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Constructing Daily Hong Kong Online Price Index and Price Dynamics: The Role of E-commerce in the Post-pandemic Era

香港網上物價指數及價格動態之建構：後疫情時代電子商貿的角色

Final Report
Project Number: 2022.A2.053.22B

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The success of this project is a testament to the collaborative efforts of all parties involved, and we are honored to have had the opportunity to work alongside such dedicated and supportive partners.

Executive Summary

Abstract

Internet of Things has catalyzed the rise of e-commerce, further accelerated by COVID-19's impact on consumer behaviors. This study leverages granular e-commerce data from 9 major Hong Kong's e-commerce platforms to construct an innovative daily Online Price Index (OPI) using transaction information on diverse products. The OPI demonstrates four advantages over the official Consumer Price Index (CPI). First, utilizing actual prices mitigates biases like out-of-stock and new product effects. Second, the high frequency, low cost, and large scale of e-commerce data enables real-time OPI derivation. Third, incorporating sales quantities allows adopting the Fisher index, canceling out over- and under-estimation issues. Fourth, including discounts in transactions better reflects actual consumer expenses. This study assesses the OPI's value in two dimensions: (1) as a complementary CPI measure given its timeliness, daily frequency, cost-effectiveness and a flexible weighting scheme that adapts to changing preferences, and (2) the use of big data from e-commerce companies to estimate price stickiness through hazard functions, providing insights into the effectiveness of monetary policy in a post-pandemic context.

繁體中文版:

物聯網推動了電子商務的興起，COVID-19 對消費者行為的影響進一步加速了這一趨勢。本研究利用來自香港 9 大主要電子商務平台細緻的電商數據，構建了一個創新的每日在線價格指數（OPI），涵蓋了多樣化產品的交易信息。OPI 相較於官方消費者價格指數（CPI）展現了四大優勢。首先，利用實際價格減少了缺貨和新產品效應等偏差。其次，電子商務數據的高頻率、低成本和大規模等特性，能夠有助我們推導實時的 OPI。第三，納入銷售數量考量的費雪指數（Fisher Index），調和了傳統指數的高估和低估問題。第四，在運算中包括交易中的「折扣」更能反映消費者真實開支。本研究的價值在於：（一）考慮到其具有的及時性、每日頻率、成本效益以及能夠適應不斷變化偏好的靈活權重方案，我們構建了一個新的價格指數，作為官方消費者價格指數（CPI）的補充衡量標準；（二）利用來自電子商務公司的大數據，通過風險函數估計價格的黏性，為我們提供了有關後疫情貨幣政策效果的深刻見解。

A Layman Summary

Measuring changes in the prices of goods and services is crucial for gaining insights into inflation and cost of living trends. Governments usually rely on periodic surveys to calculate the Consumer Price Index (CPI) as a key indicator. However, the manual collection of this data is a time-consuming process, and as a result, the CPI cannot be updated on a daily basis.

This study delves into the utilization of real-time price data from major e-commerce companies to construct a daily Online Price Index (OPI). This study analyzes big data sourced from major e-commerce companies in Hong Kong. Our findings indicate that the OPI, which tracks the day-to-day price movements, offers more informative insights than the monthly official CPI. Specifically, the OPI reveals shifts in online purchasing behavior during COVID-19 pandemic, provides near-real-time updates, and presents the price movements for both listed prices and discounted items.

The study demonstrates the potential of harnessing big data from e-commerce to improve official statistics. Broader access to online shopping data and government resources can facilitate the creation of additional economic indicators, such as a produce price index.

These innovative indices can assist households, businesses and policymakers by providing real-time insights into the cost of living. Early warning systems for inflation, based on e-commerce data, can also help shape responses to potential economic fluctuations. In essence, this research underscores how new technologies and data sharing can bolster economic measurement and ultimately serve the public good.

繁體中文版:

測量商品和服務價格的變化對於了解通脹和生活成本趨勢至關重要。政府通常依賴定期調查來計算消費者價格指數（CPI）作為關鍵指標，但收集這些數據需時，而且 CPI 難以每日發佈。

本研究探討使用來自主要電子商務公司的實時價格數據來構建每日在線價格指數（OPI）。本研究分析大量了來自在香港主要電商的數據。我們發現每日的 OPI 比月度官方 CPI 更有效地捕捉到日常價格變動。OPI 還揭示了在 COVID-19 期間人們在線購買物品的變化。

該研究顯示了利用電子商務的大數據來改進價格統計的潛力。透過廣泛地搜尋網上購物信息有助開發更及時的經濟指標。這一方面說明政府需要積極推動私人公司與各政府部門共享數據。

這些創新指數可以通過提供最新的生活成本為家庭、企業和政策制定者提供洞見。而基於電子商務數據的通脹早期警報系統亦可以反映潛在的經濟波動。總的來說，這項研究強調了新技術和數據共享如何加強經濟測量並造福於公共利益。

1. Introduction

Inflation continues to play a pivotal role in guiding monetary policy and influencing consumer behavior. In Hong Kong, the Consumer Price Index (CPI) serves as the primary metric for assessing inflation. However, the CPI has certain limitations, including infrequent monthly updates, static weighting of goods, and manual data collection methods, which hinder its ability to promptly capture real-time shifts in the dynamic digital marketplace.

With e-commerce penetration growing rapidly in Hong Kong, online platforms offer invaluable transactional data that can supplement and enhance the CPI. This study proposes leveraging e-commerce big data to achieve the following objectives:

(1) To construct a novel composite Online Price Index (OPI) at a daily frequency with big data from HKTVS, the biggest local e-commerce company, in both pandemic and the post-pandemic period.

(2) To explore similarity and dissimilarity of OPI and official CPI through matching the time-varying weights of the sub-categories of goods and services derived from the e-commerce data to the fixed weights used in the official CPI.

(3) To measure the price stickiness by estimating the hazard function of the subcategorical OPI.

Our research outcomes surpassed our initial targets, as we successfully integrated big data from 9 key e-commerce platforms, including HKTVS, into our final analysis. This research can provide policymakers and businesses with timely indicators to formulate strategies, while also offering valuable feedback to refine official statistics. The study contributes pioneering analytics to decode price dynamics in e-commerce, elucidating its economic impact. With rising digital integration, this investigation aims to harness the power of big data to advance economic monitoring and decision-making.

1.1. Background

The shift in the Consumer Price Index (CPI) is frequently utilized as a gauge for inflation, impacting consumer purchasing power, the actual returns for investors, and the efficacy of monetary policies. Given its extensive influence, inflation remains under constant scrutiny by the markets.

1.1.1. Hong Kong's Consumer Price Index

The CPI serves as a key barometer for assessing the fluctuating costs of consumer goods and services over a period. In Hong Kong, the compilation of this critical index is the responsibility of the Census and Statistics Department (C&SD). This department meticulously constructs various CPI categories — CPI(A), CPI(B), and CPI(C) — that correspond to the spending trends across households with different levels of expenditures: low, medium, and high, respectively. Additionally, a composite CPI is calculated to encapsulate the broader impact of price variations on households collectively, offering a comprehensive view of inflation's imprint on the household sector as a whole.

To capture these price shifts accurately, the C&SD executes a Monthly Retail Price Survey, manually gathering upwards of 40,000 price quotes from an extensive network of about 3,500 retail and service providers within Hong Kong. This data collection process extends to tracking rental costs for private housing. For standardized services and changes in public housing rentals, data compilation is streamlined since the C&SD can acquire information directly from the relevant corporations and governmental entities.

Aligning with international norms that advocate for the updating of expenditure weighting patterns at a minimum of every five years, the current weighting for the 2019/20-based CPI series was derived from data of the 2019/20 Household Expenditure Survey (HES). This crucial survey spanned from October 2019 to September 2020, a timeframe significantly influenced by the economic repercussions of the COVID-19 pandemic. Recognizing the exceptional circumstances of the pandemic and its potential to distort typical expenditure patterns, the C&SD has instituted additional yearly reviews to adjust the CPI expenditure weights. This ensures a level of precision and relevance until the subsequent scheduled rebase in the 2024/25 cycle.

For a more detailed exploration and understanding of this process, readers can consult the C&SD's publication titled "*2019/20 Household Expenditure Survey and the Rebasing of the Consumer Price Indices*", which offers a thorough dissection of the methodologies and findings from the survey and its subsequent impact on the recalibration of the CPI.

1.1.2. Technology development, COVID-19 and Consumers' Behavior

The academic conversation surrounding the impact of information technology (IT) on economic progression is burgeoning, with key contributions from researchers such as Goldfarb & Tucker (2019) and Hernández et al. (2011). This discourse is particularly relevant to Hong Kong, where, according to Statista (2022)[1], there has been a marked uptick in technological integration among the population. Smartphone adoption has soared from a penetration rate of 54% in the third quarter of 2012 to a staggering 92.1% by the third quarter of 2020 for individuals aged over 10 years. Simultaneously, internet usage has also escalated, jumping from 82.7% in 2015 to 90.3% in 2020.

This surge in digital adoption has laid a robust foundation for e-commerce, a sector poised for significant expansion as forecasted by Global Data[2]. They anticipate a vibrant 11.1% rise in e-commerce sales for Hong Kong in 2021, with projections pointing to a sustained growth trajectory at a compound annual growth rate of 8.3%, potentially elevating the market from HK$178.0 billion (US$22.9 billion) in 2021 to HK$226.0 billion (US$29.0 billion) by 2024. Contributory factors to this growth include not only high-tech penetration rates but also enhancements in payment and logistics infrastructure.

[1] https://www.statista.com/statistics/1093416/hong-kong-penetration-rate-of-smartphone/
[2] https://www.globaldata.com/media/banking/hong-kongs-e-commerce-growth-will-continue-beyond-covid-19-pandemic-says-globaldata/

The COVID-19 pandemic catalyzed a paradigm shift in consumer behavior, nudging a transition from traditional brick-and-mortar shopping to online commerce - a trend that has persisted into the post-pandemic landscape. Fears concerning viral transmission have notably dampened physical retail activities. To illustrate, research by Chen et al. (2021) observed that China's offline consumption plummeted by more than 1 trillion RMB in the two months following the outbreak, a decline resonating at approximately 1% of China's GDP for 2019. The pandemic-induced social restrictions have also dealt a blow to the logistics sector, affecting industries dependent on physical interaction, such as transportation, hospitality, and leisure, while concurrently boosting online expenditures on groceries and foodstuffs, as highlighted by Cavallo (2020) and Yang et al. (2021). The 2020 Visa Consumer Payment Attitudes Study corroborates this trend, indicating that over half of all shopping activities in Hong Kong during the pandemic were carried out online—a jump from the pre-pandemic figure of 40%.

The term "digital transformation" captures the essence of this shift from in-person transactions to digital dealings and the broader adoption of IT across conventional business practices. The disruptive nature of COVID-19 has not only reshaped the commercial landscape but has also expedited the digital transformation across various sectors. Amankwah-Amoah et al. (2021) refer to the pandemic as a significant catalyst for digital adoption within work environments, influencing how offices operate. In the healthcare sector, for instance, innovative technologies like the

Internet of Things (IoT) and big data analytics have been identified as critical tools in managing the challenges of COVID-19 and beyond, as per the findings of Zhang et al. (2021). The food service industry has also witnessed a transformation in its trade practices, with Luo & Xu (2021) suggesting that consumers have increasingly turned to online food purchases as a safer alternative during the pandemic. Gao et al. (2020), using data from Chinese cities, demonstrate a positive correlation between the prevalence of COVID-19 cases and the propensity of consumers to order food online. The fashion industry has not been exempted from this digital shift, with e-commerce becoming the dominant business model for fast-fashion retailers during the global pandemic, as discussed by Bilińska-Reformat & Dewalska-Opitek (2021).

The convergence of these factors—heightened technological integration, behavioral adjustments in the wake of the pandemic, and the accelerated embrace of digital platforms—underpins a transformative era for e-commerce and digital business models, reshaping economies and consumer patterns in profound ways.

