Can occupational time pressure explain processed food reliance and perceived health among households?

April 11, 2025

Abstract

This study uses nationally representative data from the 2016 FoodAPS and MEPS files to investigate whether occupational time constraints impact processed food consumption and self-rated health. A standardized household stress index is constructed from perceived barriers to healthy eating, and logistic regressions examine the relationships between stress, employment, and demographic factors on food behavior. A one standard deviation increase in stress is associated with a 1.7 percentage point rise in the likelihood of relying on a processed-heavy diet. Regionally, stress and processed food share are positively correlated with average hours worked. Time-intensive occupations are associated with modestly lower self-rated health. Though the models explain only a small share of dietary variation, findings suggest that occupational time pressure may reduce household time budgets, raise reliance on convenience foods, and thereby serve as a structural channel for economic inequality to manifest in health inequality.

Context

Occupations that demand long working hours often leave individuals with insufficient time and mental capacity for meal preparation, constraining their ability to maintain a healthy diet and nudging them towards processed foods. Though convenient, these foods are typically high in added sugars, saturated fats, sodium, and are linked to adverse health outcomes.

This study examines whether longer work hours predict greater household reliance on processed foods. Drawing on data from the U.S. Food Acquisition and Purchase Survey (FoodAPS) and the Medical Expenditure Panel Survey (MEPS), it explores how time constraints shape dietary behavior and health perceptions. The analysis integrates household-level FoodAPS data on nutrient intake, food security, employment, and perceived barriers to healthy eating with individual-level MEPS data on occupation and health. Time pressure is measured through both objective (e.g., hours worked, occupation type) and subjective indicators (e.g., time and financial barriers), enabling a multidimensional analysis of how time scarcity may drive nutritional and health disparities.

Relevant literature links time constraints to lower dietary quality. Huffman et al. (2016) find that time-constrained parents are more likely to rely on ready-to-eat meals. Micha et al. (2017) and Monteiro et al. (2019) link ultra-processed foods to chronic disease. Rogus and Dimitropoulos (2018) show that perceived time stress, not hours worked, is more strongly associated with unhealthy eating—particularly among higher-income households. Caraher and Lang (2013) note increased food purchases outside the home among time-poor women, while Kim et al. (2019) report that working over 55 hours a week heightens the likelihood of unhealthy eating. Together, these findings underscore that both actual and perceived time scarcity limit the dietary choice set available to working households.

Methodology

The empirical strategy is grounded in a household utility maximization framework, where families allocate limited time and income between food consumption and other tasks.

Health depends on diet, as represented by $H = h(F, P)$ where $\frac{\partial h}{\partial F} > 0$ and $\frac{\partial h}{\partial P} < 0$.

Households maximize utility $U(F, P, H)$ subject to:

$$p_F F + p_P P \leq I$$
$$t_F F + t_P P + t_O \leq T$$

F and P denote fresh and processed food consumption, I is income, T is total time, and t_O captures occupational time demands. As t_O rises or T falls, households substitute towards P, trading off long-run health for temporal efficiency.

FoodAPS contained detailed household-level data on food acquisitions, nutrient content, food security, and perceived barriers to healthy eating. After filtering, 24 nutrient variables were retained but not directly modeled due to high missingness (up to 85%) and challenges in defining dietary quality thresholds.

Food items were categorized into two primary groups: `Fresh` (e.g., fruits, vegetables, fresh meats, dairy) or `Processed` (e.g., sugary snacks, ready-to-eat meals). Ambiguous items were conservatively coded as `Fresh`. From this, a measure of processed food reliance (`processed_prop`) was computed; households exceeding 50% were flagged as `high_processed`.

A standardized stress index (`stress_index_standardized`) was built from four components: perceived time barriers (`perceived_healthy_time`), cost barriers (`perceived_healthy_cost`), food insecurity (`hh_food_secure`), and recent financial shocks (`large_expenditure_shock`). Covariates included household size (`hh_size`), Census region (`region`), and garden ownership (`garden_ownership`), proxying for access to fresh food.

Three logistic regression models were estimated:

Baseline Specification

$$\begin{aligned}\text{logit}\left(\Pr(\text{high\_processed}_i = 1)\right) = \beta_0 &+ \beta_1 \cdot \text{stress\_index}_i + \beta_2 \cdot \text{hh\_size}_i \\ &+ \beta_3 \cdot \text{region}_i + \beta_4 \cdot \text{garden\_ownership}_i + \varepsilon_i\end{aligned}$$

Interaction Specification

$$\begin{aligned}\text{logit}\left(\Pr(\text{high\_processed}_i = 1)\right) = \beta_0 &+ \beta_1 \cdot \text{stress\_index}_i + \sum_k \beta_{2k} \cdot \text{hh\_size}_{ik} \\ &+ \sum_k \beta_{3k} \cdot (\text{stress\_index}_i \cdot \text{hh\_size}_{ik}) \\ &+ \beta_4 \cdot \text{region}_i + \beta_5 \cdot \text{garden\_ownership}_i + \varepsilon_i\end{aligned}$$

Decomposed Specification

$$\begin{aligned}\text{logit}\left(\Pr(\text{high\_processed}_i = 1)\right) = \beta_0 &+ \beta_1 \cdot \text{perceived\_healthy\_cost}_i + \beta_2 \cdot \text{perceived\_healthy\_time}_i \\ &+ \beta_3 \cdot \text{large\_expenditure\_shock}_i + \beta_4 \cdot \text{hh\_size}_i \\ &+ \beta_5 \cdot \text{region}_i + \beta_6 \cdot \text{garden\_ownership}_i + \varepsilon_i\end{aligned}$$

MEPS provided occupational, demographic, and health perception data for employed individuals. Industry and occupation codes were recoded and grouped by time intensity.

A direct merge between FoodAPS and MEPS was not possible due to the lack of common identifiers. However, both datasets shared Census region codes, enabling a cross-dataset comparison via regional aggregation. Four unweighted means were computed across individuals or households: `FAPS_avg_processed`, `FAPS_avg_stress`, `MEPS_avg_health`, and `top_busiest_share`. Correlation analyses between these aggregates examine how structural and perceived time constraints relate to regional variation in diet and health perceptions. Differences in sampling may attenuate observed associations.

Results

Household-level analysis using FoodAPS reveals modest but consistent associations between employment status and diet composition. Figure 1 shows that employed households obtain slightly more of their diet from fresh food sources (33%) than unemployed households (31%), while processed food intake is marginally lower among the employed (54% vs. 55%).

