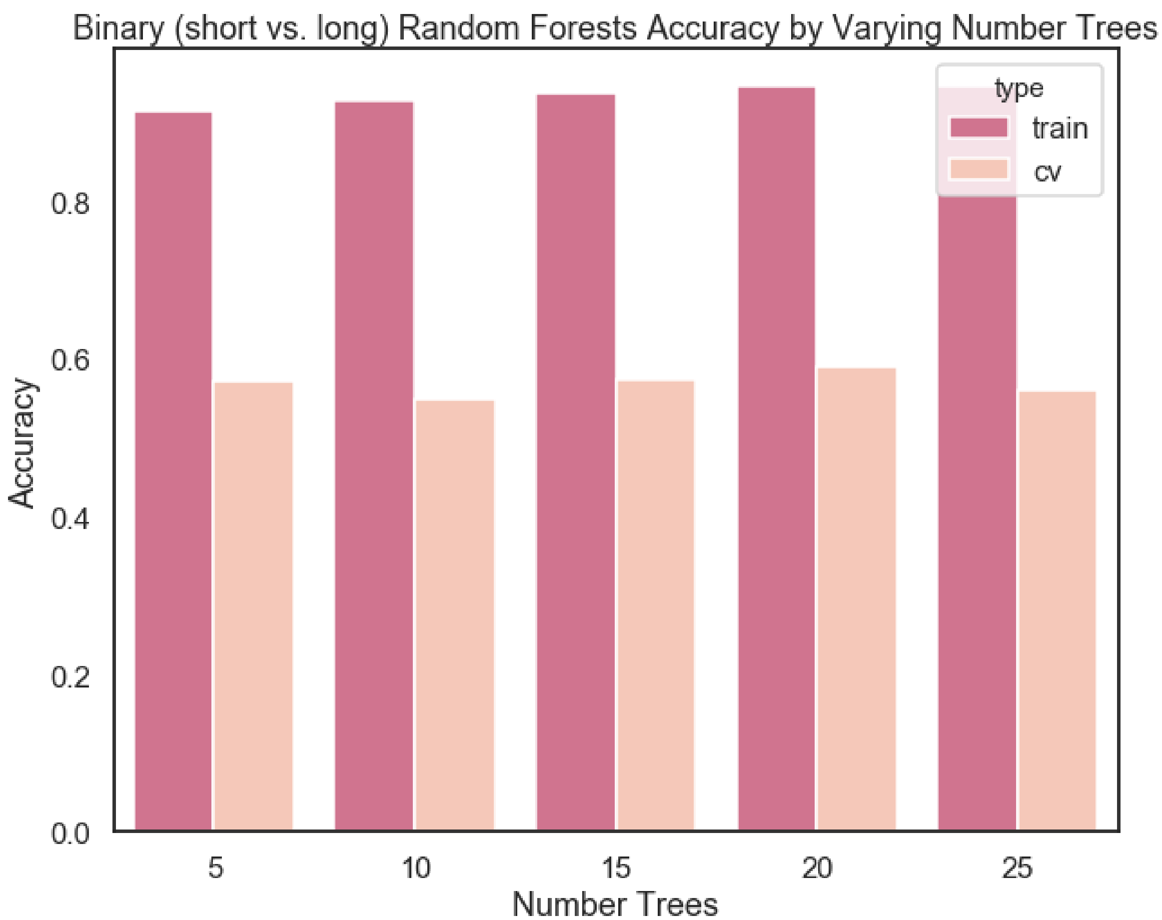
We cross-validate for number of trees and end up with 15 trees for the final model.

In [65]:

```
# to track accuracy for features
accuracy_train_rf = {}
accuracy_cv_rf = {}
n_trees = range(5, 30, 5)

# cross validate for n trees
for i in n_trees:

    # fit model
    random_forest = ensemble.RandomForestClassifier(n_estimators = i)
    random_forest.fit(X = X_train_use, y = Y_train_use)

    # obtain accuracy
    accuracy_train_rf[i] = random_forest.score(X = X_train_use, y = Y_train_use)
    accuracy_cv_rf[i] = cross_val_score(random_forest, X_train_use, Y_train_use,
```

In [66]:

```
# prepare train df for plotting
accuracy_train_df = pd.DataFrame(accuracy_train_rf.items(), columns = ['n_tree','
accuracy_train_df['type'] = 'train'
accuracy_train_df

# prepare cv df for plotting
accuracy_cv_df = pd.DataFrame(accuracy_cv_rf.items(), columns = ['n_tree','accura
accuracy_cv_df['type'] = 'cv'

# combine datasets
accuracy_df = pd.concat([accuracy_train_df, accuracy_cv_df])

# generate plot
plt.figure(figsize=(10,8))
ax = sns.barplot(x = 'n_tree', y = 'accuracy', hue = 'type', data = accuracy_df,
                palette=['#DF6589', '#FFC3AF'])
ax.set(xlabel='Number Trees',
       ylabel='Accuracy',
       title = 'Binary (short vs. long) Random Forests Accuracy by Varying Number
```



We fit the final RF model to the training and test datasets.

