Essays on Price-Setting in Online Markets

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Abstract

This thesis includes three empirical papers focusing on pricing behaviour of online sellers.

The first chapter investigates the impact of goods quality on pricing decision. We find the positive impact of product quality on the frequency of price changes. This impact can be explained with the higher search intensity of high-quality products, which put pressure on sellers to update their prices more frequently. Additionally, products with better quality have larger size of price changes due to the expensive quality premium which provides more room for sellers to adjust their prices. The analysis also reveals that the releases of successor products using new technology increase the frequency as well as the size of price adjustments of existing products.

The second chapter explores price-setting after a foreign supply shock, which in turn affected the inventory level of domestic sellers. In this chapter, we employ the 2011 Thailand flood as an exogenous hard drive supply shock which severely affected inventory of U.S. sellers to examine sellers' post-shock behaviour and the transmission of shock to relevant markets. We find that hard drive sellers raised their prices instantly in response to the shock suggesting that prices are flexible to sectoral shocks. This result shows little support for pricing models with "fear of customer anger" which suggest that sellers would not raise prices in response to such shock due to fear of damaging the relationship with customers. Further analysis provides evidence that the shock was transmitted via supply chains to other product types but the spillover is delayed and mitigated as the shock propagates through production networks.

The third chapter uncovers the impact of seller reputation on pricing decision by using the rating score of sellers rated by customers in the online market. The results show that nonprice factors (such as seller reputation, selling effort, communication, service quality, and delivery lags), which are reflected by seller rating scores, play important roles in price-setting. In particular, sellers with higher rating scores tend to increase their prices more and decrease their prices less often. This result suggests that sellers can exploit their high-reputation to gain positive price premium in online markets and shows little support for pricing models with "customer anger". Furthermore, besides the reputation level, the variations of seller reputation (standard deviation and frequency of increases/decreases of seller rating scores) are also important in price-setting as well as in explaining the price differences across sellers within a product. The findings contribute to the large literature on price stickiness and price dispersion

by uncovering the impact of seller reputation and its variations on price stickiness as well as price dispersion. This chapter is also closely related to the literature on reputation mechanism in the online market.

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Introduction

This thesis includes three empirical studies documenting some important factors affecting the pricing strategy of sellers namely product quality, inventory of sellers, and reputation of sellers. These studies are important for some main reasons. Firstly, it helps us to explain the existence of price stickiness in the market, which is vital to the real effect as well as the implementation of fiscal and monetary policy (see i.e., Woodford, 2003). Particularly, with the existence of price stickiness, the change in money supply must be reflected in the change in real output. Therefore, the increase in the money supply should raise production. However, if prices are flexible, the change in the money supply will pass directly and proportionally into prices. Thus, the effect of monetary and fiscal policy would be an increase in the price level rather than real output. Secondly, documenting price-setting helps us to understand the micro-foundations of macroeconomics. For example, how frequently sellers change their prices and if they change, by how much all contribute to the inflation rate at the national level (see i.e., Angeloni et al., 2006). Thirdly, investigating the pricing strategy of sellers can help to explain price dispersion, which is often explained by sticky prices in the existing literature. Price dispersion is a major statistic in welfare calculations and determining the cost of inflation since it leads to the misallocation of resources and finally to a welfare loss (see i.e., Nakamura et al., 2018; Sheremirov, 2019).

The first chapter titled “Quality of Goods and Price-Setting” investigates the influence of product quality measured by processor performance score on price-setting measures (such as frequency and size of price adjustments). This study contributes to several strands of literature. Firstly, it contributes to the literature focusing on the determinant of price stickiness by revealing the impact of product quality on measures of price rigidity. Secondly, it is related to the literature studying the impact of technological change on inflation. The most common finding is that technology improvement increases productivity and decreases the price level. Thirdly, this study contributes to the literature investigating the determinant of price dispersion by showing the effect of quality of goods on price dispersion level.

The comprehensive dataset employed in the first chapter includes monthly prices of CPUs in the United States online market. Each product/seller has a unique identifier. The dataset contains 814 CPUs sold across 218 online retailers between April 2009 and December 2012.

Importantly, this paper has the CPUs' performance scores thus, contrarily to previous studies, we can determine and research the prices relevant to the quality of goods.

Our results show that an increase in product quality is associated with a lower level of price stickiness (higher frequency of price changes) as well as price dispersion. Particularly, high-quality products would have a higher frequency of negative, lower frequency of positive price adjustment than low-quality products. Additionally, the quality of new products released has a significant impact on the price-setting of existing products in the market. Under the impact of new products launched, if the position of an existing product in the quality distribution drops to a lower quartile, its frequency and size are expected to increase. In which, the frequency of negative price changes increases more than that of positive price changes. Meanwhile, if the position of an existing product in the quality distribution jumps to a higher quartile, its frequency of positive price adjustments is expected to reduce. Furthermore, we find that market fundamentals, such as the number of sellers, median price, share of convenient prices and level of seller stability, are also important factors for explaining price stickiness and price dispersion. Lastly, we develop our quality index and quality-adjusted price index, which reveal the rate of quality improvement and deflation in CPU online market in the U.S, respectively.

The second chapter, "Inventory Shock and Price-Setting", documents the response of domestic sellers to a foreign shock affecting inventory level of sellers. This study amends the large literature on price stickiness by exploring the impacts of a foreign natural disaster on the pricing of storable and durable goods (computers and components). In addition, this paper contributes to the literature focusing on the transmission of shocks via supply chains. This chapter complements this literature by providing new findings of the impacts of shock propagation through input-output linkage on product availability and prices as well as exploring the role of inventory in delaying shock impacts.

Data employed in the analysis contains monthly seller-product price quotes collected from a leading price comparison website. Each product is uniquely identified by its manufacturer part number (MPN). Also, each seller in our dataset has a unique identifier. The large sample covers 34,691 products offered by 2,005 online retailers within five product types: hard drives, desktops, laptops, central processing units (CPUs), and motherboards. The data span the period between March 2010 and October 2012, which includes an exogenous shock - 2011 Thailand flood. This natural disaster disrupted the HDD production of Western Digital (WD) in Thailand and consequently triggered the inventory shock of not only WD HDD but also HDDs produced by other hard disk producers, SSD, laptops, desktops, and other computer components. Using this comprehensive dataset, we compute the product availability and price indices, which track development in each of five broadly defined markets. Then, we report the properties of price-setting (such as frequency and size of price adjustments) and analyse how price-setting in those markets changes in response to the hard drive supply shock in the U.S. Lastly, we compare our findings with the predictions of popular pricing theories.

Our results show that the foreign supply shock substantially influenced the availability of WD HDD in the U.S. online market. Although the production facilities of other hard drive producers were not affected by the flood, we observe a fall in the product availability index of HDDs made by other manufacturers as well as solid-state drives (SSDs), as there is considerable substitutability across hard drives. Final goods, like desktops and laptops, also show a decline in their availability, though these reductions were delayed and of smaller magnitude compared to hard drives. Our data also reveal a slight decrease in the availability of motherboards and processors, which are not directly related to hard drives.

Regarding price-setting behaviour, we find that the sellers of WD hard drives responded to the flood almost immediately, even before the inventory shock. Our data reveal the increase (decrease) in the frequency of positive (negative) price changes. Sellers of other HDD products had similar—but smaller in magnitude—responses. These findings suggest that prices are sensitive to inventory costs. Sellers raised the prices in anticipation of coming increases in costs related to obtaining new stocks, including money as well as time and effort. Furthermore, the price-setting of SSDs, the closest product substitute for HDD, was only affected one month after the inventory shock. Notably, the prices of final and complementary products showed little response to the shock.

The third chapter entitled "Seller Reputation and Price-Setting" documents pricing behaviour of sellers relevant to their reputation measured by the ratings rated by buyers in online markets. This study employs the dataset of online prices in Gorodnichenko and Talavera (2017). The online prices are collected weekly in the U.S. and Canada online markets, which is precisely identified at the product-seller-week-country level. The large dataset contains prices of about 118,000 products offered by 1,300 sellers between November 2008 and September 2013. Three main electronic product categories are covered in this study: cameras, computers, and electronics. Additionally, this dataset includes a unique feature which is the rating of sellers at a weekly frequency. This feature of the data allows me to track the changes in the rating of sellers and investigate the relationship between price-setting and seller reputation.

Using the dataset, we show that, prices of electronic products exhibit some stickiness even in a highly competitive e-commerce environment thus suggesting that various pricing frictions and market fundamentals—the number of sellers (a proxy for market concentration), median price (a proxy for incentives to search for better prices), share of convenient prices—are also important factors for explaining price stickiness and price dispersion. We also demonstrate that seller reputation and its variations (standard deviation of reputation and frequency of reputation increases/decreases) play an important role in pricing strategy of sellers as well as price dispersion within-product. Furthermore, the average level and variation of reputation of sellers who offer a product are important in explaining the price differences across sellers within that product.

This study contributes to the literature on price stickiness by revealing the relationship between seller rating and price-setting measures. We find that both the reputation of sellers and its changes play important roles in price-setting. In particular, high-reputation sellers tend to increase prices more and decrease price less often with the smaller size compared to low-reputation sellers. This result shows little support for pricing model with customer anger and implicit contracts theory, according to which, a seller with a high reputation would increase their prices less frequent due to fear of damaging the relationship with customers (see e.g., Rotemberg, 2005; Anderson and Simester, 2010). Also, this result supports for nonprice competition theory which argues that non-price factors (such as selling efforts, delivery time, and quality of services) also play important roles in pricing decision (see e.g., Hatfield et al., 2012; Roberts and Samuelson, 1988; Winter, 1993).

Furthermore, we contribute to the literature on price dispersion by investigating the within-product price dispersion to measure potential "mispricing" and frictions in the market since all the product characteristics are kept constant. We find that there is significant within-product price dispersion, which suggests that the market does not eliminate arbitrage opportunities. Additionally, conventional approaches to explain the price dispersion within-product may be incomplete since controlling for product and seller fixed effects maybe not enough. It is because seller fixed effects cannot control for the variation in seller's reputation, selling/communication efforts, or services quality, which are reflected by the variation in seller rating scores.

Chapter 1. Quality of Goods and Price-Setting.[1]

1.1. Introduction

Studying pricing behaviour of sellers provides important implications for determining the optimal inflation, optimal monetary policy and fiscal policy, real exchange rate convergence, and consumer welfare and cost of inflation.[2] Existing literature on price-setting has revealed the influence of customer search intensity on price-setting metrics such as frequency and size of price adjustments (see i.e., Head et al., 2010) as well as price dispersion across sellers (see i.e., Baye and Morgan, 2005). Meanwhile, better quality products often yield higher returns on search, therefore, attract higher customer search intensity. Additionally, a high-quality product often comes with the expensive quality premium which provides more room for sellers to adjust the price compare to a low-quality one. Thus, the quality of products might have impacts on the pricing strategy of sellers. However, in both theory and practice, the quality of goods is often absent in pricing models. This study aims to investigate the effect of product quality on price-setting.

Our approach is to use the performance score of computer microprocessors to measure the quality of goods. Using this quality measure, we explore the impact of product quality on price stickiness statistics (frequency and size of price changes) and price dispersion across sellers in the Central Processing Unit (CPU) market. We also investigate the effects of the launches of new product models using more advanced technology on price stickiness as well as price dispersion level. Lastly, we construct the quality index and quality-adjusted price index to capture the changing rate of the quality and price of CPUs.

We focus on the CPU market for three main reasons. First, CPUs have a high speed of quality improvement which helps to easily explore the effect of quality changes on prices. Second, the CPU is the technological centre of several electric devices. Quality improvement of CPUs is the major factor contributing to the increase in the quality of other products and services. Therefore, our results for the CPU market provide important implications for several markets such as desktops, laptops, tablets, mobile phones, software, and cloud computing which have

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[1] In this chapter, we use material that is submitted to University of Birmingham for the assignment of Advanced Research Methods module.

[2] For determining the optimal inflation see i.e., Adam and Weber (2019); Oikawa and Ueda (2018). For optimal monetary policy and fiscal policy see i.e., Fujiwara and Wang (2017); Paciello and Wiederholt (2014); Schmitt-Grohé and Uribe (2004). For real exchange rate convergence see i.e., Engel (2019). For consumer welfare and cost of inflation see i.e., Jensen (2007); Nakamura et al. (2018).

vital roles in the modern economy (see i.e., Brynjolfsson and Hitt, 2003; Jorgenson et al., 2000; Oliner and Sichel, 2000). Lastly, CPU quality can be measured precisely using CPU performance scores which helps to avoid the difficulty of quality measurement in previous studies.[3]

Our unique dataset includes monthly online prices of CPUs in the U.S. The online price quotes are collected from a leading online shopping platform. Our data covers prices of 814 CPUs sold across 218 online retailers between April 2009 and December 2012. Each product is uniquely identified by the manufacture product number. Also, every seller has a unique identifier. In total, our dataset contains 72,637 product-seller-month price quotes. Importantly, our dataset has a unique feature which is the measure of product quality – the CPU performance scores for each product, which is necessary to explore the impact of the quality of goods on prices and price-setting behaviour.

Using the dataset, we find that an increase in the product quality is associated with a lower level of price stickiness (higher frequency and smaller size of price changes) and smaller price dispersion. Particularly, a high-quality product would have a higher frequency of negative and a lower frequency of positive price adjustments than low-quality products. In addition, the quality of new products released has a significant impact on the price-setting of existing products in the market. In particular, if the position of an existing product in the quality distribution drops to a lower quartile, its frequency and size of price adjustments will increase. In which, the frequency of negative price changes increases more than that of positive price changes. We also find that market fundamentals, such as number of sellers, median price, share of convenient prices and level of competition, are also important factors for explaining price stickiness and price dispersion. Lastly, we develop the quality index and quality-adjusted price index, which reveal the rate of quality improvement and deflation, respectively, in the U.S. CPU online market.

Our study is related to several strands of the literature. The first strand studies the micro foundation of price stickiness. Previous studies have found several factors affecting the price-setting behaviour of sellers such as search costs (Benabou, 1988; Burdett and Judd, 1983; Cabral and Fishman, 2012), costs of nominal price adjustment (Golosov and Lucas Jr., 2007; Reinsdorf, 1994; Sheshinski and Weiss, 1977), transportation/delivery costs (Betancourt and Gautschi, 1993), as well as managerial costs such as costs of collecting information, decision-

[3] For the difficulty in measuring quality of wine see i.e., Combris et al. (1997).

making, and communication (Zbaracki et al., 2004). This study complements this strand of research by revealing the effects of product quality as well as technological changes on price stickiness.

The second strand of literature focuses on price dispersion at the micro-level. Existing papers often focus on the degree of price dispersion (see i.e., Kaplan et al., 2019; Kaplan and Menzio, 2015; Lach, 2002). Our study contributes to this literature by exploring the impact of product quality on price dispersion as well as documenting the dynamic properties of price dispersion. Lastly, this study is related to the strand of literature focusing on constructing hedonic price indices (see i.e., Kryvtsov, 2016; Shiratsuka, 1999), especially for computing devices (see i.e., Aizcorbe et al., 2020; Pakes, 2003) and computer components (see i.e., Byrne et al., 2018). We complement this strand of literature by introducing an improved measure of product quality for a more representative dataset of CPUs to construct the quality-adjusted price indices. Particularly, earlier studies often use physical characteristics of goods to measure processor quality. However, physical characteristics could not fully capture the end-user performance of the product. Thus, this study employs the performance scores to measure the quality of CPUs.

The structure of the rest of our paper is as follows. Section 1.2 is dedicated to describing the data. Section 1.3 provides the estimations and the regression results of the frequency and size of price adjustments. Section 1.4 investigates characteristics of price dispersion. Our quality index and quality-adjusted price index is reported in section 1.5. Finally, our conclusion is given in section 1.6.

1.2. Data description

1.2.1. Data collection

This paper uses a comprehensive and representative dataset, which includes two parts: CPUs' price quotes in the U.S. e-commercial market and performance scores data for each CPU model. The first part of our dataset contains CPU-Seller's price quotes. We have a unique identifier, which is the manufacturer product number (MPN), for each product listed by U.S. online sellers. For instance, MPN "*BX80601940*" uniquely identifies the "*Intel Core i7-940 2.93GHz Processor"*. Similarly, each online seller is uniquely identified. Our online price-quotes are gathered from a leading price comparison website (PCW) that provides price quotes for U.S. online market. Particularly, at midnight on the first day of each month, a Tcl/Python script starts automatically to download webpages with price quotes. After that, we extract information of MPNs, sellers' IDs and prices for each CPU – Seller quotes. Note that the prices included in our dataset is net prices, which are the prices before taxes and shipping fees. Additionally, different from several existing papers, which only obtain less than 12 months of data (see i.e., Lünnemann and Wintr, 2011), we exploit the advantages of a longer time series dataset, which covers for 45 months, to achieve more accurate results.

The second part of our dataset contains a unique feature, which is the performance scores for CPUs. In this dataset, we uniquely identified each CPU model by its official name. Besides performance score, the data also includes the main technical characteristics of the processor such as speed, turbo speed, and the number of cores. The data of CPU performance scores are provided by PassMark Software – a leading authority specialises in software and hardware performance benchmarking and testing. This company is also a Microsoft Partner and Intel Software Partner and owns one of the world's largest CPU benchmark website. They not only report the final scores of CPU's performances but also provide all the test results, which are used to compute the performance marks. Furthermore, their testing methods and models to produce the CPU's performance score are published on their website. Therefore, if they change their performance measure, we can produce new performance scores and update our data to be comparable with new CPU models.

Since each CPU model in the latter dataset including several product versions with different MPNs in the former dataset, we manually matched the performance score of a CPU model with all of its MPNs. For example, the CPU model "*Intel Core i7-940 2.93GHz Processor*" has three versions with the same performance. Its MPNs are: "*AT80601000921AA", "BX80601940"*, and *"BXC80601940"*.

The performance score has been used to measure the quality of electronic products instead of physical characteristics in recent research. Byrne et al. (2018) find that the quality index for microprocessors that based on technical characteristics is completely flat over 2010-2013, while the quality index based on performance scores sharply increased. The main reason is that processor producers shifted away from increasing the clock speed due to heat generation. Instead, they improved processor performance by placing multiple cores on a chip. Additionally, identifying the correct set of technical characteristics is changeling due to the rapid changes in microprocessor architecture. Thus, the performance score can provide superior control for quality of microprocessors. However, their data is limited with 177 Intel Desktop

CPUs and their price data is collected directly from Intel's website, which might not be representative. We complement their study by using the performance score as a proxy to measure precisely the product quality for a larger set of processor models including processors produced by Intel as well as AMD for desktops, laptop, and servers.

1.2.2. CPU generations over the last decade

The concept of CPU generations mainly comes after Intel released their CPU core *i* series in *Nehalem* microarchitecture family, which is also known as the first generation. The major difference between CPU generations is the differences in their microarchitecture, which is reflected by the semiconductor manufacturing process (also called "technology node" or "process technology"). The "process technology" is designated by the process's minimum feature size that is indicated by the size in nanometres. This size refers to the average haft-pitch (half the distance between identical features) of a memory cell (Hoefflinger, 2011). The smaller the process's minimum feature size, the more powerful and the more efficient in energy consumption the processor. Chip companies were able to shrink the size of their microprocessor and improve the CPU performance mainly because of the innovation in the semiconductor industry.

Figure 1.1 shows that Intel was the pioneer of microprocessor technology in our sample period from 2009 to 2012. The first generation of the Intel Core processors (*Nehalem*) was released in November 2008 and use the 45 nanometres (nm) process, the second-generation processors (*Sandy Bridge*) and the third-generation processors (*Ivy Bridge*) use 32 nm and 22 nm, respectively. Meanwhile, AMD was struggling in the technology race with Intel. AMD released its first-generation CPUs (*Bulldozer* family) using 32 nm technology 9 months after the release of *Sandy Bridge* processors. The second-generation CPUs of AMD (*Piledriver* family), which were released 5 months after Intel released *Ivy Bridge* CPUs, are still based on the 32 nm technology. In the next section, we will document the impact of the technological upgrades on the price-setting behaviour of sellers.

[Figure 1.1]

1.2.3. Data filters and data quality

Because the quality of goods is vital in our study, we dropped CPUs that do not have performance scores after merging two parts of our dataset. All used or refurbished CPUs were removed from the dataset since their prices are not comparable with prices of new CPUs. In addition, to minimise the effects of extreme values in our data, both the top and the bottom 1 percent of the prices were dropped. For time-series analyses, CPUs with less than 20 observations were removed. A CPU is considered as an available product in a month if it is offered by at least three sellers in that month. After applying all filters above, our large sample covers monthly prices of 814 CPUs sold across 218 online retailers in the United States from April 2009 to December 2012. We define an observation by its MPN, seller ID and month. Our dataset contains 72,637 product-seller-month price quotes.

One may concern about the quality of prices data on PCWs since it does not directly come from sellers. The price on PCWs may be out of date or discrepant from sellers' real prices if sellers post lower prices on PCWs than on their websites to attract visits of customers. In fact, online merchants have incentives to keep updating their latest prices on PCWs since they usually have to pay for clicks on those webpages. Therefore, if their prices are not up to date, they will not gain sales and waste their money. Similar to our dataset, Gorodnichenko et al. (2018) gathered price data from PCWs and find some differences between PCWs price and price on seller's websites. However, the price quotes are still remarkably consistent between two sources with a high correlation ($\rho = 0.98$). Additionally, they find sufficient evidence that price data from PCW is consistent with the Bureau of Labour Statistics (BLS) data and updated rapidly in response to an exogenous shock. Hence, the price data from PCWs have reasonably high quality.

1.2.4. Notation and aggregation

In this paper, we use p_{ist} to stand for the prices of CPU *i* sold by seller *s* at time *t* and q_i stand for the performance score of CPU *i*. Thus, we have the set of all CPUs, sellers and time as $\mathcal{C}$ = {1, …, C}, $\mathcal{S}$ = {1, …, S}, $\mathcal{T}$ = {1, …, T}, respectively. In which C is the total amount of CPUs, S is the total amount of sellers and T is when the period ends. The time measurement is monthly. The subscripts *i*, *s*, and *t* are corresponding to a given model of CPU, seller, and time. For example, C_{st} is the total number of CPU, which are offered by seller *s* at time *t*, while S_{it} represents the total number of sellers that sell CPU *i* at time *t*. The letter with a bar means the average, such as $\bar{p}_{it}$ is the average price of CPU *i* across all sellers at time *t*.

We use performance scores to measure accurately the goods' quality to fill, at least partially, the gap in the existing literature which do not have such features. To highlight the differences between this paper with its exclusive quality measure and previous studies, we employ two different aggregate measures for frequency, size and synchronisation rate of price adjustments over CPUs and sellers. Firstly, we calculate the raw average, which is $\bar{f}$ (unweighted mean). Secondly, we compute the aggregate across sellers that sold a CPU to collapse our data to goods level. Then we employ the performance weighting scheme to produce the average over CPUs, which we call $\overline{f^b}$. We refer $\overline{f^b}$ to between CPUs weighting. For instance, if f_{is} is the frequency of price adjustments for CPU *i* sold by seller *s*, and q_i is the performance score of CPU *i*. Those two aggregated measures have formula as:

$$\bar{f} = \sum_i \frac{1}{C} \sum_s f_{is} \frac{1}{S}$$

$$\overline{f^b} = \sum_i \frac{q_i}{\sum_i q_i} \sum_s f_{is} \frac{1}{S} \quad (1)$$

Additionally, to highlight the differences in the price per unit of performance between high and low-quality products, we compute the quality-adjusted price p^q as:

$$p_{ist}^{q} = \frac{p_{ist} * \bar{Q}}{q_i} \quad (2)$$

In which, $\bar{Q}$ is the average performance score between all CPU models and q_i is the performance score of CPU *i*.

1.2.5. Price distribution and performance

Table 1.1 shows the average price of each percentile of the distribution over products ($\bar{p}_i$), the mean and standard deviation of the average log price ($\overline{log\ p_i}$), within the sample. Overall, the median CPU in our data costs £190.43 and 25% of the CPUs have their price under £99.95; CPUs that are more expensive than £334.93 are accounted for top 25% highest prices of the sample. When we apply the performance weighting scheme to calculate the between CPUs weighted estimation, the average price of all the percentile increase. Particularly, the price of the median CPU increases by more than 50% to £300.02. This result implies that the higher the performance score of a CPU, the more expensive the CPU could be.

[Table 1.1]

To investigate the essence of the CPU performance score in the quality-adjusted price measurement, we calculate the average difference throughout the sample period between the log price of a CPU *i* offering by seller *s* at time *t*, which is $log(p_{ist})$, and the log of the median price of CPU *i* at time *t*, which is $log(\tilde{p}_{it})$. The formula is:

$$\bar{p}_{is} = \frac{1}{T} \sum_t [log(p_{ist}) - log\ (\tilde{p}_{it})] \tag{3}$$

Panel (a) of Figure 1.2 illustrates the density of the deviations without weights and with the between CPUs weights based on the performance scores, q_i. The grey dashed line presents the distribution of the log price deviation from the median across CPUs, and the black solid line presents the performance-weighted distribution of that deviation. We can see that applying the performance weights make the distribution shift to the right. This graph implies that the CPU, which has a performance score significantly higher than the median CPU score, has a higher average price.

Panel (b) of Figure 1.2 presents the relation between prices and performance scores. Similar to panel (a), we measure price and performance by the log-deviation from the median CPU for a seller on a given month. The dots show data points averaged within bins based on 99 percentile levels of the log-deviation of price from one to ninety-nine percentiles. Lowess smoother, computed with a 0.1 bandwidth, reports nonlinearities relation in the performance–price relationship. The figure clearly shows, as expected, higher prices for better-performing CPUs. However, the link is non-linear as the curve is flatter on the right-hand side of the price distribution. It suggests that for high-end CPUs, consumers have to spend lots of money to gain little performance improvement.

[Figure 1.2]

To compare the price per performance unit of CPUs in different quality standards or price levels, we divide our sample into four quartile groups of CPUs based on their performance scores or prices, respectively. Panel (a) of Figure 1.3 shows the average price per performance unit of CPUs in four price quartiles. It suggests that the more expensive the processor, the higher the price per unit of performance. Similarly, Panel (b) of Figure 1.3 shows the average price per performance unit of CPUs in four quality quartiles suggesting that the price per unit of performance is higher for high-quality products. It can be seen that high-end CPUs with powerful performance are truly “expensive”. This implies that producers and retailers spend more efforts and resources to advertise flagship products, therefore the price of a high-quality and expensive product often includes the expensive quality premium.

Then, we split our sample by CPU generation as described in Section 2.2. Panel (c) of Figure 1.3 presents the average price per performance unit of each CPU generation. In general, the price per unit of performance of AMD processors was often lower than that of Intel processors. It might be because AMD was often in the position of playing catch-up with Intel, thus it had to apply the pricing strategy to compete with the dominance of Intel in the CPU market (see i.e., Goettler and Gordon, 2011). Additionally, we observe that the technical improvement used in later CPU generations benefits customers by reducing the price per unit of performance. However, the difference in the average price per performance unit between a CPU generation and its next-generation is usually small.

[Figure 1.3]

1.2.6. Dynamic of CPU prices

Over the period 2000-2001, the percentage of CPUs that has a price drop within four quarters of introduction was 100%. Meanwhile, between 2009 and 2013, this rate dropped to only 20%.[4] It is because CPU producers changed their life-cycle pricing strategy and stopped reducing the price of old models. Consistently, we find that the CPU posted prices did not change a lot over the period of 2009-2012. The price level in the CPU market slightly increased as the new-generation CPUs released at higher prices, but the quality-adjusted prices dropped quickly due to the large improvement in CPU performance (see Figure 1.4).

[Figure 1.4]

Panel (a) of Figure 1.5 illustrates the dynamics of the median price of each generation. The median prices of AMD generations were often cheaper than that of Intel generations using similar technology. We also see that CPU producers usually set higher prices for new generation processors and the median prices tend to decrease over time. However, the median prices of *Intel Core 2* and *Intel Nehalem* CPUs were consistently higher than the median prices of new generations and remained stable for most of our sample period. This can be explained

[4] For more details see i.e., Byrne et al. (2018)

with the large demand for those two processor generations in our sample period. Since those old CPUs were popular for a long time without major changes in the processor architecture, the old systems which are not compatible with new processor generations were also popular. Thus, a large number of customers might choose to purchase an old-generation processor rather than upgrading the whole system, while the supply of these old models is limited as Intel stopped producing them. This led to a high price level of *Core 2* and *Nehalem* CPUs.