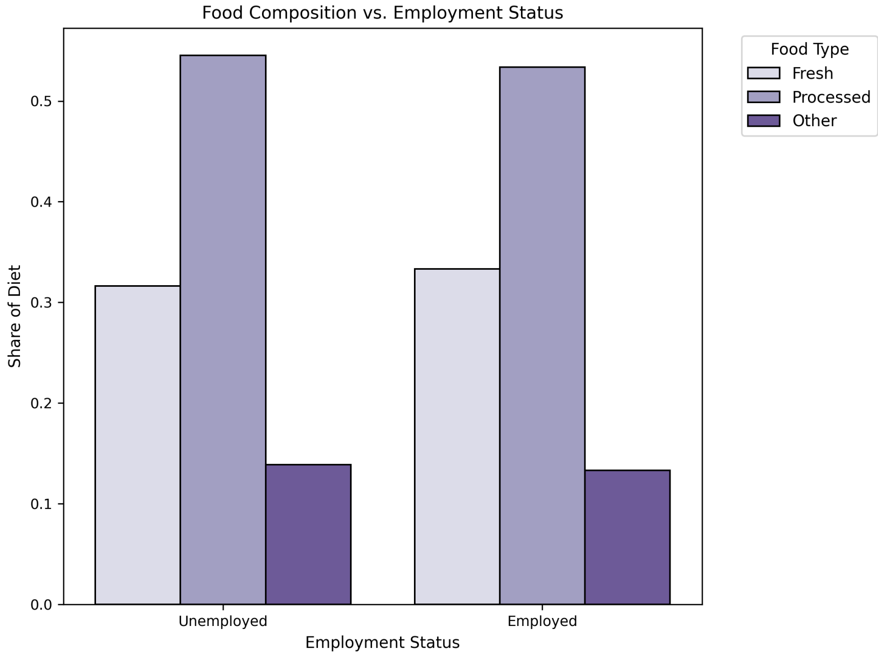
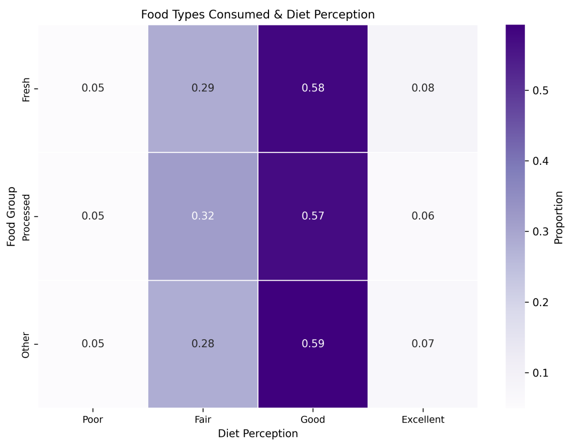


Figure 1: Diet composition among unemployed versus employed households.

Diet quality perceptions also vary by food type and security. Processed food consumers are more likely to rate their diets as "Fair" or "Poor" (37%) than fresh food consumers (34%), while the latter more frequently report "Excellent" diets (8% vs. 6%) (Figure 2a). Surprisingly, food-insecure households are less likely (28%) to rate their diets as "Fair" or "Poor" compared to food-secure households (46%), a 15 p.p. gap driven largely by differences within the "Fair" category (Figure 2b).

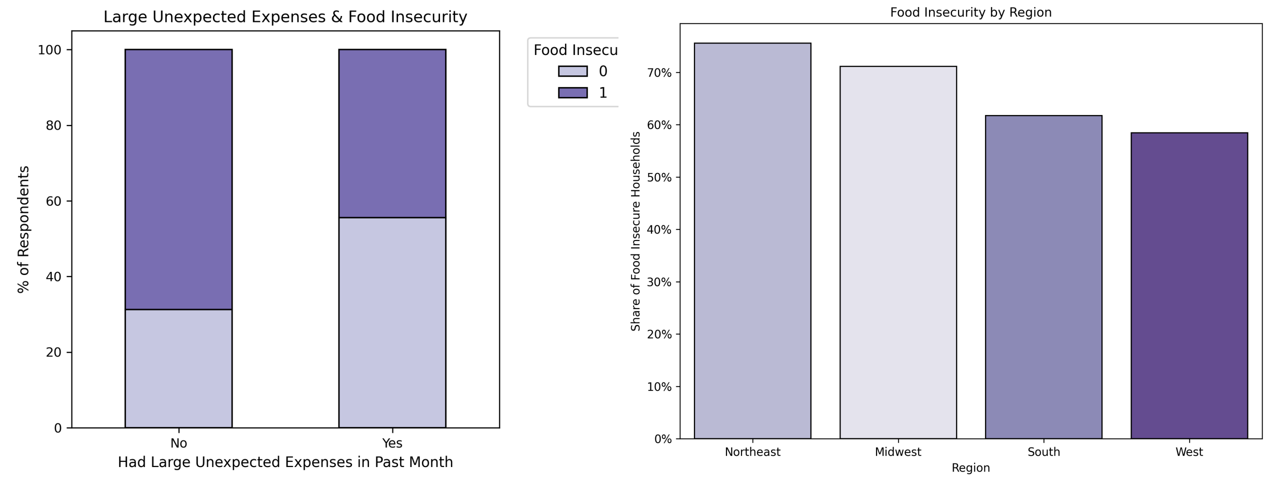


(a) By food group dominance.

(b) By food insecurity status.

Figure 2: Self-rated diet quality.

Acute financial shocks are associated with greater food insecurity: 45% of households that recently incurred large expenses fall below the food security threshold, compared to 30% of those who did not (Figure 3a). Regionally, food insecurity is most prevalent in the Northeast (76%) and least in the West (58%), reflecting plausible variation in living costs or food access (Figure 3b).

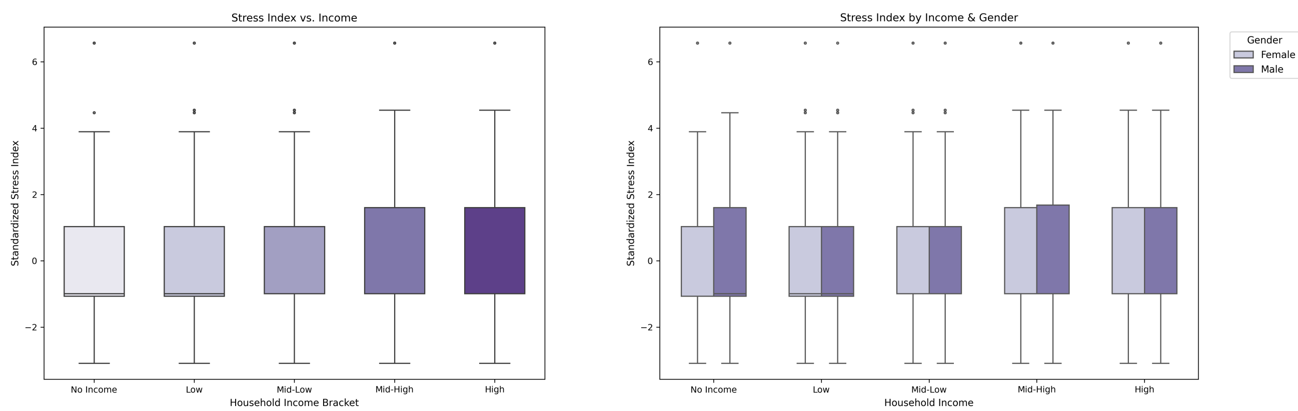


(a) By recent large expenditure.

