Direct-to-worker tipping in retail

Abstract: The global garment industry has doubled in size over the past 15 years and is powered by an estimated 60 million workers worldwide (Clean Clothes Campaign 2023). Companies like Inditex, the owner of Zara, rely on over 1,790 factories and more than one million workers, and reported a net income of €5.9 billion in fiscal year 2024 (Inditex Group 2024). Nike's network spans 500 facilities across 40 countries, and the brand earned $5.7 billion in net income in fiscal year 2024 (Nike, Inc. 2024, 2025). Despite the considerable scale and profitability of the brands, workers producing these garments often struggle to meet basic needs. To illustrate just how little money actually reaches the workers, consider that when consumers buy a €29 T-shirt, only €0.18 typically goes to the person who made it (Clean Clothes Campaign 2023).

Strategies such as higher wages and frequent auditing have been touted as potential solutions to this problem, but have provided mixed results. These strategies typically require multiple players in the supply chain to be focused on improving worker outcomes, but contrasting goals for each player make it challenging to align incentives towards a worker-centric goal. More recently, a novel direct-to-worker (DTW) tipping mechanism has been proposed by the non-profit organization *tip me* Global gGmbH (*tip me*) to improve workers' financial outcomes. This consists of a widget on retailers' websites that provides consumers (typically in developed countries) with a direct means, facilitated by the non-profit, to pay tips to the workers (typically in developing countries) who produced the products. Although this approach provides a direct means to improve worker outcomes, its success hinges on retailers' willingness to implement such a system. Motivated by this, we investigate whether such a system can provide financial benefits to retailers, alongside its social impact.

To examine this impact, we adopt a multi-method approach. First, we build an analytical model in which a profit-maximizing retailer chooses whether to adopt a DTW tipping system, and sells a product to a heterogeneous customer base. We model customer heterogeneity in two ways: (1) across their base valuation of the product, and (2) their skepticism towards DTW tipping. We find that there are parametric conditions under which adoption of the DTW tipping system can increase sales and reduce product returns. Next, we utilize point-of-sale data from a retailer that has adopted *tip me's* DTW tipping system to empirically test the findings from our analytical model. Through a variety of econometric analyses, including the use of cutting-edge techniques such as Bayesian structural time-series models (Brodersen et al. (2015)) and generalized propensity score matching (Hirano and Imbens (2004), Guardabascio and Ventura (2014)), we show the following impacts. The introduction of the DTW-tipping system is associated with a 12% increase in weekly sales at the SKU-level. This highlights the revenue boosting impact of DTW tipping. Further, orders that included a tip were approximately 4 percentage points less likely to return products. This points to the cost-savings benefits of DTW tipping. Finally, we run a controlled online experiment to show support for the aforementioned impacts of DTW tipping in a causal sense. This experiment also highlights that the positive impact of a DTW tipping option on purchase intentions is mediated by the strength of the CSR signal that is sent by the adoption of DTW tipping, but this mediating effect is observed only for retailers with a low level of social responsibility. We also see that orders with tips are associated with more positive downstream consequences such as higher levels of warm glow, trust in the retailer, positive word-of-mouth intentions, and perceived product quality.

Our work highlights the effectiveness of a novel system whose primary goal is to improve workers' financial outcomes. Its benefits to retailers is clearly quantified and provides strong support in favor of more widespread adoption of such a system.

References

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