1.1.3. The E-Commerce in Hong Kong

E-commerce in Hong Kong has emerged as a vibrant and integral component of the retail sector, particularly accentuated by the strategic utilization of substantial online transaction data to monitor price dynamics. At the forefront of this digital commerce evolution is the Hong Kong TV Shopping Network Company Limited (HKTVS), a distinguished e-commerce conglomerate renowned for its diverse range of products. HKTVS caters to an extensive array of consumer needs by offering everything from personal health care items to oversized furniture and even insurance products through its online platform, HKTVmall.

HKTVmall's innovative business model is predicated on leasing digital storefronts to a myriad of retailers who then present their goods and services to Hong Kong's city-wide consumer base. These retailers contribute to HKTVS's revenue by paying an annual fee—ranging from HK$15,000 to HK$50,000 based on their product listings—which is reminiscent of traditional retail space rental. Additionally, they share a portion of their sales turnover with the company. This structure proved lucrative for HKTVS, with sales tripling to HK$1.4 billion across the three years leading up to 2019. The advent of the COVID-19 pandemic served to further amplify HKTVmall's financial success, with sales doubling in 2020 to HK$2.88 billion and net profits escalating to HK$183.6 million, a remarkable turnaround from the previous year's loss.

This meteoric rise in e-commerce is reflected across various online supermarket stores in Hong Kong, including heavyweights such as Wellcome, Market Place by Jasons, and A.S. Watson's PARKnSHOP, among others. These platforms, many of which are lauded as top online retailers by the YouGov survey (2022) and the Retailer Preference Index study by Dunnhumby[3], have solidified their positions as stalwarts of

[3] https://www.businesswire.com/news/home/20220502005066/en/Wellcome-and-PARKnSHOP-Named-as-Hong-Kong%E2%80%99s-Top-Grocery-Chains-in-dunnhumby-Retailer-Preference-Index

e-commerce in the region. HKTVmall, in particular, has distinguished itself as the most frequented e-commerce destination, amassing a staggering 464.2 million monthly web visits in the final quarter of 2020, according to a survey by Ma (2022). This level of web traffic signifies a robust consumer engagement that other platforms also experienced during this period.

Furthermore, a study by Frost & Sullivan in 2021 illustrated that HKTVmall, ParknShop, and Watsons eShop collectively command a significant portion of the market share, with HKTVmall alone accounting for 13.9%[4]. In the broader spectrum of retail, Euromonitor International's 2021 marketing survey placed A.S. Watson Group and Dairy Farm International Holding Limited at the apex of the industry, crowning them as the leading entities in terms of sales growth for two consecutive years, 2019 and 2020[5].

The comprehensive presence of 9 online shopping platforms, including HKTVmall, Wellcome, Market Place by Jasons, Mannings from Dairy Farm, A.S. Watson's PARKnSHOP, Watsons eShop, AEON, DCH Food Mart, and Television Broadcasts Limited's Ztore, offers a panoramic view of Hong Kong's e-commerce landscape, revealing an industry that not only adapts to the challenges of modern retail but also thrives amidst them, shaping the future of shopping in this dynamic city.

[4] https://store.yohohongkong.com/ir/docs/Prospectus_Eng.pdf
[5] https://marketech-apac.com/as-watson-group-leads-top-hong-kong-retailers-in-2020/

2. Research Niche

In this comprehensive study, we set out to accomplish three pivotal objectives, each designed to leverage the vast potential of big e-commerce data. Our initial objective is to develop an innovative composite Online Price Index (OPI). This index will utilize data from 9 online e-commerce platforms to monitor the daily price fluctuations of a wide array of goods and services, offering an unprecedented near real-time view of market trends (detailed in Section 2.1).

Our secondary objective is to conduct an in-depth comparative analysis between this emergent daily OPI and the traditional monthly Consumer Price Index (CPI) issued by official sources. This will involve a meticulous component analysis where we will align the online product offerings to the categories that make up the official CPI. By assigning time-varying weights to these products and juxtaposing them with the fixed weights derived from the Household Expenditure Survey (HES), we intend to not only underscore the parallels and variances between these two indices but also to demonstrate how the OPI can serve as a complementary metric, thus bolstering the case for a more open data access policy (as elaborated in Section 2.2).

The third objective of our study is to scrutinize price stickiness, which is an indicator of how resistant nominal prices are to change promptly. Understanding the nature of price stickiness is crucial for formulating monetary policy, as it influences the real economy by affecting variables like output, consumption, and employment. Given that the official CPI from the Census and Statistics Department (C&SD) is released on a monthly basis, policymakers often face a delayed response in gauging this effect. Through our analysis, we aim to measure the price stickiness in an online context by employing hazard function calculations using our e-commerce dataset. This will not only shed light on the price adjustment speed of online retailers but will also allow us to evaluate whether these adjustments occur more rapidly compared to what has been documented in existing literature (this aspect is further explored in Section 2.3).

2.1 How can the big e-commerce data complement the traditional CPI?

2.1.1 From e-commerce to big data

The advent of big data has been heralded as the cornerstone of the fourth industrial revolution, powering advancements in machine learning, robotics, and the development of intelligent urban ecosystems, as delineated by Borhauer (2018) and Schwab (2017). The integration and dependability of the Internet of Things (IoT) are revolutionizing retail, creating a seismic shift in how consumers and retailers interact (Einav & Levin, 2014a; Schwab, 2017). This transformation has been accelerated by the global COVID-19 pandemic, which necessitated lockdowns and social distancing measures, thereby prompting a significant migration of commercial activity to the digital domain. This shift encompasses a diverse range of product categories, from daily groceries and health care items to fashion and essential goods, prompting changes in consumption patterns and retail strategies (Gao et al., 2020; Luo & Xu, 2021;

Bilińska-Reformat & Dewalska-Opitek, 2021; Barnes, 2016; De Regt, Barnes, & Plangger, 2020).

From the consumer's perspective, the online marketplace offers an enhancement in the variety and convenience of shopping, significantly reducing the cost and effort associated with searching for rare or specialized products without the need for a physical journey (Brynjolfsson et al., 2003; Goolsbee & Klenow, 2006; Brynjolfsson & Oh, 2012; Varian, 2013; Quan & Williams, 2018; Dolfen et al., 2019). Meanwhile, small-scale retailers find a cost-effective haven in e-commerce platforms, where they can circumvent the financial burdens of rent, in-person staffing, and the operational expenses associated with brick-and-mortar establishments by opting for a model that leverages a licensing fee and a commission on sales generated from online traffic.

In this new digital retail landscape, as Schwab (2017) notes, the incremental cost associated with selling additional products on an established online platform can be negligible. This shift not only democratizes retail by leveling the playing field for smaller players but also results in the accumulation of voluminous big data sets. These data sets are invaluable, providing deep insights into consumer behavior, pricing dynamics, and market trends. Capitalizing on this wealth of information, we have the opportunity to construct a nuanced Online Price Index (OPI), offering an analytical lens to decode the intricacies of e-commerce and its impact on the economy.

2.1.2 Key features in our data set

In the context of Hong Kong, the Census and Statistics Department (C&SD) engages in a manual collection of price data across various regions from the start to the end of each month, as previously outlined in Section 1.1. This process leads to the publication of the Consumer Price Index (CPI) with a one-month delay, primarily due to the extensive manpower requirements, which inhibits the C&SD's ability to reflect immediate price fluctuations within the month. To address this latency issue, Cavallo (2013) piloted a pioneering approach with the Billion Prices Project, leveraging web-scraped data from online platforms to devise an inaugural online price index for five Latin American countries, namely Argentina, Brazil, Chile, Colombia, and Venezuela. By 2010, this initiative had amassed a database of 5 million daily price records from upwards of 300 retailers across 50 nations (Cavallo & Rigobon, 2016). The findings revealed that the online price index aligns closely with the official inflation rates for all surveyed countries except Argentina. Further studies, such as those by Aparicio & Bertolotto (2020), have utilized web-scraped pricing data to anticipate future inflation trends, with the online price index projections surpassing the accuracy of several conventional survey-based forecasts across various countries including Australia, Canada, France, and the United States.

The wealth of insights from online data points to its pivotal role in refining inflation metrics. Nonetheless, the granularity of transactional data eclipses what can be gleaned from standard price quotations or web scraping. The data from HKTVS stands apart from conventional sources along four key dimensions. Firstly, it captures precise transactional details such as the quoted price, discounted price and quantities sold. Secondly, the e-commerce sector's penetration into nearly every facet of daily life ensures a more expansive and representative basket of goods and services for CPI computation than traditional methods, with the capacity for dynamic weight adjustments based on actual sales data. Thirdly, the digitized nature of e-commerce transactions allows for real-time recording in databases, thus enabling daily CPI updates at a fraction of the cost and effort of manual data collection. Fourthly, the HKTVS data encompasses elements often overlooked in CPI calculations, such as discounts, which are essential in consumer purchasing decisions and can now be integrated into the CPI to more accurately reflect the reality of consumer expenses.

Enhancing the robustness of this study, our dataset also incorporates information (quoted prices and discounted prices) from other eight prominent e-commerce entities operating in Hong Kong. This includes Wellcome, Market Place by Jasons, Mannings from Dairy Farm, A.S. Watson's PARKnSHOP, Watsons eShop, AEON, DCH Food Mart, and Television Broadcasts Limited's Ztore, all of which contribute their data to the public repository at data.gov.hk. The inclusion of these platforms not only broadens the scope of our analysis but also enriches the CPI with a multidimensional view of the territory's e-commerce ecosystem. Through the synthesis of such diverse and comprehensive data streams, our research is positioned to offer an unprecedented, real-time perspective on price dynamics in Hong Kong's vibrant online marketplace.

2.1.3 Existing biases of traditional CPI formula & big data solution

The Consumer Price Index (CPI), based on survey methodologies, is plagued by a range of biases including substitution bias, out-of-stock bias, new goods bias, and nonresponse bias, as identified by several researchers (Diewert & Fox, 2020; Soloveichik, 2020; Griffith et al., 2016; Nevo & Wong, 2019; Jaravel & O'Connell, 2020; Diewert, 1998; Feenstra, 1994; Groves, 2011).

Substitution bias arises when consumers adjust their buying preferences in response to changes in price, opting for more affordable alternatives when prices rise. The CPI often fails to account for this dynamic behavior as it typically relies on a set basket of goods and services with fixed weights. This rigidity can result in an overestimation of inflation, especially when discount mechanisms like seasonal promotions or bulk-buying incentives alter the actual prices consumers pay (Griffith et al., 2016; Nevo & Wong, 2019; Jaravel & O'Connell, 2020). Estimates by Lequiller (1997) suggest that in France, such biases could introduce an error margin ranging from 0.05 to 0.15%.

The COVID-19 pandemic underscored these biases as consumer spending patterns shifted dramatically, with increased expenditures on groceries and a drop in spending on transportation and apparel, indicating a significant shift in consumption preferences. The traditional Laspeyres Price Index, which assumes unchanging consumer spending patterns, therefore, tends to inflate the measure of inflation. The impact of new product demands and stock shortages, which are not effectively captured through manual data collection methods, further complicates accurate CPI calculations.

Our study leverages e-commerce transaction data of HKTVS to avoid the out-of-stock and new goods biases. This data set, which includes daily records, is critical in our endeavor to track accurate price movements and to avert the distortions caused by averaging over time, which can often lead to misleading price trends (Cavallo & Rigobon, 2016; Cavallo, 2017).

While the CPI in Hong Kong is rebalanced every five years, this infrequency in updating weights leads to pronounced substitution biases. The Paasche Price Index, with its reflection of current purchasing patterns and dynamic weights, can undervalue inflation in contrast to the Laspeyres approach. To strike a balance and provide a more precise cost of living measurement, Diewert (1976) and Diewert & Parkan (1983) recommend the Fisher's Ideal Price Index, which is the geometric mean of the Laspeyres and Paasche indices and serves to neutralize their respective biases. However, even this index is not immune to overlooking transaction costs such as discounts.