(b) By Census region.

Figure 3: Food insecurity.

Perceived stress does not vary strongly by income or gender, suggesting that subjective time and financial barriers affect households indiscriminately. Across income brackets, median stress scores remain remarkably stable (Figure 4a). Inter-quartile spreads are mostly comparable across genders (Figure 4b), except that males with no income report slightly higher stress levels than their female counterparts.

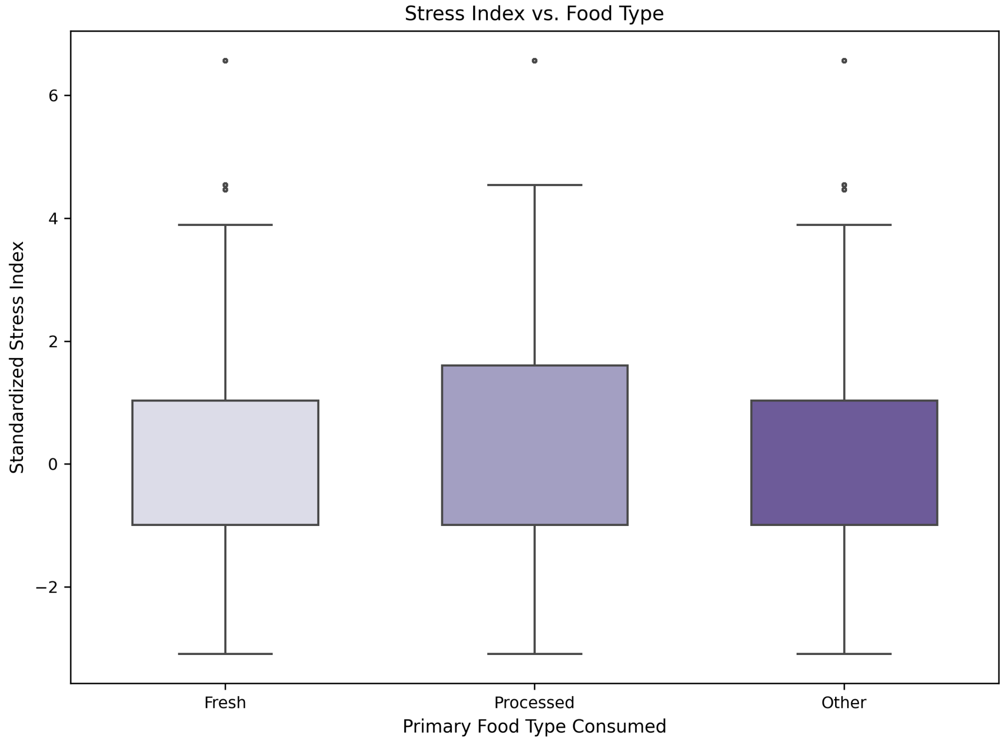


(a) By income level.

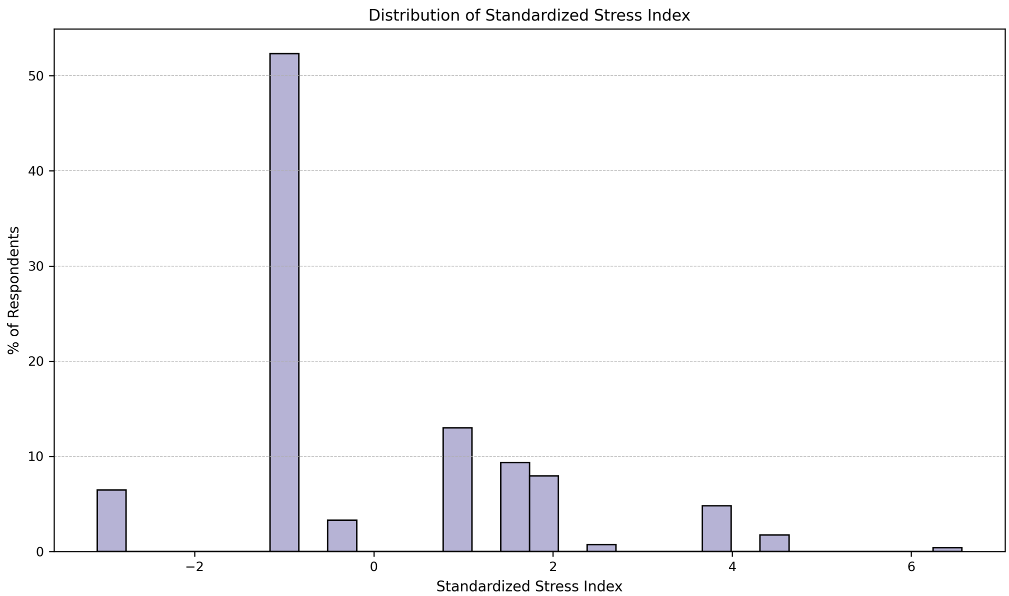
(b) By income and gender.

Figure 4: Standardized household stress index.

Households relying primarily on processed foods report higher and more variable stress levels (Figure 5a). While 52% of all households score below 1 SD on the stress index, only 13% score above it, indicating that a minority of households suffer from acute stress (Figure 5b).



(a) Household stress index scores across dietary composition.



(b) Distribution of standardized household stress index.

Figure 5: Variation in stress index by food type and population-wide distribution.

Table 1: Summary table comparing logit regression models.

