Strategic Buyers and Inventory Choice under Dynamic Pricing in the Flower Market

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Abstract

This paper develops a structural model of strategic buyers who choose purchase timings under price dynamics and stockout risk, whereas sellers optimize initial inventory size. To estimate the model parameters, I use granular data on a wholesale flower market. As a counterfactual, I simulate market outcomes under uniform pricing and perform a welfare analysis. The counterfactual results indicate that sellers would raise the initial inventory size and set lower prices under uniform pricing. In terms of welfare, uniform pricing would benefit sellers when they can optimally choose initial inventory size, whereas uniform pricing would hurt buyers relative to dynamic pricing.

KEYWORDS: Strategic buyers, dynamic pricing, revenue management, inventory management

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1 Introduction

Dynamic pricing is widely adopted by firms that sell perishable products under limited inventory size. Examples include airline tickets, fashion items, and farmer's markets. With dynamic pricing, price adjustments occur depending on realized demand and the length of remaining time. Sellers raise prices in order to avoid selling out products in advance, while prices fall near the deadline when low demand has been realized, as products perish after the deadline. These price adjustments may improve sellers' welfare because they are able to sell out their inventories smoothly. However, these price adjustments give buyers incentives to delay purchases. By delaying purchases, buyers can anticipate lower prices at the expense of product availability. Considering the trade-off between lower prices and higher stockout risk, buyers can strategically choose to wait even if their willingness-to-pay is large enough. To circumvent these delaying decisions, sellers can lower prices earlier or reduce inventory size to raise the stockout risk, whereas these actions can cause lower revenues. This raises an empirical question of who benefits from dynamic pricing and whether dynamic pricing improves total welfare.

I perform a welfare analysis through counterfactual simulations of uniform pricing to investigate how price dynamics affect purchase timings, choice of inventory size, and welfare. In contrast with dynamic pricing, uniform pricing prohibits sellers from adjusting prices within a day. This loss of flexibility in pricing leads sellers to set lower prices under uniform pricing. Since buyers cannot obtain lower prices by waiting under uniform pricing, they face fewer incentives to wait longer. Therefore, buyers are likely to purchase products earlier, intensifying the stockout risk. The combination of lower prices and heightened stockout risk drives demand, which prompts sellers to increase inventory size relative to dynamic pricing. Pressures on early purchases would hurt buyers' welfare, whereas their effects on sellers' welfare are ambiguous since the positive effects of greater inventory can dominate the negative impacts of lower prices. This indicates that it is essential to consider sellers' decisions regarding both inventory size and prices simultaneously in a welfare analysis. Based on the model parameter estimates, my quantitative analysis demonstrates that the welfare gains from increased inventory outweigh the losses from lower prices, suggesting that dynamic pricing is more beneficial to sellers.

To the best of my knowledge, this article is among the first to estimate a structural model where buyers optimize purchase timings under fluctuating prices and sellers optimize initial inventory size by predicting buyers' behavior. I estimate model primitives by drawing transaction records from the Japanese flower wholesale market, where retailers, as buyers, purchase flowers whose prices fluctuate within a market opening date, and producers, as sellers, decide how many flowers to bring before the market opens. Using model estimates, I simulate market outcomes under the scenario that prices of flowers are fixed and do not vary within a date. The counterfactual results show that dynamic pricing benefits strategic buyers relative to uniform pricing, whereas sellers would benefit more from uniform pricing as they bring more inventory. These positive (negative) effects of dynamic pricing on buyers' (sellers') surplus have not been analyzed well in previous empirical papers, as they have not modeled strategic buyers' behavior or sellers' decisions on initial inventory size.

My paper uses a novel dataset from one of the largest flower wholesale markets in Japan. The flower wholesale market is a business-to-business (B2B) wholesale market, where flower producers sell their flowers to retailers. The buyers, i.e. flower retailers, resell flowers in a business-to-consumer (B2C) market. There are some notable features of this market. First, flower prices tend to fall around the end of the day, giving buyers incentives to delay their purchases. Second, flower inventory size is fixed, and producers cannot replenish them after the market opens. This feature yields the stockout risk faced by buyers. Taking these two features into account, buyers strategically determine when to purchase. Third, this market opens daily, which suggests that shopping time windows are much shorter than those in other markets with dynamic pricing, such as airline markets. This feature makes it possible to put simple assumptions on buyers' survival periods. Fourth, flower producers can choose different sizes of initial inventory at different dates. This feature offers variations in initial inventory size, which helps estimate supply parameters. Therefore, the flower wholesale market data provides an ideal setting for me to study dynamic buyers' decisions under price adjustments and optimized initial inventory size.

I propose a structural model of strategic buyers to capture these salient data features. This model considers a dynamic game of optimal stopping problems among buyers. Each period after the market opens, arriving buyers decide whether and from whom to purchase flowers. The game ends when a buyer purchases flowers or flowers are sold out. The value of flowers varies across time periods, and the value is private information to each buyer. The changes in the value are both stochastic and deterministic. The stochastic changes come from the condition of the B2C market faced by retailers, and the value declines deterministically because buyers need to monitor the information of flowers, such as prices and remaining inventory size, until they purchase. This demand side model also includes the trade-off of waiting: if buyers wait longer, they may obtain flowers at lower prices while facing greater stockout risk.

On the supply side, I model competition among sellers who choose the size of initial inventory before the market opens. They optimize the initial inventory size by predicting demand and prices realized in the future. Under dynamic pricing, sellers are able to sell out products even if they bring the large size of initial inventory by adjusting prices. Although more inventory generates more sales, it mitigates the stockout risk and eventually leads to lower prices. Taking this and competitive environment into account, sellers optimize initial inventory size. I do not solve for prices at each period but recover the pricing function directly from the data. This is not crucial for estimating parameters and simulating counterfactuals of interest in this paper. I discuss the details in Section 4.

I bring the model to the flower wholesale market data, focusing on a specific flower variety. To identify demand parameters such as price elasticity, I need to separate the source of sales into two factors: the number of existing buyers and their valuation. In my data, I directly observe the number of individuals who remain in the market at each time period within a day. Combining this information with transaction records, I estimate price elasticity without modeling sellers' price decisions. This is unlike what most of the previous papers have done with airline industry data. The shopping time windows in airline industry are longer than those in the flower market, so it is much difficult to conjecture when each customer arrives and when to exit the market. To identify arrival parameters separately from price elasticity, the analysts have needed to build a price-setting model.

Building upon the identification statements stemming from the novel data features, I propose a multi-step estimation procedure that combines demand estimation technique using individual purchase records with a two-step estimation method developed in the literature on dynamic discrete choice games. First, I estimate conditional choice probabilities regarding purchase decisions and pricing functions, which depend on a time period and state variables, including the size of remaining inventory. Using them in forward-looking simulations, I compute the continuation value at each state. Second, the estimates of the continuation value and conditional choice probabilities are applied to the equilibrium conditions, and then demand parameters are estimated. Third, demand parameters are separated into flower valuations and price elasticity by employing instruments. Fourth, supply parameters are estimated from the equilibrium conditions on the supply side. According to the estimation results, buyers' valuations decrease deterministically, sellers compete with each other, and there are heterogeneous inventory costs.

Using the estimates of model parameters, I counterfactually simulate welfare under uniform pricing where price adjustments do not occur. If prices are fixed and sellers commit to them within a day, buyers have less incentive to wait as they cannot obtain lower prices in the future. Consequently, buyers choose to purchase earlier under uniform pricing, leading to greater stockout risk. The pressure on earlier purchases under uniform pricing would damage buyers' welfare. Anticipating fewer incentives to delay purchases, sellers would generate a larger initial inventory. They choose lower uniform prices for selling out their products, as they are not able to adjust prices under uniform pricing. Therefore, the effects of uniform pricing on producers' welfare are ambiguous. If the benefit from larger inventory size dominates the loss from lower prices, sellers' welfare is improved. For this simulation, I consider multiple scenarios as follows: (i) only uniform prices are optimized while the size of initial inventory is the same as in the data, and (ii) both fixed prices and the size of inventory are optimized. I also prepare two cases for buyers' strategic behavior: buyers can delay their purchases or must make a one-shot decision of whether to purchase flowers or exit the market.

The counterfactual analysis shows that uniform pricing would see lower prices and larger initial inventory sizes on average than dynamic pricing. Buyers' welfare decreases by 27.8% while producers' welfare increases by 10.8% if the market mechanism transitions from dynamic pricing to uniform pricing. The effect of uniform pricing on sellers' welfare is negative or small if the initial inventory size is exogenously given. When sellers can choose initial inventory size flexibly under uniform pricing, they prepare greater sizes of initial inventory and sell products at lower prices, which leads to greater producers' welfare. These welfare effects are different from the findings in the existing literature, as I newly consider two features: strategic buyers and endogenous initial inventory size. Furthermore, my counterfactuals indicate that dynamic pricing improves total welfare. This supports the fact that dynamic pricing survives as a primary market mechanism in the flower wholesale market.

The rest of the paper is organized as follows. The remainder of this section discusses the related literature. Section 2 describes the data and its background. Section 3 develops the model which explains the empirical findings. Section 4 describes estimation method and discusses the estimation results. Section 5 describes the counterfactual algorithm, performs counterfactual simulations, and discusses counterfactual results. Section 6 concludes.

Related literature This article contributes to four strands of the literature. First, it adds to the empirical literature on dynamic consumer demand. Examples include Nair (2007), Gowrisankaran and Rysman (2012), Hendel and Nevo (2013), and Mansley (2022). These empirical studies delve into the dynamic consumer behavior regarding durable goods. When buyers expect prices to drop, they have incentives to delay purchases, while they obtain more sequences of flow utility by purchasing earlier. In contrast, my paper focuses on perishable goods and the underlying dynamic motives of buyers. For perishable products, the nature of the trade-off in delaying purchase differs from the case of durable goods. Since perishable products have limited capacities, buyers face stockout risk when deciding whether to purchase immediately or wait by anticipating lower prices in the future. Soysal and Krishnamurthi (2012) study a dynamic demand model using data on US apparel stores. In their model, buyers face stockout risk, and prices fluctuate across periods. They assume that both product availability and prices are exogenous, which does not allow them to perform the welfare comparison between different market mechanisms, such as markdown pricing against uniform pricing. I develop a dynamic demand model where product availability is endogenously determined and perform the welfare analysis under uniform pricing.

Second, this paper contributes to the literature on dynamic pricing. Dynamic pricing has been extensively studied, especially in the field of operations research. Theoretical models in this area often evaluate welfare impacts through simulations. Previous papers, such as Gallego and Van Ryzin (1994); Zhao and Zheng (2000); Talluri and Van Ryzin (2004), assume short-lived buyers, where sellers encounter a different set of buyers each period. Others, including Su (2007); Aviv and Pazgal (2008); Levin et al. (2010); Hörner and Samuelson (2011), Board and Skrzypacz (2016); Dilme and Li (2019), assume long-lived buyers who strategically time their purchases. A recent empirical literature, such as Williams (2022), Aryal et al. (2024), Hortaçsu et al. (2022), D'Haultfoeuille et al. (2022), and Chen and Jeziorski (2022), integrates these models with high-frequency data to assess the welfare effects of dynamic pricing. They aim to perform welfare analysis under dynamic pricing and uniform pricing using actual data. For example, Williams (2022) shows that dynamic pricing benefits sellers by allowing price discrimination based on buyers' elasticity but reduces consumer welfare. As another example, Hortaçsu et al. (2022) solve a competitive dynamic pricing model and show that dynamic pricing can soften competition and improve sellers' welfare. In contrast to these papers, my paper demonstrates that in markets with strategic buyers and endogenous initial inventory, dynamic pricing can lead to different welfare outcomes.

The majority of these empirical studies employ data on the airline industry, in which travelers are assumed to be short-lived and non-strategic. To verify this assumption, Sweeting (2012) and Li et al. (2014) develop tests for the presence of strategic buyers. These two papers use data from the baseball game market and the airline industry respectively, and find different results; the former supports non-strategic buyers' behavior, and the latter shows the presence of strategic buyers. However, these studies do not account for the impact of remaining inventory transitions, which this paper aims to address.

Third, the decisions regarding initial inventory size in the context of dynamic pricing and strategic buyers are discussed in the literature on inventory management. Examples include Liu and Van Ryzin (2008), Cachon and Swinney (2009), Du et al. (2015), Wang et al. (2020), and Wang et al. (2021). Their models are commonly referred to as "newsvendor models". The size of initial inventory plays a critical role in dynamic pricing when buyers are strategic, as it impacts the size of remaining inventories. On the one hand, larger initial inventories reduce the stockout risk faced by buyers, which encourages buyers to wait and results in lower prices. On the other hand, larger initial inventories increase the seller's sales opportunities. To the best of my knowledge, few papers have empirically investigated a structural model where strategic buyers exist facing price dynamics, and sellers choose the size of initial inventory. The exception is Sanders (2024), which builds the newsvendor model with dynamic pricing and simulates its effects on grocery-store waste and welfare. However, Sanders (2024) assumes non-strategic buyers, whereas my paper focuses on strategic buyer behavior.

Fourth, this article also complements the empirical literature on flower wholesale markets. Examples in this literature include Steen (2014); Wang and Xiang (2014); Lu et al. (2016, 2019); Truong et al. (2022). Of these, Lu et al. (2019) are closely related to this paper. They develop a structural model of dynamic buyer behavior and apply it to data from the Dutch flower wholesale market. In their model, buyers, acting as bidders, strategically choose their bids across multiple purchase opportunities. The authors estimate model primitives to simulate an alternative mechanism designed to optimize minimum purchase quantities in auctions. While their focus is on auctions and purchase quantities in dynamic settings, the central focus of this paper is on dynamic pricing and initial inventory decisions.

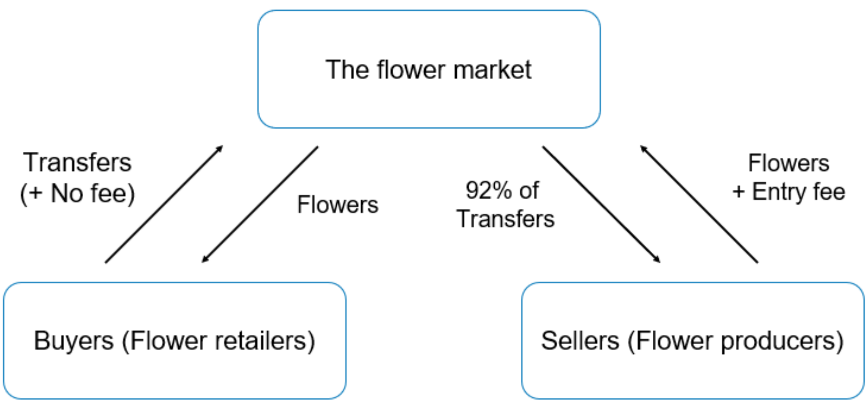
2 Data

This section outlines the institutional background of the flower wholesale market from which the data are drawn (section 2.1) and discusses key empirical patterns (sections 2.2, 2.3, and 2.4). This section focuses on the empirical patterns of price dynamics, purchase timings, and initial inventory. These patterns motivate the model and the estimation strategies which are discussed in the following sections.

2.1 Overview

In Japan, business-to-business (B2B) flower wholesale markets are present in every region. We leverage data from the company that manages one of the largest flower markets in Tokyo. Flower producers and retailers participate as sellers and buyers, respectively, with the intermediary company facilitating transactions. After buying flowers from producers, retailers resell them in business-to-consumer (B2C) markets. The intermediary company takes an 8% commission on sellers' revenue and charges an entry fee per box of flowers brought to the market. Figure 1 illustrates the relationship between market participants. The market operates almost daily, with cut flowers traded on Monday, Wednesday, and Friday, and potted flowers on Tuesday, Thursday, and Saturday. Producers can also sell flowers in other regional markets, including Tokyo.

