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ATTRIBUTION MODELS, MEDIA BUDGET ALLOCATION, AND LOSS IN CFD BROKERAGE

Summary. *Introduction. Paid customer acquisition is the dominant cost line for retail contracts-for-difference (CFD) and forex brokers, and the efficiency of that spend is judged through an attribution model that assigns conversions to marketing channels. The standard convention in retail brokerage is last-click attribution anchored to the registration (signup) event, after which the registration source is treated as the owner of all subsequent revenue.*

Purpose. The study quantifies the economic cost of this convention. It builds an economic-mathematical model of how last-click attribution combined with signup-source lock-in biases the estimated cost of acquisition (CAC) across channels and misallocates the paid media budget, and it expresses the resulting loss in monetary terms.

Materials and methods. The model formalises a forex acquisition event ladder (signup, identity verification, first-time deposit, first trade, recurring deposits and trades) and two distinct layers of distortion: touch distortion at the signup event and source lock-in across all post-signup revenue. The true contribution of each channel is approximated by the Shapley value computed over a reproducible converting-journey coalition structure. Channel response is modelled with diminishing returns and inventory ceilings; the loss is the contribution margin forgone when the budget is optimised on locked signals instead of true contribution. Parameterisation is calibrated on an aggregated, anonymised portfolio of seven EU Tier-1 CFD and forex broker acquisition projects run by the author over two years.

Results. Under the lock-in convention, closing channels (brand search and direct) capture credit far above their Shapley contribution, while initiating and post-signup activation channels are systematically under-credited or rendered invisible. Optimising the budget on these biased signals forgoes between roughly three and eleven percent of the paid budget in contribution margin, and the loss rises as the lag between signup and deposit lengthens, because a longer lag leaves more uncredited reactivation work. Discounting of delayed revenue adds a small further adjustment.

Prospects. Further work can extend the model to redeposit and trading-volume horizons, to incrementality-based truth proxies, and to multi-market parameterisations.

Key words: *attribution, last-click, customer acquisition cost, media budget allocation, Shapley value, CFD broker, forex, marketing analytics.*

Statement of the problem. For a retail CFD or forex broker, paid customer acquisition is the largest controllable cost, and the entire optimisation of that spend rests on one measurement decision: which marketing channel is credited with each conversion. That decision is made by the attribution model. The model determines the apparent cost of acquisition (CAC) of every channel, the apparent return on ad spend, and therefore where the next unit of budget is sent.

The convention that prevails in retail brokerage is narrower than the marketing literature usually assumes. Brokers do not merely apply last-click attribution to a single conversion. They fix the registration (signup) event to the last-clicked source, and then attribute every subsequent monetary event of that client, the first-time deposit, redeposits, and trading volume, to the same source. The registration source becomes the permanent owner of the client. This is a source lock-in: a touch that delivered a cheap registration is credited with revenue that may arrive months later and that other activity produced.

The practical consequence is that two clients with identical lifetime value can be valued very differently by the measurement system depending only on which channel happened to deliver the registration click, and the gap widens with the time between registration and deposit. Because the broker reallocates budget toward whatever the system reports as cheap, the measurement error becomes a spending error. The size of that spending error, in money, is the subject of this article.

Analysis of recent research and publications. The deficiencies of last-click attribution are well established. Comparative work shows that last-click systematically over-credits channels positioned late in the journey and under-credits channels that initiate it [1; 2]. Berman models the strategic and measurement distortions of last-touch crediting and shows that they bias channel valuations and equilibrium spend [3]. Mapping of full customer journeys confirms that assisting and early touches carry real conversion value that single-touch rules discard [4]. Evidence on upper-funnel media shows that display and similar formats lift search and downstream conversions, value that last-click assigns elsewhere [5; 6].

Two families of less biased estimators are used as references. Causal and incrementality-based methods aim at the marginal effect of a channel rather than its observed co-occurrence with conversions [7]. Cooperative-game methods distribute conversion credit by the Shapley value, which satisfies efficiency, symmetry, the null-player property, and additivity, and has become the formal standard for fair multi-touch attribution [8; 9]. Data-driven attribution as implemented by advertising platforms operationalises related ideas [1]. The valuation of customers over time, and the discounting of future customer cash flows, is treated in the customer-equity literature [10].

A necessary caution comes from Danaher and van Heerde, who show that attribution credit, even when computed correctly, is a backward-looking measure of contribution and is not the same as the forward investment elasticity that budget allocation requires [11]. Using any attribution output, including Shapley, to set budgets is therefore valid only under an explicit assumption that contribution shares approximate response, an assumption this article states and tests rather than hides.

