Essays on Inflation and Macroeconomic Dynamics in India

by

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Abstract

This thesis comprises of three core chapters. Chapter 2 is the first core chapter. Compiling a novel dataset on food prices in India, I show that food prices exhibit varying degrees of price stickiness and it goes up once we exclude temporary price changes. Price setting behaviour in food sector matches predictions of sticky price models. Inflation based on a measure of sticky food prices -by re-weighting food group of CPI with degree of stickiness- does not perfectly align with the conventional measure of core inflation(excluding food and fuel) and therefore, monetary policy cannot ignore the dynamics of food prices.

Chapter 3 looks at the nature of price setting in food markets in India. I show that in the case of prices in physical stores, there is a strong tendency for prices to be rounded at zero or five generating significant bunching. Bunched prices are much more likely to remain constant and price transitions are dominated by movements across bunched points. Prices are much more flexible in an online setting and bunching reduces significantly. I embed this friction of rounding at price points into a standard menu cost model to show that the extent to which price points contribute to price stickiness is conditional on the distance between price points, size of menu costs as well the level of prices. In case of offline food prices, I show that in the absence of price points, menu costs would have to be 30% higher to generate the same level of price stickiness.

Chapter 4 documents the impact of India's COVID-19 lockdown on the food supply chain. Food arrivals in wholesale markets dropped by 69% in the three weeks following the lockdown and wholesale prices rose by 8%. Six weeks after the lockdown began, volumes and prices had fully recovered. The initial food supply shock was highly correlated with early incidence of COVID-19. Using between state and within state variation in covid cases and food supply, we show that this correlation is due more to state-level lockdown policy variation than local responses of those in the food supply chain.

Lay Summary

My dissertation consists of three chapters on dynamics of inflation and its macroeconomic implications in India. The first chapter focuses on food prices in India and shows that contrary to the notion of food prices being flexible, food prices exhibit varying degrees of price rigidity which has implications for policy. The second chapter shows that for cash transactions, prices tends to be rounded at digits that reflect the denomination of currency, and that rounded prices change less often than non-rounded prices. This friction reduces substantially in an online setting. The third chapter shows that food supply in India fell precipitously during initial weeks of COVID-19 lockdown but recovered swiftly and food supply response was more on account of state level policies than individual response to heightened risk of virus spread.

Preface

Chapters 2 and 3 of the thesis are pieces of original and independent work. Chapter 4 is joint work with Professor Matt Lowe (University of British Columbia) and Professor Benjamin N. Roth (Harvard Business School). A preliminary version of chapter 2 was published as Reserve Bank of India Working Paper (RBI Working Paper No. 10/2020).[1] Chapter 4 was published in journal Food Policy December 2021 Issue.[2] The journal Food Policy grants advance permission for authors to use the journal article in their dissertation. I have been involved throughout each stage of research in chapter 4 with equal contribution in developing the database, data analysis, and presenting and drafting the results.

[1] https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=50401

[2] https://doi.org/10.1016/j.foodpol.2021.102162

Table of Contents

Appendices

List of Tables

List of Figures

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Chapter 1

Introduction

This thesis consists of three core chapters which deal with issues relating to inflation and its macroeconomic implications in India. Specifically, the thesis focuses on the dynamics of food prices, an issue which has been a subject of intense policy debate in India over the years. In India, a substantial portion of final consumption is food as reflected by a share of 45.7% in overall Consumer Price Index (CPI). Given this large share, dynamics of food prices and food supply has significant implications for welfare and poverty (Deaton 2008). Also, food prices have been a major driver of inflation in India and its volatility (Bhattacharya and Gupta 2018; Cashin and Anand 2016). Understanding dynamics of food prices therefore assumes critical importance for monetary policy especially in the context of India adopting inflation targeting as its policy framework in 2016. Questions dealt with in this thesis therefore attempts to address some of these issues.

The first core chapter (chapter 2) empirically investigates the nature of price setting in food sector in India. Food prices are generally percieved to be flexible as they are impacted by frequent supply shocks. However, the nature of price setting in terms of how often do prices change, what is the magnitude of price changes on an average and how do prices respond to different shocks could be different across various products within the food sector. Focusing on aggregate measures of price stickiness by not recognising such heterogeneity would entail risk of policy error especially when food contributes such a large share of consumption. The literature on understanding price setting behaviour is either focused on advanced economies or at the aggregate price stickiness (eg: Bils and Klenow 2004; Banerjee and Bhattacharya 2017). Therefore, the key question that we ask in this chapter is: are food prices really flexible as commonly assumed or do we find evidence of stickiness within the food sector once we look at a more disaggregated level? If so, does their behaviour align with the existing theories of price stickiness and how does the sticky component of food inflation behave in comparison with the traditional measures of sticky inflation such as the inflation excluding food and fuel?

