Frictionless Gratitude: The Digitization of Tipping and Its Impact on Social Norms

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Abstract

This paper studies how the digitization of payment changes tipping behavior and the evolution of tipping norms. We begin from Azar (2004) model of tipping as a costly social norm and extend it in two directions. First, we introduce observability into the utility from tipping, allowing visibility-dependent motives such as social image and norm pressure to vary with the payment environment. Second, we extend the model from a continuous tipping choice to a digital choice architecture in which consumers select from a discrete menu of preset tipping options. These extensions help explain why digital tipping may not simply weaken tipping, but may instead affect the extensive and intensive margins differently. Lower observability can reduce the social pressure to tip, while discrete tip menus can eliminate small positive tips that would otherwise be chosen in a continuous setting. As a result, digitization can reduce tipping participation while increasing the average size of tips conditional on tipping. The paper therefore provides a framework for understanding how the move from face-to-face to digital payment environments can reshape tipping behavior and, over time, tipping norms.

Keywords: Tipping; social norms; digital payments; observability; choice architecture; gratuities; restaurant tipping.

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1 Introduction

Tipping is a useful setting for studying costly social norms because consumers voluntarily transfer money after service has already been provided, often with little scope for future strategic interaction. In Azar (2004) framework, if consumers tip only to avoid the disutility of deviating from the prevailing norm, then the norm should erode over time. Yet Azar (2004) also points to historical evidence that tipping percentages increased rather than disappeared, implying that tipping must be sustained by more than conformity alone. More broadly, the tipping literature has emphasized that tipping behavior reflects a combination of norm compliance, reciprocity, altruism, and image concerns rather than a single motive (Azar, 2020).

That starting point remains useful, but it is built around a tipping environment that is implicitly human and face-to-face. The standard restaurant setting is one in which the server is physically present and the customer leaves cash or writes a tip on the receipt. That environment is increasingly incomplete. The shift from paper-based payment toward cards, mobile devices, and digital interfaces had already been underway, and it accelerated during and after Covid as restaurant transactions moved toward carryout, delivery, contactless checkout, app-based ordering, and QR-enabled interactions (Foster et al., 2025; Marchesi and McLaughlin, 2023). Once payment becomes digitized in this way, tipping is no longer made under the same social conditions as in the standard face-to-face setting.

This matters because digitization changes how visible the tipping decision is. In the traditional setting, the tip is embedded in a face-to-face interaction and can generate embarrassment, approval, disapproval, or reputational payoff. In a digital setting, by contrast, the same decision may be less directly observed and less socially immediate. But digital tipping does not eliminate tipping altogether. Chandar et al. (2019) show that tipping persists even in app-mediated environments, which suggests that some motives survive anonymity while others are likely to weaken. This motivates our first extension of the standard model: we introduce observability into the utility from tipping so that visibility-dependent motives can weaken without assuming that intrinsic generosity disappears.

Observability alone, however, is not enough. Digital tipping also changes the structure of the choice itself. In the standard model, the customer effectively chooses a tip from a continuous range around a prevailing norm. In many digital environments, by contrast, the customer is presented with a small set of salient preset options, often alongside a zero option. Existing evidence shows that these defaults matter. Haggag and Paci (2014) show that default tip suggestions have large effects on tip amounts, while Alexander et al. (2021) show that tip recommendations shape tipping behavior in app-based service settings. This motivates our second extension: moving from a continuous tipping environment to a digital choice architecture in which consumers choose from a discrete menu of tipping options.

These two extensions also help explain why the extensive and intensive margins of tipping need not move together. Lynn (2025) shows that during the Covid years, restaurant tipping became less frequent, while the size of the tips left increased. Our argument is that digitization provides one mechanism that can generate this kind of divergence. Lower observability can weaken norm pressure and social-image incentives, while discrete digital menus can eliminate small positive tips that would otherwise have been chosen in a continuous setting. As a result, some consumers may move from a small tip to zero even as the average size of the remaining positive tips rises (Lynn, 2025).

This paper therefore extends Azar (2004) framework in two steps. First, it introduces observability into the utility from tipping. Second, it adds digital choice architecture by modeling the tipping decision as a discrete menu choice rather than a continuous one. The broader point is that digital tipping is not simply the old tipping decision on a new device. It changes both what is socially visible and what is economically choosable, and those changes should matter for tipping behavior and for the evolution of tipping norms. The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the baseline model. Section 4 introduces observability. Section 5 extends the model to digital choice architecture and derives the implications for tipping behavior. Section 6 concludes. Formal proofs are collected in Appendix A, and Appendix B provides numerical illustrations.

2 Literature Review

The tipping literature begins from a puzzle that has attracted economists, psychologists, and hospitality researchers for decades: consumers leave voluntary payments after service has already been provided, often in situations where future interaction is limited. Early restaurant evidence already cast doubt on the view that tipping is primarily a strategic attempt to buy better future service. In one of the classic studies, Lynn and Grassman (1990) compared future-service, social-approval, and equity explanations of restaurant tipping and found stronger support for social approval and equity than for a pure repeated-interaction account. Azar (2004) later formalized this tension by modeling tipping as a costly social norm. In that framework, if consumers tip only to avoid the disutility of deviating from the prevailing norm, then the norm should erode over time. Because historical tipping percentages instead rose, Azar (2004) argued that tipping must also generate positive utility through motives such as generosity, gratitude, and image. Azar's later review articles make this broader point more explicitly. Azar (2007) surveys tipping research across economics, psychology, hospitality, and tourism, while Azar (2020) synthesizes later work and emphasizes that tipping is best understood as the outcome of several motives operating at once, including norm compliance, reciprocity, altruism, fairness, and image concerns.

A large empirical literature has examined whether restaurant tipping is in fact a strong reward for service quality. The basic result is that service quality matters, but much less than popular intuition suggests. Lynn and McCall (2000) report in a meta-analysis of 13 studies covering 2,547 dining parties at 20 restaurants that tip size is positively related to service evaluations, but that the relationship is much smaller than is generally supposed. Lynn (2001) reached the same conclusion in a managerial review and described the relationship between restaurant tipping and service quality as tenuous. Conlin et al. (2003) similarly found that observed tipping behavior contains some elements of efficiency, in the sense that percent tip depends on service quality, but does not appear fully efficient. This body of work matters because it weakens the view that restaurant tipping can be understood mainly as an incentive contract. Instead, it points toward a setting in which norms, fairness, and social context carry much of the explanatory weight.

Because service quality alone explains only a limited share of observed tipping variation, much of the empirical literature has turned to the broader social and contextual determinants of tipping. A long line of studies by Lynn and his coauthors shows that tip percentages vary with bill size, customer demographics, party size, repeat patronage, and small interpersonal features of the service encounter (Lynn, 2009; Lynn, 2018; Lynn and Thomas-Haysbert, 2003). More generally, reviews of the restaurant tipping literature conclude that tipping is shaped not only by service evaluations but also by social expectations, server characteristics, and customer-level contextual factors. This literature is important because it shows that tipping is not simply a marginal payment for measurable service quality. It is socially embedded behavior, shaped by norms, impressions, and the interpersonal structure of the transaction (Azar, 2007; Azar, 2020; Lynn, 2018).

