Status Quo Bias and the Endowment Effect: Are They Associated With a Higher WTA in the U.S. Housing Market?

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1 Introduction

Traditionally, consumer theory predicts that willingness to pay (WTP) and willingness to accept (WTA) should not significantly deviate from each other (Willig, 1976). This assumption stems from the idea that an individual's indifference curves are specified independently of their endowment and budget constraint, which is called the preference–budget independence assumption. However, in practice, WTP tends to significantly exceed WTA, resulting in lower overall trades. For example, Horowitz and McConnell (2002), who compiled data from 45 WTP-WTA studies, found that the median ratio of the mean WTA and mean WTP across these studies was 2.6. Many economists have derived different theories that violate consumer theory's preference–budget independence assumption to explain these results. For example, some theorists have hypothesized that the WTA-WTP gap stems from people perceiving losses as more severe than gains relative to some reference point; in other words, they posit that people's preferences are reference-dependent (Koszegi & Rabin, 2005). On the other hand, some behavioural economists believe that this WTA-WTP gap originates from people valuing something more simply because they have owned and used it, which they call the endowment effect (Kahneman et al., 1990; Plott & Zeiler, 2005).

2 Literature Review

Regarding this endowment effect, Kahneman et al. (1990) ran an experiment to determine whether this effect can explain the WTP-WTA gap. They hypothesized that experimental tokens, which are traditionally traded in for monetary rewards at the end of the experiment, should not evoke any endowment effect: these goods are solely acquired for resale purposes, not for utilization. On the other hand, items that we use daily, such as mugs, should result in the endowment effect driving up their value as their utility stems from resale and usability. Therefore, to test whether the endowment effect contributes to the WTA-WTP gap for "usable" goods, the researchers randomly assigned participants within a sample to a buyer or seller role, generating a market; they replicated this procedure for many different samples, creating many markets. For each market, the experimenters provided the sellers with either tokens (i.e. their value stems from resale potential) or mugs (i.e. their value originates from genuine consumer use). Then, they asked sellers and buyers to state their WTAs and WTPs for their market-specific items. For the mug markets, each participant was presented with a multiple price list where they indicated whether they would be willing to (sell)/(buy) or (not sell)/(not buy) an item at each given price. Then, the experimenters explained to the participants that one price would be randomly selected for the actual transaction to prevent participants from stating a (higher WTA)/(lower WTP) than their true valuation in hopes of extracting more consumer surplus. This random price selection process is called the Becker–DeGroot–Marschak mechanism; it is typically used to elicit truthful WTAs and WTPs that are not obfuscated by strategic misrepresentations (Becker et al., 1964). Conversely, the token market followed the same procedure; however, the experimenters used a market-clearing price instead of a random price. Results-wise, they found that the WTA-WTP gap was present for the mugs, but not for the tokens; they suggested that the endowment effect explained this WTA-WTP discrepancy.

However, some critics have argued that this WTP-WTA discrepancy was an artifact of procedural misunderstandings (Plott & Zeiler, 2005). Plott and Zeiler (2005) followed the same experimental design as Kahneman et al.'s (1990), but also provided participants with a detailed training session to help them understand why they should provide truthful valuations under the BDM mechanism. They also used 2 unpaid "practice" rounds for each market. Unfortunately, they were not able to replicate Kahneman et al.'s (1990) results, which led them to posit that this discrepancy stems from experimental misunderstandings. In particular, the BDM mechanism that Kahneman et al. (1990) used was difficult to understand as they only mentioned to participants that "1) Your decision can have no effect on the price actually used because the price will be selected at random. (2) It is in your interest to indicate your true preferences at each of the possible prices listed below." Kahneman et al. (1990) did not explicitly explain why it was in the participant's best interest to state their true valuation under the BDM mechanism. The participants had to figure out this part on their own; I posit that, given the sheer complexity behind the proof, participants would be uncertain about the best response to the BDM mechanism (i.e. they are not convinced that providing a truthful valuation is the best strategy). Consequently, to avoid the cognitive labour associated with solving for the best response to the BDM mechanism, I believe that these participants relied on cognitive heuristics instead.