In order to address these questions, we compiled a novel dataset on retail food prices in India making use of the publicly available information from Price Information System set up by the Government of India to monitor the prices of essential items on a weekly basis. Our dataset covers 46 food items for which data is collected from 85 centres across the country on a weekly basis for the period 2005-2021. The dataset is comprehensive enough to understand the dynamics of food prices as it represents more than two third of the items within food group of CPI and 30% of overall CPI. As compared with monthly data available from official CPI which is also a measure of average prices usually provided in the form of an index, our database includes individual price quotes which are at weekly frequency helping us to have a more realistic measure of the nature of price setting. Compilation of this database in itself is one of the contributions of the study to the literature.

The first question we ask in this chapter is how often do prices change? We distinguish between two types of prices. One is the posted price which is the recorded price for every week in database. In terms of posted prices, the median time taken for a price change is about 1.2 months but different product groups exhibit different level of price stickiness. For example, vegetables prices change twice a month whereas milk prices changes once in five months. Posted prices could exhibit temporary fluctuations owing to a variety of reasons like temporary local supply demand conditions. Therefore, a more realistic measure of price stickiness would be based on an underlying price, something the literature calls as reference price. Following the methodology used by Eichenbaum et al. (2011), we calculate reference price as the price which occurs most number of times (mode) within a given quarter. When we look at reference prices, the median time between price changes increases to 4.6 months. Even for the most flexible items like vegetables, reference price changes only in two months and for a more sticky item like milk, it changes once in ten months.

Next, the chapter documents a set of characteristics of price setting behaviour in food sector in India. Digging further into the heterogeneity in price setting, we find that the heterogeneity is driven more by product group characteristics as opposed to item level attributes. In other words, products within the same group are likely to have similar attributes in terms of frequency and size of price changes. There is considerable downward flexibility in prices in most products although we observe that in case of items with larger price stickiness (i.e., frequency of price change is lower), the proportion of price decreases is smaller. Size of price decreases, on an average, are higher than that of increases. Over time, frequency of price change co-moves with aggregate inflation. We also show that there are seasonal and spatial variations in frequency of price changes.

After providing a broad picture by way of stylised facts as set out above, we turn to the literature to see whether food prices in India exhibit properties that match the predictions of existing price setting models. In the literature, models of price setting can be broadly classified into time-dependent or state-dependent. In time-dependent pricing models, only a fraction of firms/sellers get to readjust their prices at any point of time. In state-dependent pricing models, firms face some form of cost of price adjustments which leads to price stickiness. We explicitly test for both time and state dependency in our data.

We first look at whether price changes are synchronised or staggered, both across product groups and locations. Staggered frequency of price adjustments would indicate that price changes are time-dependent whereas synchronised price changes indicate that prices are responding to common shocks and therefore more state-dependent. We show that price changes are synchronised both at the product and at the location level. Having rejected pure time-dependency, we look at state-dependency both in a cross section and in a time series setting. At the cross section level, we show that the relationship between size and frequency of price change is negative and significant whereas for reference prices it is not significant. In case of reference prices, heterogeneity among product groups, especially vegetables and meat showing a positive relationship between size and frequency offsets the negative relationship observed in the case of other product groups.

We further test for state-dependency in a time series set up by looking at the response of both frequency and size of price changes to inflation. We show that both for posted and reference prices, frequency of price increase responds positively to inflation while frequency of price decrease responds negatively. In case of posted prices they cancel each other out whereas in case of reference prices stronger positive response of frequency of price increase outweighs the negative response of frequency of price decrease. Thus we find a positive and significant relationship between overall frequency of price change and inflation in reference prices. Only the size of price decline responds negatively to inflation in case of posted prices. For reference prices, size of increase responds positively and that of decrease responds negatively to inflation. These results indicate both heterogeneity of price stickiness across product groups and state-dependency in price setting in food prices. Nakamura and Steinsson (2010) identifies this as a critical factor generating monetary non-neutrality. Therefore, sticky component of food prices can not be excluded from policy metric.

How do we link the implications of our finding of state-dependency in food prices to policy? To answer this, we compute a measure of sticky food prices using the degree of price stickiness derived from the data as weights. We show that inflation in sticky component of food prices remained above conventional measure of core inflation (excluding food and fuel) during the high inflation phase and it fell below during periods of low inflation. Thus focusing only on excluding food and fuel inflation as a measure of underlying inflation could lead to policy errors as the dynamics of sticky component of food inflation is not adequately captured by such a measure.

