In [1]:
```python
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sb
from sklearn.calibration import calibration_curve
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
from sklearn.metrics import make_scorer
from sklearn.model_selection import cross_val_score as cv_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import learning_curve
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
```

Executive Summary

- Performance These performance estimates are generated from cross validation, which should be a reasonable approximation of the expected test set performance. Looking at ROC AUC alone, the calibrated logistic regression model did reasonably well.

Model	Regression
ROC AUC	0.662

- Method The trained model is a calibrated logistic regression model with a ridge (L2) penalty and Platt scaling for calibration of probabilities. Performances were compared using 5 fold cross validation.

- Caveat There was no column denoting the relative time of each row. There is a concern that the cross validation results are biased as time series cross validation was not used. There was no way to ensure that there is no temporal data leakage across validation splits or between the train and test data.

Data Exploration

In [2]:
```python
DATA_PATH = "./data/"
data = pd.read_csv(DATA_PATH + "DS_Work_Sample_Data.csv")
data["sample"].value_counts()
```

Out[2]:
```
sample
Train      40000
Holdout    20000
Name: count, dtype: int64
```

In [3]:
```
data_tr = data.loc[data["sample"] == "Train", ].copy().reset_index()
data_te = data.loc[data["sample"] == "Holdout", ].copy().reset_index()
data_tr.describe()
```

Out[3]:

	index	Unnamed: 0	plcy_id	curnt_bi_low	curnt_bi_upp	c
count	40000.00000	40000.00000	40000.00000	40000.000000	40000.000000	4(
mean	19999.50000	19999.50000	20000.50000	98707.500000	193905.000000	7:
std	11547.14972	11547.14972	11547.14972	92506.822081	138671.218058	7!
min	0.00000	0.00000	1.00000	25000.000000	50000.000000	2(
25%	9999.75000	9999.75000	10000.75000	25000.000000	50000.000000	2!
50%	19999.50000	19999.50000	20000.50000	50000.000000	100000.000000	5(
75%	29999.25000	29999.25000	30000.25000	100000.000000	300000.000000	10(
max	39999.00000	39999.00000	40000.00000	750000.000000	1000000.000000	30(

8 rows × 52 columns

In [4]:
```
data_tr.dtypes, data_te.dtypes
```

```
Out[4]: (index                    int64
         Unnamed: 0               int64
         plcy_id                  int64
         sample                  object
         curnt_bi_low             int64
         curnt_bi_upp             int64
         curnt_pd_lmt             int64
         curnt_coll_ded         float64
         curnt_comp_ded         float64
         hh_veh_cnt               int64
         hh_cnt_auto              int64
         hh_cnt_mtrcyc            int64
         hh_veh_w_coll_cnt        int64
         hh_veh_w_comp_cnt        int64
         hh_veh_lien_cnt        float64
         hh_veh_lease_cnt       float64
         hh_veh_own_cnt         float64
         veh_ownership           object
         annual_mileage         float64
         veh_make                object
         veh_model               object
         veh_age                float64
         min_hh_veh_age         float64
         max_hh_veh_age         float64
         avg_hh_veh_age         float64
         hh_drvr_cnt            float64
         hh_min_age             float64
         hh_max_age             float64
         hh_avg_age             float64
         hh_min_mon_lic         float64
         hh_max_mon_lic         float64
         hh_avg_mon_lic         float64
         hh_cnt_yth             float64
         hh_cnt_female          float64
         hh_cnt_male            float64
         hoh_married            float64
         hh_cnt_majr_viol         int64
         hh_cnt_minr_viol         int64
         hh_cnt_lic_susp          int64
         prior_insurer           object
         time_w_carr            float64
         inforce_ind              int64
         multiline_ind            int64
         homeowner_ind            int64
         monthly_pay_ind          int64
         credit_score             int64
         hh_atf_clm_cnt_py1       int64
         hh_atf_clm_cnt_py2       int64
         hh_atf_clm_cnt_py3       int64
         hh_atf_clm_cnt_py4       int64
         hh_atf_clm_cnt_py5       int64
         hh_naf_clm_cnt_py1       int64
         hh_naf_clm_cnt_py2       int64
         hh_naf_clm_cnt_py3       int64
         hh_naf_clm_cnt_py4       int64
         hh_naf_clm_cnt_py5       int64
```

```
future_clm_ind         float64
dtype: object,
index                    int64
Unnamed: 0               int64
plcy_id                  int64
sample                  object
curnt_bi_low             int64
curnt_bi_upp             int64
curnt_pd_lmt             int64
curnt_coll_ded         float64
curnt_comp_ded         float64
hh_veh_cnt               int64
hh_cnt_auto              int64
hh_cnt_mtrcyc            int64
hh_veh_w_coll_cnt        int64
hh_veh_w_comp_cnt        int64
hh_veh_lien_cnt        float64
hh_veh_lease_cnt       float64
hh_veh_own_cnt         float64
veh_ownership           object
annual_mileage         float64
veh_make                object
veh_model               object
veh_age                float64
min_hh_veh_age         float64
max_hh_veh_age         float64
avg_hh_veh_age         float64
hh_drvr_cnt            float64
hh_min_age             float64
hh_max_age             float64
hh_avg_age             float64
hh_min_mon_lic         float64
hh_max_mon_lic         float64
hh_avg_mon_lic         float64
hh_cnt_yth             float64
hh_cnt_female          float64
hh_cnt_male            float64
hoh_married            float64
hh_cnt_majr_viol         int64
hh_cnt_minr_viol         int64
hh_cnt_lic_susp          int64
prior_insurer           object
time_w_carr            float64
inforce_ind              int64
multiline_ind            int64
homeowner_ind            int64
monthly_pay_ind          int64
credit_score             int64
hh_atf_clm_cnt_py1       int64
hh_atf_clm_cnt_py2       int64
hh_atf_clm_cnt_py3       int64
hh_atf_clm_cnt_py4       int64
hh_atf_clm_cnt_py5       int64
hh_naf_clm_cnt_py1       int64
hh_naf_clm_cnt_py2       int64
hh_naf_clm_cnt_py3       int64
```

```
 hh_naf_clm_cnt_py4       int64
 hh_naf_clm_cnt_py5       int64
 future_clm_ind         float64
 dtype: object)
```