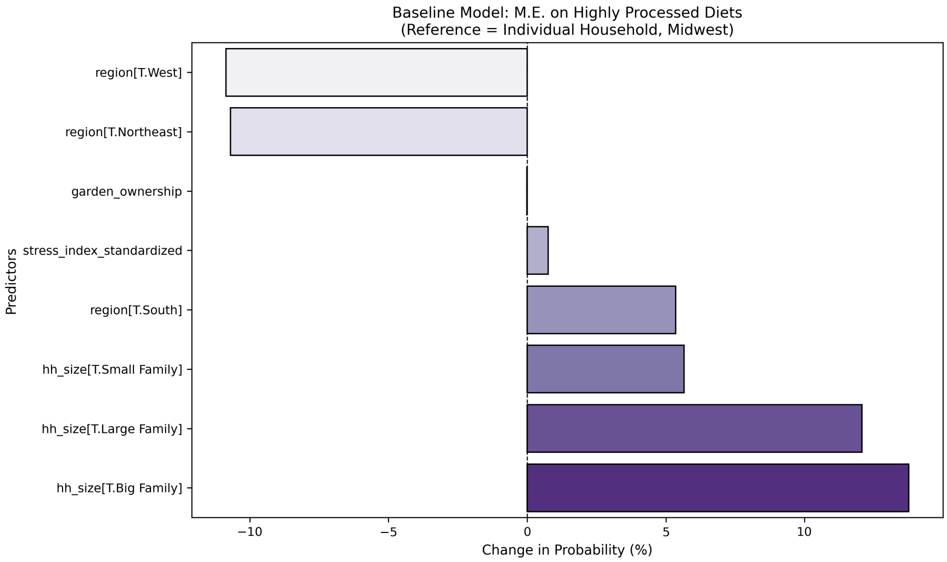
	Baseline	Interaction	Decomposed
Intercept	0.072	0.074	-0.069
	(0.085)	(0.086)	(0.089)
hh_size[T.Small Family]	0.235***	0.233***	0.228***
	(0.079)	(0.079)	(0.080)
hh_size[T.Big Family]	0.573***	0.575***	0.549***
	(0.111)	(0.111)	(0.111)
hh_size[T.Large Family]	0.502***	0.492***	0.468***
	(0.180)	(0.181)	(0.181)
region[T.Northeast]	-0.445***	-0.444***	-0.441***
	(0.097)	(0.097)	(0.097)
region[T.South]	0.223***	0.223***	0.200**
	(0.081)	(0.082)	(0.082)
region[T.West]	-0.452***	-0.451***	-0.474***
	(0.090)	(0.090)	(0.091)
stress_index_standardized	0.032*	0.050	
	(0.017)	(0.041)	
garden_ownership	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
stress_index_standardized:hh_size[T.Small Family]		-0.014	
		(0.046)	
stress_index_standardized:hh_size[T.Big Family]		-0.046	
		(0.060)	
stress_index_standardized:hh_size[T.Large Family]		-0.078	
		(0.099)	
perceived_healthy_cost			0.195***
			(0.064)
perceived_healthy_time			0.227***
			(0.080)
large_expenditure_shock			0.273***
			(0.093)
N	4352	4352	4352
Pseudo R^2	0.021	0.021	0.025

Notes: Coefficients in log-odds units. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

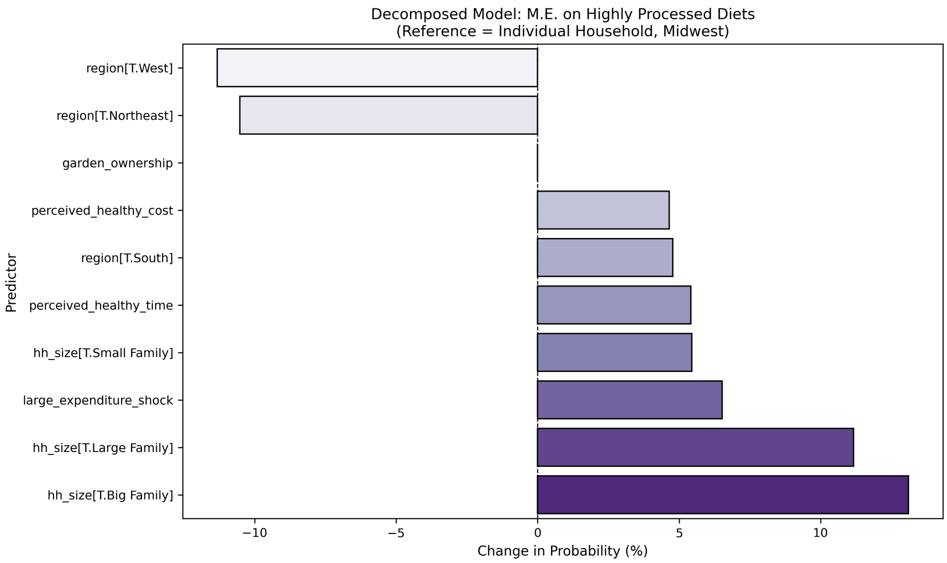
In the baseline model, a 1 SD increase in the stress index raises the likelihood of processed-heavy diets by 1.7 p.p. (Figure 6a). Larger households are significantly more likely to consume processed foods, with marginal effects of 12–13 p.p. Regional variation is also salient: households in the West and Northeast are roughly 10 p.p. less likely to rely on processed food compared to those in the Midwest, whereas the South exhibits the inverse. Garden ownership has no significant effect on dietary composition in any specification.

The interaction model tests whether the effect of stress on processed food reliance is moderated by household size, based on the intuition that larger families face ostensibly greater grocery costs and meal preparation complexity. None of the interaction terms are statistically significant, however, precluding this model from further analysis.

The decomposed model replaces the composite stress index with its individual components; Figure 6b presents the corresponding marginal effects. Experiencing a recent financial shock is the strongest predictor of processed food reliance (7 p.p.), followed by perceived time and cost barriers, which contribute about 5 p.p. each. These estimates are robust across specifications, though the models explain only a modest share of variation in dietary behavior ($R^2 = 0.021$–0.025).



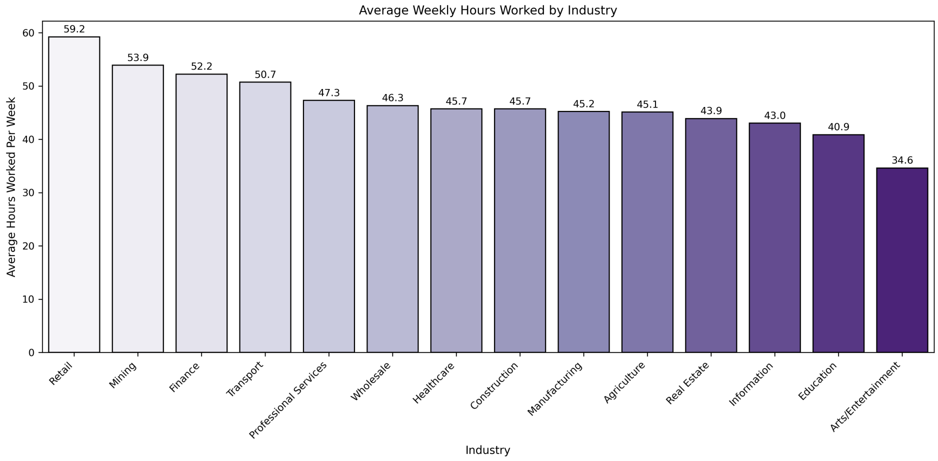
(a) Baseline model.