This chapter makes contribution to the existing literature in two different dimensions. First, this study extends the literature on empirical estimation of price stickiness in line with the works of Bils and Klenow (2004) and Nakamura and Steinsson (2008) by providing a set of stylised facts for India, an emerging economy. The study also documents evidence for heterogeneity in price stickiness being driven by product group characteristics and regional variation of price stickiness within the same country which adds to the literature in terms of new stylised facts. Testing the empirical validity of time and state-dependent pricing models in developing country context is another contribution of this chapter. Klenow and Kryvtsov (2008) attempted to calibrate both time-dependent and state-dependent pricing models to test for empirical regularities of these models and found that both types of models exhibit empirical shortcomings even though state-dependent models enjoyed greater success. Other studies which particularly looked at a specific sector or product include Cavallo (2018) who used scrapped data from online retailers in five countries and Berka et al. (2011) who studied price stickiness in online food prices in the case of a supermarket in Switzerland during a period of negative inflation. Evidence of state-dependency in prices is also in conformity with theoretical literature and evidence for advanced economies (Golosov and Lucas Jr 2007). Regression results presented in the study provide further evidence on the mechanism by which responsiveness of frequency of price changes varies between posted and reference prices. We show that the greater responsiveness of frequency of price increases as compared with that of price decreases drives the significance of response of frequency of price change to inflation in case of reference prices.

Another dimension in which the chapter adds to the existing literature is on understanding the role of food prices in monetary policy. Anand et al. (2015) showed that under incomplete markets setting, changes in prices in food sector could create demand effects from relative price induced income effects and therefore headline targeting is the optimal policy. Catao and Chang (2015) characterised food price as an important channel of transmission of commodity price shocks to the domestic economy. This study presents evidence for existence of price stickiness of different degree across different food product categories in India which in itself becomes a reason for explicitly taking into account the dynamics of food prices. This assertion follows from the findings of Eusepi et al. (2011) and Mankiw and Reis (2003) who showed that the optimal monetary policy would have to assign weights proportionately to the degree of price stickiness. The chapter makes a pioneering attempt to generate a stickiness re-weighted food inflation to show that conventional core inflation measures does not necessarily capture the dynamics of sticky food prices.

Empirical findings of chapter 2 leads us to the question of what could explain the stickiness in food prices in India. Given that most of these prices are set informally, menu costs as traditionally understood in the literature could be negligible. If so, can we identify other forms of frictions which could lead to such stickiness? In chapter 3 we address this question by looking at the nature of price setting from a micro perspective. This chapter shows that there exists significant bunching of prices at round digits in food prices. This rounding corresponds to currency denominations indicating that when most of the transactions are done using cash, there is a strong incentive for prices to be rounded in order to ease transactions. This in turn generates price stickiness. If transactions using cash is indeed the reason for such bunching, we should expect that in an environment where the use of cash is minimal, such rounding should come down. We provide empirical evidence for this using web-scraped data from one of the leading online grocery stores in India. Rounding off at currency denominations is much less in the case of online prices and prices are much more flexible. By embedding the friction on account of non divisibility of currency into a standard menu cost model, we further show that the extent to which the currency non-divisibility influences price stickiness is conditioned by the magnitude of distance between price points, level of prices as well as the size of menu costs.

The empirical section in the chapter begins by documenting that nearly half of all prices are set in digits ending zero or five in case of physical stores. These bunched prices are much more likely to remain constant as compared with non-bunched prices indicating that bunching generates price stickiness. Zero ending prices, on an average, are twice more likely to remain constant as compared with odd digit ending prices whereas five ending prices are 50% more likely to remain constant. When we look at the pattern of price changes, we see that when prices change, they are more likely to change from one rounded price to another rounded prices. In most cases, the magnitude of price change is matching currency denominations.

In case of online prices, we first document that they are much more flexible than their offline counterparts. We also show that zero and five ending prices constitute less than one third of all prices and unlike in the case of offline prices, there is a significant bunching of prices at nine ending digits, especially at higher level of prices. Looking at the probability of price being constant, we do not find evidence of zero and five bunched prices being more sticky, as the probability of price remaining constant is nearly the same for zero and five ending prices as compared with odd digit ending prices. As we see that nine ending prices have now become an important bunching point in online setting, we look at whether nine ending prices are indeed more sticky than the non nine ending prices. We find that nine ending prices are more likely to remain sticky but the magnitude of stickiness is much lesser as compared with zero and five ending prices in offline setting. There is also little evidence to show that price transitions happen between bunched price points.