Another related empirical strand asks whether tipping should be viewed as a monitoring device.

Kwortnik et al. (2009) argue that buyer monitoring can help insure personalized service in contexts where direct managerial monitoring is difficult. That perspective does not imply that tipping is a perfect incentive scheme, but it does reinforce the idea that tipping is embedded in a socially visible interaction in which the customer's evaluation matters. For the present paper, this is useful because it connects older tipping research to the observability issue directly. If part of the force of tipping lies in the visibility of the customer's evaluation, then changes in how visible the tipping act is should matter for behavior.

The more recent literature on payment method and interface design is especially relevant for the second half of this paper. One reason digital tipping matters is that digital interfaces do not simply transmit a pre-existing tipping decision. They actively structure the decision itself. Haggag and Paci (2014), using data from more than 13 million New York City taxi rides, show that default tip suggestions have large effects on tipping outcomes. Just as importantly, they show that higher suggested amounts can increase the share of customers who leave no credit-card tip at all. Alexander et al. (2021) find related effects in a field experiment with 94,571 orders from an app-based laundry service, where randomly assigned tip recommendations significantly changed tip amounts but had little effect on customer satisfaction, repatronage, or spending. These findings are directly relevant for the present paper because they show that the feasible tip menu and the salience of particular options are behaviorally consequential. In other words, digital tipping interfaces do not merely reveal preferences; they shape them.

A related body of evidence comes from app-mediated settings where tipping takes place in a more private or less directly observed environment. Chandar et al. (2019), in a large-scale nationwide tipping field experiment using Uber, show that substantial tipping persists even when the transaction is digital and relatively private. That finding matters because it rules out the simple claim that digitalization eliminates tipping by removing face-to-face social pressure. At the same time, it strongly suggests that different motives should be affected differently by digitization. Motives tied to approval, embarrassment, and impression management may weaken when the tipping act becomes less visible, while motives such as reciprocity or warm glow may remain. This is precisely the distinction that motivates the observability extension in the present paper.

The recent Covid-era literature adds another empirical result that is especially important here. Lynn (2025) shows that during the Covid years restaurant tipping became less frequent, while the size of the tips that were left increased. His paper is important not only for the result itself, but because it shows clearly that the extensive and intensive margins of tipping can move in opposite directions. That point is consistent with evidence from the literature on default tip suggestions and digital tip recommendations, where stronger prompts can increase conditional tip size while also increasing the probability of leaving no tip at all (Haggag and Paci, 2014; Alexander et al., 2021). For the present paper, the importance of Lynn's finding is not that Covid and digitalization are the same shock. Rather, it is that this recent evidence suggests that tipping participation and tip size, conditional on tipping, should not be collapsed into a single outcome. A model that combines observability with digital choice architecture is therefore well-suited to explain exactly that kind of divergence.

Taken together, the literature points to a clear gap. Azar's work provides the core benchmark for understanding tipping as a costly social norm, and the broader empirical literature shows that tipping is shaped by several motives as well as by the social structure of the transaction. More recent evidence on defaults, recommendations, and app-mediated payment environments shows that interface design can alter both whether consumers tip and how much they tip. What remains underdeveloped is a framework that links these insights directly. That is the contribution of the present paper. It extends the Azar benchmark in two directions that digital tipping makes unavoidable: observability and choice architecture.

3 Baseline Model

We begin from the model in Azar (2004). In each period (t), there is a prevailing tipping norm (n_t), where (n_t) denotes the socially appropriate tip, expressed as a percentage of the bill. A consumer chooses a tip $g \geq 0$ to maximize utility

$$u(g; n_t, \theta) = d(g - n_t) + \theta p(g) - bg, \tag{1}$$

where $d(g - n_t)$ captures the disutility from deviating from the prevailing norm, $p(g)$ captures the positive utility from tipping, and bg is the monetary cost of the tip, with $b > 0$ denoting the bill size. The parameter $\theta \geq 0$ measures the strength of the positive utility from tipping, and may vary across individuals.

The function $d(\cdot)$ represents the discomfort associated with violating the norm. We assume that d is continuously differentiable, maximized at zero deviation, and strictly concave. Thus, in the absence of other motives, the consumer prefers to remain as close as possible to the prevailing norm. The function $p(g)$ is increasing in g, reflecting that tipping may generate positive utility through motives such as generosity, reciprocity, or the desire to impress others.

The tipping norm evolves endogenously according to average behavior. Denoting the optimal tip of a consumer of type θ in period t by $g_t(\theta, n_t)$, the norm in period $t + 1$ is given by

$$n_{t+1} = \mathbb{E}_\theta \left[g_t(\theta, n_t) \right]. \tag{2}$$

The consumer takes the current norm as given when choosing g, and does not internalize the effect of their own choice on future norms.

A key result in Azar (2004) is that conformity alone is not sufficient to sustain tipping. To see this, consider the case in which $\theta = 0$, so that consumers derive no positive utility from tipping beyond avoiding deviation from the norm. In this case, the consumer solves

$$\max_{g \geq 0} \left(d(g - n_t) - bg \right) \tag{3}$$

Under the maintained assumptions, the optimal tip satisfies

$$g_t = \max[n_t - k, 0], \tag{4}$$

for some constant $k > 0$ that does not depend on the current norm. Thus, whenever tipping remains positive, the consumer chooses a tip strictly below the prevailing norm.

This implies that if all consumers are of type $\theta = 0$, then the norm declines over time. Since all individuals tip below the norm, the average tip is lower than n_t, and therefore

$$n_{t+1} < n_t. \tag{5}$$

Iterating this process leads to convergence of the norm to zero in a finite number of periods.

This erosion result highlights a central implication of the model: if tipping is motivated solely by conformity, then it cannot persist as a stable social norm. Sustained tipping behavior, therefore, requires that at least some individuals derive positive utility from tipping beyond conformity alone.

While this framework captures the role of norms in shaping tipping behavior, it abstracts from two features that are central in contemporary payment environments. First, it does not distinguish between motives that depend on observability and those that do not. Second, it treats the tipping decision as continuous, whereas many digital payment interfaces present consumers with a discrete set of tipping options. The following sections extend the baseline model along these two dimensions.

4 Observability

We now extend the baseline model by making the visibility of the tipping act explicit. In Azar (2004) baseline, visibility is implicit: the disutility from norm deviation and the positive utility from tipping are both captured in reduced-form terms. That is appropriate when the goal is to show that conformity alone cannot sustain tipping, but it is too coarse once tipping moves into digital payment environments. The shift from face-to-face payment to screen-mediated payment changes how easily the tip can be seen and socially interpreted. If visibility changes, then motives that require an audience should not be modeled in the same way as motives that do not. This is the reason for the decomposition introduced in this section.