Panel (b) of Figure 1.5 shows the median quality-adjusted price of CPU generations. Similar to the median prices presented in panel (a), we observe that the median quality-adjusted prices of AMD generations were often lower than that of Intel generations. Also, after adjusting for quality, we see that new technology development benefited customers by reducing the price per performance unit of new-generation CPUs. Although the median quality-adjusted price of processor generation tends to decline over time, it did not fall enough to equilibrate with the price-performance ratio of new-generation CPU models even when we excluded the two old CPU generations of Intel which have high price level. This is consistent with the finding of Aizcorbe et al. (2020).

[Figure 1.5]

1.3. Price stickiness and price-setting

Studying price-setting behaviour of sellers is vital since it helps to determine the price stickiness in sellers' responses to aggregate shocks such as monetary shocks. In several macroeconomic models, price stickiness is an important factor of the monetary policy transmission mechanism. Numerous studies have attempted to measure the rigidity of the price and investigate its properties (see i.e., Bils and Klenow, 2004; Boivin et al., 2009; Ellison et al., 2018; Midrigan, 2011; Nakamura and Steinsson, 2013). They have found several types of price-adjustment frictions that make price become inflexible. However, in online markets, we expect to find smaller price-change friction than what we witnessed in the conventional market because of the characteristics of e-commerce, such as small nominal price change costs, small searching costs and small monitoring competitors' prices costs (Ellison and Ellison, 2005). Therefore, studying online pricing behaviour should provide better implications for the relationship between product quality and price rigidity. This section aims to contribute to the existing literature by providing new empirical evidence of the impact of product quality on price-setting in the U.S. online market.

1.3.1. Regular and Posted Prices

Several studies show the impact of temporary price changes on price stickiness. For example, Nakamura and Steinsson (2008) find that temporary sales have an important role in generating price flexibility. Similarly, Klenow and Malin (2010) argue that temporary price changes (sale-related price changes) do not wash out with aggregation and each model of "sales" have a different implication for measuring stickiness level of price. Meanwhile, Eichenbaum et al. (2011) and Kehoe and Midrigan (2015) reached a consensus that aggregate price is still sticky even when the frequency of temporary price changes is high. In line with that, Dhyne et al. (2006) stated that it is more appropriate to analyse regular price changes than focus on sales for the investigation of price flexibility at an aggregate level. Therefore, in this paper, we distinguish between posted prices (prices posted by sellers) and regular prices (prices excluded temporary price changes) and report both results.

We do not have sales flag as in scanner data such as BLS. Thus, following previous studies (see i.e., Chahrour, 2011), we identify temporary sales by "sales filter", which is the ∨-shape or ∧-shape in price changes. Particularly, we consider an increase or decrease in price as temporary price changes if the price returns to its previous price level within one month.

The monthly frequency and size of sales in our data are shown in Table 1.2. The number of observations is presented in column (4). It shows that there are 535 products in our sample having sales. The mean frequency of sales across products is 1.88% (see column (1)) and the median size of sales across CPUs is 2.28% (see column (3)). Applying performance weights increases the frequency of sale to 2.34%, while the size of sales decreases to 1.96%. It indicates that the price of high-performance CPU temporarily changes more often with a smaller size than the price of low-performance CPU.

[Table 1.2]

1.3.2. Frequency and Size of Price Changes

1.3.2.1. Frequency of Price Changes

Following previous studies (for example Bils et al., 2004; Nakamura et al., 2008), we determine the frequency of price adjustment as the proportion of non-zero price changes to the total number of price changes observed within our dataset. Particularly, we consider a price change that is smaller than 0.1% as a zero-price change, which means it is not counted as a non-zero price change. In other words, if we use $\varphi_{ist} = \mathbb{I}\{q_{is,t} > 0\}\,\mathbb{I}\{q_{is,t-1} > 0\}$ to identify a price adjustment that is observed (for both zero and non-zero price changes); the number of observed price adjustment per CPU-seller quote is $\prod_{is} = \sum_t \varphi_{ist}$; the conditional function of a non-zero change is $\chi_{ist} = \mathbb{I}\{|\Delta\, log\, p_{ist}| > 0.001\}$. Hence, the formula of the frequency of price adjustments of CPU *i* sold by seller *s* is:

$$f_{is} = \frac{\sum_t \chi_{ist}}{\prod_{is}} \tag{3}$$

After that, we collapse the result to CPU-level by computing the raw average frequency ($\bar{f_i}$) for each CPU, which has more than two observations, as follow:

$$\bar{f_i} = \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>2\}} \sum_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 2\} \tag{4}$$

Then, we compute the no weights average ($\bar{f}$) and between-CPU weights average ($\overline{f^b}$) for both posted and regular price changes frequency, which is reported in Table 4, as below:

$$\bar{f} = \sum_{i\in C}\frac{1}{\mathrm{C}} \sum_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 2\} * \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>2\}} \tag{5}$$

$$\overline{f^w} = \sum_{i\in C}\frac{q_i^{\prod}}{\sum_i q_i^{\prod}} \sum_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 2\} * \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>2\}} \tag{6}$$

Lastly, we compute the implied duration of price spell as:

$$\bar{d_i} = -\frac{1}{\ln(1-\bar{f_i})} \tag{7}$$

Table 1.3 reports the median of the frequency of posted price adjustment is 42.17% and the implied duration is 1.83 months, correspondingly, when no weights are applied (see column (1)). When we use the one-month sales filter to compute the same statistic for regular price, the median frequency drops to 39.37% and the implied duration raise to 2.00 months. Applying the performance weights between CPUs to compute the frequency of price adjustments for both posted and regular prices, we find that they rise to 44.66% and 40.56%, respectively, and the implied duration of price spells drops to the range between 1.69 and 1.92 months.

Our statistics suggest that high-quality CPUs might have a higher frequency of price changes. Furthermore, we find that the price spells of CPU online stores in the US are up to 2.00 months, which is shorter than the results reported in previous studies for other segments in the online market (see i.e., Boivin et al., 2012; Lünnemann and Wintr, 2011). Nonetheless, the price of CPUs in the e-commercial market is still not completely flexible.

[Table 1.3]

1.3.2.2. Size of Price Changes

Using the same symbols in the notation part, our formula to calculate the average absolute size of price adjustment for CPU *i* is:

$$\overline{|\Delta \, log \, \rho_i|} = \frac{1}{\sum_{s \in \mathcal{S}_i} \sum_t \chi_{ist}} \sum_{s \in \mathcal{S}_i} \sum_t |\Delta \, log \, \rho_{ist}| \cdot \chi_{ist} \tag{8}$$

Then, we calculate the raw average size ($\overline{|\Delta \, log \, p|}$) and the between-CPU weighted average size of price adjustments ($\overline{|\Delta \log p|}^w$).

The last row of each panel in Table 1.3 presents the median absolute size of price adjustment. It suggests that the more powerful a processor is, the smaller the size of price changes. In particular, the results for posted prices and regular prices are similar, which are 7.97% and 8.20%, respectively. When we employ performance weights, the size of price changes drops to the range between 5.12% and 5.35%. These results are smaller than the results reported in Gorodnichenko et al. (2018), which is also for the U.S. online market but including a wider range of products.

1.3.2.3. Pricing moments and technology shocks

In the sample period, we focus on four technology shocks, which are the releases of new processor generations with large improvements in CPU performance. The first one is in January 2011 when Intel introduced Sandy Bridge CPUs (the second generation of Intel Core processors) using 32 nm technology node. Following Intel, their competitor also released AMD

Bulldozer Family 15h (the first generation) using 32 nm process technology in October 2011. The third shock is the release of Ivy Bridge processors (the third generation of the Intel Core processors), which is manufactured in the 22 nm process. Lastly, in September 2012, AMD released Piledriver Family 15h (the second generation), which has some improvements but still uses the same module design (32 nm) with Bulldozer.

Figure 1.6 illustrates the monthly frequency and average absolute size of positive and negative price adjustments throughout these shocks. Figure 1.6, panel (a) uses the whole sample, while panel (b) uses the data that is restricted to the old generations namely AMD K10, Intel Core 2, and Intel Nehalem. It can be seen in panel (a) that, in general, the release of a new generation might decrease the frequency and size of positive price changes, however, increase the frequency and size of negative price changes. These effects seem to be stronger with old models of CPU in panel (b).

[Figure 1.6]

1.3.3. Predictors of price stickiness

The features of market and goods might be correlated with the heterogeneity of price stickiness across goods. Thus, we control for six variables namely: (1) number of sellers that sell product *i*; (2) quality of product *i*; (3) the median price of product *i*; (4) share of price points, which is the percentage of price quotes that end at 95-99 cents of product *i*; (5) The stability of sellers for product *i* is the ratio of number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which covers the given month; and (6) CPU producer, which is a dummy variable that equals 1 if it is an Intel CPU and equals zero otherwise. The first variable illustrates market competition (see, i.e., Ginsburgh and Michel, 1988; Martin, 1993). The second variable captures goods' characteristic. The third one is a proxy for the returns of buyers' search (see i.e., Head et al., 2010). The fourth one reflects the level of inattention to prices when choosing between products (see i.e., Knotek, 2011). The fifth variable, stability of sellers is a proxy for the turnover of sellers (see i.e., Gust, Leduc, and Vigfusson, 2010). Lastly, the CPU manufacturer controls for the brand of the product.

Table 1.4 reports the results of regression for the frequency of price adjustments, frequency of positive, negative price adjustments, and size of adjustments. We estimate the pricing moment and our predictors at product-level. For instance, the frequency of price changes at the product-level for a specific product is computed as follow. First, the frequency of price adjustments for each seller offering that product is calculated. After that, the data is collapsed to product-level by taking the raw average across sellers to use as a dependent variable and run the regression with no weights. In the regression, we control for time fixed effects.

The results in Table 1.4 suggest that all explanatory variables have some predictive power. First, a market with more sellers should have a higher (lower) frequency of positive (negative) price changes, and smaller size of adjustment. Second, the quality of goods in the market is positively associated with the degree of price flexibility (higher frequency and smaller size of price adjustments). This result can be explained with the higher search intensity for high-quality products due to higher advertising expenses and higher returns on search for customers.[5] In addition, the more flexible prices of products with better quality might be explained with the lower inventory level due to the lower level of demand and higher costs of high-end products.[6] Also, we find that a more powerful processor has price increases less often and price decreases more often. This can be explained with the observed expensive quality premium, which provides more room for sellers to adjust prices. Third, for products with low- and moderate-prices, price changes more often and have larger size when the median price across sellers of product increase. This result is consistent with Head et al. (2010), according to which the higher returns on search would put more pressure on the seller to adjust prices. Nevertheless, the very expensive CPUs (less than 25% of products in our data) tend to have fewer price changes with smaller size. Fourth, a product, which has a high proportion of price points, have a lower frequency of price changes, particularly the frequency of positive price changes. This result is consistent with Levy et al. (2011), who find that prices ending with 9 have a lower frequency of price changes. Fifth, an increase in the degree of seller stability, which implies that it is more difficult for new sellers to enter the market, is associated with a decrease in the frequency of price changes, particularly, the frequency of negative price changes. Lastly, on average, Intel processors tend to change prices more frequent than AMD products.

[Table 1.4]

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[5] For the negative relationship between customer search and price stickiness level see i.e., G. D. Ellison & Ellison (2009).

[6] For the positive relationship between inventory level and the degree of price rigidity see i.e., Blinder (1982); Boileau and Letendre (2011).

Next, we investigate the impacts of the entry/exit of low/high-quality products on the price-setting of existing products. Table 1.5 reports the results of regression for the frequency of price adjustments, frequency of positive, negative price adjustments, and size of adjustments on our predictors at the product-month level. Four variables were constructed by calculating the monthly number of CPUs entering/exiting the market, which have higher/lower performance scores than an existing processor. For other independent variables, we compute them monthly for each processor using a similar method discussed above, but without collapsing to product-level. We regress the pricing moment on the same set of independent variables in the regression presented in Table 1.4 and add these four new explanatory variables. The regression includes product and time fixed effects.

The results reported in Table 1.5 suggest that the existing products would change price more often when the number of product's entries increases. This result supports the idea that the higher the degree of market competition, the higher the frequency of price changes (see i.e., Álvarez et al., 2010). However, we find little evidence suggesting the relationship between the number of product launches and the size of price adjustments. Furthermore, the number of products that exit the market is positively associated with the size of price adjustments. We also find that the frequency of price changes of an existing product would not be significantly affected by the number of CPUs exiting the market with better performance. Meanwhile, sellers would increase their prices less frequently when the number of CPUs exiting the market with lower performance scores increases.

[Table 1.5]

To dig deeper into the impact of quality improvement on price-setting behaviour, we divide the CPUs into four quartile groups each month based on their performance scores and then construct two new dummy variables based on their monthly quartile. The first dummy called "Upgrading" equals one if the product *i* jumps to a higher performance quartile at time *t* compared to time *t-1* and equals zero otherwise. For instance, when the number of product entering the market with lower performance scores than product *i* and/or the number of products exiting the market with better quality than the product *i* are sufficient, the product *i* will jump to a higher quality quartile. The second dummy called "Downgrading" equals one if the product *i* falls to a lower performance quartile at time *t* compared to the previous period and equals zero otherwise. Similar to the regression reported in Table 1.5, we compute our variables at the product-month level and include product and time fixed effects in the regression.

The results in Table 1.6 illustrate that when an existing product jumps to a higher quality quartile, its frequency of positive price adjustments would decrease and its size of price changes would be similar. Meanwhile, when the product drops to a lower quality quartile, it would have a higher frequency of price changes with a larger size of adjustments. Together with results reported in Table 1.5, these results imply a shift in customer search to new products with better quality due to the advertising expenses shifting to these products. In addition, the release of new products with better quality will push existing products to a lower quality quartile and set a new quality standard in the market. It put pressure on sellers to decrease the price of old models more frequently with larger size of adjustments.

[Table 1.6]

1.4. Price dispersion and price-setting

Numerous popular macro models have pointed out the tight relationship of price dispersion and price stickiness level (see i.e., Sheremirov, 2019). Those models also highlighted that price dispersion is a key statistic in welfare calculations and determining the cost of inflation because it could lead to misallocation of resources and finally to a welfare loss (see i.e., Andrade et al., 2019; Calvo, 1983). However, Klenow and Kryvtsov (2008) claim that the implications for the properties of macroeconomic variables, welfare calculations and the optimal policy can be different, depending on the price rigidity structure.[7]

Previously, numerous empirical studies are focusing on price dispersion in the conventional market (see i.e., Benabou, 1992; Borenstein and Rose, 1994; Dahlby and West, 1986; Kaplan and Menzio, 2015). Meanwhile, the rapid development of the internet and technology makes online market becoming a more promising source of data. Thus, the number of studies, which investigate the properties of price dispersion in the e-commerce market using online prices, is increasing rapidly. Although e-commerce has special characteristics that can minimise the effects of price frictions, earlier papers still find significant evidence of price dispersion in the online market (see i.e., Baye et al., 2004; Chevalier et al., 2003).

[7] See i.e., Woodford (2011) for time-dependent pricing models. See i.e., Head and Kumar (2005) for state-dependent pricing models.

In this section, we extend the literature by including quality of products – an important factor that is often omitted in previous studies – in the estimation of price dispersion among CPU retailers in the U.S. online market. Firstly, we still find significant price dispersion among sellers even when the product and seller fixed effects are removed. Secondly, the high-performance processor has a smaller price dispersion than low-performance one. Thirdly, the price dispersion among CPU sellers gradually increases over the processor's lifetime. Lastly, our evidence from the data support for spatial price dispersion, despite that consumer can easily learn the pricing behaviour of sellers overtime since search costs in online markets are inexpensive. This result is consistent with the evidence support for spatial dispersion in the U.S. online market in previous studies (see i.e., Gorodnichenko et al., 2018).

1.4.1 Intra-month dispersion across sellers

This section reports the coefficient of variation (CV) and standard deviation of the monthly log prices since they are the most commonly reported measures in earlier studies of price dispersion. Together with that, we also generate other measures for price dispersion such as the value of information (VI), which equal to the log difference of the average and the lowest price; interquartile range (IQR); Range, which is the gap between the lowest and highest log price; Gap, which is the difference between the two lowest log prices.

First, we calculate the measure of price dispersion between sellers for an identified CPU in a month, then collapse our data to product level by taking the raw average overtime. Finally, we apply weighting schemes to calculate the non-weighted average and the performance-weighted average across products. Since the frequency of our monthly sales is quite small, which is up to 2.23% (see Table 1.2), the results for price dispersion is nearly the same between regular prices and posted prices. Therefore, we only report the results of the posted price in Table 1.7.

[Table 1.7]

As it can be seen in Table 1.7, in general, all measures of price dispersion decrease when the performance-weighting scheme is applied. Column (1) reports the value of CV, which is 22.27% and significantly drops to 14.98% when applying performance weights. The results of the standard deviation of log prices are similar to the CV for both weighting schemes (see column (2)).

One might argue that the observed price dispersion is caused by the distinction in the shopping experience of customer among sellers (see i.e., Stigler, 1961). This difference is not likely to be significant when customers shopping online as consumers only deal directly with a seller after completing the transaction. To fully solve this potential problem, we follow existing studies (see i.e., Gorodnichenko et al., 2018a) to employ the regression below:

$$log\ p_{ist} = \alpha_i + \gamma_s + \varepsilon_{ist} \tag{10}$$

Where α_i and γ_s control for product and seller fixed effects, respectively. The fixed effects can capture the differences in reputation, delivery conditions, and return costs between CPU retailers. Thus, the dispersion of the residuals (ε_{ist}) gives us the price dispersion net of sellers' heterogeneity in, for example, shipping costs, return policies, which are likely to remain unchanged in a short time (see i.e., Nakamura and Steinsson, 2008).

The results in Table 1.7 show that seller fixed effects account for about 15% - 20% of the variation in actual price dispersion of CPU in the US online market (see column (7)). The residual price dispersion is 18.83 log points when no weights are applied. Once we use performance weights, it significantly drops to 11.90 log points. These results suggest that, in general, the price dispersion of the high-quality product is smaller than that of the low-quality product. In addition, even after removing sellers fixed effects, the residual price dispersion is still high in the U.S. online market.

1.4.2. Dynamic properties of price dispersion

1.4.2.1. Price Dispersion over CPU lifetime

The price dispersion across sellers of a product may depend on the stage of the product lifecycle. It is expected to be higher at the release time of product then decrease overtime in case there are no shocks since customers can be aware of pricing strategy of sellers and sellers can collect information of their competitors' prices. It might be easier to see this trend in online market than in the offline market as people can search easily online.

To study this aspect of price dispersion, we calculate the average price dispersion across CPUs for month *j* after their introduction. We identify the time of product introduction by taking the time that the product appeared in the data. CPUs, which enter within the first quarter, are excluded as we cannot know whether the CPU was released before or it came back after being temporarily unavailable. After that, the measure of price dispersion over CPU lifetime is computed as follow. We generate the time variable for each processor as the number of months since the month that the processor appeared in the dataset to replace for the calendar months. Then we use cross-sectional price dispersion of each processor and the new time variable to compute the average price dispersion across CPUs for *j* month after their release month.

We find little evidence of price convergence over CPU lifetime. Figure 1.7 shows that price dispersion rises slowly over the first 20 months since they released. In average, the actual-price dispersion (no weights measure) raises from around 14% to nearly 20%. After the first 20-month period, the price dispersion of product quickly increases. This increase in price dispersion level can be explained with the increasing search costs over the product lifecycle.[8] Furthermore, the performance-weighted price dispersion behaves similarly over product life but at a lower level. The smaller size of performance-weighted dispersion suggests that high-quality CPUs would have smaller price dispersion than low-quality CPUs that are in the same stage of product life.

[Figure 1.7]

1.4.2.2. Spatial and temporal dispersion

The findings of the significant dispersion of prices across CPU online retailers, and that dispersion is quite stable in the first 20-month period since product's introduction, does not imply a low frequency of price changes for a product in its early stage of life (Table 1.3 shows that the median monthly frequency of adjustments is 42.19%). The position of retailers within the price distribution might change over time (temporal dispersion) or sellers might keep their position in the price distribution stable by changing prices in the same direction with similar size with others (spatial dispersion). Answering these questions can provide us with useful explanations about the nature of competition as well as the relationship between price stickiness and price dispersion in the US online market.

Varian (1980) argues that sellers would not set their price consistently high or low as overtime buyer should learn sellers' pricing behaviour and identify the seller who offers the best price. In line with that, Sheremirov (2019) pointed out that popular models with menu-cost also can have a similar prediction. For instance, in a high inflation economy, retailers charge higher than the mean price then their prices move to the left of the price distribution due to the rise of the

[8] For the positive relationship between search costs and price dispersion see i.e., Chandra and Tappata (2011); Pereira (2005).

price level. In line with that, using data from the conventional market in Israel, Lach (2002) finds empirical evidence of temporal price dispersion. However, his data coverage is rather small (31 products) in a short period (18 months). Therefore, using a larger coverage of data in the online market, we would expect to find evidence of temporal rather than spatial dispersion since searching in the online market is simple.

Contrary, in the absence of shocks, several models in the search or industrial-organisation literature predict the existence of spatial dispersion (see i.e., Baye et al., 2006). Empirically, by using a large coverage of products and sellers in the U.S. online market, Gorodnichenko et al. (2018) find strong evidence that supports spatial price dispersion.

Following the method employed by existing studies (see i.e., Gorodnichenko et al., 2018a; Lach, 2002), we assign the price of a product offered by a seller to a quartile group of the price distribution across all sellers of that product in a given month then analyse the changes in the quartile of that price line overtime. For example, the price of retailer *s* for CPU *i* in month *t* is p_{ist} and three cut-off points for product *i* in month *t* are $Q_{1it}, Q_{2it}, Q_{3it}$. Then, a seller with the price for product *i* as $Q_{1it} < p_{ist} < Q_{2it}$ is in the second quartile of the cross-sectional distribution in month *t*, while a seller with the price $p_{ist} > Q_{3it}$ is in the fourth quartile (meaning that price for CPU *i* higher than 75% of all sellers offering CPU *i* in month *t*). After that, we construct the fraction of time that p_{is} spends in each quartile and the average fractions across CPUs.

[Table 1.8]

If sellers often change their positions in the distribution (temporal dispersion), the fractions for a given price line should be near to 25%. Meanwhile, if sellers consistently charge lower- or higher-price (spatial dispersion), p_{is} would spend more time in one of the quartiles. We find evidence support for spatial price dispersion in our data. The results for observed prices and residual price are similar, thus, we only reported results using observed prices in Table 1.8. Column (2) shows that 20.3% of price lines spend more than 95% of the time to stay in one quartile of the cross-sectional distribution. In which, 9.7% of price lines almost always stays in the lowest quartile, but surprisingly 7.1% of price lines almost always stays in the highest quartile. Additionally, column (1) shows that from 36.8% to 49.8% of price lines spend almost no time in a given quartile. Such as 42.4% of price lines rarely stay in the cheapest quartile and 49.8% of price lines rarely stay in the most expensive quartile. The performance weighted results are similar. Furthermore, Figure 1.8 plots the distribution of these fractions over observed price lines to provide a clear picture of the existence of the spatial dispersion.

[Figure 1.8]

The last row in Table 1.8 presents a further statistic of the price lines position in price distribution over time, which is the average standard deviation across price lines of the fractions of time spent in a particular quartile. The average standard deviation equal to 0 implying perfect temporal price dispersion, meanwhile, the average standard deviation equal to $\sqrt{3}/4$ (≈ 0.43) implying perfect spatial price dispersion. As we can see, the average standard deviation is 0.284 (the result is similar when weighted), which is closer to 0.43. Hence, both approaches suggest spatial price dispersion rather than temporal price dispersion. These results suggest that a higher frequency of price changes does not necessarily lead to a lower level of price dispersion.

1.4.3. Predictors of price dispersion

Existing literature often explain the price dispersion existence by three main causes, which are search costs, frequency of price changes – the channel in price stickiness models (the difference in prices exist since the price changes are set at a different time), and price discrimination (see i.e., Coibion et al., 2015). To document these sources of price dispersion, we employ the regression of the standard deviation of the log prices on a number of variables, which measure market size, quality of product, returns on search, price stickiness, stability of sellers, share of price points and product brand. Due to the similarity between non-weighted and performance-weighted results, we only report the performance-weighted results in Table 1.9.

[Table 1.9]

Table 1.9 reports the results for the regression of standard deviation of log price in column (1) and the regression results after removing seller fixed effects in column (2). We find that the quality of products has a significantly negative effect on the measure of price dispersion in both cases, before and after removing sellers fixed effects. Meanwhile, median price, frequency and size of regular price adjustments have a positive impact on the level of price dispersion. The results are similar between the regression of posted prices and residual prices after removing seller fixed effects.

Models with price stickiness often predict that an increase in the level of price stickiness is associated with an increase in the level of price dispersion. Since we find a negative relationship between product quality and price stickiness (price changes more frequently and have smaller size), product quality is expected to be negatively associated with the price dispersion level. The evidence of the association between product quality and price dispersion level is consistent with that prediction. Furthermore, our result suggests a positive relationship between the frequency of price changes and the level of price dispersion. This result can be explained with the spatial price dispersion in the market that we observe.

1.5. Technological changes and quality-adjusted price index

1.5.1. Technological changes

1.5.1.1. Sellers' adoption

Panel (a) of Figure 1.9 shows the number of CPU models of each generation overtime since a new CPU generation release. The number of available new generation CPU models gradually increase, while old generation CPU models leave the market. It implies that processor producers do not release all models of a generation when they introduce new technology. Instead, they often release a few new models first, then launch more models using that new microarchitecture and stop selling old generation products.

To adopt the technological upgrades in the market from processor manufacturers and consumer demand, sellers' response by updating the list of CPUs that they are offering. Panel (b) and (c) of Figure 1.9 clearly show a rapid increase in the number of sellers that offer new generation processors and in the number of new-generation models offered by a seller, respectively. As a result, the number of observations of new technology CPU dramatically rise after their releases. These facts suggest that the change in performance scores of CPUs offered by sellers, which is caused by the entry of new CPUs and the exit of old CPUs, can be able to reflect the technological upgrades in the market.

[Figure 1.9]

1.5.1.2. Quality index

In this section, we construct the quality index to capture the technology changes. Since sellers can easily modify their list of products, the changes in quality measures of sellers' product lists might reflect the changes of quality in the processor market.

We estimate the quality changes in the CPU market by employing the following regression for each overlapping two-year period:

$$\overline{logQ_{st}} = \alpha + D_2\beta_1 + logC_{st}\beta_2 + \overline{logP_{st}}\beta_3 + \overline{logP_{st}}^2\beta_4 + SPP_{st}\beta_5 + Intel_{st}\beta_6 + + \gamma_t + \phi_s + \varepsilon_{st} \quad (11)$$

Where $\overline{Q_{st}}$ is the mean of processor performance scores of seller s in month t, D_2 is a dummy variable that equals 1 if the observation is in the 2nd year of the 2-year overlapping period. C_{st}, P_{st}, SPP_{st} and $Intel_{st}$ are the number of CPUs, price of median CPU, the share of convenient prices and share of Intel CPUs offered by seller s in month t, respectively. We estimate the regression at the seller-month level and control for seller and month fixed effects. The coefficient of the dummy variable D_2 measures the changing rate in quality of processors from the first year to the second year in the two-year period.

Table 1.10 reports the regression result for the overlapping two-year periods between 2009 and 2012. Overall, our results capture the quality improvement in chip market over the sample period. Particularly, the growth rate of product quality is 12.1%, 15.7% and 15.8% in the period 2009-2010, 2010-2011 and 2011-2012, respectively. The coefficients of the dummy D_2 are positively significant at 1 percent level. Additionally, we find that other characteristics of the seller such as size of the seller (number of goods), target market segment (median price), pricing behaviour (share of price points), and share of Intel processors in the product list of the seller have some predictive power on the quality of the products offered by the seller.