In [67]:
```
# fit model
binary_use_random_forest = ensemble.RandomForestClassifier(n_estimators = 15)
binary_use_random_forest.fit(X = X_train_use, y = Y_train_use)

# obtain accuracies
train_accuracy_rf_use = binary_use_random_forest.score(X = X_train_use, y = Y_tra
test_accuracy_rf_use  = binary_use_random_forest.score(X = X_test_use, y = Y_test

# print
[train_accuracy_rf_use, test_accuracy_rf_use]
```

Out[67]:
```
[0.9428104575163399, 0.6108374384236454]
```

4. Assessing Precision and Recall

Finally, we want to use apply our predictive models to our test set which was not used anywhere in our predictive modeling process.

4a. Multiclass prediction

For the multiclass setting, we examined the medians and standard deviations of the predicted probabilities per each subject. This measure explains how definitive our model was at predicting their classes.

For example, the row `[0.629948, 0.257109, 0.112943]` has a median of 25.71% and standard deviation of 21.78%. Based on the boxplot of medians below, the median is quite small. Based on the boxplot of standard deviations below, a definitive row of predicted probabilities like this has a high standard deviation in comparison to the rest of the predictions. These two pieces of evidence show that our model is predicting probabilities that are quite uniform.

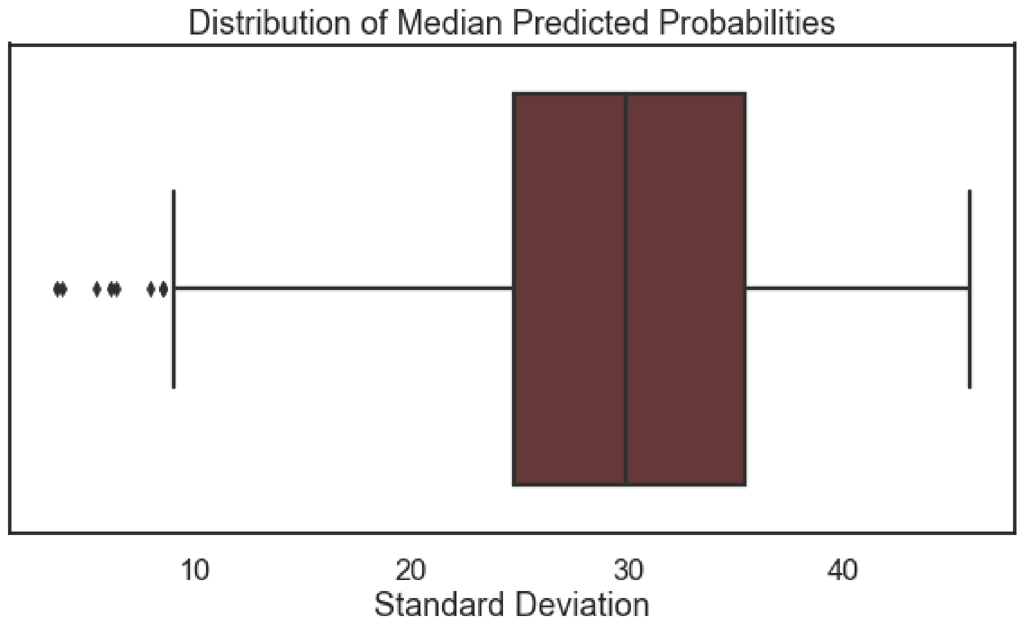
In [68]:
```
# training data
# remove the first 2 because they are the response
# remove age_bin because they were used for another variable
# remove education_gap because it was coded into a categorical variable
X_train = contra_train_clean.drop(['contraceptive', 'contraceptive_use', 'age_bir
                                   'education_gap', 'wife_age', 'num_child'], axis = 1)
Y_train = contra_train_clean['contraceptive']

# test data
X_test = contra_test_clean.drop(['contraceptive', 'contraceptive_use', 'age_bin_l
                                 'education_gap', 'wife_age', 'num_child'], axis = 1)
Y_test = contra_test_clean['contraceptive']
```