Our empirical results point to the importance of price points (where bunching occurs) in generating price stickiness. Therefore we try to understand the role of this friction in generating price stickiness through the lens of an augmented menu cost model. We incorporate discontinuity in price setting in a standard menu cost model to allow for pricing points. In our model, prices can only be set in multiples of a fixed number (say like 5, 10 so on). We adopt a hybrid approach where both menu costs and price points are present as frictions in price setting. First, we show that a hybrid model successfully replicates the key data moments. We also want to understand how much do price points contribute to price stickiness in our specific case. For this we calibrate the model with price points and then we recalibrate it without price points to match the same set of moments. We show that the menu costs would have to be 30% higher in order to generate the same level of price stickiness once we remove the friction induced by price points. We also demonstrate that neither a price point only model nor a menu cost model can produce all the key moments observed in the data on its own.

We present a set of simulations that help us understand the dynamic interaction between price points, menu costs and price levels. We show that when distance between price points are large, price points contribute more to price rigidity as it reduces the number of feasible price points that a firm can set. Also, when menu costs are small, price points are a significant source of price rigidity. In an environment of low menu costs, firms would want to adjust prices more frequently and therefore are likely to face this constraint more often. In the presence of high menu costs, however, price points become less binding as a constraint. Our simulations also show that the effect of price points on price stickiness is much larger for low level of prices as when price levels are low, the number of pricing points available will be less.

This chapter is closely related to the growing literature on micro-evidence of price stickiness which extends the idea of menu cost to include other forms of rigidity caused by behavioural preferences. Levy et al. (2011), found that preference for setting prices at certain price points, say like digits ending nine, could create price rigidity. Knotek (2011) also introduced the concept of convenience pricing where he showed that prices would be set at those denominations which minimise the time taken for transactions at places where the speed of transaction matters. Snir et al. (2021), using data on runaway inflation in Israel, found that zero ending prices are less likely to change even in a high inflation environment. A number of other studies have also looked at the role of bunching in price setting in different contexts (Ater and Gerlitz 2017; Snir et al. 2017). In case of labour market, Dube et al. (2020) show that optimisation frictions faced by the employer with monopsony power contribute to bunching of wages at round numbers. We look at cash as a form of friction which creates stickiness even in markets where prices are informally set. Our work also compares the role of price points and price stickiness in an offline and online environment and finds that prices are much more flexible in online setting and bunching is less likely to generate price stickiness in an online environment which contradicts the results in Cavallo (2017).

This study also contributes to the literature on how does existence of preferences over price points influence price rigidity. Head et al. (2012) argued that preference for setting prices in nominal terms would make prices more sticky in real terms as prices of individual item may not respond to changes in aggregate price levels. Knotek (2016) showed that preference over price points contribute much more to price rigidity than physical cost of changing prices and when price points are present, menu costs become irrelevant. Hahn and Marenčák (2020) incorporated both price points and sticky information into a price setting model to show that such models can generate empirically tractable predictions about key moments of price stickiness. Levy et al. (2020) showed that nine ending prices are more flexible downwards than upwards. Basu (2006) argued that prices rounded upwards in the presence of pricing points in oligopolistic markets creating price stickiness. Our empirical findings show that bunching at round digits leads to price stickiness, lending further support to the price point theory of price stickiness (Blinder 1991). However, the literature has so far not explored the nature of interaction between price points and existence of other menu costs and its implications for price stickiness. Our model simulations show that the price points' effect on price stickiness is conditional on level of prices and size of menu cost. Specifically, we show that Knotek (2016) results hold only when distance between price points are larger than the size of the menu cost.

While the first two core chapters dealt with price setting in food sector in India, the third core chapter (chapter 4) looks at the response of food supply and prices during the lockdown induced by COVID-19 pandemic. India was one of the countries to impose a strict lockdown in response to the pandemic which brought the country to a virtual standstill. Even though supply of essential items were excluded from the purview of the lockdown, a number of impediments on geographical movement of goods as well as people led to concerns on food supply being adversely affected by the pandemic. In this context, we ask the question, could food supply chains remain functional in the face of a national lockdown even though it was excluded from its purview and how did the supply chain evolve and prices behave during this period?

In order to address this question, first we compile a database on wholesale volumes and prices for 271 food varieties traded at 1,804 agricultural markets in 24 states of India using web-scraped daily data. India first announced a strict lockdown for 21 days on March 24, 2020 which was extended in three additional phases of 14 days each. We document the evolution of supply and prices of food during these phases by looking at the size of the shock and the extent of the recovery. We also use geographical variation in virus spread and food supply shock to see whether the shock to food supply could be attributed to state level policies or the response of individuals to the risk of virus spread.