Let n denote the prevailing tipping norm within a period, and let $\phi \in (0, 1]$ measure observability. Higher values of ϕ correspond to more visible tipping environments, while lower values correspond to less visible or more anonymous ones. Lower values of ϕ therefore capture the reduced visibility associated with digitized payment environments, while the limiting case $\phi \downarrow 0$ corresponds to effective anonymity. A consumer of type (α, β) chooses a tip $g \in [0, \bar{g}]$ to maximize

$$u(g; n, \alpha, \beta, \phi) = \phi d(g - n) + \alpha w(g) + \phi \beta s(g) - bg. \tag{6}$$

The term $\phi d(g - n)$ captures the disutility from deviating from the norm, scaled by observability. The interpretation is that norm pressure is stronger when the tipping act is more visible and weaker when it is less visible. The term $\alpha w(g)$ captures visibility-independent motives for tipping, such as reciprocity, altruism, fairness, or warm glow. The term $\phi \beta s(g)$ captures visibility-dependent motives, such as social image, reputational concerns, or the desire to avoid appearing ungenerous, and is therefore also scaled by observability. The final term, bg, is the monetary cost of tipping.

This specification refines Azar's reduced-form term $\theta p(g)$. In the baseline model, $\theta p(g)$ collects all positive utility from tipping into a single object. That is useful for showing that some positive motive must exist, but it is not rich enough for the present purpose because it bundles together motives that should respond differently to digitization. Some benefits from tipping do not require an audience. A customer may tip because doing so feels fair or reciprocal even when no one directly observes the act. Other benefits are visibility-dependent. The desire to appear generous, to avoid embarrassment, or to satisfy a socially enforced norm is naturally weaker when the tipping act becomes less observable. If one were simply to let Azar's θ vary with ϕ, the model would force all positive motives to move together with visibility. That would incorrectly treat lower visibility as if it directly reduced intrinsic generosity. By splitting $\theta p(g)$ into a visibility-independent component, $\alpha w(g)$, and a visibility-dependent component, $\phi \beta s(g)$, the model allows digitization to weaken social-image returns without requiring it to change the underlying warm-glow or reciprocity motive.

We impose the following assumptions. The norm-conformity function $d : \mathbb{R} \to \mathbb{R}$ is twice continuously differentiable, satisfies $d(0) = 0$ and $d'(0) = 0$, and is strictly concave, with

$$d''(x) < 0 \qquad \text{for all } x \in \mathbb{R}, \tag{7}$$

and

$$xd'(x) < 0 \qquad \text{for all } x \neq 0. \tag{8}$$

These conditions imply that utility is maximized at the norm and falls as the chosen tip moves away from it. The visibility-independent and visibility-dependent benefit functions $w, s : [0, \bar{g}] \to \mathbb{R}$ are twice continuously differentiable, strictly increasing, and weakly concave:

$$w'(g) > 0, \qquad s'(g) > 0, \tag{9}$$

and

$$w''(g) \leq 0, \qquad s''(g) \leq 0 \tag{10}$$

for all $g \in (0, \bar{g})$.

Given n, α, β, and ϕ, the consumer solves

$$\max_{g \in [0,\bar{g}]} \left\{ \phi d(g-n) + \alpha w(g) + \phi \beta s(g) - bg \right\}. \tag{11}$$

Lemma 4.1. *Under the assumptions above, the individual problem has a unique solution $g^*(n, \alpha, \beta, \phi) \in [0, \bar{g}]$.*

The proof is reported in Appendix A. The lemma guarantees that the optimal tip is well defined. When the solution is interior, $g^*(n, \alpha, \beta, \phi) \in (0, \bar{g})$, the first-order condition is

$$\phi d'(g^* - n) + \alpha w'(g^*) + \phi \beta s'(g^*) - b = 0. \tag{12}$$

This condition makes the role of observability transparent. A reduction in ϕ weakens the force of both norm pressure and social image, while leaving visibility-independent motives unchanged.

To study comparative statics with respect to observability, define

$$F(g; n, \alpha, \beta, \phi) = \phi d'(g-n) + \alpha w'(g) + \phi \beta s'(g) - b. \tag{13}$$

At an interior optimum, $F(g^*; n, \alpha, \beta, \phi) = 0$. Applying the implicit function theorem yields the following result.

Proposition 4.1. *Suppose $g^*(n, \alpha, \beta, \phi) \in (0, \bar{g})$. Then*

$$\frac{\partial g^*(n, \alpha, \beta, \phi)}{\partial \phi} = -\frac{d'(g^* - n) + \beta s'(g^*)}{\phi d''(g^* - n) + \alpha w''(g^*) + \phi \beta s''(g^*)}. \tag{14}$$

Since the denominator is negative, the sign of $\partial g^* / \partial \phi$ is determined by the sign of

$$d'(g^* - n) + \beta s'(g^*). \tag{15}$$

Hence the effect of observability on tipping is generally ambiguous.

The ambiguity has a natural interpretation. Observability strengthens both norm pressure and image motives, but the net effect depends on the customer's position relative to the norm and on the strength of the social-image channel. When the chosen tip lies above the norm, the marginal norm term $d'(g^* - n)$ is negative, so it can offset the positive image term $\beta s'(g^*)$. For that reason, observability need not raise tipping for every individual in every state.

At the same time, a natural sufficient condition delivers the intuitive comparative static.

Proposition 4.2. *Suppose* $g^*(n, \alpha, \beta, \phi) \in (0, \bar{g})$ *and*

$$g^*(n, \alpha, \beta, \phi) \leq n. \tag{16}$$

Then

$$\frac{\partial g^*(n, \alpha, \beta, \phi)}{\partial \phi} \geq 0. \tag{17}$$

The inequality is strict whenever $g^* < n$ *or* $\beta > 0$.

This proposition identifies the baseline observability mechanism of the paper. When consumers tip at or below the prevailing norm, greater observability raises tipping by strengthening norm pressure and, when present, social-image incentives. Conversely, lower observability weakens these channels and reduces tipping. This is the mechanism through which a shift from face-to-face payment to less visible digital payment can lower tipping even if intrinsic generosity or reciprocity remain unchanged.

The decomposition of Azar's positive-utility term also clarifies what happens in the limit of effective anonymity. As $\phi \downarrow 0$, both the norm-conformity term and the social-image term vanish, and utility converges to

$$u(g; n, \alpha, \beta, 0) = \alpha w(g) - bg. \tag{18}$$

In that limit, the tipping decision is driven entirely by visibility-independent motives. This does not imply that tipping disappears under digitization. Rather, it implies that lower visibility weakens only those motives that depend on being seen. That is precisely why the split of $\theta p(g)$ is important: it allows the model to distinguish between a decline in observability and a decline in generosity.

The observability extension also changes the evolution of the tipping norm. If observability is fixed at level ϕ, the law of motion becomes

$$n_{t+1} = \mathbb{E}_{(\alpha,\beta)}\big[g^*(n_t, \alpha, \beta, \phi)\big]. \tag{19}$$

Thus, a reduction in observability can affect not only current tipping behavior, but also the future path of the norm itself.

The observability extension therefore identifies the first way in which digital payment environments differ from the standard tipping setting. Even if the choice set remains continuous, a move toward less visible payment can change tipping behavior by weakening norm enforcement and social-image returns. At the same time, observability alone does not capture the full effect of digital tipping. Digital interfaces also change the structure of the choice itself by presenting consumers with a discrete menu of salient options rather than a continuous range. We turn to that feature in the next section.