[Table 1.10]

1.5.2. Quality-adjusted price index

Regarding product quality, the quality bias in the price index (such as substitution issue, new goods issue, and quality change issue) has motivated researcher to find the appropriate approach to measure the quality of products and its impact on the price index. Existing studies often employ hedonic regression to show the positive quality bias in the consumer price index

(CPI) due to quality improvements (see i.e., Bils, 2009; Gordon and Griliches, 1997). An alternative approach is to adjust for quality using the matched-model methodology. However, in an environment with stable prices over product life and with quality improvement over time, matched-model price indices would underestimate the amount of price decrease, therefore, hedonic indices are more appropriate to capture price trends (see i.e., Byrne et al., 2018). Also, the matched-model methodology is inappropriate to construct the price index using sample including short-lived models (see i.e., Deltas and Zacharias, 2004).

Since in the CPU market, the rate of quality improvement is high and the product lifetime is relatively short, this study employs hedonic regression to estimate the quality-adjusted price index. Using a similar method to which in Aizcorbe (2014) and Byrne et al. (2018), we estimate the cross-section regression for every period and then construct the price index based on the results of those regressions. However, the hedonic regressions in previous studies are simple and might not fully capture the changes in the price level. Hence, in this study, besides quality measure, we include market fundamentals in the regression to get more precise estimates. Our dummy-variable hedonic specification is as follow:

$$\overline{logP_{it}} = D_2\beta_1 + logQ_i\beta_2 + log\,S_{it}\,\beta_3 + SPP_{it}\beta_4 + Stab_{it}\beta_5 + Intel_i\beta_6 + \gamma_t + \varepsilon_{it} \qquad (12)$$

Where $\overline{Q_i}$ is the quality (measure by performance score) of processor *i*. D_2 is a dummy variable that equals 1 if the observation is in the 2nd year of the 2-year overlapping period. $\overline{P_{it}}$, S_{it}, SPP_{it} and $Stab_{it}$ are the median price across sellers, number of sellers, the share of convenient prices and seller stability of chip *i* in month *t*, respectively. $Intel_i$ is a dummy, which equals 1 if the processor brand is Intel. We run the regression at the product-month level and control for month fixed effects. Similar to the regression in quality index section, the coefficient of the dummy variable D_2 measures the changing rate in the price level of processors from the first year to the second year in the two-year period.

Table 1.11 shows the result for the overlapping two-year periods. The coefficients of the dummy D_2 are negative and significant at 1 percent level between 2010 and 2012. These results reveal the deflation in the CPU market in this period. However, the insignificant coefficient in column (1) implies the stagnation in the quality-adjusted price level of CPU market during 2009-2010, given that we do not observe any new generations of processor released in this period and the observed price level is stable. Additionally, the estimated coefficients of our explanatory variables are in line with our expectation and stay consistent during the sample period. The processor that has higher quality would have a higher price. Intel processors and processors, which have a higher level of seller stability, are more expensive. Meanwhile, the number of sellers and share of price points have significant and negative impacts on chip price.

[Table 1.11]

1.6. Conclusion

The online data of CPUs provide an exceptional opportunity to dig deeper into the absent factor in existing price-setting literature – product's quality. We exploit this opportunity by using a precise measure for CPU performance as a proxy for product quality to enlighten the important role of quality of goods in price-setting and its impacts on the degree of price stickiness, price dispersion and price level. Our study uses this unique quality measure and a comprehensive dataset, which covers a large number of CPU models and sellers in a long period.

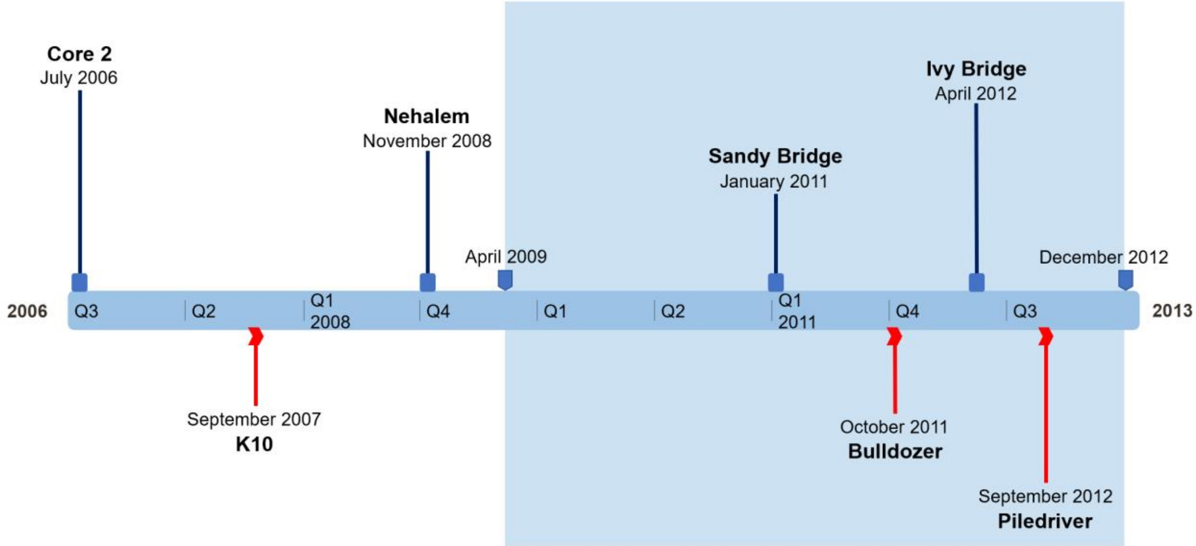
Our findings show that the quality of goods indeed does play a role in price-setting in the online market. High-quality products have prices that are more flexible (higher frequency and smaller size of adjustments) and lower price dispersion than low-quality products. Particularly, better performance CPUs have a higher frequency of negative and lower frequency of positive price changes. As a result, an increase at the aggregate level in product quality in the market should lead to a lower level of price stickiness and price dispersion. A possible explanation for this result is that consumers have incentives to search for high-quality products more than low-quality products since high-quality products have a higher return on search. The pressure from customer search and the higher revenue generated by high-quality products make sellers pay more attention to high-quality products and adjust prices more often (see i.e., Head et al., 2010). In other words, with limited time and attention ability, sellers have to choose to spend their managerial attention on products that benefits them more. Also, this result can be explained with the lower level of inventory for high-quality products due to their expensive cost and lower level of demand. According to pricing models with inventory (see i.e., Aguirregabiria, 1999; Amihud and Mendelson, 1983; Blinder, 1982), sellers can use inventory of finished goods to buffer changes in production and prices. Thus, products with lower level of inventory should have more flexible prices.

Furthermore, we find that the market fundamental, such as number of sellers, median price, share of convenient prices, level of seller stability and product brand are also important factors for explaining price stickiness and price dispersion. In particular, we find that a more competitive market should have a smaller size of price changes, higher frequency of price increase and lower frequency of price decrease. A market with a higher proportion of price points has prices increase less often, while a market with high seller stability level has prices reduce less often. This indicates that bounded rationality could have some roles in the level of price rigidity. Our results also reveal the association between price rigidity and price dispersion: a larger size of regular price adjustment is associated with a higher degree of price dispersion; however, the frequency of regular price changes is positively correlated with price dispersion degree.

It is also interesting to point out the increase in price dispersion over product life and the evidence of spatial dispersion in the online market, given that searching online is easy. In addition, our quality index clearly shows the improvements in processor performance and our quality-adjusted price index reveals the deflation in the U.S. CPU online market in the sample period. We suggest that it is necessary to take the quality of goods into modelling to avoid potential biases and improve the precision in the measurement of traditional economic indicators.

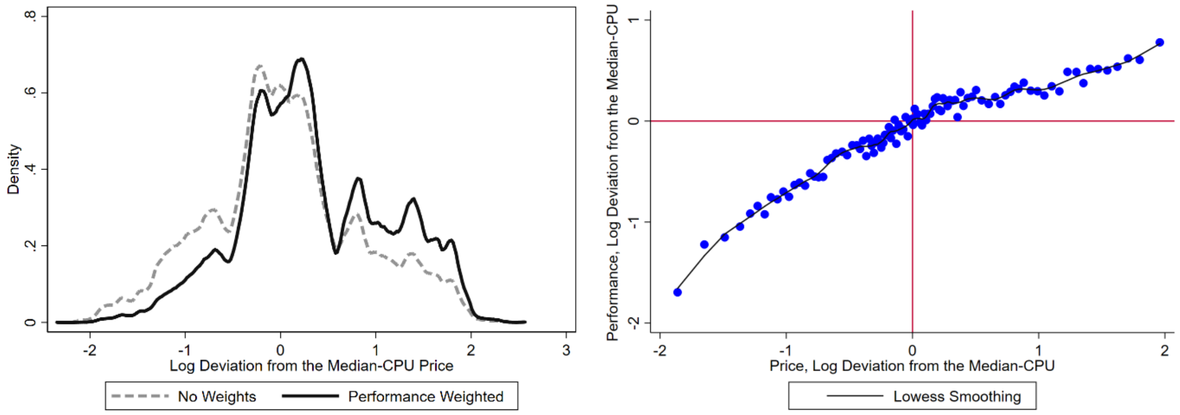
Figures

Figure 1.1. CPU Generations and Release Dates.



Note: This figure presents the timeline of the release date of CPU generations. The blue vertical lines mark the release dates of Intel CPU generations. The red vertical lines mark the release dates of AMD CPU generations. The shaded area indicates the time period covered by our data.

Figure 1.2. Prices and Performances, Log Deviation from the Median-CPU.

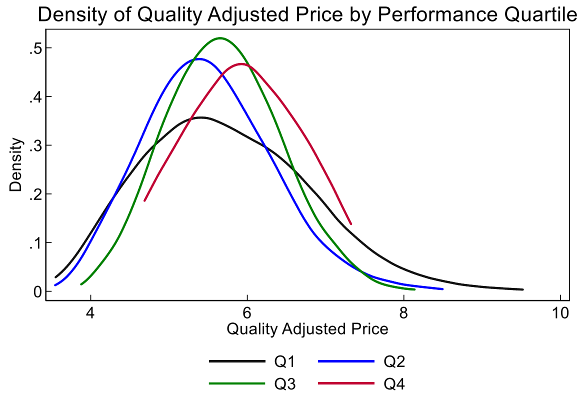


(a) (b)

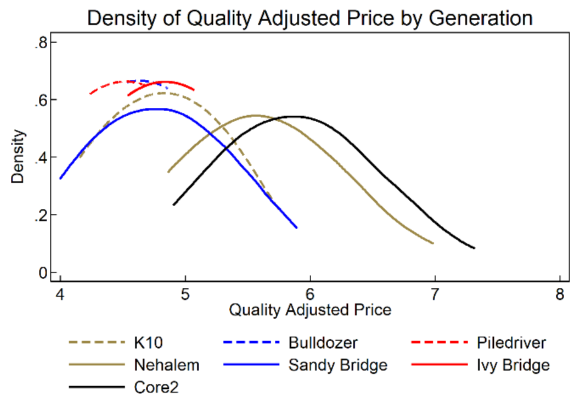
Note: In panel (a), the dashed line illustrates the distribution of the log price deviation from the median price across CPUs, while the solid line illustrates the performance-weighted distribution of that deviation. In panel (b), the dots are data points averaged within bins based on percentiles of the log-deviation of price. Lowess smoother is computed with a 0.1 bandwidth.

Figure 1.3. Quality-Adjusted Price Distribution.

(a)



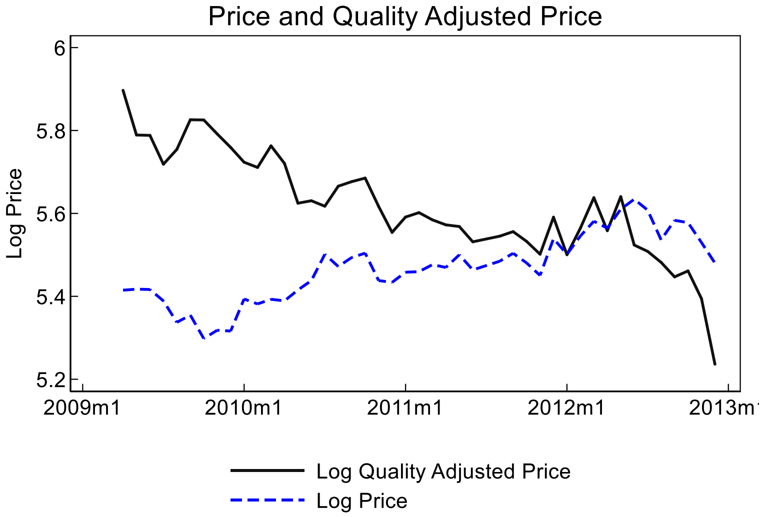
(b)



(c)

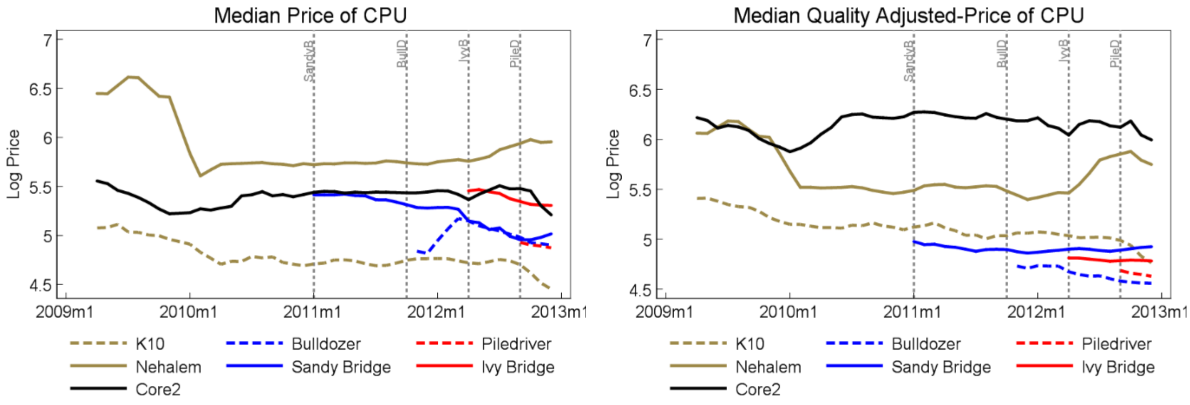
Note: In panel (a), each line illustrates the distribution of the log quality-adjusted price in a price quartile. In panel (b), each line illustrates the distribution of the log quality-adjusted price in a quality quartile. In panel (c), each line illustrates the distribution of the log quality-adjusted price for a CPU generation.

Figure 1.4. Dynamics of Price and Quality-Adjusted Price.



Note: The dashed blue line shows the monthly median log price. The black solid line shows the monthly median log quality-adjusted price.

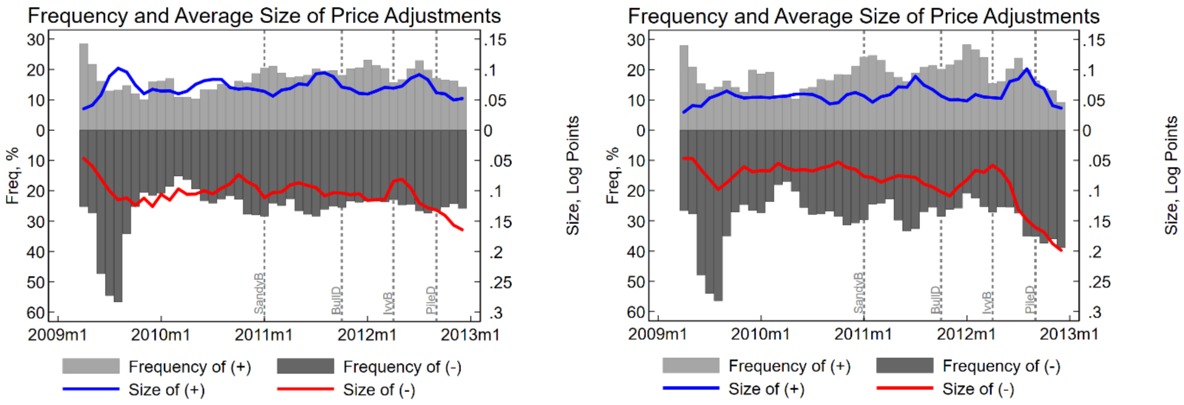
Figure 1.5. Dynamics of CPU Prices.



(a) (b)

Note: In panel (a), each line shows the monthly median log price of a CPU generation. In panel (b), each line shows the monthly median log quality-adjusted price of a CPU generation. In all panel, each grey dashed vertical line marks the release month of the corresponding CPU generation.

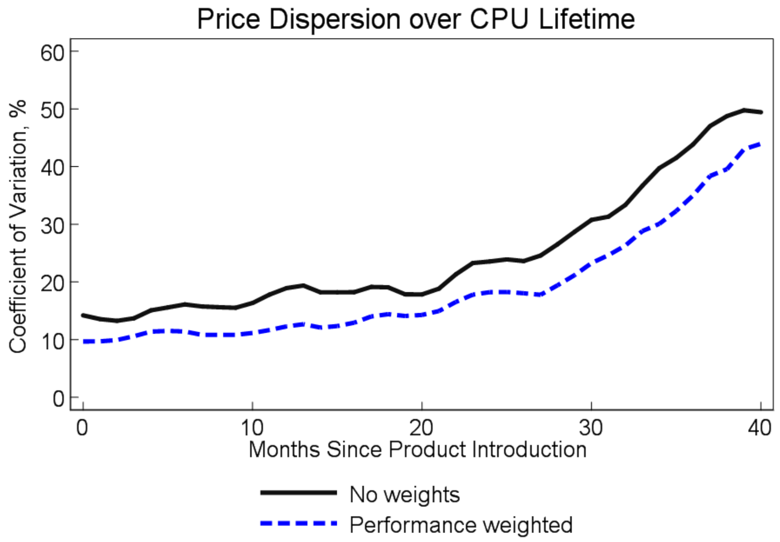
Figure 1.6. Dynamics of Frequency and Size of Price Changes.



(a) Whole Sample (b) Old Models (Core2, K-10 and Nehalem)

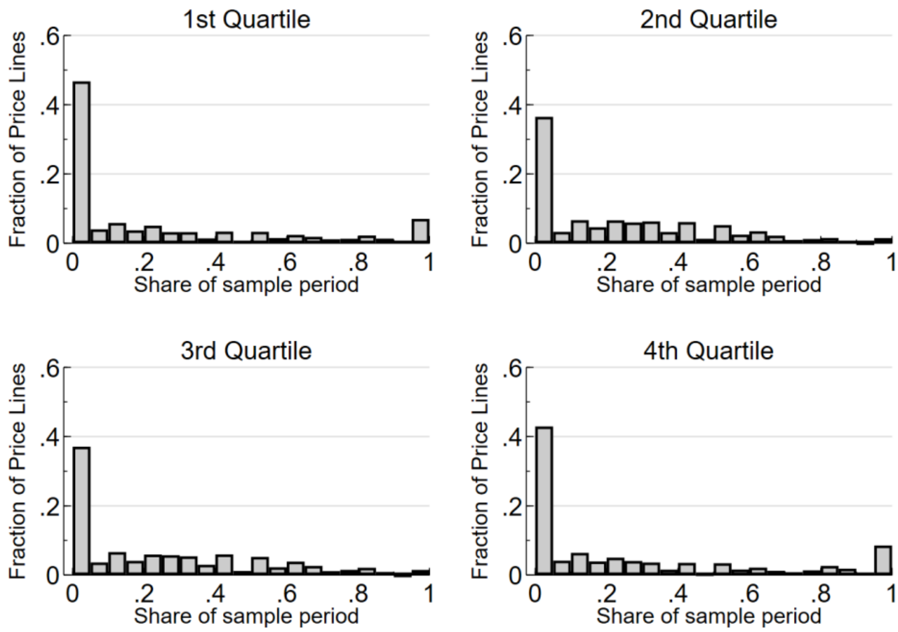
Note: This figure shows the monthly frequency and absolute size of positive and negative price adjustments. In all cases, the vertical axis on the left is the frequency of price changes (%), and the vertical axis on the right is the size of price changes (log points). Each grey dashed vertical line marks the release months of the corresponding CPU generation.

Figure 1.7. Average Price Dispersion over CPU Life.



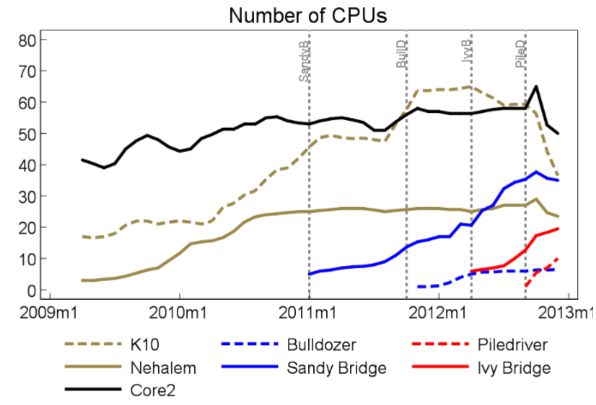
Note: The figure plots the non-weighted and performance-weighted average (over CPUs) of the coefficient of variation for posted prices against the month passed since the product introduction. CPUs introduced during the first quarter are removed to account for truncated observations, and only CPUs with more than a year of life duration are considered.

Figure 1.8. Fraction of Price Lines in each Quartile of the CPU Price Distribution.

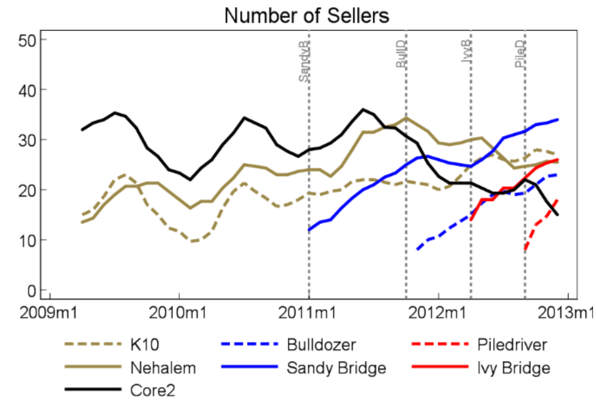


Note: For each monthly product–seller price quote, the portion that the price quote stayed in each of the 4 quartiles of cross-seller price distribution is calculated. The figure illustrates the distribution across price quotes.

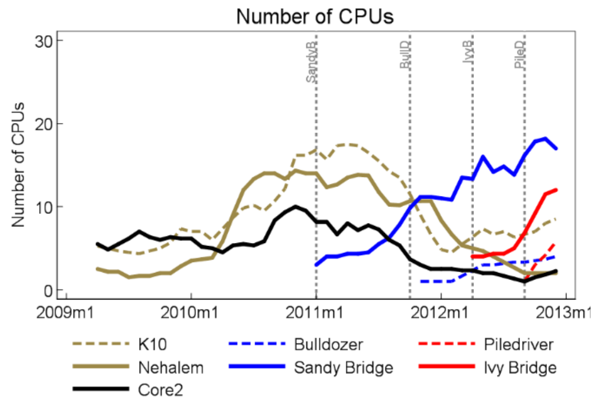
Figure 1.9. CPU Market Composition.



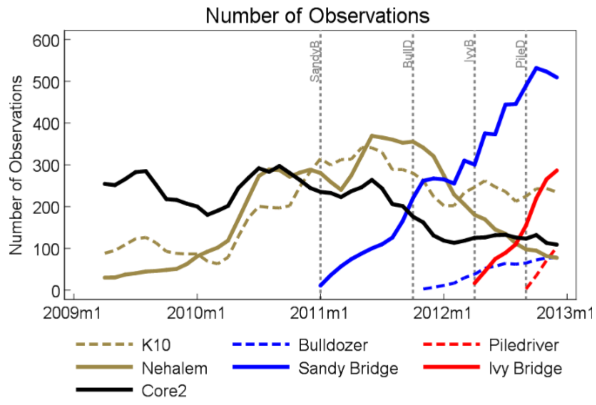
(a) Number of CPU Models in Market



(b) Number of Sellers in Market



(c) Number of CPU Models per Seller



(d) Number of Observations

Note: Panel (a) shows the monthly number of products in each CPU generation. Panel (b) shows the monthly number of sellers in each CPU generation. Panel (c) shows the monthly average number of products in each CPU generation offering by a seller. Panel (d) shows the monthly number of price quotes in each CPU generation. In all panels, each grey dashed vertical line marks the release months of the corresponding CPU generation.

Tables

Table 1.1. Descriptive Statistics for Prices, USD.

	Mean Log Price		Mean Price, Percentile					
	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
No Weights	5.23	0.90	53.33	99.95	190.43	334.93	1106.91	654
Performance Weighted	5.77	0.89	82.41	184.11	300.02	625.31	1529.33	654
Quality-Adjusted Price	5.76	0.86	92.18	157.77	300.26	586.30	1445.70	654

Note: Column (1) and (2) present the mean and standard deviation of the average log price for a CPU ($\overline{log\ p_i}$); column (3)-(7) present the mean price for each percentile of the CPU's price ($\bar{p}_i$); column (8) shows the total number of products, N.

Table 1.2. Monthly Frequency and Size of Sales.

	One-month Two-sided Sales Filter			
	Mean Frequency	SD Frequency	Median Size	N
	(1)	(2)	(3)	(4)
No Weights	1.88	3.64	2.28	535
Performance Weighted	2.34	3.45	1.96	535

Note: Column (1) shows the monthly average of sales frequency across CPUs (%). Column (2) reports the standard deviation of sales frequency across CPUs. Column (3) shows the absolute size of sales for the median CPU, in which the absolute size of sales equal to the gap between the log of sales price and the log of regular price (multiple by 100). Column (4) shows the number of CPUs. A sales is identified by using the one-month, two-sided sales filter.

Table 1.3. Monthly Frequency and Size of Price Changes.

	No Weights (1)	Performance Weighted (2)
Posted Price		
Median Frequency, %	42.17	44.66
Implied Duration, Months	1.83	1.69
Median Absolute Size, Log Points	7.92	5.02
Regular Price		
Median Frequency, %	39.37	40.56
Implied Duration, Months	2.00	1.92
Median Absolute Size, Log Points	8.10	5.26

Note: Column (1) shows the raw frequency and size of price adjustments. Column (2) shows those results after applied performance weighting scheme. We compute the regular prices based on a one-month, two-side sales filter and all missing values are excluded.