We show that despite Government's effort to keep essential supplies out of lockdown, food arrivals in wholesale markets dropped by 69% in the first three weeks of the lockdown. However, food supply recovered swiftly thereafter, reaching similar levels to those in 2019 by early-May. Wholesale prices initially responded to the supply shock exhibiting an increase of 8%, but quickly returned to a downward trend. Initially, food supply shock was highly correlated with the exposure to COVID-19 at the state level. States which reported more COVID-19 incidence suffered larger drops to food arrivals after the lockdown relative to previous years. This correlation disappeared during the recovery phase, suggesting that food supply volumes recovered irrespective of the incidence of the virus spread. Finally, we look at a more granular detail at the district level and show that districts which were more exposed to COVID-19 *did not* have larger food supply disruptions than less-exposed districts belonging to the same state. This implies that the correlation between COVID-19 incidence and food supply which was witnessed in the initial period is driven by state-level policies, rather than local responses. We also demonstrate a strong positive relationship between state-level declines in mobility and the severity of the food supply shock, further highlighting the role of state-level policies in evolution of food supply during the lockdown.

This study contributes to the growing literature on the impact of the COVID-19 shock on the food sector in the developing world (Abay et al. 2020; Adjognon et al. 2020; Aggarwal et al. 2020; Ceballos et al. 2020; Kansiime et al. 2021; Mahmud and Riley 2021; Hirvonen et al. 2021). Closest to this study are the contemporaneous studies of Rawal and Verma (2020) and Varshney et al. (2020). These studies use the same principal data source to study the evolution of food volumes and prices in India during the lockdown. We complement their analyses by extending the sample to cover more food varieties, and more states. This allows us to explore richer patterns between COVID-19 exposure and the health of the food supply chain. In particular, by exploiting both within-state and between-state variation in COVID-19 incidence we attribute the food supply shock largely to state-level policies rather than the voluntary behavioral response of market participants. We also demonstrate that the impacts on the food supply chain are similar in urban versus rural districts, and establish a relationship between state-level mobility patterns and the food supply shock.

Other work in India finds that prices in urban food markets rose 3% in the 28 days post-lockdown (Narayanan and Saha 2021) and that supply to a major online retailer fell by 10% (Mahajan and Tomar 2021). More generally, studies have raised concerns on the food security risks faced in India as a result of COVID-19 (Ceballos et al. 2020; Reardon et al. 2020; Ray and Subramanian 2020; Kesar et al. 2021). Our work shows that such concerns on account of food supply chain disruptions remained short lived. Outside of food supply chain concerns, Jain and Dupas (2020) document the impact of the lockdown on India's non-COVID-19 health outcomes and Ravindran and Shah (2020) examine the impact of the Indian lockdown on rates of domestic abuse. More broadly, our work connects to the literature examining the consequences of policy responses to COVID-19 in the developing world (see e.g. Banerjee et al. (2020) and Ajzenman et al. (2021) on the impacts of public health messaging, and Banerjee et al. (2020) and Londoño-Vélez and Querubin (2020) on the impacts of emergency cash assistance).

Our work also connects to the more general global debate on whether economic responses to COVID-19 are more policy-driven or more related to voluntary individual responses. This debate informs central questions: does lifting a lockdown cause economic activity to increase? Or will people stay at home regardless of the official lockdown policy in the hope of mitigating personal and social risks? Coibion et al. (2020) estimate that lockdowns account for close to 60% of the decline in the employment to population ratio in the US. Our results suggest that the shock to food supply in India was driven more by lockdown policies, which varied in stringency across states, than by local responses to COVID-19 risk, which also varied within each state.

We also contribute to the broader literature on impact of COVID-19 on different economic activities throgh multiple contagion channels. Woodford (2022) shows that COVID-19 led to disruption of the circular flow of payments, resulting in a failure of effective demand. Guerrieri et al. (2022) argue that reduction in potential output in a sector caused by the pandemic could spillover to other sectors through the demand channel. Similarly, Baqaee and Farhi (2021) study the impact of COVID-19 shock on production networks. Our study shows that in India food supply shocks following lockdown remained short-lived and the recovery was broad based irrespective of COVID-19 incidence intensity.

A preliminary version of chapter 2 was published as *Reserve Bank of India Working Paper (RBI Working Paper No. 10/2020).*[3] Chapter 4 was published in journal *Food Policy December 2021 Issue.*[4]

[3] `https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=50401`
[4] `https://doi.org/10.1016/j.foodpol.2021.102162`

Chapter 2

Are Food Prices Really Flexible?: Evidence From India

2.1 Introduction

Food prices are generally considered to be flexible, driven by frequent supply shocks exhibiting large volatility. Monetary policy based on a New-Keynesian sticky price framework would then require that the relevant measure of inflation should abstract from such price changes and a measure of inflation which excludes food and fuel (referred to as core inflation), is considered as an appropriate target for monetary policy (Mishkin 2008; Aoki 2001). The notion of flexible food prices, however, has not been subject to much empirical scrutiny. Most of the empirical estimates of price stickiness did include food prices in their list of items but the focus was on estimating the aggregate measure of price stickiness (Klenow and Malin (2010) provides a summary of this literature).