Figure 1: Flower Wholesale Market



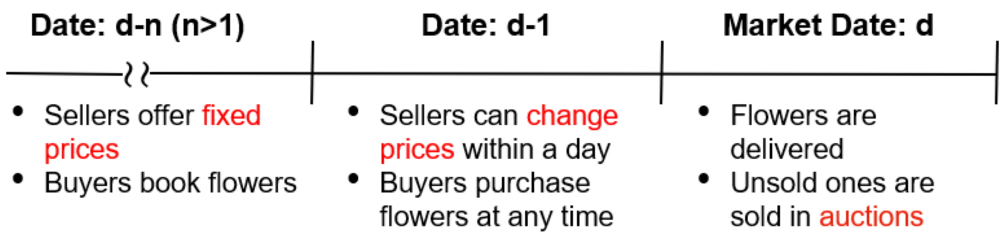
The market transactions follow a sequential process: Booking, over-the-counter (OTC), and auction. Although transactions occur on different dates, all buyers receive flowers on the same day, referred to as the market date. Figure 2 depicts the timeline, and the detailed descriptions of each stage are as follows:

Booking: Buyers aiming to secure flower availability contact the market a few days before a specific market date. Then, the market identifies suitable sellers and inform their prices to buyers. If buyers accept, the flowers are booked at these prices. It is anecdotally known that offered prices in the booking stage do not fluctuate depending on the timing of orders. This format is favored by buyers with high demand certainty, although it accounts for 37% of total transaction value.

Over-The-Counter (OTC): A day before the market date, sellers post information to the platform owned by the data-providing company. This information includes seller's identity, the flower variety, size of inventory, quality, and production details. Potential buyers view this information. Then, buyers contact the market to inquire about prices and decide whether to purchase or not. Employees in the market are in charge of setting prices as representatives of sellers. In other words, flower producers lose their control over pricing after they decide on inventory size and post the information discussed above. Buyers can participate in the market anytime within a date, indicating that transactions occur sequentially. The information on remaining inventory size is updated upon the realization of demand so that buyers can choose the timing of their purchases. In this stage, the market can charge different prices at different periods, making this the primary dynamic pricing phase.

Auction: Unsold flowers from the OTC stage become objects to bid in auctions on the market date. The auctions follow a descending price mechanism, similar to Dutch flower auctions (Lu et al. (2019)). As prices fall, a bidder presses a button to indicate that the bidder accepts the current prices. The winning bidder chooses how many units to purchase at the current prices. The auctions resume from the current prices until flowers are sold out. Flowers that remain unsold after the auctions are usually disposed of, although this is rare, as sellers generally accept low prices to avoid wastage. The auction format accounts for 15% of total transaction value.

Figure 2: Timeline in the market



This paper focuses on cut flower transactions during the OTC stage, as this phase accounts for more than 50% of transactions and displays clear dynamic pricing patterns. As Table 1 shows, the OTC format generates the most significant monetary value (2.5 million transactions, totaling $1.1 billion), while booking transactions generate higher average value per transaction but represent a smaller volume. This is because buyers aiming to secure flower availability are likely to accept higher prices in the booking stage, whereas these buyers are not the majority. The auction stage has the most negligible transaction value compared to the other two formats. This is because buyers who join auctions have already taken the stockout risk, so they cannot accept prices unless they are lower than those in the other two formats. The OTC format is in the middle between booking and auction formats in terms of prices, and it is the most preferred format by buyers according to Table 1. Additionally, I check whether a single buyer purchases the same flower variety across multiple transaction formats. The data indicates that only 3.5% of buyers use multiple transaction formats for purchasing a specific flower variety on the same market date.

Table 1: Transaction formats comparison for cut flowers

Format	Value ($M)	Transaction (M times)	Quantity (M)	# of sellers	# of buyers
Booking	850	0.9	119	2,771	723
OTC	1100	2.5	194	3,288	684
Auction	300	1.0	58.8	3,429	638

Notes: This table reports statistics for each transaction format. “Value” represents transaction amounts measured in a dollar. “Transaction” refers to the number of recorded transactions. “Quantity” captures units (number of stems) of flowers traded. “# of sellers (buyers)” means the number of unique sellers (buyers) participating in each transaction format.

The data used in this paper comes from the records of transactions between buyers and sellers in the OTC stage from April 2018 to March 2019. For every single transaction, I observe (i) when transactions occur, (ii) prices and quantities, (iii) name of flower varieties, (iv) seller’s identity and buyer’s identity, (v) the amounts of the remaining inventory, and (vi) flower characteristics. Table 2 describes summary statistics for each variable. The sample contains 2.4 million transactions. Panel A in the table indicates that unit prices vary from less than 1 JPY to 90,000 JPY (1 JPY = 0.0091 USD in 2018). Panel A also shows that the number of boxes demanded in each transaction does not vary; most buyers purchase a single box for a specific flower variety. Panel B presents daily statistics. According to the third and fourth rows, there are generally more sellers than buyers on any given day. The fifth and sixth rows represent the number of flower types and varieties at each market date. Flower types are broader flower categories and include multiple flower varieties. These rows suggest that sellers bring multiple varieties of flowers. The seventh row in Panel C represents the number of sellers per flower variety at each market date. This row implies that only one or two sellers sell a specific flower variety, implying that flowers are marketed under unique seller brands. Therefore, this study focuses on monopoly and duopoly markets in the following sections. The eighth row in Panel D represents the stockout status for each flower brought by each seller. A stockout dummy variable is assigned to each flower, which takes value one if the given seller sells out the given flower variety within the OTC stage. According to the data, more than 80% of flowers are sold out in the OTC stage, indicating that buyers face the stockout risk. Stockout risk is one of the most essential features of this paper, as it creates a trade-off in purchase timing decisions.

Table 2: Summary statistics

	Min	1st Qu.	Med	Mean	3rd Qu.	Max	Observations
Panel A: Unconditional							
Unit Prices	0.2	40.0	65	103.4	110.0	90000	2.4M
Boxes	1	1	1	1.4	1	169	2.4M
Panel B: Given date							
Buyers	228	261	291	285.9	301.8	347	154
Sellers	420	617.8	658.5	654.3	694.8	815	154
Flower Types	70	83	91	91.0	98	107	154
Varieties	2169	2994	3250	3246	3484	4155	154
Panel C: Given date and variety							
Sellers per Variety	1	1	1	1.7	2.0	43	0.5M
Panel D: Given date, variety, and seller							
Stockout	0	1	1	0.87	1	1	1.3M

2.2 Price adjustments

As previously mentioned, prices fluctuate across periods in the OTC stage. This is because the employee in the market, acting as a representative of flower producers, has a strong incentive to sell out inventory at the highest possible prices since the operator receives a percentage of the revenue. For clarity, I refer to the operator in the market as the "seller" in discussions of pricing because of its intermediary role. Figure 3 illustrates the pattern of price fluctuations from 8 a.m. to 7 p.m. To account for heterogeneity across flower varieties, I normalize prices to average prices within each variety. Initially, prices are approximately 4% higher than the average, but by 2 p.m., they start to decline, reaching about 6% below the average by the end of the day. Buyers looking to secure flowers are likely to purchase flowers earlier in the day, accepting higher prices, while buyers aiming for lower prices wait until late in the day when unsold flowers drive prices down.

The transaction timings are correlating to the price patterns. Figure 4 displays the number of transactions across periods ranging from 8 a.m. to 7 p.m., showing a clear concentration of activity around 2 p.m. Notably, this coincides with the peak in prices, as illustrated in Figure 3. This suggests that strategic buyers are likely to purchase flowers in the middle of the day to avoid the stockout risk, and sellers respond to it by offering higher prices.

Figure 3: Price path

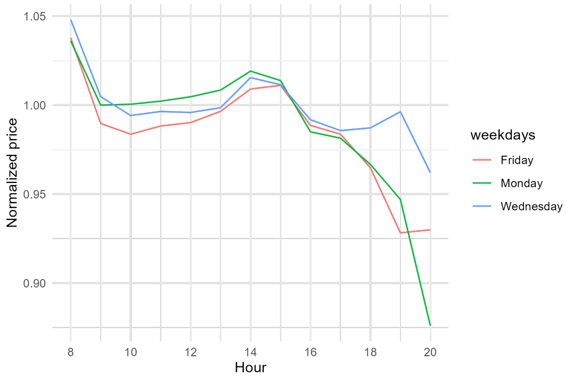
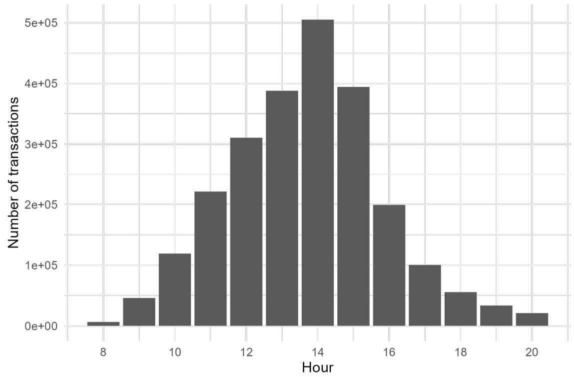


Figure 4: Number of transactions



Notes: The left panel displays price paths across periods. Different lines capture the patterns on different weekdays. The right plot projects the number of transactions across periods. Both figures are about all flower varieties.

The remaining stock levels also influence prices, with the impact varying depending on the time of day. Since market demand is uncertain at the start of the day, sellers deal with this uncertainty by adjusting prices dynamically. As shown in Table 1, auctions generally result in lower prices, giving sellers an incentive to sell as many flowers as possible during the OTC stage. This often leads to price reductions in the evening when unsold inventory remains. Conversely, when stocks are limited earlier in the day, sellers tend to set higher, more aggressive prices. We confirm this pricing behavior by running regression of log unit price on the number of remaining stocks and its interaction with time in hours as the covariates. In this regression, we also control prices by the number of boxes involved in a single transaction and fixed effects regarding seasonality and flower variety.

Table 3 displays the regression results, showing that sellers lower prices when they have larger inventory left unsold. The interaction term in the third row indicates that this negative relationship between stock levels and prices becomes stronger as time progresses. The negative sign of the coefficient of this interaction term implies that the negative effect of inventory on prices is enlarged as it is closer to the deadline. The last term, Box, represents the effects of the number of boxes involved in a single transaction on prices. The majority of transactions involve a single box, but the sign of the coefficient reveals that unit prices tend to decrease as the number of boxes increases. The R-squared is more than 0.7 when the regression includes variety fixed effects, implying that prices are mainly determined by heterogeneity across varieties rather than seasonality.

Table 3: Determinants of prices (All flower varieties)

	Dependent Variable: log(Price)					
Constant	5.560^{***}					
	(0.0017)					
$\log(\text{Stocks}_t)$	-0.2272^{***}	-0.2284^{***}	-0.0666^{***}	-0.0680^{***}	-0.0631^{***}	-0.0635^{***}
	(0.0010)	(0.0077)	(0.0034)	(0.0034)	(0.0035)	(0.0035)
$\log(\text{Stocks}_t) \times t$	-0.0043^{***}	-0.0041^{***}	-0.0025^{***}	-0.0022^{***}	-0.0021^{***}	-0.0021^{***}
	(4.68×10^{-5})	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Box					-0.0135^{***}	
					(0.0016)	
Box> 2						-0.0640^{***}
						(0.0062)
month FE		Yes		Yes	Yes	Yes
weekdays FE		Yes		Yes	Yes	Yes
variety FE			Yes	Yes	Yes	Yes
Observations	$2,373,623$	$2,373,623$	$2,373,623$	$2,373,623$	$2,373,623$	$2,373,623$
R^2	0.21009	0.22319	0.73251	0.74617	0.74664	0.74366

Notes: This table reports OLS results. Observation is based on each transaction pair of a seller and a buyer. The dependent variable is log of unit price. The covariates include the number of remaining stocks, their interaction with the current period, and the number of boxes involved in the transaction.

2.3 Strategic buyers

Next, transaction data show empirical patterns of buyers' behavior. Since we model strategic buyers, it is essential to check whether buyers behave strategically or not. Figure 5 and 6 represent the initial period and the last period of transactions for each buyer at each market date. These figures indicate that most buyers arrive at the market around 10 a.m. and leave by 8 p.m. Additionally, anecdotal evidence suggests that buyers tend to make early purchases for flowers they urgently need, even if this requires paying higher prices. Conversely, for flowers that are less immediately necessary, buyers often delay purchases, anticipating lower prices as the day progresses. This behavior underscores the strategic nature of buyers' decisions, as they weigh the trade-off between securing flowers early at higher prices and waiting for potential discounts later in a day.

Figure 5: Initial purchase timing

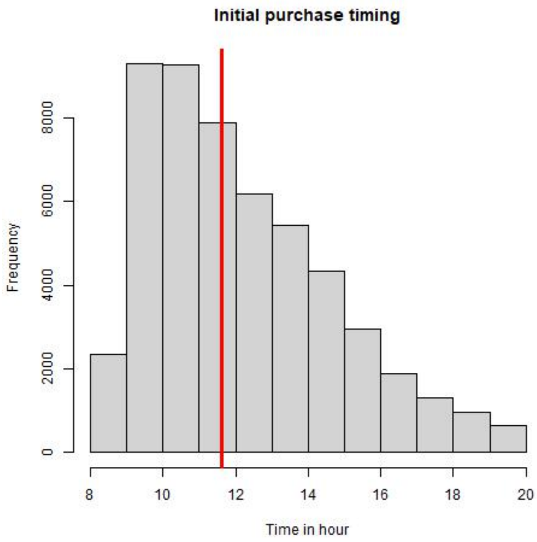
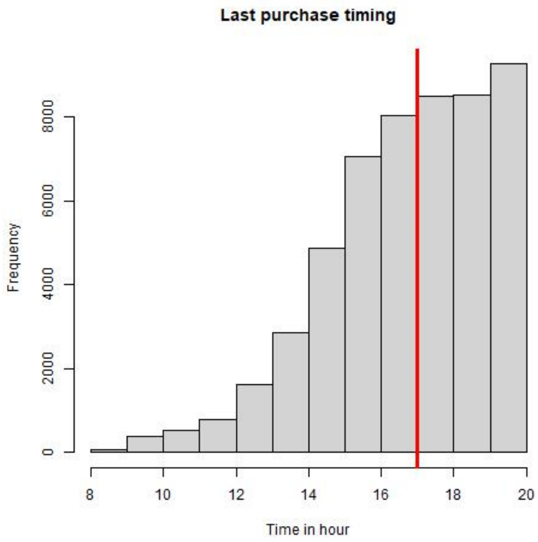


Figure 6: Last purchase timing



Notes: The left (right) panel displays the histogram of initial (last) transaction timing at a given buyer and market date. The red vertical line presents the median. Both figures are about all flower varieties.

2.4 Initial inventory

Since this study focuses on the decisions of initial inventory size, I examine its empirical patterns. First, I present evidence that highlights the variation in initial inventory size across different dates. In Figure 7 and 8, I track initial inventory size over the sample periods using Calypso, an Orcid variety, since it is used in the estimation section. The red lines project the size of initial inventory for each seller, showing noticeable fluctuations across dates. In these figures, the blue lines depict the transition of the market size, defined by the number of buyers who purchase Calypso within a given week. The patterns of red and blue lines are similar, suggesting a correlation between initial inventory size and the number of potential buyers. This correlation suggests that sellers can partially forecast the potential demand and decide the initial inventory size based on the predictions. One can consider the possibility of reverse causality: more buyers arrive as sellers increase their inventory. However, since I define potential buyers based on purchases within the week rather than the day, the likelihood of reverse causality is minimal.

I examine whether sellers consider their competitors' behavior when determining their initial stock levels, as the model incorporates competition between sellers in terms of initial inventory size. To investigate the competition effects on initial stocks, I run a regression of initial inventory size on the market size - measured by the number of potential buyers - and the size

Figure 7: Initial inventory (first seller)

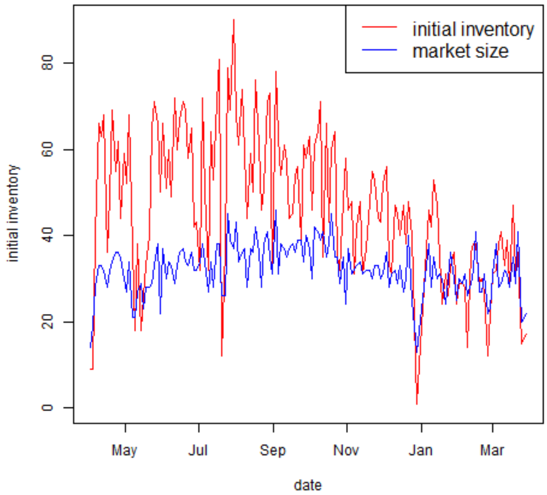
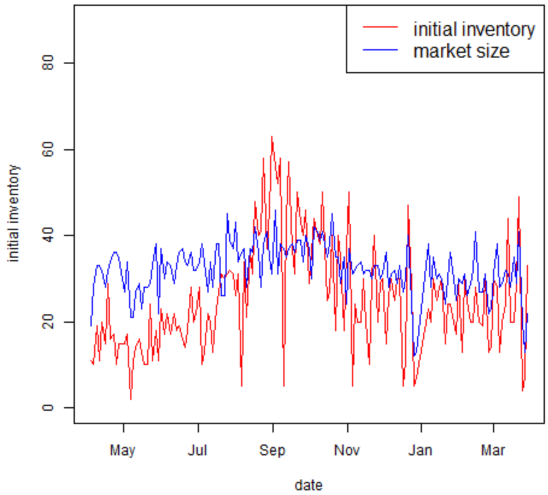


Figure 8: Initial inventory (second seller)



Notes: The left (right) panel displays the transition of the first (second) seller's initial inventory size across dates. The red lines project the transition based on actual data, while the blue lines capture the market size defined by the number of buyers who purchase Calypso within a week.

of initial inventory prepared by a competing seller, controlling for seasonality and sellers' fixed effects. Using Calypso as the reference flower variety, Table 4 presents the regression results. This table presents the coefficients of each covariate in the regressions. The significant coefficients indicate that sellers consider their opponent's initial inventory size as well as the market size when choosing initial inventory size.