5 Digital Choice Architecture

The observability extension shows how lower visibility changes tipping when the consumer chooses from a continuous range of possible tips. Digital tipping environments, however, differ from the standard setting along a second dimension as well: they replace the continuous tipping decision with a finite menu of salient options. This matters because even if the utility function were unchanged, a discrete menu can alter both whether consumers tip at all and how large the remaining positive tips are. In other words, observability changes the payoff from tipping, while choice architecture changes the feasible set from which the tip is chosen.

To isolate this second channel, it is useful to begin by holding observability fixed. Let $\phi \in (0, 1]$ be given, and consider two regimes. In the human regime, denoted H, the consumer chooses a tip from

$$G_H = [0, \bar{g}]. \tag{20}$$

In the digital menu regime, denoted Q, the consumer chooses from

$$G_Q = \{0, g_1, g_2, \ldots, g_K\}, \tag{21}$$

where

$$0 < g_1 < g_2 < \cdots < g_K \leq \bar{g}. \tag{22}$$

The zero option is explicit, and the remaining menu points are the preset positive tipping options displayed by the interface. Utility is unchanged across the two regimes and is given by

$$u(g; n, \alpha, \beta, \phi) = \phi d(g - n) + \alpha w(g) + \phi \beta s(g) - bg. \tag{23}$$

Let

$$g_H^*(n, \alpha, \beta, \phi) \in \arg\max_{g \in G_H} u(g; n, \alpha, \beta, \phi) \tag{24}$$

denote the optimal tip in the human regime, and let

$$g_Q^*(n, \alpha, \beta, \phi) \in \arg\max_{g \in G_Q} u(g; n, \alpha, \beta, \phi) \tag{25}$$

denote the optimal tip in the digital menu regime. Since utility is strictly concave, the continuous optimum is unique. To guarantee uniqueness in the menu problem as well, assume that ties are broken in favor of the lower tip. This tie-breaking rule is innocuous for generic parameter values and reflects the idea that when two options yield the same utility, the consumer selects the lower-cost one.

The discrete menu problem inherits a useful property from the strict concavity of the underlying utility function. Let g_H^* denote the unique continuous optimum. If g_H^* lies between two adjacent menu points, then the menu optimum can only be one of those two points.

Lemma 5.1. *Suppose* $g_H^*(n, \alpha, \beta, \phi) \in [g_j, g_{j+1}]$ *for some* $j \in \{0, 1, \ldots, K-1\}$, *where* $g_0 \equiv 0$. *Then*

$$g_Q^*(n, \alpha, \beta, \phi) \in \{g_j, g_{j+1}\}. \tag{26}$$

In particular, if

$$0 < g_H^*(n, \alpha, \beta, \phi) < g_1, \tag{27}$$

then

$$g_Q^*(n, \alpha, \beta, \phi) \in \{0, g_1\}. \tag{28}$$

The proof is in Appendix A. The lemma formalizes the sense in which a digital menu coarsens the continuous optimum. Because utility rises up to g_H^* and falls thereafter, any menu point farther away from g_H^* than the two adjacent grid points must yield lower utility.

This immediately gives the first mechanism of interest. If the continuous optimum is a small positive tip below the lowest positive menu option, then the digital interface forces the consumer to choose between zero and the smallest displayed tip. Small positive tips can therefore disappear.

Proposition 5.1. *Suppose*

$$0 < g_H^*(n, \alpha, \beta, \phi) < g_1. \tag{29}$$

Then

$$g_Q^*(n, \alpha, \beta, \phi) \in \{0, g_1\}. \tag{30}$$

Moreover,

$$g_Q^*(n, \alpha, \beta, \phi) = 0 \quad \textit{if and only if} \quad u(0; n, \alpha, \beta, \phi) \geq u(g_1; n, \alpha, \beta, \phi). \tag{31}$$

The proof is in Appendix A. Proposition 5.1 is the simplest expression of the extensive-margin mechanism. A consumer who would have left a small positive tip in a continuous environment may leave no tip at all once the choice is compressed into a digital menu. The menu does not merely record the customer's desired tip; it removes some desired tips from the feasible set.

To study aggregate implications, define the tipping decision in each regime by

$$T_m = \begin{cases} 1 & \text{if } g_m^* > 0, \\ 0 & \text{if } g_m^* = 0, \end{cases} \qquad m \in \{H, Q\}. \tag{32}$$

The extensive margin is

$$\Pr(T_m = 1), \tag{33}$$

and the intensive margin is

$$\mathbb{E}[g_m^* \mid g_m^* > 0]. \tag{34}$$

The next proposition shows that, holding observability fixed, a discrete menu cannot create positive tipping by a consumer whose continuous optimum is zero. In this sense, the digital menu weakly reduces participation.

Proposition 5.2. *For every type* (α, β)*,*

$$T_Q \leq T_H. \tag{35}$$

Hence

$$\Pr(T_Q = 1) \leq \Pr(T_H = 1). \tag{36}$$

If a positive-measure set of types satisfies

$$0 < g_H^*(n, \alpha, \beta, \phi) < g_1 \quad \textit{and} \quad u(0; n, \alpha, \beta, \phi) \geq u(g_1; n, \alpha, \beta, \phi), \tag{37}$$

then

$$\Pr(T_Q = 1) < \Pr(T_H = 1). \tag{38}$$

The proof is in Appendix A. The weak inequality $T_Q \leq T_H$ follows from the fact that the digital menu is a subset of the continuous feasible set. If the best continuous tip is zero, then no positive menu option can do better. The strict inequality arises when there is a non-negligible set of consumers who would choose small positive tips continuously but choose zero when faced with the menu.

The intensive margin requires one additional step. A lower participation rate does not automatically imply a larger conditional mean, because surviving consumers could also round down under the menu. Still, the menu creates a natural lower-tail truncation effect. Once consumers who would have chosen tips in $(0, g_1)$ move to zero, the distribution of positive tips loses its smallest observations. Under a mild condition on the remaining positive tippers, this increases the average size of tips conditional on tipping.

Let

$$\mathcal{M} = \{(\alpha, \beta) : T_H = 1 \text{ and } T_Q = 0\} \tag{39}$$

denote the set of types who stop tipping under the menu, and let

$$\mathcal{S} = \{(\alpha, \beta) : T_Q = 1\} \tag{40}$$

denote the surviving positive tippers.

Proposition 5.3. *Suppose that*

$$\mathcal{M} = \{(\alpha, \beta) : 0 < g_H^*(n, \alpha, \beta, \phi) < g_1 \text{ and } u(0; n, \alpha, \beta, \phi) \geq u(g_1; n, \alpha, \beta, \phi)\}, \tag{41}$$

so that the only types who stop tipping under the menu are those whose continuous optimum lies below the smallest positive menu option, and suppose further that for every type in $\mathcal{S}$,

$$g_Q^*(n, \alpha, \beta, \phi) \geq g_H^*(n, \alpha, \beta, \phi). \tag{42}$$

If $\mathcal{M}$ has positive measure, then

$$\mathbb{E}[g_Q^* \mid g_Q^* > 0] > \mathbb{E}[g_H^* \mid g_H^* > 0]. \tag{43}$$

The proof is in Appendix A. Proposition 5.3 identifies a sufficient condition for the intensive-margin result. The menu removes low positive tips from the support, and if the surviving positive tips are not reduced relative to their continuous counterparts, then the conditional mean must rise. The logic is simply truncation from below: once small positive tips are converted into zeros, the average among those who still tip becomes larger.