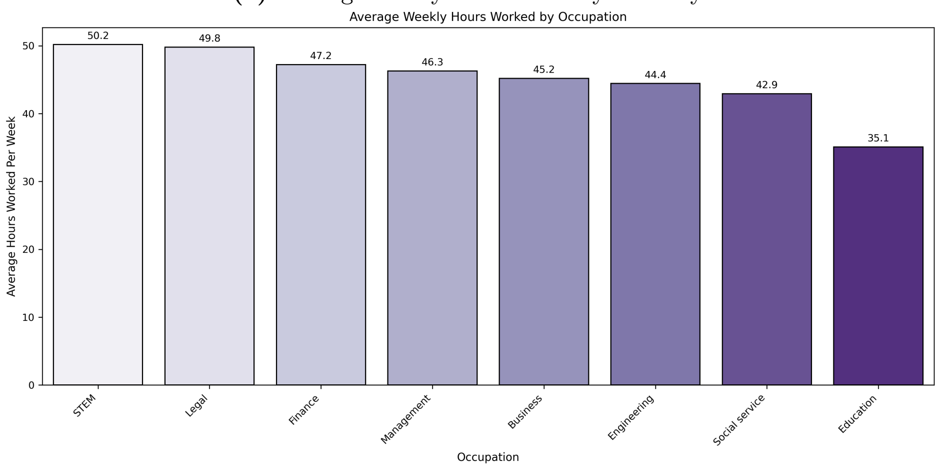
(b) Decomposed stress model.

Figure 6: Marginal effects.

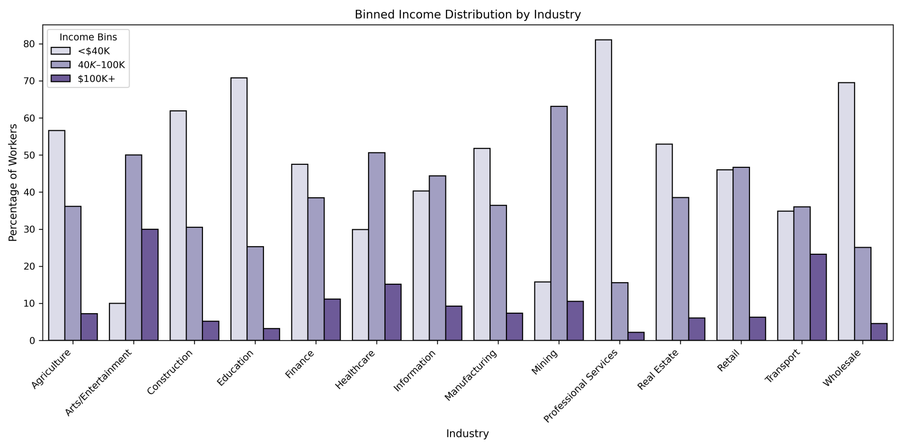
Complementary analysis using MEPS data examines how occupational structure relates to health perceptions. Figures 7a and 7b show that industries such as Retail, Mining, and Finance report average workweeks of up to 59 hours while STEM, Legal, and Finance occupations approach 50. Contrary to expectations, high-hour sectors are not predominantly high-income. In fact, the largest shares of high earners appear to work in the Arts/Entertainment and Transport industries (Figure 7c).



(a) Average weekly work hours by industry.



(b) Average weekly work hours by occupation.



(c) Income distribution within time-intensive industries.

Figure 7: Occupational structure across work hours and income.

However, Figure 8 shows that individuals employed in the most time-intensive occupation–industry combinations (e.g., Legal–Agriculture, Management–Professional Services) report moderate health. Only 10–50% rate their health as "Excellent", with most clustering around "Good" or "Very Good". Results are to be interpreted conservatively due to the small sample sizes.

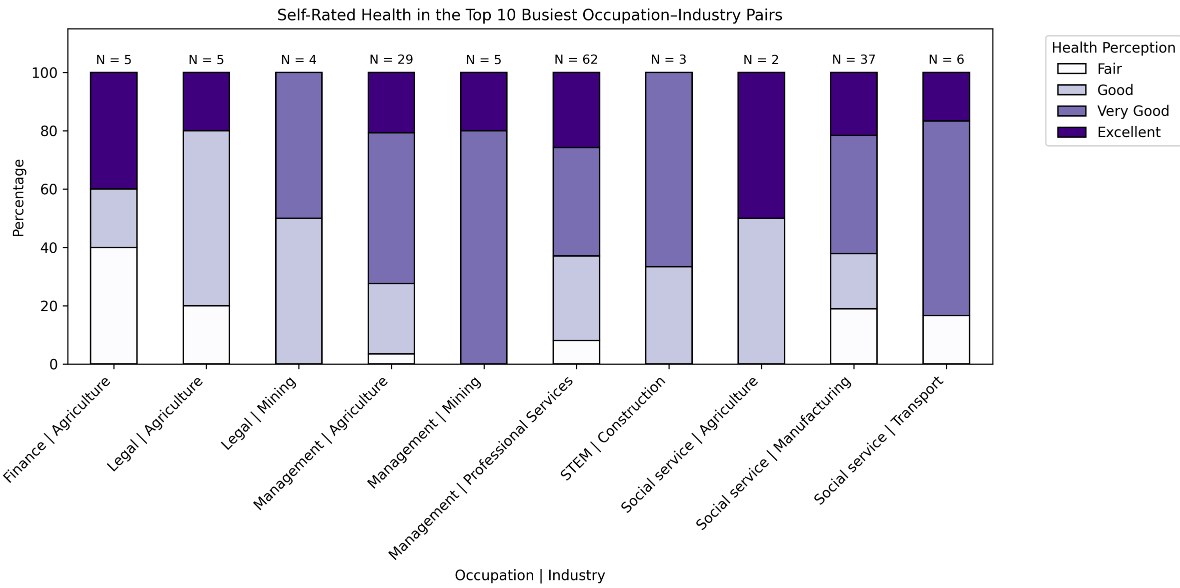
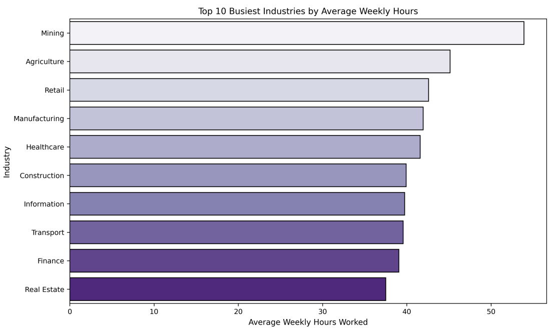
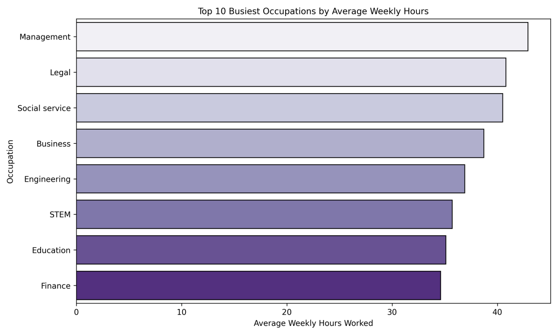


Figure 8: Self-rated health distribution across the ten most time-intensive occupation–industry combinations.

Figure 9a shows that Mining and Agriculture top industry-level hours at 55 and 46, respectively. Industries further down the ranking (e.g., Finance and Real Estate) exceed 38 hours per week—showcasing the above-average workloads within this subset. Figure 9b illustrates that Management and Legal occupations have the longest average workweeks at 44 and 41 hours per week, respectively.