Importantly, Kahneman's (2011) dual-system framework strongly complements my argument. This framework states that individuals draw upon two distinct types of problem-solving: System 1, which is automatic, implicit, rapid, associative, and heavily dependent on cognitive heuristics; and System 2, which is effortful, deliberate, slow, rule-guided, and grounded in normative reasoning. Crucially, when a task imposes substantial cognitive complexity or uncertainty, people disproportionately rely on System 1. This system invokes a broad array of heuristics, including status quo bias, accessibility, framing, attribute substitution, affect, and prototype-based reasoning (Tversky and Kahneman, 1974). Among these, status quo bias refers to the tendency for individuals to prefer to remain in their current state; individuals engage in this heuristic avoid the additional cognitive costs required to change their current state. In the context of Kahneman et al.'s (1990) mug markets, this heuristic would manifest itself as follows: if a seller were confronted with a complex WTA elicitation mechanism (i.e. BDM), then they would be more uncertain about their best response to said mechanism, leading them to default to System 1. Then, their System 1 would invoke status quo bias. As a result, the seller would prefer to stay in their current state of owning a mug, culminating in the seller stating an inflated WTA. Conversely, when buyers encounter a complex WTP elicitation mechanism, they would also experience uncertainty and shift to System 1. To preserve their current state of not owning a mug, they would state a lower WTP, reducing the likelihood of acquiring the item. Crucially, my theory explains the results found in Kahneman et al.'s (1990) experiment: a WTA–WTP gap was observed in the mugs market due to the cognitively complex BDM mechanism being used whereas no such difference was noted in the tokens market due to the absence of the BDM mechanism. My theory also explains Plott and Zeiler's (2005) results: given that participants were thoroughly explained why truthful valuations were the best response to the BDM mechanism, they were never placed in a cognitively demanding setting that would prompt role-based status quo bias. Ultimately, this culminates in no WTA-WTP gap for the mug and token markets. All together, I hypothesize that the following causal channel explains the WTA-WTP discrepancy:

$$\text{Cognitive Complexity} \rightarrow \text{Cognitive Uncertainty} \rightarrow \text{System 1 Processing} \rightarrow \text{Status Quo Bias} \rightarrow \text{WTA-WTP Discrepancy} \tag{1}$$

Unfortunately, given that I must use open-source data for this paper, it would be difficult for me to find a dataset that would provide me with evidence for each causal link. Luckily for me, Enke and Graeber (2023) have found evidence supporting the first one; Tversky and Kahneman (1974) have also substantiated the second and third ones. Therefore, I am solely interested in providing evidence for the following pathway:

$$\text{Cognitive Complexity} \rightarrow \text{WTA-WTP Discrepancy} \tag{2}$$

To accomplish my goal, I seek to examine this issue within the context of the U.S. housing market. More specifically, I posit that the status quo bias, not the endowment effect, influences the homeowner's predicted market value of their home, being my outcome variable. In the following subsections, I will operationalize the status quo bias and the endowment effect consistent with previous literature.

2.1 Status Quo Bias

Selling a home involves multiple cognitively demanding steps, such as estimating its price, gathering documentation, and completing repairs. Therefore, homeowners may be reluctant to engage in these cognitively demanding tasks unless sufficiently compensated. In other words, buyers may need to offer a higher price to incentivize the homeowner to overcome their status quo preference. In this study, status quo bias will be operationalized through a "cognitive cost of selling home" index. This index encapsulates the difficulties that the homeowner encounters on a daily basis (memory, seeing, walking, running errands, hearing, and self-care). Crucially, past research has indicated that people who suffer from physical and cognitive difficulties suffer more from status quo bias: Saposnik et al. (2022) found that patients with relapsing remitting multiple sclerosis who had cognitive processing difficulties were more likely to continue taking a previously selected but inferior treatment when intensification was warranted. In addition, some psychological theories about status quo bias posit that greater cognitive processing difficulties should engender greater status quo bias (Eidelman & Crandall, 2012). Thus, I predict that sellers who have more daily difficulties will encounter greater cognitive difficulty with selling their house, resulting in the seller imposing a "cognitive compensation tax" on the buyer.

2.2 Endowment Effect

Interestingly, Ko (2013) extends the endowment effect by stating that its effects strengthen through time, allowing me to argue that longer tenure leads to higher WTA. Therefore, I posit that house sellers who have owned their house for a lengthy period of time might overvalue their homes, resulting in a "ownership tax" being applied to the buyer.