Taken together, Propositions 5.2 and 5.3 give the basic choice-architecture mechanism of the paper. Holding observability fixed, a discrete digital menu can reduce the probability of tipping by eliminating small positive choices, while at the same time increasing the average size of positive tips by removing the bottom tail of the positive-tip distribution. This is precisely the extensive-versus-intensive-margin split that motivates the section.

The digital choice architecture extension also changes the evolution of the tipping norm. In a pure human regime with continuous choice, the norm evolves according to

$$n_{t+1}^H = \mathbb{E}_{(\alpha,\beta)}\left[g_H^*(n_t, \alpha, \beta, \phi)\right], \tag{44}$$

while in a pure digital menu regime it evolves according to

$$n_{t+1}^Q = \mathbb{E}_{(\alpha,\beta)}\left[g_Q^*(n_t, \alpha, \beta, \phi)\right]. \tag{45}$$

Thus, even holding observability fixed, the move from a continuous tipping environment to a discrete menu can alter the future path of the norm by changing the unconditional mean tip.

The full digital environment combines this menu effect with the observability effect from the previous section. Let a share $\lambda_t \in [0, 1]$ of transactions occur in the digital regime and the remaining share occur in the human regime. Let the human regime have observability ϕ_H and a continuous choice set, and let the digital regime have observability $\phi_Q < \phi_H$ and menu G_Q. Then the aggregate probability of tipping is

$$\Pr(T_t = 1) = (1 - \lambda_t) \Pr(T_H = 1) + \lambda_t \Pr(T_Q = 1). \tag{46}$$

The evolution of the tipping norm is then given by

$$n_{t+1} = (1 - \lambda_t)\mathbb{E}_{(\alpha,\beta)}\left[g_H^*(n_t, \alpha, \beta, \phi_H)\right] + \lambda_t \mathbb{E}_{(\alpha,\beta)}\left[g_Q^*(n_t, \alpha, \beta, \phi_Q)\right]. \tag{47}$$

Since digitization can reduce tipping participation while increasing conditional tip size, its effect on the unconditional mean tip, and therefore on the future evolution of the norm, is theoretically ambiguous. The aggregate effect depends on the relative magnitude of the decline in tipping frequency and the increase in the size of positive tips.

6 Conclusion

This paper develops a theory of tipping in digital payment environments. Starting from Azar (2004) model of tipping as a costly social norm, it extends the baseline framework in two directions that become central once tipping is mediated by screens, apps, QR codes, and digital payment terminals. First, the paper introduces observability into the utility from tipping. This makes it possible to distinguish between motives that depend on being seen, such as norm pressure and social image, and motives that survive even in less visible environments, such as warm glow, reciprocity, or fairness. Second, the paper extends the tipping decision from a continuous choice to a digital choice architecture in which consumers select from a discrete menu of salient preset options. Taken together, these two extensions adapt the standard tipping model to a payment environment in which both the visibility of the act and the structure of the choice have changed.

The analysis delivers two main results. The observability extension shows that lower visibility weakens norm-conformity and social-image incentives, and therefore can reduce tipping even when intrinsic generosity remains unchanged. The choice-architecture extension shows that a discrete digital menu can eliminate small positive tips that would otherwise be chosen in a continuous setting. As a result, digital tipping can affect the extensive and intensive margins differently. Participation in tipping may fall because some consumers move from a small positive tip to zero, while the average size of the remaining positive tips may rise because the lower tail of the positive-tip distribution is truncated. In that sense, the model provides a theoretical mechanism through which digitization can reduce tipping frequency while increasing tip size conditional on tipping.

These results also have implications for the evolution of tipping norms. In the baseline Azar framework, norms evolve through average tipping behavior. Once observability and choice architecture are introduced, the payment environment itself enters that process. Lower observability can shift the law of motion for the norm downward by weakening norm pressure and social-image returns. A discrete digital menu can further alter norm dynamics by removing small positive tips from the feasible set. More generally, when a growing share of transactions occurs in the digital regime, the effect of digitalization on the unconditional mean tip, and therefore on the future path of the tipping norm, is theoretically ambiguous. It depends on the relative strength of two opposing forces: the reduction in tipping participation and the increase in the size of the positive tips that remain.

The broader implication is that digital tipping should be understood as an institutional change rather than as a neutral technological one. Digital payment systems do not merely transmit an unchanged tipping decision through a new device. They reshape the social and economic conditions under which that decision is made by changing both what is visible and what is choosable. This suggests a natural agenda for future empirical work. The model generates predictions about how payment visibility, menu design, and the diffusion of digital tipping should affect both tipping participation and conditional tip size, as well as the longer-run evolution of tipping norms. More generally, the paper shows that understanding digital tipping requires attention not only to preferences, but also to observability, interface design, and the institutional environment in which social norms operate.

Appendix A Proofs

A.1 Proofs for Observability Extension

Proof of Lemma 4.1. Fix n, α, β, and $\phi \in (0, 1]$. The utility function

$$u(g; n, \alpha, \beta, \phi) = \phi d(g - n) + \alpha w(g) + \phi \beta s(g) - bg \tag{48}$$

is continuous in g on the compact set $[0, \bar{g}]$. By the Weierstrass theorem, a maximizer exists.

To show uniqueness, compute the second derivative for $g \in (0, \bar{g})$:

$$\frac{\partial^2 u}{\partial g^2}(g; n, \alpha, \beta, \phi) = \phi d''(g - n) + \alpha w''(g) + \phi \beta s''(g). \tag{49}$$

Because $\phi > 0$, $d''(x) < 0$ for all x, and $w''(g), s''(g) \leq 0$, it follows that

$$\frac{\partial^2 u}{\partial g^2}(g; n, \alpha, \beta, \phi) < 0 \tag{50}$$

for all $g \in (0, \bar{g})$. Hence $u(\cdot; n, \alpha, \beta, \phi)$ is strictly concave on $[0, \bar{g}]$, so the maximizer is unique. □

Proof of Proposition 4.1. Assume that $g^*(n, \alpha, \beta, \phi) \in (0, \bar{g})$. Define

$$F(g; n, \alpha, \beta, \phi) = \phi d'(g - n) + \alpha w'(g) + \phi \beta s'(g) - b. \tag{51}$$

At an interior optimum,

$$F(g^*; n, \alpha, \beta, \phi) = 0. \tag{52}$$

Differentiate F with respect to g:

$$\frac{\partial F}{\partial g} = \phi d''(g - n) + \alpha w''(g) + \phi \beta s''(g). \tag{53}$$

By the assumptions,

$$\frac{\partial F}{\partial g}(g^*; n, \alpha, \beta, \phi) < 0. \tag{54}$$

Therefore, the implicit function theorem applies, and $g^*(n, \alpha, \beta, \phi)$ is differentiable with respect to ϕ.