Identification of previously unsolved parts of the problem. The literature treats attribution mainly as a touch-crediting problem within a single conversion: which of the touches before the conversion should receive credit. Three features specific to retail brokerage are not jointly addressed. First, the unit of revenue is not a single purchase but a ladder of events (signup, verification, first deposit, first trade, recurring deposits and trades) along which value accrues for months. Second, the prevailing convention locks all of that downstream value to the registration source, so the distortion is not confined to the conversion path but extends across the entire client lifetime. Third, the gap between registration and deposit is often long, and the longer it is, the more post-signup reactivation work is performed by channels that the lock-in credits with nothing. No prior model prices these three features together. This article does.

Formulation of the aim of the article. The aim is to build a reproducible economic-mathematical model that (1) formalises the last-click plus signup-source lock-in convention as two layers of distortion over the forex acquisition event ladder, (2) measures the resulting bias in channel-level CAC against a Shapley contribution benchmark, (3) translates that bias into the misallocation of a fixed paid budget, and (4) expresses the loss in money, as a share of budget, and as excess effective CAC, including its dependence on the signup-to-deposit lag and a discount adjustment for delayed revenue.

Presentation of the main material

The acquisition event ladder and the lock-in convention. A retail forex client passes through an ordered ladder of events: registration (signup), identity verification (KYC), first-time deposit (FTD), first trade, and then recurring deposits and trades that generate the broker revenue. The cost of producing a funded client is the cost-per-acquisition, which decomposes through the funnel cascade

$$CPA = CPS \,/\, (CR_{k\gamma C} \times CR_{mt\partial}) \qquad (1)$$

where CPS is the cost per signup, CR is the conditional conversion from signup through verification to deposit, and the product of conversion rates maps registrations into funded clients. Under the prevailing convention the last click before the signup fixes the registration source s, and that source is credited with the funded client and with the client lifetime value, irrespective of any later activity:

$$C^{look}(i) = \Sigma_j \, FTD_j \cdot \text{U0001D7D9}[s(j) = i] \qquad (2)$$

$$V^{look}(i) = \Sigma_j\, LTV_j \cdot \text{U0001D7D9}[s(j) = i] \quad (3)$$

Two distinct layers of distortion follow. The first layer is touch distortion at the signup: the last click takes the whole registration, and every assisting touch before it takes nothing. This is the classic last-click problem. The second layer, specific to brokerage, is source lock-in after the signup: the registration source inherits the deposit and the full lifetime value, so every post-signup activation touch (reactivation email, customer-relationship messaging, retargeting) is credited with nothing. The second layer grows with the signup-to-FTD lag. A client who registers from one channel and deposits ten months later, after repeated reactivation, still books the deposit and all lifetime revenue to that first channel. The longer the lag, the larger the share of real conversion work that is uncredited, so the distortion is a function of the lag distribution. Fig. 1 sets out the event ladder and the two distortion layers.