In response, our study capitalizes on the rich dataset provided by HKTVmall, which encompasses comprehensive daily e-commerce data including prices, quantities, discounts, and product categories. We also extend the data set by including other 8 major e-commerce companies' daily quoted and discounted prices.

This enables us to refine the estimation of the Fisher's Ideal Price Index by incorporating discounts (a typical type of transaction cost), hence addressing the biases associated with fixed weights and substitutions. By modifying both the Laspeyres and Paasche indices to factor in the discounts involved in transactions, we are poised to offer a more nuanced and precise evaluation of inflation that is better aligned with the actual consumer experience.

2.1.4 Is the cost of living higher or lower in the post-pandemic era?

In the aftermath of the COVID-19 pandemic, the issue of whether the cost of living has risen or fallen remains a critical question. Researchers like Einav & Levin (2014a, 2014b) and Cavallo (2013, 2017, 2018) highlight the importance of big data in understanding the nuances of inflation, particularly in the context of the pandemic's economic upheaval. For instance, Jaravel & O'Connell (2020) observed a remarkable shift in the UK where 96% of households faced inflation in 2020 post-pandemic, in contrast to prior years when a significant portion experienced deflation. The value of real-time data in swiftly identifying inflationary trends amidst economic turmoil is underscored, indicating that traditional measures may not sufficiently capture the rapid changes during a crisis. Cavallo's (2020) approach, utilizing credit and debit card transactions to adjust the official CPI weights, revealed an initial underestimation of inflation during the pandemic's early stages. This finding underscores the imperative for developing an up-to-the-minute inflation gauge for Hong Kong to supplement the traditional, less responsive CPI, thereby providing stakeholders with timely insights into prevailing market conditions.

The imposition of state-wide lockdowns resulted in profound impacts on both demand and supply (Brinca et al., 2021; Guerrieri et al., 2020; Baqaee & Farhi, 2020). From the demand perspective, the pandemic's effect was uneven across various sectors, with a marked shift in consumption patterns towards food and groceries (Cavallo, 2020), leading to disparate sectoral inflation rates. Concurrently, heightened economic uncertainty and the reduction in household incomes and liquid assets introduced deflationary forces into the economy (Jaravel & O'Connell, 2020). On the supply side, the interruption of supply chains and labor restrictions due to social distancing measures elevated the prices of imported goods. The fluctuation of natural resource commodity prices peaked during the pandemic, adding to the inflationary pressures (Sun & Wang, 2021). The rise in production costs also contributed to escalating inflation expectations globally (Cavallo, 2020).

Given these opposing dynamics of demand and supply, the pandemic could potentially lead to a range of outcomes including deflation, disinflation, or heightened inflation (Jaravel & O'Connell, 2020). The pandemic triggered a composite effect of a negative demand shock paired with supply chain disruptions, culminating in increased price levels across various sectors (Cavallo, 2020). This study aims to broaden the scope of our existing Online Price Index (OPI) data to encompass the post-pandemic era. The objective is to ascertain whether Hong Kong is currently undergoing inflation, disinflation, or deflation, and to dissect these trends across different product categories.

2.2 What is the degree of complementarity of OPI with the official CPI?

The Consumer Price Index (CPI) plays a pivotal role in guiding policymakers in crafting economic strategies, adjusting tax systems, and establishing public sector pay scales. This index, which captures the ebbs and flows of inflation or deflation, acts as a barometer for price trends, offering citizens a lens through which they can assess and adjust to shifts in the cost of living. A timely and precise CPI is indispensable for enabling individuals to make knowledgeable financial choices that protect their savings and strive for fair investment yields.

In the exposition presented in Section 1.1, it is noted that the Census and Statistics Department (C&SD) compiles this critical data monthly, an interval dictated by workforce limitations. It's important to recognize, however, that there are specific categories of goods and services that are uniquely tracked by the C&SD which do not appear on HKTVS or the other eight e-commerce platforms. This set includes key areas like "Meals out and takeaway food", "Housing", "Transport", "Miscellaneous services”, and “Utility costs” (Electricity, gas, and water). Accordingly, our Online Price Index (OPI) should be characterized as “OPI: All Items Except for Energy, Housing, and Transport”, reflecting these key omissions. Nevertheless, due to its comprehensive high-frequency data, our OPI is a significant supplement to the more sporadically updated official CPI. This online index not only aids stakeholders in making well-timed and informed business choices but also provides C&SD with nuanced insights into the dynamic patterns of consumer spending, a consideration that is critical given the static-weight premise inherent in the official CPI formula. Table 1 juxtaposes the HKTVS and other eight e-commerce platforms’ datasets with the C&SD's, shedding light on the breadth and detail that each data source offers.

To clarify the extent of the OPI’s complementary relationship with the official CPI, it is essential to align the product categories present in our e-commerce data with those of the C&SD. Additionally, calculating the weights for each sub-category in our e-commerce data serves as a robust method to evaluate the accuracy and relevance of the fixed-weight hypothesis traditionally assumed in the official CPI calculations. By doing this, we can discern the degree to which the OPI can enhance, and perhaps refine, our understanding of consumer price changes in the digital marketplace vis-à-vis the more traditional channels monitored by C&SD.

Table 1. Comparison of the data from the nine e-commerce platforms and C&SD

	HKTVS[6]	Other eight e-commerce platforms	HK Census[7]
Data frequency	Daily	Daily	Monthly
No. of retailers	≥ 5,800 small to medium retailers	8 large online supermarkets	3,500 outlets
No. of unique consumers	1,107,000	N.A.	Random sampling 7056 households
No. of products categories	4,273	≥ 2,264	900 (2019 to 2020)
Real-time availability	Yes	Yes	No
Quantity sold for each basket	Yes	No	No
Discounted price	Yes	Yes	No
Weight update	Daily	N.A.	Every 5 years. Recent update is the survey from 2019-Oct to 2020-Sep.
Data Collection	Automated database		10,000 field visits and 1,000 phone interviews per month.

2.3 How does online price stickiness differ from offline one?

The concept of price stickiness, which refers to how quickly prices are adjusted during a given period, is a critical element within macroeconomic research, and it has gained particular importance during and after the COVID-19 crisis. The increased

[6] https://ir.hktv.com.hk/pdf/announcement/file/EW01137-IR.PDF
[7] https://www.censtatd.gov.hk/en/data/stat_report/product/B1060003/att/B10600082020XXXXB0100.pdf

economic uncertainty of this era has prompted consumers to hold onto their savings as a precautionary measure. Yet, the presence of price stickiness can redirect the intended increase in savings, driven by this uncertainty, away from potential investments, leading instead to a reduction in the demand for goods. This can cause a consequent downturn in economic activities (Basu & Bundick, 2018). A scenario where prices are slow to change (positive price stickiness) indicates that monetary policies can significantly impact the real economy, allowing policymakers to utilize these tools to reach specific economic targets.

In contrast to traditional retail, online prices are typically less sticky (Brynjolfsson & Smith, 2000; Ellison & Ellison, 2009; Gorodnichenko, Sheremivov & Talavera, 2018), meaning they adjust more swiftly and frequently in response to market fluctuations. This could be due, in part, to the lower costs associated with changing prices in the digital marketplace, allowing retailers to modify prices with greater ease (Eichenbaum et al., 2014; Gorodnichenko & Talavera, 2017; Cavallo, 2018). The advent of digital price tags and the growth of e-commerce are factors that Ou et al. (2021) credit for the ease of implementing price changes, reducing the degree of nominal rigidity in pricing.

Nevertheless, empirical findings on the subject are not consistent. While Gorodnichenko & Talavera (2017) report that inflation in the online world is less persistent, with price adjustments happening more frequently than in brick-and-mortar stores, Cavallo (2018) presents evidence of longer durations between price changes in online stores across 31 countries. This discrepancy presents a research opportunity to explore the underlying reasons and to empirically examine price stickiness across different regions.

By leveraging the granular e-commerce data, this study aims to provide insights into the pricing behaviors of online retailers. Specifically, it investigates how frequently prices are updated and explores the broader economic interactions at play. Such detailed analysis could illuminate the dynamics of online pricing and contribute to a better understanding of price stickiness in the digital economy.

3. Research Methodology and Data

3.1. Construction of the Online Price Index

3.1.1. Review of the HK C&SD' Method

The C&SD uses the Laspeyres Price Index $P_{0,t}^{\mathcal{L}}$ to construct the official CPI. This index is formulated as follows:

$$P_{0,t}^{\mathcal{L}} = \frac{\sum_{i=1}^{I} p_{i,t} q_{i,0}}{\sum_{i=1}^{I} p_{i,0} q_{i,0}} = \sum_{i=1}^{I} \frac{p_{i,0} q_{i,0}}{\sum_{i=1}^{I} p_{i,0} q_{i,0}} \times \left(\frac{p_{i,t}}{p_{i,0}}\right) = \sum_{i=1}^{I} w_{i,0} \times \left(\frac{p_{i,t}}{p_{i,0}}\right). \tag{1}$$

Here, $P_{0,t}^{\mathcal{L}}$ represents the Laspeyres-CPI at time t with a base period at time 0. The price quotation and quantity of consumption item $i = 1, \dots, I$ in the base period are represented by $p_{i,0}$ and $q_{i,0}$, respectively, while $p_{i,t}$ represents its price quotation for goods i at time t. The fixed weight at time 0 is denoted by $w_{i,0}$, which is a time-invariant ratio. The most recent basket weights were estimated from the 2019/20 Household Expenditure Survey (HES), which are updated every 5 years in accordance with international standards. However, the fixed-weight assumption is likely to be invalid as consumers' preferences have changed drastically during the pandemic. Additionally, the fixed-weight approach fails to account for the substitution effect[8], leading to an upward bias (Allen 1975, Diewert 1998, Diewert and Fox 2022a).

3.1.2. Paasche Index

Alternatively, one can use Paasche index, denoted as $P_{0,t}^{\mathcal{P}}$, to measure price movement. It differs from the Laspeyres index in that it considers the quantity sold $q_{i,t}$ at each time point:

$$P_{0,t}^{\mathcal{P}} = \frac{\sum_{i=1}^{I} p_{i,t} q_{i,t}}{\sum_{i=1}^{I} p_{i,0} q_{i,t}} = \sum_{i=1}^{I} \frac{p_{i,0} q_{i,t}}{\sum_{i=1}^{I} p_{i,0} q_{i,t}} \times \left(\frac{p_{i,t}}{p_{i,0}}\right) = \sum_{i=1}^{I} w_{i,t} \times \left(\frac{p_{i,t}}{p_{i,0}}\right). \tag{2}$$

Here, the weight, $w_{i,t} = \frac{p_{i,0} q_{i,t}}{\sum_{i=1}^{I} p_{i,0} q_{i,t}}$, is time-varying, accounting for the substitution effect over time. However, $P_{0,t}^{\mathcal{P}}$ tends to underestimate inflation compared to Laspeyres

[8] The substitution effect refers to the change in consumption patterns that occurs when consumers respond to relative price changes of goods and services. When the price of a particular good increases relative to the prices of other goods, consumers tend to substitute away from the more expensive good towards relatively cheaper alternatives.

(Allen 1975, Diewert 1998, Diewert and Fox 2022a). Besides, estimating the $q_{i,t}$ at every time point through HES is costly and time-consuming.