Differentiating the identity $F(g^*; n, \alpha, \beta, \phi) = 0$ with respect to ϕ gives

$$\frac{\partial F}{\partial g} \frac{\partial g^*}{\partial \phi} + \frac{\partial F}{\partial \phi} = 0. \tag{55}$$

Now

$$\frac{\partial F}{\partial \phi} = d'(g^* - n) + \beta s'(g^*). \tag{56}$$

Solving for $\partial g^* / \partial \phi$ yields

$$\frac{\partial g^*}{\partial \phi} = -\frac{d'(g^* - n) + \beta s'(g^*)}{\phi d''(g^* - n) + \alpha w''(g^*) + \phi \beta s''(g^*)}. \tag{57}$$

Since the denominator is negative, the sign of $\partial g^*/\partial \phi$ is determined by the numerator. Because $s'(g^*) > 0$ and $\beta \geq 0$, the term $\beta s'(g^*)$ is nonnegative. However, $d'(g^* - n)$ is positive when $g^* < n$, zero when $g^* = n$, and negative when $g^* > n$. Hence the numerator can be positive, zero, or negative, so the effect of observability is generally ambiguous. □

Proof of Proposition 4.2. From Proposition 4.1,

$$\frac{\partial g^*}{\partial \phi} = -\frac{d'(g^* - n) + \beta s'(g^*)}{\phi d''(g^* - n) + \alpha w''(g^*) + \phi \beta s''(g^*)}. \tag{58}$$

If $g^* \leq n$, then $g^* - n \leq 0$. By the assumption $x d'(x) < 0$ for $x \neq 0$ and $d'(0) = 0$, it follows that

$$d'(g^* - n) \geq 0. \tag{59}$$

Also, since $s'(g^*) > 0$ and $\beta \geq 0$,

$$\beta s'(g^*) \geq 0. \tag{60}$$

Therefore,

$$d'(g^* - n) + \beta s'(g^*) \geq 0. \tag{61}$$

The denominator in Proposition 4.1 is strictly negative, so

$$\frac{\partial g^*}{\partial \phi} \geq 0. \tag{62}$$

The inequality is strict whenever the numerator is strictly positive, which occurs if $g^* < n$ or if $\beta > 0$. □

A.2 Proofs for Digital Choice Architecture Extension

Proof of Lemma 5.1. Let g_H^* denote the unique maximizer of $u(g; n, \alpha, \beta, \phi)$ over $[0, \bar{g}]$. Since utility is strictly concave, it is strictly increasing on $[0, g_H^*]$ and strictly decreasing on $[g_H^*, \bar{g}]$.

Suppose $g_H^* \in [g_j, g_{j+1}]$. If $g < g_j$, then g lies farther to the left of g_H^* than g_j, so strict monotonicity on $[0, g_H^*]$ implies

$$u(g; n, \alpha, \beta, \phi) < u(g_j; n, \alpha, \beta, \phi). \tag{63}$$

Similarly, if $g > g_{j+1}$, then g lies farther to the right of g_H^* than g_{j+1}, so strict monotonicity on $[g_H^*, \bar{g}]$ implies

$$u(g; n, \alpha, \beta, \phi) < u(g_{j+1}; n, \alpha, \beta, \phi). \tag{64}$$

Therefore no menu point outside $\{g_j, g_{j+1}\}$ can maximize utility over G_Q. Hence

$$g_Q^* \in \{g_j, g_{j+1}\}. \tag{65}$$

The special case $0 < g_H^* < g_1$ follows by taking $g_0 = 0$. □

Proof of Proposition 5.1. If $0 < g_H^* < g_1$, Lemma 5.1 implies that

$$g_Q^* \in \{0, g_1\}. \tag{66}$$

Therefore the menu optimum is zero if and only if

$$u(0; n, \alpha, \beta, \phi) \geq u(g_1; n, \alpha, \beta, \phi), \tag{67}$$

with ties resolved in favor of zero by the tie-breaking rule. This proves the proposition. □

Proof of Proposition 5.2. Because $G_Q \subseteq G_H$, the human regime solves the same utility maximization problem over a superset of the digital menu's feasible set. If $T_H = 0$, then

$$g_H^* = 0 \tag{68}$$

maximizes utility over all $g \in [0, \bar{g}]$. In particular,

$$u(0; n, \alpha, \beta, \phi) \geq u(g; n, \alpha, \beta, \phi) \qquad \text{for all } g \in G_Q. \tag{69}$$

Hence $g_Q^* = 0$, so $T_Q = 0$. Therefore

$$T_Q \leq T_H \tag{70}$$

for every type, which implies

$$\Pr(T_Q = 1) \leq \Pr(T_H = 1). \tag{71}$$

Now suppose there is a positive-measure set of types such that

$$0 < g_H^* < g_1 \quad \text{and} \quad u(0) \geq u(g_1). \tag{72}$$

By Proposition 5.1, each such type has $T_H = 1$ and $T_Q = 0$. Since the set has positive measure, the weak inequality above is strict:

$$\Pr(T_Q = 1) < \Pr(T_H = 1). \tag{73}$$

□

Proof of Proposition 5.3. Let

$$\mathcal{S} = \{(\alpha, \beta) : T_Q = 1\} \tag{74}$$

and

$$\mathcal{M} = \{(\alpha, \beta) : T_H = 1,\ T_Q = 0\}. \tag{75}$$

By assumption, $\mathcal{M}$ consists exactly of the types for whom

$$0 < g_H^* < g_1 \quad \text{and} \quad u(0) \geq u(g_1), \tag{76}$$

so every type in $\mathcal{M}$ has

$$g_H^* < g_1. \tag{77}$$

Also, every type in $\mathcal{S}$ chooses a positive menu option, so

$$g_Q^* \geq g_1. \tag{78}$$

By the additional assumption of the proposition,

$$g_Q^* \geq g_H^* \qquad \text{for all types in } \mathcal{S}. \tag{79}$$

Define

$$\mu_Q = \mathbb{E}[g_Q^* \mid \mathcal{S}], \qquad \mu_H = \mathbb{E}[g_H^* \mid \mathcal{S}], \qquad \mu_M = \mathbb{E}[g_H^* \mid \mathcal{M}]. \tag{80}$$

Then

$$\mu_Q \geq \mu_H \tag{81}$$

by the survivor condition. Moreover, since every type in $\mathcal{M}$ has $g_H^* < g_1$ and every type in $\mathcal{S}$ has $g_Q^* \geq g_1$, we have

$$\mu_M < g_1 \leq \mu_Q. \tag{82}$$

Because $\mathcal{M}$ has positive measure, the continuous positive-tip mean is

$$\mathbb{E}[g_H^* \mid g_H^* > 0] = \lambda\mu_H + (1-\lambda)\mu_M \tag{83}$$

for some $\lambda \in (0,1)$. Since $\mu_Q \geq \mu_H$ and $\mu_Q > \mu_M$, it follows that

$$\mu_Q > \lambda\mu_H + (1-\lambda)\mu_M. \tag{84}$$

Hence

$$\mathbb{E}[g_Q^* \mid g_Q^* > 0] > \mathbb{E}[g_H^* \mid g_H^* > 0]. \tag{85}$$

This proves the proposition. □

Appendix B Numerical Illustration

This appendix provides a simple numerical illustration of the mechanisms developed in the paper. The exercise is not intended to calibrate the model to data or to generate quantitative predictions. Rather, its purpose is to illustrate that the theoretical model can generate the qualitative patterns discussed in the main text. We first isolate the role of observability in a continuous-choice environment. We then illustrate how digital choice architecture can generate a decline in tipping participation together with an increase in the average size of tips conditional on tipping.

