

THE VALUE OF ESTIMATING THE PRICE OF ART: A LESSON FOR AUCTION HOUSES

WILLIAM ZACHARY HODGES[†]

ABSTRACT. What is the value of art? Auction houses provide a more liquid market for art and estimates of the range of values of individual pieces. Estimation ranges are published before auctions take place, providing all participants with expert information. This work posits that the relative magnitude of the estimate range signals to buyers the experts' confidence in a work's value. A smaller relative magnitude signals higher expert confidence in its value and its liquidity (its ability to be resold). A larger relative magnitude signals an illiquid work, one whose final sale price is depressed by an illiquidity discount. This study looks at whether works of art at auction also suffer this discount. Data collected from Sothebys New York Impressionist and Modern Art Sales suggest this is the case. We conclude that the prices of artwork at auction are priced in a similar manner as financial assets.

1. INTRODUCTION AND BRIEF HISTORY

The market for fine art is an example of an extreme deviation from the assumptions of a competitive market, and there is no accounting for taste. To one person a work could be worthless and to another it is priceless. Unlike many goods, the price of a work does not simply cover the cost of production with a small margin for profit. Once created, art becomes a unique good whose value varies drastically from person to person.

Some of this variation comes from the structure of the market itself—it happens to be a very involved process to sell that Monet you've got hanging in the back room. Individual pieces may be unique, but we can observe, on average, that the prices for different artists, movements, and media follow trends similar to different industries in the stock market. However, unlike the stock market that is a relative ocean of liquid assets, the art market is confined to galleries and auction houses.

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[†] Many thanks to Prof. Lumsdaine, Prof. Hansen, and countless others. Data available upon request. All errors contained herein are my own.

Email: **Hodgeswz@gmail.com**.

Before the turn of the 19th century, the market for art was principally made up of artists and their commissioners (usually nobility, the Church, and the more well-off bourgeoisie). When major collections were put up for sale, the possessions of Charles I after his execution for instance, they were priced before inviting potential buyers to come and browse. Needless to say, even by 17th century standards, this process bore both large logistical challenges and a high margin for economic inefficiency through mis-pricing, but no substantive innovation took place in the market for art until the end of the 18th century with onset of the French Revolutionary and Napoleonic Wars. In addition to the significant death tolls, art was also targeted for destruction. Great Britain became a safe haven for many rich aristocrats attempting to escape the destruction—bringing their collections with them[25].

With the growing supply of fine art and the growing demand for art by the burgeoning bourgeoisie and nobility during the Industrial Revolution, the market for art needed to decrease transaction costs and increase liquidity. Auction houses provided these improvements. By selling through an auction house, an owner of a work was insured that a group seriously interested buyers would at least look at it. The benefit of this would allowing an increase price discrimination by having bidders bid up to their valuation. The buyers also benefit from the larger, more centralized market that allows for greater variety and a venue to peruse many works at once. With the new influx of product, auction houses (like Christie’s, founded in 1766) found widespread success and began establishing their reputations. Since that time, auctions continue to be the chosen method of pricing and sale of fine art.

2. ART AND ENGLISH AUCTIONS

The prevailing method of auction in the art market is the English auction. Sotheby’s, from whom the data of this study are collected, uses English style auctions for art. An English auction is one of the most commonly known styles of auction. The rules are plain—the auctioneer starts the bidding by announcing some price lower than the estimated price and the bidding begins. When the bidding stops, whoever has the highest bid gets the right (legally, the obligation) to purchase an object. When there are no more bids, a hammer or gavel is traditionally stuck, giving rise to the term “hammer price.” To this price a “buyer’s premium” is usually applied that is a transaction fee paid directly to the house, and if an object fails to meet the set reserve price, the object is considered “bought in.” Reservation prices are the absolute minimum that a seller is willing to accept. These reservation prices are fiercely

guarded state secrets, as it is in the house's profit maximization best interests to let bidders bid as high as possible. Revealing this before the hammer falls would result in potential buyers to only bid up to this reservation price, even if they were willing to pay more.¹

3. MODEL

A comparison can be drawn between bid-ask spreads in finance and estimation windows, insofar as it is similar in practice to how estimation windows operate in determining price. With bid-ask spreads, the current price of an asset lies somewhere between these two quotes, usually at the mid-price. The bid and ask quotes are then determined by some function of this current price and other exogenous factors. By publishing an estimation window, an auction house asserts with a certain level of confidence that the true value is within that window. The auction participants then set the true price, using some function of the estimation prices and other factors. So, if some price informs some bid-ask spread, is the converse true in the market for art? That is to ask, can estimation windows be compared to bid-ask spreads and be used to infer the true price of a work based on this window's characteristics?