3.1.3. Fisher Index

To address various biases present in traditional CPI measures, such as substitution bias (Diewert 1998, Diewert and Fox 2022a), out-of-stock bias (Cavallo and Kryvtsov 2023), new goods bias (Feenstra, 1994; Diewert, 1998), and non-response bias (Groves 2011), Fisher (1921,1922) proposed the Fisher (ideal) Price Index. The Fisher index, denoted as $P_{0,t}^{\mathcal{F}}$, is the geometric mean of the Laspeyres Index and the Paasche Index:

$$P_{0,t}^{\mathcal{F}} = \sqrt{P_{0,t}^{\mathcal{L}} \times P_{0,t}^{\mathcal{P}}}. \tag{3}$$

3.1.4. Our Online Price Index (OPI)

While the Fisher Price Index helps mitigate biases in the official Laspeyres-type CPI, it still relies on price quotations to approximate the true cost of living. To address this limitation, we modify the quotation-based indices to create a discount-priced Fisher Price Index by using discounted prices instead of price quotations. The discount-priced Laspeyres index and the discount-priced Paasche index are respectively given by:

$$P_{0,t}^{\mathcal{L}*} = \frac{\sum_i (p_{i,t} - d_{i,t}) q_{i,0}}{\sum_i p_{i,0} q_{i,0}}, \tag{4}$$

and

$$P_{0,t}^{\mathcal{P}*} = \frac{\sum_i (p_{i,t} - d_{i,t}) q_{i,t}}{\sum_i p_{i,0} q_{i,t}}, \tag{5}$$

where $d_{i,t}$ is the discount on goods i at time t. The weight of $P_{0,t}^{\mathcal{P}*}$ are updated at each t. Our discount-priced Fisher Price Index is calculated as the geometric average of $P_{0t}^{\mathcal{L}*}$ and $P_{0,t}^{\mathcal{P}*}$:

$$P_{0,t}^{\mathcal{F}*} = \sqrt{P_{0,t}^{\mathcal{L}*} \times P_{0,t}^{\mathcal{P}*}}. \tag{6}$$

It is worth noting two aspects related to the treatment of $p_{i,0}$. First, the denominators of the Laspeyres Price Index and the Paasche Price Index represent consumption expenditures measured at base-period prices, using the base-period and current-period consumption bundles, respectively. When incorporating discounts, these denominators can be computed using either quoted prices or discounted prices. Given that official CPI calculations predominantly employ quoted prices, we have maintained consistency by using quoted prices in the denominators of both the discount-priced Laspeyres Price Index and the discount-priced Paasche Price Index, while discounts are incorporated in their numerators. This choice enables a more direct comparison between the discount-priced indices and their traditional counterparts and provides a clearer assessment of the impact of discounts on the price indices, thereby offering a more accurate evaluation of the influence of discounts on consumers' cost of living.

Second, to ensure comparability with the base year of the official CPI, we calculate the average of all the daily Lasperyres index from day 1 to day 365 in 2021. This consistent base year allows for a meaningful comparison between the official CPI and our OPIs, while the use of 7-day moving-average smoothing helps observe the time-varying patterns in our data, which are inherently more volatile than official CPI data due to additional variations stemming from basket weights and daily price adjustments.

3.2. Measuring Hazard Function

The intricate interplay between price stickiness and the real effect of monetary policy is a focal point of understanding economic dynamics. The degree of stickiness in prices – essentially, the resistance firms exhibit to altering their prices – has direct implications for the impact of monetary policy. The more resistant prices are to change, the more pronounced the real effects of monetary policy become. Understanding firms' pricing behavior, particularly the frequency and timing of price updates, is crucial in measuring this stickiness.

The hazard function emerges as a prominent non-parametric method for examining the conditional probability of price changes over time, provided the prices have yet to change. This statistical tool offers insights into the firm's pricing strategies by delineating the likelihood of a price update as time progresses. According to Caballero & Engel (1993, 2007), it facilitates the estimation of the correlation between price stickiness and the tangible consequences of monetary policy, bypassing the need for a detailed microeconomic model.

Furthermore, Dotsey, King, and Wolman (1999) contribute to this dialogue by suggesting that in the presence of enduring aggregate shocks, and within a state-dependent pricing framework, prices tend to increasingly deviate from their ideal points as time elapses. This implies that the hazard function should exhibit an upward trajectory, reflecting a growing probability of price changes as more time passes without such changes.

Delving into the causes of price stickiness, the discourse is enriched by several models, particularly the menu cost model and the sticky price model. The menu cost model, as expounded by Ball and Mankiw (1994), introduces the concept of small, yet significant costs incurred by firms when they modify prices. Although seemingly inconsequential, these menu costs, when interwoven with imperfect competition and inherent real rigidities, lead to extensive aggregate price stickiness. The model argues that these costs create a divergence between private incentives for adjusting prices and the broader social benefits, thus sustaining money's non-neutrality. It is posited that, akin to other economic parables, menu costs serve as a simplified, foundational element for explaining nominal rigidity and the substantial real effects of monetary policies.

In parallel, Golosov and Lucas (2007) formulate a menu cost model that is attuned to empirical price adjustment patterns. Their model, which is fine-tuned using granular price change data, suggests that monetary policy alterations have muted and ephemeral effects on output and employment. This stems from firms' optimal pricing decisions influenced by both idiosyncratic shocks and broader economic fluctuations.

Adding empirical weight to these theories, Anderson, Jaimovich, and Simester (2015) affirm that menu costs significantly contribute to price stickiness. Their research, using data from a large retailer, indicates that items with numerous variants – and thus higher labor costs for price adjustments – are less likely to experience price hikes in response to cost increases. This effect, which is both persistent and asymmetric, indicates that menu costs impede frequent price changes, particularly when dealing with minor cost upticks.

The sticky price model (the conventional time-dependent model) sheds light on the difficulties in price coordination when updates occur at staggered intervals, leading to a sluggish aggregate price response to economic shifts.

Together, these models provide a multifaceted framework for analyzing the nuances of price stickiness and its broader economic ramifications, underlining the complexity of firms' pricing strategies and their interactions with monetary policy.

However, empirical studies often find decreasing hazards (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). Álvarez et.al. (2005) suggest that heterogeneity effect at firms or goods level is one of the reasons because hazards are estimated in an aggregated form. If the price-setting rules among firms are very different, the heterogeneity effect will make the hazard slope negative. As our data set involves different retailers and products, we can model the heterogeneity effect at both firm- and product-level. Another reason for a downward-sloping hazard is probably sourced from the time-averaging issue as conjectured by Campbell and Eden (2014). Weekly averaging makes a single price change look like two consecutive smaller changes driving up the frequency of small prices changes and leading to a negatively sloped hazard function. As our e-commerce big data is at daily frequency, we can mitigate the problem by controlling the frequency of "technical" price changes.

To estimate the hazard function, we denote the time between two prices updates of the same good by T, which is also called a price spell. A hazard function $h(t)$ is the limiting probability that the spell occurs at time t conditional on "constant price scenario" to that point in time, i.e., $t < T$.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t | t < T)}{\Delta t}. \quad (7)$$

As price stickiness measures the tendency of prices to remain the same or the speed of prices adjustment, hazard function is a common measure as it measures the probability of a price change at time t. We consider product heterogeneity by utilizing the detail product classification in our dataset to estimate the hazard at daily frequency across different types of goods and investigate whether the hazards are downward- or upward-sloping.

To estimate the $h(t)$ in (7), we follow Cavallo's (2018) non-parametric Nelson-Aalen estimator approach in estimating the cumulative hazard function:

$$\widehat{H}_c(t) = \sum_{c|t_j \le t} \frac{d_{c,j}}{n_{c,j}}, \tag{8}$$

where $d_{c,j}$ is the number of price changes at time t_j for subcategory c, $n_{c,j}$ is the number of price spells that change at time t_j for sub-category c, and $\frac{d_{c,j}}{n_{c,j}}$ is the incremental steps being an estimate for the probability of price change at time t_j for sub-category c conditional on constant price up to that time point. A smoothed hazard function $\hat{h}_c(t)$ for subcategory c is derived from:

$$\hat{h}_c(t) = \frac{1}{b} \sum_{j \in J} K\left(\frac{t - t_j}{b}\right) \Delta \widehat{H}_c(t_j) \tag{9}$$

where K is a symmetric kernel density, b is the smoothing bandwidth, and J is the set of times with price changes.

3.3. E-commerce Data

In an endeavor to develop daily OPIs with real-time capabilities, our methodology incorporated daily transactional records from Hong Kong spanning 788 days, from August 4, 2020, to September 30, 2022. The source of this data was twofold: the big dataset from the Hong Kong TV Shopping Network Company Limited (HKTVmall) and other 8 e-commerce companies such as Wellcome, Market Place by Jasons, Mannings of Dairy Farm, A.S. Watson's PARKnSHOP and Watsons eShop, AEON, DCH Food Mart, and TVB's Ztore. These entities are among the most prominent online retail destinations in Hong Kong, with six featuring in the top ranks according to the 2022 YouGov survey and the Retailer Preference Index by Dunnhumby[9]. HKTVmall in particular has been distinguished by its web traffic, amassing an impressive 464.2 million monthly visits in the last quarter of 2020, as reported by Ma (2022), making it the most frequented e-commerce site during that time. The other platforms similarly registered substantial online traffic. Moreover, market shares reported by Frost & Sullivan in 2021 placed HKTVmall, ParknShop, and Watsons eShop at 13.9%, 2.4%, and 1.8% respectively, with HKTVmall enjoying the lead position[10]. Additionally, A.S. Watson Group and Dairy Farm International Holding Limited were identified by Euromonitor International's 2021 market survey as the top two retail giants in terms of sales growth for the years 2019 and 2020[11].

Our data set is robust, featuring approximately 6,200 retailers and exceeding one million distinct product offerings, catering to over one million unique consumers. HKTVmall, a publicly traded e-commerce platform founded in 2015, serviced 1,287,000 unique consumers in 2021 alone, representing a penetration rate of about 22.6% within the demographic of 20 to 74-year-olds. This data set is comprehensive, detailing around 21.82 million anonymized purchases, documenting specifics such as

[9] https://www.businesswire.com/news/home/20220502005066/en/Wellcome-and-PARKnSHOP-Named-as-Hong-Kong%E2%80%99s-Top-Grocery-Chains-in-dunnhumby-Retailer-Preference-Index
[10] https://store.yohohongkong.com/ir/docs/Prospectus_Eng.pdf
[11] https://marketech-apac.com/as-watson-group-leads-top-hong-kong-retailers-in-2020/

stock-keeping unit pricing, volumes sold, generated revenue, transaction expenses, and a plethora of product classifications. These classifications span an extensive array of sectors including groceries, health and personal care, beauty and skincare, home goods, fashion for women and men, products for mothers and babies, children's fashion, electrical gadgets, Disney products, sports and travel gear, pet accessories, toys and literature, dining deals, and electronic devices. Furthermore, the other 8 e-commerce companies' dataset delivers daily pricing updates and various discount formats, including percentage markdowns, fixed-dollar reductions, and bulk purchase deals, across a sweeping total of around 2,264 distinct product categories.

4. Research Findings

In this section, we delve into a comparative analysis between the OPI and the official CPI, both at aggregate and categorial levels, focusing on volatility and basket weights. Moreover, we quantify the influence of discounts on measuring the cost of living across time by contrasting the quoted-price and the discount-price OPIs.

Subsequently, we delve into an estimation of price stickiness to ascertain whether price adjustments occur more rapidly in the online marketplace. We also examine whether the likelihood (hazard rate) of price changes in the online sector shows an upward or downward trend over time.

4.1. OPI vs Official CPI

Figure 1 presents a comparative visualization, juxtaposing the official monthly composite Consumer Price Index (CPI) depicted by a stepwise grey line, against the Online Price Index (OPI) represented by both quoted (orange line) and discounted (blue line) prices. While the official monthly CPI exhibits a modest incremental ascent, with minor downturns noted in October of both 2020 and 2021, the daily OPIs generally trend downwards, with notable deviations during the first and third quarters of 2022 suggesting intermittent price fluctuations.

The outset of this period under review aligns with the escalation of Hong Kong's third COVID-19 wave, an episode marked by a sharp increase in the incidence and mortality rates following a stretch of no local cases. In response to this resurgence, the Hong Kong government enacted stringent containment protocols, including dine-in service prohibitions, mandated closures of various facilities, curtailed public assembly, and enhanced border controls (Alea 2023). With the advent of the fourth wave in November 2020, authorities amplified these restrictions, introduced a mobile application to track elusive infections, barred incoming flights from the UK, and enforced mandatory testing within selected residential zones to thwart the virus's spread (OT&P Healthcare 2023).