3 Model

I develop a structural model in which buyers solve optimal stopping problems, while sellers strategically determine the initial inventory size by predicting buyers' strategic behavior. Buyers face a trade-off each period: although waiting may result in lower prices, it also increases the risk of stockouts. The model assumes that buyers' payoff from flowers depends on the purchase timing, with earlier purchases offering the advantage of avoiding the need to monitor inventory and prices post-purchase. On the supply side, sellers strategically choose the initial inventory size, understanding that the initial inventory size influences the likelihood of stockout, which in turn shapes buyers' dynamic incentives.

Table 4: Determinants of initial Stocks (Calypso, Orchid)

Dependent Variable:	initial_stock		
Model:	(1)	(2)	(3)
market_size	77.41***	62.02**	53.86**
	(5.013)	(8.022)	(10.30)
opponent_stock	-0.6076**	-0.3012	-0.4352*
	(0.0616)	(0.1171)	(0.1239)
Fixed-effects			
weekdays	Yes	Yes	Yes
seller_id		Yes	Yes
month			Yes
Observations	303	303	303
R^2	0.52542	0.61688	0.69256
Within R^2	0.52424	0.41978	0.36288

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports OLS results. The dependent variable is the units of initial stocks, and the covariate includes market size defined by the number of potential buyers and the number of initial stocks brought by an opponent. I also control for fixed effects of weekdays, sellers, and months. Standard errors are provided in parentheses.

3.1 Setup

Suppose that J sellers with multiple boxes of flowers sell them during finite time periods $t \in \{1,2,...,T\}$ within a day d. To simplify the notation, I suppress the subscript related to the market date d in the following discussion, where it is clear from the context. There are N_t potential buyers at period t. Each buyer chooses whether to purchase flowers at price p_{jt} from seller $j \in A_t$ at each time t. Let $a_{it} = j$ if buyer i purchases flowers from seller j at time t, and $a_{it} = 0$ if the buyer chooses to wait. If buyer i chooses $a_{it} \neq 0$, then the buyer becomes inactive in the following periods. If $a_{it} = 0$, the buyer goes to the next period $t+1$. In other words, buyers solve optimal stopping problems. The choice set A_t varies across periods depending on flowers' availability. It always includes 0 as a waiting option, but $j \notin A_t$ if seller j sells out his flowers by period t.

At each time t, buyer i observes a vector of current stocks $\boldsymbol{c}_t = \{c_{1t},...,c_{Jt}\}$, offered prices $\boldsymbol{p}_t = \{p_{1t},...,p_{Jt}\}$, and the number of active buyers N_t. I summarize these variables into a vector $\boldsymbol{s}_t := \{t, \boldsymbol{c}_t, \boldsymbol{p}_t, N_t\}$. Also, buyer i privately observes an action-specific random shock $\{\varepsilon_{it}^j\}_{j\in\{0,1,...,J\}}$ that follows a Type-I extreme value distribution, which is commonly known among buyers.

For the production rationing, I assume that if the number of interested buyers exceeds the number of available flowers at period t, flowers are randomly rationed. Although this assumption may appear inconsistent with reality — where transactions are bilateral and can occur continuously — it reflects practical constraints. Buyers cannot continuously monitor state variables (e.g., every second), as they are simultaneously managing their own B2C operations while sourcing flowers in the wholesale market. This justifies the use of discrete time intervals instead of continuous time. Buyers who decide to purchase during period t are assumed to contact the market at random points between t and $t+1$. Consequently, random rationing of the product at each period is a reasonable assumption.

Buyers who purchase flowers from seller j at period t recieve payoff given by $u_{ijt} := \lambda_{jt} - \beta p_{jt} + \varepsilon^{j}_{it}$, where λ_{jt} represents fixed payoff from seller j's flowers, β is a price elasticity parameter, and ε^{j}_{it} is a stochastic demand error. If buyers opt not to purchase, they obtain only ε^{0}_{it}. The fixed payoff λ_{jt} fluctuates deterministically across periods, reflecting the empirical observation that buyers tend to avoid purchasing flowers in the evening, leading to a lower payoff of flowers later in the day. Additionally, if buyers incur significant mental costs from monitoring the time-varying states of flowers, their payoff decreases as the day progresses. I also assume that the payoff consists of a stochastic element $\boldsymbol{\varepsilon}$, which is action-specific and independently drawn across both periods and buyers. As noted by Lu et al. (2019), this stochastic component accounts for buyers' volatility in the payoff, which can arise from unexpected demand shocks in their B2C retail operations.

Furthermore, I impose two assumptions on the demand side. First, buyers have unit demand for a given flower variety. This assumption simplifies the model notations and is supported by the data in Table 2, which shows that most buyers purchase a single box per transaction. While the model could remain tractable without this assumption by treating the number of boxes demanded as exogenous, unit demand allows for clearer notations. Second, buyers do not consider the bundle of multiple flower varieties. This assumption may not be practical because buyers can purchase multiple flower varieties to gain synergies or because they may substitute flowers across varieties or types. For the model tractability, I assume that buyers are locked into a specific flower variety during the day, disregarding the presence of other flower varieties. This paper focuses on Calypso, a variety of Orchid, in the following application. I find that 67% of buyers who purchase at least one variety of Orchid every day choose to purchase Calypso.

Given the large number of varieties in the Orchid category (58 varieties on average each day), this fact suggests that buyers are not likely to purchase other Orchid varieties to substitute Calypso.

On the supply side, I focus on decisions regarding initial inventory size rather than prices. I remain agnostic about price determination because sellers have no control over prices upon sending flowers to the market. The staff in the market set prices for each flower, but the analyst does not observe the exact mechanism by which the market staff balances sellers' profit and buyers' welfare. The empirical patterns show that prices depend on the amount of remaining inventory size and the periods. Therefore, modeling the initial inventory size is partially equivalent to modeling prices because the inventory size indirectly affects prices. The omission of explicit price modeling does not compromise the estimation strategy or the counterfactual analysis discussed in Sections 4 and 5.

To model the size of the initial capacity, I denote cost parameters by $\boldsymbol{\gamma} = \{\gamma_j\}_{j \in J}$ and the marginal cost is specified as follows:

$$\mathrm{mc}_{jd} = \gamma_j + \xi_{jd}, \tag{1}$$

where γ_j denotes seller j's marginal cost and ξ_{jd} represents a random supply shock which is independently drawn across each market date d and unknown to the analyst.

3.2 Equilibrium

I consider the Markov-perfect equilibrium (MPE) as an equilibrium concept. Let the set of strategies be $\boldsymbol{\alpha} = \{\alpha_{it}(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}) : i \in N, t \in \{1, 2, ..., T\}\}$, where each α_{it} maps state variables and random shock into discrete actions chosen by buyer i at period t. Then, the Bellman equation can be written as

$$V_t^{\alpha}(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}) = \max_{a_{it} \in A_t} \{v_t^{\alpha}(a_{it}, \boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it})\},$$

where

$$
v_t^{\alpha}(a_{it},\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{it}) = \begin{cases} E_{\boldsymbol{\varepsilon}_{-it}}\left[\int V_t^{\alpha}\left(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1}\right) dF\left(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1} | a_{it}=0, \alpha_{-it}(\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{-it}),\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{it}\right)\right] + \varepsilon_{it}^0 \\ \qquad \text{if } a_{it}=0 \text{ (wait)} \\ E_{\boldsymbol{\varepsilon}_{-it}}\left[\frac{c_{jt}}{\max\left(\sum_{-i} I[\alpha_{-it}(\boldsymbol{s}_t,\varepsilon_{-it})=j]+1, c_{jt}\right)}\left(\lambda_{jt}-\beta p_{jt}\right) + \left(1-\frac{c_{jt}}{\max\left(\sum_{-i} I[\alpha_{-it}(\boldsymbol{s}_t,\varepsilon_{-it})=j]+1, c_{jt}\right)}\right)\right. \\ \left. \times \int V_t^{\alpha}\left(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1}\right) dF\left(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1} | a_{it}=j, \alpha_{-it}(\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{-it}),\boldsymbol{s}_t, c_{j,t+1}=0,\boldsymbol{\varepsilon}_{it}\right)\right] + \varepsilon_{it}^j \\ \qquad \text{if } a_{it}=j \text{ (purchase)} \end{cases} \tag{2}
$$

captures the action-specific expected value function. The indicator function $I[\alpha_{lt} = j]$ takes value one if buyer l purchases flowers from seller j at period t, and it takes value zero otherwise. The term involving maximum operator,

$$
\frac{c_{jt}}{\max\left(\sum_{-i} I[\alpha_{-it}(\boldsymbol{s}_t,\varepsilon_{-it})=j]+1, c_{jt}\right)}, \tag{3}
$$

represents the probability of product rationing. Its numerator represents supply, while the denominator represents demand. For example, $\sum_{-i} I[\alpha_{-it}(\boldsymbol{s}_t,\varepsilon_{-it}) = j]+1 > c_{jt}$ indicates that demand exceeds supply, and products are rationed randomly with the probability (3). The first case $a_{it} = 0$ implies that buyer i chooses to wait and obtain the continuation value. For the second case $a_{it} = j$, the first term captures the temporary payoff from purchasing flowers from the seller j. The notation λ_j represents the deterministic payoff from flowers from seller j, and βp_{jt} captures the disutility from paying prices. The second term in (2) represents the continuation value when buyer i fails to purchase flowers from seller j and proceeds to the next period. Each buyer is heterogeneous regarding their random shocks $\boldsymbol{\varepsilon}_{it}$. These shocks vary independently across periods within each buyer, as their business conditions in the downstream retail B2C markets change over time. For example, this stochastic payoff suddenly becomes larger if buyers receive large orders in the B2C market, which is hard to predict exactly in previous periods, so this is the stochastic part of the payoff. Additionally, it is important to note that buyers do not discount the continuation value because they receive flowers the day after the transactions regardless of their purchase timings.

Player i's best response function is

$$
b_{it}\left(\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{it},\boldsymbol{\alpha}_{-i}\right) = \arg\max_{a_{it}\in A_t}\left\{v_t^{\alpha}(a_{it},\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{it})\right\}.
$$

Then, the MPE is defined as a set of strategies $\boldsymbol{\alpha}^*$ such that for any $(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it})$,

$$\alpha_{it}^*(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}) = b_{it}\left(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}, \alpha_{-i}^*\right). \tag{4}$$

When the random shock $\boldsymbol{\varepsilon}$ follows a type-I extreme value distribution, the conditional choice probability is

$$P_i^*\left(a_i = j|\boldsymbol{s}_t\right) = \frac{\exp(v_t^{\alpha}(a=j, \boldsymbol{s}_t))}{\sum_{l\in\{1,\ldots,J\}}\exp(v_t^{\alpha}(a=l, \boldsymbol{s}_t)) + \exp(v_t^{\alpha}(a=0, \boldsymbol{s}_t))}. \tag{5}$$

The strategies in the MPE are expressed within a probability space, from which I confirm the existence of the equilibrium. Given a set of strategy functions $\boldsymbol{\alpha} = \{\alpha_i(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}) : i \in N_t\}$, the choice probability associated with these strategies, $\boldsymbol{P}^{\boldsymbol{\alpha}}$ can be written as follows:

$$\begin{aligned} \boldsymbol{P}^{\boldsymbol{\alpha}} &:= \{P_i^{\boldsymbol{\alpha}}(a_{it}|\boldsymbol{s}_t) : (i, a_{it}, \boldsymbol{s}_t) \in \{1,2,\ldots,N_t\} \times \{0,1,\ldots,J\} \times S\}, \\ \text{where } P_i^{\boldsymbol{\alpha}}\left(a_i|s_t\right) &= \int I\left\{a_i = \arg\max_{a=\{0,1,\ldots,J\}}\left\{v_t^{\boldsymbol{\alpha}}(a, s_t) + \varepsilon_{it}^a\right\}\right\} dG_\varepsilon(\boldsymbol{\varepsilon}_{it}). \end{aligned} \tag{6}$$

Using this notation based on the conditional choice probability, the expected value $E_{\boldsymbol{\varepsilon}_{-it}}\left[\ldots\alpha_{-i}(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{-it})\ldots\right]$ in the action specific value function, which is discussed in (2), can be replaced by $\sum_{a_{-it}\in\{0,1,\ldots,J\}^{N_t-1}} \Pr(a_{-it}|\boldsymbol{s}_t; \boldsymbol{\alpha})\left[\ldots a_{-it}\ldots\right]$. To represent this action-specific value function based on the conditional choice probability, I use the notation $v_t^{\boldsymbol{P}}$ and then, player i's best response probability function is expressed as follows:

$$\Lambda_i(a_i|v_t^{\boldsymbol{P}}(\boldsymbol{s}_t)) := \int I\left\{a_i = \arg\max_{a=\{0,1,\ldots,J\}}\left\{v_t^{\boldsymbol{P}}(a, s_t) + \varepsilon_{it}^a\right\}\right\} dG_\varepsilon(\boldsymbol{\varepsilon}_{it}).$$

Let $\boldsymbol{\alpha}^*$ be a set of the MPE strategies and let $\boldsymbol{P}^{\boldsymbol{\alpha}^*} := \{P_i^{\boldsymbol{\alpha}^*}(a_i|\boldsymbol{s}_t) : (i, a_{it}, \boldsymbol{s}_t) \in \{1,2,\ldots,N_t\} \times \{0,1,\ldots,J\} \times S\}$ be the corresponding conditional choice probability as discussed in (6). By construction, $P_i^{\boldsymbol{\alpha}^*}(a_i|\boldsymbol{s}_t) = \Lambda_i(a_i|v_t^{\boldsymbol{P}^{\boldsymbol{\alpha}^*}}(\boldsymbol{s}_t))$, which means $\boldsymbol{P}^{\boldsymbol{\alpha}^*}$ are fixed points. The existence of these fixed points is guaranteed from the Brower's fixed point theorem, although the equilibrium may not be unique.

On the supply side, seller j sets initial inventory size each day d by solving the following maximization problem:

$$\max_{c_{j1d}} E\left[\sum_{t=1}^{T} \tilde{W}_{jtd} | \boldsymbol{c}_{1d}, N_{1d}\right] - (\gamma_j + \xi_{jd})\, c_{j1d}, \tag{7}$$

where $\tilde{W}_{jtd}$ represents seller j's profit at period t and the second term represents total inventory cost discussed in (1). The profit $\tilde{W}_{jtd}$ is a random variable, as seller j does not observe buyers' demand shocks and how transactions proceed when deciding the size of initial inventory. Initial inventory size c_{j1d} is determined through the pure strategy Nash equilibrium since cost shock ξ_{jd} is common knowledge among sellers, and the opponents' initial inventory size affects seller j's revenue due to competition. In equilibrium, the initial inventory satisfies the following equation for each seller $j \in \{1, ..., J\}$;

$$\xi_{jd} = \left. \frac{\partial E\left[\sum_{t=1}^{T} \tilde{W}_{jtd} | c_{j1d}, \boldsymbol{c}^{*}_{-j1d}, N_{1d}\right]}{\partial c_{j1d}} \right|_{c_{j1d}=c^{*}_{j1d}} - \gamma_j. \tag{8}$$

According to Vives (1999), the existence of equilibrium is guaranteed if seller j's expected revenue function $E\left[\sum_{t=1}^{T} \tilde{W}_{jtd} | \boldsymbol{c}_{1d}, N_{1d}\right]$ is quasi-concave in initial inventory size c_{j1}. As I compute this function numerically, its quasi-concavity cannot be confirmed analytically. Instead, I check the quasi-concavity in Appendix A.1 using revenue functions numerically implied by the estimates of demand parameters.