In [5]:
```
# Check if data is missing.
data_tr.isnull().sum(), data_te.isnull().sum()
```

```
Out[5]: (index                    0
 Unnamed: 0               0
 plcy_id                  0
 sample                   0
 curnt_bi_low             0
 curnt_bi_upp             0
 curnt_pd_lmt             0
 curnt_coll_ded        9688
 curnt_comp_ded       12375
 hh_veh_cnt               0
 hh_cnt_auto              0
 hh_cnt_mtrcyc            0
 hh_veh_w_coll_cnt        0
 hh_veh_w_comp_cnt        0
 hh_veh_lien_cnt       5184
 hh_veh_lease_cnt      5184
 hh_veh_own_cnt        5184
 veh_ownership         4578
 annual_mileage        1293
 veh_make                 0
 veh_model                0
 veh_age                  0
 min_hh_veh_age           0
 max_hh_veh_age           0
 avg_hh_veh_age           0
 hh_drvr_cnt              0
 hh_min_age               0
 hh_max_age               0
 hh_avg_age               0
 hh_min_mon_lic           0
 hh_max_mon_lic           0
 hh_avg_mon_lic           0
 hh_cnt_yth               0
 hh_cnt_female            0
 hh_cnt_male              0
 hoh_married              0
 hh_cnt_majr_viol         0
 hh_cnt_minr_viol         0
 hh_cnt_lic_susp          0
 prior_insurer            0
 time_w_carr              0
 inforce_ind              0
 multiline_ind            0
 homeowner_ind            0
 monthly_pay_ind          0
 credit_score             0
 hh_atf_clm_cnt_py1       0
 hh_atf_clm_cnt_py2       0
 hh_atf_clm_cnt_py3       0
 hh_atf_clm_cnt_py4       0
 hh_atf_clm_cnt_py5       0
 hh_naf_clm_cnt_py1       0
 hh_naf_clm_cnt_py2       0
 hh_naf_clm_cnt_py3       0
 hh_naf_clm_cnt_py4       0
 hh_naf_clm_cnt_py5       0
```

```
future_clm_ind           0
dtype: int64,
index                    0
Unnamed: 0               0
plcy_id                  0
sample                   0
curnt_bi_low             0
curnt_bi_upp             0
curnt_pd_lmt             0
curnt_coll_ded        4928
curnt_comp_ded        6189
hh_veh_cnt               0
hh_cnt_auto              0
hh_cnt_mtrcyc            0
hh_veh_w_coll_cnt        0
hh_veh_w_comp_cnt        0
hh_veh_lien_cnt       2562
hh_veh_lease_cnt      2562
hh_veh_own_cnt        2562
veh_ownership         2272
annual_mileage         635
veh_make                 0
veh_model                0
veh_age                  0
min_hh_veh_age           0
max_hh_veh_age           0
avg_hh_veh_age           0
hh_drvr_cnt              0
hh_min_age               0
hh_max_age               0
hh_avg_age               0
hh_min_mon_lic           0
hh_max_mon_lic           0
hh_avg_mon_lic           0
hh_cnt_yth               0
hh_cnt_female            0
hh_cnt_male              0
hoh_married              0
hh_cnt_majr_viol         0
hh_cnt_minr_viol         0
hh_cnt_lic_susp          0
prior_insurer            0
time_w_carr              0
inforce_ind              0
multiline_ind            0
homeowner_ind            0
monthly_pay_ind          0
credit_score             0
hh_atf_clm_cnt_py1       0
hh_atf_clm_cnt_py2       0
hh_atf_clm_cnt_py3       0
hh_atf_clm_cnt_py4       0
hh_atf_clm_cnt_py5       0
hh_naf_clm_cnt_py1       0
hh_naf_clm_cnt_py2       0
hh_naf_clm_cnt_py3       0
```

```
hh_naf_clm_cnt_py4        0
hh_naf_clm_cnt_py5        0
future_clm_ind        20000
dtype: int64)
```

In [6]:
```
# Check class balance of the binary classification problem.
data_tr.future_clm_ind.value_counts()
```

Out[6]:
```
future_clm_ind
0.0    37532
1.0     2468
Name: count, dtype: int64
```

In [7]:
```
data_tr.shape, data_te.shape
```

Out[7]:
```
((40000, 57), (20000, 57))
```

In [8]:
```
print(f"The positive class frequency is {round(data_tr.future_clm_ind.sum()
```

```
The positive class frequency is 0.1%.
```

There is missing data and it isn't clear if it is MNAR or missing completely at random. To be safe, a dummy variable will be created to account for missingness. For missing values where the feature column is a float, median imputation will be used to fill in the missing data. Given the massive class imbalance, it's important to check the calibration of the model's probability estimates. It isn't clear if there is any temporal dependence in the data. If there is, it is important to use time series cross validation to respect the order of the data over time. Using k-fold cross validation and shuffling the data could lead to data leakage and biased performance estimates.