Table 1.4. Predictors of Regular-Price Stickiness (at Product Level).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.000	0.002***	-0.002**	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln Performance Scores	0.023*	-0.012*	0.034***	-0.028***
	(0.012)	(0.006)	(0.010)	(0.007)
Ln Median Price	0.193***	0.079**	0.115**	0.128***
	(0.069)	(0.036)	(0.055)	(0.041)
Ln Median Price Squared	-0.019***	-0.007**	-0.012**	-0.010***
	(0.006)	(0.003)	(0.005)	(0.004)
Share of Price Points	-0.056*	-0.069***	0.013	0.029
	(0.030)	(0.016)	(0.024)	(0.020)
Stability of Sellers	-0.481***	-0.068	-0.413***	0.016
	(0.101)	(0.053)	(0.081)	(0.058)
Intel CPU	0.052***	0.029***	0.023*	-0.005
	(0.016)	(0.008)	(0.013)	(0.009)
R^2	0.381	0.357	0.304	0.435
N	608	608	608	607

Note: This table shows the regression results of the frequency of price changes in column (1), frequency of positive price changes in column (2), frequency of negative price changes in column (3), and absolute size of price changes in column (4) of regular price on the set of dependent variables above. All regressions are at product level and include time fixed effects. All variables are unweighted and measured at product level. All regressions include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 1.5. Predictors of Regular-Price Stickiness (at Product-Month Level).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	-0.001	0.013***	-0.014***	-0.031***
	(0.005)	(0.004)	(0.005)	(0.003)
Ln Median Price	0.467***	0.272***	0.195***	-0.078**
	(0.058)	(0.043)	(0.051)	(0.038)
Ln Median Price Squared	-0.053***	-0.019***	-0.033***	0.001
	(0.006)	(0.004)	(0.005)	(0.004)
Share of Price Points	-0.104***	-0.055***	-0.048***	0.021***
	(0.011)	(0.008)	(0.009)	(0.008)
Stability of Sellers	-0.075***	-0.085***	0.010	0.027***
	(0.014)	(0.011)	(0.013)	(0.009)
Ln Number of Higher CPU Enter	0.018**	0.015**	0.003	-0.002
	(0.009)	(0.007)	(0.008)	(0.005)
Ln Number of Lower CPU Enter	0.019**	0.011*	0.008	-0.007
	(0.008)	(0.006)	(0.007)	(0.006)
Ln Number of Higher CPU Exit	-0.004	-0.008	0.004	0.016***
	(0.009)	(0.007)	(0.008)	(0.005)
Ln Number of Lower CPU Exit	-0.021**	-0.012*	-0.009	0.016**
	(0.009)	(0.007)	(0.008)	(0.006)
R^2	0.347	0.201	0.282	0.336
N	14448	14448	14448	8498

Note: This table shows the regression results of the frequency of price changes in column (1), frequency of positive price changes in column (2), frequency of negative price changes in column (3), and absolute size of price changes in column (4) of regular price on the set of dependent variables above. All regressions are at product-month level and include product and time fixed effects. All variables are unweighted and measured at product-month level. All regression include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 1.6. Predictors of Regular-Price Stickiness (at Product-Month Level).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.005	0.015***	-0.010**	-0.030***
	(0.005)	(0.004)	(0.005)	(0.003)
Ln Median Price	0.489***	0.281***	0.208***	-0.073*
	(0.057)	(0.043)	(0.051)	(0.038)
Ln Median Price Squared	-0.055***	-0.020***	-0.034***	0.000
	(0.006)	(0.004)	(0.005)	(0.004)
Share of Price Points	-0.103***	-0.055***	-0.048***	0.020**
	(0.011)	(0.008)	(0.009)	(0.008)
Stability of Sellers	-0.079***	-0.085***	0.006	0.023**
	(0.014)	(0.011)	(0.013)	(0.010)
Upgrading	-0.047**	-0.040**	-0.008	0.008
	(0.021)	(0.016)	(0.019)	(0.014)
Downgrading	0.119***	0.036***	0.083***	0.022***
	(0.010)	(0.007)	(0.009)	(0.006)
R^2	0.354	0.202	0.287	0.336
N	14448	14448	14448	8498

Note: This table shows the regression results of the frequency of price changes in column (1), frequency of positive price changes in column (2), frequency of negative price changes in column (3), and absolute size of price changes in column (4) of regular price on the set of dependent variables above. All regressions are at product-month level and include product and time fixed effects. All variables are unweighted and measured at product-month level. All regressions include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 1.7. Average Dispersion of Posted-Price across Sellers.

	CV	Std(log P)	VI	IQR	Range	Gap	Std(ε)	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Weights	22.27	23.18	24.70	32.48	47.16	22.49	18.83	539
Performance Weighted	14.98	14.85	16.17	18.97	36.99	10.62	11.90	539

Note: Column (1) – (7) report the average dispersion of posted prices measured with: the coefficient of variance (CV), which is computed as the standard deviation divided to the mean (in %); std(log *p*), which is the standard deviation of the log price; value of information (VI), which is computed as the log difference between the average and the minimum price; interquartile range (IQR) equal to the log difference between the 75th and 25th percentile; range is the log difference between the highest and lowest price; gap is the log difference between the two lowest prices; and std(ε), in which ε is the error term in the regression of log *p* on good and seller fixed effects; respectively, for CPU online-market in the US. Column (8) shows the number of products, N.

Table 1.8. Spatial versus Temporal Price Dispersion.

	No Weights		Performance Weighted	
	<5%	>95%	<5%	>95%
	(1)	(2)	(3)	(4)
1st Quartile	42.4	9.7	44.1	9.6
2nd Quartile	37.8	1.4	37.8	1.1
3rd Quartile	36.8	2.1	37.3	1.9
4th Quartile	49.8	7.1	48.4	6.9
Mean SD of Time in Each Quartile	0.284		0.286	

Notes: For each price line, we calculate the proportion of the time that the price line stays in each quartile of the cross-seller price distribution. The table reports the proportion of price lines that almost never (less than 5% of the time) or almost always (more than 95% of the time) fall into a given quartile. The bottom line shows the average (across price lines) standard deviation of the proportion of time spent in each quartile. Under perfectly temporal dispersion, this measure is 0, while under perfectly spatial dispersion, it is approximately 0.43.

Table 1.9. Predictors of Posted-Price Dispersion (at Product Level).

Predictors	Standard Deviation of Log Price (1)	Net of seller fixed effects (2)
Ln Number of Sellers	-0.004***	-0.001
	(0.001)	(0.001)
Ln Performance Scores	-0.095***	-0.081***
	(0.019)	(0.014)
Ln Median Price	0.064***	0.059***
	(0.015)	(0.012)
Share of Price Points	0.098*	0.032
	(0.054)	(0.041)
Frequency of Regular Price Changes, %	0.222***	0.129**
	(0.069)	(0.052)
Size of Regular Price Changes, Log Points	0.009***	0.007***
	(0.001)	(0.001)
Seller Stability	0.186	0.103
	(0.137)	(0.105)
Intel CPU	0.012	-0.003
	(0.022)	(0.017)
R^2	0.527	0.555
N	496	496

Note: This table shows the results of the regression of the standard deviation of log price in column (1), and the regression results after removing seller fixed effects in column (2) on the set of dependent variables above. All regressions are at product-level and include time fixed effects. All the reported variables in this table are unweighted and measured at product-level. All regressions include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 1.10. Quality Index of Sellers over 2009-2012.

	2009-2010	2010-2011	2011-2012
	(1)	(2)	(3)
Year Dummy	0.121***	0.157***	0.158***
	(0.020)	(0.014)	(0.011)
Ln Number of CPUs	0.007	0.054***	0.110***
	(0.016)	(0.014)	(0.013)
Ln Median Price	0.903***	0.264	0.997***
	(0.185)	(0.202)	(0.210)
Ln Median Price Squared	-0.051***	0.005	-0.069***
	(0.017)	(0.019)	(0.019)
Share of Price Points	0.039	-0.076**	0.013
	(0.038)	(0.038)	(0.036)
% of Intel CPU	-0.130**	-0.030	-0.159***
	(0.058)	(0.046)	(0.043)
R^2	0.954	0.957	0.973
N	831	1037	1087

Note: In this table, the dependent variable is ln(*average performance*). Each regression is run separately for each overlapping two-year period between 2009 and 2012. Seller and time fixed effects are included. All the reported variables in this table are unweighted and measured at seller-month level. All regressions include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 1.11. Regression Results for 2009 – 2012.

	2009-2010	2010-2011	2011-2012
	(1)	(2)	(3)
Year Dummy	0.034	-0.124***	-0.071***
	(0.027)	(0.021)	(0.018)
Ln Performance scores	0.801***	0.705***	0.566***
	(0.016)	(0.014)	(0.010)
Ln Number of Seller	-0.229***	-0.195***	-0.130***
	(0.021)	(0.015)	(0.011)
Share of Price Points	-0.754***	-0.618***	-0.547***
	(0.054)	(0.051)	(0.041)
Stability of sellers	0.397***	0.467***	0.306***
	(0.068)	(0.059)	(0.043)
Intel CPUs	0.508***	0.520***	0.426***
	(0.033)	(0.025)	(0.019)
R^2	0.528	0.434	0.373
N	2804	4199	6786

Note: In this table, the dependent variable is ln(*price*). The regression is run separately for each overlapping two-year period between 2009 and 2012. Time fixed effects are included. All the reported variables in this table are unweighted and measured at product-month level. All regressions include a constant, not shown above. Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Chapter 2. Inventory Shock and Price-Setting.[9]

2.1. Introduction

The reasons for price stickiness have vital implications for the real effect of nominal shocks as well as the implementation of monetary and fiscal policy. Common causes proposed in earlier works to explain the substantial price rigidity reported in empirical papers are time-dependent pricing models (e.g., Calvo, 1983), search costs (e.g., Burdett and Judd, 1983), menu costs (e.g., Sheshinski and Weiss, 1977), transportation and delivery costs (e.g., Betancourt and Gautschi, 1993), and bounded rationality (e.g., Akerlof and Yellen, 1985).[10] Later investigations often explain sticky prices through pricing models with inventory (e.g., Boileau and Letendre, 2011), fear of "customer anger" (e.g., Rotemberg, 2005; Anderson and Simester, 2010), and rational inattention (e.g., Sims, 2003; Reis, 2006). While dynamic pricing studies often emphasise the important role of inventory in price-setting, there is little empirical evidence to support this argument.[11] This paper aims to test some of the predictions of common price-setting models in later works using an unanticipated and exogenous supply shock.

Our approach is to explore the response of price setters to a production disruption event, which, in turn, affected the costs and ability to restock. Specifically, the 2011 Thailand flood is used as a trigger of the inventory shock of hard drive sellers throughout the world. This flood started on July 25, 2011, and lasted 158 days. In late October 2011, the flood affected the major hard disk drive (HDD) manufacturing facility of Western Digital Corporation (WD). This company was the world's biggest manufacturer of HDDs. Producing one-third of the total hard drives shipped globally.[12] One month after the suspension of WD's operations in Thailand, the total value of hard drive imports to the U.S. dropped by half, which, in turn, affected the production of computers and components. Leading manufacturers of laptops, desktops, and processors had

[9] In this chapter, we use material that is submitted to University of Birmingham for the assignment of Advanced Research Methods module.
[10] See also Chari, Kehoe, and Mcgrattan (2000) for time-dependent pricing; Benabou (1988) for search costs; Reinsdorf (1994), Golosov and Lucas (2007), and Midrigan (2011) for menu costs; and Dixon (2020) for bounded rationality.
[11] See, e.g., Bilotkach, Gorodnichenko, and Talavera (2010); Abrate, Fraquelli, and Viglia (2012); and Bilotkach, Gorodnichenko, and Talavera (2012) for dynamic pricing, and see, e.g., Lloyd, McCorriston, Morgan, and Rayner (2001) for evidence of the unresponsive prices to shocks that influence the inventory of sellers.
[12] See "Thai floods hit global hard drive production" (Financial Times, October 20, 2011) (Available at: https://tinyurl.com/yczhv35a), accessed on May 1, 2020.

to reduce their production and forecasted revenue for the quarter following the flood.[13] This natural disaster provides us with a unique laboratory for estimating the impact of the inventory shock on the price-setting of not only HDDs but also their substitute products (e.g., solid-state drives), complementary products (e.g., processors and motherboards), and final goods (e.g., laptops and desktops).

Our price quotes dataset contains monthly seller-product price quotes collected from a leading price comparison website. Each product is uniquely identified by its manufacturer part number (MPN). Also, each seller in our dataset has a unique identifier. The large sample covers 34,691 products offered by 2,005 online retailers within five product types: hard drives, desktops, laptops, central processing units (CPUs), and motherboards. The data span the period between March 2010 and October 2012, which also includes the 2011 Thailand flood. Using this comprehensive dataset, we compute the product availability and price indices, which track development in each of five broadly defined markets. Then, we report the properties of price-setting (such as frequency and size of price adjustments) and analyse how price-setting in those markets changes in response to the hard drive supply shock in the U.S. Lastly, we compare our findings with the predictions of popular pricing theories.

Our results show that the foreign supply shock substantially influenced the availability of products in local markets. In particular, we observe that it took about one month for the Thailand production shock to reach U.S. markets, causing a huge reduction in the total value of U.S. hard drive imports. This reduction immediately affected sellers' inventories and caused the availability of hard drives to fall by over one-quarter, which was largely caused by the 58% drop in WD product availability. Although the production facilities of other hard drive producers were not affected by the flood, we observe a fall in the product availability index of HDDs made by other manufacturers as well as solid-state drives (SSDs), as there is considerable substitutability across hard drives. Final goods, like desktops and laptops, also show a decline in their availability, though these reductions were delayed and of smaller magnitude compared to hard drives. Our data also reveal a slight decrease in the availability of motherboards and processors, which are not directly related to hard drives.

Regarding price-setting behaviour, we find that the sellers of WD hard drives responded to the flood almost immediately, even before the inventory shock. Our data reveal the increase

[13] See "Intel cuts revenue forecast as Thai floods hit PC sales" (The Guardian, December 12, 2011) (Available at: https://tinyurl.com/ybz4hcnb), accessed on May 1, 2020.

(decrease) in the frequency of positive (negative) price changes. Sellers of other HDD products had similar—but smaller in magnitude—responses. These findings suggest that prices are sensitive to inventory costs. Sellers raised the prices in anticipation of coming increases in costs related to obtaining new stocks, including money as well as time and effort. Furthermore, the price-setting of SSDs, the closest product substitute for HDD, was only affected one month after the inventory shock. The responses of hard drive sellers to the flood and to the inventory shock peaked within one month following the event, then quickly lessened during the next two-month period. Notably, the prices of final and complementary products showed little response to the shock.

Our study is related to the large literature on price stickiness. Firstly, consistent with models of price-setting and inventory, we document that pricing behaviour is strongly associated with inventory level—in particular, a stockout event.[14] However, our findings show that sellers increased prices before the reduction in their inventories, which suggests that inventory plays a limited role in price smoothing. Secondly, we find that prices are flexible to the sectoral shock as online price-setters regularly keep track of the conditions in their markets. In addition, Gorodnichenko, Sheremirov, and Talavera (2018b) document the inflexible prices in response to aggregate shock even in online markets where common price frictions are small. In line with that, numerous studies using sectoral data find evidence that prices respond slowly to aggregate shocks and are fast to disaggregate shocks.[15] These findings are consistent with the predictions of pricing models with rational inattention (See, e.g., Maćkowiak and Wiederholt, 2015; Matějka, 2016). Lastly, this work is related to price-setting behaviour following natural disasters. For instance, Cavallo et al. (2014) and Gagnon and López-Salido (2020) study the local impact of natural disasters on the price stickiness of supermarket goods and find that prices are unresponsive to shocks due to fear of “customer anger”. We amend this literature by exploring the impacts of a foreign natural disaster on the pricing of storable and durable goods (computers and components).

In addition to price stickiness, this paper contributes to the literature that focuses on the transmission of shocks via supply chains. Empirical studies usually report evidence of the impact of shock propagation via production networks on total gross output (see, e.g., Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019). The shock

[14] See, e.g., Blinder (1982); Reagan (1982); Amihud and Mendelson (1983); Aguirregabiria (1999).
[15] See, e.g., Boivin, Giannoni, and Mihov (2009); Maćkowiak, Moench, and Wiederholt (2009); Kaufmann and Lein (2013); Beck, Hubrich, and Marcellino (2016).

propagation and amplification can be explained with a large contribution to the total output of affected firms (see, e.g., Gabaix, 2011; V. Carvalho and Gabaix, 2013) or the input-output linkages between industries (see, e.g., Horvath, 2000; Giovanni and Levchenko, 2010; Caliendo, Parro, Rossi-Hansberg, and Sarte, 2018; Baqaee, 2018). In addition, Barrot and Sauvagnat (2016) suggest that inventories of intermediate products in the supply chains could help delay the transmission of shock. Our study complements this literature by providing new findings about the impacts of shock propagation through input-output linkage on product availability and prices as well as exploring the role of inventory in delaying shock impacts.

The rest of the paper is organised as follows. Section 2.2 presents our natural experiment—the 2011 Thailand flood. Section 2.3 describes the dataset that we collected and reports the basic statistics. Section 2.4 shows the consequences of the Thailand flood in terms of product availability and the price indices of electronic goods in the U.S. Section 2.5 reports the properties of price changes (such as the frequency and size of price changes) for each product type in our sample and analyses the responses of U.S. electronic sellers. Lastly, section 2.6 is our conclusion.

2.2. The 2011 Thailand Flood

Our analysis makes use of the 2011 Thailand flood, which began at the end of July 2011, then spread through the capital of Bangkok and persisted in several regions until January 2012. It affected two-thirds of the country.[16] The estimated total economic losses in Thailand were about 12.56% of the GDP (see Cavallo et al., 2014). This natural phenomenon caused widespread production disruption and damaged logistics systems. Automobile and hard disk drive were among the most affected industries.[17] The flood heavily damaged several manufacturing plants, including the main production facilities of the world's biggest HDD manufacturer—Western Digital Corporation.

Western Digital was the only HDD producer that had to suspend its production due to the flood. In particular, the company suspended the operation of its main production plant in Thailand on October 21, 2011. This production plant accounted for about 60% of the total HDD production

[16] See "Thailand floods disrupt production and supply chains" (BBC, October 13, 2011) (Available at: https://www.bbc.co.uk/news/business-15285149), accessed on May 1, 2020.
[17] See "Thai Prime Minister to Take Command of Flood Control Efforts" (The New York Times, October 21, 2011) (Available at: https://tinyurl.com/yaul42o5), accessed on May 1, 2020.

of this giant hard drive producer.[18] Consequently, the global HDD shipments dropped about 30% in the quarter following the disaster.[19] Additionally, SSD—the faster, smaller in volume, and more expensive alternative to HDD—was not popular at that time. Therefore, the HDD production disruption triggered a large supply shock in the whole hard drive market in the U.S., although the HDD and SSD production plants of other hard disk manufacturers were not affected.

[Figure 2.1]

The total value of hard drive imports to the U.S. dropped about 50% to reach its bottom four months following the flood. It took U.S. hard drive imports three months to recover to their pre-shock level. In particular, Figure 2.1 shows that the value of hard drives imported to the U.S. from Thailand fell nearly two-thirds just one month after WD suspended the operation of its production plant in Thailand. Meanwhile, the total value of hard drives imported from other countries started to drop two months earlier than that but also hit its bottom at the same time with the hard drive supply shock from Thailand. The total value of U.S. hard drive imports recovered to attain its original level seven months after the flood occurred, then overshot in the following year. Besides being a final product, HDD is a key intermediate product of the computer industry. As a result, the hard drive shortage heavily affected the markets of other computer components as well as final goods. Several large computer manufacturers announced that they were cutting down on their production. Facing the reduction in computer production, Intel—the world's largest processor maker—also had to reduce its production and forecasted revenue for the quarter following the flood.[20] This announcement caused Intel's stocks to fall by over 4% on the same day.[21]

Therefore, besides hard drives, we also document the impact of the hard drive supply shock on the product availability and price-setting of final products as well as other important computer components. In the next section, we describe our dataset and discuss the descriptive statistics

[18] See “Capital Equipment Costs to Repair Flooded HDD Factories in Thailand Will be Considerable” (Forbes, November 7, 2011) (Available at: https://tinyurl.com/ybuu9caq), accessed on May 1, 2020.
[19] See “Global shipments of hard disk drives (HDD) from 4th quarter 2010 to 3rd quarter 2019” (Statista, 2019) (Available at: https://tinyurl.com/y982az7a), accessed on May 1, 2020.
[20] See “Intel cuts revenue forecast as Thai floods hit PC sales” (The Guardian, December 12, 2011) (Available at: https://tinyurl.com/ybz4hcnb), accessed on May 1, 2020.
[21] See “Intel cuts revenue forecasts because of shortages” (BBC, December 12, 2011) (Available at: https://www.bbc.co.uk/news/business-16146355), accessed on May 1, 2020.

of five product types in our dataset: hard drives, desktops, laptops, processors, and motherboards.

2.3. Data

To investigate the impacts of the hard drive supply shock on price-setting behaviour, we constructed a unique dataset of monthly product-seller price quotes for five main product types: hard drives, desktops, laptops, processors, and motherboards. The data were collected from a leading U.S. price comparison website (PCW) for the period from March 2010 to October 2012, which covers the time of the shock.[22] Specifically, on the first day of each month, a Python file was triggered to collect websites and extract prices as well as other relevant information (such as product names, product descriptions, product identifications, seller identifications, and product prices for each seller). The data allowed us to uniquely identify each online seller. Also, each product listed online has a unique identifier, which is the manufacturing product number (MPN). For instance, MPN "WD2500AAKX" uniquely identifies WD Internal 250 GB 3.5″ PC Desktop Hard Disk Drive, which is necessary for the categorisation of products by producers.

The prices in our dataset are net prices, which are the prices before taxes and shipping fees. We exclude all used, refurbished, and pre-order product prices because they are not comparable to the prices of new products. In addition, to minimise the effects of extreme values in our data, we winsorized our variables at both the top and the bottom one percent of their distributions. Lastly, products with fewer than three sellers were excluded from analysis. After application of all the filters above, our dataset included 34,691 electronic products sold across 2,005 sellers in the U.S. e-commerce market.

Using prices collected from our PCW allows us to limit the impact of potential problems such as outdated price quotes (sellers may not have incentives to change prices when they cannot restock). This is because only products that are in stock and available for sale are listed on the PCW. If a product is out of stock, it will instantly disappear from the PCW and appear again only when (and if) it becomes available. Online merchants have incentives to keep their listings on PCWs up to date, as they pay for clicks from price aggregators to their webpages. If their listings are not up to date, they might not gain sales and, thus, waste their advertising money.

[22] See Gorodnichenko and Talavera (2017) for a detailed discussion of a similar dataset.

Furthermore, there exists the possibility that online merchants will post low prices on the PCW to attract customers to their websites, which then offer the products at higher prices. However, Gorodnichenko and Talavera (2017) argue that the price quotes and aggregated prices at the product level are highly consistent across those sources. Thus, PCW price quote data are of rationally high quality and can be used to capture the changes in pricing behaviour in response to shocks.

[Table 2.1]

Table 2.1 shows the average price of each percentile of the distribution over products ($\bar{p}_i$), the mean and standard deviation of the average log price ($\overline{log\, p_i}$), within the dataset. Regarding computer components, the average of log prices in our sample is 5.32 log points (or approximately $204). The product prices are often in the range from around $43 to $2476. Our main interest is the hard drive, which is also the largest product type in our dataset, covering 9,707 products. In our data, the median hard drive cost is $140.65. One-quarter of our hard drives sample are priced under $89.80. while the top 25% of the most expensive hard drives are priced above $247.07. Final products, like laptops and desktops, have higher average prices and a wider price range than computer parts. The average price is approximately $932. Their prices are often in the range between $381 (fifth percentile) and $3,111 (ninety-fifth percentile).

2.4. Impact on Product Availability and Prices

Natural disasters (such as earthquakes, hurricanes, and floods) often disrupt production and significantly influence seller inventory. However, numerous studies have found evidence that price level did not respond to those commodity shortages for several months after the disaster, even in online markets where price frictions are small.[23] Existing literature explains it with price-setting models, where sellers do not increase prices due to a fear of "customer anger" (see, e.g., Rotemberg, 2005). This section challenges this idea by showing the quick response of aggregate prices to the decrease in product availability.

[23] See, e.g., Lloyd et al. (2001); Gagnon and López-Salido (2020) for offline prices, and see, e.g., Cavallo et al. (2014) for online prices.

2.4.1. Product availability

We construct a simple index for the product availability of each product type using the total number of available price quotes of the product type in a month. As described in the data section, a product is very likely to be in our dataset if it is available for purchase on a seller's website. Out-of-stock products will disappear immediately and reappear only when, and if, they are in stock again. Additionally, we focus on the short time period around the natural disaster, in which the number of entries (exits) of new (old) products, as well as online sellers, is small. Therefore, our product availability index can rationally reflect the impact of the supply shock on sellers' inventories and the availability of products in the market. Figure 2.2 shows the product availability indices of HDDs (including WD HDDs and HDDs made by other hard disk drive producers), final products (desktops and laptops), and other computer components (motherboards and CPUs).

[Figure 2.2]

Panels A and B present the HDD availability indices. We observe that the product availability of HDDs remained stable for three months after the flooding disaster occurred. It then fell by 27% to its lowest level in the month of the hard drive imports reduction and did not recover to its original level in the next half-year. In particular, inventories of hard drive sellers were affected by the supply disruption in the fourth month following the flood, causing the product availability of WD HDDs to massively decline by 58%. Similarly, the product availability of HDDs produced by other manufacturers dropped by 24% in the same month, and by a further 16% over the following two months. In contrast, we do not observe this huge drop in product availability indices of HDDs in the same period of the previous year. This evidence suggests that the substitutability across hard drives exists and that the role of sellers' inventory in delaying the supply shock impact in the retail sector might be smaller than previously thought. Furthermore, our product availability indices of hard drives did not increase when the total value of hard drive imports to the U.S. was overshot after the shock. This implies that the supply shock only delays the sales of electronic products and sales overshot after the shock.

Panels C and D of Figure 2.2 show that the product availability of final products did not change a lot over the five-month period following the flood. In the sixth month, two months after the drop of U.S. hard drive imports, we observe a sudden drop of 30% to 36% in the availability indices of desktops and laptops. Meanwhile, in the same period of the year before the flood, we observe an increasing trend in the number of available price quotes of these products. This result is consistent with the literature on the transmission of shocks via production networks. It highlights the impact of HDD production disruption on the product availability of final goods and emphasises the role of intermediate goods inventories in delaying the shock impact on final goods supply. Furthermore, in line with Barrot and Sauvagnat (2016), we observe that the supply shock of an intermediate product is propagated horizontally to other intermediate products of the same final product. In particular, Panels E and F show that the shock affected the product availability of other important computer components in the same month as final products. The availability indices of CPUs and motherboards fell by 18% to 26% compared to their pre-shock level.

2.4.2. Prices

To document the shock impact on prices, we construct our price index for each product type using the relative of geometric mean prices. This method is widely used to construct a price index for the lowest level of aggregation. In particular, we first aggregate prices to the product level by taking the median price across sellers of a product in a month. Secondly, we calculate the monthly price change ratios at the product level. Thirdly, the unweighted geometric mean of all price ratios in a month and product type is computed. Fourthly, for each product type, we set the index value of the first month in the sample to 100 and construct the price index for a month, as the previous month's index value multiplies the unweighted geometric mean of that month. Lastly, we normalize the index to a value of 100 in the month when the flood occurred to make it easier to track the response of prices to the shock as well as to compare responses across product types.

[Figure 2.3]

Figure 2.3 shows our price indices of HDDs, final goods, and two more types of computer components. Panels A and B of this figure present the price indices of WD HDDs and HDDs produced by other manufacturers. We observe that the price indices of HDD are affected within one month after the drop in the hard drive availability index. In particular, in the month of the inventory shock, the price index of WD HDDs increased by 13.8%, and peaked at 138.1% two months later. Similarly, the price index of other HDDs increased at the same time as the WD HDD price index, with a smaller increase of 2.1%. Three months later, it peaked at 114%. On the other hand, in the same time period of the year before the flood, we observe a decreasing trend in the prices of HDDs. Regarding desktops, laptops, CPUs, and motherboards, Panels C-F show little responses of the price indices of these product types after the flood. Their price indices behaved similarly to those of the year before. This suggests that the supply shock impacts could be absorbed, at least partially, in production networks (see, e.g., Carvalho et al., 2016).

2.5. Price Stickiness

In the previous section, we show how the supply shock affected the product availability and price level of hard drives as well as final goods and other intermediate products. The result suggests that "customer anger" is not important in our experiment, where the impact of demand shock is limited. This section extends the assessment to analyse the response of price stickiness at a good level. We aim to explore how price-setters behave around the time of the supply shock and, consequently, the inventories shock, in a market where price frictions are minimal.

2.5.1. Regular and posted prices

Several price-setting studies report a popular practice of sellers, which is changing the prices temporarily for a short period. Existing literature argues that temporary price changes (sales) are unlikely to affect the aggregate prices (e.g., Eichenbaum, Jaimovich, and Rebelo, 2011; Kehoe and Midrigan, 2015); thus, these price quotes are often filtered out. To measure price stickiness, this paper follows standard methods in price-setting literature. We compute the main properties of price changes (frequency and size) and report the results for both posted prices (the prices in our dataset) and regular prices (the prices excluding temporary changes).