In this model, I do not solve for prices on the supply side for simplicity. It would be problematic if one needs to estimate marginal costs or solve price equations under some counterfactuals. However, in the context of a dynamic pricing problem, production costs are already sunk when sellers set prices because sellers cannot replenish stocks once the market opens. As I discuss in the following Section 4, it is feasible to estimate every parameter of interest with the pricing function directly obtained from data outside the model. Also, I simulate market outcomes under uniform pricing as a counterfactual analysis. It does not require me to solve price equations in a dynamic framework.

3.3 State transition

The transition of remaining stocks $\boldsymbol{c}_t$ and the number of potential buyers N_t can be expressed as follows:

$$\begin{aligned} \tilde{c}_{j,t+1}|s_t &= c_{jt} - \min(c_{jt}, \tilde{q}_{jt}); \\ \tilde{N}_{t+1}|s_t &= N_t - \sum_{j \in \{1,\dots,J\}} \min(c_{jt}, \tilde{q}_{jt}), \\ \text{where } \tilde{q}_{jt} &\sim Bin\left(P^* \left(a_i = j|\boldsymbol{s}_t\right), N_t\right). \end{aligned} \tag{9}$$

Note that $\tilde{q}_{jt}$ represents demand for seller j's flowers at time t, and its binomial distribution is conditional on $\tilde{q}_{jt} < c_{jt}$. For $\tilde{q}_t = c_t$, I express $Pr(\tilde{q}_t = c_t) = \sum_{q \geq c_t} Pr(\tilde{q}_t = q)$ by construction. I assume that prices are determined through the seller-specific pricing function $f_j : \{1, 2, .., T\} \times \mathbb{R}_+ \to \mathbb{R}_+$ where it takes period and the size of remaining stocks as arguments. This function is known to each potential buyer, as buyers are experienced through repeated transactions. I directly recover the pricing function from data as discussed in Section 4.3.1.

3.4 Monopoly market

As Table 2 shows, sellers tend to grow their own branded flower varieties to differentiate their products from the other sellers. The model discussed so far includes the extreme case where a specific seller is a monopolist for a flower variety. Consider buyers who are interested in a specific flower variety and decide when to purchase it. They solve a dynamic binary choice model instead of a dynamic discrete choice model. Buyer i's action a_{it} becomes a dummy variable which takes value one if the buyer chooses to purchase the flower at time t and zero otherwise. The buyers' Bellman equation is rewritten as follows:

$$V_t^{\alpha}\left(\boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it}\right) = \max_{a_i \in \{0,1\}} \left\{v_t^{\alpha}(a_i, \boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it})\right\},$$

where

$$
v_{it}^{\alpha}(a_{it},\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{it}) = \begin{cases} E_{\boldsymbol{\varepsilon}_{-it}}\left[\int V_t^{\alpha}(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1})\, dF(\boldsymbol{s}_{t+1},\boldsymbol{\varepsilon}_{it+1}|\, a_{it}=0, \alpha_{-it}(\boldsymbol{s}_t,\boldsymbol{\varepsilon}_{-it}), \boldsymbol{s}_t, \boldsymbol{\varepsilon}_{it})\right] + \varepsilon_{it}^{0} \\ \quad \text{if } a_{it}=0 \\ E_{\boldsymbol{\varepsilon}_{-it}}\left[\frac{c_{jt}}{\max\left(\sum_{-i} I[\alpha_{-it}(\boldsymbol{s}_t,\varepsilon_{-it})=j]+1, c_{jt}\right)}(\lambda_t - \beta p_t)\right] + \varepsilon_{it}^{1} \\ \quad \text{if } a_{it}=1. \end{cases} \tag{10}
$$

The difference between (2) and (10) is that buyers do not need to consider the continuation value when flowers are not assigned to them in the latter. In the case of a monopoly, if flowers are sold out, the buyers do not have any option, while they can switch to other sellers in the case of an oligopoly.

4 Estimation

The goal of this section is to estimate the model parameters. I divide the parameters to be estimated into two parts: supply and demand parameters. The supply parameters govern the marginal costs which are heterogeneous across sellers. This article estimates the supply parameters from the first-order condition (8) in the static model of the supply side. The demand parameters govern the purchase timings made by buyers, which affect the pattern of prices and the size of remaining stock. The demand parameters include the time-varying mean utility, price elasticity, and the demanded quantities. I estimate the demand parameters by mixing estimation techniques of dynamic demand models and individual discrete choice models.

Estimating dynamic games presents a computational challenge when the size of state space is large, as it requires deriving the value function and solving for optimal actions for each grid point in state space and for each player. To alleviate this computational burden, Hotz and Miller (1993) propose the use of nonparametric estimates of conditional choice probability (CCP) before estimating primitives underlying the dynamic parts. This approach, known as the Hotz-Miller CCP method, has been further developed in subsequent papers, including Aguirregabiria and Mira (2002, 2007), Pesendorfer and Schmidt-Dengler (2008), and Kasahara and Shimotsu (2009).[1] However, despite the CCP method reducing the computational load associated with action choice probabilities, it does not fully resolve the challenge of computing

[1] I refer readers to Aguirregabiria and Mira (2010) for a thorough survey.

the continuation value. To address this, Bajari et al. (2007) introduce a forward-simulation method, which allows for calculating the continuation value only at the observed grids in the state space, eliminating the need to compute values for unobserved states and thus reducing the computational burden. This forward-looking CCP estimation approach has been applied in studies such as Ryan (2012), Fowlie et al. (2016), Nishiwaki (2016), Santos (2017), Ko (2022), and Barwick et al. (2021). I explain how this method works in my context in Section 4.1.2.

Using the estimates of the continuation value and conditional choice probability, I compute the likelihood function based on the model outlined in Section 3. The demand parameters are estimated by maximum likelihood drawing on individual purchase records. This method is discussed in Goolsbee and Petrin (2004), Bayer et al. (2007), and Epple et al. (2018). When separating demand parameters into those related to flower-specific fixed payoff and price elasticity, I use two instrumental variables that are associated with prices but not related to flower fixed payoff itself; the remaining inventory size and the remaining number of buyers.

I also estimate supply parameters associated with the inventory marginal cost using the estimated conditional choice probabilities. I apply simulated revenues based on the observed inventory size to the first-order condition (8). Since unobserved cost shocks may correlate with revenues through their influence on the inventory size, I use instrumental variables that are related to the inventory size but independent of supply costs.

4.1 Two-step CCP estimation

I use the two-step CCP estimation method, as discussed earlier, to reduce the computational burden. Specifically, the policy functions are estimated by the multinomial-logit model and the continuation value is computed through forward-looking simulations. Once these components are recovered, I estimate the demand parameters using pseudo-maximum likelihood estimation. A similar estimation procedure is adopted by Huang and Smith (2014) and Ko (2022). With the estimated demand parameters, I numerically solve the first-order condition (8) for initial inventory choices and estimate the supply parameters using the generalized method of moments (GMM) estimation.

4.1.1 First step estimation

The policy function, denoted by the strategy profile $P^{\alpha}(s_t)$, is estimated using a parametric specification. Since buyers hold three options - to purchase from seller j, or not to purchase - I employ the multinomial logit regression. The conditional choice probabilities are specified as follows:

$$Pr(a_{it} = j | \boldsymbol{x}; \boldsymbol{\beta}_x) = \frac{\exp(\boldsymbol{x}\boldsymbol{\beta}_x)}{1 + \sum_{j \in J} \exp(\boldsymbol{x}\boldsymbol{\beta}_x)}, \tag{11}$$

where $\boldsymbol{x}$ includes the remaining stock, offered prices, period, and seasonality fixed effects. This multinomial logit regression yields the estimated conditional choice probabilities $\hat{\boldsymbol{P}}^0$ stacked with each grid of states.

The continuation value is estimated using forward-looking simulations as proposed by Bajari et al. (2007). The algorithm, based on a given value of the deterministic part in payoff $\delta_{jt} := \lambda_{jt} + \beta p_{jt}$, is outlined in Algorithm 1. An important observation is that the continuation value $V_t(s_t, \varepsilon_{it}; \delta_{jt})$ is linear in the demand parameter δ_{jt}, allowing me to express it as $V_t(s_t, \varepsilon_{it}; \delta_{jt}) = W(s_t, \varepsilon_{it})\delta_{jt}$. This linearity is helpful when estimating δ_{jt} in the second step, as I do not need to go back to the first step in the algorithm to compute the continuation value. Once I obtain the simulated value of $W(s_t, \varepsilon_{it})$ for each grid of state, I can update $V_t(s_t, \varepsilon_{it}; \delta_{jt})$ for a new value of δ_{jt} in the optimization routine without re-running the forward-looking simulations.

Algorithm 1 Foward-looking simulations for the continuation value

1: Draw random shocks $\{\varepsilon_t^j\}_{j \in A_t}$ for each state
2: Based on the random draws and estimated choice probability in the previous step, compute action $a_t = j \in A_t$.
3: Next state s_{t+1} is realized by following the transition rule in Section 3.3.
4: Repeat step 1-3 up to the terminal period and compute V_t by summing up the flows of temporal payoff.
5: Repeat step 1-4 for R times and take an average of the continuation value.

4.1.2 Second step estimation

In the second step, I estimate the mean utility $\boldsymbol{\delta} := \{\delta_{jt}\}_{j \in A_t, t \in \{1,2,\ldots,T\}}$ using the information of the policy function and the continuation value estimated in the previous step. To estimate it, I solve the following maximum log-likelihood problem for $\boldsymbol{\delta}$:

$$\hat{\boldsymbol{\delta}} = \arg\max_{\boldsymbol{\delta}} \frac{1}{DTN} \sum_{d=1}^{D} \sum_{t=1}^{T} \sum_{i=1}^{N} \ln \Psi_i \left(a_{idt} | s_{dt}; \hat{\boldsymbol{P}}^0, \boldsymbol{\delta} \right), \tag{12}$$

$$\text{where } \Psi_i \left(a_{idt} = j | s_{dt}; \hat{\boldsymbol{P}}^0, \boldsymbol{\delta} \right) = \frac{\exp(v_t^{\hat{\boldsymbol{P}}^0}(a=j, \boldsymbol{s}_t))}{\sum_{l \in \{1,\dots,J\}} \exp(v_t^{\hat{\boldsymbol{P}}^0}(a=l, \boldsymbol{s}_t)) + \exp(v_t^{\hat{\boldsymbol{P}}^0}(a=0, \boldsymbol{s}_t))}.$$

For the deterministic demand parameter δ_{jt}, I define the following specification:

$$\begin{aligned} \delta_{jt} &= \lambda_{jt} + \beta p_{jt} \\ &:= \alpha_j + \tau_1 t + \tau_2 I(t \leq 4) + \beta p_{jt} + \zeta_{jt}. \end{aligned} \tag{13}$$

This specification implies that flower fixed payoff varies deterministically across periods. Flowers purchased earlier are more valuable to buyers, as early purchases allow buyers to develop business plans for their retail B2C markets sooner and eliminate the need to monitor the state of the flowers after purchase. As I discuss in the following section, my estimation results suggest that flower fixed payoff decreases over periods (negative τ_1), with a particularly sharp drop in the terminal period (negative τ_2). The initial term α_j captures the seller-specific fixed effects because each seller may offer a different quality.

I denote the unobserved payoff from flowers sold by j at time t as ζ_{jt}. I interpret this as the conditions of the B2C retail markets that all the buyers face in common. This unobserved payoff may be correlated with price p_{jt}, potentially leading to endogeneity issues. To address this, I use data on the number of remaining stock and the number of potential buyers as instrumental variables. These variables at time t can affect prices at t but do not relate to current demand shocks originating from the consumer side in the retail B2C markets. I denote these instruments as $\boldsymbol{Z}_{jt}^D$ and estimate demand parameters by the linear IV regression based on (13). I omit the subscript d, which represents the market date, for simplicity, but it is important here to emphasize that δ, p, and ζ have this subscript and they lead to heterogenous demand across the market dates.

4.2 Estimation of supply parameters

To estimate supply parameters γ_j, I first compute the expected revenue $E\left[\sum_{t=1}^{T} \tilde{W}_t | \boldsymbol{c}_1, N_1\right]$ for each $\boldsymbol{c}_1$ and N_1. For observed initial inventory size and market size $(\boldsymbol{c}_1, N_1)$, I simulate demand using the estimated conditional choice probability $\hat{P^{\alpha}}(s_1)$. This simulation provides the transition of state variable from s_t to s_{t+1}, and I repeat this step until $t = T$. If there are unsold stocks after the terminal period $t = T$, I compute the auction prices. I predict the auction prices drawing on the transaction records in the auction stage mentioned in Section 2, and the expected auction prices serve as salvage value for sellers. I run this simulation 1000 times and take the average to obtain the expected revenue. This process is summarized in Algorithm 2. For predicting the auction prices, I use the following regression model:

$$p_{jd}^{A} = \beta_A c_{T+1,j,d} + \theta_j + \theta_w + \theta_m + e_{jd}, \tag{14}$$

where $c_{T+1,j,d}$ represents remaining stock after the terminal period, and each θ captures fixed effects regarding seller j, weekday w, and month m. Then, the predictions can be expressed by $E[p_{jd}^{A}|c_{T+1,j,d}]$ based on the estimated parameters.

I apply the expected revenue to the first-order condition (8) and search for γ_j for each seller j that satisfy the following moment condition:

$$E[\xi_d \boldsymbol{Z}_{jd}^{S} | \boldsymbol{c}_{1d}; \boldsymbol{\gamma}] = 0, \tag{15}$$

where $\boldsymbol{Z}_{jd}^{S}$ is a vector of instrumental variables. The subscript d represents the market date, which I suppress in other equations for simplicity. In the context of my data, I interpret the cost shock ξ_d as unobserved shipping costs and greenhouse management costs. Estimating the parameters requires instrumental variables because the cost shock ξ_d may relate to the expected revenue through its impacts on initial inventory size. To address this endogeneity issue, I use two variables as instruments: market size and auction price index. Market size, denoted by N_{1d}, affects the expected revenue but does not relate to the cost shock. The auction prices matter in the expected revenue since unsold flowers go to the auction markets on the subsequent date. For each market date, I use $E[p_{jd}^{A}|\bar{c}_j]$ as an auction price index, where $\bar{c}_j$ represents the average remaining stock over the sample period. This index measures how active the auction markets are, which positively correlates with sellers' revenue by influencing the demand side but does not relate to inventory cost.

Algorithm 2 Expected revenue

1: For some $\boldsymbol{c}_1$ and N_1, we predict p_1 using the pricing function $f(\cdot)$, which is estimated beforehand.
2: At given $s_1 = (\boldsymbol{c}_1, N_1, p_1)$, we simulate demand S times using initially estimated choice probability. Let d_{1s} be realized demand at $t = 1$ in simulation s.
3: The number of d_{1s} leads to $(\boldsymbol{c}_{2s}, N_{2s})$. Then, we use $f(\cdot)$ again to predict p_{2s}.
4: Given $s_{2s} = (\boldsymbol{c}_{2s}, N_{2s}, p_{2s})$, we simulate demand d_{2s}.
5: Repeat these steps until $t = T$ and sum up these temporal revenues $\sum_{t=1}^{T} W_{ts}$ over each simulation s. If there are unsold stocks after $t = T$, revenues in auction markets will be added.
6: Lastly, I take average $\frac{1}{S}\sum_{s=1}^{S}\sum_{t=1}^{T} W_{ts}$. This provides $E\left[\sum_{t=1}^{T} \tilde{W}_t | \boldsymbol{c}_1, N_1\right]$, where $S = 1000$ represents the number of simulations.

4.3 Discussions

4.3.1 Price imputation

In some cases, no transaction occurs during a given period, meaning that there is no price information since only accepted transactions are observed. To address this issue, I use the pricing function introduced in Section 3.3. To derive this function, I employ a random forest model. It allows me to use multiple covariates to predict prices nonparametrically without encountering curse of dimensionality. In this prediction, the key covariates are the size of remaining stock and remaining periods.

4.3.2 Relaxing unit demand assumption

In the model discussed above, I assume that buyers purchase a single box of flowers. However, there is an instance where buyers purchase multiple boxes of flowers at once, although this is not the majority case. To account for this, I assume that buyers' quantity demands are exogenously determined by the Poisson distribution. Since one can observe the number of boxes purchased in each transaction, it is possible to estimate the Poisson parameters. The state transition regarding the remaining inventory size is then modeled as follows:

$$\tilde{q}_t \sim Bin\left(P^*\left(a_i = 1|s_t\right), N_t\right)\tilde{x}$$

instead of (9), in which Bin represents binomial distribution discussed in (9), and $\tilde{x}$ represents the units of demand following the Poisson distribution. The Poisson parameter for each seller is estimated by maximizing the likelihood. Additionally, I assume that potential buyers can observe the number of remaining buyers. This assumption is not necessary in the single-unit demand case because buyers can infer the number of buyers based on the transition of the remaining inventories.