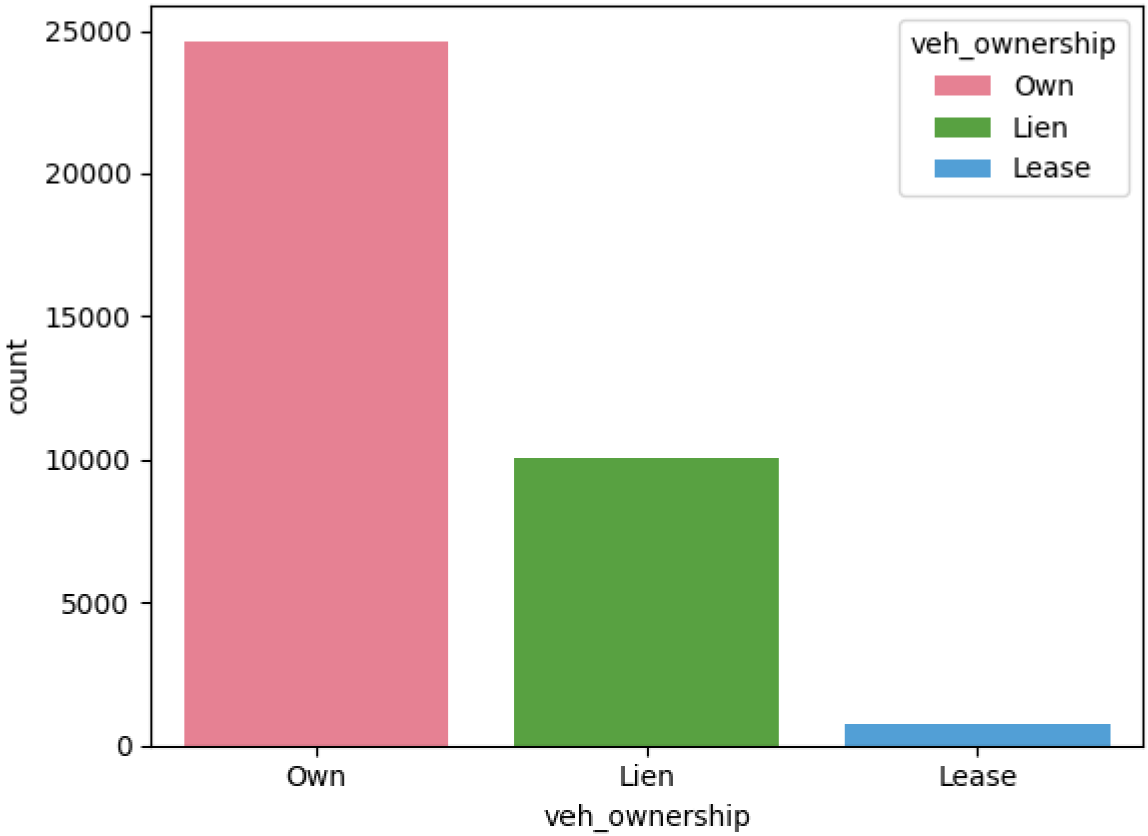
In [9]:
```
TARGET_COL = "future_clm_ind"

DROP_COLS = [
    "index",
    "sample",
    "plcy_id",
    "future_clm_ind",
    "Unnamed: 0",
    "veh_model"
]

CAT_COLS = data_tr.select_dtypes(include = "object").columns
data_tr[CAT_COLS].isnull().sum()
```

Out[9]:
```
sample              0
veh_ownership    4578
veh_make            0
veh_model           0
prior_insurer       0
dtype: int64
```

In [10]:
```
sb.countplot(
    data = data_tr,
    x = "veh_ownership",
```

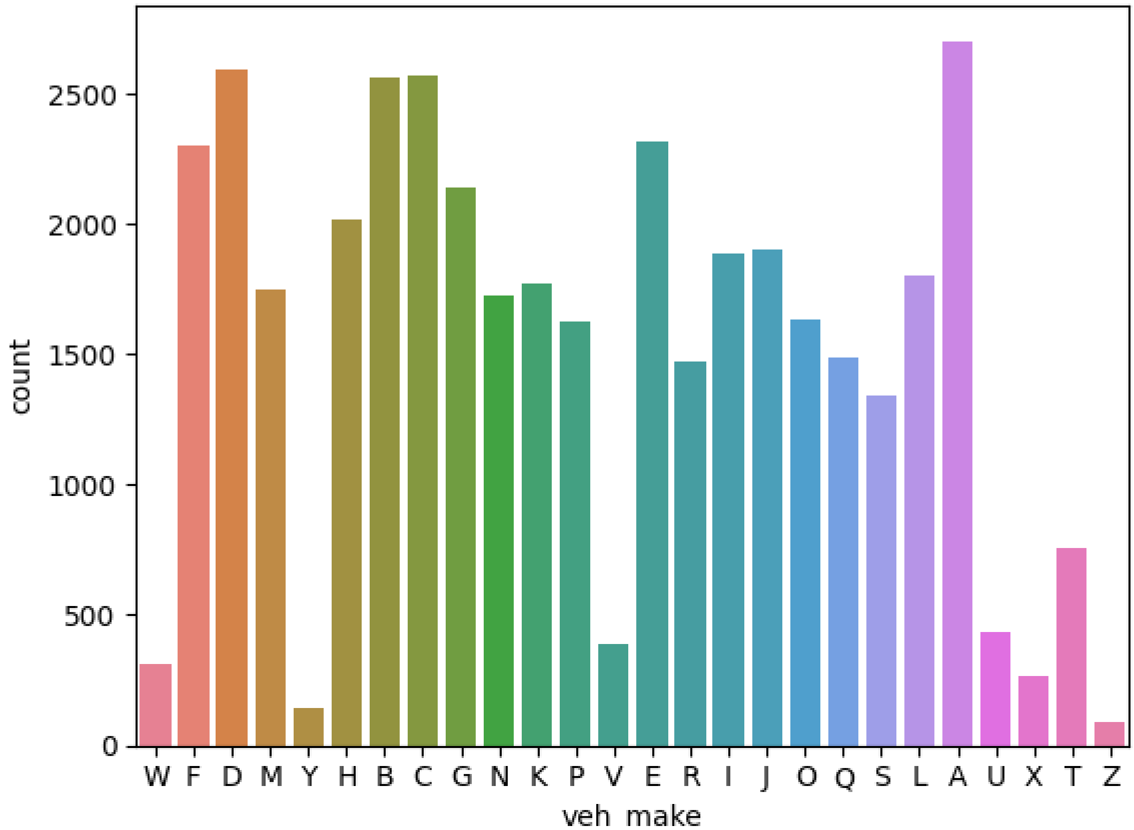
```
    hue = "veh_ownership",
    palette = "husl"
)
```