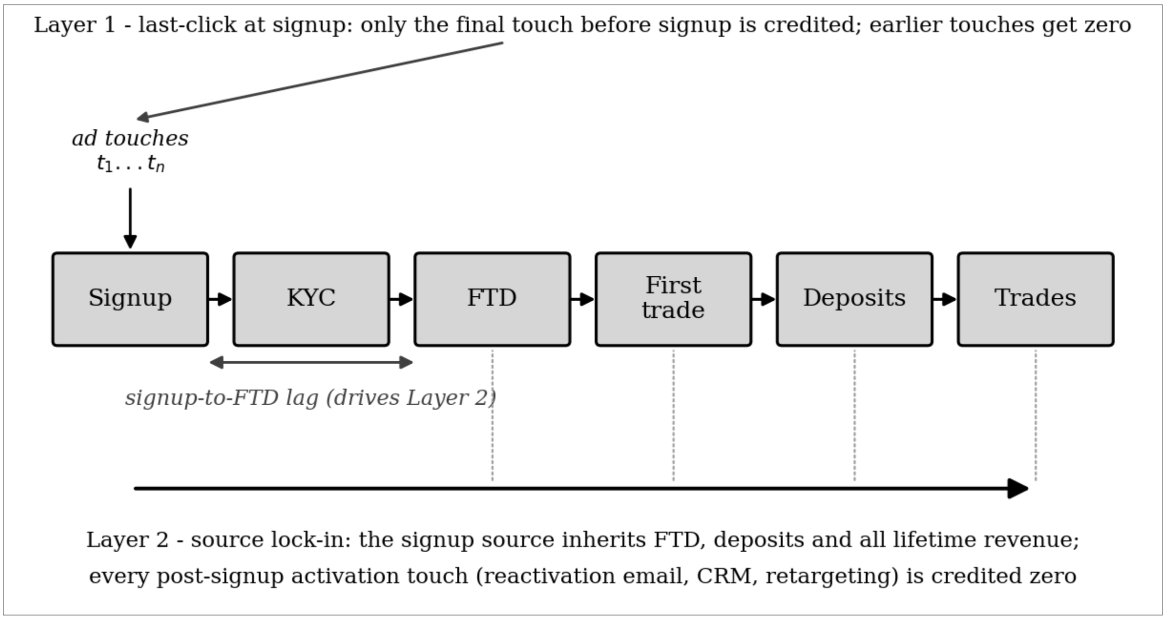

Fig. 1. The forex acquisition event ladder and the two layers of attribution distortion
Source: author construction

The Shapley contribution benchmark. To measure the bias we need an estimate of each channel true contribution. We use the Shapley value over a cooperative game on the set of channels N. For a coalition S of channels, the coalition value $v(S)$ is the volume of converting journeys whose channel set is contained in S,

$$v(S) = \Sigma\ \{f(\mathrm{a}) : \text{channels}(a) \subseteq S\} \quad (4)$$

where a indexes converting-journey archetypes and f(a) their frequency. The Shapley value of channel i is its average marginal contribution across all orderings,

$$\varphi_i = \Sigma\_\{S \subseteq N \setminus \{i\}\}\ [\,|S|!\ (n - |S| - 1)! / n!] \cdot (v(S \cup \{i\}) - v(S)) \quad (5)$$

The Shapley value distributes the entire converting volume across the channels that participated in producing it, including post-signup activation touches, and satisfies efficiency (the shares sum to the total), symmetry, the null-player property, and additivity [8; 9]. It is the contribution benchmark against which the locked credit is judged. Computation is exact over the eleven channel clusters defined below.

Bias in channel-level CAC. Given a paid spend S_i on channel i, the apparent (locked) CAC and the true (Shapley) CAC are

$$\mathrm{CAC}^{look}(i) = S_i / C^{look}(i),\ CAC^{true}(i) = S_i / (\varphi_i \cdot F) \quad (6)$$

where F is total funded clients. The relative bias of the locked estimate is

$$\mathrm{bias}(i) = CAC^{look}(i) / CAC^{true}(i) - 1 \quad (7)$$

A closing channel that hoards locked credit shows a negative bias (it looks cheaper than it is); an initiating or activation channel shows a large positive bias or, when it never closes, an infinite apparent *CAC* because the lock-in credits it with zero.

From biased CAC to budget misallocation. Channel response is modelled with diminishing returns, $F_i(S_i) = \alpha_i\, S_i$^β with $0 < \beta < 1$, where α_i is calibrated at the baseline spend. The broker allocates the fixed budget B to maximise the credit it observes, subject to inventory ceilings c_i (brand search and affiliate inventory are finite):

$$\max_{si}\ \Sigma_i \alpha_i\, S_i\text{\^{}}\beta \text{ s.t. } \Sigma_i S_i = B,\ 0 \le S_i \le c_i\, B \quad (8)$$

Solving (8) with the locked coefficients gives the allocation the broker adopts; solving it with the Shapley coefficients gives the true optimum. The economic loss is the contribution margin forgone by allocating on locked rather than true signals,

$$L = m \cdot [\Sigma_i\ \alpha_i\text{^\{true\}}\ (S_i\text{^\{true*\})^}\beta - \Sigma_i\ \alpha_i\text{^\{true\}}\ (S_i\text{^\{lock*\})^}\beta] \quad (9)$$

where m is the contribution margin per funded client, $m = LTV \cdot$ margin rate, and the true response coefficients value both allocations. Because the deposit revenue arrives after the signup, the present value of the loss applies the lag distribution and a discount rate r,

$$PV(L) = L \cdot \Sigma_k\ w_k / (1 + r)\text{^}\{t_k\} \quad (10)$$

with w the share of deposits in lag bucket k and t its midpoint in months. Equation (9) makes explicit the assumption flagged by Danaher and van Heerde [11]: the Shapley contribution share is used as a proxy for the response coefficient. The robustness of the result to this assumption is discussed below.