The downward trajectory of the Online Price Index (OPI) until December 2021 can be primarily attributed to the decline in the "food" category prices, as depicted in Figure 2. This trend is in accordance with the observed price reductions of the online grocery service Amazon Fresh Hillen (2021). Notably, due to the significant weighting of the "food" category, evident in Figure 5, its price reductions significantly outweighed the price escalations in the "alcoholic drinks & tobacco" and "miscellaneous" categories. Moreover, the "food" category's OPI closely mirrors the composite OPI, barring the marked fluctuations that occurred from March 26th to March 28th, 2021.

The inception of the fifth wave of the pandemic, a period marked by a confluence of Omicron and Delta variant cases, commenced in early 2022 (as noted by OT&P Healthcare in 2023). In the wake of stricter social distancing mandates and the implementation of localized lockdowns, there was a notable increase in online shopping activity, spurred by the restrictions on physical movement. Concurrently, the period was marked by considerable supply chain perturbations, which led to the initial price increase witnessed across various sectors. Trade analysts had previously forewarned of profound disruptions to international commerce, forecasting a significant uptick in container shipping costs and an anticipated short-term surge of 10-20% in ocean freight expenses (as reported by the South China Morning Post in 2021).

However, with the abatement of the pandemic's intensity, the Hong Kong government incrementally withdrew some of the social distancing restrictions. This relaxation spurred a gradual economic revival, culminating in a second price rise across all categories during the third quarter of 2022. It is imperative to recognize that, despite these shifts, the volatility inherent in the OPIs outstripped that of traditional offline price indices. This variability underscores the OPI's sensitivity to market conditions and highlights its capacity to capture real-time economic dynamics, offering insights into the fluctuating patterns of consumer behavior and pricing within the digital marketplace.

Figure 1. Monthly Official Composite CPI vs Daily OPIs

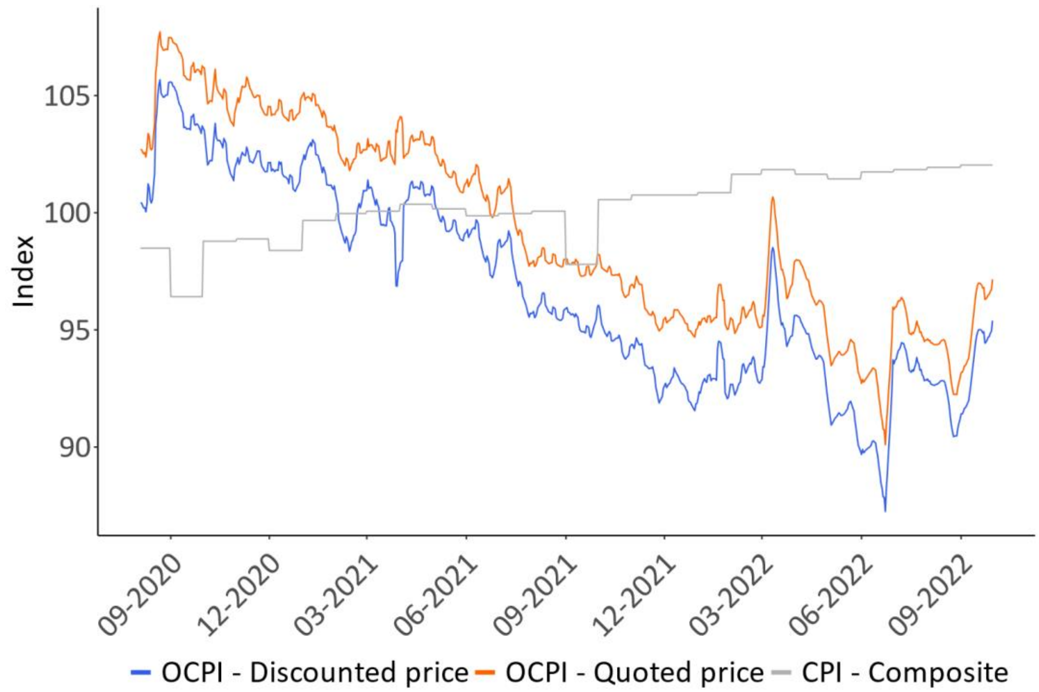
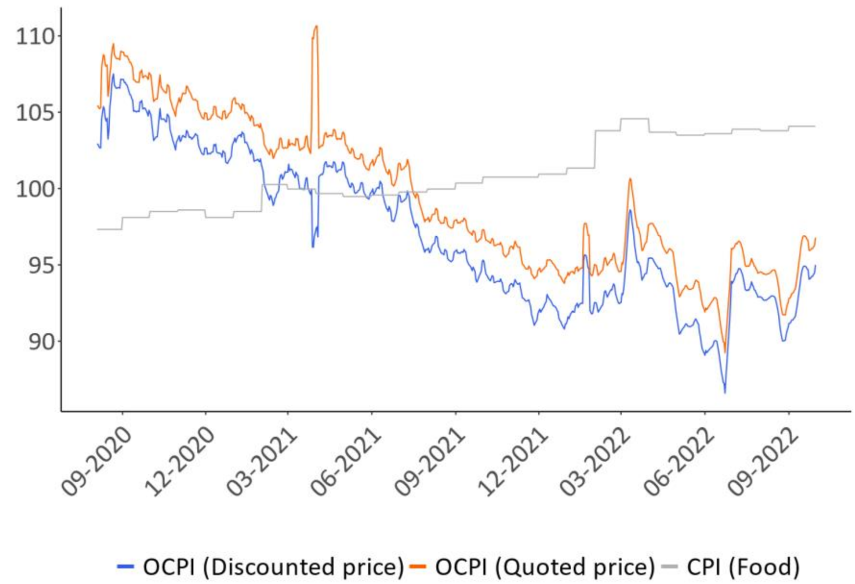


Figure 2 presents the Online Price Indices (OPIs) for four distinct categories. Similar to the overarching composite OPI, these individual category indices demonstrate increased volatility compared to their respective official Consumer Price Indices (CPIs). The "food" category, in particular, reveals a more distinct downward trajectory, whereas the other categories fail to show a uniform pattern of price escalation or reduction.

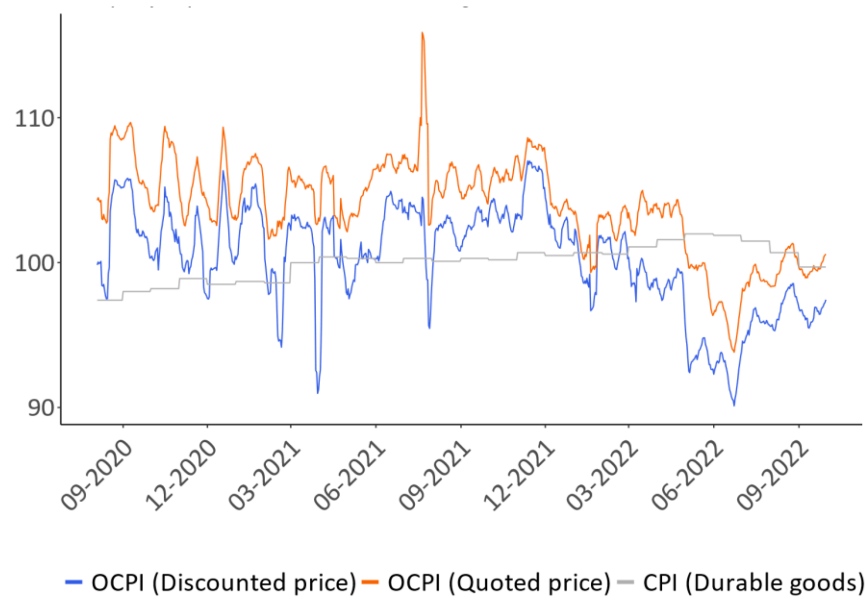
Figure 2. Categorical Offline CPI vs OPIs

(a) Food

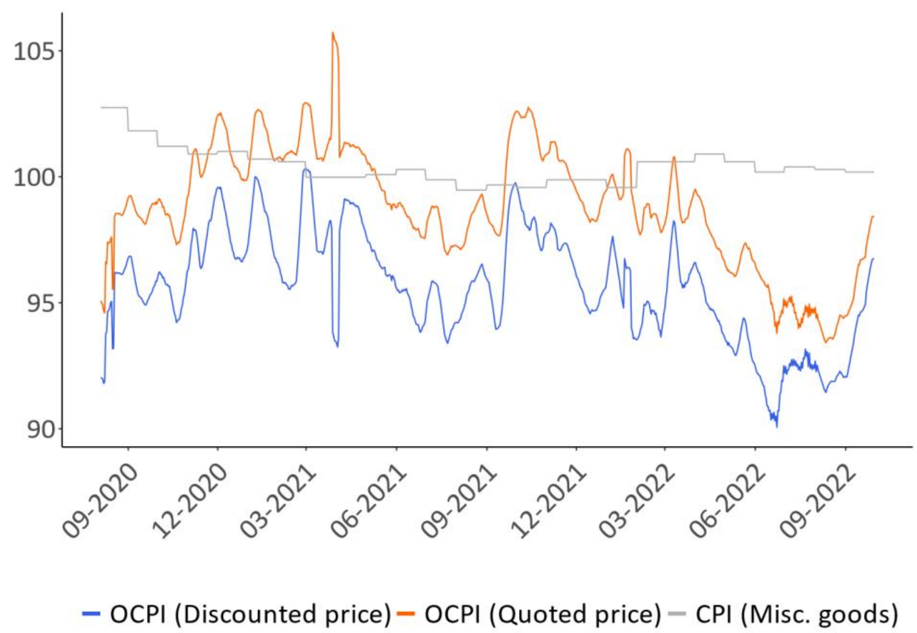


(b) Alcoholic Drinks

(c) Durable Goods



(d) Miscellaneous Goods

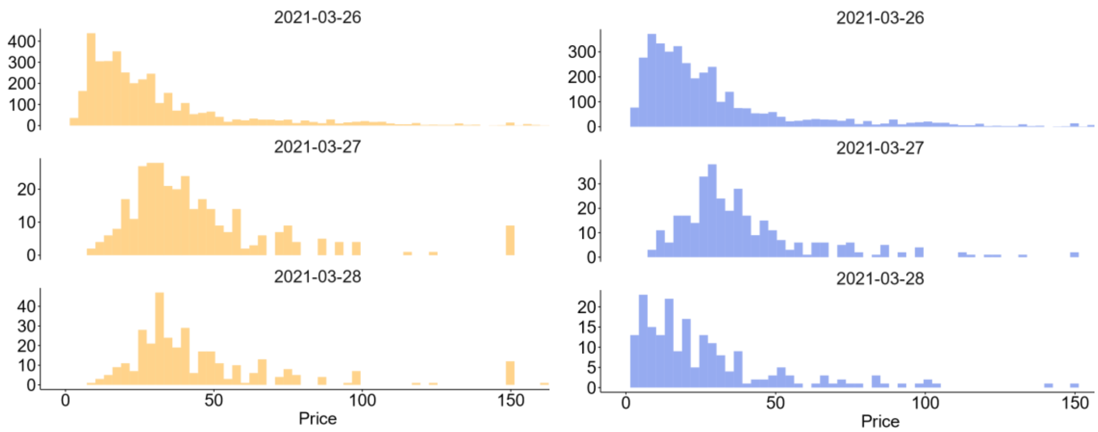


Nonetheless, a noteworthy divergence is observed between the 26th and 28th of March, 2021, where the trajectories of discount-priced and quoted-price Online Price Indices (OPIs) deviate in a contrary manner. The quoted-price OPI experiences a sharp increase, whereas the discount-priced OPI significantly declines within this interval. A plausible interpretation of this divergence is the anticipation of prospective supply chain disruptions following the obstruction of the Suez Canal on March 23rd, 2021, leading to a simultaneous decrease in supply and surge in demand, which is likely to have propelled the quoted-price OPI upward. Concurrently, retailers may have engaged in a "High-Low" pricing tactic, imposing higher initial quoted prices with subsequent substantial discounts, a strategy designed to instill a sense of immediacy among consumers, as suggested by Hoch et al. (1994).