Out[10]: <Axes: xlabel='veh_ownership', ylabel='count'>



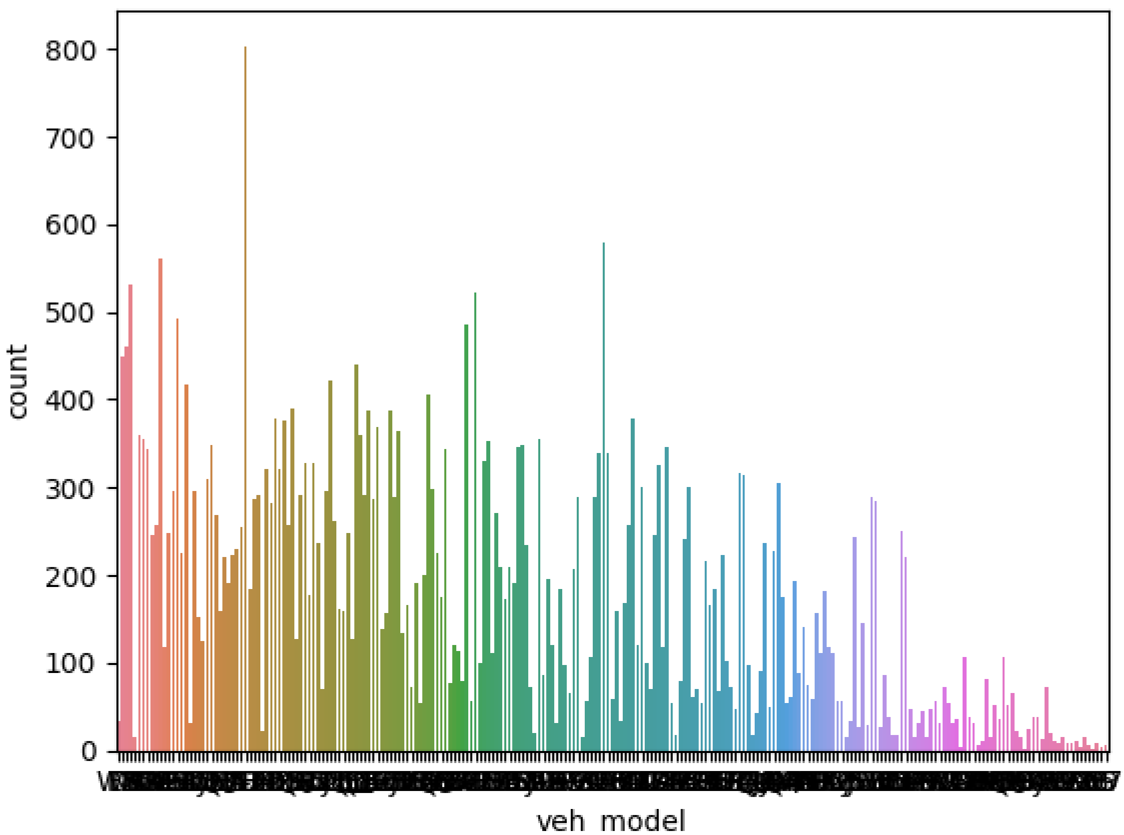
In [11]:
```
sb.countplot(
    data = data_tr,
    x = "veh_make",
    hue = "veh_make",
    palette = "husl"
)
```

Out[11]: <Axes: xlabel='veh_make', ylabel='count'>



In [12]:
```
sb.countplot(
    data = data_tr,
    x = "veh_model",
    hue = "veh_model",
    palette = "husl"
)
```