Table 1

Channel clusters, funnel role and Tier-1 unit metrics

Channel cluster	Type	Funnel role	CPS, USD	signup→FTD
Generic / competitor search	paid	initiator	45	4.5%
Paid social prospecting	paid	initiator	32	2.5%
Native / display	paid	initiator	26	2.0%
Video	paid	warm-up	37	2.5%
Remarketing	paid	intermediate	30	7.5%
Brand search	paid	closer	14	12.0%
Affiliates / IB	paid	initiator	40 (CPA)	15.0%
Organic search / SEO	non-paid	mixed	n/a	7.0%
Direct / type-in	non-paid	closer	n/a	14.0%
Email / CRM, owned push	non-paid	reactivation	n/a	activation
Referrals / community	non-paid	mixed	n/a	10.0%

Source: aggregated anonymised portfolio of seven CFD/forex broker acquisition projects (FINFORCEONE, EU Tier-1, two years). The blended cost per funded client, total budget divided by funded clients, is set at the author CPA anchor of 650 USD; the per-channel figures are standalone funnel descriptors

Data and parameterisation. The parameters are calibrated on an aggregated, anonymised portfolio of seven EU Tier-1 CFD and forex broker acquisition projects run by the author over two years. The worked example uses a representative monthly paid budget of 1,500,000 USD, a blended CPA of 650 USD, and therefore about 2,308 funded clients per month. Net deposits per funded client are 1,263 USD; extending to the full lifetime through redeposits and trading volume applies a depth multiplier of 1.8, giving a lifetime value of 2,273 USD, and a contribution margin of 30 percent gives 682 USD per funded client. The discount rate is 10 percent per year (tested over an 8 to 15 percent band) and the diminishing-returns exponent is 0.6. The eleven clusters, their funnel roles, and the per-cluster unit metrics are in Table 1. The cost per signup and conversion in Table 1 describe each channel standalone funnel; the cost per funded client the broker later observes (Table 3) diverges from them because the lock-in reassigns credit across channels, and that divergence is the distortion the model measures.

The Shapley benchmark is computed over a reproducible set of converting-journey archetypes calibrated on the observed portfolio patterns: initiators (generic and competitor search, paid social, affiliates, native, video) open journeys, intermediate channels warm them, and the closers that most often deliver the last click before signup are brand search and direct, with the other channels assisting without usually delivering it. In the portfolio a large share of journeys require post-signup reactivation by email, customer-relationship messaging and retargeting before the deposit; that share rises with the signup-to-FTD lag. The archetype frequencies and channel roles are calibrated on the portfolio; the lag distribution is not directly measured and is therefore varied across three scenarios as a sensitivity, and all of this is labelled as such.

Locked credit versus contribution. Table 2 shows the distortion directly. The two closing channels absorb 2,130 of the 2,308 credited funded clients, while the Shapley benchmark assigns them only 992. Brand search alone is credited with 1,410 funded clients but contributes 669. The mirror image is on the initiating side: generic search, paid social and affiliates contribute 701 funded clients between them yet are credited with only 178. Email and customer-relationship messaging carry 181 of the true contribution and remarketing 130, both by reactivating dormant registrations, yet both receive zero locked credit, because they never deliver the last click before a signup and act only after it. Under last-click plus signup lock-in they are invisible. Fig. 2 plots the two credit columns side by side.

Table 2

Locked versus Shapley credit by channel, funded clients per month (mixed-lag scenario)

Channel	Role	Locked	Shapley	Gap
Brand search	closer	1,410	669	–741
Direct / type-in	closer	720	323	–397
Generic / competitor search	initiator	65	287	+222
Paid social prospecting	initiator	48	194	+146
Affiliates / IB	initiator	65	220	+155
Remarketing	intermediate	0	130	+130
Email / CRM, owned push	reactivation	0	181	+181
Native / display	initiator	0	108	+108
Video	warm-up	0	105	+105
Organic search / SEO	mixed	0	59	+59
Referrals / community	mixed	0	32	+32
Total		**2,308**	**2,308**	

Source: author calculations (model output, equations 2 and 5)