This study looks at price setting behaviour within the food sector both from a macro and micro perspective in an emerging economy context where dynamics of food prices matter much for policy. Specifically, I ask the question: are food prices really flexible as commonly assumed or do we find evidence of price stickiness within the food sector? If so, does their behaviour align with the existing theories of price stickiness and what are the implications for policy? This question assumes importance in the background of recent developments in the literature on understanding the extent and role of price stickiness for policy. While initial works focused on a single parameter of price stickiness, Nakamura and Steinsson (2010) show that heterogeneity in degree of price stickiness across product groups raises monetary non-neutrality. Also, Kehoe and Midrigan (2015) argue that distinguishing between temporary and more permanent price changes is necessary to understand the role of price stickiness in monetary policy transmission. Therefore, this study accounts for both heterogeneity across products and the difference between temporary and permanent price changes in assessing price stickiness.

In order to accomplish these tasks, I compiled a dataset on retail prices using the information available from the Price Information System set up by the Government of India. The compiled dataset comprises of 1.9 million price data points covering 46 food items on a weekly basis across 85 centres in India for the period 2005-2021. To my knowledge, this is the first attempt at compiling actual price data for estimating price stickiness in India. These products represent more than two third of the items in the official CPI for food category and has products representing each of the 10 product groups within the food component of CPI. Weekly frequency and wider geographical coverage gives the opportunity to have a better identification of price flexibility, especially in those items with very frequent price changes as compared with monthly data (Cavallo 2018).

Choice of India for this study is motivated by the fact that degree of stickiness in food prices has more relevance for policy in India as food accounts for 46% in overall consumer price index (CPI), by far the highest among inflation targeting countries. Therefore the risk of policy errors from excluding sticky component, if any, in food sector is large in India as compared with most of the advanced economies where food has a low share in CPI (typically less than 10%). Also, food price inflation showed considerable variability in India during the sample period (ranging between an annual average of 1.5% in 2017-18 to 12.4% in 2009-10) which gives us an opportunity to understand degree of price stickiness in an environment of high variability in inflation. So far, most of the empirical work on price stickiness, with the exception of Gagnon (2009), was done in developed country context where the variability in inflation is generally low. Moreover, food sector in India is also documented to have a market structure which is far from perfect competition. Chatterjee (2017) estimates significant market power for intermediaries in food market in India while Banerji and Meenakshi (2004) document evidence of collusion among suppliers. Monopolist tendencies in the food market therefore provide a further case for understanding the price stickiness from a New-Keynesian point of view. Finally, though India adopted flexible inflation targeting as the framework for monetary policy in 2016, there exists no study on the extent of price stickiness in India using the actual price data, a critical parameter for calibrating monetary policy models.

I start with documenting the extent of stickiness of food prices in India. In terms of posted prices,[5] the median duration of a price spell is 1.2 months. However, there is large heterogeneity between product groups as it varies between about half a month for vegetables to more than 5 months for milk. Following the methodology used by Eichenbaum et al. (2011), I then estimate an underlying price -the reference price- for each of the item as the price which occurs most number of times (mode) within a given quarter to assess the stickiness of permanent component of prices. In terms of reference prices, the median duration increases to 4.6 months and the product level heterogeneity continue to persist with milk prices having a duration of 10 months. These results, therefore, does not support the hypothesis of food prices being completely flexible.

Being one of the first empirical work on price stickiness in India, the study also presents a set of stylised facts in line with Nakamura and Steinsson (2008) which characterise the price setting

[5]Posted prices refer to prices reported in the survey for the week.

behaviour. 76% of the variation in frequency of price change across products is contributed by variation between product groups. I also find that prices are downward flexible with more than 45% of the recorded price changes being price declines, even though aggregate inflation remained positive for most of the time period. In terms of size of price change, it averages between 5 to 18% across product groups and absolute size of price decreases, on an average, is higher than that of increases. Over time, frequency of price change co-move with aggregate inflation. Many products also exhibit seasonality in frequency of price changes. Spatially, perishable items show much larger variability in price levels across regions. Also, frequency of price changes vary considerably across regions with northern and north-eastern regions showing lower frequency of price change. These patterns point towards the importance of both product and region level factors in conditioning price setting behaviour.