Out[12]: <Axes: xlabel='veh_model', ylabel='count'>



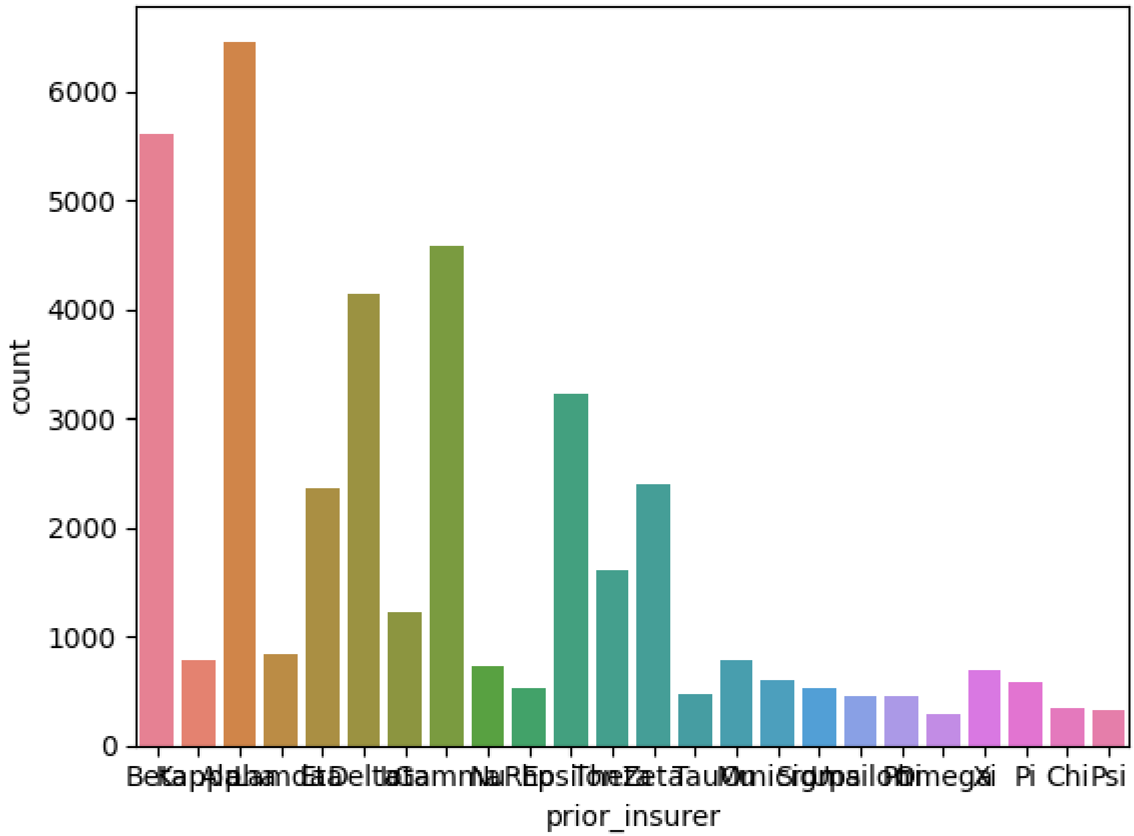
In [13]:
```
data_tr["veh_model"].value_counts()
```

Out[13]:
```
veh_model
A1    804
C1    580
B1    560
M1    531
A2    522
     ...
Z9      4
Y9      4
Z8      3
X7      2
X8      1
Name: count, Length: 233, dtype: int64
```

There are 233 different vehicle models. One hot encoding these categorical features can become massive in memory. Given how sparse this would become and the low number of positive class examples, we can exclude this feature from the baseline model. Alternatively, we can include this feature in the model while using an L2 penalty, which is preferable for sparse training data.

In [14]:
```
sb.countplot(
    data = data_tr,
    x = "prior_insurer",
    hue = "prior_insurer",
    palette = "husl"
)
```

Out[14]: <Axes: xlabel='prior_insurer', ylabel='count'>



In [15]:
```
data_tr["prior_insurer"].value_counts()
```

Out[15]:

```
prior_insurer
Alpha      6464
Beta       5603
Gamma      4581
Delta      4146
Epsilon    3226
Zeta       2401
Eta        2366
Theta      1617
Iota       1217
Lamda       836
Kappa       789
Mu          776
Nu          727
Xi          692
Omicron     591
Pi          583
Rho         532
Sigma       520
Tau         476
Upsilon     459
Phi         448
Chi         348
Psi         319
Omega       283
Name: count, dtype: int64
```

Data Preprocess

Split into training and validation sets. The validation set is for plotting the calibration curves of the models. The final models used for estimating test set probabilities will use all of the available data for training. Categorical columns are one hot encoded. Missing floating point values are filled in using median imputation and a dummy variable column is created to account for the missingness incase the data is MNAR.

In [16]:

```python
TARGET_COL = "future_clm_ind"

DROP_COLS = [
    "index",
    "sample",
    "plcy_id",
    "future_clm_ind",
    "Unnamed: 0"
]

Ytr = data_tr[TARGET_COL]
Yte = pd.DataFrame(data_te["plcy_id"].copy())
Xtr = data_tr.drop(columns = DROP_COLS)
Xte = data_te.drop(columns = DROP_COLS)

# Categorical column names after drop columns are excluded.
CAT_COLS = Xtr.select_dtypes(include = "object").columns

# Replace any missing categories.
```

```python
Xtr_cat = Xtr[CAT_COLS].copy().fillna(value = "missing")
Xte_cat = Xte[CAT_COLS].copy().fillna(value = "missing")
# Fit one hot encoder to categorical columns.
enc = OneHotEncoder().fit(Xtr_cat)
col_names = enc.get_feature_names_out()
Xtr_cat = enc.transform(Xtr_cat).toarray()
Xte_cat = enc.transform(Xte_cat).toarray()

Xtr = pd.concat([Xtr.drop(columns = CAT_COLS),
                 pd.DataFrame(Xtr_cat, columns = col_names)],
                axis = 1)

Xte = pd.concat([Xte.drop(columns = CAT_COLS),
                 pd.DataFrame(Xte_cat, columns = col_names)],
                axis = 1)

# Use median imputation for missing floating point values.
imp = SimpleImputer(
    missing_values = np.nan,
    strategy = "median",
    add_indicator = True
)

imp.fit(Xtr)
Xtr = imp.transform(Xtr)
Xte = imp.transform(Xte)
column_names = imp.get_feature_names_out()

# Given the class imbalance, use stratified split.
skf = StratifiedKFold(n_splits = 5)

Xtr, Xva, Ytr, Yva = train_test_split(
    Xtr,
    Ytr,
    test_size = 0.2,
    stratify = Ytr
)

del Xtr_cat, Xte_cat

Xtr.shape, Xte.shape
```

Out[16]:

```
((32000, 341), (20000, 341))
```

Baseline Logistic Regression Model

Use a logistic regression with an L2 (ridge) penalty. As an aside, using an L2 penalty is preferable when the inputs are sparse. Stratified k-fold cross validation is used for model hyper parameter selection. Given the class imbalance, it is important to stratify on the binary target class so that the positive class is equally represented across the cv folds.