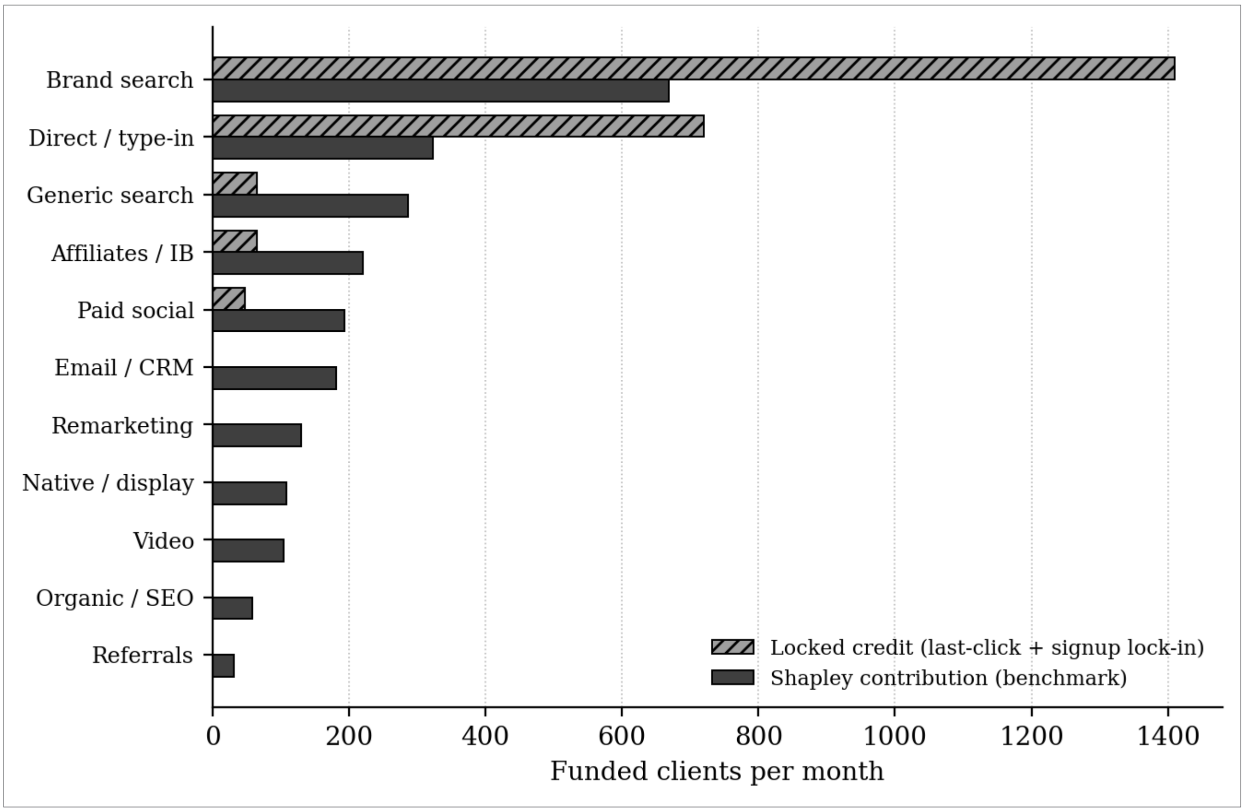

Fig. 2. Locked credit versus Shapley contribution by channel, funded clients per month (mixed-lag)

Source: author calculations (model output, equations 2 and 5)

The spending error. Table 3 converts the credit distortion into prices. Brand search appears 52 percent cheaper than its true CAC, so the system marks it as the best buy. The initiating channels appear far more expensive than they are: generic search and paid social by roughly 300 to 340 percent, affiliates by about 240 percent, and the pure assist and activation channels (native, video, remarketing) appear infinitely expensive because they receive no credit at all. A budget optimised on these prices behaves predictably. Table 4 reports the allocation the broker adopts when it optimises on locked signals, against the true optimum.

Optimising on locked signals fills brand search and affiliates to their inventory ceilings (20 and 25 percent) and pushes the rest of the budget into generic search at 29 percent and paid social at 26 percent, while zeroing the three activation channels that the lock-in renders invisible. The true optimum keeps brand search at its ceiling, funds video, native and remarketing, and trims generic to 21 percent, paid social to 14 percent and

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Table 3

Apparent (locked) versus true (Shapley) CAC and bias, paid channels (mixed-lag)

Paid channel	Spend, USD	Locked CAC	True CAC	Bias
Generic / competitor search	375,000	5,769	1,307	+341%
Paid social prospecting	255,000	5,312	1,314	+304%
Native / display	150,000	no credit	1,389	∞
Video	120,000	no credit	1,143	∞
Remarketing	165,000	no credit	1,269	∞
Brand search	180,000	128	269	–52%
Affiliates / IB	255,000	3,923	1,159	+238%