The chapter then provides evidence on how much the behaviour of food prices in India align with testable predictions of models of pricing in the literature; both state and time-dependent[6]. First, I check for perfect staggering of frequency of price changes over time, a prediction of pure time-dependent pricing (Dias et al. 2005). I reject the hypothesis of perfect staggering of frequency of price changes and find that frequency of price change is synchronized, both at the product as well as centre level implying that frequency of price change is endogenous. In order to investigate the nature of state-dependency in a cross section setting, I then look at the relationship between size and frequency of price change. This could either be negative or positive depending on the nature of menu costs (fixed or variable across products) and the type (temporary versus permanent) of cost and demand shocks (Berka et al. 2011). When shocks are transient and small, this relationship is negative if menu costs vary across firms. In case of permanent and large shocks driving price changes, this relationship will be positive. Our results show that for posted prices, the relationship between size and frequency of price change is negative and significant whereas for reference prices it is not significant. In case of reference prices, vegetables and meat shows a positive relationship between size and frequency offsetting the negative relationship observed in the case of other product groups. This suggests that for some products, shocks could be large and frequent, driving both size and frequency higher.

Theory predicts that the frequency and size of price change should be responsive to marginal cost changes over time in a state-dependent set up (Eichenbaum et al. 2011). I test this prediction using inflation as a proxy for marginal cost changes. For posted prices, frequency of price increase responds positively while frequency of price decrease responds negatively to inflation. At the aggregate, they cancel each other out leading to no significant response of overall frequency of price change to inflation. Reference prices react in the same direction as posted prices, but show greater responsiveness. However, stronger positive response of frequency of price increase outweighs the negative response of frequency of price decrease leading to a

[6] In time-dependent pricing, timing of price change is exogenous whereas in state-dependent models, it is driven by changes in underlying state variables such as marginal cost or demand shocks.

positive and significant relationship between overall frequency of price change and inflation in reference prices. In terms of size of price change, only the size of price decline responds negatively to inflation in case of posted prices. For reference prices, size of increase responds positively and that of decrease responds negatively to inflation. These findings suggest that price setting behaviour in food exhibit properties of state-dependency where menu costs are important.

Finally, I look at the implications of the estimated price stickiness in food for policy. I construct a measure of sticky food prices by re-weighting the official CPI with degree of stickiness estimated from our results. I find that inflation in sticky component of food prices remained above excluding food and fuel inflation during the high inflation phase and subsequently fell below as inflation moderated. This dichotomy implies that focusing only on excluding food and fuel inflation as a measure of underlying inflation entails the risk of policy errors by neglecting the dynamics of sticky component of food inflation.

The rest of the chapter is organised as follows. Section 2.2 describes the data used in the study and also provide definitions of various measures of price stickiness. In section 2.3, I document the stylised facts with respect to food price setting in India and section 2.4 provides estimates of price stickiness for posted and reference prices. Reduced form estimates of theoretical predictions from pricing models are provided in section 2.5. Section 2.6 compares inflation derived from sticky measure of food prices to that of overall food prices and core (excluding food and fuel) prices. Finally in Section 2.7, I offer the concluding remarks and sketch out possible areas for further research.

2.2 Data and Measurement of Price Stickiness

2.2.1 Data

Currently, the Central Statistics Office (CSO) of Government of India releases only the item level price indices aggregated at the national level and no information about the actual level of prices is available. The Labour Bureau of Government of India releases item level price across 78 centres in the country which goes into the compilation of CPI for Industrial Workers.[7] These prices are not for the identical products and also the price information is provided as average prices at the centre level. Therefore, using the price data which forms part of CPI has its limitations given our primary objective of understanding the extent of price stickiness.

Given the inadequacy of the official CPI data, I use the data on prices available from the Price Information System set up by the Department of Agriculture and Co-operation, Government

[7]Index used for wage indexation.

of India.[8] The system was set up for monitoring the retail prices of essential commodities in different parts of the country on a weekly basis. The retail prices[9] are collected in respect of 46 food items which cover the broad spectrum of consumption basket. Some of the items have prices quoted for more than one variety leading to a total number of 56 products/varieties for which prices are available. This covers 30% of all India CPI and 65% of the items covered within the food category of CPI. Appendix table A.2 lists the number of items along with their weight in overall CPI. The geographical coverage of this data is extensive with data reported from 85 centres spread all over the country.