Because we do not have an identifier for temporary price changes, we follow previous studies to identify sales by "sales filter" (see, e.g., Nakamura and Steinsson, 2008; Chahrour, 2011). In particular, we identify an increase or decrease in price as a temporary price change if the price returns to its previous level within one month. After that, we construct the regular prices by replacing the price at the time of the temporary price change with the "regular price" (i.e., the price at the original level).

[Table 2.2]

Table 2.2 reports the monthly frequency and size of sales for five product types in our dataset. Generally, the frequency and size of sales in our dataset are in a similar range with the statistics reported in other empirical studies on online prices for the U.S. The average monthly frequency of sales for five product types in our dataset is similar in scale, ranging from 1.32% to 2.18%. In terms of size, CPUs, motherboards, laptops, and desktops have a similar size of sales, with the median size of each product type ranging from 2.66% to 3.75%. Meanwhile, hard drives often have a larger size of sales than other products, with a median size of 6.22%. Because temporary price changes are not popular in our data, we expect that the difference between the results of posted prices and regular prices is not large.

2.5.2. Frequency of price changes

Following previous studies (e.g., Bils and Klenow, 2004), we consider a price change as a non-zero price change if its size is greater than 0.1%. Firstly, the monthly frequency of price changes for each product is calculated as the proportion of non-zero price changes to the total number of price changes observed within the product in a month. Secondly, we aggregate this measure to product type level by taking the no weights average across products within the product type in a month. Lastly, we calculate the average implied duration of price changes for each product type from the average frequency. This measure translates the frequency of price changes into the implied duration of price spells for a product keeping its price unchanged. It is calculated as $\overline{d_C} = (-1)/\ln{(1 - \overline{f_C})}$, where $\overline{d_C}$ is the average implied duration of product type *C* and $\overline{f_C}$ is the average frequency of price changes of product type *C*.

[Table 2.3]

The estimated monthly frequency and the corresponding implied duration for each product type are reported in Table 2.3. In general, all our product types have a median implied duration smaller than 2.5 months for posted price results. Filtering out temporary sales increases the implied duration by 5.6% to 17.8%. Hard drives have the most flexible prices in our sample, with median implied durations of 1.36 months for the posted price and 1.47 months for the regular price. The prices of final products are slightly stickier. Their median durations range from 1.74 to 2.07 months. The stickiest prices in our sample are for CPUs and motherboards, which have median durations in the range of 2.22 to 2.91 months. These results are similar to the statistics reported for the U.S. online market in existing studies and are lower than statistics in the offline market. For example, Gorodnichenko et al. (2018) report that the average implied duration of all products is from 1.54 to 2.54 months, respectively. Similarly, the implied duration of hardware products is in the range of 1.63 to 2.69 months. Meanwhile, in offline markets, Nakamura and Steinsson (2008) observe stickier prices, with a duration of 4.5 to 11 months. However, personal computers and the peripheral equipment category tend to exhibit more flexible prices, with a duration in the range of 2.35 to 3.35 months.

Figure 2.4 shows how the frequency of price adjustments responded to the shock for five product types: HDD (including HDD made by WD and other producers), desktop, laptop, CPU, and motherboard. Panel A shows that in the month of the inventory shock (i.e., the third month following the flood), WD HDD sellers increased and decreased the frequency of positive and negative price changes, respectively. Although production facilities of other hard disk producers were not hit by the flood, Panel B presents similar, but smaller-magnitude, reactions in the pricing of non-WD HDDs. Meanwhile, we do not observe similar changes in the year before the flood.[24] Regarding final products and other computer components, Panels C-F indicate that the frequency of the price adjustments of laptops, desktops, CPUs, and motherboards show only small responses after the shock. Sellers of these products still had a pricing strategy similar to that of the previous year.[25] This result is consistent with the unresponsive price indices of these products to the shock presented in Figure 2.3.

[Figure 2.4]

2.5.3. Size of price changes

Similar to the frequency calculations, we first compute the size of price changes for each quote line as the absolute value of price changes. Second, we aggregate this measure to product level by taking the raw average of non-zero price changes across sellers without seller weights. Third, at the product type level, the raw average size of price changes across products within the product type is computed.

Table 2.3 presents the median absolute size of price adjustments for each product type. The median size of price changes in our sample is close to the reported statistics for both online and offline markets in the existing literature.[26] In particular, we observe that the prices of hard

[24] See Online Appendix Panels A and B of Figure FA2.1.
[25] See Online Appendix Panels C-F of Figure FA2.1.
[26] For the U.S. online market, Gorodnichenko et al. (2018) report that the median size of price changes varies from 10.9% to 11% for all products and is slightly higher for hardware products, from 13.7% to 13.8%. Similarly, for the U.S. offline market, Nakamura and Steinsson (2008) report that the median size of price

drives have the largest adjustment size among all product types. The results for posted prices and regular prices are similar: 14.39% and 14.62%, respectively. Over half of our CPUs have an average size of price adjustments larger than 12%. Meanwhile, the median sizes of price adjustments of other product types (motherboard, desktop, and laptop) are smaller, all below 5.5%.

The dynamics of the size of price changes are presented in Figure 2.4. As can be seen in Panel A, the inventory shock caused the considerable increase in the size of positive price changes of WD HDDs, which was not observed in the previous year. Their size of negative adjustments increased as well. However, it does not necessarily reflect the downward trend in prices of WD HDDs. This increase is due to the large drop in the number of price decreases around the time of the inventory shock. In particular, we have only 95 price decreases in the month of the inventory shock (compared to about 900 price increases). Most of the price decreases in this period are used to adjust prices after irrational price increases. For example, the prices of the WD CaviarBlack 1.5TB hard drive offered by two out of 25 sellers increased dramatically from about $160 to above $2000, while other sellers kept their prices at a more reasonable level.[27] Thus, after their price increase, these two sellers had to decrease their prices, though the new prices after reduction were still nearly double the prices in the pre-flood period. Regarding HDDs produced by other manufacturers, Panel B shows a similar response of their size of price changes, though at a smaller magnitude. In contrast, Panels C-F of Figure 2.4 show that the sizes of the price changes of other intermediate products, such as CPUs and motherboards, as well as final goods, such as desktops and laptops, were only slightly affected.

2.5.4. Predictors of price stickiness

This section aims to contribute to the existing literature by analysing how price stickiness behaves around the time of a large exogenous shock. We use shock dummies that control for time periods before and after the flooding disaster to run the regression of price-setting measures (frequency and size of price changes). Because the features of the market and goods might be related to the heterogeneity of price stickiness across goods, we control for those factors in our analysis.

changes is from 8.5% to 10.7% for all products and from 9.3% to 11.3% for personal computers and peripheral equipment.

[27] See Online Appendix Figure FA2.2.

Firstly, existing literature often highlights the role of market power in price-setting (see, e.g., Ginsburgh and Michel, 1988; Martin, 1993). This paper uses the number of sellers as a proxy for the degree of market power. In particular, a market with more sellers is more competitive. Thus, sellers in such a market are expected to have less market power and to change prices more frequently.

Secondly, firm entry could affect sellers' pricing strategies (see, e.g., Gust, Leduc, and Vigfusson, 2010). This is because a market that is easy for sellers to enter should be more competitive. Therefore, sellers in such a market should adjust their prices faster. This paper uses the stability of sellers, which is the ratio of the number of sellers offering a product in a given month to the number of sellers ever selling that product in the quarter covering the given month, to reflect the degree of difficulty that sellers experience in selling a product. Similar to the number of sellers, we expect that seller stability is positively associated with degree of price rigidity.

Thirdly, numerous studies state that consumers' search costs influence pricing decisions (see, e.g., Head, Kumar, and Lapham, 2010). The idea is that the higher search intensity of customers would put more pressure on price setters to set competitive prices. Because the more expensive products should have a higher return on search, we use the log median prices to capture the returns on the search of consumers.

Finally, we use the percentage of convenient prices, which are price quotes that end in 95 to 99 cents, to reflect the level of customer inattention to prices when choosing a product across sellers. According to Knotek (2011), categories that have a higher share of convenient prices usually have stickier prices. This positive association can be explained with the price friction caused by the large difference between convenient price points.

Because our main interest is documenting the shock impact, we focus on and keep only the 10-month period around the event (two months before and seven months after the month of the flood) in the sample to run the regression. This time period is relatively short. Therefore, we estimate the pricing moment and our predictors at the product-month level. In particular, we compute, for instance, the monthly frequency of price changes for a specific product, as the fraction of non-zero adjustments of that product in a month to use as our dependent variable. Regarding the shock impact, because the shock occurred in the middle of the month, we consider the two-month period covering the shock as shock months. Therefore, we include, in the right-hand side, variables of our regression four dummies to capture the responses of price-setting measures to the shock. Each dummy represents a two-month period starting from the time of the shock. We run the regressions below with no weights and control for product fixed effects.

$$f_{it} = log\, S_{it}\, \beta_1 + \overline{logP_{it}}\beta_2 + \overline{logP_{it}}^2\beta_3 + SPP_{it}\beta_4 + Stab_{it}\beta_5 + \\ + \sum_k Shock_{T+k,\, k+1}\, \alpha_k + \theta_i + \varepsilon_{it} \qquad (1)$$

In which, f_{it} is the frequency, frequency of positive, frequency of negative, or size of price changes for product *i* at month *t*; S_{it} is the number of sellers offering product *i* at month *t*; $\overline{logP_{it}}$ is the log of the median price of product *i* at month *t*; SPP_{it} is the share of price points of product *i* at month *t*; $Stab_{it}$ is the stability of the number of sellers offering product *i* at month *t* (1 quarter base); $Shock_{T+k,\, k+1}$ is a dummy variable that is equal to 1 if the month is *k* or *k+1* months following the shock; and θ_i is the goods fixed effect.

[Table 2.4]

Table 2.4 reports the estimates of regular prices for the WD HDD sample. Regarding our control variables, the result suggests that almost all of them have some predictive power. Firstly, the median price across sellers of a product is positively (negatively) associated with the frequency of price increases (decreases). This finding is consistent with Richards et al. (2014), who also find that consumer search makes prices increase faster and decrease slower. Secondly, products that have a higher proportion of price points tend to have stickier prices. This result is consistent with Levy et al. (2011), according to whom products with 9-ending prices have a lower frequency and a larger size of price adjustments as compared to products with non-9-ending prices. Thirdly, measures of market competitiveness (such as the number and stability of sellers) are unlikely to affect the pricing of WD HDDs in this sample period.

Regarding the response of price-setting to the shock, our results show that WD HDD sellers responded to the expected inventory shock one month following the flood, although their products were still available for sale. However, two months after that, when the shock hit their inventory, their response was even stronger than it was before. In particular, in the period within one month after the flood, on average, the frequency of positive adjustments is 22.2% higher and the size of adjustments is 5.6% larger than in the pre-flood period. However, this reaction lessened in the next two months. After that, WD announced the further extension of its production suspension.[28] The impact of this announcement and the inventory shock caused by the reduction of imports in the fourth month after the flood led to the stronger response of WD HDD sellers. In this period, WD HDD sellers raised their prices 40.2% more frequently and decreased their prices 14.5% less frequently as compared to the pre-flood level. Also, the size of adjustments was 27.6% larger than in the pre-flood period. However, this reaction to the inventory shock lasted only within this period.

These responses are consistent with the prediction of pricing models with rational inattention (e.g., Maćkowiak and Wiederholt, 2009) and sticky information (e.g., Mankiw and Reis, 2002), according to whom prices are flexible to sectoral shocks because sellers frequently update the conditions of their sectors. However, these models assume that sellers update information perfectly, therefore suggesting a too-high degree of price flexibility on the micro-level. Meanwhile, the observed price quotes in our dataset change less frequently than in those models. Instead, the model of rational inattention with discrete pricing in Matějka (2016), in which sellers update information continually but not perfectly, could generate the price rigidity on the micro-level that is closer to the characteristics of our dataset. Additionally, sellers' instant response to the flood, despite having their products available for sale, shows little support for models of price stickiness with "fear of customer anger" as well as the role of inventory in price smoothing.

Next, we want to distinguish the shock impact on the price-setting of WD HDDs to non-WD HDDs. We therefore run the regression on a sample including all HDD products. Applying the same setting with regression (1), we add four interaction terms between our shock dummies and *WD*, a dummy variable that equals one if the product is produced by WD and zero otherwise. The results are presented in Table 2.5. Regarding our control variables, in general, the estimated coefficients are consistent with the regression results for the WD HDD sample. For example, the median price and share of price points have qualitatively similar results to those reported in Table 2.4. Meanwhile, measures of market competitiveness have significant predictive power on price-setting when we expand our sample size. In particular, a higher number of sellers and a lower level of seller stability are positively associated with a higher degree of price flexibility. This result supports the view that a more competitive market should have more flexible prices.

[28] See "WD: Thailand floods worse than feared" (The Register, October 17, 2011) (Available at: https://tinyurl.com/yb5qfu63), accessed on May 1, 2020.

[Table 2.5]

Regarding price-setting behaviour after the shock, our results show that the price-setting of non-WD HDDs had a similar, but smaller in magnitude, response to the inventory shock compared to WD HDDs. This finding suggests that the disruption of WD production affected the pricing of HDDs made by other manufacturers. This is because sold-out WD products increased the demand for their substitute products, therefore indirectly triggering the inventory shock of non-WD HDDs.[29] However, the magnitude of non-WD HDD inventory shock should be smaller, as not all WD customers move to other brands. As a result, the price-setting of WD HDDs reacted to the inventory shock more strongly than non-WD HDDs response. In particular, in the inventory shock period, on average, the frequency of positive adjustments of WD HDDs was 15.7% higher than that of non-WD HDDs, while their frequency of negative adjustments was similar. Also, the size of adjustments of WD HDD was 13.6% larger in this period. Yet, in the next two months, while the reaction of WD HDD sellers ended, non-WD HDD sellers kept increasing their prices.

Then, to distinguish the response of HDD sellers from that of sellers of other types of hard drives (such as SSD), we run the regression on the whole hard drive sample covering all hard drive products. Applying the same setting, we replace the four interaction terms in the previous regression with four new interaction terms between the shock dummies and *HDD*, a dummy variable that equals one if the product is an HDD and zero otherwise. The estimates reported in table 2.6 show that the coefficients of our predictors of price stickiness (e.g., the number of sellers, the median price across sellers, the share of price points, and the stability of sellers) are consistent with our previous analysis. The results of a comparison of the responses of HDDs to other types of hard drives suggest that SSD sellers did not respond to the flood, but, rather, reacted to the inventory shock. Their reaction to the inventory shock is similar to, but smaller in magnitude than, that of HDD sellers. This finding is consistent with, and generates similar implications to, the Table 2.5 results.

[Table 2.6]

[29] For the effects of stock-out products on substitute products see, e.g., Campo, Gijsbrechts, and Nisol (2003); Ge, Messinger, and Li (2009).

To test whether the changes in price-setting reported in Tables 2.4-6 are the responses of sellers to the supply shock or, instead, represent some sort of seasonal effect, we perform the "placebo test".[30] The idea is to analyse the pricing behaviour of U.S. sellers in the same period of a year in which such a supply shock did not exist, then compare it to the reported evidence of the shock impact. In particular, we run the three regressions above with their corresponding sample for the same 10-month sample period, but in the year before the flood occurred. The results are reported in Online Appendix Table TA2.1-3. We find that WD HDD, non-WD HDD, and SSD sellers also increased their frequency of positive adjustments and decreased their frequency of negative adjustments in some months. However, the magnitude of these changes was relatively small compared to the reactions reported above. Additionally, there are mostly no differences between the price-setting of WD HDDs, non-WD HDDs, and SSDs in that sample period.

Finally, we analyse the price-setting of final products and other intermediate goods. The regression results for desktops, laptops, CPUs, and motherboards are reported in Online Appendix Table TA2.4-7. In general, we find that the price-setting of these products was only marginally affected in the five-month period following the flood, which covers the month of the hard drive inventory shock. However, in the next two months, when the inventories of final and complementary products were affected, sellers in these markets started responding similarly to hard drive sellers. While pricing models with rational inattention provide little explanation for the delayed response of sellers of final goods and complementary products, models with bounded rationality can better explain this behaviour. According to bounded rationality models, sellers do not react to all shocks; they react only to shocks that move them out of their "comfort zone", which in this case is the shock to their inventories (see, e.g., Akerlof and Yellen, 1985; Dixon, 2020). Additionally, this finding can be explained by multi-sector price stickiness models with input-output linkages (see, e.g., Petrella and Santoro, 2011).

Regarding the magnitude of the response of sellers of final goods and complementary products compared to the pre-flood level, we find a substantial increase (by 19% to 23.5%) and drop (by 10.4% to 13%) in the frequency of positive and negative price adjustments, respectively, of final goods. Pricing behaviours of other complementary computer parts exhibited weaker responses. The frequency of the price increases of CPUs and motherboards increased by 22.7% and 13.4%, respectively. Meanwhile, their frequency of price decreases was similar to the pre-flood level. This finding validates the results in Carvalho et al. (2016), who argue that the

[30] For the existence of seasonal patterns in price-setting see, e.g., Dhyne et al. (2006); Vermeulen et al. (2012), and for placebo tests see, e.g., DiNardo and Pischke (1997); Abadie and Gardeazabal (2003).

magnitude of propagation effects weakens as the shock transmits through the production network.

2.6. Conclusion

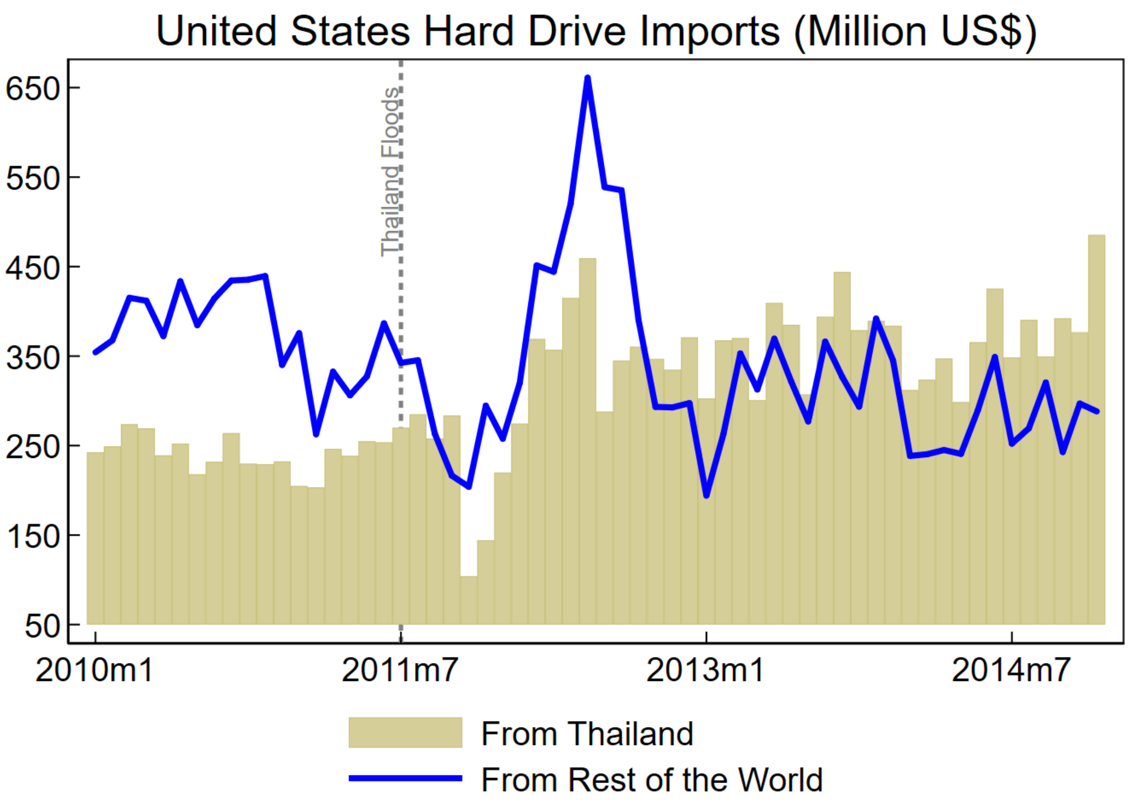
We study the response of price-setting behaviour to a well-identified inventory shock. Representing a natural experiment, the 2011 Thailand flood forced the closure of the main production plant of the world's biggest HDD producer—Western Digital. This event triggered a large and exogenous shock to the global supply of HDD as well as to the HDD supply in the U.S. The total value of hard drive imports to the U.S. fell drastically about one month after WD suspended its operations in Thailand. Consequently, the inventory of sellers and the product availability in the U.S. hard drive market were severely affected.

In this paper, we employ a large and comprehensive dataset of online price quotes in the U.S. This dataset not only allows us to capture impacts of the shock on sellers' inventory and product availability but also provides useful insight into how price-setting behaves in response to the event. We observe that the inventories of U.S. retailers were instantly affected by the supply shock, causing a large drop in the product availability of hard drives. Furthermore, we observe the reductions in the product availability of final goods (desktops and laptops) as well as important computer components (processors and motherboards), although these reductions were delayed and of a smaller magnitude as compared to that of hard drives. While the former result points out the trivial role of retailers' inventory in delaying the shock's impact, the latter result suggests that inventory in production networks could considerably absorb and delay the shock's impact on production and, consequently, on the inventory of final goods and complementary products. This finding is in line with Barrot and Sauvagnat (2016), who also document that inventories delay the impact of supply shock propagation via input-output linkages.

Regarding price-setting, we find that hard drive sellers increased their prices almost instantly in response to the inventory shock. Sellers of final goods and complementary products had similar, but smaller-magnitude, responses when their inventories were affected. This reaction is consistent with pricing models involving inventory (see, e.g., Boileau and Letendre, 2011), which predict that prices are set based on inventory levels. However, the response of hard drive sellers to the flood, before the inventory shock, is inconsistent with inventory models, which usually emphasise the role of inventory in price smoothing. Our results also support price-setting models with rational inattention (see, e.g., Matějka and McKay, 2015; Matějka, 2016), according to which prices are responsive to sectoral shocks. Nevertheless, models with rational inattention hardly explain the delayed response in the price-setting of final goods and complementary products. Meanwhile, models with bounded rationality (see, e.g., Dixon, 2020) and models with input-output linkages (see, e.g., Petrella and Santoro, 2011) can sufficiently explain this delay. Furthermore, our findings show little support for pricing models with "customer anger" in the absence of demand shock, which is strongly associated with the needs and fears of customers after a natural disaster.

Figures

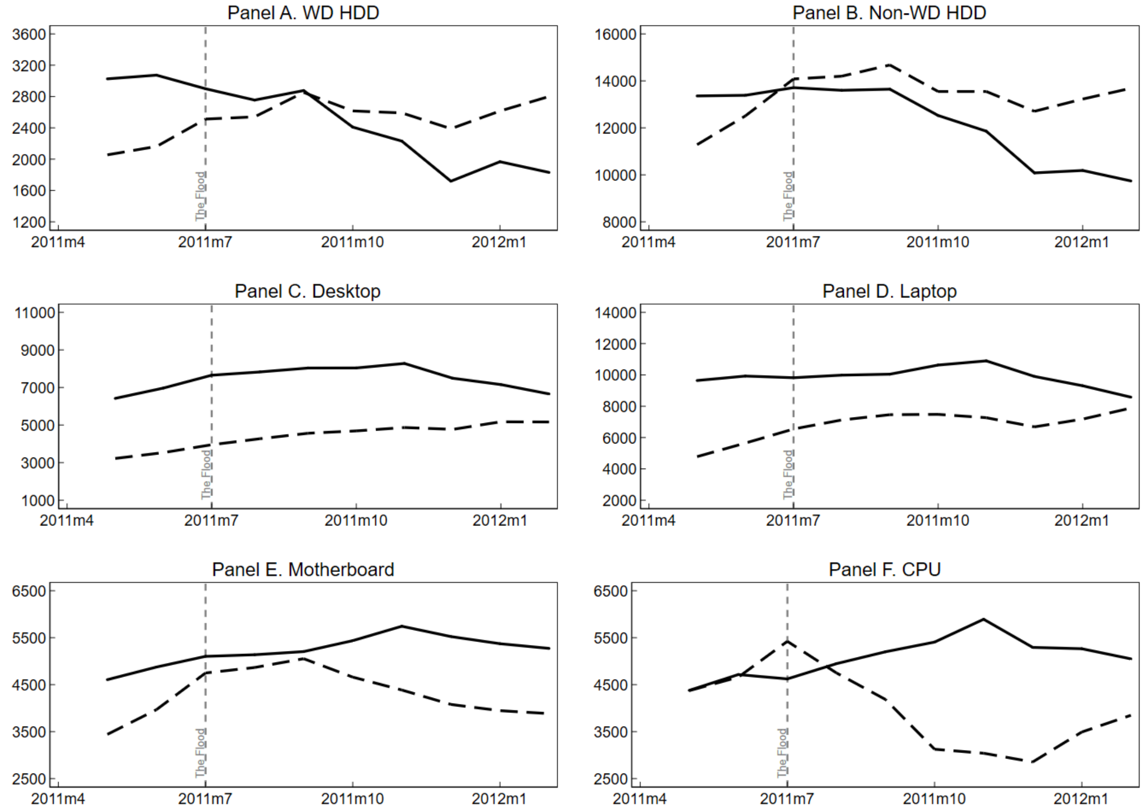
Figure 2.1. Value of United States Hard Drive Imports.



Source: UN Comtrade (2019)

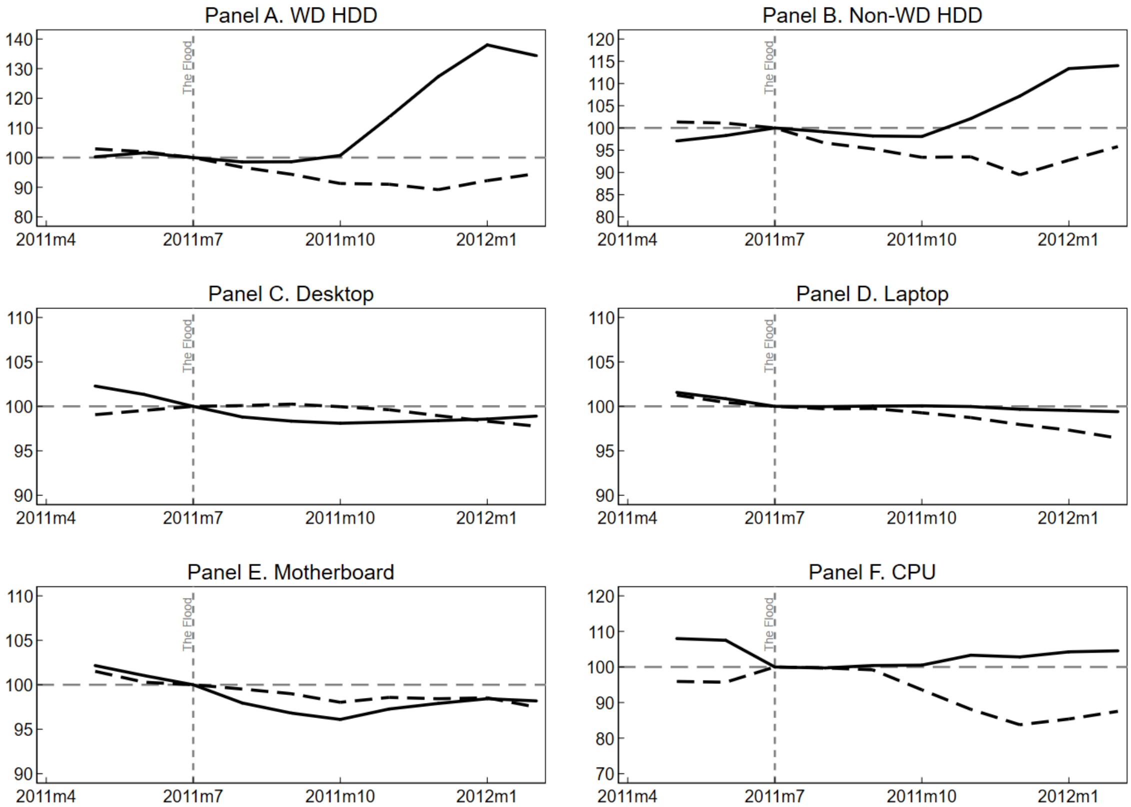
Note: This figure shows the monthly value of hard drives (in million US$) were imported to United States. The grey dashed vertical line marks the month of the flood.