It has been generally established in the financial literature that bid-ask spreads are a measure of liquidity; assets traded with lower volume results in a larger bid-ask spreads and signal illiquidity[9]. Furthermore, there is a body of evidence that supports the claim that illiquid securities suffer from an illiquidity "discount"[8]. This discount arises from search and transactions costs in the market. When these costs on the seller reach a certain threshold, it is no longer profitable or perhaps too risky to search for the highest paying buyer, and a steep price reduction is used to ensure sale[18]. How much to reduce the price to secure a sale while trying to maximize profit proves to be a difficult problem for sellers of art. Reservation prices set a price floor of sorts on a work's estimation window, as it is not in the profit maximizing interest of the auction house to have hammer prices close or below the reserve price.

There are three strategies that auction houses may employ to set prices. They can either estimate prices below the true price, at the true price, or above the true price. In auction theory, laid down by

¹It has been attested to that auctioneers will not reveal if a lot has sold or not until the end of the auction, and take extensive measures to "make it as difficult as they can for bidders to infer it." However, this is not true in New York, as this practice is prohibited by law—auctioneers are required, at the end of bidding, to reveal whether it has sold or not.[2]

TABLE 1. Summary of Estimation Bias Literature*

Author(s)	Sample	Result
Milgrom and Weber (1982)		“Honesty is the best policy”
Ashenfelter (1989)	Impressionist Art	Auctioneers are truthful
Chanel et al. (1996)	Jewelry	Works generally underestimated
Beggs and Graddy (1997)	Impressionist and Contemporary Art	Both under and over estimation
Bauwens and Ginsburgh (2008)	English Silver	Christie’s underestimates, Sotheby’s overestimates inexpensive pieces and underestimates expensive pieces
Valsan and Sproule (2008)	European Art (1986-2003)	Overestimation relative to midpoint
Mei and Moses (2002)	American, 19th Century, Old Master, Impressionist, and Modernist (1950-2002)	Auction houses strategically set prices to increase realized prices
Mei and Moses (2005)	American, 19th Century, Old Master, Impressionist, and Modernist (1950-2002)	Upward bias over time for expensive works

*This table is reproduced, in part, from Ashenfelter& Graddy (2003), p.780 [3]

Milgrom and Weber, it is argued that “honesty is the best policy” [24], and the art auction literature has studies that provide evidence this theory [2]. It is argued that since reputation is very important to an auction house, they would be risking future prices by compromising the veracity of their price estimates. Furthermore, if an auction house continuously under or over values systemically, this will lead buyers to adjust and determine the true estimated price. Producing estimates that are below the true price may increase the likelihood of sale, leading to a greater number of transactions and buyer’s premiums. Producing estimates that are above the true price may increase the hammer price, leading to higher valued buyer premiums, but this has the trade off of a lower likelihood of sale. Findings of various studies are shown in Table 1.

This study contends that whatever the potential strategic price settings, larger estimation windows will signal to bidders that a work is more illiquid than other works and therefore would result in lower realized prices. This hypothesis is informed by financial literature and

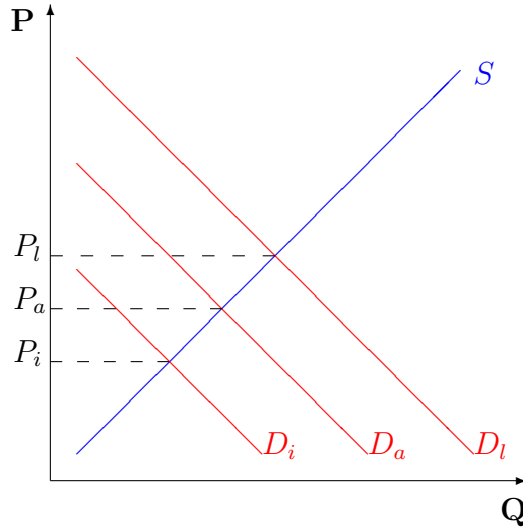


FIGURE 1. Market for Art

assumes that bidders are rational². Rationality in this case involves bidders gauging their own marginal utility from a work against the marginal cost of the work itself. Bidders must process several factors when evaluating a work that include, but not limited to, possibility of resell, historical value, overpaying, etc. Many of these factors depend on how liquid the market is for that work, and therefore effect the realize price. For example, when deciding on bids, a rational bidders will lower their valuation of a work if there is a lower chance of resale (due to increased supply or decreased demand or animal spirits) and seek to become informed of a work's liquidity. So, if an auction house sets a wide range for an estimate, then a bidder will see that as a signal of illiquidity and reduce the amount they are will to pay for it.

