

To: U.S. President
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RE: Consumer Spending Shifts Following Life Events—Implications for Targeted Support Programs

Executive Summary

Our project investigates whether major life events, such as having a child, moving, or losing a job, affect customers' purchasing behaviors on Amazon. Our analysis indicates that among the five events examined, job loss has a statistically significant effect, and divorce shows a marginally significant effect, with both events associated with increases in individuals' total spending on the platform. This rise in spending may reflect a channel preference shift toward Amazon's wider range of lower-cost substitutes when individuals face financial constraints, or it may signal increased reliance on online shopping as a coping mechanism during periods of stress. In summary, while the overall explanatory power of life events is limited, our results suggest that some life events may shape consumers' shopping habits and decision-making after controlling for individual and year fixed-effects.

Background & Methodology

Previous research has demonstrated that contextual factors play a key role in shaping shopping behavior. For example, major disruptions such as the COVID-19 pandemic shifted many consumers' purchasing choices and channel preferences toward online platforms due to heightened safety concerns and restrictions in the physical retail environment (Gigliotti & Rizzi, 2023). Building on this literature, our project examines how different types of life events influence consumers' purchase behavior over time. We use the dataset from Berke et al. (2023), which contains a record of 13,677 Amazon users, including demographic information and purchase records from 2018 to 2023. The dataset includes two subsets: a survey dataset capturing demographics (household size, ethnicity, gender, income, location) and indicators of whether respondents experienced specific life events in 2021; and a purchase dataset containing transaction-level data such as order ID, purchase price, and purchase quantity.

To analyze this relationship, we merged the two subsets using Response ID and constructed a total spending variable ($\text{unit price} \times \text{quantity}$) as our outcome measure. We then used the natural logarithm of this total spending as the outcome variable in our regression model. Since the dataset spans five years but records life events only for 2021, we restricted our measurement of time frame to three years, specifically from 2020 to 2022, to capture one year before and one year after the event. This allows us to better observe within-person changes in spending around the timing of the life event. We re-coded the original

life changes variable into 5 binary variables, each representing the experience of the following events: job loss, divorce, moving, pregnancy, and having a child. Since the survey only reports whether an event occurred during 2021, we re-coded the data to introduce approximated year-to-year variation. For events that are temporary (e.g., job loss, moving), we reset the indicator to 0 in 2022. For events that are irreversible or longer-lasting (e.g., divorce, pregnancy, having a child), the indicator remains 1 in subsequent years. Using this prepared panel data, we estimated a two-way fixed-effects model in R, controlling for both individual and year fixed effects, to isolate within-person changes in spending associated with each type of life event. We then clustered the standard errors at the state level to account for potential geographic correlations in consumer behavior and ensure more robust inference.

Key Findings

The results of our analysis indicate that major life events can alter consumers' purchasing behavior, but only some of them can have a meaningful impact.

Within all these five major life events, the coefficient on job loss is positive and statistically significant, indicating that individuals increase their Amazon spending by roughly 12% in the year they lose their job ($p < 0.05$). This finding suggests that the increase in online shopping may reflect a substitution towards lower-cost online retailers. After losing their jobs, displaced employees face financial pressure and look for cheaper options. In that way, Amazon provides a platform for a wide variety of products at lower prices, making it ideal for displaced employees to fulfill their basic life needs.

What's more, the model also indicates that divorce is associated with an increase in Amazon total spending, with individuals spending an estimated 23% more in the year of the event. This effect is almost statistically significant ($p \approx 0.06$), which suggests mixed effects on spending behaviors. For example, after a divorce, individuals may face a period of household reconfiguration, such as purchasing or replacing furniture, which increases the frequency of purchasing online. Also, they may overcome the sorrow of divorce through shopping online to redirect attention away from the event.

Other life events, including moving, pregnancy, and having a child, do not show robust within-person changes in spending. Possible explanations include the fact that many products associated with these life events are more commonly purchased offline than online. For individuals preparing for a child, baby products become a purchase priority. Yet, these items only account for 3% of our dataset, indicating that physical inspection and safety assurance requirements likely lead consumers to purchase them offline. Therefore, their total spending on Amazon won't be affected much in the year those events occur.

The high overall R^2 (0.87) indicates that the model explains a large share of total variation in online shopping, largely driven by strong common time trends. In particular, the 2020–2021 period coincides

with major COVID-19 disruptions that increased online shopping across consumers. These pandemic-related shifts are absorbed by the year fixed effects, which account for macro-level changes. By contrast, the within R² (0.002) is very low, indicating that the life-event variables explain only a small share of the variation within individuals over time. This pattern is expected: large macro shocks, such as COVID, drive year-to-year changes in online spending, while individual life events contribute modest explanatory power.