B.1 Functional forms

We adopt simple functional forms that are consistent with the assumptions imposed in the model. The norm-conformity function is quadratic,

$$d(x) = -\gamma x^2, \qquad \gamma > 0,$$

while the warm-glow and social-image functions are linear,

$$w(g) = g, \qquad s(g) = g.$$

Under these assumptions, utility becomes

$$u(g; n, \alpha, \beta, \phi) = -\phi\gamma(g-n)^2 + \alpha g + \phi\beta g - bg.$$

The quadratic norm-conformity term is strictly concave and maximized at zero deviation. The functions w and s are increasing and weakly concave. Since $\phi > 0$ in the numerical exercises, the objective remains strictly concave in the continuous-choice environment.

B.2 Observability

We first isolate the role of observability by considering a continuous-choice environment. In this exercise, the individual chooses $g \in [0, \bar{g}]$, and the only parameter that varies is ϕ. Under the functional forms above, the first-order condition for an interior optimum is

$$-2\phi\gamma(g^* - n) + \alpha + \phi\beta - b = 0.$$

Solving for g^* gives

$$g^*(n, \alpha, \beta, \phi) = n + \frac{\alpha + \phi\beta - b}{2\phi\gamma}.$$

Imposing the bounds of the feasible set, the realized optimal tip is

$$g^*(n, \alpha, \beta, \phi) = \min\left\{\bar{g}, \max\left\{0,\ n + \frac{\alpha + \phi\beta - b}{2\phi\gamma}\right\}\right\}.$$

Figure 1 plots the optimal tip as a function of observability for an illustrative parameterization. The figure is intended to show the baseline observability mechanism in a region where norm pressure and social-image incentives reinforce one another. It should not be interpreted as showing that observability raises tipping for every possible type or state. As shown in the main text, the comparative static with respect to observability is generally ambiguous, and becomes positive under the sufficient conditions stated in Proposition 4.2.

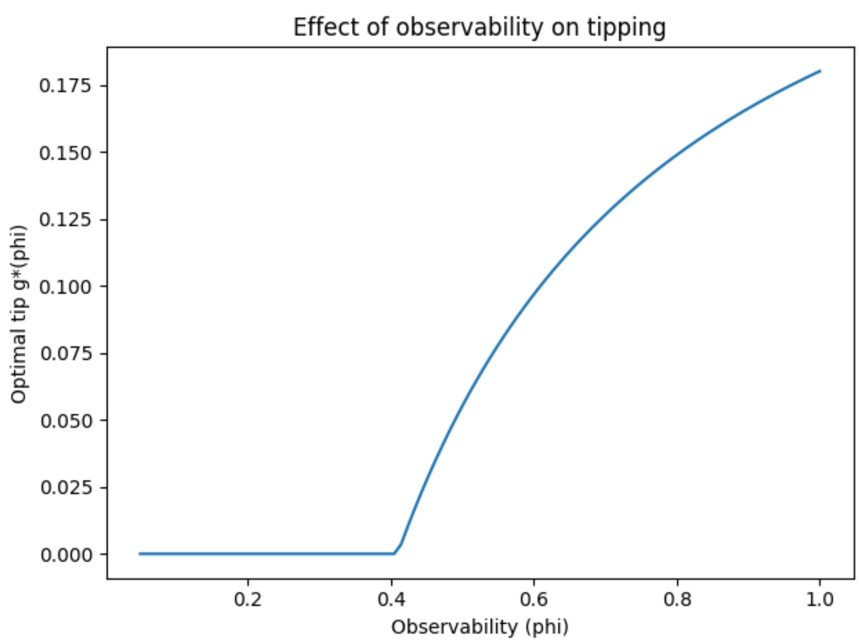

Figure (1) Optimal tipping as a function of observability.

B.3 Digital choice architecture

We now illustrate the digital choice-architecture mechanism. The human regime is characterized by a continuous choice set,

$$\mathcal{G}_H = [0, \bar{g}],$$

and observability ϕ_H. The digital regime is characterized by lower observability $\phi_Q < \phi_H$ and a discrete menu,

$$\mathcal{G}_Q = \{0, g_1, g_2, \dots, g_K\}.$$

For each consumer i, with type (α_i, β_i), the human-regime tip is computed as

$$g^*_{H,i}(n) = \min\left\{\bar{g}, \max\left\{0,\, n + \frac{\alpha_i + \phi_H\beta_i - b}{2\phi_H\gamma}\right\}\right\}.$$

The digital-regime tip is computed by discrete maximization over the menu,

$$g^*_{Q,i}(n) \in \arg\max_{g\in\mathcal{G}_Q} \left\{-\phi_Q\gamma(g-n)^2 + \alpha_i g + \phi_Q\beta_i g - bg\right\}.$$

Ties are resolved in favor of the lower tip. The binary tipping decision in regime $m \in \{H, Q\}$ is

$$T_{m,i} = \begin{cases} 1 & \text{if } g^*_{m,i} > 0, \\ 0 & \text{if } g^*_{m,i} = 0. \end{cases}$$

The extensive margin is measured by the fraction of consumers with $T_{m,i} = 1$, while the intensive margin is measured by the average tip among consumers with $g^*_{m,i} > 0$.

For the numerical exercise, we use a heterogeneous population of $N = 100{,}000$ consumers. Types are drawn independently according to

$$\alpha_i \sim U[0, 1.2], \qquad \beta_i \sim U[0, 0.8].$$

The remaining parameter values are

$$\gamma = 2, \qquad b = 1, \qquad \phi_H = 1, \qquad \phi_Q = 0.25,$$

with

$$\bar{g} = 0.35, \qquad n_0 = 0.18,$$

and digital menu

$$\mathcal{G}_Q = \{0, 0.15, 0.18, 0.22, 0.25\}.$$

These values are illustrative and are not estimated from data.

B.4 Extensive and intensive margins

In the dynamic numerical exercise, we let $\lambda_t \in [0, 1]$ denote the share of transactions that occur in the digital regime in period t. Thus, $\lambda_t = 0$ corresponds to an economy in which all transactions take place in the human regime, while $\lambda_t = 1$ corresponds to an economy in which all transactions take place in the digital regime. For each value of λ_t, the tipping norm n_t is updated according to the average realized tip, and tipping behavior in both regimes is then evaluated along this simulated norm path.

Figure 2 shows the probability of tipping in the human and digital regimes along the simulated adoption path. The digital regime produces a lower tipping probability because some individuals who would have chosen small positive tips in the continuous human regime instead choose zero when faced with a discrete menu and lower observability.