To illustrate, let S represent the supply curve of all art. This figure implies a level of elasticity that may not hold true in practice; S may be more inelastic as the supply is restricted to a particular artist or genre. Then let D_l represent the demand curve in a perfectly liquid market in equilibrium. This price is then represented by P_l . Then let D_i represent demand in a gallery or commission based market for art. D_i is a transformation of D_l for obvious reasons- it is harder for buyers to find sellers and vice versa. So this leads to price P_i . The difference in price between P_l and P_i is the illiquidity discount.

²There is, of course, no account for taste or animals spirits, but, as this study will argue, these phenomenon are more uncommon then one would expect in the market for expensive art.

TABLE 2. Summary of Literature on the Role of Estimates*

Author(s)	Sample	Result
Ashenfelter et al. (2003)	Impressionist and Contemporary	Relative estimation window does not effect the % of items sold
Czujack (1997)	Picasso	Pre-sale estimates do not influence realized price
Ekelund, Ressler, and Watson (1998)	Latin American	Smaller estimation windows result in lower % of items sold

*This table is reproduced, in part, from Ashenfelter& Graddy (2003), p.780 [3]

D_a represents the demand curve for the auction market- bringing together more buyers and sellers, but due to the infrequency of auctions, it cannot achieve perfect market liquidity. P_a is thus the equilibrium price, which we expect to be lower than the perfectly liquid price of P_l and above the illiquid price of P_i . Rational buyers are concerned a work's liquidity and look for any signal or information that makes them more fully informed³. Therefore, if a bidder is concerned with or has information about a work being illiquid, the highest bid they are willing to submit will fall from P_a to some P^* between P_a and P_i .

The role of estimation windows on final realized prices is a less studied topic. The literature mainly focuses on the relation between sale rates and relative window size, as indicated in Table 2. Czujack (1997) explores the possibility that these estimates do influence final prices, but found no conclusive evidence. This study seeks to further this body of research.

4. DATA AND VARIABLES

The data that for the basis for this study are collected from publicly available records from Sotheby's⁴. The auction house publishes pre-sale catalogs that contain the following information on each lot:

- an image of the work,
- the title of the work,
- the artist,
- the birth and death dates of the artist,
- if the work is signed or marked,
- the media used,

³On the other hand, as mentioned before, auction houses go to great lengths to impede this process as much as possible. For example, Edvard Munch's *The Scream* sold for USD\$119,922,500 (with buyer's premium) at Sotheby's New York on May 2, 2012, but the estimate is only available to "serious" bidders.

⁴Available here: <http://www.sothebys.com/en/catalogues/buybrowse.html>

- dimensions,
- date of execution,
- provenance (if available),
- the current owner (may be anonymous),
- and estimates of value.

Once a work has been sold, the hammer price that includes the buyer's premium is published. This premium is a commission—a percentage based on the final hammer price⁵. There are 556 observations collected from Sotheby's Impressionist and Modern Art Sales catalogs for 6 auctions during the period May 2010–May 2011.. Sculpture, furniture, and other 3D works are excluded, and so the sample is left with only two-dimensional works. Many studies use a specific artist [10, 13] or confine themselves to a selective list of artists that are qualitatively determined to be related. [29] Some are even vaguer, including artists that “have had an [...] impact on art history.” [28] This study includes all artists represented in the sample collected.

While there is burgeoning body of literature on obtaining meaningful information from images [1], it remains without a standard method of analysis. Therefore, a quantitative measure of the image of a work is left out, and by the same logic the title of the work as well is left out. From the birth date of the artist, it is possible to construct a measure of an artist's age, which has been found by some as significant [14]. However, a caveat of the Galenson and Weinberg study is that price fluctuates to demand for a particular artist during the artist's lifetime. Since the vast majority of the artists represented are deceased, this is not considered in this study.