All in all, I am interested in answering the following question "Are the status quo bias and the endowment effect associated with homeowners providing higher valuations when stating their home's market value in the U.S.?" Despite my theory being causal 2, my research question is not; this amendment emerged from an issue that will be discussed in the third section of this paper.

2.3 Summary of Model, Data, Findings, and Limitations

To examine whether the status quo bias or the endowment effect strongly contribute to homeowners' predicted market value of their home, I used a two-way fixed effects model, controlling for year and house fixed effects. I created my panel dataset using the bi-yearly surveys conducted by the American Housing Survey between 2015 to 2023; the AHS collects its data from the same set of homes over time. From these surveys, I collected all variables related to the status quo bias and the endowment effect, as well as the homeowner's predicted market value. I found that the status quo bias, not the endowment effect, elicits a higher WTA in homeowners: my cognitive cost of selling coefficient was statistically and economically significant unlike the the tenure coefficient. One prominent limitation in my approach is that I cannot make any claims with respect to the WTP-WTA discrepancy as I simply do not have any data on consumers' WTP for each home.

3 Data

My panel dataset is directly sourced from the American Housing Survey (n.d.). This survey collects its data from the same set of houses across a broad range of large metropolitan areas, such as New York and Chicago, every two years from 2015 to 2023. Thus, my unit of observation is the individual housing unit, not the homeowners who temporarily occupied said unit. In terms of variables, I collected each homeowner's daily difficulties (seeing, walking, running errands, memorization, self-care, and hearing), tenure, and hypothesized market value of their home if they were to sell at the time they took the survey. To construct my dataframe, I merged all of my bi-yearly household surveys (2015, 2017, 2019, 2021, 2023) using the CONTROL variable, being a 12-digit variable unique to each housing unit in the national survey data. I discarded all rows that were unmatched or had missing codes for my variables of interest. In addition, I discarded all columns that were unrelated to my variables of interest. To account for non-linear relationships, I logged the homeowner's predicted market value of their home and tenure (James, 2023).

3.1 Cognitive Cost Index

I used Kling et al.'s (2007) standardized averaging method to create my cognitive cost of selling a home index. Equation-wise, I used the following model:

$$\text{CognitiveCostIndex}_{it} = \frac{1}{|X|} \sum_{x_{it} \in X_{it}} \left(\frac{x_{it} - \mu_t}{\sigma_t} \right) \tag{3}$$

where:

- $X_{x_j t}$: Homeowner of home i's daily difficulties status at time t
- $X_{it} = \{\text{SelfCareDifficulty}_{it}, \text{RunningErrandsDifficulty}_{it}, \text{HearingDifficulty}_{it}, \text{MemoryDifficulty}_{it}, \text{WalkingDifficulty}_{it}\}$

I constructed the cognitive cost index using standardized averaging due to its transparency and ease of implementation. In addition, this approach is appropriate for my setting because many of its key assumptions are reasonably satisfied. First, all component variables $x_{it} \in X_{it}$ are expected to influence $\text{CognitiveCostIndex}_{it}$ in the same direction. Second, the method requires that each predictor exhibits sufficient variance, which is satisfied in my data (See Table 1). Third, standardized averaging assumes an additive structure among components; although this is more difficult to verify definitively, it is a reasonable simplifying assumption in this context. Fourth, all of my constructs $x_{it} \in X_{it}$ are related to the cognitive cost of selling a home (Eidelman & Crandall, 2012; Saposnik et al., 2022). Finally, the method assumes that all $x_{it} \in X_{it}$ contribute equally to the composite index. While this equal-weighting assumption is challenging to validate empirically, it is commonly accepted when no strong theoretical basis exists for a differential weighting (OECDJRC, 2008). I used standardized averaging over other popular index-creation methods, such as PCA and IVM, as standardized averaging does lead to non-standard limiting distributions and does not produce negative weights on some variables despite all variables having the same directionality (Lau, 2025).