In [17]:

```python
# Grid of potential inverse L2 penalty parameters.
L2_grid = {"C": [1e-04, 1e-03, 1e-02, 1e-01, 1]}
```

```
reg_model = LogisticRegression(
    penalty = "l2",
    solver = "liblinear",
    max_iter = 100000,
    verbose = 0
)

gscv = GridSearchCV(
    reg_model,
    scoring = make_scorer(
        roc_auc_score,
        needs_proba = True
    ),
    param_grid = L2_grid,
    n_jobs = 1,
    cv = skf.split(Xtr, Ytr)
)

# Run grid search cross validation.
gscv.fit(Xtr, np.array(Ytr).ravel())
```

Out[17]:

```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [18]:

```
gscv.best_score_
```

Out[18]:

```
0.663667953730841
```

In [19]:

```
gscv.best_params_
```

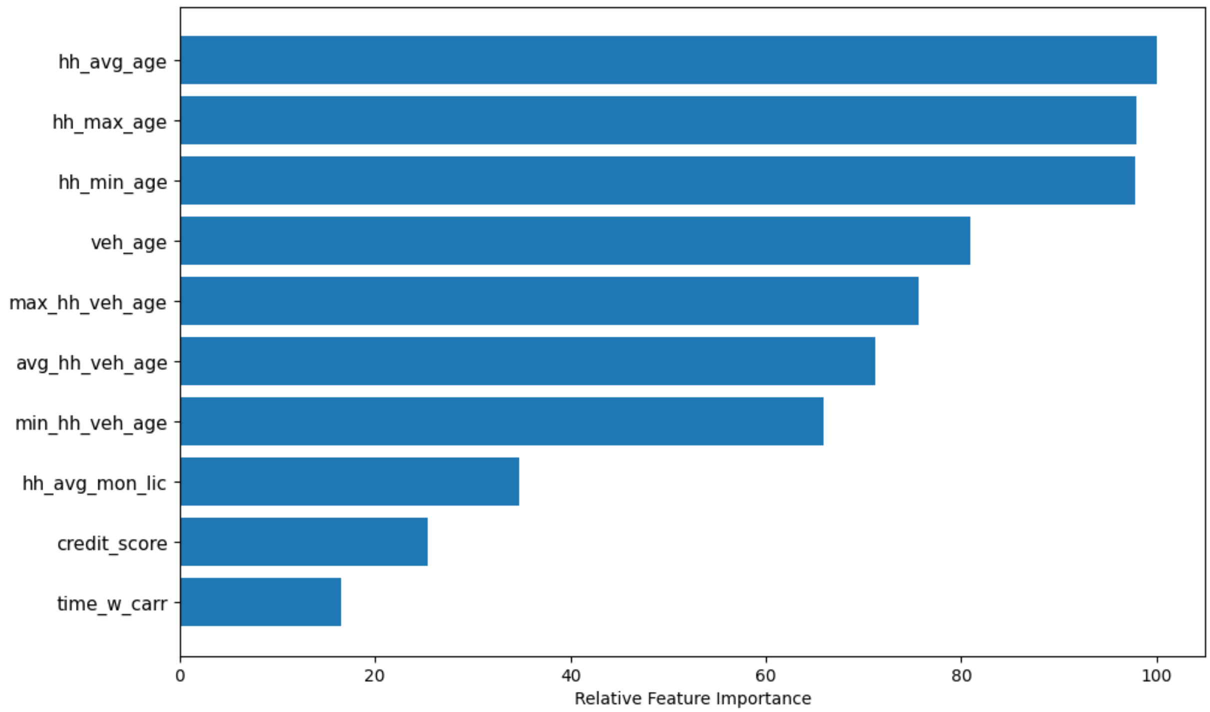
Out[19]:

```
{'C': 0.001}
```

Feature Importances

In [21]:

```
column_names = imp.get_feature_names_out()
fi = abs(gscv.best_estimator_.coef_)[0] # Absolute value of coefficient esti
fi = (fi / fi.max()) * 100.0 # Scale by largest value.
idx = np.argsort(fi)[-10:] # Sort by relative importance and subset top 10.
pos = np.arange(idx.shape[0]) + .5
fig = plt.figure()
fig.set_size_inches(11, 7)
ax = fig.add_subplot(1, 1, 1)
ax.barh(pos, fi[idx], align = "center")
ax.set_yticks(pos)
ax.set_yticklabels(np.array(column_names)[idx], fontsize = 11)
ax.set_xlabel("Relative Feature Importance")
plt.show()
```



In [23]:
```
gscv.best_estimator_.coef_[0][idx]
```

Out[23]:
```
array([-0.00081854, -0.00126121, -0.00172608, -0.00327427, -0.0035363 ,
       -0.00375309, -0.00401692, -0.00485747, -0.00486539, -0.00496558])
```

In [24]:
```
Y_pred = gscv.best_estimator_.predict_proba(Xva)[:, 1]
cc_y, cc_x = calibration_curve(
    y_true = Yva,
    y_prob = Y_pred,
    n_bins = 10
)
```

Use the optimal L2 hyperparameter from grid search cross validation to train a calibrated classifier. Then use this trained classifier to visualize the learning curves across different data set sizes to help diagnose potential issues from bias or variance.

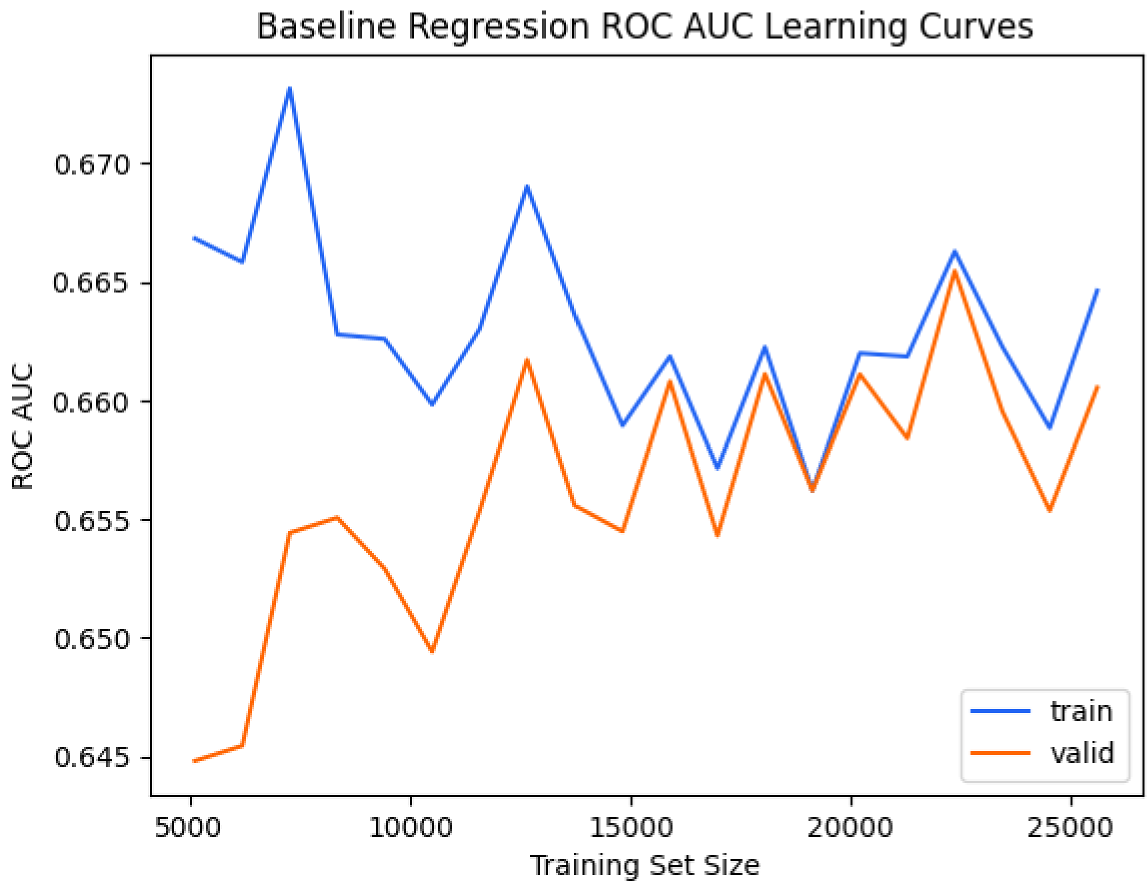
In [25]:
```
# Use optimal C parameter from grid search.
reg_model = LogisticRegression(
    C = gscv.best_params_["C"],
    penalty = "l2",
    solver = "liblinear",
    max_iter = 100000,
    verbose = 0
)

# Use Platt Scaling for calibration of model.
reg_model_calibrated = CalibratedClassifierCV(
    estimator = reg_model,
    method = "sigmoid",
    ensemble = True,
    n_jobs = -1
)
```

```
train_sizes, train_scores, valid_scores = learning_curve(
    reg_model_calibrated,
    Xtr,
    np.array(Ytr).ravel(),
    train_sizes = np.linspace(0.2, 1, 20),
    cv = skf.split(Xtr, Ytr),
    scoring = make_scorer(
        roc_auc_score,
        needs_proba = True
    )
)

# Average precision score across the cross validation folds.
train_scores = [np.mean(m) for m in train_scores]
valid_scores = [np.mean(m) for m in valid_scores]
```

Visualize Baseline Learning Curves

In [26]:

```
# Training and validation ROC AUC learning curves.
plt.plot(train_sizes, train_scores, color = "#2164F3")
plt.plot(train_sizes, valid_scores, color = "#FF6600")
plt.title(f"Baseline Regression ROC AUC Learning Curves")
plt.ylabel(f"ROC AUC")
plt.xlabel("Training Set Size")
plt.legend(["train", "valid"],
           loc = "lower right")
plt.show()
```

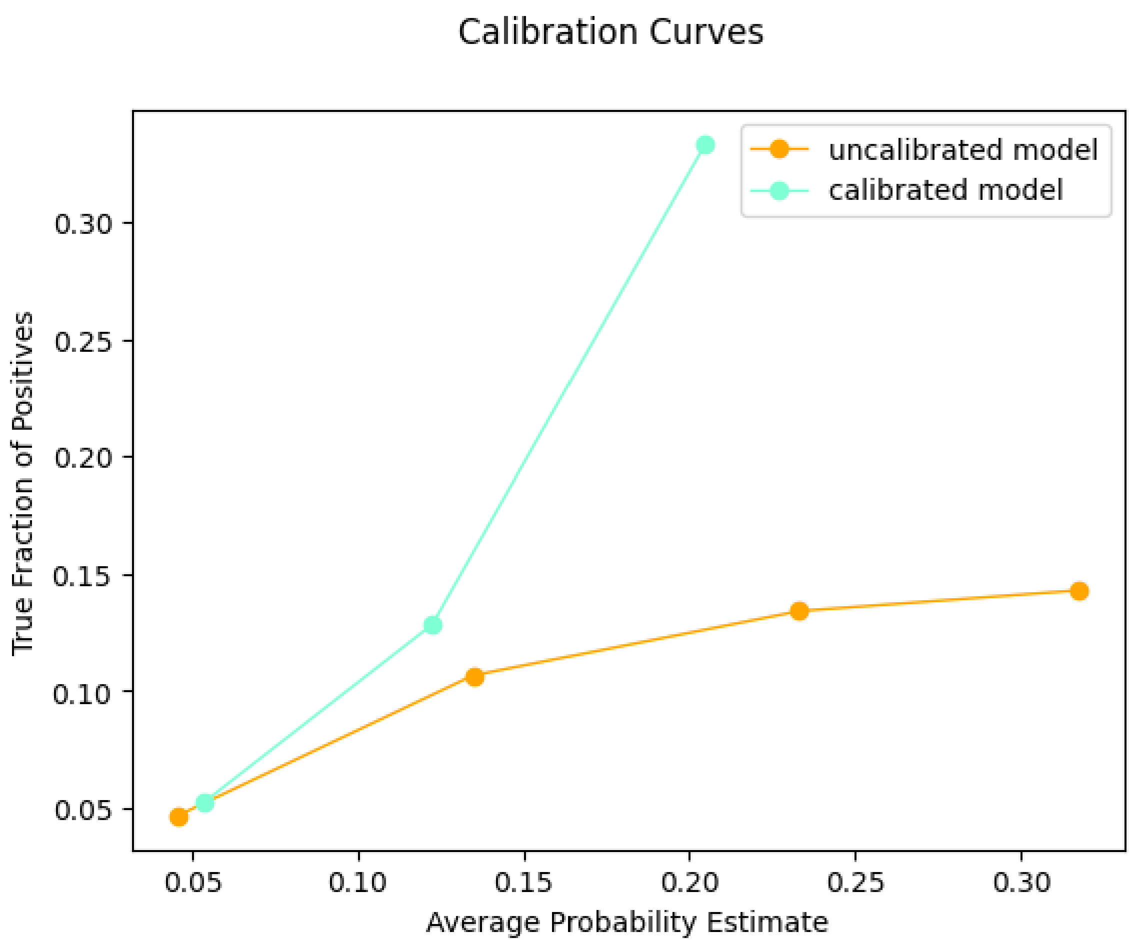


The variance gap doesn't seem too large but the average precision is really low. It seems like gathering more data would improve the performance slightly as the learning curves have not flattened out as the training set size is increased.

In [27]:
```
reg_model_calibrated = CalibratedClassifierCV(
    estimator = reg_model,
    method = "sigmoid",
    ensemble = True,
    n_jobs = -1,
    cv = skf.split(Xtr, Ytr)
)
reg_model_calibrated.fit(
    Xtr,
    np.array(Ytr).ravel()
)

# Create a calibration plot to visualize probability calibration.
Y_pred_c = reg_model_calibrated.predict_proba(Xva)[:, 1]
cc_cal_y, cc_cal_x = calibration_curve(
    y_true = Yva,
    y_prob = Y_pred_c,
    n_bins = 10
)
```

In [28]:
```
fig, ax = plt.subplots()
plt.plot(cc_x,
         cc_y,
```

```
         marker = "o",
         linewidth = 1,
         color = "orange",
         label = "uncalibrated model")

plt.plot(cc_cal_x,
         cc_cal_y,
         marker = "o",
         linewidth = 1,
         color = "aquamarine",
         label = "calibrated model")

fig.suptitle("Calibration Curves")
ax.set_xlabel("Average Probability Estimate")
ax.set_ylabel("True Fraction of Positives")
plt.legend()
plt.show()
```



Performance

Generate the performance metrics of the calibrated baseline logistic regression model using the average ROC AUC over the stratified cross validation folds. This should give a reasonable expectation of the test set performance. Use all of the available data for training.

In [29]:
```
# Combine training and validation into a single data set.
Xtr = np.vstack((Xtr, Xva))
Ytr = pd.concat([Ytr, Yva])

Xtr.shape, Ytr.shape
```

Out[29]:
```
((40000, 341), (40000,))
```

In [30]:
```
reg_model_calibrated = CalibratedClassifierCV(
    estimator = reg_model,
    method = "sigmoid",
    ensemble = True
)

cv_score_baseline = cv_score(
    reg_model_calibrated,
    Xtr,
    np.array(Ytr).ravel(),
    cv = skf.split(Xtr, Ytr),
    scoring = make_scorer(
        roc_auc_score,
        needs_proba = True
    ),
    n_jobs = -1
)
```

In [31]:
```
print(f"The expected ROC AUC from the baseline model is { round(np.mean(cv_s
```

```
The expected ROC AUC from the baseline model is 0.662.
```

Test Set Predictions

In [32]:
```
# Train models using all available data.
reg_model_calibrated.fit(Xtr, np.array(Ytr).ravel())

pred_baseline = reg_model_calibrated.predict_proba(Xte)[:, 1]
Yte["glm_pred"] = np.round(pred_baseline, 4)

# Append the probabilities to the plcy_id in Yte and save as a csv.
Yte.to_csv(
    DATA_PATH + "DS_Work_Sample_Scored.csv",
    index = False,
    header = True
)
```