Figure 2.2. Number of Available Price Quotes.



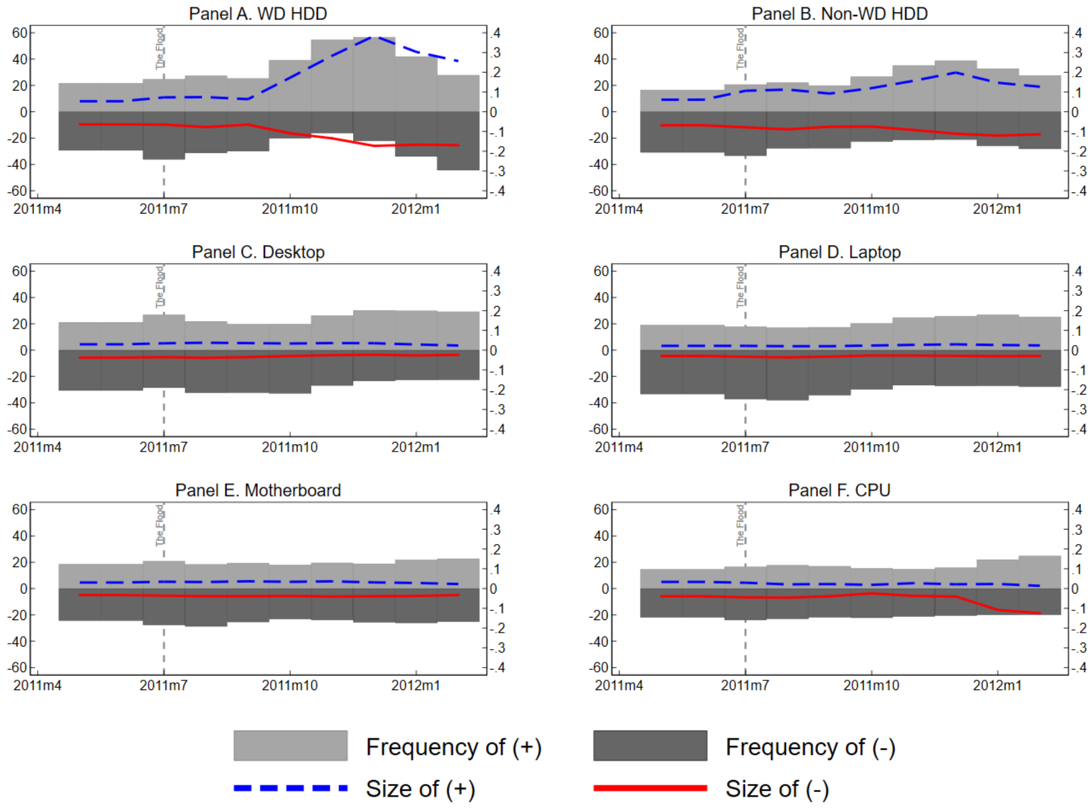
Note: This figure shows the monthly product availability indices. In all cases, the black solid line presents the number of available price quotes in the 10-month period around the flood, between May 2011 and Feb 2012. The black dashed line presents the number of available price quotes in the period of 12 months before, between May 2010 and Feb 2011. The vertical axis is the number of price quotes. The grey dashed vertical line marks the month of the flood.

Figure 2.3. Price Index.



Note: This figure shows the monthly price indices. In all cases, the black solid line presents the price index in the 10-month period around the flood, between May 2011 and Feb 2012. The base month is July 2011, in which the flood occurred in Thailand. The black dashed line presents the price index in the period of 12 months before, between May 2010 and Feb 2011. The base month is July 2010, 12 months before the month of the flood. The vertical axis is the price index (%). The grey dashed horizontal line marks the price level in the base month. The grey dashed vertical line marks the month of the flood.

Figure 2.4. Frequency and Size of Price Changes.



Note: This figure shows the monthly frequency and absolute size of positive and negative price adjustments in the 10-month period around the flood, between May 2011 and Feb 2012. In all cases the vertical axis on the left is the frequency of price changes (%), and the vertical axis on the right is the size of price changes (log points). The grey dashed vertical line marks the month of the flood.

Tables

Table 2.1. Distribution of Prices, USD.

Product type	Mean Log Price		Mean Price, Percentile					
	Mean	SD	5%	25%	50%	75%	95%	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hard Drive	5.10	1.00	48.00	89.80	140.65	247.07	1038.89	9,707
CPU	5.85	1.22	52.26	135.62	349.26	846.10	2475.54	4,039
Motherboard	5.34	1.13	42.99	94.89	198.99	399.99	1523.21	3,503
Desktop	6.80	0.64	389.00	599.99	827.97	1243.99	2829.49	8,037
Laptop	6.87	0.65	381.32	619.99	884.99	1450.70	3110.96	9,405

Note: Column (1) and (2) report the mean and standard deviation of the distribution of the average log price for a product ($\overline{log\ p_i}$); column (3)-(7) report the mean for each percentile of the average price for a product ($\bar{p}_i$); column (8) shows the total number of products, N.

Table 2.2. Monthly Frequency and Size of Sales.

Product	One-month Two-sided Sales Filter			
	Mean Frequency	SD Frequency	Median Size	N
	(1)	(2)	(3)	(4)
Hard Drive	1.49	2.85	6.22	5,420
CPU	1.32	3.36	2.66	2,420
Motherboard	2.18	4.13	3.75	2,500
Desktop	1.62	4.25	2.95	3,259
Laptop	1.51	3.83	2.57	3,624

Note: Column (1) shows the monthly average of sales frequency across products (%). Column (2) reports the standard deviation of sales frequency across products. Column (3) shows the absolute size of sales for the median product, in which the absolute size of sales equal to the gap between the log of sales price and the log of regular price (multiple by 100). Column (5) shows the number of products. A sale is identified by using the one-month, two-sided sales filter.

Table 2.3. Monthly Frequency and Size of Price Changes.

Product	Desktop	Laptop	Motherboard	CPU	Hard Drive
Posted Price					
Median Frequency, %	40.00	43.73	33.33	36.32	51.97
Implied Duration, Months	1.96	1.74	2.47	2.22	1.36
Median Absolute Size, Log Points	5.21	4.79	5.38	12.17	14.39
Regular Price					
Median Frequency, %	38.33	40.00	29.07	33.57	49.30
Implied Duration, Months	2.07	1.96	2.91	2.44	1.47
Median Absolute Size, Log Points	5.10	4.76	5.40	12.33	14.62

Note: The first and second row of each panel present the estimated monthly frequency and the corresponding implied duration for each product type. The last row of each panel shows the median absolute size of price adjustments for each product type. We exclude missing values and compute the regular prices based on a one-month, two-sided sales filter.

Table 2.4. Predictor of Regular-Price Stickiness (WD HDD Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.002	-0.006	0.008	-0.011
	(0.018)	(0.018)	(0.019)	(0.012)
Ln Median Price	0.454***	0.748***	-0.294***	0.354***
	(0.089)	(0.089)	(0.092)	(0.057)
Ln Median Price Squared	-0.034***	-0.052***	0.018**	-0.027***
	(0.008)	(0.008)	(0.008)	(0.005)
Share of Price Points	-0.110***	0.016	-0.126***	0.113***
	(0.027)	(0.028)	(0.029)	(0.019)
Stability of Sellers	-0.063	-0.047	-0.016	-0.001
	(0.047)	(0.047)	(0.049)	(0.030)
$\text{Shock}_{\text{T+0,1}}$	0.213***	0.222***	-0.008	0.056***
	(0.020)	(0.020)	(0.021)	(0.012)
$\text{Shock}_{\text{T+2,3}}$	-0.040**	0.055***	-0.095***	0.018*
	(0.016)	(0.016)	(0.017)	(0.010)
$\text{Shock}_{\text{T+4,5}}$	0.257***	0.402***	-0.145***	0.276***
	(0.018)	(0.018)	(0.018)	(0.011)
$\text{Shock}_{\text{T+6,7}}$	0.146***	0.058***	0.088***	0.110***
	(0.019)	(0.019)	(0.020)	(0.012)
R^2	0.481	0.461	0.263	0.527
N	3,123	3,123	3,123	2,561

Note: This table shows the results of the WD HDD sample regression using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\text{Shock}_{\text{T+(k),(k+1)}}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\text{Shock}_{\text{T+0,1}}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 2.5. Predictor of Regular-Price Stickiness (HDD Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.020**	0.028***	-0.008	-0.006
	(0.008)	(0.008)	(0.008)	(0.005)
Ln Median Price	0.237***	0.614***	-0.377***	0.217***
	(0.032)	(0.029)	(0.030)	(0.024)
Ln Median Price Squared	-0.016***	-0.036***	0.019***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.002)
Share of Price Points	-0.171***	-0.106***	-0.064***	0.026***
	(0.013)	(0.012)	(0.012)	(0.008)
Stability of Sellers	-0.178***	-0.036**	-0.142***	0.036***
	(0.020)	(0.018)	(0.019)	(0.012)
$\mathrm{Shock}_{\mathrm{T+0,1}}$	0.147***	0.225***	-0.078***	0.074***
	(0.008)	(0.007)	(0.007)	(0.004)
$\mathrm{Shock}_{\mathrm{T+2,3}}$	-0.090***	0.012**	-0.102***	0.019***
	(0.007)	(0.006)	(0.006)	(0.004)
$\mathrm{Shock}_{\mathrm{T+4,5}}$	0.116***	0.255***	-0.140***	0.144***
	(0.007)	(0.007)	(0.007)	(0.004)
$\mathrm{Shock}_{\mathrm{T+6,7}}$	0.048***	0.130***	-0.082***	0.069***
	(0.008)	(0.007)	(0.007)	(0.004)
$\mathrm{Shock}_{\mathrm{T+0,1}} * \mathrm{WD}$	0.076***	0.000	0.076***	-0.019
	(0.023)	(0.021)	(0.022)	(0.012)
$\mathrm{Shock}_{\mathrm{T+2,3}} * \mathrm{WD}$	0.057***	0.046***	0.012	-0.003
	(0.018)	(0.017)	(0.017)	(0.010)
$\mathrm{Shock}_{\mathrm{T+4,5}} * \mathrm{WD}$	0.148***	0.157***	-0.009	0.136***
	(0.019)	(0.017)	(0.018)	(0.010)
$\mathrm{Shock}_{\mathrm{T+6,7}} * \mathrm{WD}$	0.123***	-0.061***	0.184***	0.042***
	(0.019)	(0.017)	(0.018)	(0.010)
R^2	0.471	0.408	0.313	0.448
N	25,370	25,370	25,370	18,177

Note: This table shows the results of the HDD sample regression using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\mathrm{Shock}_{\mathrm{T+(k),(k+1)}}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\mathrm{Shock}_{\mathrm{T+0,1}}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. WD is a dummy variable, which equals 1 if product *i* is WD product, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

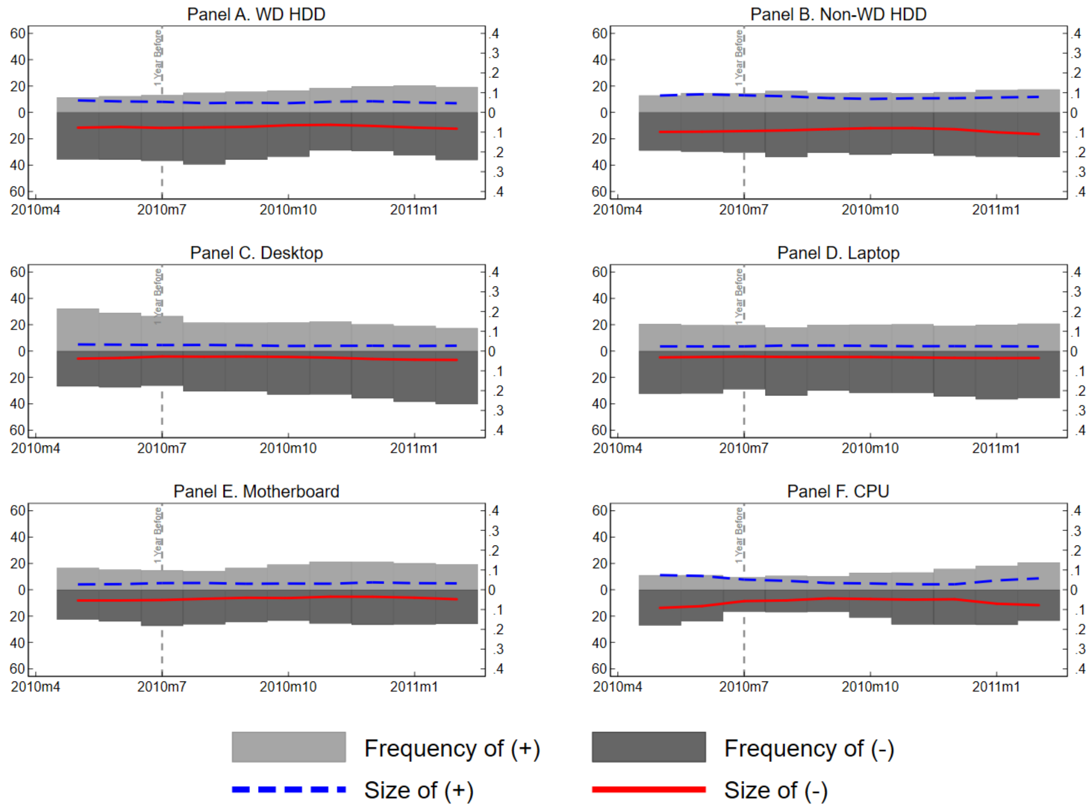
Table 2.6. Predictors of Regular-Price Stickiness (Hard Drive Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.013*	0.016**	-0.003	-0.007*
	(0.008)	(0.007)	(0.007)	(0.004)
Ln Median Price	0.252***	0.627***	-0.375***	0.255***
	(0.030)	(0.028)	(0.028)	(0.023)
Ln Median Price Squared	-0.017***	-0.036***	0.019***	-0.015***
	(0.003)	(0.002)	(0.002)	(0.002)
Share of Price Points	-0.173***	-0.100***	-0.073***	0.029***
	(0.012)	(0.011)	(0.011)	(0.007)
Stability of Sellers	-0.157***	-0.048***	-0.110***	0.023**
	(0.019)	(0.017)	(0.018)	(0.011)
$\text{Shock}_{T+0,1}$	0.110***	0.038*	0.072***	0.040***
	(0.022)	(0.021)	(0.021)	(0.011)
$\text{Shock}_{T+2,3}$	0.007	0.040**	-0.033*	0.008
	(0.019)	(0.017)	(0.018)	(0.010)
$\text{Shock}_{T+4,5}$	0.001	0.079***	-0.078***	0.046***
	(0.019)	(0.017)	(0.018)	(0.010)
$\text{Shock}_{T+6,7}$	-0.021	0.091***	-0.112***	0.038***
	(0.019)	(0.018)	(0.018)	(0.010)
$\text{Shock}_{T+0,1} * \text{HDD}$	0.045*	0.187***	-0.142***	0.032***
	(0.023)	(0.022)	(0.022)	(0.012)
$\text{Shock}_{T+2,3} * \text{HDD}$	-0.091***	-0.023	-0.068***	0.011
	(0.019)	(0.018)	(0.018)	(0.010)
$\text{Shock}_{T+4,5} * \text{HDD}$	0.134***	0.193***	-0.059***	0.117***
	(0.020)	(0.018)	(0.019)	(0.010)
$\text{Shock}_{T+6,7} * \text{HDD}$	0.083***	0.025	0.058***	0.036***
	(0.020)	(0.019)	(0.019)	(0.011)
R^2	0.467	0.397	0.319	0.447
N	28,245	28,245	28,245	20,485

Note: This table shows the results of all hard drives sample regression using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\text{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\text{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. HDD is a dummy variable, which equals 1 if product *i* is HDD product, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

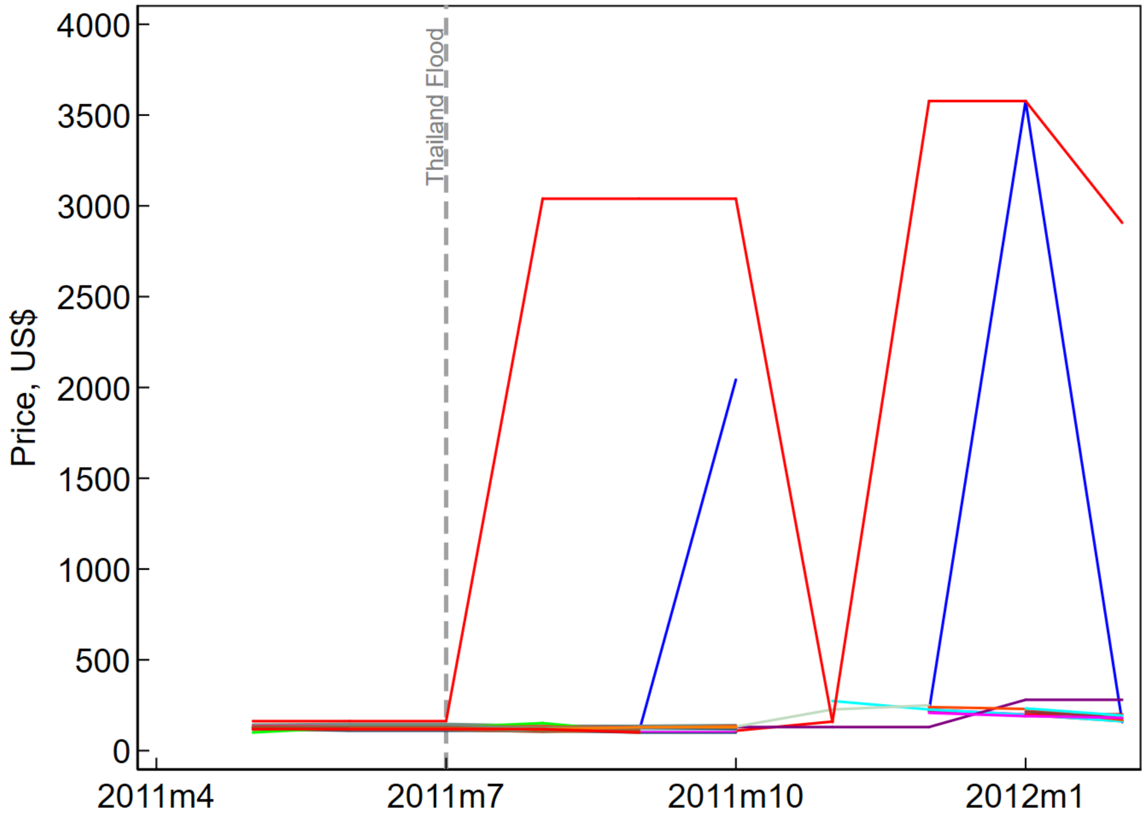
Appendix

Figure FA2.5. Frequency and Size of Price Changes.



Note: This figure shows the monthly frequency and absolute size of positive and negative price adjustments in the 10-month period, between May 2010 and Feb 2011. In all cases the vertical axis on the left is the frequency of price changes (%), and the vertical axis on the right is the size of price changes (log points). The grey dashed vertical line marks the month that is one year before the month of the flood.

Figure FA2.6. WD CaviarBlack 1.5TB Hard Drive.



Note: This figure shows the price lines of the WD CaviarBlack 1.5TB hard drive. Each price line shows a path of price quotes for a given seller. The grey dashed vertical line marks the month that the floods occurred in Thailand.

Table TA2.7. Predictor of Regular-Price Stickiness (Placebo Test, WD HDD Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	-0.042**	-0.017	-0.025	-0.021**
	(0.019)	(0.014)	(0.019)	(0.009)
Ln Median Price	-0.275**	0.390***	-0.665***	-0.013
	(0.125)	(0.091)	(0.126)	(0.060)
Ln Median Price Squared	0.020*	-0.029***	0.049***	-0.000
	(0.011)	(0.008)	(0.011)	(0.005)
Share of Price Points	-0.100**	-0.034	-0.066	0.018
	(0.040)	(0.029)	(0.041)	(0.020)
Stability of Sellers	0.039	0.011	0.028	0.023
	(0.041)	(0.030)	(0.042)	(0.020)
$\text{Shock}_{T+0,1}$	0.038**	0.021*	0.017	0.013
	(0.018)	(0.013)	(0.018)	(0.008)
$\text{Shock}_{T+2,3}$	0.034*	0.051***	-0.018	0.001
	(0.017)	(0.012)	(0.017)	(0.008)
$\text{Shock}_{T+4,5}$	-0.002	0.076***	-0.077***	0.018**
	(0.018)	(0.013)	(0.019)	(0.009)
$\text{Shock}_{T+6,7}$	0.076***	0.086***	-0.010	0.037***
	(0.018)	(0.013)	(0.018)	(0.008)
R^2	0.390	0.286	0.318	0.426
N	2,784	2,784	2,784	2,262

Note: This table shows the results of the WD HDD sample regression using the monthly regular price adjustments between May 2010 and Feb 2011 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\text{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\text{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.8. Predictor of Regular-Price Stickiness (Placebo Test, HDD Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	-0.057***	-0.032***	-0.025***	-0.012***
	(0.008)	(0.006)	(0.008)	(0.004)
Ln Median Price	-0.136**	0.357***	-0.493***	-0.027
	(0.058)	(0.044)	(0.057)	(0.030)
Ln Median Price Squared	0.004	-0.015***	0.020***	0.003
	(0.006)	(0.005)	(0.006)	(0.003)
Share of Price Points	-0.097***	-0.013	-0.084***	0.025***
	(0.016)	(0.012)	(0.016)	(0.009)
Stability of Sellers	0.008	-0.009	0.018	0.041***
	(0.014)	(0.011)	(0.014)	(0.008)
$\text{Shock}_{T+0,1}$	0.064***	0.036***	0.028***	-0.007*
	(0.007)	(0.005)	(0.007)	(0.004)
$\text{Shock}_{T+2,3}$	0.017***	0.039***	-0.023***	-0.004
	(0.006)	(0.005)	(0.006)	(0.004)
$\text{Shock}_{T+4,5}$	0.056***	0.054***	0.002	0.003
	(0.007)	(0.006)	(0.007)	(0.004)
$\text{Shock}_{T+6,7}$	0.077***	0.069***	0.008	0.025***
	(0.007)	(0.006)	(0.007)	(0.004)
$\text{Shock}_{T+0,1} * \text{WD}$	-0.027	-0.011	-0.016	0.020**
	(0.019)	(0.015)	(0.019)	(0.010)
$\text{Shock}_{T+2,3} * \text{WD}$	0.016	0.020	-0.004	0.006
	(0.019)	(0.015)	(0.019)	(0.010)
$\text{Shock}_{T+4,5} * \text{WD}$	-0.069***	0.030**	-0.100***	0.023**
	(0.019)	(0.015)	(0.019)	(0.010)
$\text{Shock}_{T+6,7} * \text{WD}$	-0.009	0.023	-0.032*	0.018*
	(0.019)	(0.015)	(0.019)	(0.010)
R^2	0.458	0.306	0.371	0.451
N	25,804	25,804	25,804	18,801

Note: This table shows the results of the HDD sample regression using the monthly regular price adjustments between May 2010 and Feb 2011 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\text{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\text{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. WD is a dummy variable, which equals 1 if product *i* is WD product, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.9. Predictor of Regular-Price Stickiness (Placebo Test, Hard Drive Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	-0.057***	-0.032***	-0.025***	-0.013***
	(0.007)	(0.006)	(0.007)	(0.004)
Ln Median Price	-0.106*	0.346***	-0.452***	-0.013
	(0.056)	(0.044)	(0.056)	(0.028)
Ln Median Price Squared	0.000	-0.014***	0.014**	0.001
	(0.006)	(0.005)	(0.006)	(0.003)
Share of Price Points	-0.096***	-0.006	-0.090***	0.021***
	(0.015)	(0.011)	(0.015)	(0.008)
Stability of Sellers	0.016	-0.011	0.028**	0.040***
	(0.014)	(0.011)	(0.014)	(0.007)
$\text{Shock}_{\text{T+0,1}}$	0.091***	0.043**	0.047**	0.001
	(0.022)	(0.017)	(0.022)	(0.010)
$\text{Shock}_{\text{T+2,3}}$	0.017	0.034**	-0.017	0.006
	(0.021)	(0.016)	(0.021)	(0.010)
$\text{Shock}_{\text{T+4,5}}$	0.029	0.060***	-0.031	0.013
	(0.021)	(0.016)	(0.021)	(0.010)
$\text{Shock}_{\text{T+6,7}}$	-0.028	0.080***	-0.108***	0.022**
	(0.021)	(0.017)	(0.021)	(0.010)
$\text{Shock}_{\text{T+0,1}} * \text{HDD}$	-0.029	-0.008	-0.021	-0.005
	(0.023)	(0.018)	(0.023)	(0.011)
$\text{Shock}_{\text{T+2,3}} * \text{HDD}$	0.002	0.008	-0.006	-0.009
	(0.022)	(0.017)	(0.022)	(0.010)
$\text{Shock}_{\text{T+4,5}} * \text{HDD}$	0.019	-0.002	0.020	-0.008
	(0.022)	(0.017)	(0.022)	(0.011)
$\text{Shock}_{\text{T+6,7}} * \text{HDD}$	0.104***	-0.008	0.111***	0.005
	(0.022)	(0.017)	(0.022)	(0.011)
R^2	0.460	0.304	0.375	0.456
N	28,200	28,200	28,200	20,813

Note: This table shows the results of all hard drives sample regression using the monthly regular price adjustments between May 2010 and Feb 2011 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\text{Shock}_{\text{T+(k),(k+1)}}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\text{Shock}_{\text{T+0,1}}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. HDD is a dummy variable, which equals 1 if product *i* is HDD product, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.10. Predictor of Regular-Price Stickiness (Desktop Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.133***	0.094***	0.040***	-0.006***
	(0.009)	(0.007)	(0.007)	(0.002)
Ln Median Price	-1.169**	3.017***	-4.186***	-2.405***
	(0.498)	(0.408)	(0.424)	(0.124)
Ln Median Price Squared	0.080**	-0.158***	0.238***	0.171***
	(0.036)	(0.030)	(0.031)	(0.009)
Share of Price Points	-0.080***	-0.049***	-0.031*	0.009*
	(0.021)	(0.017)	(0.017)	(0.005)
Stability of Sellers	-0.200***	-0.122***	-0.078***	0.006
	(0.021)	(0.018)	(0.018)	(0.006)
$\mathrm{Shock}_{T+0,1}$	0.009	0.012	-0.003	0.014***
	(0.009)	(0.008)	(0.008)	(0.003)
$\mathrm{Shock}_{T+2,3}$	-0.003	0.029***	-0.032***	0.008***
	(0.010)	(0.008)	(0.008)	(0.003)
$\mathrm{Shock}_{T+4,5}$	-0.054***	0.043***	-0.097***	0.012***
	(0.011)	(0.009)	(0.009)	(0.003)
$\mathrm{Shock}_{T+6,7}$	0.105***	0.235***	-0.130***	0.004
	(0.012)	(0.010)	(0.010)	(0.003)
R^2	0.459	0.360	0.385	0.540
N	17,889	17,889	17,889	7,120

Note: This table shows the result of the regression on desktop sample using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\mathrm{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\mathrm{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.11. Predictor of Regular-Price Stickiness (Laptop Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.093***	0.043***	0.050***	-0.004***
	(0.007)	(0.005)	(0.006)	(0.002)
Ln Median Price	-2.066***	0.191	-2.257***	0.681***
	(0.627)	(0.497)	(0.554)	(0.138)
Ln Median Price Squared	0.119***	0.067*	0.052	-0.066***
	(0.046)	(0.036)	(0.041)	(0.010)
Share of Price Points	-0.021	-0.000	-0.021	0.014***
	(0.016)	(0.013)	(0.014)	(0.004)
Stability of Sellers	-0.024	-0.034**	0.011	0.002
	(0.017)	(0.013)	(0.015)	(0.004)
$\mathrm{Shock}_{\mathrm{T+0,1}}$	0.032***	0.034***	-0.001	0.011***
	(0.009)	(0.007)	(0.008)	(0.002)
$\mathrm{Shock}_{\mathrm{T+2,3}}$	-0.011	0.045***	-0.056***	0.010***
	(0.009)	(0.007)	(0.008)	(0.002)
$\mathrm{Shock}_{\mathrm{T+4,5}}$	-0.016	0.068***	-0.084***	0.012***
	(0.010)	(0.008)	(0.009)	(0.003)
$\mathrm{Shock}_{\mathrm{T+6,7}}$	0.086***	0.190***	-0.104***	0.013***
	(0.011)	(0.009)	(0.010)	(0.003)
R^2	0.487	0.388	0.421	0.528
N	18,483	18,483	18,483	9,278

Note: This table shows the result of the regression on laptop sample using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\mathrm{Shock}_{\mathrm{T+(k),(k+1)}}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\mathrm{Shock}_{\mathrm{T+0,1}}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.12. Predictor of Regular-Price Stickiness (CPU Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.013	0.001	0.013	0.020***
	(0.010)	(0.008)	(0.009)	(0.006)
Ln Median Price	0.457***	0.170***	0.287***	0.605***
	(0.068)	(0.054)	(0.059)	(0.045)
Ln Median Price Squared	-0.052***	-0.003	-0.049***	-0.062***
	(0.006)	(0.005)	(0.005)	(0.004)
Share of Price Points	-0.134***	-0.055***	-0.080***	-0.012
	(0.017)	(0.014)	(0.015)	(0.013)
Stability of Sellers	-0.014	-0.033**	0.019	0.010
	(0.019)	(0.015)	(0.016)	(0.013)
$\mathrm{Shock}_{T+0,1}$	0.085***	0.061***	0.024***	0.008
	(0.009)	(0.008)	(0.008)	(0.006)
$\mathrm{Shock}_{T+2,3}$	0.049***	-0.012*	0.061***	-0.013**
	(0.009)	(0.007)	(0.008)	(0.006)
$\mathrm{Shock}_{T+4,5}$	0.002	0.013*	-0.011	0.034***
	(0.009)	(0.007)	(0.008)	(0.006)
$\mathrm{Shock}_{T+6,7}$	0.237***	0.227***	0.011	0.040***
	(0.011)	(0.009)	(0.009)	(0.007)
R^2	0.441	0.327	0.382	0.565
N	12,684	12,684	12,684	5,915

Note: This table shows the results of the desktop sample regression using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\mathrm{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\mathrm{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. The measures of price stickiness are unweighted. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA2.13. Predictor of Regular-Price Stickiness (Motherboard Sample).

