E-companion:

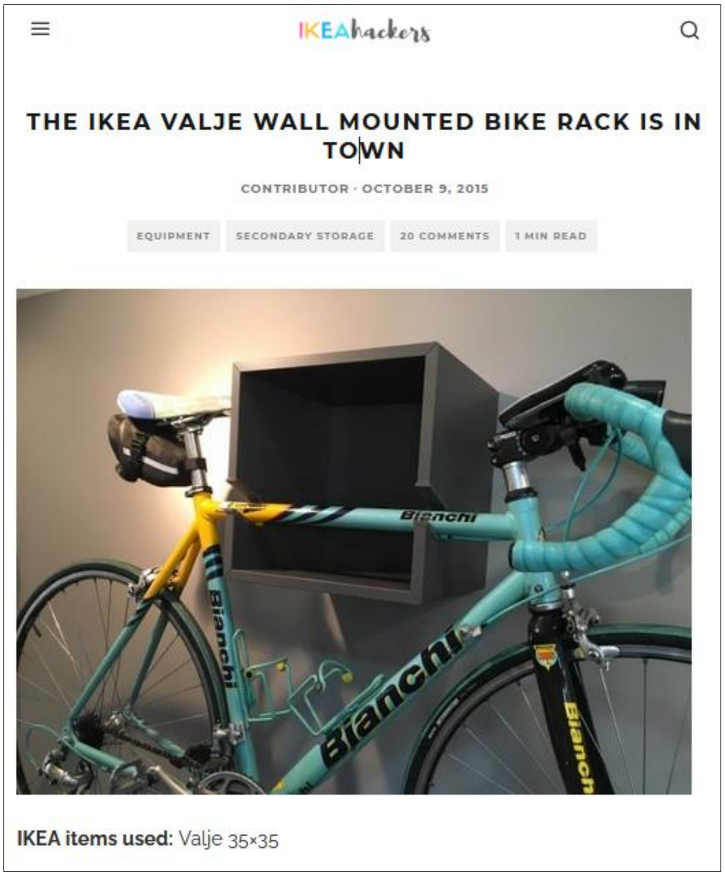
The emergence of novel product uses: An investigation of exaptations in IKEA hacks

This e-companion for the paper, “The emergence of novel product uses: An investigation of exaptations in IKEA hacks” contains several appendices:

- Appendix A: A sample hack from IKEAHackers.net (p. A2)
- Appendix B: Details of the surveys deployed on the Amazon Mechanical Turk platform that were used to measure exaptation, identify search triggers, and hack novelty (p. A3)
- Appendix C: A table showing the distribution of hacks across broad product categories (p. A6)
- Appendix D: Results and discussion of (1) a linear probability model, (2) product random effects model, (3) a hacker random effects model, and (4) the recursive bivariate probit model (p. A7)

APPENDIX A: A SAMPLE HACK FROM IKEAHACKERS.NET

The figure below shows a sample hack from IKEAHackers.net. We detail the title and the first picture of the hacked product. The hack also contains text descriptions (included below) and other pictures detailing steps of the hack (not included here). The full content of this hack can be found at https://ikeahackers.net/2015/10/valje-wall-mounted-bike-rack-town.html.



Text description:
IKEA items used: Valje 35×35

Just needed to hang my road bike in my flat. But wanted something that did not look too ugly with no bike on it …I also want something cheap… A [*sic*] use my Bosch jigsaw for cutting and my “look a like” Dremler for finishing.

~ Julien C

APPENDIX B: DETAILS OF MTURK SURVEY

In this appendix, we provide details of the MTurk survey. We first describe the overall setup common to all MTurk surveys we implemented (B.1). We then describe separately the survey instructions for measuring exaptation (B.2), identify search triggers (B.3), and measuring the novelty of hacks (B.4).

B.1 Enrollment of MTurk observers

We enrolled online observers from Amazon's Mechanical Turk platform. We limited participants of our survey to MTurkers who completed more than 500 tasks on the platform and had achieved more than a 97% task approval rate on those tasks.

Each participant first saw the following preamble. Participants had to key in the word "all" in the gray box below to continue the survey.

IKEA HACKS
- IKEA hacks are modifications of IKEA products. It could range from repurposing the product, combining and reassembling different products, or adding personalization to the product.
- You are invited to read 20 articles about hacks comprising IKEA products and answer some questions regarding the hacks.

DESCRIPTION OF THE STUDY:
- The entire study should take about 40 minutes and is designed to be completed on a desktop or laptop computer (not suitable for tablets or mobile phones).
- You will receive $4.50 for approved completion of this study.
- You can exit the study at any time. If you choose not to finish or exceed the maximum time limit (3 hours), you will forfeit your pay.

IMPORTANT:
- Be sure to fully complete the study and note the completion code at the very end. Both steps are necessary to approve your HIT completion and guarantee your payment.
- Make sure you accept the HIT on MTurk before beginning the study, otherwise you might finish the study with all HITs already completed and closed.
- Read all instructions carefully! Simple attention checks will be included throughout the study to ensure your understanding (see below).
- The researchers conducting this study reserve the right to reject your completion, if you do not answer **ALL** attention checks correctly.