Table 1 Summary Statistics (Only Observations with *Market Value* Within 4 Standard Deviations)

Variable	Count	Mean	Std. Dev.	Min	Median	Max
Homeowner Trouble Self-Care (HSC)	56,945	1.983	0.129	1.000	2.000	2.000
Homeowner Trouble Errands (HRE)	56,945	1.967	0.178	1.000	2.000	2.000
Homeowner Trouble Hearing (HTH)	56,945	1.927	0.261	1.000	2.000	2.000
Homeowner Trouble Memory (HTM)	56,945	1.972	0.165	1.000	2.000	2.000
Homeowner Trouble Seeing (HTS)	56,945	1.974	0.159	1.000	2.000	2.000
Homeowner Trouble Walking (HTW)	56,945	1.920	0.271	1.000	2.000	2.000
Market Value ($)	56,945	403,018.572	501,852.108	1.000	287,525.000	9,999,998.000
Tenure (years)	56,945	19.557	14.256	1.000	17.000	85.000

Note: Codes 1 and 2 correspond to "Yes" and "No," respectively for HSC, HRE, HTH, HTM, HTS, and HTW. Market value is measured by asking the homeowner the following question: "If someone were to buy your home today, about how much do you think it would sell for?"

From the summary statistics, the daily difficulty metrics are overwhelmingly skewed toward the 'No difficulty' category, indicating a strong right-hand skew with very limited variation. On the other hand, market value and tenure also exhibit left-hand skewness; however, they display also high variability. Applying the natural logarithm substantially reduces this skewness, yielding distributions that are more symmetric and suitable for regression analysis. Again, using this procedure allows me to analyze non-linear relationships across my dependent and independent variables. The tenure variable was derived by doing: currentyear -

yearmovedin. Finally, the 1$ minimum in the home market value row is not a fluke: some homes have sold for 1$ in the U.S. (Skinner, 2023).

4 Econometric Model

To estimate the association between the homeowner's tenure and the cognitive cost associated with selling their home on their predicted market value of their home, I estimated the following regression model:

$$\ln(\text{PMV}_{it}) = \beta_0 + \beta_1 \text{CCSH}_{it} + \beta_2 \ln(\text{Tenure}_{it}) + \gamma_t + \delta_i + \epsilon_{it} \tag{4}$$

where:

- PMV_{it}: The homeowner's own predicted market value of home i at time t.
- CCSH_{it}: The homeowner's cognitive cost of selling home i at time t.
- Tenure_{it}: The number of years that the homeowner has lived in home i at time t.
- γ_t: Fixed effect for time t
- δ_i: Fixed effect for house i
- ϵ_{it}: Error term

To begin, I analyze whether my dataset and regressions satisfy the fixed effects regression assumptions for causal inference (Stock and Watson, 2020). Firstly, I have 283 outliers that are outside 4 standard deviations of the mean; thus, outliers in my dataset are very unlikely (0.4970% of the entire sample). Secondly, the houses in my dataset are not independently and identically distributed as the American Housing Survey collected its data using a complex multistage sampling process that uses survey weights, not simple random sampling. In particular, the AHS splits the population into specific subgroups before sampling, meaning that samples are drawn from different probability distributions. Also, when a house is drawn, it affects the probability of another house being drawn within the same subgroup. In addition, my data set suffers from attrition: most houses do not complete the AHS survey every time it is offered. Given that my observations are not i.i.d., my sample mean will not converge in probability to the population mean. Therefore, this sampling design may not yield a sample that is fully representative of the U.S. population, limiting the generalizability of my results. Thirdly, my ϵ_{it} term does not have conditional mean 0 given all t values of my independent variables as my independent variables are not randomly assigned relative to the unobserved determinants of the outcome: they may correlate with time and house. To control for this possibility, I implemented fixed effects for time and location. This process accounts for omitted variables that are constant over time but vary across houses. For example, home i may have certain time-invariant characteristics that make them more accessible for older/disabled people (e.g., driveway slope), leading to a higher cognitive cost index for home i across all time periods. It also accounts for effects that are constant across houses but vary over time. For example, COVID-19 government shutdowns may have made it more difficult to run errands, leading to a higher cognitive cost index at time t for all houses. In addition, this assumption requires that, for panel data, the current ϵ_{it} is not correlated with past, present, and future values of X. Unfortunately, I believe that there are some omitted variables that are autocorrelated, leading to an autocorrelation in ϵ_{it}. For example, suppose that I am fixating on a single home that has changed ownership from an overly optimistic homeowner to a more realistic homeowner. Given that the former owner may consistently state a predicted market value that strongly deviates from my model's predicted market value, ϵ_{it} may be correlated across time. However, given the change in ownership, this effect would not be captured in the house fixed effect: this effect captures all time-invariant unobservables. I will discuss how to solve this issue in the next paragraph. Fourthly, I did not observe perfect multicollinearity, as the scatter plot of the reference price and starting price do not have a perfect linear relationship (See Appendix A).