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Price Changes, Log Points (4)
Ln Number of Sellers	0.057***	0.008	0.050***	-0.009***
	(0.009)	(0.007)	(0.007)	(0.003)
Ln Median Price	0.134	0.503***	-0.370***	-0.014
	(0.101)	(0.081)	(0.085)	(0.056)
Ln Median Price Squared	-0.020**	-0.040***	0.020***	-0.002
	(0.009)	(0.007)	(0.007)	(0.005)
Share of Price Points	-0.002	-0.011	0.009	0.011*
	(0.015)	(0.012)	(0.013)	(0.007)
Stability of Sellers	-0.083***	-0.069***	-0.014	-0.006
	(0.019)	(0.015)	(0.016)	(0.008)
$\mathrm{Shock}_{T+0,1}$	0.013	0.020***	-0.007	0.011***
	(0.009)	(0.008)	(0.008)	(0.004)
$\mathrm{Shock}_{T+2,3}$	-0.019**	0.027***	-0.046***	0.005
	(0.009)	(0.007)	(0.008)	(0.004)
$\mathrm{Shock}_{T+4,5}$	-0.029***	0.010	-0.039***	0.014***
	(0.009)	(0.008)	(0.008)	(0.004)
$\mathrm{Shock}_{T+6,7}$	0.138***	0.134***	0.003	-0.010**
	(0.011)	(0.009)	(0.009)	(0.005)
R^2	0.380	0.261	0.301	0.495
N	13,179	13,179	13,179	6,178

Note: This table shows the results of the desktop sample regression using the monthly regular price adjustments between May 2011 and Feb 2012 on the set of dependent variables above. Particularly, Ln Number of Sellers and Ln Median Price are the natural logarithm of the number of sellers and the median price across sellers of product *i*, respectively. Share of price points is the proportion of price quotes that end at 95-99 cents of product *i*. Stability of sellers for product *i* is the ratio of the number of sellers offering product *i* in a given month to the number of sellers ever selling this product in the quarter, which cover the given month. $\mathrm{Shock}_{T+(k),(k+1)}$ are dummy variables which show whether the month is (k) or (k+1) months following the month of the flood. For example, $\mathrm{Shock}_{T+0,1}$ equals 1 if the month is the month of the flood or one month after the flood, otherwise it is 0. All dependent variables are unweighted price-setting measures. We run regressions at product-month level and control for goods fixed effects. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Chapter 3. Seller Reputation and Price-Setting.[31]

3.1. Introduction

The implications of price-setting measures are significant. They are a vital tool used by policymakers and academics to determine the optimal inflation (Adam and Weber, 2019; Oikawa and Ueda, 2018), optimal monetary and fiscal policies (Fujiwara and Wang, 2017; Paciello and Wiederholt, 2014; Schmitt-Grohé and Uribe, 2004), real exchange rate convergence (Engel, 2019), consumer welfare and cost of inflation (Jensen, 2007; Nakamura et al., 2018). Empirical research often finds a significant degree of price stickiness in both offline markets (Nakamura and Steinsson, 2008; Klenow and Malin, 2010) and online markets (Cavallo, 2017; Gorodnichenko et al., 2018a). Theoretical studies often explain the existence of sticky prices with time-dependent pricing models (e.g., Calvo, 1983), search costs (e.g., Burdett and Judd, 1983), menu costs (e.g., Sheshinski and Weiss, 1977), bounded rationality (e.g., Akerlof and Yellen, 1985), fear of "customer anger" (e.g., Rotemberg, 2005; Anderson and Simester, 2010), and rational inattention (e.g., Sims, 2003; Reis, 2006). In addition, several studies have pointed out that the reputation of the seller influences customer searches, the sales performance of the seller (Bente et al., 2012; Cabral and Hortaçsu, 2010), and the price of products (Houser and Wooders, 2006; Melnik and Alm, 2003). Thus, we would expect that the seller's reputation affects the pricing behaviour of the sellers. However, there are limited studies that focus on this relationship. The purpose of this study is to investigate the impact of seller reputation and variations to it on price-setting behaviour.

Theoretical research on price stickiness suggests that price stickiness can be caused by non-price factors, since sellers may adjust factors other than price, i.e., selling efforts, product quality, and delivery time (Blinder et al., 1998; Carlton, 1989). However, in empirical research, those factors are often absent in pricing models due to measuring difficulties. Those omitted variables can lead to errors in measures of price-setting. Understanding of this issue can be improved by studying this long-standing omitted factor using a precise measure of seller reputation. The objective of this paper is to fill the gap in the existing literature by using a unique feature found in the online market, this being the seller rating, in order to measure seller reputation and to introduce this factor into a pricing model.

[31] In this chapter, we use material that is submitted to University of Birmingham for the research proposal of Advanced Research Methods module.

Online markets have unique characteristics, which are different from standard markets. For example, search costs are low, they do not depend upon physical location, and the costs of price changes are minimal. Therefore, in addition to providing a precise measure for seller reputation, investigating price-setting behaviour in online markets also offers an exceptional opportunity to eliminate common price frictions. Gathering price data in e-commercial market is also less costly and more convenient than in conventional markets, but is still of a reasonably high quality (see Cavallo and Rigobon, 2016).

This study employs the dataset of online prices in Gorodnichenko and Talavera (2017). The online prices are collected weekly in the U.S. and Canada online markets, which are identified precisely at the product level by the manufacturing product numbers. All used or refurbished product prices, as well as pre-order prices, are removed. After applying filters, the large dataset contains the prices of around 118,000 products offered by 1,300 sellers between November 2008 and September 2013. Three main electronic product categories are covered in this study: cameras, computers, and electronics. An observation is identified by the manufacturing product number (product ID), identifications of sellers (seller ID), and the week and country in which the data was collected. Using this comprehensive dataset provides a relatively presentative set of products, compared with other studies on online prices, which allows for the generalisation of the results. Additionally, this dataset includes a unique feature, this being the rating of the seller at a weekly frequency. This feature of the data allows for the tracking of any changes to the rating of the seller and for the investigation into the relationship between price-setting and seller reputation.

Using the dataset, we show that prices of electronic products exhibit some stickiness even in a highly competitive e-commerce environment, thus suggesting that various pricing frictions and market fundamentals—the number of sellers (a proxy for market concentration), median price (a proxy for incentives to search for better prices), share of convenient prices—are also important factors for explaining price stickiness and price dispersion. We demonstrate that seller reputation and its variations (standard deviation of reputation and frequency of reputation increases/decreases) play an important role in the pricing strategy of sellers, as well as price dispersion within-product. Furthermore, the average level and variation of the reputation of sellers, who are offering a product, are important in explaining the price differences across sellers within that product.

The structure of the rest of the proposal is as follows. Section 3.2 is dedicated to describing the related literature. Section 3.3 describes the dataset employed in this study. Section 3.4 provides the basic facts about seller reputation and pricing behaviour and the relationship between them. Finally, our conclusion is given in section 3.5.

3.2. Related Literature

3.2.1. Price stickiness

Price stickiness is a key factor in several macroeconomic models. These models predict that an increase to the supply of money would raise levels of production due to the price or wage stickiness. If prices or wages are flexible, any changes to money supply within an economy should transmit directly into prices, causing the effect of monetary and fiscal policy on real output to disappear. Indeed, empirical research often reports substantial price rigidity, which suggests the existence of price stickiness. A significant number of economists have attempted to explain this phenomenon. However, they were still unable to reach a consensus on the sources of price stickiness.

Firstly, initial attempts to explain sticky wages with implicit contracts were proposed by Azariadis (1975) and Gordon (1974). The key idea is that firms are motivated to keep the wages stable for their risk-averse workers in response to fluctuations in demand. This leads to variations to the level of employment while wages stay stable. Following this, Okun (1981) applies this theory to prices. He argues that firms are motivated to keep prices stable to maintain a positive relationship with customers. Firms that change prices frequently usually have difficulties in developing long-term relationships with customers. In line with this, Rotemberg (2005) and Anderson and Simester (2010) develop their models based on this theory. They argue that firms fear that price increases would trigger “customer anger” and damage their business in the long-term. Thus, prices are sticky in response to shocks. The important feature of these pricing models is that prices are unresponsive to temporary shocks.

Secondly, a number of studies highlight that sellers of goods hold products in their inventory. Since changing the output is often expensive, sellers use their inventories to lessen the impact of demand fluctuations on their sales. Thus, the output becomes stickier. Applying this idea to price-setting models, Blinder (1982) and Boileau and Letendre (2011) state that sellers of physical goods (not services) would use their inventories to absorb, at least partially, the demand shock impacts by reducing their inventory level. In this case, the prices will rise less than they would without changes to the inventory level. As a result, inventories of sellers cause sticky prices. An important prediction of these models is that sellers will not change their prices before changes are made to their inventory level.

Thirdly, another common cause of price stickiness is "menu cost" (see Golosov and Lucas, 2007, and Midrigan, 2011). The main idea in these models is that prices are sticky because it is costly for firms to adjust the prices, for example, higher costs related to printing a new "menu" and changing existing advertisements. According to "menu cost" models, firms will not change the price if the difference between the optimal price and the current price is smaller than the cost of the price adjustment. It means that the larger the "menu cost", the larger the size of price changes, and the lower the probability of price changes. Therefore, a key prediction of these models is that the frequency of price changes is negatively associated with the size of price changes and the size of the costs related to price adjustment.

Lastly, a number of studies have highlighted that consumer search costs influence pricing decisions. For example, Head, Kumar, and Lapham (2010) investigate the impact of consumer searches on the market power of sellers and the sensitivity of prices to the variation in supply. They argue that a high search intensity of buyers would put more pressure on price-setters and lead to a higher frequency of price adjustments.

Regarding empirical research on price-setting, there is a large and growing empirical literature, which documents price stickiness in micro pricing data. A significant level of price stickiness is often found, even in the online market, where price frictions, such as costs of price changes, are small (for offline markets see Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Klenow and Malin, 2010; for online markets see Gorodnichenko and Talavera, 2017; Cavallo, 2018; Sheremirov, 2019). The level of price rigidity reported in online markets is not qualitatively different from that reported for offline markets. This finding shows little support for traditional causes of price stickiness, such as menu cost.

Furthermore, empirical research on price stickiness often finds that the responses of price changes to shocks are smaller than suggested in theoretical models. For example, Taylor (2000) stated that prices are less responsive to cost variation when the inflation rate is low. Similarly, Gagnon (2009) finds that the size of price adjustments is positively correlated with inflation rate. Meanwhile, Nakamura and Steinsson (2008) argue that in a high inflation environment in the United States, prices are more likely to increase. Empirical evidence also shows that the pass-through of nominal exchange rate variation to prices is positively associated with inflation rate (see Campa and Goldberg, 2005; Choudhri and Hakura, 2006). The results reported in these empirical studies above can be explained by the extensive literature which focuses on the sources and influence of incomplete price changes in sticky prices models (see Clarida et al., 1999; Goodfriend and King, 1997; Woodford, 2003). They suggest that there may be non-price factors influencing price changes and price level. This explanation is consistent with the theory of implicit contracts and non-price competition proposed in earlier theoretical works (see Clay et al., 2003; Iyer, 1998; Roberts and Samuelson, 1988; Spence, 1977; Stigler, 1968; Winter, 1993). It is also supported by empirical evidence reported in Maccini (1973), who finds that firms prefer to lengthen the delivery lags instead of raising prices in response to demand increase. However, the empirical evidence of the impact of non-price factors on pricing strategy remains limited, due to the difficulty in measuring non-price factors. This study complements existing literature by exploring the impact of non-price factors on the pricing behaviour of sellers.

3.2.2. Fairness and reputation

The reputation of firms was first used in macroeconomic models to explain the wage stickiness or incomplete wage adjustment in the market. A number of authors have argued that, even in the case of high unemployment, firms would not pay their employees a salary that is lower than a fair level (see Akerlof, 1979; Akerlof, 1980; Solow, 1995). This is because the social norms of fairness and equity influence the behaviour of firms. Firms fear that paying unfair wages would damage the firm's reputation, which in turn would make it more difficult for the company to recruit future employees. Applying this idea into the goods and service markets, researchers believe that the behaviours of participants in such markets are also affected by reputation mechanisms.

For example, in the theoretical work of Okun (1981), the pricing behaviour of suppliers of goods and services is also affected by reputation mechanisms. He argues that firms would not fully exploit the excess in demand to increase prices of products, since price increases may cause customers to stay away from the company's products in the future. He explained that this reaction of customers to price increases is due to the increases being considered to be unfair, in that they are not caused by increases in costs to produce the products. Customers only accept price increases as being fair if the increase is justified by an increase in costs. If customers suspect that they are being treated unfairly by a supplier, they are likely to change to another supplier. As a result, firms are motivated to maintain a good reputation amongst their customers in order to keep their business running in the long term, and to also be able to operate in markets that have information asymmetric problems (see Arrow, 1973; Akerlof, 1982). Consistently, Kahneman et al., (1986) find evidence supporting this idea by conducting a research survey via telephone. He finds that suppliers may avoid increasing prices due to fear of reputational damage. These findings are consistent with the prediction of implicit contracts theory and we expect that sellers who have a higher reputation level should have stickier prices. However, empirical evidence on the relationship between seller reputation and pricing behaviour in traditional markets is limited, due to the challenge in measuring the reputation of sellers.

Over the last two decades, a new type of market – the online market - has been booming. While traditional markets depend mainly on the trust established from repeated purchases and personal relations, e-commerce markets are more likely to involve anonymous transactions. Therefore, one of the greatest challenges in online markets is establishing methods for addressing online fraud. In online markets, buyers often have to pay for products in advance and accept the risk that sellers may not deliver the products, or the products may not match the online description and advertisement. To combat this issue, a reputation mechanism has been created. After each online transaction, the buyer can review and rate the seller, based on key criteria such as delivery time, delivery fees, product description, and seller communication. The reviews and the rating score of sellers are publicly available so that the buyer can assess the seller’s reputation before making a purchase.

Using this unique feature of online markets, a number of studies have used the ratings of sellers in online markets to investigate the impact of seller reputation on sales. For example, Bente et al. (2012) carry out an experiment to investigate the effect of seller reputation in online markets on the purchase decision of customers. They find that purchase rate and seller reputation are positively correlated. In line with this, Cabral and Hortaçsu (2010) use a dataset of eBay auction prices to investigate the importance of seller reputation in online markets. They find that negative feedback reduces the quantity of sales, sellers with a low rating are more likely to close their eBay accounts, and just before closing, sellers receive feedback which is more negative than their lifetime average. On the one hand, we expect sellers with a better reputation to have stickier prices. This is because a good reputation helps sellers to achieve a higher rate of sales and revenue, therefore, sellers with good reputations are likely to have a higher inventory level. According to pricing models with inventory, sellers that have higher inventory levels should change their price less frequently. On the other hand, we expect sellers with good reputations to attract more customer searches. Thus, according to pricing models with search costs, sellers with good reputations should have more flexible prices.

Theoretical research into seller reputation also suggests a positive relationship between reputation and price (see Allen, 1984; Houser and Wooders, 2006; Klein and Leffler, 1981; Shapiro, 1982). Empirical evidence on the relationship between reputation and prices presents a mixed picture. There is empirical evidence demonstrating that a bad reputation reduces prices, but positive feedback does not have an impact on price (see Lucking-Reiley et al., 2007). Melnik and Alm (2003) find a positive relationship between reputation and price, however the effect is marginal. Meanwhile, Liu et al. (2012) find that high-reputation sellers offer lower prices than low-reputation sellers. Increased market competition increases and decreases prices of low- and high-reputation sellers, respectively. Furthermore, Hardy and Norgaard (2016) find that the variation to a seller's rating is more important than the actual rating level.

The majority of studies on seller reputation in the online market focus on customer behaviour in response to published feedback and rating of seller by conducting controlled field experiments (e.g., Resnick et al., 2006), laboratory experiments (e.g., Ba and Pavlou, 2002), and auction prices (e.g., Dewally and Ederington, 2006; Dewan and Hsu, 2004; Livingston, 2005; McDonald and Slawson, 2002). In contrast with existing studies, this study aims to document the impact of seller reputation on the pricing behaviour of the seller.

3.3. The Gorodnichenko-Talavera Data

3.3.1. Data coverage

This paper uses a comprehensive and representative dataset, which is employed in Gorodnichenko and Talavera (2017) (hereinafter GT). The dataset contains online prices collected weekly from a leading price comparison website (PCW) for two countries: the U.S. and Canada. Four main electronic product categories are covered by the dataset: cameras, computers, electronics, and software. Each product in the dataset has a unique identifier, which is the manufacturing product number (MPN). Similarly, each seller is uniquely identified using a seller ID. The prices included in the dataset are net prices, which are the prices before taxes and shipping fees.

This study chooses to employ the GT dataset for five main reasons.[32] First, the GT dataset contains a larger and more diverse set of products compared to other studies using online prices, which is helpful for generalising the results. Second, the GT dataset includes prices from a relatively large number of sellers, while other studies usually focus on price data from one seller or some large retailers. This characteristic is important, since the objective of this study is to investigate the impact of reputation on seller behaviour in general, and not for the investigation of one, or a specific group of sellers. Third, prices collected from PCWs are closer to transaction prices. This trait of the dataset helps us to avoid any irrational pricing behaviour of low rated and/or small sellers. This ensures that the relationship between prices and reputation is more precisely reflected. Fourth, in contrast with a number of existing papers, which obtain less than 12 months of data (for example Lünnemann and Wintr, 2011), I exploit the advantages of a longer time series dataset, which spans five years of data, to achieve more accurate results. Lastly, the GT dataset contains a unique feature used to measure seller reputation in the online market, this being the rating of sellers.

Gorodnichenko and Talavera (2017) employed a number of data filters. First, all prices of used or refurbished products were removed, since their prices are not comparable with the price of new products. Second, to minimise the effects of extreme values in the data, both the top and the bottom one percent of prices are dropped. Third, for time series analyses, products with less than 20 observations are dropped. Additionally, only products which have at least three sellers are used in the calculation of the duration that the product stayed on the market. Lastly, they only retain products offered in both the U.S. and Canada, which significantly decreases the number of products in their sample. Due to the difference between the purpose of their study and this study, I do not employ the last data filter. Instead, we drop all software products, since the pricing of this category is less likely to be influenced by seller reputation.

After applying all filters above, the extensive sample in this paper covers weekly prices of more than 10,000 products, sold across around 1,200 online retailers in the U.S. and Canada from September 2008 to December 2012. An observation is defined at the product-seller-week-country level. In total, the dataset contains nearly 17 million observations. The dataset covers three main electronic product categories: cameras, computers, and electronics. The categories covered in the dataset are presented in Table 3.1.. The ratio of products included in the dataset is skewed toward the computers' category, with more than 50,000 products offered by 815

[32] For more details of the data discussion see Gorodnichenko and Talavera (2017).

sellers. The electronics category has nearly 39,000 products sold across 676 sellers. Cameras is the smallest category in the dataset with around 12,000 products sold across 405 sellers. Regarding the size of sellers in terms of number of products sold, the average size of sellers is similar across categories. Although the data covers a large number of sellers, only 5% of the largest sellers account for around 90% of the number of price quotes.

[Table 3.1]

3.3.2. Seller ratings in online markets

The reputation system in the online market was introduced by eBay in 2004 with the purpose of informing buyers about the past behaviour of sellers and to develop a rational foundation for trust in this new market (see Schofield and Joinson, 2008). After the purchase of a product, the buyer can rate the seller (with 1-5 stars or positive/negative feedback) to inform future customers about seller behaviour. This trust-building mechanism was quickly adopted by shopping platforms and price comparison websites. Panel A of Figure 3.1 shows an example of a typical price comparison website operating in the U.S., in which buyers observe information about the seller, such as name of seller, overall reputation, delivery fees, product price, and the link to seller's website. When the buyer chooses a seller from which to purchase the product, the detailed information about a seller's rating will appear, including average rating, the quantity and corresponding proportion of 1-5 star ratings (see Panel B of Figure 3.1). As can be seen in Figure 3.1, not all sellers have their rating displayed on the price comparison website. This is because only sellers with a certain number of reviews have their rating scores shown publicly. Therefore, the rating scores for several sellers in the dataset are missing.

Panel A of Table 3.2 presents the distribution of seller rating scores in the dataset. In general, the average rating score of sellers in Canada was higher than that of U.S. sellers (see row (1)). The average difference in rating across sellers in Canada was smaller than in the U.S. (see row (2)). More than 25% of U.S. sellers and more than half of Canada sellers in the data have missing rating scores. Panel B of Table 3.2 shows the weekly variation in seller rating scores. The frequency of rating score increases is 3% and 2% in the U.S. and Canada, respectively. Meanwhile, a seller in Canada is more likely to experience a rating score decrease than a U.S. seller (12% vs. 9%).

[Table 3.2]

3.3.3. Notion and aggregation

In this chapter, we use p_{ist} to stand for the prices of product *i* sold by seller *s* at time *t* and r_{st} stands for the rating score of seller *s* at time *t*. Thus, we have the set of all products, sellers and time as $\boldsymbol{\mathcal{N}}$ = {1, …, N}, $\mathcal{S}$ = {1, …, S}, $\boldsymbol{\mathcal{T}}$ = {1, …, T}, respectively. In which N is the total amount of products, S is the total amount of sellers and T is when the period ends. Time measurement is week. The subscripts *i, s* and *t* correspond to a given product, seller or time. For example, N_{st} is the total number of products, which are offered by the seller *s* at time *t*, while S_{it} represents the total number of sellers that sell product *i* at time *t*. The letter with a bar means the average, such as $\bar{p}_{it}$ is the average price of product *i* across all sellers offering it at time *t*.

The rating scores are used to accurately measure the seller reputation in the online market. This unique feature of the data can help to fill the gap in the existing studies that focus on the conventional market, which does not have such features. To investigate the impact of seller reputation on prices and the pricing strategy of sellers, we compute and then compare two different aggregate measures for the product price as well as frequency and size of price adjustments across products and sellers. First, the raw average, which is $\bar{f}$ (unweighted mean), is computed. Secondly, the across-sellers weighting scheme is employed to aggregate across sellers that offer a product to collapse our data to the goods level. Then the raw average over products is calculated, which we call $\overline{f^b}$. We refer $\overline{f^b}$ to across-sellers weighting. For instance, f_{is} is the frequency of price adjustments for product *i* sold by seller *s*, and r_s is the rating score of seller *s*. Those two aggregated measures have the following formula:

$$\bar{f} = \sum_i \frac{1}{N} \sum_s f_{is} \frac{1}{S}$$

$$\overline{f^b} = \sum_i \frac{1}{N} \sum_s f_{is} \frac{r_s}{\sum_s r_s} \tag{1}$$

Due to the missing values of rating scores in the dataset, we constructed rating-weighted results using a standard "imputation" method in the literature. Specifically, in the first approach, we assume that the rating score of a seller with a missing rating score is 1 (the lowest rating score). In the second approach, we assume that the rating score of a seller with a missing rating score is 2.5. As the results are similar across approaches, we report statistics only for the second imputation approach (replacing missing values of rating scores with 2.5) to preserve space.[33]

3.3.4. Price Distribution

Table 3.3 shows the average price of each percentile of the distribution over products ($\bar{P}_i$), the mean and the standard deviation of the average log price ($\bar{p}_i$) within the sample. Overall, in our data for the U.S., the median product costs $293.25 and 25% of the products have prices under $99.79; products that are more expensive than $1,191.15 account for the top 25% of the highest prices in the sample. Meanwhile, in Canada, the price of the median product is higher ($329.99) and 25% of the products are priced below $102.13; the top 25% of products that have the highest prices in the Canada sample have are priced above $1,099.99.

When we adjust prices for seller rating scores, we observe that price dispersion (measured as the standard deviation of log prices) rises by 1 and 4 log points for Canada and the U.S., respectively (see column (2)). Additionally, rating-weighted results reported in column (1) suggest that there are positive price premium effects (i.e., sellers with better reputations charge higher prices) since applying the weighting scheme increases the average prices in both the U.S. and Canada.

[Table 3.3]

3.4. Seller Reputation and Pricing Behaviour

In this section, we document the basic facts relating to price-setting in the online retail market. Specifically, we focus on the frequency of price changes, the size of price changes, and within-product price dispersion. We build on existing studies on price-setting (e.g., Gorodnichenko, Sheremirov, and Talavera, 2018) to compute these pricing moments. Then we relate each of these moments to market fundamentals and introduce seller rating score levels, as well as its variation, into the pricing model. We expect to find reduced pricing frictions in online markets compared with conventional “brick-and-mortar” markets, due to the fact that e-commerce has small nominal price change costs (“menu costs”), small search costs, and small monitoring

[33] We computed seller rating-weighted results, where seller rating is the raw number of stars that buyers rated sellers (from 1 to 5 including missing values), the 1-star imputed, or the 2.5-star imputed. We also removed all sellers with an average review rating of below 4-stars from our sample. Statistics for all other approaches are similar with the statistics for 2.5-star imputed, which are reported in this Chapter. These are available upon request.

competitors' prices costs (Ellison and Ellison, 2005). Thus, online price quotes provide us with the most effective way of detecting quick repricing of products in response to changes in seller reputation.

This section aims to contribute to existing literature by providing new empirical evidence of the impact of seller reputation on price-setting. Our results suggest that the rating of sellers and variations to ratings significantly affect the pricing behaviour of sellers.

3.4.1. Frequency and Size of Temporary Price Changes

As we do not have access to the scanner data which flags up sale products, we follow previous studies (e.g., Chahrour, 2011) to identify temporary sales with a "sales filter", which is the ∨-shape or ∧-shape in price changes. Specifically, we consider an increase or decrease in price as being temporary price changes if the price returns to its previous price level within one week.

