**RESULTS**

**HEDONIC REGRESSION**

We begin by fitting a hedonic regression model to our three datasets in order to construct a measure of artistic value for each piece. For Impressionist art (as in Beggs & Graddy (2009)), though, predictions are fit separately for observations in London and in New York due to currency differences, then recombined for the anchoring regressions. Tables 4-7 below show the results of the hedonic predictions.

Overall, hedonic characteristics such as the painting dimensions, the presence of a signature, medium, and artist and time effects (both omitted for brevity; both highly significant) have a significant impact on the sale price of the painting. It is surprising that a painting’s date of creation is generally not significant, which can be explained by the importance of artist variables. For Impressionist Art and Contemporary Art, much of the variation in price is explained by our regression model, indicated by generally high values. For our new dataset, however, the value is extremely low although variables are significant. This is to be expected: our dataset covers a very large variety of paintings, and so we should see very high variance across prices in our regression model (though far lower bias, as indicated by our highly significant hedonic variables). The F-statistic is extremely significant in all cases, which shows that our regression variables are relevant as a whole. In general, the most impactful variables are those for the art medium and the dimensions. This may be attributed to large pieces and pieces from specialized mediums selling for more, as indicated by large, significant coefficients for certain mediums and not for others. Despite a high value for Impressionist art, the intercept is highly significant. This suggests that non-hedonic factors likely play a large role in determining value for Impressionist pieces, which is understandable given the relatively more pronounced age and renown of those works. Additionally, the presence of a signature specifically, rather than other signs of authenticity such as a monogram, generally seems to be more important to determining hedonic value. As an additional note, regressing on only artist and time dummies corresponds to a reduction in in the Impressionist and Contemporary datasets, as noted in Beggs & Graddy (regressions not included). Generally, it is clear that hedonic factors such as size and medium do play a large role in determine value for the works we examine.

**REPLICATION OF BEGGS & GRADDY (2009), “ANCHORING EFFECTS: EVIDENCE FROM ART AUCTIONS”**

Here, we attempt to replicate some of the work of Beggs & Graddy (2009), who analyze the same Impressionist and Contemporary datasets to test whether the first sale of a painting produces an anchoring effect on its later sales. In this research we only consider sale price, but they also run regressions for presale estimate and the probability of sale. As mentioned earlier, they identified resale observations by cross-checking against presale catalogs, so it is not possible for us to entirely replicate their work. We make the assumption that duplicate hedonic observations refer to multiple sales of the same item, and run our regressions for the full datasets each.

Tables <> to <> show our results, as well as the original tables of Beggs & Graddy. We were able to reproduce the discovery of highly significant anchoring effects in Impressionist art, and the more weakly significant effects in Contemporary art. However, our coefficients are not nearly as large, although significant. For Impressionist art, a 10% increase in the difference between past price and current hedonic prediction (anchoring) only corresponds to a 1.7% increase in the current sale price (original: 6.2-8.5%), while for Contemporary art this is only a 1.3% predicted increase (original: 5%). On the other hand, our regressions show that the residuals from past price (unobserved inputs into past price, such as bidding activity) are much strong than anchoring in the case of Impressionist art (5% increase for Impressionist), which differs from the results of Beggs & Graddy. One explanation could be that the reputation of Impressionist pieces grows over time as these pieces trade ownership across collectors and museums, so that reputation effects tend to drive up buyer demand beyond hedonic value or even past price anchors. We do find a weaker impact of the past residuals on current price in the case of Contemporary art, a result which is shared by Beggs & Graddy. They attribute this to the heavy time-dependent variation in prices in this Contemporary art dataset (not shown here), which suggests past prices would not serve as meaningful anchors. We also replicated their discovery of relatively small time coefficients, particularly for Contemporary art. This indicates that the specific number of months between sales seems to not be a major influence in determining the current price of a work. Finally, our anchoring regressions also share the very high and adjusted values of Beggs & Graddy, indicating that much of the variation in hammer prices is explained by this model.

In addition to Impressionist and Contemporary art, we also ran their original anchoring regression on our new dataset of recent assorted painting sales.

Running anchoring regression for our new data

(5% increase for Impressionist, 1.9% for Contemporary).

than Beggs & Graddy find (3.2% for Impressionist, 3.8% for Contemporary). One explanation could be that

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As noted before, we do

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Table 4: Hedonic predictions, Impressionist Art (London). Half-year time dummies omitted for brevity.

Estimate Std. Error t value Pr(>|t|)

(Intercept) 10.667134 6.703545 1.591 0.112783

DATE\_PTG -0.002122 0.003513 -0.604 0.546317

DIM\_A 0.026975 0.007665 3.519 0.000512 \*\*\*

DIM\_B 0.016575 0.006388 2.595 0.010018 \*

SIGNED1 0.266633 0.350862 0.760 0.447990

SIGNED2 -0.064880 0.434096 -0.149 0.881308

SIGNED3 -0.429974 0.413009 -1.041 0.298822

ART\_MED6 1.779714 0.677907 2.625 0.009178 \*\*

ART\_MED9 0.348789 0.684150 0.510 0.610622

ART\_MED12 2.270866 0.674249 3.368 0.000874 \*\*\*

ART\_MED15 1.473253 0.698082 2.110 0.035791 \*

ART\_MED18 2.952254 0.642515 4.595 6.80e-06 \*\*\*

ART\_MED24 1.457382 0.771532 1.889 0.060030 .