Due to my data set being a panel, there exist strong serial correlations within a home; to remediate this issue, I clustered my standard errors at the house level to allow for heteroskedasticity and serial correlations within my houses but also treat the errors as uncorrelated across houses. Therefore, these clustered standard errors allow for heteroskedasticity and autocorrelation, such that it is consistent with my third causal inference assumption. Finally, I did not include an interaction effect between the cognitive cost of selling a home and the tenure as no previous research has documented a link between status quo bias and endowment effect. Finally, given that my data violates the second causal inference assumption, I will not interpret my findings from a causal perspective.

5 Results

Concerning regression results, the coefficient of the cognitive cost index is 0.0199 and its tenure counterpart is -0.0133. Interpretation-wise, a one-unit increase in the cognitive cost index (presence of 2 daily difficulties approximately) is associated with an approximate 1.99% increase in the homeowner's reported market value of their home. Ergo, given the median home market value ($287,525), a one-unit increase in the cognitive cost index is associated with an $5,702 increase in the homeowner's predicted market value of their home: the cognitive cost index's impact on the predicted market value of the home is economically significant. A 1% increase in tenure is approximately associated with a very small (-0.0133%) decrease in stated market value; hence, the tenure coefficient is not economically significant. The former regressor is statistically significant at the 5% level whilst the latter is statistically significant at the 10% level.

Again, remember that my sample was drawn using survey weights. Therefore, to the extent that I am not using survey weights, the notion of status quo bias being associated with higher WTA is more empirically supported than the endowment effect: the cognitive cost index coefficient is more economically and statistically significant than the tenure coefficient. This finding converges with my initial hypothesis. Again, there is no evidence for the endowment effect, if anything, owning your home for longer is associated with a marginally lower stated market value.

	(1)
CCSH	0.0199**
	(0.0089)
ln(Tenure)	-0.0133*
	(0.0075)
Intercept	12.5120***
	(0.0208)
House Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	56,945
R-squared	0.0035
F-statistic	4.7814
Clustered SEs	Yes (House level)

Robust standard errors clustered by CONTROL in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Robustness Checks

Regarding robustness checks, I reran the same regression but omitted select fixed effects to examine their impact on the regression coefficients.

	(2)	(3)	(4)
CCSH	0.0314***	0.2038***	0.2108***
	(0.0087)	(0.0120)	(0.0121)
ln(Tenure)	0.1589***	-0.0527***	-0.0188**
	(0.0091)	(0.0090)	(0.0089)
Intercept	12.043***	12.623***	12.530***
	(0.0250)	(0.0258)	(0.0257)
House Fixed Effects	Yes	No	No
Year Fixed Effects	No	Yes	No
Observations	56,945	56,945	56,945
R-squared	0.0111	0.0188	0.0166
F-statistic (robust)	153.78	187.39	168.03
Clustered SEs	Yes	Yes	Yes

Table 2 PanelOLS Regression Results with Different Fixed Effects Specifications

Concerning my pooled regression model 4), it uses all of the variation across time and across units. Regarding my time fixed effects model 3), it utilizes the variation over the houses within each time period. Finally, regarding my house fixed effects model 2), it uses the variation over the years within each house. Given that the cognitive cost regression coefficient is largely similar between 3) and 4), I posit that the coefficient in the pooled regression model is largely driven by variation across houses within the same time period. This argument also applies to the tenure coefficient. In addition, the cognitive cost coefficient depletes when accounting for home fixed effects, meaning that accounting for time-invariant differences attenuates the relationship between the homeowner's predicted market value and their cognitive cost of selling. On the other hand, the tenure coefficient depletes when accounting for time fixed effects, meaning that accounting for home-invariant differences diminishes the relationship between the homeowner's predicted market value and their tenure. When comparing 4) to 2), removing the house fixed effects results in the cognitive cost coefficient to skyrocket, suggesting that this coefficient's high magnitude is the result of omitted variable bias. Interpretation-wise, the cognitive cost of selling variable is positively correlated with the unobserved, time-invariant characteristics of each home. On the other hand, removing the home fixed effects leads the tenure coefficient to plummet, indicating that the tenure variable is negatively correlated with the unobserved, time-invariant characteristics of each home. When comparing 4) to 3), omitting the year fixed effects does not significantly change the cognitive cost coefficient, meaning that cognitive cost is unrelated to the unobserved, home-invariant characteristics of each time period. However, the tenure coefficient increases, meaning that the tenure variable is positively correlated with the unobserved, home-invariant characteristics of each time period. Therefore, using two-way fixed effects seems like a reasonable approach to control for omitted variable bias in my coefficients.