In [69]:
```
probs = multinomial_logit.predict_proba(X_test)
probs_df = pd.DataFrame(probs, columns={0,1,2})
probs_df.head(5)
```

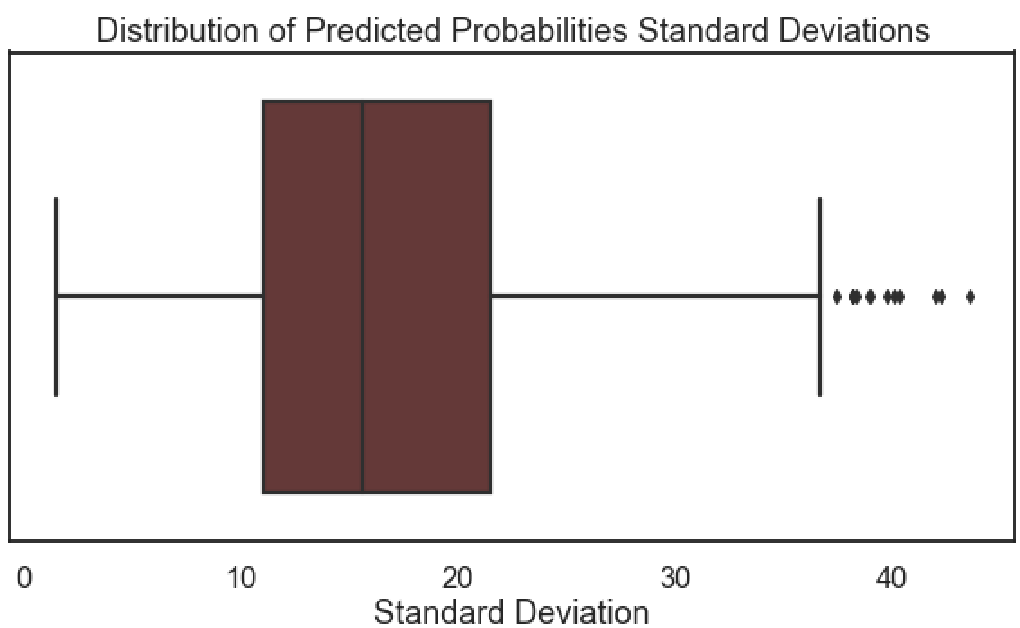
Out[69]:

	0	1	2
0	0.449391	0.435117	0.115492
1	0.392212	0.395012	0.212776
2	0.195485	0.470948	0.333568
3	0.268488	0.316035	0.415477
4	0.256269	0.245607	0.498124

In [70]:
```
plt.figure(figsize=(10,5))
ax = sns.boxplot((probs_df*100).apply(np.median, axis=1))

ax.set(ylabel='',
       xlabel='Standard Deviation',
       title='Distribution of Median Predicted Probabilities');
```



In [71]:
```
plt.figure(figsize=(10,5))
ax = sns.boxplot((probs_df*100).apply(np.std, axis=1))

ax.set(ylabel='',
       xlabel='Standard Deviation',
       title='Distribution of Predicted Probabilities Standard Deviations');
```



4b. Binary prediction: Use vs. No Use

We calculated the precision and recall for our predictions on our test set.

In [72]:

```
# training data
X_train_binary = contra_train_clean.drop(['contraceptive', 'contraceptive_use', '
                                    'education_gap', 'wife_age'], axis = 1)
Y_train_binary = contra_train_clean['contraceptive_use']

# test data
X_test_binary = contra_test_clean.drop(['contraceptive', 'contraceptive_use', 'ag
                                  'education_gap', 'wife_age'], axis = 1)
Y_test_binary = contra_test_clean['contraceptive_use']
```

Logistic Regression

We had a 67.32% precision rate and a 85.22% recall rate. We also plotted the precision-recall curve for our logistic regression model and a "no skill" predictor which would predict the classification probabilities to be the sample average.