To further investigate this trend, Figure 3 plots the number of items against their prices over the mentioned three days. Notably, there is a greater concentration of items with higher prices in the quoted-price distribution compared to the discount-price distribution on March 27th and 28th. This suggests that retailers simultaneously offered deep discounts while setting higher quoted prices, possibly as part of a pricing strategy. This dynamic leads to the opposite trends observed in the two OPIs during this period.

Figure 3. Price Distribution of Food Category

(a) Quoted-price (b) Discount-price



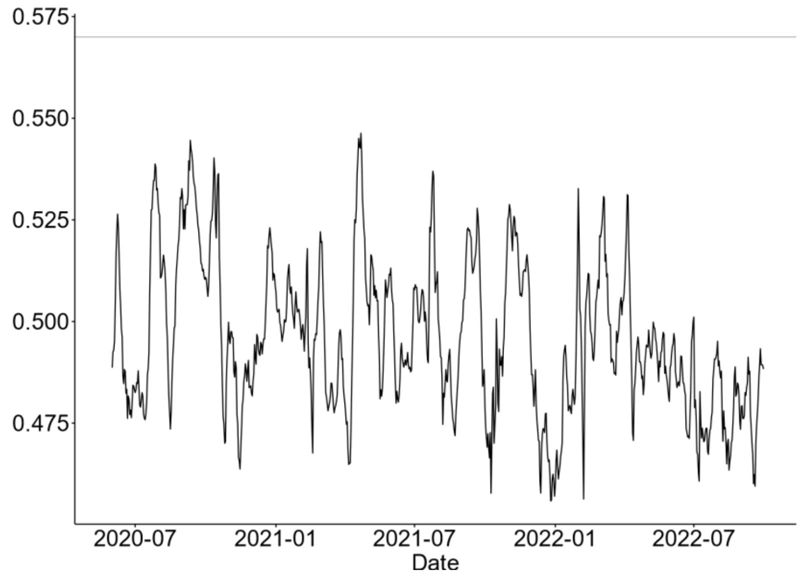
In summary, the empirical examination uncovers marked variability within the Online Price Indices, exhibiting distinctive trends influenced by shifting consumer habits, supply chain disturbances, and tactical pricing maneuvers. This pronounced volatility in OPIs, surpassing that of traditional brick-and-mortar price levels, implies the impact of a multitude of evolving elements affecting the landscape of online pricing.

4.2. Basket Weights

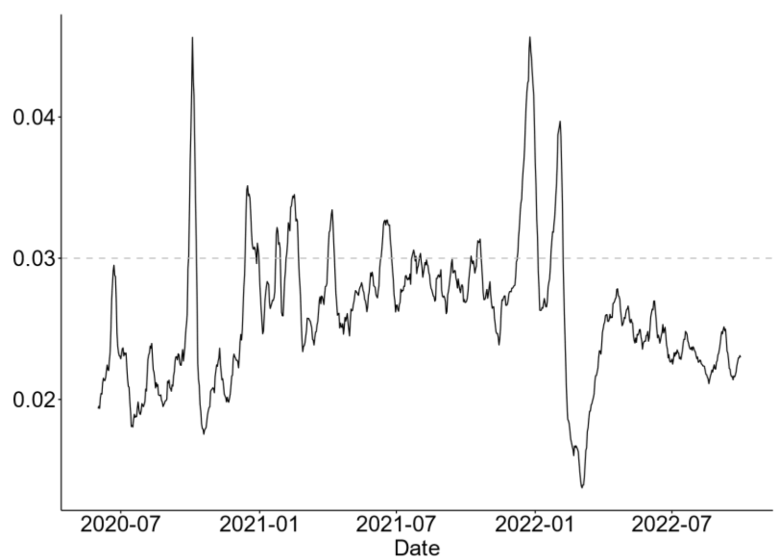
The dynamic updating of basket weights in the OPI is crucial for accurately capturing the shifts in consumer preferences throughout the pandemic period. Displayed in Figure 4 are the evolving weights for calculating the four categorical Online Price Indices, represented by solid lines, alongside the static five-year weights from the official Consumer Price Index adjusted for the four categories under investigation, indicated by dashed lines. Within the structure of the official CPI, “food” and “alcoholic drinks” constitute the heaviest and lightest categories, respectively. In the online setting, the weight for “durables” is markedly reduced compared to its traditional retail counterpart, reflecting a consumer tendency to purchase substantial items such as furniture and electronics in person. In stark contrast, the importance of “miscellaneous goods” for online shopping is significantly amplified relative to physical stores, highlighting a clear preference among Hong Kong consumers to procure everyday essentials like home and personal care items via online channels. This adjustment in basket weights is emblematic of the OPI’s flexibility in tracking the changing patterns of consumer spending.

Figure 4. Changes in Consumption Pattern for Each Category

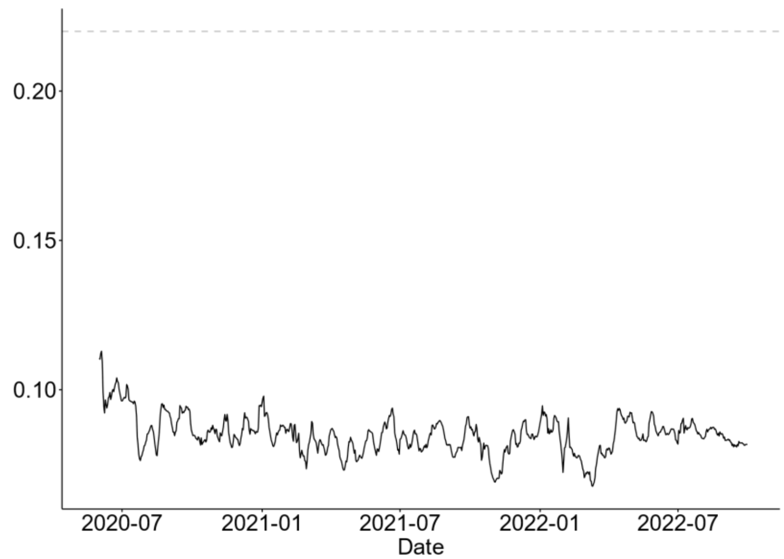
(a) Food



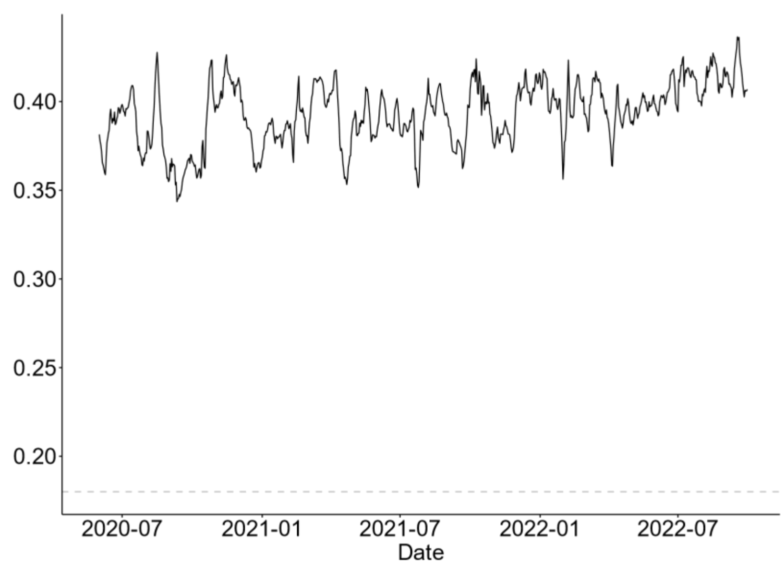
(b) Alcoholic Drinks



(c) Durable Goods



(d) Miscellaneous Goods



4.3. Inflation Rates

Figure 5 presents the month-over-month inflation rates for the official Consumer Price Index (CPI) depicted in grey, alongside the online quoted-price OPI and discount-priced OPI illustrated in orange and blue respectively at a composite level. The inflation rates for the four categories are further delineated in Figure 6. The rates obtained from the OPI are noticeably more volatile than those from the official CPI. The OPI-derived inflation rates oscillate between roughly -3% and +4%, in stark contrast to the official inflation rates, which are contained within a more constrained range of ±2.5%.

The composite inflation rates derived from both online data and official measures exhibit a strong alignment with the "food" category trends. The substantial variability in online prices for both the "food" and "alcoholic drinks" categories throughout 2022 has led to a notable increase in the volatility of the composite online inflation rate. During the time frame under analysis, the inflation rate for "durables" fluctuated within a range of ±4.5%. In contrast, the official inflation rates showed relatively steady trends, a result of adhering to static basket weights. However, such consistency may not reflect exceptional circumstances during the pandemic that stem from evolving consumer behaviors. The Online Price Index (OPI) introduced in this research acts as an essential adjunct to the traditional indices, adeptly adjusting for shifting consumer patterns and unique occurrences brought on by the pandemic. It provides a more expansive view of inflation dynamics, thereby enriching the toolkit available for informed economic decision-making.

Figure 5. The Online and Official Inflation Rates

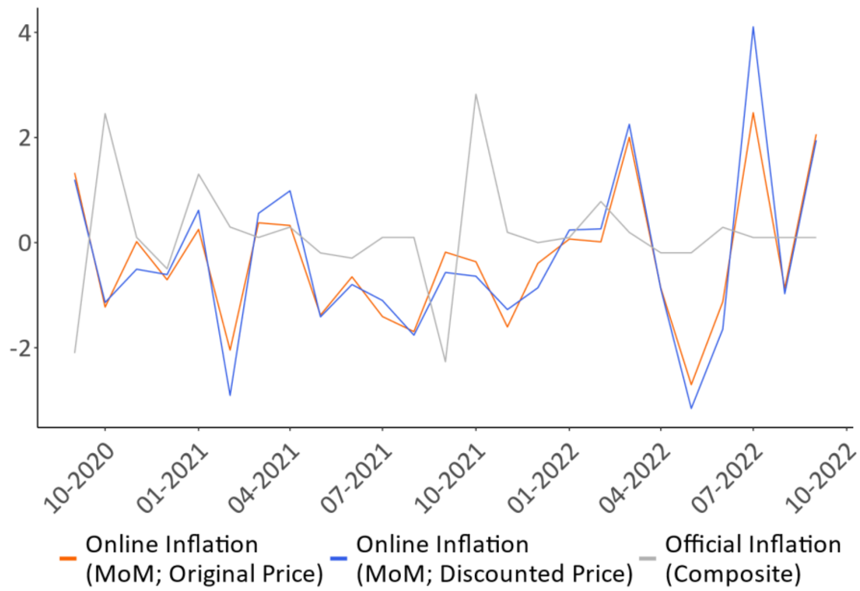
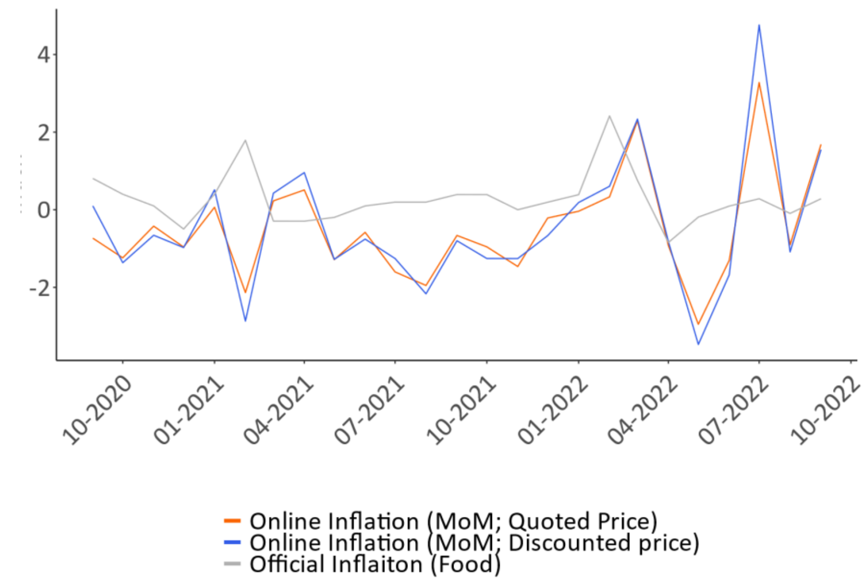
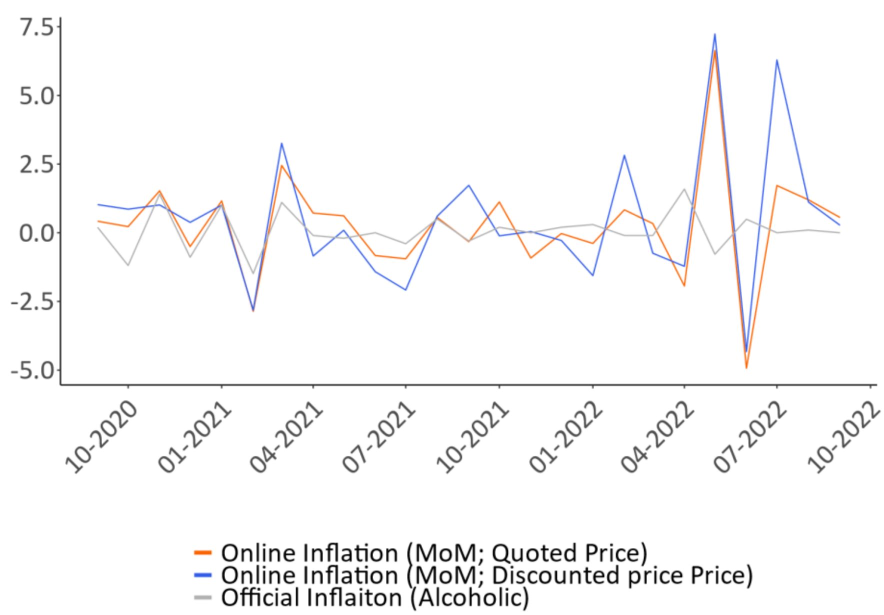