7 Conclusion

All in all, the WTA part of my model 2 seems to be supported to the extent that I am not using survey sampling weights. From my results, it seems like the notion of status quo bias being associated with higher WTA is more empirically supported than the endowment effect as the cognitive cost of selling coefficient was both statistically and economically significant unlike the tenure coefficient. Crucially, I cannot make any claims about the discrepancy between WTA and WTP as I do not have data on how much people would be willing to buy these homes. Therefore, I cannot claim that the homes are under/overvalued due to status quo bias. A natural extension of this study would incorporate buyer-side valuation data (WTP) to measure the WTA–WTP gap in housing. This process can be accomplished by showing various people the homes themselves and asking them how much they would be willing to pay for them. In addition, I can render my results more generalizable by using the AHS survey weights directly in my regression.

8 References

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A Collinearity Between Cognitive Cost Index and ln(Tenure)

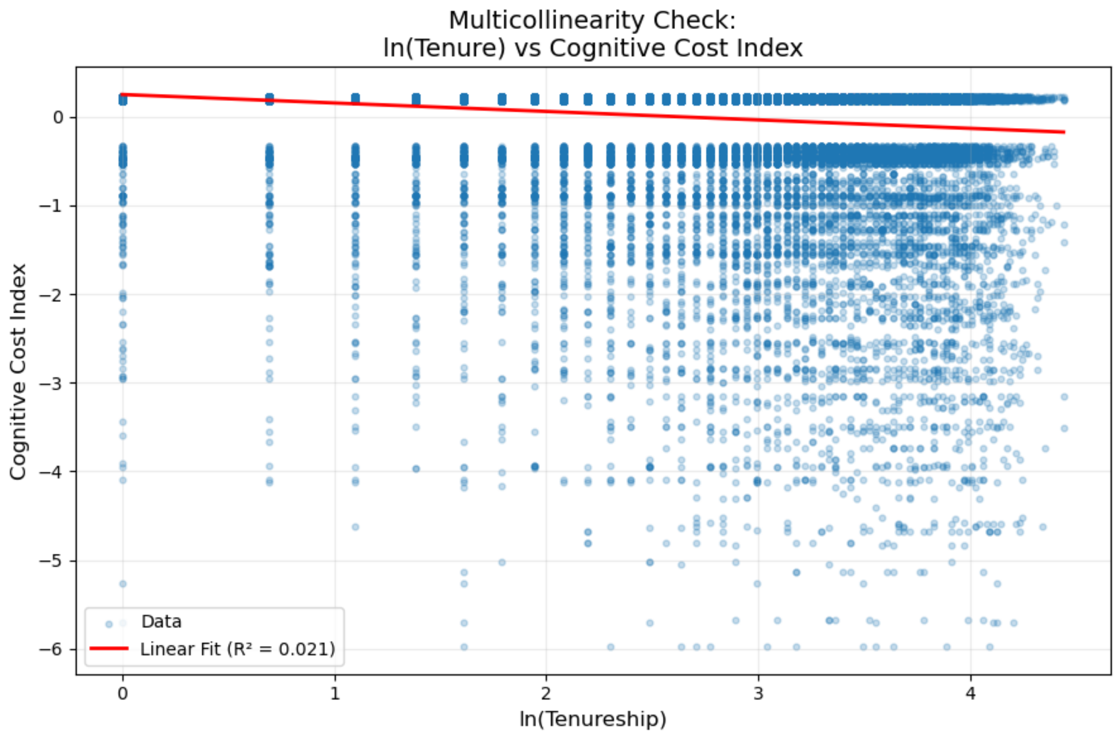

Fig. 1 Collinearity Between Cognitive Cost Index and ln(Tenure)