ART\_MED27 1.093956 0.661039 1.655 0.099170 .

ART\_MED30 0.490681 0.658584 0.745 0.456923

ART\_MED33 1.278982 0.846104 1.512 0.131866

ART\_MED39 1.767484 0.660349 2.677 0.007918 \*\*

R^2: 0.8664

Adjusted R^2: 0.8251

F-statistic: 21.01 on 79 and 256 DF, p-value: < 2.2e-16

Table 5: Hedonic predictions, Impressionist Art (NYC). Half-year time dummies omitted for brevity.

Estimate Std. Error t value Pr(>|t|)

(Intercept) 20.536155 5.799675 3.541 0.000458 \*\*\*

DATE\_PTG -0.006033 0.002998 -2.013 0.044995 \*

DIM\_A 0.040589 0.007452 5.447 1.03e-07 \*\*\*

DIM\_B 0.012602 0.007114 1.771 0.077433 .

SIGNED1 1.059125 0.156739 6.757 6.69e-11 \*\*\*

SIGNED2 0.301338 0.245387 1.228 0.220348

SIGNED3 0.203128 0.217131 0.936 0.350234

ART\_MED6 -0.364772 0.687000 -0.531 0.595814

ART\_MED9 -0.060186 0.642117 -0.094 0.925382

ART\_MED12 1.014323 0.618434 1.640 0.101960

ART\_MED15 -0.131242 0.665053 -0.197 0.843687

ART\_MED18 1.248101 0.615153 2.029 0.043296 \*

ART\_MED21 0.773179 0.877041 0.882 0.378669

ART\_MED24 0.361094 0.661262 0.546 0.585401

ART\_MED27 -0.342484 0.656519 -0.522 0.602264

ART\_MED30 -0.075431 0.646362 -0.117 0.907170

ART\_MED38 -0.404069 0.807695 -0.500 0.617227

ART\_MED39 0.645365 0.630585 1.023 0.306876

R^2: 0.8377

Adjusted R^2: 0.8

F-statistic: 22.24 on 74 and 319 DF, p-value: < 2.2e-16

Table 6: Hedonic predictions, Contemporary Art. Half-year time dummies omitted for brevity.

Estimate Std. Error t value Pr(>|t|)

(Intercept) -1.54229 1.91849 -0.804 0.422029

log(date\_ptg) -0.67160 0.42660 -1.574 0.116371

log(len) 0.59158 0.11574 5.111 5.42e-07 \*\*\*

log(wid) 0.61585 0.11764 5.235 2.94e-07 \*\*\*

mediuma 0.37892 0.36754 1.031 0.303314

mediumbr -1.00407 0.47045 -2.134 0.033555 \*

mediumchk -0.51240 0.50577 -1.013 0.311749

mediumcol -2.01051 0.54342 -3.700 0.000253 \*\*\*

mediumcr -0.85626 0.37571 -2.279 0.023304 \*

mediumf -1.19646 0.49004 -2.442 0.015148 \*

mediumg -0.92343 0.40669 -2.271 0.023817 \*

mediumik -0.66618 0.38336 -1.738 0.083193 .

mediumo 0.33903 0.31500 1.076 0.282582

mediumpas -0.76427 0.55061 -1.388 0.166063

mediumpg 3.84267 0.64429 5.964 6.33e-09 \*\*\*

mediumph -2.97383 0.71974 -4.132 4.57e-05 \*\*\*

mediumpl 1.43608 0.66003 2.176 0.030281 \*

mediumpn 0.73305 0.79588 0.921 0.357696

mediums -0.30325 0.49084 -0.618 0.537122

mediumsk 2.78109 0.57888 4.804 2.36e-06 \*\*\*

mediumt -0.77276 0.39024 -1.980 0.048510 \*

mediumtp 0.25322 0.55431 0.457 0.648099

mediumw -0.41915 0.36663 -1.143 0.253758

R^2 0.9232

Adjusted R^2 0.8892

F-statistic: 27.17 on 146 and 330 DF, p-value: < 2.2e-16

Table 7: Hedonic predictions, assorted art. Half-year time dummies omitted for brevity. Artist and medium were omitted due to computational constraints.

Estimate Std. Error t value Pr(>|t|)

(Intercept) 6.224144 0.018000 345.782 <2e-16 \*\*\*

log(height) 0.614017 0.008031 76.454 <2e-16 \*\*\*

log(width) 0.230060 0.008092 28.431 <2e-16 \*\*\*

signed -0.634735 0.008009 -79.255 <2e-16 \*\*\*

monogrammed -0.203214 0.022359 -9.089 <2e-16 \*\*\*

stamped 0.086423 0.016030 5.391 7e-08 \*\*\*

R^2 0.1006

Adjusted R^2 0.1006

F-statistic: 5907 on 5 and 264109 DF, p-value: < 2.2e-16