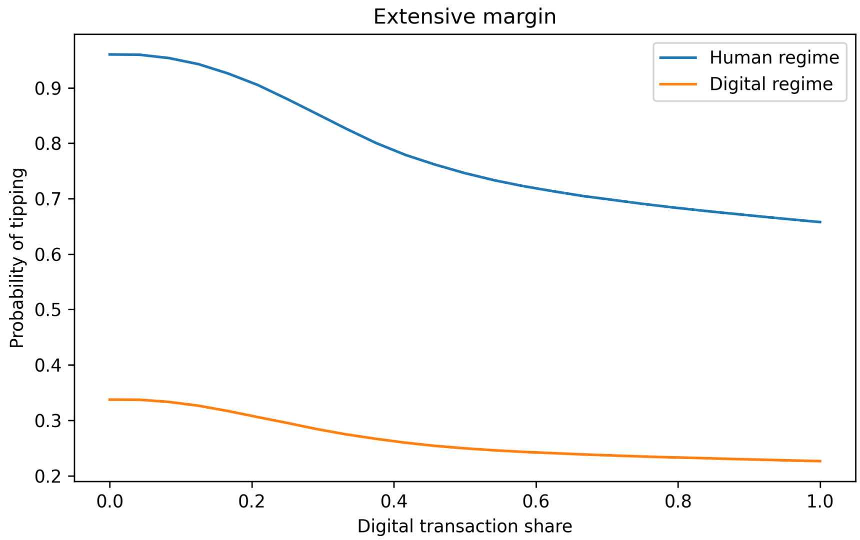

Figure (2) Extensive margin along the simulated adoption path. The horizontal axis reports the digital adoption share λ_t, and the vertical axis reports the probability of tipping in each regime, evaluated at the norm n_t generated by the simulation.

Figure 3 shows the average tip conditional on tipping. The conditional mean is higher in the digital regime because small positive tips are removed from the positive-tip distribution. Those who continue to tip select from a menu whose smallest positive option is strictly above zero.

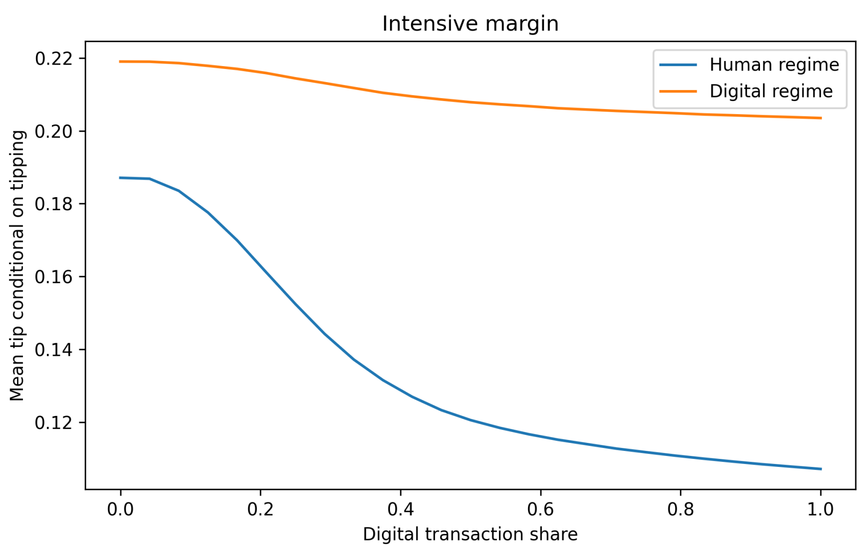

Figure (3) Intensive margin along the simulated adoption path. The horizontal axis reports the digital adoption share λ_t, and the vertical axis reports the average tip conditional on tipping in each regime, evaluated at the norm n_t generated by the simulation.

Together, Figures 2 and 3 illustrate the main two-margin mechanism of the model. Digitalization can reduce the likelihood of tipping while increasing the size of tips among those who continue to tip.

B.5 Norm dynamics

Finally, we illustrate how the tipping norm evolves when the share of digital transactions increases over time. In this exercise, the horizontal axis reports periods t. The digital adoption share λ_t increases linearly over time from 0 to 1, so later periods correspond to a larger share of transactions occurring in the digital regime.

The norm evolves according to

$$n_{t+1} = (1-\lambda_t)\mathbb{E}\left[g_H^*(n_t,\alpha,\beta)\right] + \lambda_t\mathbb{E}\left[g_Q^*(n_t,\alpha,\beta)\right].$$

The right-hand side is the average realized tip in period t, which becomes next period's norm n_{t+1}. Thus, n_t is the inherited norm at the beginning of period t, while the average realized tip is the realized behavior that updates the norm.

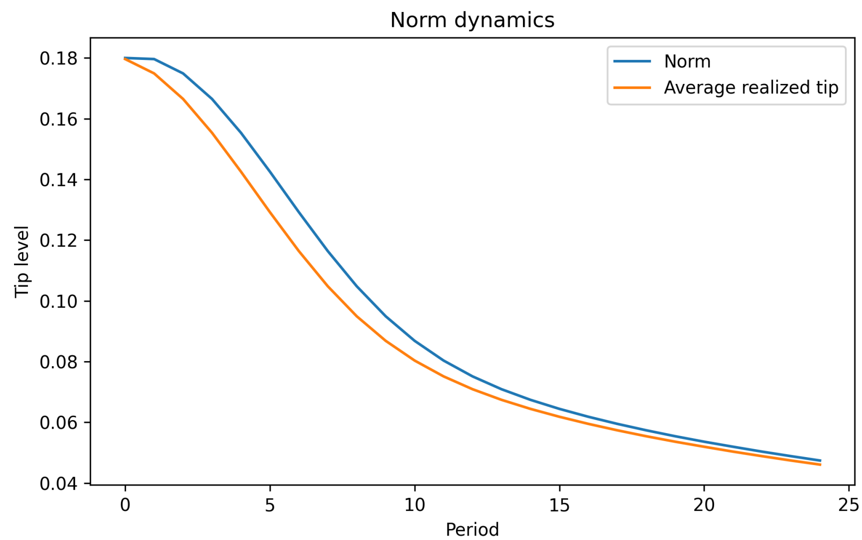

Figure (4) Norm dynamics under rising digital adoption. The horizontal axis reports periods t. The norm n_t is the inherited tipping norm at the beginning of period t. The average realized tip is the average tip chosen during period t, which becomes next period's norm n_{t+1}. The digital adoption share λ_t increases linearly over time.

Figure 4 reflects the interaction of two opposing forces. The decline in tipping participation tends to reduce the unconditional average tip, while the increase in conditional tip size among remaining tippers works in the opposite direction. As emphasized in the main text, the net effect on the tipping norm is therefore theoretically ambiguous and depends on parameter values.

B.6 Interpretation

The numerical exercises illustrate the two mechanisms developed in the paper. The first exercise isolates observability and shows how lower visibility can reduce tipping incentives in the region where norm pressure and social-image motives reinforce each other. The second exercise shows how digital choice architecture can reshape tipping behavior across the extensive and intensive margins. Marginal small tippers may switch to zero, reducing tipping participation, while the remaining positive tips are concentrated at larger menu options, raising the conditional mean tip.

The parameter values used in this appendix are illustrative. The exercises should not be interpreted as empirical calibration or as quantitative predictions. Their purpose is only to show that the model can generate the qualitative patterns described in the paper.

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