Source: author calculations (model output, equations 6 and 7). "no credit" denotes channels the lock-in credits with zero funded clients, giving an infinite apparent CAC

Table 4

Paid budget allocation: baseline, locked-optimal, true-optimal, percent of budget (mixed-lag)

Paid channel	Baseline	Locked-optimal	True-optimal
Generic / competitor search	25%	29%	21%
Paid social prospecting	17%	26%	14%
Native / display	10%	0%	7%
Video	8%	0%	9%
Remarketing	11%	0%	10%
Brand search	12%	20%	20%
Affiliates / IB	17%	25%	19%

Source: author calculations (model output, equation 8). Inventory ceilings: brand search 20%, affiliates 25%, remarketing 15%

affiliates to 19 percent. The broker starves precisely the channels that do the uncredited reactivation work, which is what makes the loss grow with the lag. Fig. 3 contrasts the three allocations.

Results: the lag is the engine. Table 5 reports the headline loss. Optimising the budget on locked signals forgoes 3.3 percent of the paid budget when deposits arrive quickly, rising to 11.0 percent in the long-tail

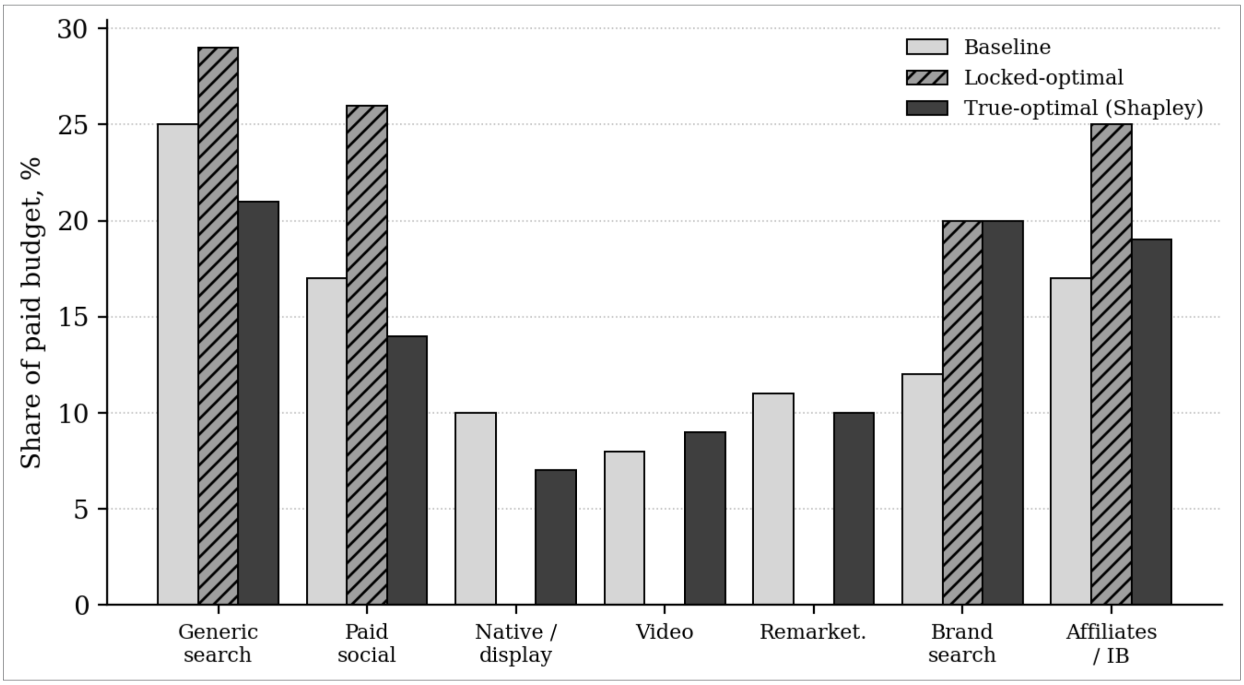

Fig. 3. Paid budget allocation: baseline, locked-optimal, and true-optimal (mixed-lag)

Source: author calculations (model output, equation 8)

Table 5

Loss from attribution-driven misallocation by signup-to-FTD lag scenario

Lag scenario	Long-lag share	Lost FTD	Loss L, USD/mo	L, % budget	Excess CAC
Fast	10%	72	49,105	3.3%	26
Mixed	30%	147	100,257	6.7%	66
Long-tail	45%	243	165,731	11.0%	127