4.3.3 Outside option

I assume that buyers who have purchased no flowers do not obtain any deterministic payoff. One might argue that it would be more realistic to assume that buyers who make no purchases still receive some fixed deterministic payoff at the end of the day, as they can purchase other varieties of flowers in practice. However, I set the payoff value to zero as the outside option in my analysis. The choice of outside option value does not significantly affect the model fitting since it is absorbed into the deterministic payoff λ_{jt}.

4.4 Estimation results

Following the estimation procedure discussed in the previous sections, I estimate the model primitives. This paper focuses on a specific Orchid variety, "Calypso". I select this flower variety for several reasons. First, the subsample contains a large number of transaction records on each date. Second, Calypso is traded almost daily during the sample period, allowing me to include seasonality fixed effects. Third, each seller holds a significant market share, aligning with the oligopolistic model discussed earlier. Fourth, buyers tend to purchase this flower variety only once per day, which justifies the use of the optimal stopping model. Fifth, stockout occurs frequently, making the stockout risk a key factor in the model.

Two sellers dominate the majority of Calypso transactions, and their transactions occur regularly throughout the sample period. Table 5 displays prices, the initial inventory size, stockout frequency, and the number of boxes sold per transaction by sellers A and B. The variable "Stockout" is defined on a daily basis, taking the value of one if the flowers go out of stock on that day. This table suggests that seller A is more vital than seller B, as seller A brings larger inventories and sets more aggressive prices. Conversely, seller B prepares less inventories and faces stockout more frequently relative to seller A. It is also evident that a significant portion of transactions involves multiple boxes, necessitating the relaxation of the unit demand assumption as discussed in Section 4.3.2.

Figure 9 indicates that prices fall as time progresses. This pricing pattern encourages buyers to wait, which is empirically supported by Figure 10. To fit the structural model to the Calypso

Table 5: Summary statistics of Calypso

	Min	1st Qu.	Med	Mean	3rd Qu.	Max	Obs
Price (Seller A)	0.03	1.2	1.35	1.39	1.65	2.4	3179
Price (Seller B)	0.03	1.2	1.35	1.35	1.5	2.1	1756
Initial inventory (Seller A)	1	35	47	46.94	61	90	150
Initial inventory (Seller B)	2	16	24	25.43	31	63	150
Stockout (Seller A)	0	0	0	0.30	1	1	150
Stockout (Seller B)	0	0	0	0.40	1	1	150
Num of Box (Seller A)	1	1	1	2.00	3	27	3179
Num of Box (Seller B)	1	1	1	1.81	2	20	1756
Initial market size	24	42	45.5	44.91	49	55	150

Notes: This table reports summary statistics about Calypso, a variety of Orchid flowers. "Price" refers to the price per box, measured in units of 1,000 JPY. "Initial inventory" denotes the initial inventory size, measured in units of boxes. "Stockout" is a dummy variable, taking the value of one if the flowers are out of stock on a given day. "Num of Box" captures the number of boxes involved in each transaction, while "Initial market size" represents the number of potential buyers at the initial time period.

data, I focus on business hours from 9 a.m. to 6 p.m., dividing the day into five discrete periods, $t \in \{1,2,...,5\}$, with each period representing a 2-hour interval. I aggregate transaction prices for each period by calculating the average. For periods without any transactions, I impute prices based on the pricing function mentioned earlier.

In the first-step estimation, I estimate conditional choice probability using the multinomial logit regression specified as follows:

$$\Pr(a_t = j) = \frac{\exp(\beta_c c_{jt} + \beta_{-c} c_{-j,t} + \beta_p p_{jt} + \beta_{-p} p_{-j,t} + \beta_N N_t + FE_t + FE_m)}{1 + \sum_{k \in J} \exp(\beta_c c_{kt} + \beta_{-c} c_{-k,t} + \beta_p p_{kt} + \beta_{-p} p_{-k,t} + \beta_N N_t + FE_t + FE_m)}. \quad (16)$$

In this specification, the option to "wait" is defined as the outside option, which yields zero deterministic payoff. The coefficients, β_c and β_p represent the effects of a unit increase in j's own remaining stock and prices on the log odds ratio of j being chosen, respectively. The coefficients β_{-c} and β_{-p} capture the effects of a unit increase in j's opponent's own remaining stock and prices on the same log odds ratio. Since there are only two sellers in this application, the coefficients related to the opponent's state are scalars rather than vectors.

Table 7 reports the effects of a unit increase in each covariate on log odds ratio of seller $j \in \{A,B\}$ being chosen. This table shows that a unit increase in seller j's prices increases the log odds ratio of seller k being chosen by 0.12-0.13. This result indicates that flowers are substitutable across sellers. Table 8 compares the actual and predicted conditional choice probabilities based on the estimated parameters of the multinomial logit regression, showing a

Figure 9: Mean price (Calypso)

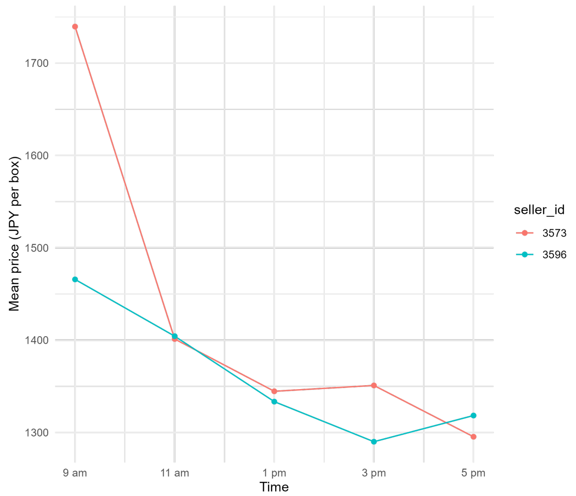
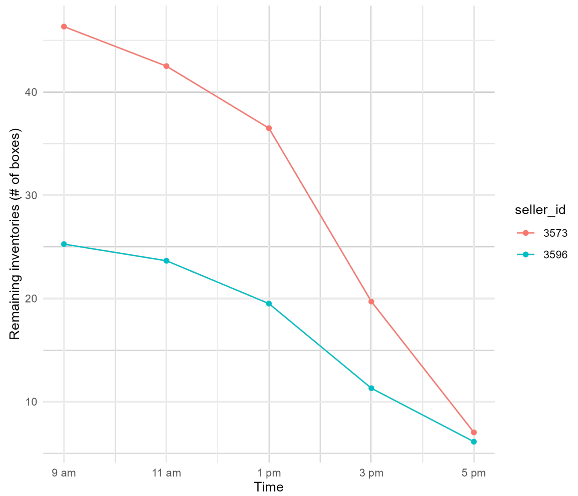


Figure 10: Mean remaining stock (Calypso)



Notes: The left (right) panel displays the transition of the average price (initial inventory size) across time periods. The red lines project the information on the first seller's flower, while the blue lines capture the information on the second seller's flower.

good fit between the model and the observed data.

Using estimated conditional choice probability, I compute the continuation value $V_t(\boldsymbol{s}_t;\boldsymbol{\delta})$. To compute this value, I perform the forward-looking simulation described in Algorithm 1. Due to the linear separability of $V_t(\boldsymbol{s}_t;\boldsymbol{\delta})$, expressed as $V_t(\boldsymbol{s}_t;\boldsymbol{\delta}) = W_t(\boldsymbol{s}_t)\boldsymbol{\delta}$, I only need to average over multiple simulated paths once, which reduces computational burden. To implement this simulation, I estimate the number of demanded boxes, assumed to follow a Poisson distribution. I estimate the Poisson parameters for each seller and for each remaining inventory size using the maximum log-likelihood method. Table 6 provides summary statistics of both actual and predicted numbers of demanded boxes, demonstrating that the predictions closely fit the actual data.

In the second step, I estimate aggregated deterministic payoff δ_{jt} by applying the estimates of the continuation value, $\hat{V}_t(\boldsymbol{s}_t;\boldsymbol{\delta})$, to the maximum likelihood objective function (12). Plugging estimated $\hat{\boldsymbol{\delta}}$ into (13), I estimate demand parameters in (13) using linear IV regression. As instrumental variables, I use market size N_t and remaining stock c_{jt} as they affect j's prices but do not relate to the fixed payoff from j's flower, ζ_{jt}. A similar approach to using remaining stock information as instruments is found Hortaçsu et al. (2022). Table 10 lists the estimated parameters. The coefficient of prices is significantly negative, which is intuitive since it is natural for buyers to prefer lower prices. The fixed effects α_0 and α_1 imply that the first seller's flowers yield a higher fixed payoff. This is consistent with the empirical findings in Table 5, where the first seller sells more flowers despite higher prices. The coefficients regarding periods, τ_1 and

Table 6: Fitting: number of demanded boxes

Seller A

# of boxes	10pct	25pct	Med	Mean	75pct.	90pct
Actual	1	1	1	1.995	3	4
Predicted	1	1	2	2.001	3	4

Seller B

# of boxes	10pct	25pct	Med	Mean	75pct.	90pct
Actual	1	1	1	1.813	2	3
Predicted	1	1	2	1.804	2	3

Notes: This table reports percentiles of the actual number of demanded boxes from the data and the predicted number of demanded boxes from the estimated Poisson parameters. The upper panel is for the first seller, and the bottom panel is for the second seller.

τ_2, are also significant. The negative sign of τ_1 implies that flower fixed payoff deterministically decreases as time progresses, reflecting the presence of monitoring costs. Along with that, τ_2 suggests a sharp drop in the fixed payoff during the terminal period. These coefficients regarding the periods play an important role in a welfare analysis under dynamic pricing and uniform pricing, as they relate to the trade-off between earlier purchases and delaying purchases.

Before estimating supply parameters, I compute the expected revenue as a function of the initial inventory size and the number of potential buyers. This computation requires the predictions of auction prices for flowers that remain unsold at the end of the day. Leveraging auction data, I run regressions of average auction prices on the quantity of unsold flowers. These regressions include the fixed effects regarding weekdays, seller index, and months. Table 9 summarizes these regression results, showing that sellers earn lower revenue from auctions when they have larger unsold inventories.

Table 7: multinomial logit

	(Intercept)	price A	price B	current_box A	current_box B
A	-10.71	0.03	0.13	0.02	-0.01
	(0.31)	(0.02)	(0.03)	(0.003)	(0.003)
B	-7.16	0.12	-0.06	0.001	0.007
	(1.53)	(0.02)	(0.03)	(0.002)	(0.003)

Notes: This table reports multinomial logit regression results. The numbers in each entry capture the changes in log odds from the unit increase of each covariate. In this regression, each observation takes one of three choices as an outcome: purchasing from seller A, purchasing from seller B, or not purchasing. Covariates include prices of A's and B's flowers, the amount of their remaining stock, and fixed effects of weekdays.

Table 8: Fitting choice probabilities

	A		B		Wait	
t	Data	Pred	Data	Pred	Data	Pred
1	0.035	0.035	0.019	0.018	0.947	0.947
2	0.075	0.076	0.051	0.051	0.873	0.873
3	0.204	0.201	0.113	0.113	0.683	0.685
4	0.227	0.241	0.105	0.109	0.669	0.650
5	0.067	0.066	0.053	0.056	0.880	0.878

Notes: The column labeled "Data" ("Pred") shows conditional choice probability from the data (prediction). These predicted values are computed by applying the estimated parameters from the multinomial logit regression to the covariates realized in the data and taking their average for each period.

Combining the estimated conditional choice probabilities with the predicted auction revenues, I calculate the expected revenues $E\left[\sum_{t=1}^{T}\tilde{W}_{jtd}|\boldsymbol{c}_{1d},N_{1d}\right]$ for each seller by using the algorithm described in Algorithm 2. Plugging this into the first-order condition (8) yields the GMM objective function (15). From GMM estimation, I obtain parameters of the marginal costs for each seller and each season. I account for seasonality in inventory costs, which can affect both shipment and opportunity costs associated with the initial inventory size. To do this, I discretize the sample period into two seasons: spring (January to July) and fall (August to December). Table 11 displays the estimated marginal costs for initial inventory, which range from 600 to 1,000 JPY, accounting for approximately 65% of revenue. These estimates are consistent with the previous reports on flower production costs.[2]

To validate the model fit, I simulate demand for each period to compare the estimators' performance against empirical patterns. Figure 11 and 12 display the remaining inventory size transitions for each seller, showing that the estimators capture the empirical patterns well, particularly the steep decline in inventory after period $t = 3$. For the supply side, I simulate the size of initial inventory based on the estimated parameters. Table 12 summarizes the actual and predicted initial inventory size for each season, showing that the estimators yield a good fit.

5 Counterfactual Analyses

In this section, I compare the welfare effects of dynamic pricing with those of uniform pricing. In uniform pricing, prices remain fixed throughout the given market date. These fixed prices

[2]For example, Ghimiray et al. (2017) estimates the ratio of benefits to costs of Orchid flowers. His estimate shows that the cost accounts for 55% of revenue. As flowers in my sample are imported, the cost could be more than 55%.

Table 9: Determinants of auction prices

Dependent Variable:	auction prices		
Model:	(1)	(2)	(3)
unsold flowers	-0.972*	-1.040***	-1.006***
	(0.374)	(0.133)	(0.132)
Fixed-effects			
weekdays		Yes	Yes
seller_id	Yes		Yes
month		Yes	Yes
Observations	199	199	199
R^2	0.214	0.577	0.622
Within R^2	0.155	0.273	0.281

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports OLS results. The dependent variable is the auction prices, and the covariate is the number of boxes found at the beginning of auctions. Standard errors are provided in parentheses.

Table 10: Estimated Demand Parameters

Parameter	Estimated value
β	-0.18
	(0.061)
α_0	11.00
	(3.32)
α_1	-0.91
	(0.25)
τ_1	-1.05
	(0.174)
τ_2	0.40
	(0.061)

Table 11: Estimated Supply Parameters

Parameter	Estimated value
$\gamma_{A,Spring}$	892.75
	(24.96)
$\gamma_{B,Spring}$	1043.21
	(40.22)
$\gamma_{A,Fall}$	613.68
	(78.88)
$\gamma_{B,Fall}$	1006.52
	(59.09)

Notes: Table 10 reports demand parameters in (13). Table 11 reports supply parameters in (1). Standard errors are provided in parentheses.

Table 12: Fitting: initial inventory

Panel A: Spring

Initial Stocks	Min	25pct	Med	Mean	75pct.	Max
Actual	2	18	29	32.52	42	90
Predicted	1.41	17.89	28.32	32.67	45.21	92.60

Panel B: Fall

Initial Stocks	Min	25pct	Med	Mean	75pct.	Max
Actual	1	31	43	41.72	54	78
Predicted	2.51	26.64	42.41	43.09	56.89	95

Notes: These tables report the size of initial inventory from the data and the predicted size of initial inventory from the simulated uniform pricing equilibrium. As I estimate inventory costs depending on the seasonality, there exist two tables. The upper panel is based on inventory cost in spring, and the bottom panel is based on the cost in fall.

would eliminate the incentive for buyers to delay their purchases, which is observed under dynamic pricing. I explore how this impacts buyers' decisions and how sellers adjust through changes in both prices and inventory size. I consider two scenarios regarding inventory size: one where the initial inventory size is fixed, and another where it is determined endogenously. In the first scenario, I assume that the initial inventory size under uniform pricing is the same as that observed under dynamic pricing, with uniform prices set optimally. In the second scenario, both initial inventory size and prices are endogenously determined under uniform pricing. By simulating these two scenarios, I demonstrate that neglecting the role of strategic buyers and inventory decisions can lead to different conclusions about whether dynamic or uniform pricing is more advantageous for sellers.

In the counterfactual simulations, I solve the purchase timing problem faced by buyers and determine the sellers' optimal initial inventory size. The buyers' decisions are solved using a backward induction approach. First, I calculate conditional choice probability as fixed points at the terminal period $t = T$ for each state grid. From there, I compute the expected continuation value at time $t = T$ for each grid of states in closed form, as I assume type-I extreme random shocks. Given the large state space, it is hard to compute the conditional choice probability for each state grid, so I limit the number of grids and use interpolation techniques to estimate the continuation values for grids outside the calculated set. The random forest model is adopted as the interpolation technique because it allows one to include multiple covariates without the curse of dimensionality.