Table 3.4 shows that the mean frequency of sales across products is 0.42-0.45% and the median size of sales across products is 5% in the U.S. In Canada, the frequency of sales is around 1% with a slightly smaller median size, which is 3%. Applying the weighting scheme only has marginal effects on the frequency and size of sales, which suggests that sellers behave similarly in their use of temporary price changes, regardless of their reputation level.

[Table 3.4]

3.4.2. Frequency and Size of Price Changes

3.4.2.1. Basic facts

Frequency. Following previous studies (e.g., Bils and Klenow, 2004; Nakamura and Steinsson, 2008), we determine the frequency of price adjustment as the proportion of non-zero price changes to the total number of price changes observed within the dataset. Specifically, we consider a price change that is smaller than 0.1% as a zero-price change, which means it is not counted as a non-zero price change. Then, the frequency of price changes for each price line is calculated as the proportion of non-zero price changes to the total number of price changes observed within the price line over time. Following this, the average frequency across sellers within a product is calculated with no weights and with seller rating weights.

Size. Similar to the frequency calculations, we first compute the size of price changes for each quote line in a week as the absolute value of price changes. Second, we aggregate this measure to the price-line level by taking the raw average of non-zero price changes over time without weights. Third, at the product type level, the average size of price changes across sellers within a product is computed without weights and with seller reputation weights.

Regarding pricing moments, we employ the one-week sales filter to compute the regular prices. Table 3.5 reports that the median frequency of posted price adjustments is 14.28% and 13.41% per week and the corresponding implied durations for the U.S. posted and regular prices are 6.49 and 6.95 weeks, respectively.[34] The seller rating weights increase the frequency of price changes and decrease the implied duration for both posted and regular prices. These results imply that, in the U.S., high-reputation sellers change prices more frequently than low-reputation sellers. In contrast, for Canada, we observe a negative impact of the rating weighting scheme on the frequency of price changes. Applying the rating weights decreases the frequency of price adjustments for both posted and regular prices, which suggests that a high-reputation Canada seller changes prices less often than a low-reputation one. Furthermore, the results reported in Table 3.5 show a minimal effect of seller reputation on the average absolute log price change ($|\Delta p_{ist}|$). Additionally, the average change for all price adjustments is similar between the results of regular and posted prices.

[Table 3.5]

3.4.2.2. Predictors of frequency and size of price changes

This section aims to contribute to the existing literature by analysing how seller reputation affects pricing strategy. We include in the pricing model the average seller rating scores to control for seller reputation level and the weekly frequency of the changes in seller rating scores. We run the regression at the seller-product-quarter-country level on price-setting measures (frequency and size of price changes). Since the features of the market, seller, and goods might have an impact on price-setting behaviour, we control for these factors in the analysis.

In particular, we regress the pricing moments on eight variables: (1) number of sellers that sell product *i* at time *t*; (2) the median price of product *i* at time *t*; (3) share of price points at time *t*, which is the percentage of price quotes that end at 9, or 95-99 for product *i* (e.g., $199, $349,

[34] If $\bar{f}_i$ is the average frequency of price adjustment for product i, the mean implied duration is given by $\bar{d}_i = -[\log(1-\bar{f}_i)]^{-1}$.

\$495); (4) the stability of sellers for product *i* at time *t* is the average ratio of number of sellers offering product *i* at quarter *t* to the number of sellers that ever sell this product in the year covering the given quarter; (5) average ratings of the seller at time *t*; (6) standard deviation of seller rating at time *t*; (7) frequency of seller rating increase at time *t*; and (8) frequency of seller rating decrease at time *t*. The first variable is a proxy for market competition (e.g., Ginsburgh and Michel, 1988; Martin, 1993). The second variable is a proxy for the returns of buyer searches (e.g., Head et al., 2010). The third reflects the level of inattention to prices when choosing between products (e.g., Knotek, 2011). The fourth variable (stability of sellers) is a proxy for the turnover of sellers (e.g., Gust, Leduc, and Vigfusson, 2010). The fifth variable aims to capture the reputation level of sellers. The sixth, seventh, and eighth variables aim to capture the variation of seller reputation (e.g., Hardy and Norgaard, 2016).

We run the regressions below with no weights and control for country, product, seller, and time fixed effects.

$$f_{istc} = log\, S_{itc}\, \beta_1 + \overline{logP_{itc}}\beta_2 + \overline{logP_{itc}}^2 \beta_3 + SPP_{itc}\beta_4 + Stab_{itc}\beta_5 +$$

$$+ log\, Rating_{stc}\, \beta_6 + SD\ Rating_{stc}\beta_7 + F\_Rating(+)_{stc}\beta_8 + F\_Rating(-)_{stc}\beta_9 +$$

$$+ \theta_i + \psi_s + \phi_c + \gamma_t + \varepsilon_{it}$$

In which, f_{istc} is the frequency, frequency of positive, frequency of negative or size of price changes for product *i* sold by seller *s* at time *t* in country *c*; S_{itc} is the number of sellers offering product *i* at time *t* in country *c*; $\overline{logP_{itc}}$ is the log of the median price of product *i* at time *t* in country *c*; SPP_{it} is the share of price points of product *i* at time *t* in country *c*; $Stab_{itc}$ is the stability of the number of sellers that are offering product *i* at time *t* in country *c* (1-year base); $log\, Rating_{stc}$ is the log of rating score of seller *s* at time *t* in country *c*; $SD\ Rating_{stc}$ is the standard deviation of the log of rating score of seller *s* at time *t* in country *c*; $F\_Rating(+)_{stc}$ and $F\_Rating(-)_{stc}$ is the frequency of rating score increase and decrease of seller *s* at time *t* in country *c*; $\theta_i, \psi_s, \phi_c, \gamma_t$ are the goods, seller, country, and time fixed effects, respectively.

As sales are not common for products in the dataset, we report results only for regular prices (that is, non-sale prices) to preserve space.[35] Additionally, we considered several imputation methods for seller rating scores and the results are similar across methods. Thus, we report

[35] Results for posted prices (that is, prices with sales) are similar with results for regular prices and are available upon request.

results only for the "2.5-star imputed" method (where we replaced the missing values of seller rating scores with 2.5).[36]

Table 3.6 reports the estimates of regular prices. Regarding our control variables, the results suggest that all of them have some predictive power. Firstly, the median price across sellers of a product is positively associated with the degree of price flexibility (increase frequency and decrease size of price adjustments). Markets with higher levels of competition often experience higher (lower) frequency of negative (positive) price changes. Secondly, for products with low- and moderate-prices, price changes occur more often and are larger when the median price across sellers of the product increases. This result is consistent with Head et al. (2010), documenting that higher returns on searches would put more pressure on the seller to adjust prices. Nevertheless, given the estimated nonlinearity, highly expensive products tend to have fewer price changes of a smaller size. Thirdly, products that have a higher proportion of price points tend to have stickier prices. This result is consistent with Levy et al. (2011), according to whom products with 9-ending prices have a lower frequency and a larger size of price adjustments, compared to products with non-9-ending prices. Fourthly, an increase in the degree of seller stability, which implies that it is more difficult for new sellers to enter the market, is associated with an increase in the degree of price flexibility. Fifthly, a seller with a higher level of ratings increases prices more frequently and decreases prices less frequently. Additionally, their price changes tend to be of a smaller size. The results suggest that sellers are able to exploit their good reputation to gain a positive price premium by charging higher prices. This is consistent with Ba and Pavlou (2002) and Li et al. (2009). Sixth, the variation level of seller ratings is negatively associated with the frequency and size of price changes. In other words, sellers who receive new ratings which differ greatly from their current level of rating scores tend to change prices less frequently and make smaller changes to the price. Lastly, sellers who are more likely to have an increase in their rating scores tend to raise prices more and drop prices less often. Meanwhile, sellers who are more likely to have a decrease in their rating scores tend to change prices more often and make larger changes to the prices.

[Table 3.6]

[36] We considered using the raw number of stars with which buyers rated sellers (including missing values), the 1-star imputed series, or the 2.5-star imputed series of seller rating scores to construct variables. We also considered removing all sellers with the average rating below 4-star reviews from our sample. Results for all other approaches are similar to the results for 2.5-star imputed, which are reported in this Chapter. Results of other approaches are available upon request.

3.4.3. Within-product price dispersion

3.4.3.1 Intra-month dispersion across sellers

We use some common measures of price dispersion, which reflect different features of price variation: the coefficient of variation (CV), standard deviation of the weekly log prices, the log difference of the average and the lowest price (the value of information (VI)), interquartile range (IQR), range (the log difference between the lowest and highest price), and gap (the difference between the two lowest log prices).

We compute measures of weekly price dispersion across sellers for a product. Following this, the data is collapsed to the product level by taking the raw average over time. We also construct the price dispersion measure that is adjusted for product and seller fixed effects (e.g., the differences in reputation, delivery conditions, and return costs between sellers).[37] Thus, the adjusted dispersion measure provides us with the price dispersion net of sellers' heterogeneity in, for example, shipping costs and return policies, which are likely to remain unchanged over a short period of time (see Nakamura and Steinsson, 2008).

We report price dispersion for P_{istc} and ε_{istc} for the entire sample in Table 3.7. CV (column (1)) for P_{istc} is 14.98%, which suggests that there is considerable heterogeneity in prices, even for a specific product. The standard deviation of log prices (column (2)) is also relatively high at 15.13%. Seller fixed effects account for around 27% of the variation in actual price dispersion across sellers (see row (7)) and the residual price dispersion is 13.81 log points.

[Table 3.7]

3.4.3.2. Predictors of within-product price dispersion

Economists generally rationalize price dispersion with three forces: search costs, price stickiness, and price discrimination (for detailed discussion, see Gorodnichenko et al., 2018). To assess the role of these forces and to explain within-product price dispersion, we regress the

[37] We run the following regression:

$$log\ p_{ist} = \alpha_i + \gamma_s + \varepsilon_{ist}$$

where α_i and γ_s control for product and seller fixed effects, respectively. The dispersion of the residuals (ε_{ist}) gives us the adjusted price dispersion.

within-product standard deviation of the log prices for product i in country c at time t on the product's market concentration, median price (proxy for returns on search), price stickiness, stability of sellers, share of price points, average reputation level of sellers who offer product i in country c at time t, and the variations in reputation of sellers who offer product i in country c at time t.

Table 3.8 reports the results for the regression of standard deviation of log price in column (1). We find that all explanatory variables have some predictive power. The average seller reputation in a quarter is negatively correlated with price dispersion in that quarter. On the other hand, changes in seller reputation (frequency of rating score increases and decreases) are positively associated with price dispersion level. Products that are offered by a group of sellers with a higher standard deviation of rating scores tend to experience larger price dispersion. Consistent with the predictions of models with sticky prices, we find that price stickiness and price dispersion are positively correlated. Products that have stickier prices tend to have larger price dispersion. Markets with higher levels of competition (a larger number of sellers and lower level of seller stability) tend to have a smaller price dispersion. Lastly, median price and proportion of price points are negatively associated with price dispersion level. The results are similar between the regression of posted prices and residual prices after removing seller fixed effects (column 2).

[Table 3.8]

3.5. Conclusion

In this paper, we document the impact of seller reputation and price-setting behaviour. This study employs the dataset of Gorodnichenko and Talavera (2017), which includes online prices for a wide range of products and has a unique feature – weekly seller rating to measure the reputation of sellers.

This study contributes to the literature on price stickiness by revealing the relationship between seller rating and price-setting measures. The key finding is that both the reputation of seller, and changes to it, play important roles in price-setting. In particular, high-reputation sellers tend to increase prices more frequently and decrease prices less often and to a lesser degree compared with low-reputation sellers. This result shows little support for the pricing model incorporating the customer anger and implicit contracts theory, according to which, sellers with a high reputation would increase their prices less frequently through fear of damaging the relationship with customers (see Rotemberg, 2005; Anderson and Simester, 2010). Additionally, this result supports the non-price competition theory, which argues that non-price factors (such as selling efforts, delivery time, and quality of services) also play important roles in pricing decisions (see Hatfield et al., 2012; Roberts and Samuelson, 1988; Winter, 1993).

Furthermore, we contribute to the literature on price dispersion by investigating the within-product price dispersion to measure potential "mispricing" and frictions in the market, since all the product characteristics are the same. We find that there is significant within-product price dispersion, which suggests that the market does not eliminate arbitrage opportunities. Additionally, conventional approaches to explain the price dispersion within-product may be incomplete, since controlling for product and seller fixed effects may not be sufficient. This is due to the fact that seller fixed effects cannot control for the variation in a seller's reputation, selling/communication efforts, or service quality, which are reflected by the variation in seller rating scores.

Figures

Figure 3.1. Price Comparison Website Screenshot: A Product Listing in the U.S.

Panel A: The Price Comparison Website Interface.

Apple - iPad mini (2019) with Wi-Fi - 64GB - Space Gray

★★★★★ (5,264)

☐ Free shipping ☐ Refurbished / used About ⓘ

Sold by	Details & special offers	Item price	Total price	
River Hawk Shop	Arrives Oct 4 – 7	£297.34 ($379.00)	£329.69 ⓘ	Visit site
Staples	Free shipping	£321.66 ($409.99)	£350.29 ⓘ	Visit site
Back Market 91% positive (15,558)	Free shipping	£297.34 ($379.00)	£323.81 ⓘ	Visit site
Datavision 87% positive (243)	Free shipping · Arrives Sep 30 – Oct 7	£324.80 ($414.00)	£324.80 ⓘ	Visit site
Best Buy	Free shipping · Arrives Sep 30	£313.81 ($399.99)	£341.74 ⓘ	Visit site
Newegg.com - uShopMall	Free shipping	£298.12 ($379.99)	£324.65 ⓘ	Visit site
Adorama 97% positive (19,872)	Free shipping · Arrives Sep 30 – Oct 5	£313.81 ($399.99)	£341.74 ⓘ	Visit site

Panel B: A typical online seller's rating.

Note: The screenshot was taken in September 2020 from a typical Price Comparison Website operating in the United States.

Tables

Table 3.1. Category Description

Category	Price quotes (1)	Products (2)	Sellers (3)	Product per seller (4)
Cameras	1,398,396	12,215	405	62
Computers	11,260,217	50,240	815	69
Electronics	4,313,179	38,883	676	60

Notes: Column (1) presents the number of unique price lines. Column (2) presents the number of products. Column (3) presents the number of sellers. Column (4) presents the average products offered by a seller.

Source: Gorodnichenko and Talavera (2017)

Table 3.2. Seller Rating

Row		Unite States	Canada
		(1)	(2)
	Panel A: Descriptive Statistics of Seller Rating		
(1)	Mean Log Rating	1.49	1.52
(2)	Standard Deviation of Log Rating	0.14	0.09
(3)	5^{th} Percentile of Rating	0.00	0.00
(4)	25^{th} Percentile of Rating	0.00	0.00
(5)	50^{th} Percentile of Rating	4.41	0.00
(6)	75^{th} Percentile of Rating	4.74	4.50
(7)	95^{th} Percentile of Rating	5.00	5.00
	Panel B: Seller Rating Variation		
(8)	Frequency of reputation increase	0.03	0.02
(9)	Frequency of reputation decrease	0.09	0.12
(10)	Frequency of reputation remained	0.88	0.86

Note: In Panel A, row (1)-(2) report the mean and standard deviation of the distribution of the average log seller rating scores; column (3)-(7) report the mean for each percentile of the average seller rating scores. In Panel B, row (8)-(10) show the average frequency of reputation increase, decrease, and unchanged across sellers, respectively.

Table 3.3. Descriptive Statistics for Prices, USD.

	Mean Log Price		Mean Price, Percentile					
	Mean	SD	5%	25%	50%	75%	95%	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: United States								
No Weights	5.73	1.57	23.13	99.79	293.25	1,191.15	3,096.99	63,927
Rating-Weighted	5.74	1.61	21.00	96.43	292.98	1,222.99	3,287.99	63,927
Panel B: Canada								
No Weights	5.73	1.57	21.44	102.13	329.99	1,099.99	3,029.00	97,640
Rating-Weighted	5.75	1.58	20.99	103.99	336.25	1,112.87	3,047.72	97,640

Note: Column (1) and (2) report the mean and standard deviation of the distribution of the average log price for a product ($\overline{log\ p_i}$); column (3)-(7) report the mean for each percentile of the average price for a product ($\bar{p}_i$); column (8) shows the number of products, N.

Table 3.4. Frequency and Size of Sales.

	One-week filter		
	Mean Frequency	SD Frequency	Median Size
	(1)	(2)	(3)
Panel A: United States			
No Weights	0.42	1.26	0.05
Rating-Weighted	0.45	1.33	0.05
Panel B: Canada			
No Weights	1.11	2.38	0.03
Rating-Weighted	1.10	2.39	0.03

Note: Column (1) shows the weekly average of sales frequency across products (%). Column (2) reports the standard deviation of sales frequency across products. Column (3) shows the absolute size of sales for the median product, in which the absolute size of sales equal to the gap between the log of sales price and the log of regular price (multiple by 100). A sale is identified by using the one-week, two-sided sales filter.

Table 3.5. Monthly Frequency and Size of Price Changes.

	No Weights	Rating-Weighted
	(1)	(2)
Panel A: United States		
Posted Price		
Median Frequency, %	14.28	14.44
Implied Duration, weeks	6.49	6.41
Median Absolute Size, Log Points	0.06	0.06
Regular Price		
Median Frequency, %	13.41	13.77
Implied Duration, weeks	6.95	6.75
Median Absolute Size, Log Points	0.06	0.06
Panel B: Canada		
Posted Price		
Median Frequency, %	43.09	42.86
Implied Duration, weeks	1.77	1.79
Median Absolute Size, Log Points	0.04	0.04
Regular Price		
Median Frequency, %	40.64	40.00
Implied Duration, weeks	1.92	1.96
Median Absolute Size, Log Points	0.04	0.04

Note: Column (1) reports the frequency, the corresponding implied duration, and size of price changes for posted prices and regular prices when no weights are applied. Column (2) reports rating-weighted results using the between-sellers weighting method. We exclude missing values and compute the regular prices based on the one-week, two-sided sales filter.

Table 3.6. Predictors of regular-price stickiness.

Predictors	Frequency of Price Changes, % (1)	Frequency of Positive Changes, % (2)	Frequency of Negative Changes, % (3)	Absolute Size of Changes, Log Points (4)
Log Number of Sellers	0.003***	-0.001***	0.003***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log Median Price	0.195***	0.086***	0.108***	0.024***
	(0.003)	(0.002)	(0.002)	(0.001)
Log Median Price Squared	-0.023***	-0.007***	-0.016***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of Price Points	-0.029***	-0.012***	-0.018***	0.010***
	(0.001)	(0.000)	(0.000)	(0.000)
Stability of Sellers	0.006***	-0.028***	0.034***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.001)
Log Average Reputation	-0.002	0.013***	-0.015***	-0.005***
	(0.002)	(0.001)	(0.001)	(0.001)
SD of Reputation	-0.199***	-0.053***	-0.146***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.002)
Frequency of Reputation Increase	-0.042***	0.009***	-0.051***	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)
Frequency of Reputation Decrease	0.245***	0.045***	0.200***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.538	0.328	0.407	0.295
N	2,210,334	2,210,334	2,210,334	1,428,852

Note: This table shows the regression results of the frequency of price changes in column (1), frequency of positive price changes in column (2), frequency of negative price changes in column (3), absolute size of price changes in column (4) for regular prices on the set of dependent variables above. Country, seller, good, time fixed effects, and the constant are included in all regressions but not reported. All variables are unweighted and constructed based on 2.5-star imputed series of seller rating scores (missing values in seller rating score are replaced by 2.5). Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 3.7. Measures of price dispersion.

CV	Std(log p)	VI	IQR	Range	Gap	Std(ε)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
14.98	15.13	16.24	22.25	30.59	14.52	13.81

Note: This table reports the average dispersion of regular prices measured with: the coefficient of variance (CV), which is computed as the standard deviation divided to the mean (in %); std(log *p*), which is the standard deviation of the log price; value of information (VI), which is computed as the log difference between the average and the minimum price; interquartile range (IQR) equal to the log difference between the 75th and 25th percentile; range is the log difference between the highest and lowest price; gap is the log difference between the two lowest prices; and std(ε), in which ε is the error term in the regression of log *p* on good and seller fixed effects; respectively.

Table 3.8. Predictors of within-CPU Regular-Price Dispersion.

Predictors	Standard Deviation of Log Price (1)	Net of Seller Fixed Effects (2)
Number of sellers quarterly	-0.002***	-0.002***
	(0.000)	(0.000)
Median log price	-0.028***	-0.022***
	(0.000)	(0.000)
Convenient price indicator	-0.047***	-0.040***
	(0.001)	(0.001)
Stability of sellers, 1 quarter based	0.037***	0.020***
	(0.002)	(0.002)
Frequency of regular price changes	-0.042***	-0.025***
	(0.001)	(0.001)
ABS mean log regular price change	0.335***	0.338***
	(0.004)	(0.004)
Log average reputation	-0.015***	-0.025***
	(0.001)	(0.001)
Standard deviation of reputation	0.021***	0.015***
	(0.002)	(0.002)
Frequency of reputation increase	0.047***	0.036***
	(0.004)	(0.004)
Frequency of reputation decrease	0.013***	0.020***
	(0.002)	(0.002)
R^2	0.231	0.199
N	484595	484595

Note: This table shows the results of the regression of the standard deviation of log price in column (1), and the regression results after removing seller fixed effects in column (2) on the set of dependent variables above. Country, time fixed effects, and the constant are included in all regressions but not reported. All the reported variables in this table are unweighted and constructed based on 2.5-star imputed series of seller rating scores (missing values in seller rating score are replaced by 2.5). Robust standard errors are in parentheses. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Conclusion

This thesis studies several important determinants of price stickiness that currently receive limited attention from the existing literature. In the first chapter, we introduce a new determinant to the price-setting literature, namely product quality by exploiting the online data of CPUs. Particularly, we employ the CPU performance score as a precise proxy for product quality as well as a dataset that covers a large number of CPU models and sellers during a long period. The unique measure of quality, coupled with the comprehensive dataset provide a unique opportunity to document the essential role of goods quality in price-setting and its effects on the extent of price stickiness, price dispersion and price level.

The findings from our fixed effects models suggest that the quality of goods does have impact on price-setting behaviour in the online market. That is, prices of higher-quality products tend to be more flexible (higher frequency and smaller size of price changes) than low-quality products. Moreover, higher-quality products would have lower price dispersion than low-quality products. More specifically, CPUs with better performance have higher frequency of negative and lower frequency of positive price adjustments. As a consequence, a rise in goods quality at aggregate level in the market should result in a lower degree of price stickiness and price dispersion. This finding shows support for customers' attention theory, which suggests that consumers have greater incentives to search for high-quality goods than low-quality goods, since high-quality goods have larger return on search than low-quality goods. The pressure from customers' attention as well as greater revenues generated by high-quality products induce sellers to pay more attention to better-quality products. In other words, due to limited time and attention capacity, sellers would pay most of their managerial attention to products that can generate higher benefits.

Moreover, our results confirm that market fundamentals, i.e., the number of sellers, median price, share of convenient prices, level of seller stability and product brand can also be important determinants of price stickiness and price dispersion. Particularly, we find that a more competitive market should have a smaller size of price changes, higher frequency of price increase and lower frequency of price decrease. A market with larger proportion of price points experiences price rise less often than a market with lower percentage of price points. A market with lower seller stability level experiences price drop more often than a market with higher seller stability level. This indicates that the theory of bounded rationality could help explain the level of price rigidity. Our findings also suggest the link between price stickiness and price dispersion: a larger size of regular price change is associated with a higher degree of price dispersion. However, the frequency of regular price changes is positively correlated with price dispersion degree.

Furthermore, we also document a rise in price dispersion over product life as well as an evidence of spatial dispersion in the online market, given that online search is effortless. Additionally, our products quality measure and quality-adjusted price index clearly shows the enhancements in CPUs performance and the deflation in the U.S. CPU online market over the sample period. We suggest that it is important to take into account the quality of goods in modelling to avoid potential biases and improve the accuracy in measuring traditional economic indicators.

In the second chapter, we investigate the response of price-setting behaviour to a production disruption event, namely an inventory shock. We employ the 2011 Thailand flood as a trigger of the inventory shock of hard drive sellers throughout the world. The main production plant of the world's biggest HDD producer—Western Digital was forced to close as a consequence of this natural disaster. The flood triggered a large and exogenous shock to the global supply of HDD and to the HDD supply in the U.S. The total value of hard drive imports to the U.S. fell drastically about one month after WD suspended its operations in Thailand. As a result, the inventory of sellers and the product availability in the U.S. hard drive market were severely affected.

Besides this well-identified natural experiment, we use a big and comprehensive dataset of online price quotes in the U.S. This dataset not only enables us to investigate impacts of the event on sellers' inventory and product availability but also provides useful insight into how price-setting responds to the shock. We document that the inventories of U.S. retailers were instantly influenced by the supply shock, leading to a large decline in the product availability of hard drives. Moreover, we also observe subsequent drops in the product availability of final goods (desktops and laptops) and important computer components (processors and motherboards). Yet, these declines were delayed and of a smaller magnitude as compared to that of hard drives. While the former finding points out the insignificant role of retailers' inventory in delaying the shock's impact, the latter finding suggests that inventory in production networks could significantly absorb and delay the shock's effect on production and, therefore, on the inventory of final goods and complementary products. This result is in line with that of Barrot and Sauvagnat (2016), which suggests that inventories can delay the impact of supply shock propagation via input-output linkages.

Regarding price-setting behaviour, our results suggest that hard drive sellers raised their prices almost immediately following the inventory shock. Sellers of final goods and complementary products had similar, but smaller-magnitude, responses when their inventories were influenced. This finding is in line with pricing models involving inventory (see, e.g., Boileau and Letendre, 2011), which predict that prices are set based on inventory levels. Nevertheless, the reaction of hard drive sellers to the flood, before the inventory shock, is inconsistent with inventory models, which usually stresses the role of inventory in price smoothing. Our results also support price-setting models with rational inattention (see, e.g., Matějka and McKay, 2015; Matějka, 2016), which suggest that prices are responsive to sectoral shocks. However, models with rational inattention could not explain the delayed response in the price-setting of final goods and complementary products. Meanwhile, models with bounded rationality (see, e.g., Dixon, 2020) and models with input-output linkages (see, e.g., Petrella and Santoro, 2011) can sufficiently explain such delay. Furthermore, our findings show little support for pricing models with "customer anger" in the absence of demand shock, which is strongly linked with the needs and fears of customers after a natural disaster.

The third chapter contributes to the literature on price stickiness and price dispersion by revealing the relationship between seller reputation and price-setting measures. This chapter employs the dataset of Gorodnichenko and Talavera (2017), which contains online prices of a large range of goods and features a distinct factor – weekly seller rating to measure the reputation of sellers.

Our main finding is that both the reputation of seller and its changes have significant impacts on price stickiness. In particular, high-reputation sellers tend to increase price more and decrease price less often with smaller size compared to low-reputation sellers. This result shows little support for pricing model with customer anger and implicit contracts theory, according to which, seller with high reputation would increase their prices less frequent due to fear of damaging the relationship with customers (see e.g., Rotemberg, 2005; Anderson and Simester, 2010). Also, this result supports for nonprice competition theory which argues that non-price factors (such as selling efforts, delivery time, and quality of services) also play important roles in pricing decision (see e.g., Hatfield et al., 2012; Roberts and Samuelson, 1988; Winter, 1993).

Furthermore, we amend the literature on price dispersion by investigating the within-product price dispersion to measure potential “mispricing” and frictions in the market since all the product characteristics are the same. We find that there is significant within-product price dispersion, which suggest that the market does not eliminate arbitrage opportunities. Additionally, conventional approaches to explain the price dispersion within-product may be incomplete since controlling for product and seller fixed effects may be not enough. It is because seller fixed effects cannot control for the variation in seller’s reputation, selling/communication efforts, or services quality, which are reflected by the variation in seller rating scores.

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