Source: author calculations (model output, equation 9). Excess CAC is per funded client. Long-lag share is the proportion of deposits arriving more than 90 days after signup

scenario, with a central estimate near 6.7 percent. On the 1,500,000 USD monthly budget this is between 49,000 and 166,000 USD per month, or roughly 1.2 million USD per year at the central estimate. The excess effective CAC rises from 26 to 127 USD per funded client. The loss more than triples from the fast to the long-tail scenario for one reason: a longer signup-to-deposit lag means more of the real conversion work is post-signup reactivation, which the lock-in credits with nothing, so the misallocation widens. Discounting the delayed revenue at 10 percent per year, over the 8 to 15 percent band, changes the present value of the loss by under two percent, so the time value of money is a second-order adjustment, not the mechanism. The mechanism is the lag-driven growth of uncredited activation. Fig. 4 plots the loss against the long-lag share.

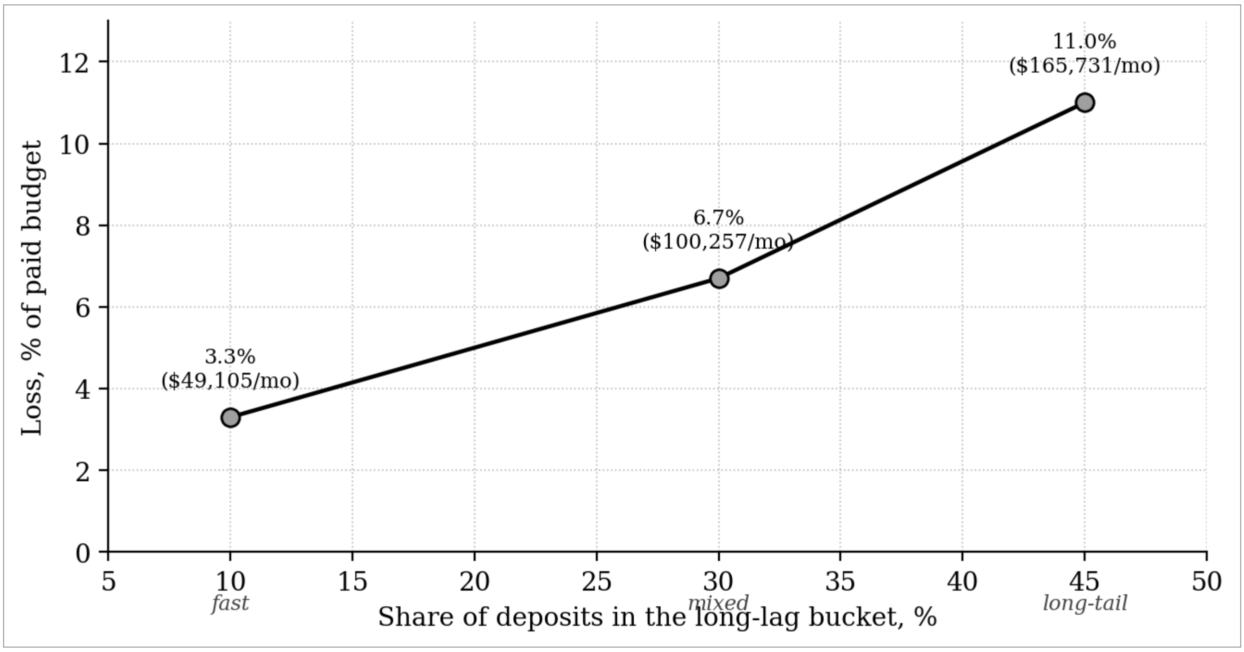

Fig. 4. Loss from attribution-driven misallocation as a function of the signup-to-FTD lag
Source: author calculations (model output, equation 9)

Robustness and limitations. Three limitations bound the result. First, equation (9) uses the Shapley contribution share as a proxy for the forward response coefficient; as Danaher and van Heerde show, contribution is not elasticity, and a fully causal allocation would require incrementality experiments [11]. The loss reported here should therefore be read as the misallocation under the contribution-truth assumption, and an incrementality-based replication is the natural validation. Second, the Shapley benchmark is computed over a stylised archetype structure calibrated to the author judgement of channel roles, not over an empirical path dataset; the qualitative result (closers over-credited, initiators and activation channels under-credited) is robust to the structure, but the exact magnitudes depend on it. Third, the parameterisation is an aggregated EU Tier-1 portfolio; markets with cheaper registrations and longer lags would show larger losses, which the lag sensitivity already indicates. None of these limitations affects the direction or the order of magnitude of the finding.