In [73]:

```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

# CALCULATE PRECISION AND RECALL VALUES
precision = precision_score(Y_test_binary,
                            binary_logit.predict(X=X_test_binary))

recall = recall_score(Y_test_binary,
                      binary_logit.predict(X=X_test_binary))

print('Precision: %f' % precision)
print('Recall: %f' % recall)
```

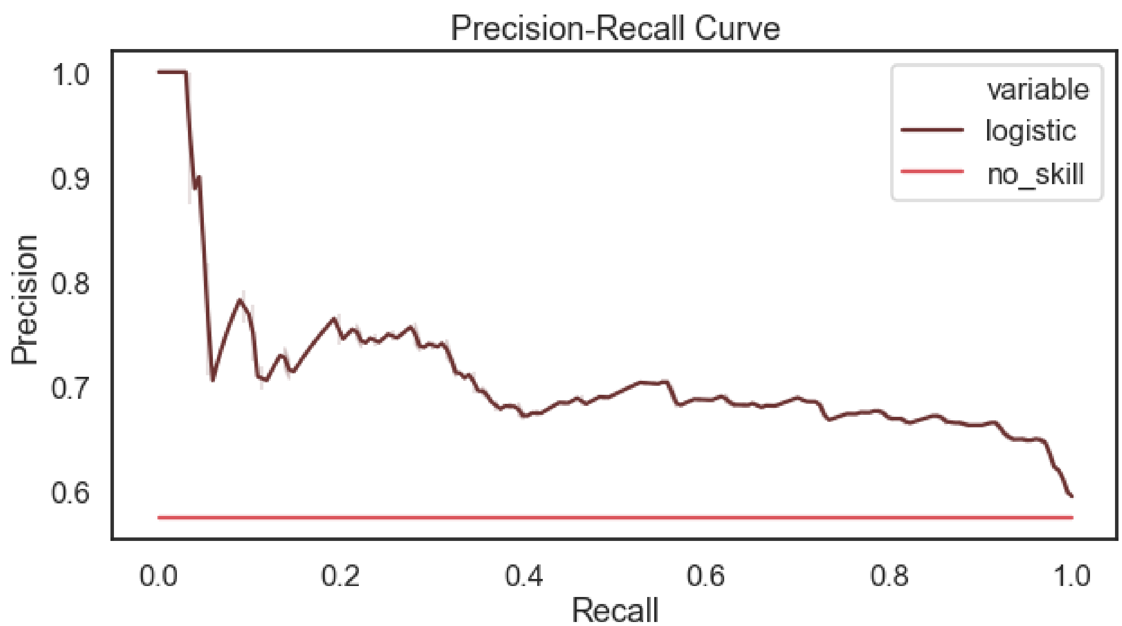
```
Precision: 0.673152
Recall: 0.852217
```

In [74]:

```
from sklearn.metrics import precision_recall_curve

# LF PRECISION/RECALL
lr_probs = binary_logit.predict_proba(X_test_binary)
lr_probs = lr_probs[:, 1]
lr_precision, lr_recall, _ = precision_recall_curve(Y_test_binary, lr_probs)

# PREDICTING AT AVG
no_skill = len(Y_test_binary[Y_test_binary==1]) / len(Y_test_binary)

# CREATE A PLOTTABLE DF
our_df = pd.DataFrame({'recall':lr_recall, 'logistic':lr_precision, 'no_skill':[r
our_df = pd.melt(our_df, id_vars='recall')
```

In [75]:

```
plt.figure(figsize=(10,5))
ax = sns.lineplot(x='recall',
                  y='value',
                  hue='variable',
                  data=our_df)

ax.set(ylabel='Precision',
       xlabel='Recall',
       title='Precision-Recall Curve');
```



Random Forest

We had a 70.80% precision rate and a 78.82% recall rate. We also plotted the precision-recall curve for our logistic regression model and a "no skill" predictor which would predict the classification probabilities to be the sample average.

In [76]:

```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score

# CALCULATE PRECISION AND RECALL VALUES
precision = precision_score(Y_test_binary,
                            binary_random_forest.predict(X=X_test_binary))

recall = recall_score(Y_test_binary,
                      binary_random_forest.predict(X=X_test_binary))

print('Precision: %f' % precision)
print('Recall: %f' % recall)
```

```
Precision: 0.708696
Recall: 0.802956
```

In [77]:

```
# RF PRECISION/RECALL
rf_probs = binary_random_forest.predict_proba(X_test_binary)
rf_probs = rf_probs[:, 1]
rf_precision, rf_recall, _ = precision_recall_curve(Y_test_binary, rf_probs)

# PREDICTING AT AVG
no_skill = len(Y_test_binary[Y_test_binary==1]) / len(Y_test_binary)

# CREATE A PLOTTABLE DF
our_df = pd.DataFrame({'recall':rf_recall, 'random forest':rf_precision, 'no_skil
our_df = pd.melt(our_df, id_vars='recall')
```

In [78]:

```
plt.figure(figsize=(10,5))
ax = sns.lineplot(x='recall',
                  y='value',
                  hue='variable',
                  data=our_df)

ax.set(ylabel='Precision',
       xlabel='Recall',
       title='Precision-Recall Curve');
```