(a) By industry.



(b) By occupation.

Figure 9: Average weekly hours worked across labor market dimensions.

Figure 10 reveals the most time-intensive occupation–industry pairing to be Management in Mining, with an average of 72.6 hours worked per week. Other high-hour combinations include Legal in Mining (53.8 hours) and STEM in Construction (51.7 hours), indicating that extreme time demands are concentrated in specific occupational niches.

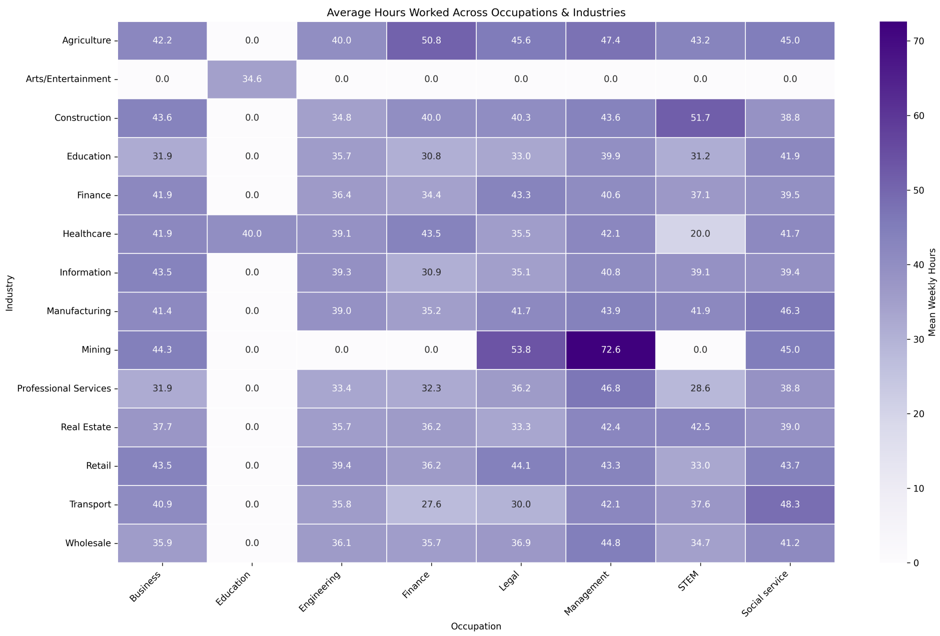


Figure 10: Heatmap of average weekly hours by occupation–industry pair.

Self-employed individuals report higher perceived health than their counterparts; nearly half (49%) rate their health as "Very Good" or "Excellent" (Figure 11). This may be reflective of greater schedule autonomy and flexibility, which can reduce exposure to time stress and allow for healthier food choices.

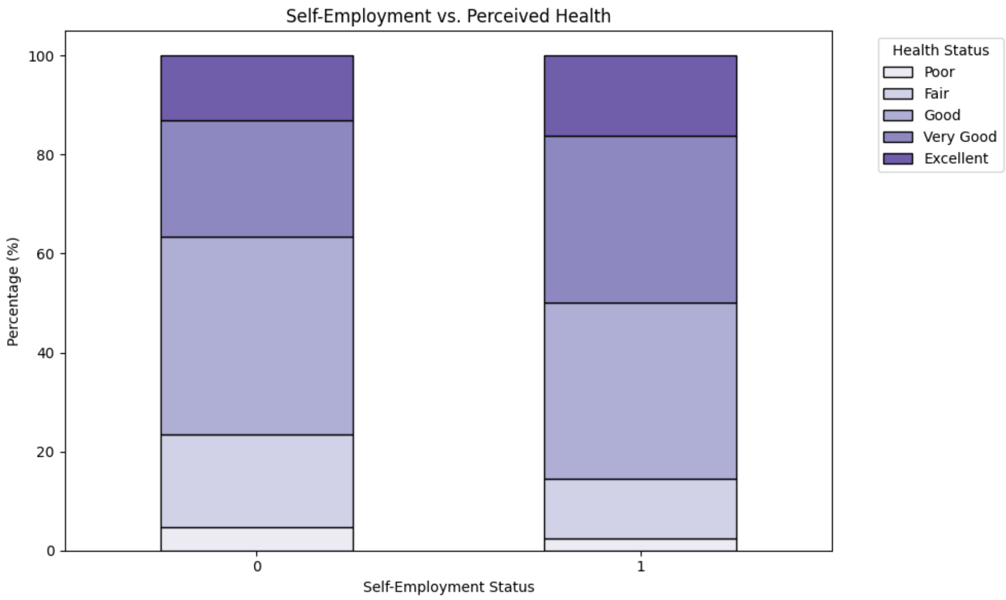


Figure 11: Perceived health by employment status.

Region-level aggregation reveals significant spatial clustering. Per Figure 12, average work hours correlate positively and strongly with health perceptions ($r = 0.98$), time barriers ($r = 0.74$), stress ($r = 0.60$), and processed food reliance ($r = 0.51$). Counterintuitively, processed food reliance is only weakly correlated with health perceptions ($r = 0.34$). Because the composite stress index is a weighted function of its components, presenting both in the same analysis may distort results and warrants cautionary interpretation.