Of these characteristics, provenance and media are the most qualitative, and therefore trickiest, variables to address. Provenance, when available, is a summary of the work's life—from creation to the present. This may include a detailed list of owners (both well known and obscure), an attestation from an artist's living relative, a list of exhibitions it has taken part in, or nothing at all. Attempting to construct a variable that captures the “celebrity” of owners would be difficult, and ultimately a qualitative decision on the part of the researcher, and there is no objective list of famous art owners or even characteristics that would define one. So, to include an objective measure from the information provided in a work's provenance, a binary measure of whether or not the work has been exhibited in a public museum is formulated. This measure is to capture a work's known exposure to

⁵Available at <http://www.sothebys.com/content/dam/sothebys/PDFs/BuyersPremium2012.pdf>

TABLE 3. Sample and Variable Statistics

Variable	n	Mean	Std. Dev.
Low Estimate	556	662.7	1923.7
High Estimate	556	954.3	2788.5
Hammer*	484	842.9	2289.4
Exhibited	556	.433	.496
Year of Work	512	1925.6	26.0
Height/Width	556	1.10	.346
Log(Hammer)*	484	5.27	1.56

* The variables Hammer and Log(Hammer) do not include 72 observed buy-ins.

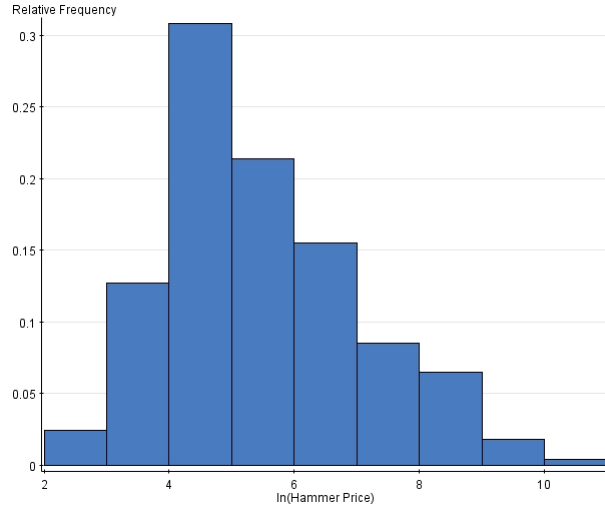


FIGURE 2. Histogram of the Hammer Prices (Logarithmic scale)

the general public and the possibility that by being exhibited, more information may be available to all participants.

The variable Hammer Price, and the low and high estimates are skewed, the data having a few very high priced items. To adjust for this, log transformations are employed. The resulting distribution of $\text{Log}(\text{Hammer Price})$ is shown in Figure 2. As the buyer's premium is charged after the hammer price and Sotheby's only reports hammer prices that include the premium, the hammer prices have been corrected to exclude the post-sale premium.

In order to measure the relative estimation window, a variable is defined using the stated high and low estimates as: $\frac{\text{High Estimate}}{\text{Low Estimate}}$, which

lies in the range from 0 to infinity and is undefined when the low estimate is 0. However, in practice this cannot be the case—an auction house is not a charity and would not auction an item deemed to possibly be worthless. With this measure, if a work is perfectly liquid, that is to say everyone knows its price, the relative window measure presented would equal 1. As the distance between the high and low estimates increases, the measure would increase toward infinity for very small low estimates. This study seeks to determine whether this measure has a significant impact on realized prices, so if there is no impact, the estimated coefficient should be 0. If, as postulated, the coefficient is less than 0, this would indicate that larger windows correlate with lower hammer prices.

5. METHODOLOGY

5.1. Testing for Unbiasedness. Using nonlinear least squares, it is possible to test for unbiasedness. Biased estimates, in the scope of this study, is defined to be a pattern of deviation from the actual realized price, some P_h , and the estimated price, some P_e ; we expect this difference to be 0 if the estimates are unbiased. That is to say, the expected value of a work is the published estimated price.

$$E(P_h - P_e) = 0$$

The estimated price, P_e , is made up of some weighed average of two estimates, the low estimate (E_L) and the high estimate (E_H). Let τ be the weight in the interval $[0, 1]$.

$$P_e = \tau E_L + (1 - \tau) E_H$$

It is commonly assumed in the literature that the midpoint of E_L and E_H is the estimate that experts formulate to which they add some band. To test this hypothesis, a nonlinear model is used. If this assumption is true, then we expect τ to be .5, if it is not there is a bias in the expert's estimation. A value greater than .5 would indicate undervaluation, and a value less than .5 would indicate overvaluation.