Figure 11: First seller

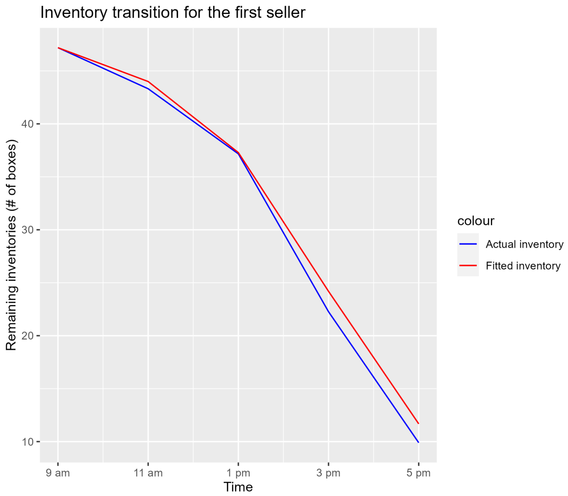
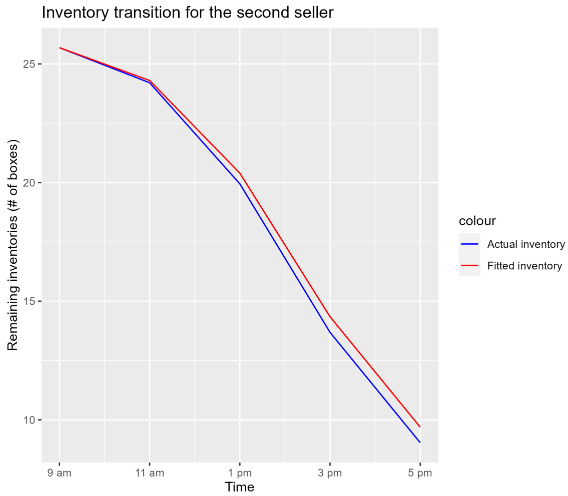


Figure 12: Second seller



Notes: The left (right) panel displays the transition of the first (second) seller's remaining inventory size across periods. The blue line projects it based on actual data, while the red line projects it from the simulations implied by the estimates.

Using the computed choice probability and the estimated supply parameters, I numerically calculate the expected profits for each seller j when setting initial inventory to c_{1j}, given the opponent's inventory choice $c_{1j'}$ (where $j' \neq j$). From these expected profits, I derive the optimal size of initial inventory by iterating the best responses. I assume that uniform prices are chosen from a discrete set, $p_j \in \{35, 40, 45, 50, 55, 60\}$. A summary of the counterfactual simulation procedure is provided in Algorithm 3.

When solving the uniform pricing model for conditional choice probability $P(\boldsymbol{s}_t)$ and initial inventory size $\boldsymbol{c}_1$, the issue of multiple equilibria arises. This is due to the nonlinear specification of conditional choice probability in (2), which can lead to multiple fixed points. Additionally, both initial inventory size $\boldsymbol{c}_1$ and uniform prices (p_A, p_B) are chosen from a discrete set through the best response iterations, but the iterated values may not always converge. To address this issue, I use multiple starting values for the conditional choice probability and verify that these different initial values converge to nearly identical conditional choice probabilities at equilibrium. For initial inventory size and uniform prices, I test the iteration process under various initial values for prices and confirm that they do not generate different conclusions. Appendix A.2 summarizes these results.

Figure 13 displays the simulated sales for each pair of given uniform prices. This figure involves multiple scenarios where sellers set different uniform prices. The blue line captures the value of the remaining inventory made by the larger seller, and the red line represents

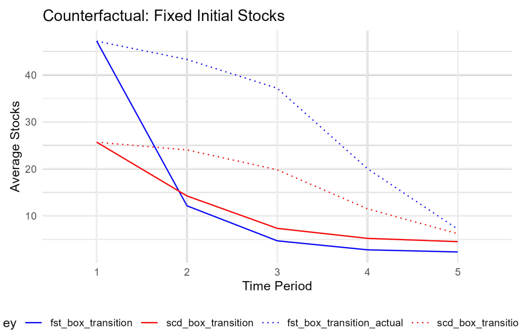
Algorithm 3 Optimal choice probability, initial inventory, and prices

Set grids of states $s_T = (c_T, c_T, p_A, p_B, N_T) \in S_T$.
For each grid s_T, guess initial choice probability as $P^0(s_T)$.
while $P^l(s_T) \neq P^{l+1}(s_T)$ **do**
    compute rationing probability h based on $P^l(s_T)$
    update choice probability $P^{l+1}(s_T)$ using (5)
end while
Compute the expected continuation value $V(s_T)$ for each s_T using updated choice probability $P^l(s_T)$.
For s'_T which is not included in S_T, use random forest model for predicting $V(s'_T)$.
for t = T-1 to 1, **do**
    compute rationing probability h based on the initial guess of $P^0(s_t)$
    while $P^l(s_t) \neq P^{l+1}(s_t)$ **do**
        compute rationing probability h
        update choice probability $P^l(s_t)$ using (5) with the information of $V(s'_T)$.
    end while
    Compute the expected continuation value $V(s_t)$ for each s_t using choice probability $P^l(s_t)$.
    For s'_t which is not included in S_t, use random forest model for predicting $V(s'_t)$.
end for
Based on $\{P(s_t)\}_{t=1}^{T}$, we compute the expected profits $E\left[\sum_{t=1}^{T} \tilde{W}_{jt} | \boldsymbol{c}_1, N_1\right] - c_{j1}\gamma_j$ by simulating purchase decisions 1000 times.
For each number of market size N_1, I solve for initial inventory (c_{A1}, c_{B1}) and fixed prices (p_A, p_B) by iterating the best response.

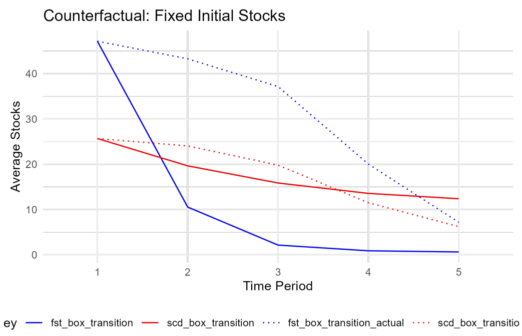
that by the smaller seller. The solid line depicts the patterns of the remaining inventory under uniform pricing, while the dotted line represents the patterns under dynamic pricing, based on actual data. The set of sub-figures in Figure 13 indicates that uniform pricing results in different sales dynamics compared to dynamic pricing. Specifically, under uniform pricing, more sales occur earlier in the day, as buyers are encouraged to purchase flowers sooner. This is because buyers do not anticipate lower prices in the future, although they still have incentives to wait in anticipation of favorable random shocks. The sub-figures on the right-hand side further illustrate that early purchases persist, even for flowers priced higher than those sold by competitors.

When uniform pricing generates different selling patterns, how do sellers adjust their strategies? To address this, I compute the optimal choice of initial inventory size for each pair of given uniform prices. Table 13 presents summary statistics of the optimal initial inventory size. Each row corresponds to a different pair of uniform prices. From this table, one observes that sellers bring less (more) inventory to the market when they must commit to higher (lower) unit prices. On average, the sellers double the size of initial inventory when the selling price

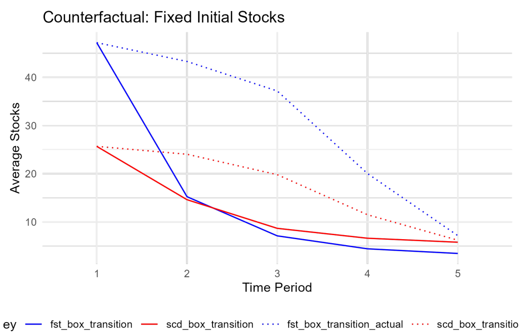
Figure 13: Remaining stocks across time periods



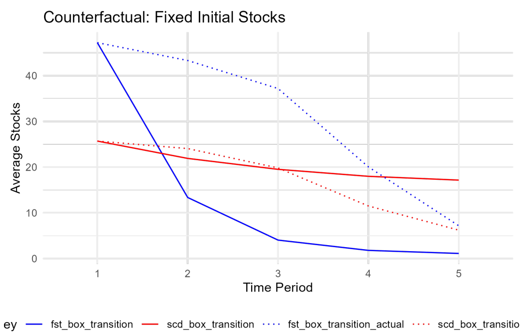
(a) Fixed stocks; $(p_A, p_B) = (35, 35)$



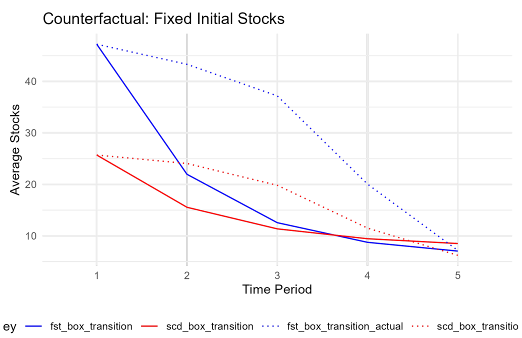
(b) Endogenous stocks; $(p_A, p_B) = (35, 45)$



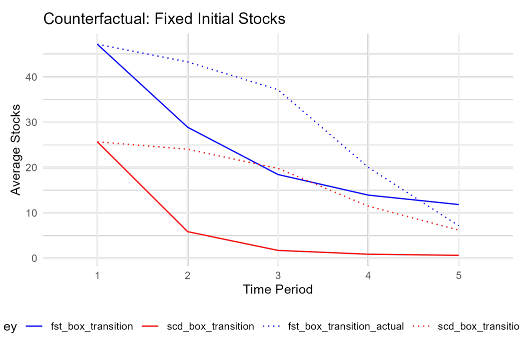
(c) Fixed stocks; $(p_A, p_B) = (40, 40)$



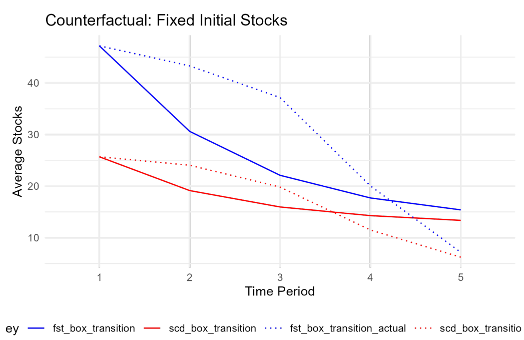
(d) Endogenous stocks; $(p_A, p_B) = (40, 50)$



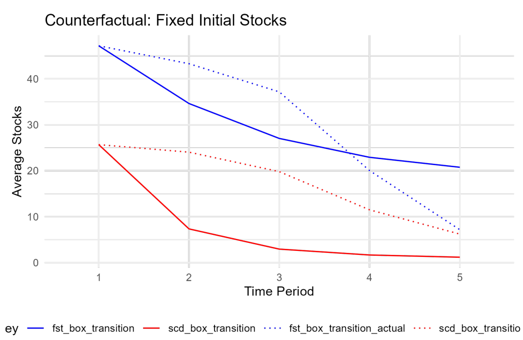
(e) Fixed stocks; $(p_A, p_B) = (45, 45)$



(f) Endogenous stocks; $(p_A, p_B) = (45, 35)$



(g) Fixed stocks; $(p_A, p_B) = (50, 50)$



(h) Endogenous stocks; $(p_A, p_B) = (50, 40)$

Notes: Figures present paths of the remaining stocks across each period. The figures present simulated paths under uniform pricing, given that the size of the initial inventory is equal to the actual data. Each figure generates different lines based on different pairs of prices. The actual data generate the blue (red) dotted line for the first (second) seller, while the solid lines are based on the simulations.

Table 13: Choice of initial inventory size

	Initial Inventory (unit: box)					
Price	Min	1st Qu.	Median	Mean	3rd Qu.	Max
35-35	9.00	21.00	51.00	49.37	75.00	94.00
40-40	12.00	21.00	43.50	47.04	69.00	88.00
45-45	9.00	21.00	37.50	42.19	63.00	81.00
50-50	9.00	18.00	30.00	33.09	48.00	63.00
55-55	12.00	18.00	24.00	23.95	30.00	39.00

Notes: This table represents summary statistics for the initial inventory size. Each row corresponds to each pair of prices.

is 35 JPY per unit, as compared to when the selling price is 55 JPY per unit. This behavior reflects the constraint of uniform pricing: Since sellers cannot adjust prices in response to lower-than-expected demand, they bring less inventory when setting more aggressive (higher) prices. Another key finding from Table 13 is that sellers' inventory decisions under uniform pricing differ from those under dynamic pricing. According to Table 5, sellers set 45 unit prices and bring 36 boxes on average under dynamic pricing. However, the third row of 13 shows that sellers bring 42 boxes on average when they commit to a unit price of 45 JPY. This suggests that sellers are likely to generate more inventory under uniform pricing than dynamic pricing likely because uniform pricing heightens the stockout risk, thereby stimulating demand. However, it is still ambiguous how sellers simultaneously decide on prices and initial inventory size under uniform pricing and whether these decisions enhance welfare.

When solving the uniform pricing model for optimal prices and initial inventory size, I also consider a different scenario where potential buyers are short-lived agents making a one-shot purchasing decision. In this setting, potential buyers arrive at time period $t = 3$, and make purchase decisions. This scenario is labeled "Uniform Pricing 2" (UP2), while the previous scenario, discussed in Algorithm 3 is labeled as "Uniform Pricing 1" (UP1). The main difference between UP1 and UP2 is that in UP1, buyers retain dynamic incentives, as they have the option to wait and potentially encounter more favorable demand shocks $\boldsymbol{\varepsilon}_{it'}$ by waiting. These idiosyncratic demand shocks originate from the consumer side in the B2C market, but flower fixed payoff declines deterministically due to the monitoring costs estimated in the previous section. In contrast, the UP2 model excludes these changes in fixed payoff since buyers are not given the option to wait.

Table 14 displays summary statistics of prices and initial inventory size determined under dynamic pricing and uniform pricing. The table shows that sellers set lower prices for their flowers and bring more flowers to the market under uniform pricing. Sellers set lower prices under uniform pricing relative to dynamic pricing on average because uniform pricing prevents sellers from adjusting prices when they observe realized demand. Furthermore, buyers would shift their purchase timing to an earlier period because they cannot anticipate discounts under uniform pricing and face fewer incentives to delay purchases. Figure 14 indicates this shift, and it would intensify stockout risk. Those two forces - lower prices and enhanced stockout risk - drive demand in the market. Indeed, the probability of flowers selling out increases by 10% under uniform pricing, assuming the same initial inventory levels as dynamic pricing. This motivates sellers to set more inventory sizes. The two uniform pricing models, UP1 and UP2, show slightly different results. UP1 leads to higher sales, as it allows buyers to wait for more favorable random shocks, whereas UP2 prohibits potential buyers from delaying purchases. This difference leads to the prediction that sellers are more likely to stock larger inventories under UP1 compared to UP2. The last two columns in Table 14 support this prediction. Figure 14 and 15 track the remaining inventory transition path over periods for both scenarios, showing that the initial inventory size is around 45 boxes on average, with 10 or more boxes remaining unsold at the end of the day in both cases.

Figure 14: Remaining stocks under UP1

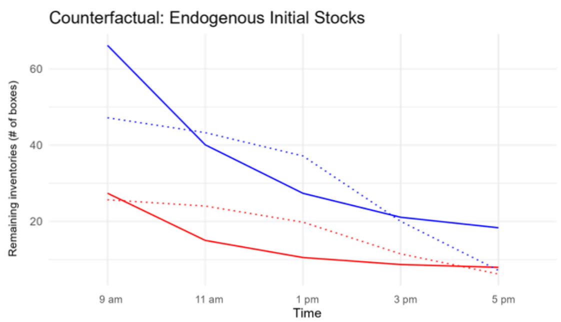
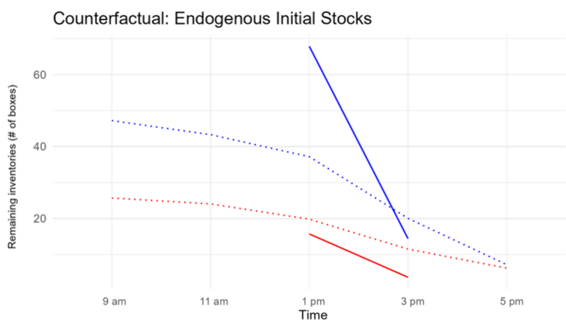


Figure 15: Remaining stocks under UP2



Notes: Figures present paths of the remaining stocks across each period. The figures on the left are simulated paths under the UP1 scenario. The figures on the right are simulated paths under the UP2 scenario. The actual data generate the blue (red) dotted lines for the first (second) seller, while the solid lines are based on the simulations.