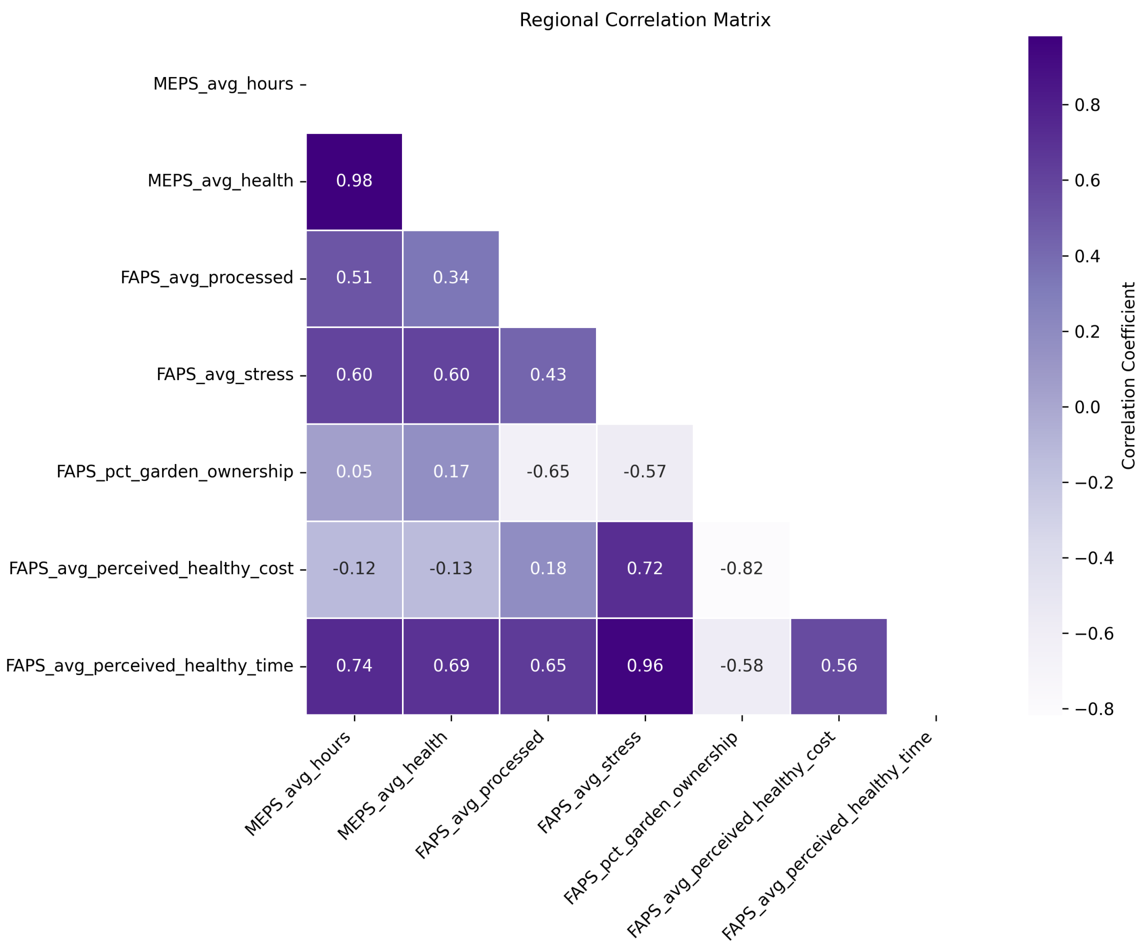


Figure 12: Correlation matrix heatmap.

Figure 13 reveals no obvious correlation between the percentage of processed food comprising a region's diet and its overall health ratings. The South stands out with the highest processed share (0.57), second-lowest health ratings (2.27), as well as elevated stress (0.11) and time barriers (0.21) (Figures 14 and 15). In contrast, the West reports lower processed shares (0.50) and comparatively greater access to fresh food, as proxied by garden ownership (0.24).

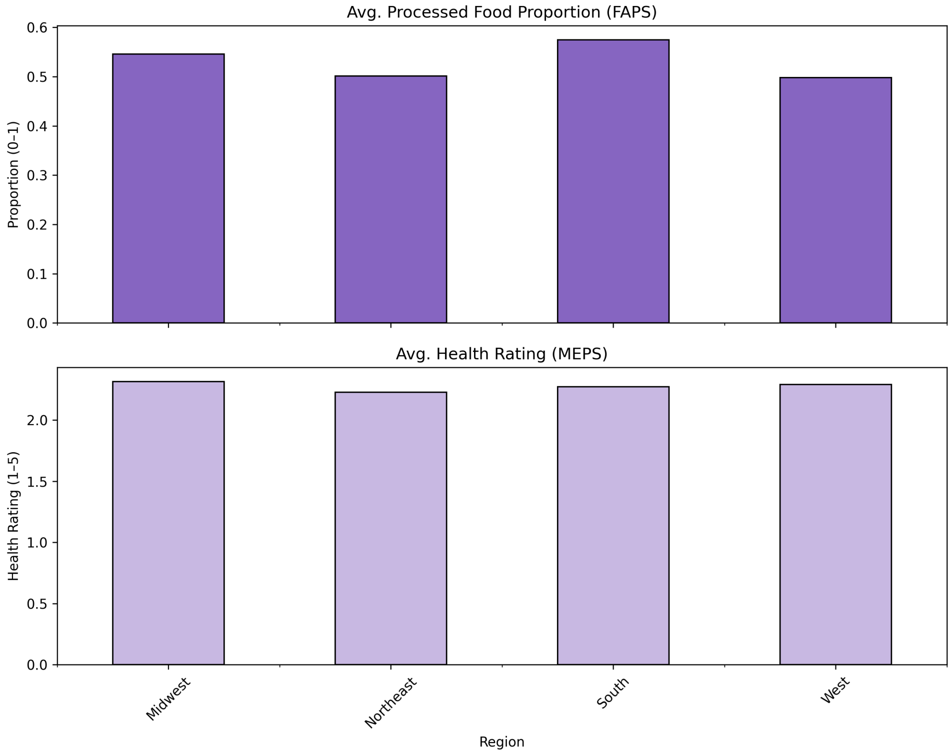


Figure 13: Average health ratings by processed food share across regions.

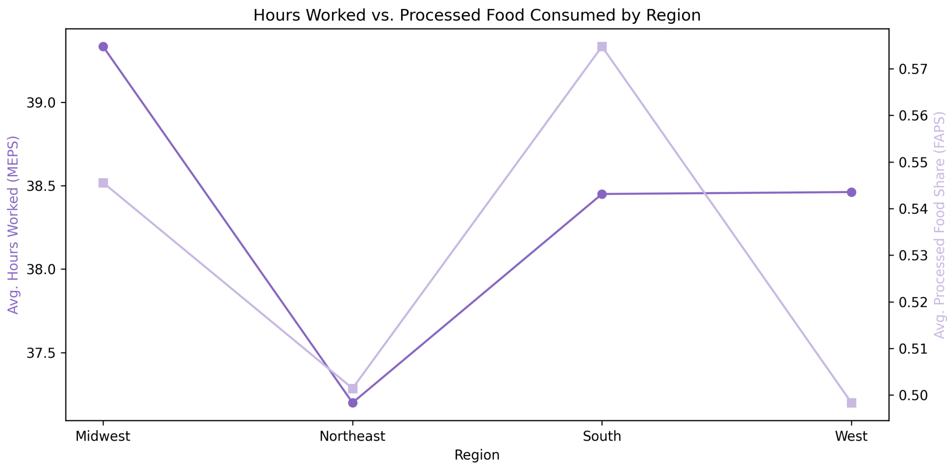


Figure 14: Relationship between average work hours and processed food consumption by region.