The following two models are estimated using nonlinear least squares, and the results displayed in Table 4. To estimate τ , all buy-ins are dropped, as there is no observed hammer price.

$$(1) \quad \text{Hammer}_i = \tau_1 \text{LowEstimate}_i + (1 - \tau_1) \text{HighEstimate}_i$$

$$(2) \quad \text{Hammer}_i = \tau_1 \text{LowEstimate}_i + (1 - \tau_1) \text{HighEstimate}_i + \tau_2 \text{relwin}_i$$

TABLE 4. Nonlinear Results for Bias Estimation

	(1) NLS		(2) NLS	
	Coeff.	Std. Error	Coeff.	Std. Error
Low Estimate	.757	.034	.791	.036
Relative Win.			71.64	24.19
R^2	.913		.915	

5.2. Potential Selection Bias. In practice, not all works are sold. This leaves our dependent variable (the hammer price) is truncated as it is only observed if a sale occurs. To complete a sale, the hammer price, P_h , must exceed some reservation price, r . If it does not, this constitutes a buy-in (a no-sale), signaling that the work was overvalued as the low estimate must equal or exceed the reservation price⁶.

So, a Heckman correction is used to test for the possibility of selection bias[17]. Let (3) and (4) be the selection and price equations, respectively. The selection equation consists of factors that influence the probability of a work being sold. The relative price estimation window, the log transformation of the estimates midpoint, and whether or not it was in the day or evening sales. The price equation consists of the factors that may influence final realized prices with the selection equation acting as an indicator function.

$$(3) \quad \text{Sold}_i = 1(\gamma_0 + \gamma_1 \text{relwin}_i + \gamma_2 \ln \text{mid}_i + \gamma_3 \text{bigsale}_i + \varepsilon > 0)$$

$$(4) \quad (\text{LnHammer}_i)(\text{Sold}_i) = (\beta_0 + \beta_1 \text{relwin}_i + \beta_2 \ln \text{mid}_i \\ + \beta_3 \text{workage}_i + \beta_4 \text{Exhibited}_i \\ + \beta_5 \text{Heightwidth}_i + u_i) \text{Sold}_i$$

6. RESULTS

6.1. Testing for Unbiasedness. As previously stated, if we assume the estimation window is built around some “true” estimation and assume that the estimated price is the expected value of a work, then

⁶It is not in the best interests of a profit maximizing auction house to risk selling below the reservation price, especially in the case that the house experts believe a reservation price has been set above a work’s estimated price. This is bad business as it would lead to a reputation for underselling—scaring off sellers and frustrating bidders.

TABLE 5. Heckman Method results

	Coeff.	Std. Error
Selection Eq.		
Rel. Window	.454	.612
Log(Midpoint)	-.037	.049
Evening Sale	-.045	.178
Constant	.572	.897
Price Eq.		
Rel. Window	-.224	.188
Log(Midpoint)	.983	.012
Age of Work	-.0004	.0005
Exhibited	.010	.028
Height/Width	-.022	.0396
Constant	.434	.269

we would expect the mean of the high and low estimates to be the realized price.

However, it is clear from the results, displayed in Table 4, that does not seem to be the case. With coefficients of .75 and .79, significantly different from .5 at the 95% level, these data show a significant pattern of undervaluation of the works observed.

6.2. Heckman and MLS. From the results in Table 5 demonstrate, there is no significance in the coefficient estimated for the selection equation, so we can proceed with a multiple linear regression (5).

$$\begin{aligned}
 (5) \quad \text{LnHammer}_i = & (\beta_0 + \beta_1 \text{relwin}_i + \beta_2 \text{lnmid}_i \\
 & + \beta_3 \text{workage}_i + \beta_4 \text{Exhibited}_i \\
 & + \beta_5 \text{Heightwidth}_i + \beta_6 \text{bigsale} + u_i)
 \end{aligned}$$

Table 6 displays the results of this regression. As one would expect, percentage increases in the estimation midpoint correlates with an almost one-to-one percentage increase in realized prices. While this study makes not hypothesis about the sale being an evening or day sale, the fact that a work was part of a “big sale,” a sale with the more expensive work and more sophisticated clientele, corresponded to decreased hammer prices (significant at the 10% level).

Using a one-sided t-test, the relative window measure is also significant, with a p-value of .09. A one-sided test is appropriate in the case because, as stated above, we expect a value less than 0. So, it seems to

TABLE 6. MLS results

	Coeff.	Std. Error
Rel. Window	-.229*	.169
Log(Midpoint)	.944**	.0161
Age of Work	-.00065	.00063
Exhibited	.462	.351
Height/Width	-.017	.045
Evening Sale	-.116*	.261
Constant	.572	.897
R^2	.956	

be the case that larger relative windows have a significantly negative impact on hammer prices.