Applied decision rule. For a practitioner the model reduces to a procedure. Do not value a channel by the revenue locked to its registrations. Estimate contribution with a multi-touch or Shapley method that credits post-signup activation, treat the signup-to-deposit lag as a parameter that inflates the value of reactivation channels, and cap the closing channels at their real inventory rather than letting locked ROAS pour budget into them. Where contribution shares drive budget, validate them against holdout or geo-incrementality tests before reallocating at scale.

Conclusions and prospects for further research. Last-click attribution anchored to the signup event, followed by lock-in of all lifetime revenue to the registration source, is the prevailing measurement convention in retail forex acquisition, and it is not neutral. It systematically over-credits closing channels and renders initiating and post-signup activation channels invisible, biasing channel-level CAC by a factor of two or more and, where a channel never closes, to infinity. Optimising a fixed budget on these biased signals forgoes a measurable share of contribution margin, between roughly 3 and 11 percent of the paid budget in the worked example, with the loss growing as the signup-to-deposit lag lengthens because longer lags leave more reactivation work uncredited. The time value of delayed revenue is a minor additional adjustment. In the worked example the central loss is near 100,000 USD per month, about 1.2 million USD per year on a 1,500,000 USD monthly budget, money that buys no additional funded clients and is recoverable by valuing channels on their contribution rather than on the revenue locked to their registrations. The contribution of the article is to price these three brokerage-specific features, the event ladder, the source lock-in, and the lag, jointly and on reproducible parameters.

Further research can extend the lifetime horizon explicitly to redeposit and trading-volume curves, replace the Shapley contribution proxy with incrementality-based estimates to address the contribution-versus-elasticity caveat, and parameterise the model across multiple markets to map how registration cost and lag jointly determine the size of the loss.

ДОДАТКОВА ІНФОРМАЦІЯ

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ВПЛИВ МОДЕЛЕЙ АТРИБУЦІЇ НА РОЗПОДІЛ МЕДІАБЮДЖЕТУ CFD-БРОКЕРА: ГРОШОВА ОЦІНКА ВТРАТ

Анотація. *Вступ. Платне залучення клієнтів є основною статтею витрат роздрібних брокерів контрактів на різницю (CFD) та форекс, а ефективність цих витрат оцінюють через модель атрибуції, яка приписує конверсії маркетинговим каналам. Галузевим стандартом у роздрібному брокериджі є атрибуція останнього кліку, прив'язана до події реєстрації (signup), після чого канал реєстрації вважається власником усього подальшого доходу.*

Мета. Дослідження кількісно оцінює економічну ціну цієї конвенції. Побудовано економіко-математичну модель того, як атрибуція останнього кліку в поєднанні з прив'язкою джерела реєстрації зміщує оцінку вартості залучення (CAC) за каналами та призводить до хибного розподілу медіабюджету, і виражає отримані втрати у грошовому вимірі.

Матеріали і методи. Модель формалізує каскад подій залучення (реєстрація, ідентифікація, перший депозит, перша угода, повторні депозити та угоди) і два окремі шари викривлення: викривлення дотику на події реєстрації та прив'язку джерела щодо всього подальшого доходу. Справжній внесок кожного каналу апроксимується значенням Шеплі, обчисленим на відтворюваній структурі коаліцій конверсійних шляхів. Відгук каналу змодельовано зі спадною віддачею та стелями ємності; втрата це недоотримана контрибуційна маржа при оптимізації бюджету за зміщеними сигналами замість справжнього внеску. Параметризацію взято з практики залучення автора для профілю EU Tier-1.

Результати. За конвенції прив'язки закривальні канали (брендовий пошук і прямі заходи) отримують кредит значно вищий за їхній внесок за Шеплі, тоді як ініціювальні та пост-реєстраційні активаційні канали систематично недокредитовані або зовсім невидимі. Оптимізація бюджету за цими зміщеними сигналами призводить до втрати від приблизно трьох до одинадцяти відсотків медіабюджету у контрибуційній маржі, і втрата зростає зі збільшенням лагу між реєстрацією та депозитом, бо довший лаг лишає більше некредитованої реактиваційної роботи. Дисконтування відкладеного доходу додає незначну поправку.

Перспективи. Подальша робота може поширити модель на горизонти повторних депозитів і торгового обсягу, на еталони на основі інкрементальності та на багаторинкову параметризацію.

Ключові слова: *атрибуція, останній клік, вартість залучення клієнта, розподіл медіабюджету, значення Шеплі, CFD-брокер, форекс, маркетингова аналітика.*