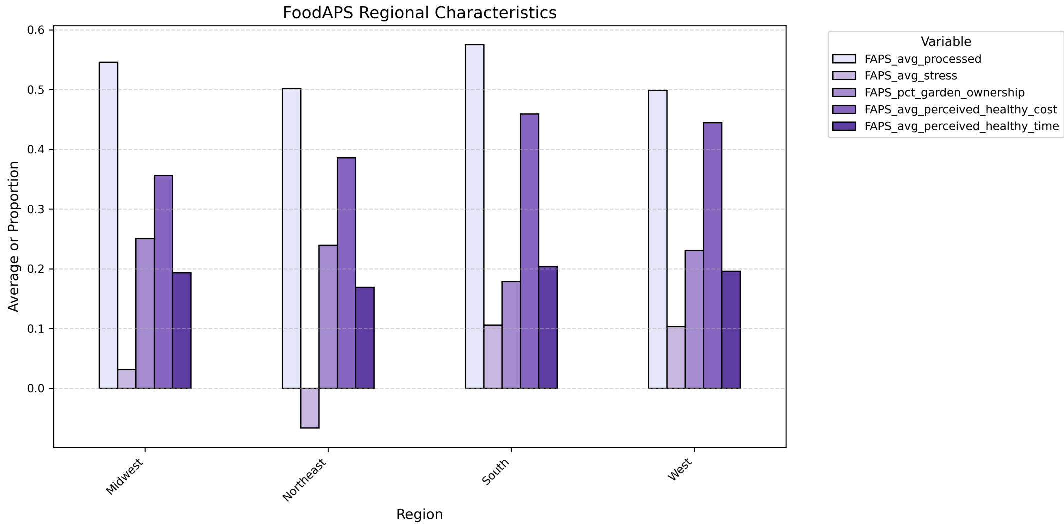


Figure 15: Regional variation in processed food consumption, stress, garden ownership, and perceived barriers to healthy eating.

Figure 16 presents the most comprehensive view of regional variation, overlaying four choropleth maps. The South and parts of the West consistently rank highest in processed food share (0.57), average stress index (0.08), average weekly hours worked (48), and share of workers in top time-intensive occupations (4%). This spatial clustering suggests that occupational time demands and stress jointly shape regional dietary patterns.

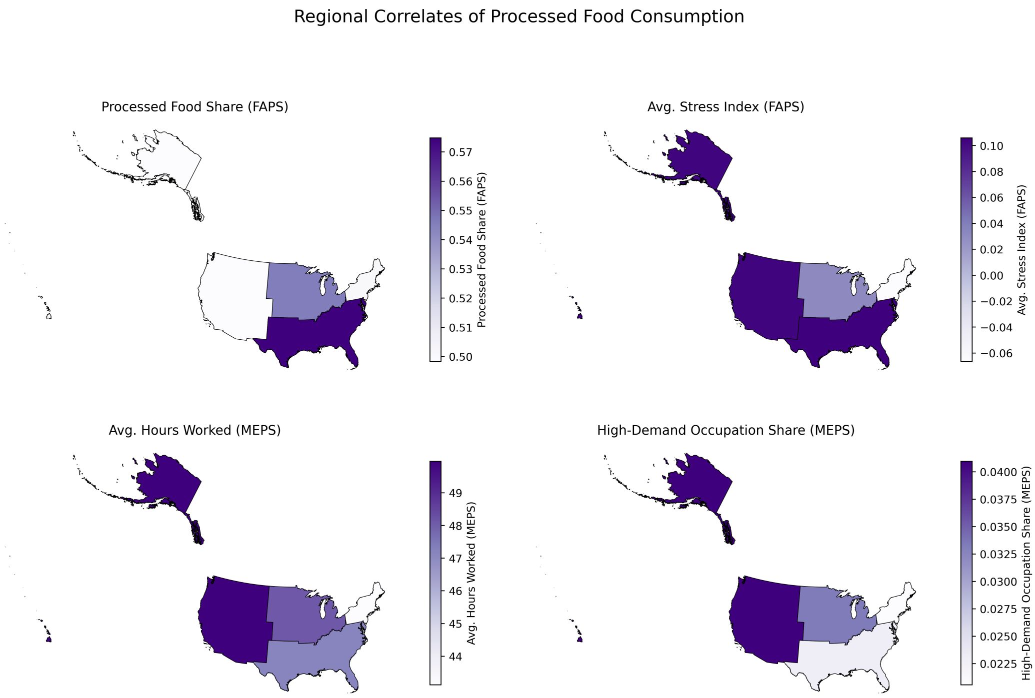


Figure 16: Choropleth maps of regional indicators: (1) processed food share, (2) average stress, (3) hours worked, and (4) top-busiest occupation share.

Results suggest a modest link between time constraints and dietary behavior. Households citing time and financial barriers consume more processed foods, even after controlling for household size and region. At the occupational level, time-intensive careers report marginally worse self-rated health. Regionally, stress and processed food consumption increase with average hours worked. Although the effect sizes are small and the models leave considerable variation unexplained, the cross-level consistency points to a cumulative role of occupational time scarcity—particularly when experienced as stress—in reinforcing health inequalities.

Limitations

This study suffers from several limitations. Most obviously, the analysis is constrained by the inability to merge FoodAPS and MEPS at the respondent level; regional aggregation obscures within-region heterogeneity and true individual-level behavior. The lack of temporal variation and subsequent cross-sectional design inherently precludes causal inference, though associations between time demands, diet, and health appear robust. Next, the possibility of endogeneity cannot be ruled out; time scarcity, stress, and processed food consumption may reinforce each other in a recursive loop. A reliance on processed foods may itself exacerbate stress or health, undermining occupational productivity and further compounding time pressures. Additionally, occupational self-selection may bias results; healthier individuals may sort into more demanding careers, attenuating observed health penalties. Conversely, poor health may constrain available job opportunities, confounding effects. Also, logit regressions assume independence of irrelevant alternatives. Violations—such as collinearity between stress and income—may obscure the genuine effects of occupational time constraints. Finally, the key health outcome—self-rated health—is subjective and may diverge drastically from respondents' observed health in real life.

References

Caraher, M. and Lang, T. (2013). Public health and the food modernities: The role of the state in the food system. *Public Health Nutrition*, 16(12):2260–2265.

Huffman, S. K., Jensen, H. H., and Guthrie, J. F. (2016). Reasons parents buy prepackaged, processed meals: It is more complicated than "i don't have time". *Appetite*, 107:528–537.

Kim, S.-S., Subramanian, S. V., Gortmaker, S. L., and Kawachi, I. (2019). Association between long working hours and diet quality and patterns: Results from the korea national health and nutrition examination survey, 2013–2015. *Journal of Preventive Medicine and Public Health*, 52(6):362–369.

Micha, R., Peñalvo, J. L., Cudhea, F., Imamura, F., Rehm, C. D., and Mozaffarian, D. (2017). Association between dietary factors and mortality from heart disease, stroke, and type 2 diabetes in the united states. *JAMA*, 317(9):912–924.

Monteiro, C. A., Cannon, G., Levy, R. B., Moubarac, J. C., Louzada, M. L. C., Rauber, F., Khandpur, N., Cediel, G., Neri, D., Martinez-Steele, E., Baraldi, L. G., and Jaime, P. C. (2019). Ultra-processed foods: What they are and how to identify them. *Public Health Nutrition*, 22(5):936–941.

Rogus, S. and Dimitropoulos, A. (2018). Examining the influence of perceived and objective time constraints on the food purchases of u.s. households. *Appetite*, 125:556–562.