7. REMARKS AND FURTHER STUDY

This study tested whether Sotheby’s Impressionist and Modern Art auctions have unbiased price estimations and if larger price estimates correlated with lower realized prices. Using nonlinear techniques, estimates were found to be biased, indicating expert error or the like. Finding no selectivity bias by using the Heckman method, ordinary multiple least squares regression was applied. Our hypothesis that larger price estimate windows was confirmed by the results presented. We assert that the reason we observe this phenomenon is that larger windows are a signal of illiquid and therefore suffer a discount.

There are many other possible research paths available to pursue. One of the implicit assumptions made when determining variables was that all artists’ names had the same “branding” effect, that is to say, all artists were equal in ability, popularity, and prestige. This is simply not the case in a real world setting. Further inquiry would be benefited by a study that is able to include an objective measure of an artist’s popularity in the market. Another would be to expand the data set to include more auctions, genres, and auction houses. this study intentionally avoided a game theoretical analysis of these auctions; however, such a study would be of great benefit for both consumers and auction houses. It would be interesting to analyze bidding practices in relation to the price window—does a smaller window receive more or less bids? What are the magnitudes of those bids? Such a project would require many hours observing and recording auctions in action and goes beyond the limits of this study.

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STATA CODE

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*William Hodges

import excel "G:\Impressionist Art for Capstone.xlsx", sheet("Data") cellrange(A7:Q564) firstrow

drop in 541
**^^^^ Bad observation

summarize

tabulate SaleIdentifier, generate(salenum)
generate bigsale =0
replace bigsale = 1 if salenum1==1|salenum3==1|salenum5==1
* ^^^ coding a bigsale

replace Hammer=-1 if Hammer==0

generate lnlow = log(LowEstimate)
generate lnhigh = log(HighEstimate)
generate workage = 2010-YearofWork
generate relwin = HighEstimate/LowEstimate
generate mid = (HighEstimate+LowEstimate)/2
generate lnmid = log(mid)
** ^^^^^ various variables

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generate HammerBp=Hammer
***^^ HammerBp includes the hammer price and the buyer's premium

generate lnhammerBp = log(HammerBp)
****^^ lnhammerBp is the log of the hammer price with the premium included

replace Hammer=Hammer/1.25 if Hammer>0 & Hammer<=50
replace Hammer=Hammer/1.2 if Hammer>50 & Hammer<=1000
replace Hammer=Hammer/1.12 if Hammer>1000
* ^^ correcting for buyer's premium in Hammer

generate lnhammer=log(Hammer)
* ^^ lnhammer is the log of the hammer price, corrected for buyer's premium

reg lnhammerBp lnmid relwin

*****
*Onesided T Test- look carefully at Ho
test _b[relwin]=0
local sign_relwn = sign(_b[relwin])
display "Ho: coef <=0 p-value =" ttail(r(df_r), 'sign_relwn'*sqrt(r(F)))
*****

reg lnhammer lnmid relwin

```



```

*****
*Onesided T Test- look carefully at Ho
test_b[relwin]=0
local sign_relwn = sign(_b[relwin])
display "Ho: coef <=0 p-value =" ttail(r(df_r), 'sign_relwn'*sqrt(r(F)))
*****

heckman lnhammer relwin lnmid workage Exhibited HeightWidth, select(relwin lnmid bigsale)

reg lnhammer relwin lnmid workage Exhibited HeightWidth bigsale
*****
*Onesided T Test- look carefully at Ho
test_b[relwin]=0
local sign_relwn = sign(_b[relwin])
display "Ho: coef <=0 p-value =" ttail(r(df_r), 'sign_relwn'*sqrt(r(F)))
*****

reg lnhammerBp relwin lnmid workage Exhibited HeightWidth bigsale
*****
*Onesided T Test- look carefully at Ho
test_b[relwin]=0
local sign_relwn = sign(_b[relwin])
display "Ho: coef <=0 p-value =" ttail(r(df_r), 'sign_relwn'*sqrt(r(F)))
*****

drop if Hammer==-1

```

```

***^^^ will screw up nl reg

nl (Hammer = {b} *LowEstimate +(1- {b} ) *HighEstimate), initial(b .5)
nl (HammerBp = {b} *LowEstimate +(1- {b} ) *HighEstimate), initial(b .5)
nl (Hammer = {b} *LowEstimate +(1- {b} ) *HighEstimate + {b2} *relwin), initial(b .5)
*^^ For estimating with a "floating" ematimate (not just .5)

summarize

histogram relwin, discrete
twoway (scatter lnhammer relwin)

```