Please enter your response below! To avoid rejection of my completion of the study, I have to answer all attention checks correctly. [response format: word with three letters]

The participant next saw a page consisting of the task—be it identifying exaptation (described in B.2), search triggers (B.3), or measuring hack novelty (B.4). They repeated the same task across 20 randomly selected hacks in our data.

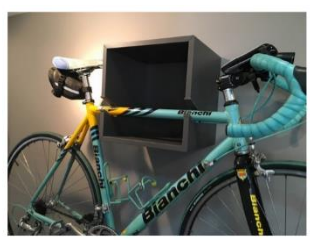
Participants ended the survey with an attention check (see example below). Response choices (yes or no) are shaded in gray. The few responses that failed this simple attention check were excluded in our analyses. All participants, regardless of whether they correctly answered this question, were paid USD $4.50 for tasks B.2 / B.3, and USD $2.50 for task B.4.

> Please answer the question correctly: is 2 more than 8? Yes / **No**

B.2 Survey instructions for measuring exaptation

The text box below details the survey instructions presented to MTurkers for measuring exaptation. Response choices (yes or no) are shaded in gray. A sample response for this hack was presented in bold. We collected 9,942 valid responses for this task.[1]

1. Please take a minute to review this hack [link to hack].
2. For your reference, we identified the VALJE wall cabinet as one of the original IKEA products used in the hack. We include a picture of it on the left below. We also include the first image of the hack on the right below.



Did the hack change the original intended use of the main IKEA product? (i.e., a wall shelf becomes a table, a product becomes a dual-purpose product, or a kitchen countertop becomes a tabletop in the home office).

Yes / No

[1] Note that the number of valid responses is not exactly divisible by 20, because our initial survey included randomization and posts that were eventually excluded for reasons listed in Section 3 of the paper.

B.3 Survey instructions to identify search triggers

The text box below presents the survey instructions presented to MTurkers for identifying search triggers. Response choices (yes or no) are shaded in gray. A sample response for the hack shown in Appendix A is presented in bold. We collected 11,009 valid responses for this task.

1. Please take a minute to review this hack [link to hack].
2. Did the hacker mention a specific problem (e.g. space or budget problems) faced as the reason for doing the hack?

   Yes / No

3. Did the hacker mention that he or she owned or saw a specific IKEA product (e.g., in the as-is section) and was inspired to hack it?

   Yes / **No**

B.4 Survey instructions to measure hack novelty

The text box below shares the survey instructions presented to MTurkers for measuring a hack's novelty. Response choices (yes or no) are shaded in gray. A sample response for the hack shown in Appendix A is presented in bold. We collected 8,629 ratings for this task.

1. Please take a minute to review this hack [link to hack].
2. Rate the degree to which you think the hack is novel (that is, the degree to which you find the idea rare, ingenious, imaginative, or surprising).

   Low / **Medium** / High

APPENDIX C: DISTRIBUTION OF HACKS

Table A1 reports the distribution of hacks across each broad product category of IKEA products. We also report the average product modularity (as measured by *LogProdModularity*) in each broad category. The list is sorted in order of the product category from the highest average product modularity to the lowest.

Table A1: The number of hacks and the average product modularity (of the hacked product) in each broad category of IKEA products

Category	Number of Hacks	Average Product Modularity
Storage & organization	1106	0.89
Bathroom	100	0.68
Kitchen & appliances	244	0.61
Cookware	107	0.45
Others	158	0.41
Beds & mattresses	130	0.41
Lighting	214	0.26
Furniture	474	0.26
Baby & kids	83	0.23
Home textiles	99	0.08
Laundry & cleaning	73	0.08
Home décor	241	0.08

APPENDIX D: ADDITIONAL ROBUSTNESS MODELS

In this appendix, we show the robustness of our results to alternative model specifications. These include:

1. A logit model with product random effects (RE): Model D1
2. A linear probability model with product RE: Model D2
3. A logit model with hacker RE: Model D3
4. The recursive bivariate probit (RBP) model: Model D4

We present the results of these models in Table A2 below. All our results are robust to these alternative models. These models impose some distributional assumptions to deliver identification. We discuss these models in more detail in sections D.1 and D.2 of this e-companion, and where appropriate, test for the possible violations of the distribution assumptions.

Table A2: Alternative robustness models (N = 3,029 hacks)