Table 15 compares welfare between dynamic pricing and uniform pricing. The numbers in the table capture percentage changes in welfare under uniform pricing relative to dynamic pricing. The table provides two key insights regarding the welfare of both producers and buyers. First, producers' welfare increases by 5-10 % under uniform pricing at equilibrium, with the increase becoming more pronounced when sellers can optimize the initial inventory size. The

Table 14: Prices and Initial Inventory

	Price			Initial Inventory		
	DP	UP 1	UP 2	DP	UP 1	UP 2
Min	10.00	35.00	35.00	1.00	9.00	3.00
1st Qu.	40.00	40.00	40.00	21.75	24.00	15.00
Median	45.00	45.00	40.00	33.00	39.50	31.50
Mean	45.79	43.05	40.95	36.44	45.11	41.77
3rd Qu.	50.00	45.00	45.00	49.00	63.00	75.00
Max	80.00	45.00	50.00	90.00	94.00	94.00

Notes: DP represents dynamic pricing, actual data. UP 1 (2) represents the uniform pricing model where prices are stable during the given market date and buyers can(not) delay purchases.

bottom panel of this table also indicates that producers' welfare would increase under UP2, in which buyers are not given option to delay purchases. These differ from the findings in past empirical studies by (Williams (2022) and Hortaçsu et al. (2022)). My results suggest that the presence of strategic buyers diminishes sellers gain from dynamic pricing, and neglecting the endogeneity of initial inventory can result in an underestimation of the welfare effects associated with dynamic pricing.

Second, uniform pricing reduces buyers' welfare across all specifications, regardless of whether inventory size is endogenous. UP1 results in less welfare loss for buyers than UP2, as UP1 allows buyers to time their purchases based on realized demand in the retail market. From this difference, we can conclude that buyers face lower welfare under uniform pricing, with further reductions when strategic waiting is not allowed.

The third column of Table 15 presents the results about total welfare. The negative effects of uniform pricing on buyers' welfare dominate the positive effects on producers' welfare, even in UP1, where buyers can still delay purchases. This finding implies that dynamic pricing leads to higher overall welfare than uniform pricing, aligning with previous literature. Also, this result justifies the use of dynamic pricing mechanism in the flower wholesale market because the market, as an intermediary, aims to maximize the aggregate welfare of both producers and buyers.

6 Conclusion

This paper performs a structural analysis of strategic buyers' behavior and sellers' decisions regarding initial inventory size under dynamic pricing. In my model, buyers strategically solve

Table 15: Welfare comparison

	Producer Welfare	Buyer Welfare	Total Welfare
UP 1 (with waiting option):			
Fixed initial inventory	$+5.62\%$	-27.8%	-13.5%
Endogenous initial inventory	$+10.8\%$	-21.8%	-12.2%
UP 2 (without waiting option):			
Fixed initial inventory	-11.2%	-43.7%	-31.7%
Endogenous initial inventory	$+4.77\%$	-41.9%	-24.3%

Notes: The numbers in entries represent percent changes in welfare from dynamic pricing.

the optimal stopping problem by deciding whether to purchase products immediately or wait longer at each period. It explains that buyers face a trade-off between lower prices and the increasing risk of the product selling out with each period of delay. Producers optimally choose their initial inventory size to balance this stockout risk while considering price dynamics.

This paper uses an estimation method that integrates dynamic game estimation with demand estimation techniques, leveraging individual purchase data from the Japanese flower wholesale market. This approach allows me to recover key parameters governing the buyers' dynamic decision model, which includes both deterministic and stochastic valuation components across periods. Additionally, the information regarding the size of initial inventory allows me to estimate supply costs.

Using estimated parameters, I perform counterfactual scenarios under uniform pricing. The counterfactual results show that uniform pricing intensifies buyers' urgency to make earlier purchases, while simultaneously encouraging sellers to set lower prices and generate larger initial inventories. From a welfare perspective, my counterfactuals show that sellers would obtain more welfare, and buyers' welfare decreases under uniform pricing. These findings shed new light on the empirical dynamic pricing literature by addressing the limitations of prior research, which often overlooked the strategic behavior of buyers and treated initial inventory size as fixed. This paper shows that accounting for these aspects can lead to different conclusions about the welfare effects of dynamic pricing on sellers' and buyers' welfare.

My analysis faces several avenues for future research. While I have modeled buyers as ex-ante homogeneous, incorporating heterogeneity in their impatience or arrival timing could provide deeper insights. These heterogeneities might align with the finding that the buyer's payoff deterministically declines as time proceeds. Additionally, my application focuses on a single flower variety of Orchid. Expanding the analysis to include multiple flower varieties would open the door to investigating important questions, such as substitution patterns among different varieties and their influence on market outcomes under both dynamic pricing and uniform pricing.

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A Appendix

A.1 Expected revenue function

As discussed in the main text (Section 3), the existence of equilibrium requires log-concavity of the expected revenue in terms of the initial inventory size. However, it is hard to verify log-concavity because I do not derive the expected revenue functions in closed form. Thus, to verify the shape of the expected revenue function, I rely on estimation and simulation. Table 16 displays the Poisson regression results. The signs of the coefficients regarding the initial inventory size and its square are positive and negative, respectively. These findings indicate that the expected revenue is concave in the initial inventory size, which supports the presence of equilibrium.

Table 16: Determinants of expected revenues

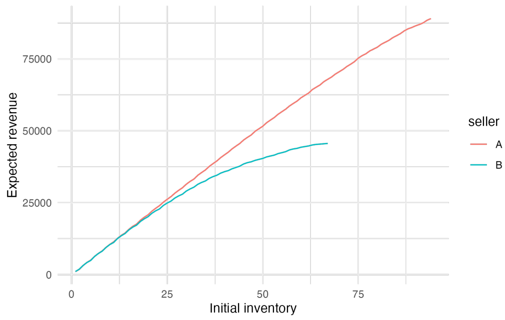
Dependent Variable:		revenue	
Model:	(1)	(2)	(3)
Variables			
market_size	0.0148*	0.0149*	0.0137***
	(0.0076)	(0.0079)	(0.0044)
initial_box	0.0534***	0.0504***	0.0483***
	(0.0041)	(0.0044)	(0.0045)
initial_box squared	-0.0003***	-0.0003***	-0.0003***
	(3.2×10^{-5})	(3.33×10^{-5})	(2.81×10^{-5})
opponent_box	-0.0009	0.0006	-0.0036***
	(0.0012)	(0.0014)	(0.0013)
Fixed-effects			
weekdays	Yes	Yes	Yes
seller_id		Yes	Yes
month			Yes
Fit statistics			
Observations	300	300	300
Squared Correlation	0.84697	0.85278	0.92975
Pseudo R^2	0.86130	0.86579	0.92834

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

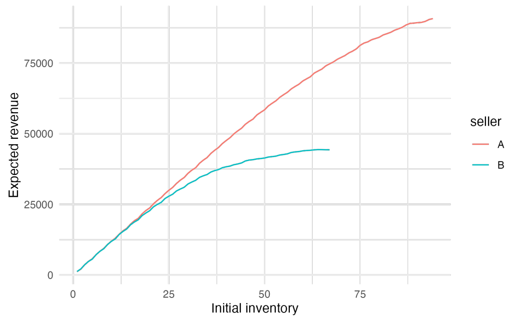
Notes: This table reports Poisson regression results. The dependent variable is revenues, and the covariate is the number of boxes and market size. It also includes fixed effects for weekdays, seller's identity, and months. Standard errors are provided in parentheses.

In the counterfactual simulations discussed in Section 5, I solve for the initial inventory size under a uniform pricing model. I compute the expected revenues for each initial inventory size at a given initial market size. Figure 16 shows that the expected revenue functions are concave with respect to the initial inventory size for each pair of uniform prices. This concavity supports the existence of equilibrium in which inner solution(s) can be found.

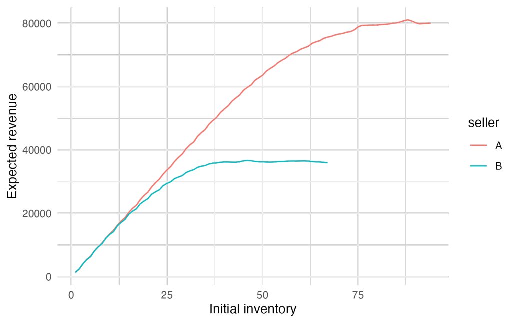
Figure 16: Expected revenue and initial inventory size



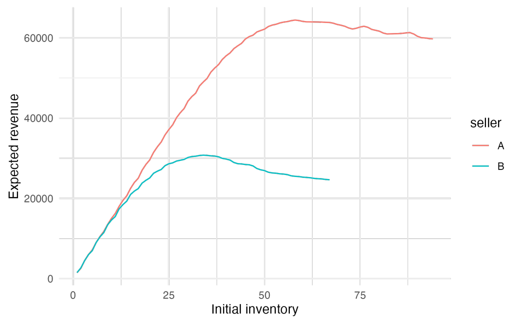
(a) Fixed stocks; $(p_A, p_B) = (35, 35)$



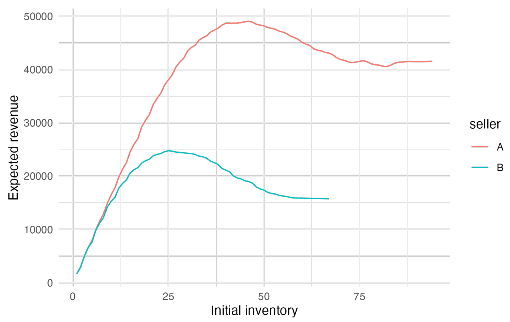
(b) Endogenous stocks; $(p_A, p_B) = (40, 40)$



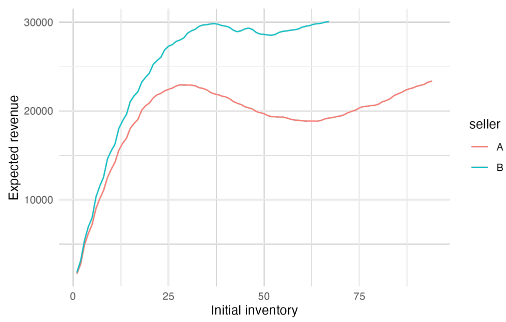
(c) Fixed stocks; $(p_A, p_B) = (45, 45)$



(d) Endogenous stocks; $(p_A, p_B) = (50, 50)$



(e) Fixed stocks; $(p_A, p_B) = (55, 55)$



(f) Endogenous stocks; $(p_A, p_B) = (60, 60)$

Notes: Figures present the expected revenues as a function of the initial inventory size. Each figure shows this relationship for different pairs of fixed prices.

A.2 Equilibrium outcomes in counterfactuals

In the counterfactual simulations, I solve for conditional choice probability $P(\boldsymbol{s}_t)$ and initial inventory size $\boldsymbol{c}_1$ by following Algorithm 3. When solving the model, a potential issue of multiple equilibria may arise due to the nonlinear relationship of the conditional choice probability in (2) and because both initial inventory size $\boldsymbol{c}_1$ and uniform prices (p_A, p_B) are simultaneously chosen from a discrete set using the best response iteration.

To verify the presence of multiple equilibria, I derive conditional choice probability $P(\boldsymbol{s}_t)$ under different sets of initial values. Table 17 and 18 display conditional choice probability for each set of initial values. As discussed in Algorithm 3, $P(\boldsymbol{s}_t)$ is derived as a fixed point. I search a fixed point given multiple initial values, pairs of the conditional choice probability representing the likelihood of the first and second sellers being selected, denoted as "initial_p1" and "initial_p2", respectively. As I compute $P(\boldsymbol{s}_t)$ for each grid of state variables, variations in $P(\boldsymbol{s}_t)$ across states exist. Each column in Tables 17 and 18 presents the quantiles of these variations. Across a wide range of quantiles, the results show that $P(\boldsymbol{s}_t)$, implied by the algorithm, does not differ across different initial value pairs. For example, for the 50 percentile, $P(\boldsymbol{s}_t)$ for the first seller takes 8.16% at every initial value, while $P(\boldsymbol{s}_t)$ for the second seller takes 3.28% regardless of the initial values. This consistency suggests that multiple equilibria do not affect our analysis.

I also solve for uniform prices p_j and initial inventory size c_{1j} for each seller j at equilibrium under various initial values. As discussed in the main text, these variables are computed by iterating the best responses. Thus, I set multiple pairs of uniform prices as initial values. Tables 19-22 display uniform prices and initial inventory size at equilibrium under multiple sets of initial values. According to these tables, equilibrium outcomes are stable across multiple initial values, further implying that the presence of multiple equilibria does not affect the conclusions of my analysis.

Table 17: Choice probability for the first seller

	initial_p1	initial_p2	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
1	0.1	0.1	0.00000	0.05059	0.08147	0.08160	0.08166	0.08234	0.08469	0.09726	0.32358	0.40574	0.45944
2	0.2	0.1	0.00000	0.05059	0.08149	0.08160	0.08167	0.08239	0.08473	0.09826	0.32373	0.40574	0.45944
3	0.3	0.1	0.00000	0.05059	0.08149	0.08160	0.08167	0.08240	0.08474	0.09832	0.32373	0.40731	0.45944
4	0.4	0.1	0.00000	0.05059	0.08150	0.08160	0.08167	0.08241	0.08476	0.09833	0.32412	0.40731	0.45944
5	0.5	0.1	0.00000	0.05059	0.08150	0.08160	0.08167	0.08241	0.08476	0.09904	0.32412	0.40733	0.45944
6	0.1	0.2	0.00000	0.05059	0.08123	0.08160	0.08164	0.08224	0.08459	0.09565	0.32268	0.40394	0.45944
7	0.2	0.2	0.00000	0.05059	0.08126	0.08160	0.08164	0.08225	0.08460	0.09728	0.32285	0.40572	0.45944
8	0.3	0.2	0.00000	0.05059	0.08137	0.08160	0.08164	0.08226	0.08464	0.09757	0.32300	0.40574	0.45944
9	0.4	0.2	0.00000	0.05059	0.08142	0.08160	0.08165	0.08229	0.08468	0.09757	0.32373	0.40575	0.45944
10	0.5	0.2	0.00000	0.05059	0.08142	0.08160	0.08165	0.08229	0.08468	0.09765	0.32373	0.40575	0.45944
11	0.1	0.3	0.00000	0.05059	0.08110	0.08160	0.08164	0.08222	0.08457	0.09498	0.32281	0.40382	0.45944
12	0.2	0.3	0.00000	0.05059	0.08117	0.08160	0.08164	0.08224	0.08459	0.09655	0.32282	0.40398	0.45944
13	0.3	0.3	0.00000	0.05059	0.08117	0.08160	0.08164	0.08224	0.08459	0.09753	0.32289	0.40573	0.45944
14	0.4	0.3	0.00000	0.05059	0.08123	0.08160	0.08164	0.08225	0.08460	0.09753	0.32321	0.40574	0.45944
15	0.5	0.3	0.00000	0.05059	0.08123	0.08160	0.08164	0.08225	0.08460	0.09765	0.32321	0.40575	0.45944
16	0.1	0.4	0.00000	0.05059	0.08110	0.08160	0.08164	0.08222	0.08457	0.09478	0.32268	0.40360	0.45944
17	0.2	0.4	0.00000	0.05059	0.08110	0.08160	0.08164	0.08222	0.08457	0.09653	0.32288	0.40571	0.45944
18	0.3	0.4	0.00000	0.05059	0.08117	0.08160	0.08164	0.08224	0.08459	0.09724	0.32289	0.40574	0.45944
19	0.4	0.4	0.00000	0.05059	0.08117	0.08160	0.08164	0.08224	0.08459	0.09750	0.32290	0.40574	0.45944
20	0.5	0.4	0.00000	0.05059	0.08123	0.08160	0.08164	0.08225	0.08459	0.09759	0.32307	0.40575	0.45944
21	0.1	0.5	0.00000	0.05059	0.08110	0.08160	0.08164	0.08222	0.08456	0.09478	0.32268	0.40360	0.45944
22	0.2	0.5	0.00000	0.05059	0.08110	0.08160	0.08164	0.08222	0.08457	0.09653	0.32288	0.40542	0.45944
23	0.3	0.5	0.00000	0.05059	0.08116	0.08160	0.08164	0.08224	0.08459	0.09720	0.32289	0.40573	0.45944
24	0.4	0.5	0.00000	0.05059	0.08116	0.08160	0.08164	0.08224	0.08459	0.09739	0.32290	0.40574	0.45944
25	0.5	0.5	0.00000	0.05059	0.08117	0.08160	0.08164	0.08224	0.08459	0.09753	0.32290	0.40574	0.45944

Notes: This table reports the conditional choice probability for the first seller at equilibrium during the period $t = 5$ in the counterfactual (uniform pricing) model. Each row corresponds to different initial values. initial_p1 and initial_p2 represent the initial choice probability that flowers are purchased from the first or second seller, respectively. Each column labeled $X\%$ represents the X-th percentile of conditional choice probability at equilibrium.