Figure 6. The Online and Official Categorical Inflation Rates

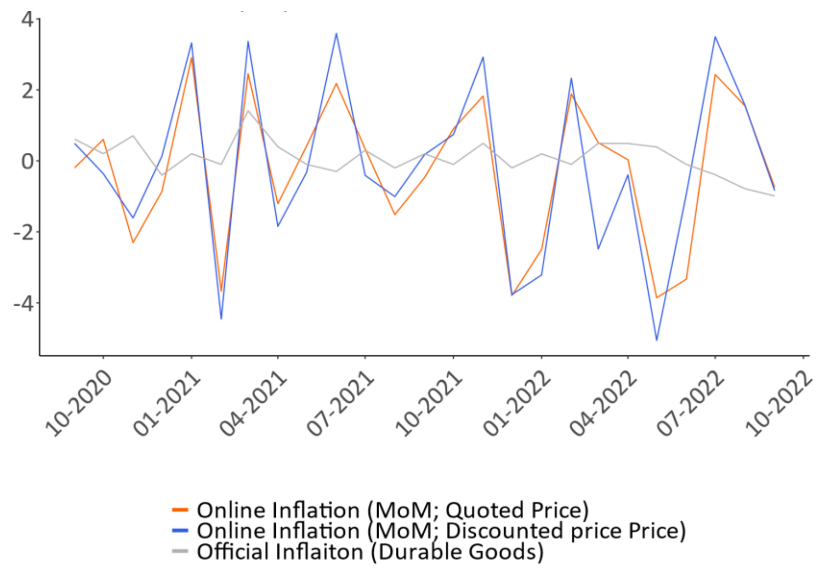
(a) Food



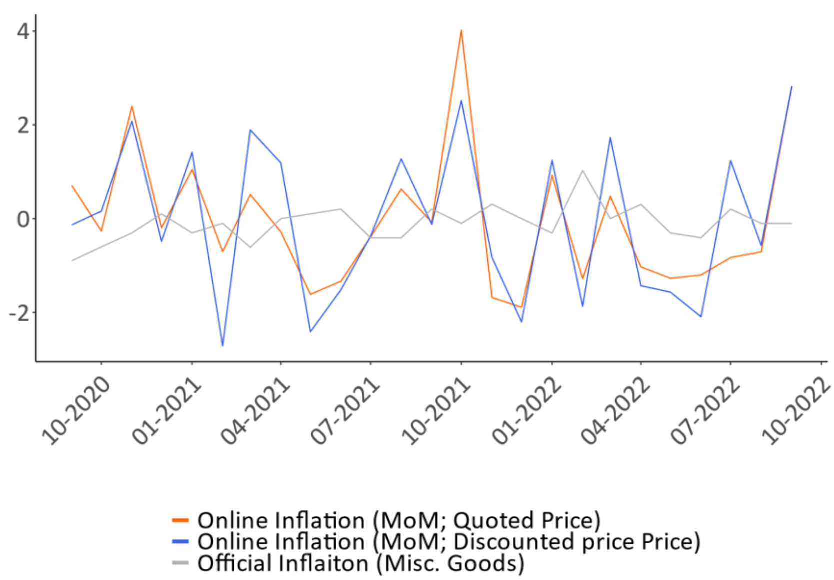
(b) Alcoholic Drinks



(c) Durable Goods



(d) Miscellaneous Goods



4.4. Role of Discount in OPI Measurement

Among the four categories, the most substantial bias emerges in the "alcoholic drinks" category, with an approximate bias of 8.42%. This phenomenon can be attributed to merchants offering significant quantity discounts to encourage bulk purchases of beverages during the pandemic. Following closely is the "miscellaneous" goods category with a bias of 3.21%, followed by the "food" category (2.25%) and the "durables" category (1.02%). These findings align with the UNECE's recommendation to consider the purchaser's price, reflecting the amount actually paid by the consumer.

The analysis by McKinsey (Abdelnour et al. 2020) emphasizes the significant impact that pricing strategies and the way they are communicated can have on a company's immediate performance and their capacity for a strong post-downturn recovery. In times of economic distress, it is common for companies to reduce their listed prices reflexively; however, our research underlines the strategic advantage of utilizing flexible discounting practices while keeping the listed prices steady as a mean to boost consumer demand. This tactic has shown to be more successful in several contexts. Our dataset particularly illustrates the critical role that discounting has played during the period marked by the occurrence of three distinct waves of COVID-19 infections in the area. The trends in our discount-priced Online Price Index (blue) have consistently remained beneath those of the quoted-price OPI (orange), as demonstrated in both the composite and individual category analyses seen in Figures 2 and 3. It is worth noting that the composite OPI reflects an estimated upward deviation of around 2.41%.

4.5. Price Stickiness and the Hazard Function Shape

The analysis of online price spells, or the duration for which online prices remain unchanged, reveals that the average span for quoted prices is 11.7 days, while for discounted prices, it is shorter at 8.9 days, in aggregate level. Breaking it down by category, the durations are as follows: for food items, average quoted price remain unchanged for 11.1 days and discounted prices for 8.6 days. In the alcoholic drinks category, the duration for quoted prices is 13.2 days, whereas for discounted prices, it is 9.8 days. For durable goods, quoted prices typically hold for 13.8 days compared to 10.0 days for discounted prices. Lastly, in the miscellaneous goods category, the period is 14.1 days for quoted prices and 10.5 days for discounted prices. The adjustment period for the prices of miscellaneous goods, including both quoted and discount prices, is the lengthiest. Generally, it takes longer for quoted prices to undergo adjustments.

These findings are different from the study of Hung and Kwan (2022) who use the official (offline) CPI and the New Keynesian Phillips Curve framework to estimate the price stickiness of 1 to 1.5 quarters. This comparison suggests that online prices in Hong Kong display less stickiness, indicating a more dynamic pricing environment.

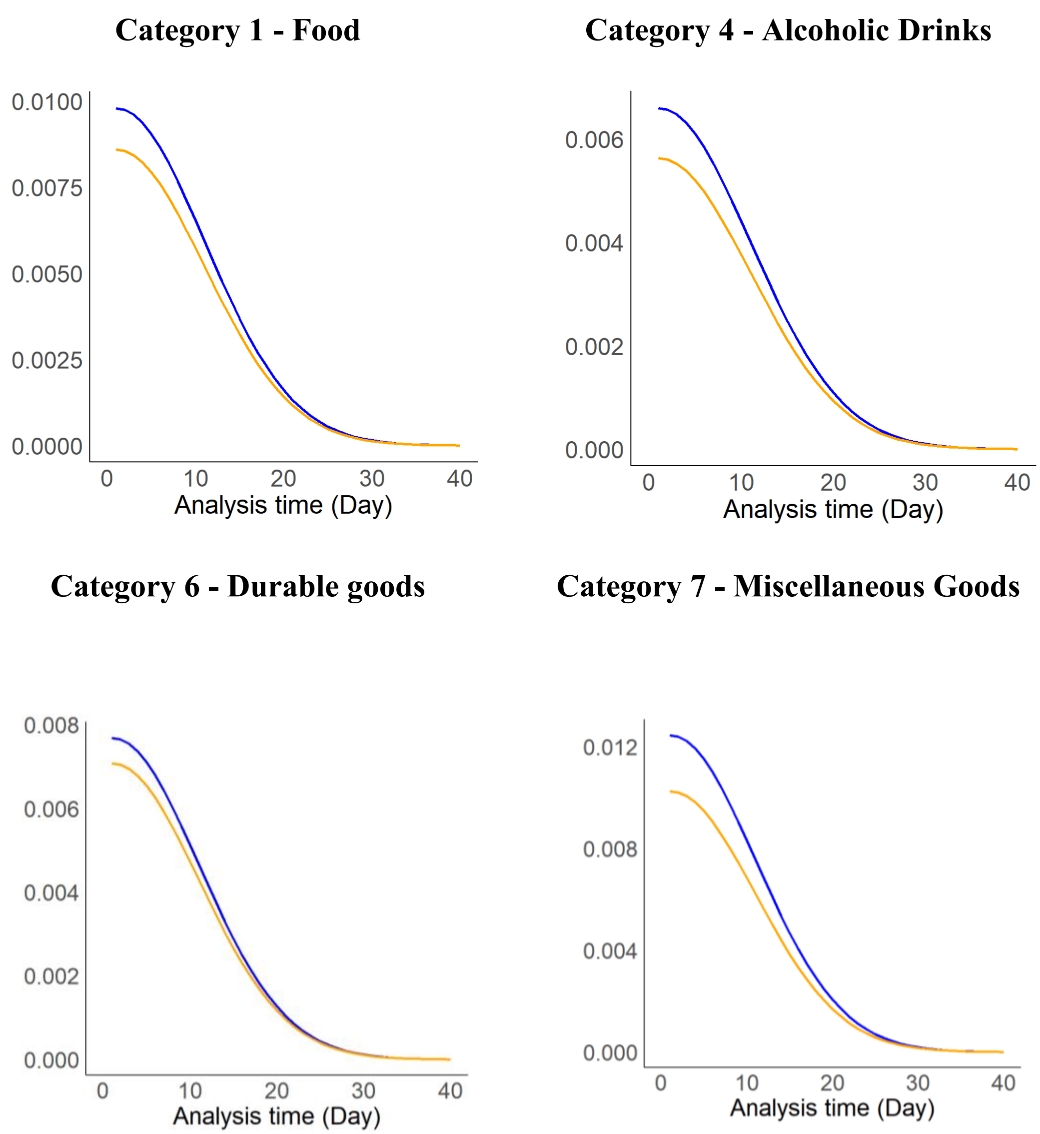
Following Cavallo's (2018) methodology, we have employed the Nelson-Aalen estimator to calculate the smoothed hazard function of price changes for each category. Our findings interestingly align with the predictions of time-dependent pricing models, which typically suggest a downward sloping hazard function. This outcome implies that despite the lower cost and higher frequency of online price updates, firms are not necessarily synchronizing their price changes. Instead, there is a staggered pattern of updates, contributing to increasing stickiness in the general price level over time.