A key limitation of our analysis is that life events are only recorded for 2021, requiring us to approximate year-to-year variation when constructing the panel. As a result, events that occurred in 2022, for example, may not be captured, introducing potential measurement error in the treatment indicators. Therefore, the estimated coefficients are likely attenuated, and the true effects are probably larger than those observed.

Recommendation

Since life events explain only a small proportion of within-person spending variation, policies that are promoted should not directly regulate consumer behaviors. Instead, some low-cost interventions, such as short-term essential goods support, financial counseling, and mindfulness training, can help those people navigate the challenges throughout the events. As job loss is the only event that consistently and significantly impacts individuals' overall spending on Amazon, one specific proposal would be to provide coupons or vouchers for their online shopping or to directly support them with monthly essential goods, which can help reduce their financial burden and pressure posed by job loss.

Conclusion

By examining Amazon purchase records from 2019 to 2021, we find that external life events can significantly impact individuals' spending on the platform. In particular, disruptive events, such as job loss and divorce, are associated with noticeable increases in Amazon purchases, demonstrating how financial pressure and emotional stress can impact consumers' decision-making and purchasing behaviors. Those findings shed light on how policymakers should support individuals affected by major life events. Policy interventions, ranging from financial counseling to targeted for essential goods, are essential to help individuals navigate the challenges posed by major disruptions.

References

- Berke, A., Calacci, D., Mahari, R., Yabe, T., Larson, K., & Pentland, S. (2023). *Open e-commerce 1.0: Five years of crowdsourced U.S. Amazon purchase histories with user demographics* (Version V1) [Data set]. Harvard Dataverse. <https://doi.org/10.7910/DVN/YGLYDY>
- Gigliotti, M., & Rizzi, F. (2023). *Resilient shopping behaviours by change, not by chance: Are disruptive events' effects permanent?* *Journal of Retailing and Consumer Services*, 74, 103391. <https://doi.org/10.1016/j.jretconser.2023.103391>

Technical Appendix

Table 1: Descriptive Statistics for Numerical Variables

Variable	n	Missing %	Mean	SD
Total Spend	13,677	0.0%	2,248.7	2,635.7
Log Spend	13,677	0.0%	7.1	1.3
Income	13,491	1.4%	76,584.4	45,793.3

Table 2: Descriptive Statistics for Categorical Variables

Variable	Category	Count	Percent
Order.Year	2020	4,559	33.3%
Order.Year	2021	4,559	33.3%
Order.Year	2022	4,559	33.3%
Order.Year	Missing	0	0.0%
Gender	Female	7,158	52.3%
Gender	Male	6,183	45.2%
Gender	Other	312	2.3%
Gender	Prefer not to say	24	0.2%
Gender	Missing	0	0.0%
Household	1	3,246	23.7%
Household	2	4,398	32.2%
Household	3	2,658	19.4%
Household	4+	3,375	24.7%
Household	Missing	0	0.0%
LifeChange_LostJob	0	13,149	96.1%

LifeChange_LostJob	1	528	3.9%
LifeChange_LostJob	Missing	0	0.0%
LifeChange_Divorce	0	13,559	99.1%
LifeChange_Divorce	1	118	0.9%
LifeChange_Divorce	Missing	0	0.0%
LifeChange_Moved	0	12,713	93.0%
LifeChange_Moved	1	964	7.0%
LifeChange_Moved	Missing	0	0.0%
LifeChange_Pregnant	0	13,407	98.0%
LifeChange_Pregnant	1	270	2.0%
LifeChange_Pregnant	Missing	0	0.0%
LifeChange_HadChild	0	13,381	97.8%
LifeChange_HadChild	1	296	2.2%
LifeChange_HadChild	Missing	0	0.0%

Table 3: Fixed Effect Model Result

	<i>Model 1: Fixed Effects</i>	<i>Model 2: Clustered SEs (State)</i>
<i>Lost Job</i>	0.116*** (0.039)	0.116*** (0.039)
<i>Divorce</i>	0.204* (0.110)	0.204* (0.108)
<i>Moved</i>	0.028 (0.031)	0.028 (0.022)
<i>Pregnant</i>	-0.050 (0.079)	-0.050 (0.091)
<i>Had Child</i>	0.100 (0.076)	0.100 (0.068)
<i>Num.Obs.</i>	13677	13677
<i>R2</i>	0.812	0.812
<i>R2 Adj.</i>	0.719	0.719
<i>R2 Within</i>	0.002	0.002
<i>R2 Within Adj.</i>	0.001	0.001
<i>Std.Errors</i>	<i>IID</i>	<i>by: State</i>
<i>FE: Survey.ResponseID</i>	<i>X</i>	<i>X</i>
<i>FE: Order.Year</i>	<i>X</i>	<i>X</i>

$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses.

Coefficients reported as changes in log spending.

Model 1: Fixed effects with Survey.ResponseID and Order.Year

Model 2: Fixed effects with Survey.ResponseID and Order.Year; Standard errors clustered at the State level