Variable	**Model D1** Product random effects	**Model D2** Linear probability mode	**Model D3** Hacker random effects	**Model D4** Recursive bivariate probit
ProductFirst(dm)	-0.58^{***} (0.10)	-0.13^{***} (0.02)	-0.65^{***} (0.11)	-1.65^{***} (0.03)
ProductFirst(dm) × *LogHackExperience(dm)*	0.70^{*} (0.30)	0.16^{*} (0.07)	0.82^{*} (0.36)	0.22^{**} (0.07)
ProductFirst(dm) × *LogProdModularity(dm)*	0.27^{*} (0.12)	0.05^{+} (0.03)	0.25^{+} (0.14)	0.10^{*} (0.05)
Control variables				
LogHackExperience(dm)	–0.07 (0.15)	–0.02 (0.03)	–0.16 (0.19)	–0.03 (0.09)
LogProdModularity(dm)	0.00 (0.10)	0.01 (0.02)	0.04 (0.08)	0.00 (0.05)
LogProdPrice	–0.07 (0.11)	–0.03 (0.02)	-0.15^{+} (0.09)	-0.12^{*} (0.05)
LogProdUserBase	–0.06 (0.05)	–0.01 (0.01)	-0.07^{+} (0.04)	–0.01 (0.02)
LogProdWeight	–0.08 (0.09)	–0.01 (0.02)	–0.05 (0.08)	0.05 (0.03)
Year FE	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes
Product-random effects	Yes	Yes	No	No
Hacker-random effects	No	No	Yes	No
Log-likelihood	–1946.5	—	–1962.1	–3958.6
R^2	—	0.085	—	—

Notes: Standard errors (in parentheses) are clustered by product category. FE = fixed effects, *(dm)* = de-meaned.
We note that coefficient interpretations for logit (D1 and D3), linear (D2), and probit (D4) are different. The linear coefficient captures the effect of a unit change in the regressor on the probability of exaptation. The coefficient of a logit (alternatively, probit) model captures the effect of a unit change in the regressor on the log-odds (alternatively, z-score) of exaptation.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

D.1 Product and Hacker Random Effects

In Models D1 and D2, we attempt to capture possible unobserved heterogeneity at the product level by controlling for finer product-level effects. Given that we have a large number (574) of distinct products in our data, we use RE as opposed to fixed effects (FE). The RE model is more statistically efficient (that is, lower variance), at the cost of assuming that the individual product-level effects are normally distributed. To ensure that such distributional assumptions are not driving our results, we first compared the outputs of the RE model in Model D1 against the more flexible FE model based on the Hausman test (see Wooldridge 2010). The test indicates no statistically meaningful difference between the two models: $\chi^2(17) = 21.8$ ($p > 0.10$).

Second, we repeated the analysis with product random effects in Model D2, but with a linear probability model estimated with ordinary least squares (OLS). Such a model estimates the effects of regressors directly on the probability of exaptation (as opposed to log-odds of exaptation in a logit model). Again, we return robust results. A Hausman test showed that the estimates from an OLS with product-level RE was not statistically different from estimates obtained with OLS but with product-level FE: $\chi^2(17) = 24.4$ ($p > 0.10$).

We can also model possible unobserved heterogeneity at the hacker level by controlling for finer hacker-level effects. We do so in Model D3. All our results remain robust to this alternative as well. However, we note that we do not have enough repeated observations at the hacker level to run the more stringent hacker fixed-effects model (required to execute the Hausman test to compare models), because a large portion of our data would need to be dropped to incorporate hacker fixed effects.

D.2 Recursive Bivariate Probit

In Model D4, we implement a recursive bivariate probit (RBP) model (Greene and Hensher 2010). This model is useful when one wishes to account for the possible endogenous choice of a hacker engaging in product-first (versus a problem-first) hack. The RBP model is tailored to the situation when both the key independent variable (*ProductFirst*) and dependent variable (*Exaptation*) are binary. The specification is:

$$ProductFirst^{*} = \boldsymbol{\beta_1 X} + u_p \quad (1)$$

$$Exaptation^{*} = \alpha_0\ ProductFirst + \alpha_1\ ProductFirst \times X_1 + \alpha_2\ ProductFirst \times X_2 + \boldsymbol{\beta_2}\ \boldsymbol{X} + u_e \quad (2)$$

$$ProductFirst = \{1 \text{ if } ProductFirst^{*} > 0,\ \ 0 \text{ otherwise}\} \quad (3)$$

$$Exaptation = \{1 \text{ if } Exaptation^{*} > 0,\ \ 0 \text{ otherwise}\} \quad (4)$$

In this model, both $ProductFirst^{*}$ and $Exaptation^{*}$ are latent (continuous) variables. Equation 1 represents a model of the latent propensity (measured as z-scores) of a hacker engaging in a product-first hack. Equation 2 represents an equation predicting the latent propensity of exaptation (measured as z-scores). We only observe the binary outcomes *ProductFirst* and *Exaptation* (when the latent variables exceed a threshold, as in Equations 3 and 4). $\boldsymbol{X}$ is the set of all control variables (including product category and year dummies). X_1 and X_2 are the first two elements of $\boldsymbol{X}$: X_1 = *LogHackExperience* and X_2 = *LogProdModularity*. Therefore, *ProductFirst* × X_1 and *ProductFirst* × X_2 represent the two moderation effects in which we are interested.

The model assumes that the latent errors $\{u_p, u_e\}$ jointly come from a bivariate normal distribution. These two error terms may be correlated, therefore allowing us to account explicitly for possible endogeneity due to correlation of our variable of interest (*ProductFirst*) and u_e (the error term of the equation with *Exaptation** as dependent variable). Such models can deliver identification without instruments (Wilde 2000). Like other instrument-free approaches (see e.g., Park and Gupta 2012), however, they impose distributional assumptions and require those assumptions to hold. All our insights are robust to this analysis as well.

REFERENCES

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