Figure 7 presents the categorical smoothed hazard functions for price changes, represented in two distinct colors: orange for quoted prices and blue for discounted prices. For each category, both hazard functions are plotted against time, with time on the x-axis and the hazard rate on the y-axis, and they each showcase a descending trajectory. The implication of this decline is that the probability of a price change decreases as more time passes since the last alteration.

The distinct positions of the two hazard functions – with the discounted price (blue) above the quoted price (orange) – underscore the variances in the likelihood of price changes under different conditions or within different market segments. The elevated stance of the blue curve suggests that discounted prices are more prone to change over the observed period, indicating a more fluid pricing scenario when discounting is considered. This may reflect a market where discounted prices are less sticky and more responsive to market dynamics, which could be attributable to competitive pressures or strategies designed to stimulate sales through frequent promotions.

In essence, the higher and decreasing discounted price hazard function points to a market that initially has a higher responsiveness to change, yet over time, this responsiveness diminishes. This is contrasted with the lower and similarly decreasing hazard function for quoted prices, which signifies a market with a lower initial probability of change that further decreases with time. This finding reveals that the actual degree probability of price change may be lower because discounts play a role, especially in the short run.

Figure 7. The Smoothed Hazard function of Price Changes for each category



5. Policy implications and recommendations

Our research, centered on the development of a novel online price index, has yielded significant insights into pricing dynamics within the digital marketplace. The findings reveal that online prices exhibit greater fluctuation compared to the official CPI and demonstrate notably lower price stickiness than offline prices. These outcomes have profound implications for economic policy and strategy.

5.1. Enhanced Inflation Monitoring

The higher fluctuation in OPI suggests a more sensitive and immediate response to market changes than traditional CPI measures. Policymakers, particularly those in central banking and fiscal authorities, may consider integrating online price metrics (as a complementary indicator) into their inflation monitoring frameworks. This integration could provide a more nuanced and timely understanding of inflation trends, especially in sectors heavily influenced by digital commerce.

5.2. Monetary Policy Adjustment

With the increasing prevalence of online consumption (especially after the pandemic), online e-commerce data is becoming more and more significant for policymaking. Given the more fluctuating nature of the OPI compared to the offline CPI, central banks might consider using a combination of both CPI and OPI as reference points to recalibrate their understanding of the delayed effects of policy interventions. In a market where prices adjust more quickly, the impact of monetary policy shifts could manifest sooner, requiring a more agile and responsive approach to interest rate decisions and liquidity management.

Furthermore, the diminishing hazard function observed in online price changes suggests that the probability of price adjustments aligns with the time-dependent model. This highlights the challenges in synchronizing price changes when they occur at irregular intervals, resulting in a delayed overall price response to economic fluctuations. Central banks might therefore contemplate adopting the staggered-pricing model assumptions for more precise macroeconomic modeling.

5.3. Encouraging Data Sharing and Collaboration

The effectiveness of OPIs heavily relies on the continuous inflow of e-commerce data. To ensure the availability and accessibility of such data, governments, regulatory bodies, and e-commerce platforms should foster a culture of collaboration. This can be achieved through public-private partnerships or regulatory frameworks designed to facilitate data sharing, while still upholding privacy and competition laws.

6. Details of the public dissemination held

- Conference and academic meetings

We participated in three meetings to promote our research and engage in idea exchanges.

Date	Institution	Name
3/5/2023	Hong Kong Economic Association	2023 Annual General Meeting of Hong Kong Economic Association
21/7/2023	Hong Kong Trade Development Council (HKTDC)	The E-Commerce Route into Central & Eastern Europe
20/9/2023	Hong Kong Baptist University	Buyer-Optimal Platform Design by Prof. Daniele CONDORELLI

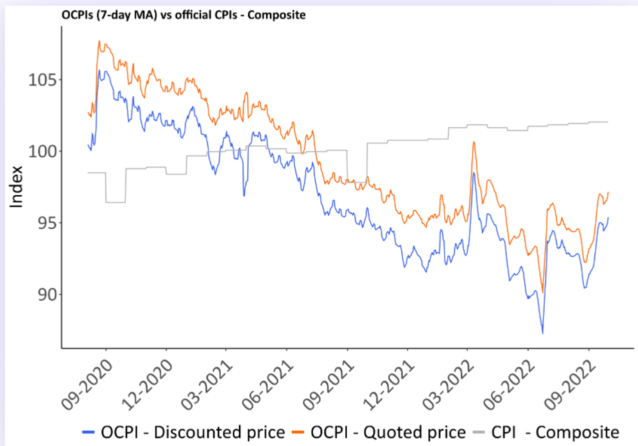
- Webpage development

We have created a website with the goal of providing easy access to the Online Price Index (OPI) for the public, researchers, businesses, and policymakers. This platform serves as a means to disseminate our work and encourage the utilization of big data analytics. The website comprises four primary pages: Home, OPI, About Us, and Collaboration.

The site is designed to showcase OPI charts and report on its influence through journals, news, and social media. For more information, please visit our website at https://www.onlinepricetrend.com/

6.1. Home

Online Price Index (OPI)

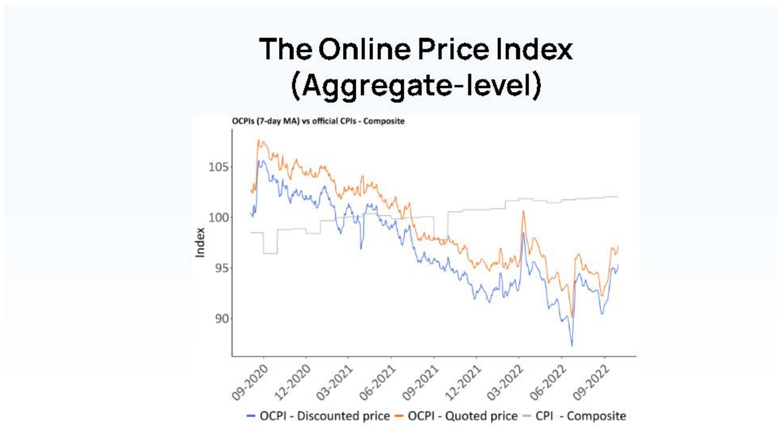


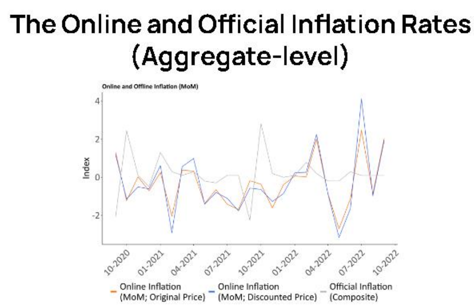
The Online Price Index (OPI), Hong Kong's inaugural daily dynamic weighted index for online prices, was first introduced at the Asian Meeting of the Econometric Society in China in June 2022. It takes into account discounts and purchasing volumes, drawing from detailed granular-level data sourced from 9 online platforms in Hong Kong over a span of 788 days, from 2020-08-04 to 2022-09-30. The OPI is a valuable tool for tracking daily shifts in online inflation and price levels, complementing the traditional offline CPI.

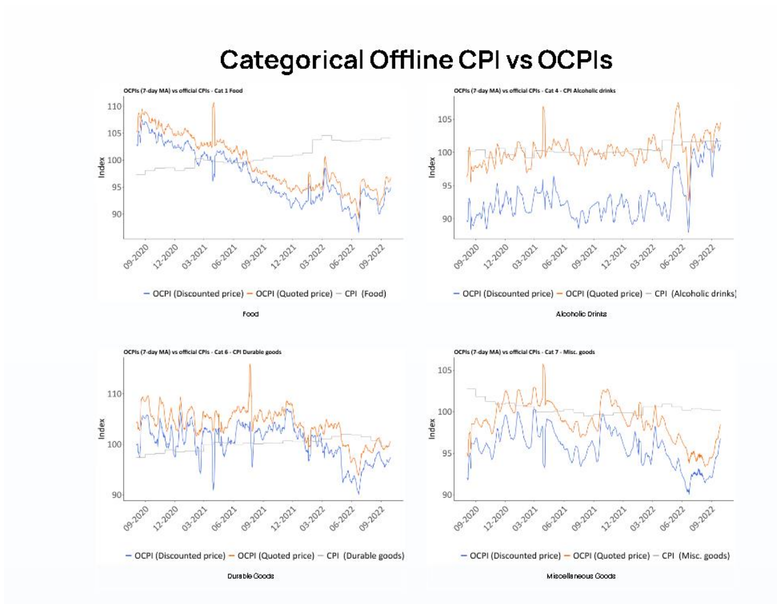
This project, "*Constructing Daily Hong Kong Online Price Index and Price Dynamics: The Role of E-commerce in the Post-pandemic Era*" is funded the Government of the Hong Kong Special Administrative Region of the People's Republic of China under the Public Policy Research Funding Scheme 2022-23 (Project Number: 2022.A2.053.22B). We would like to extend our heartfelt gratitude to the Government for its generous support and funding of this project. Its contribution has been instrumental in bringing our vision to fruition. We deeply appreciate its belief in our endeavor and its commitment to advancing research and innovation.

Explore More

6.2. OPI


The Online Price Index
(Aggregate-level)
OCPIs (7-day MA) vs official CPIs - Composite
Index
OCPI - Discounted price
OCPI - Quoted price
CPI - Composite


The Online and Official Inflation Rates
(Aggregate-level)
Online and Offline Inflation (MoM)
Index
Online Inflation (MoM; Original Price)
Online Inflation (MoM; Discounted Price)
Official Inflation (Composite)


Categorical Offline CPI vs OCPIs
OCPI (Discounted price)
OCPI (Quoted price)
CPI (Food)
Food
CPI (Alcoholic drinks)
Alcoholic Drinks
CPI (Durable goods)
Durable Goods
CPI (Misc. goods)
Miscellaneous Goods

7. Conclusion

In this study, we introduce a novel daily Online Price Index (OPI) that harnesses extensive transaction data from e-commerce platforms. By considering discounts and quantities sold, we have constructed both a composite OPI and a categorical OPI that align with the official classification. This methodology yields a timely and cost-effective index, providing near-real-time price indicators to stakeholders. Notably, the Fisher-type index helps mitigate the biases inherent in the Laspeyres index employed by the official Statistics Departments.

Furthermore, we conduct a comparative analysis between our OPI and the official CPI. The limitations of fixed basket weights within the CPI make it inadequate for tracking the rapid and profound changes in consumer preferences during the COVID pandemic. Estimating quantities based on household surveys may also introduce measurement errors. Our findings, based on actual quantities sold, reveal substantial changes in the basket weights. While our OPI may exhibit some noise due to daily updates of weights, we do observe shifts in consumption patterns during and after the pandemic, underscoring the deficiencies of fixed weights.

Additionally, our research delves into price stickiness in online commerce. We discover that the estimated duration of price spells is significantly shorter than what is typically observed in offline pricing. However, downward-sloping hazard functions suggest staggered price adjustments, aligning with conventional time-dependent models.

Despite the official CPI's credibility stemming from its adherence to international standards, our OPI demonstrates its timeliness, cost-effectiveness, and broad coverage of products favored by individuals inclined toward online shopping. As this demographic continues to expand, the OPI will become more representative. However, realizing its full potential necessitates enhanced data sharing between the government and the private sector. Wider adoption of open data policies can nurture Hong Kong's technology ecosystem and cultivate innovations that benefit the economy. The OPI serves as a precursor, highlighting the promise of such collaborations.

This groundbreaking study has developed an innovative real-time OPI using granular e-commerce data. By highlighting the strengths and limitations of both traditional methodology and our approach, it underscores the potential and insights that can be drawn from big e-commerce data. By setting a precedent for synthesizing public and private data streams, the OPI ushers in a new paradigm for official statistics suited to the digital age through government-business-academia partnerships to advance economic measurement.

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