Table 18: Choice probability for the second seller

	initial_p1	initial_p2	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
1	0.1	0.1	0.00000	0.01981	0.02232	0.03139	0.03268	0.03275	0.03275	0.03296	0.03566	0.29962	0.43970
2	0.2	0.1	0.00000	0.01981	0.02232	0.02950	0.03267	0.03275	0.03275	0.03295	0.03566	0.29465	0.43970
3	0.3	0.1	0.00000	0.01981	0.02232	0.02884	0.03267	0.03275	0.03275	0.03293	0.03566	0.29321	0.43970
4	0.4	0.1	0.00000	0.01981	0.02232	0.02877	0.03267	0.03275	0.03275	0.03293	0.03566	0.29148	0.43970
5	0.5	0.1	0.00000	0.01981	0.02232	0.02865	0.03267	0.03275	0.03275	0.03293	0.03566	0.27918	0.43970
6	0.1	0.2	0.00000	0.01981	0.02232	0.03161	0.03269	0.03275	0.03275	0.03298	0.03566	0.30804	0.43970
7	0.2	0.2	0.00000	0.01981	0.02232	0.03066	0.03269	0.03275	0.03275	0.03297	0.03566	0.30549	0.43970
8	0.3	0.2	0.00000	0.01981	0.02232	0.02908	0.03267	0.03275	0.03275	0.03296	0.03566	0.30585	0.43970
9	0.4	0.2	0.00000	0.01981	0.02232	0.02900	0.03267	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
10	0.5	0.2	0.00000	0.01981	0.02232	0.02895	0.03267	0.03275	0.03275	0.03295	0.03566	0.30601	0.43970
11	0.1	0.3	0.00000	0.01981	0.02232	0.03161	0.03269	0.03275	0.03275	0.03298	0.03566	0.30877	0.43970
12	0.2	0.3	0.00000	0.01981	0.02232	0.03120	0.03269	0.03275	0.03275	0.03298	0.03566	0.30641	0.43970
13	0.3	0.3	0.00000	0.01981	0.02232	0.02978	0.03269	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
14	0.4	0.3	0.00000	0.01981	0.02232	0.02924	0.03268	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
15	0.5	0.3	0.00000	0.01981	0.02232	0.02906	0.03268	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
16	0.1	0.4	0.00000	0.01981	0.02232	0.03165	0.03269	0.03275	0.03275	0.03299	0.03566	0.30961	0.43970
17	0.2	0.4	0.00000	0.01981	0.02232	0.03126	0.03269	0.03275	0.03275	0.03297	0.03566	0.30663	0.43970
18	0.3	0.4	0.00000	0.01981	0.02232	0.03022	0.03269	0.03275	0.03275	0.03297	0.03566	0.30611	0.43970
19	0.4	0.4	0.00000	0.01981	0.02232	0.02959	0.03268	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
20	0.5	0.4	0.00000	0.01981	0.02232	0.02931	0.03268	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970
21	0.1	0.5	0.00000	0.01981	0.02232	0.03165	0.03269	0.03275	0.03275	0.03299	0.03566	0.30969	0.43970
22	0.2	0.5	0.00000	0.01981	0.02232	0.03139	0.03269	0.03275	0.03275	0.03298	0.03566	0.30663	0.43970
23	0.3	0.5	0.00000	0.01981	0.02232	0.03051	0.03269	0.03275	0.03275	0.03297	0.03566	0.30612	0.43970
24	0.4	0.5	0.00000	0.01981	0.02232	0.02987	0.03269	0.03275	0.03275	0.03297	0.03566	0.30601	0.43970
25	0.5	0.5	0.00000	0.01981	0.02232	0.02950	0.03268	0.03275	0.03275	0.03296	0.03566	0.30601	0.43970

Notes: This table reports the conditional choice probability for the second seller at equilibrium during the period $t = 5$ in the counterfactual (uniform pricing) model. Each row corresponds to different initial values. initial_p1 and initial_p2 represent the initial choice probability that flowers are purchased from the first or second seller, respectively. Each column labeled $X\%$ represents the X-th percentile of conditional choice probability at equilibrium.

Table 19: Initial inventory size for the first seller

	fst_price	scd_price	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	35	35	30.0	51.2	63.0	65.1	75.8	94.0
2	40	35	30.0	51.0	63.0	64.9	76.0	94.0
3	45	35	30.0	51.0	60.0	64.8	77.5	94.0
4	50	35	30.0	51.0	60.0	64.6	78.0	94.0
5	55	35	30.0	51.0	60.0	64.7	78.0	94.0
6	60	35	30.0	51.0	60.0	64.5	78.0	94.0
7	35	40	30.0	51.2	63.0	65.1	75.8	94.0
8	40	40	30.0	51.0	63.0	64.9	76.0	94.0
9	45	40	30.0	51.0	60.0	64.8	77.5	94.0
10	50	40	30.0	51.0	60.0	64.6	78.0	94.0
11	55	40	30.0	51.0	60.0	64.7	78.0	94.0
12	60	40	30.0	51.0	60.0	64.5	78.0	94.0
13	35	45	30.0	51.2	63.0	65.1	75.8	94.0
14	40	45	30.0	51.0	63.0	64.9	76.0	94.0
15	45	45	30.0	51.0	60.0	64.8	77.5	94.0
16	50	45	30.0	51.0	60.0	64.6	78.0	94.0
17	55	45	30.0	51.0	60.0	64.7	78.0	94.0
18	60	45	30.0	51.0	60.0	64.5	78.0	94.0
19	35	50	30.0	51.2	63.0	65.1	75.8	94.0
20	40	50	30.0	51.0	63.0	64.9	76.0	94.0
21	45	50	30.0	51.0	60.0	64.8	77.5	94.0
22	50	50	30.0	51.0	60.0	64.6	78.0	94.0
23	55	50	30.0	51.0	60.0	64.7	78.0	94.0
24	60	50	30.0	51.0	60.0	64.5	78.0	94.0
25	35	55	30.0	51.2	63.0	65.1	75.8	94.0
26	40	55	30.0	51.0	63.0	64.9	76.0	94.0
27	45	55	30.0	51.0	60.0	64.8	77.5	94.0
28	50	55	30.0	51.0	60.0	64.6	78.0	94.0
29	55	55	30.0	51.0	60.0	64.7	78.0	94.0
30	60	55	30.0	51.0	60.0	64.5	78.0	94.0
31	35	60	30.0	51.2	63.0	65.1	75.8	94.0
32	40	60	30.0	51.0	63.0	64.9	76.0	94.0
33	45	60	30.0	51.0	60.0	64.8	77.5	94.0
34	50	60	30.0	51.0	60.0	64.6	78.0	94.0
35	55	60	30.0	51.0	60.0	64.7	78.0	94.0
36	60	60	30.0	51.0	60.0	64.5	78.0	94.0

Notes: This table reports the size of initial inventory for the first seller at equilibrium in the counterfactual model. Each row corresponds to different initial values. fst_price and scd_price represent uniform prices of flowers sold by the first and second seller used as initial values, respectively.

Table 20: Initial inventory size for the second seller

	fst_price	scd_price	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	35	35	9.0	15.0	15.0	17.5	21.0	36.0
2	40	35	9.0	15.0	15.0	17.6	21.0	36.0
3	45	35	9.0	15.0	15.0	18.0	21.0	36.0
4	50	35	9.0	15.0	15.0	18.1	21.0	36.0
5	55	35	9.0	15.0	15.0	18.0	21.0	36.0
6	60	35	9.0	15.0	15.0	17.9	21.0	36.0
7	35	40	9.0	15.0	15.0	17.5	21.0	36.0
8	40	40	9.0	15.0	15.0	17.6	21.0	36.0
9	45	40	9.0	15.0	15.0	18.0	21.0	36.0
10	50	40	9.0	15.0	15.0	18.1	21.0	36.0
11	55	40	9.0	15.0	15.0	18.0	21.0	36.0
12	60	40	9.0	15.0	15.0	17.9	21.0	36.0
13	35	45	9.0	15.0	15.0	17.5	21.0	36.0
14	40	45	9.0	15.0	15.0	17.6	21.0	36.0
15	45	45	9.0	15.0	15.0	18.0	21.0	36.0
16	50	45	9.0	15.0	15.0	18.1	21.0	36.0
17	55	45	9.0	15.0	15.0	18.0	21.0	36.0
18	60	45	9.0	15.0	15.0	17.9	21.0	36.0
19	35	50	9.0	15.0	15.0	17.5	21.0	36.0
20	40	50	9.0	15.0	15.0	17.6	21.0	36.0
21	45	50	9.0	15.0	15.0	18.0	21.0	36.0
22	50	50	9.0	15.0	15.0	18.1	21.0	36.0
23	55	50	9.0	15.0	15.0	18.0	21.0	36.0
24	60	50	9.0	15.0	15.0	17.9	21.0	36.0
25	35	55	9.0	15.0	15.0	17.5	21.0	36.0
26	40	55	9.0	15.0	15.0	17.6	21.0	36.0
27	45	55	9.0	15.0	15.0	18.0	21.0	36.0
28	50	55	9.0	15.0	15.0	18.1	21.0	36.0
29	55	55	9.0	15.0	15.0	18.0	21.0	36.0
30	60	55	9.0	15.0	15.0	17.9	21.0	36.0
31	35	60	9.0	15.0	15.0	17.5	21.0	36.0
32	40	60	9.0	15.0	15.0	17.6	21.0	36.0
33	45	60	9.0	15.0	15.0	18.0	21.0	36.0
34	50	60	9.0	15.0	15.0	18.1	21.0	36.0
35	55	60	9.0	15.0	15.0	18.0	21.0	36.0
36	60	60	9.0	15.0	15.0	17.9	21.0	36.0

Notes: This table reports the size of initial inventory for the first seller at equilibrium in the counterfactual model. Each row corresponds to different initial values. fst_price and scd_price represent uniform prices of flowers sold by the first and second seller used as initial values, respectively.

Table 21: Price for the first seller

	fst_price	scd_price	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	35	35	40.0	40.0	45.0	42.7	45.0	45.0
2	40	35	40.0	40.0	45.0	42.9	45.0	45.0
3	45	35	40.0	40.0	45.0	42.9	45.0	45.0
4	50	35	40.0	40.0	45.0	43.0	45.0	45.0
5	55	35	40.0	40.0	45.0	43.0	45.0	45.0
6	60	35	40.0	40.0	45.0	43.0	45.0	45.0
7	35	40	40.0	40.0	45.0	42.7	45.0	45.0
8	40	40	40.0	40.0	45.0	42.9	45.0	45.0
9	45	40	40.0	40.0	45.0	42.9	45.0	45.0
10	50	40	40.0	40.0	45.0	43.0	45.0	45.0
11	55	40	40.0	40.0	45.0	43.0	45.0	45.0
12	60	40	40.0	40.0	45.0	43.0	45.0	45.0
13	35	45	40.0	40.0	45.0	42.7	45.0	45.0
14	40	45	40.0	40.0	45.0	42.9	45.0	45.0
15	45	45	40.0	40.0	45.0	42.9	45.0	45.0
16	50	45	40.0	40.0	45.0	43.0	45.0	45.0
17	55	45	40.0	40.0	45.0	43.0	45.0	45.0
18	60	45	40.0	40.0	45.0	43.0	45.0	45.0
19	35	50	40.0	40.0	45.0	42.7	45.0	45.0
20	40	50	40.0	40.0	45.0	42.9	45.0	45.0
21	45	50	40.0	40.0	45.0	42.9	45.0	45.0
22	50	50	40.0	40.0	45.0	43.0	45.0	45.0
23	55	50	40.0	40.0	45.0	43.0	45.0	45.0
24	60	50	40.0	40.0	45.0	43.0	45.0	45.0
25	35	55	40.0	40.0	45.0	42.7	45.0	45.0
26	40	55	40.0	40.0	45.0	42.9	45.0	45.0
27	45	55	40.0	40.0	45.0	42.9	45.0	45.0
28	50	55	40.0	40.0	45.0	43.0	45.0	45.0
29	55	55	40.0	40.0	45.0	43.0	45.0	45.0
30	60	55	40.0	40.0	45.0	43.0	45.0	45.0
31	35	60	40.0	40.0	45.0	42.7	45.0	45.0
32	40	60	40.0	40.0	45.0	42.9	45.0	45.0
33	45	60	40.0	40.0	45.0	42.9	45.0	45.0
34	50	60	40.0	40.0	45.0	43.0	45.0	45.0
35	55	60	40.0	40.0	45.0	43.0	45.0	45.0
36	60	60	40.0	40.0	45.0	43.0	45.0	45.0

Notes: This table reports the equilibrium prices for the first seller at equilibrium in the counterfactual model. Each row corresponds to different initial values. fst_price and scd_price represent uniform prices of flowers sold by the first and second seller used as initial values, respectively.

Table 22: Price for the second seller

	fst_price	scd_price	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	35	35	40.0	45.0	45.0	43.8	45.0	45.0
2	40	35	40.0	45.0	45.0	44.0	45.0	45.0
3	45	35	40.0	45.0	45.0	44.1	45.0	45.0
4	50	35	40.0	45.0	45.0	44.2	45.0	45.0
5	55	35	40.0	45.0	45.0	44.2	45.0	45.0
6	60	35	40.0	45.0	45.0	44.2	45.0	45.0
7	35	40	40.0	45.0	45.0	43.8	45.0	45.0
8	40	40	40.0	45.0	45.0	44.0	45.0	45.0
9	45	40	40.0	45.0	45.0	44.1	45.0	45.0
10	50	40	40.0	45.0	45.0	44.2	45.0	45.0
11	55	40	40.0	45.0	45.0	44.2	45.0	45.0
12	60	40	40.0	45.0	45.0	44.2	45.0	45.0
13	35	45	40.0	45.0	45.0	43.8	45.0	45.0
14	40	45	40.0	45.0	45.0	44.0	45.0	45.0
15	45	45	40.0	45.0	45.0	44.1	45.0	45.0
16	50	45	40.0	45.0	45.0	44.2	45.0	45.0
17	55	45	40.0	45.0	45.0	44.2	45.0	45.0
18	60	45	40.0	45.0	45.0	44.2	45.0	45.0
19	35	50	40.0	45.0	45.0	43.8	45.0	45.0
20	40	50	40.0	45.0	45.0	44.0	45.0	45.0
21	45	50	40.0	45.0	45.0	44.1	45.0	45.0
22	50	50	40.0	45.0	45.0	44.2	45.0	45.0
23	55	50	40.0	45.0	45.0	44.2	45.0	45.0
24	60	50	40.0	45.0	45.0	44.2	45.0	45.0
25	35	55	40.0	45.0	45.0	43.8	45.0	45.0
26	40	55	40.0	45.0	45.0	44.0	45.0	45.0
27	45	55	40.0	45.0	45.0	44.1	45.0	45.0
28	50	55	40.0	45.0	45.0	44.2	45.0	45.0
29	55	55	40.0	45.0	45.0	44.2	45.0	45.0
30	60	55	40.0	45.0	45.0	44.2	45.0	45.0
31	35	60	40.0	45.0	45.0	43.8	45.0	45.0
32	40	60	40.0	45.0	45.0	44.0	45.0	45.0
33	45	60	40.0	45.0	45.0	44.1	45.0	45.0
34	50	60	40.0	45.0	45.0	44.2	45.0	45.0
35	55	60	40.0	45.0	45.0	44.2	45.0	45.0
36	60	60	40.0	45.0	45.0	44.2	45.0	45.0

Notes: This table reports the equilibrium prices for the second seller at equilibrium in the counterfactual model. Each row corresponds to different initial values. fst_price and scd_price represent uniform prices of flowers sold by the first and second seller used as initial values, respectively.