Prices are collected by using a proforma where a single price quote is obtained for each of the product from each centre. Since the basic objective is to monitor market prices of essential commodities, price data is collected only for items sold in the open market. Therefore, regulated or subsidised prices do not form part of the dataset. Various nodal agencies work as the agents of price collection which includes Market Intelligence Units, State Government's Bureau of Economics and Statistics, Agriculture Producing Market Committee (APMCs), District Supply Offices, Agriculture Marketing agencies *etc.* Each week, the proforma is received by post by the central agency. Consistency is ensured by making sure that the prices are received for the identical item from all the centres by specifying the exact variety for which the price is collected.[10] The agency also makes sure that the reporting is regular by sending fortnightly reminders in case of missed reporting and also seeking clarifications from the data supplying agencies if the received data has a variation of more than 10%. The data is compiled and disseminated in the "Retail Bulletin of Food Items" which is published every week. Part of this data is also hosted in the Ministry of Agriculture, Government of India website.

I compiled this data using both the Weekly Bulletin and data hosted in the government website. Although the data is available from 2001, the reporting was quite irregular and data is available only for a few centres. Observation of the compiled data as well as discussions with the government officials revealed that the regular reporting of data started from 2005. Therefore, for the purpose of analysis, I use the data from first week of January 2005 to last week of July 2021 (a total of 865 weeks). The total number of price records are 1.9 Million, spread across 46 products and 85 centres. Data consistency was ensured by manually checking for reporting errors like zero coding of missing observations as well as errors in decimal points. Since the database is survey based, there could be a possibility of reporting error which could remain even after the checks are carried out. To make sure that I do not include minor errors in data entry as price changes, I exclude all price changes which are denominated as less than 50 paise[11] for price levels below 100 rupees and below 1 rupee for prices above 100. This filtering leads to

[8] This is managed by the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India.

[9] Defined as the price which the ultimate consumer pays when buying from a retailer.

[10] For example, for Apple, it is defined as delicious, medium size in Kilograms; for biscuit as Glucose biscuit, 80 gram packet and for banana it is fair average quality per dozen.

[11] 50 paise is the smallest denomination of coin in circulation.

dropping of a marginal amount of price changes from the data (about 2500 from 1.19 million change observations).

In order to ensure data robustness, Appendix A.1 gives a number of checks to ensure that the results are not biased on account of missing observations and unbalanced nature of the panel. Moreover, to specifically address the question of whether more than 10% variation is reported in the data, Appendix figure A.3 plots the percentage change distribution of prices for a few select items to show that such a cut off for requirement of an explanation does not lead to bunching of prices at 10% level.

2.2.2 Measuring Price Stickiness

There are two different approaches towards measuring price stickiness. The direct measure of price stickiness is duration of a price spell which is the amount of time elapsed between two price changes. Counting the number of price spells in the data and taking the average of the observed durations can give the measure of price stickiness. This method, however, has two important limitations. First, the sample period is fixed and therefore observed price spells are truncated both at the beginning and end of the sample which could create bias in the estimation of duration. Secondly, in the presence of missing data, which is a case in the dataset used in this study, some restrictive assumptions will have to be made about the unobserved data points.

Most empirical works on price setting, therefore, use the frequency approach, which is an indirect method of estimating duration of price spells which I also follow. Price for a specific item in a single local market/store in a centre is denoted as P_{ict} where i, c and t stands for product, centre and week respectively. For each product, frequency of price change is computed as

$$Fchange_i = \frac{\sum_c \sum_t \mathbf{1}\{P_{ict} \neq P_{ict-1}\}}{\sum_c \sum_t \mathbf{1}\{P_{ict} \neq missing \cap P_{ict-1} \neq missing\}} \tag{2.1}$$

This gives the fraction of price observations at time t which were different from $t-1$ over all the observations for which prices at t and $t-1$ were observed summed across both centre and weeks. Similarly, I calculate the frequency of price increase and price decrease as

$$Fincrease_i = \frac{\sum_c \sum_t \mathbf{1}\{P_{ict} > P_{ict-1}\}}{\sum_c \sum_t \mathbf{1}\{P_{ict} \neq missing \cap P_{ict-1} \neq missing\}} \tag{2.2}$$

and

$$Fdecrease_i = \frac{\sum_c \sum_t \mathbf{1}\{P_{ict} < P_{ict-1}\}}{\sum_c \sum_t \mathbf{1}\{P_{ict} \neq missing \cap P_{ict-1} \neq missing\}} \tag{2.3}$$

Inverse of $Fchange_i$ would be a broad approximation of duration of price spells. However, if we assume that prices could change at any point of time, in a continuous time set up, the duration of a price spell for a commodity is estimated as[12]

$$Duration_i = -\frac{1}{log(1 - Fchange_i)} \tag{2.4}$$

Once I estimate the duration at product level, for arriving at measures of duration at product category and aggregate (all products) levels, I use product level weights obtained from all India item level CPI (Base: 2012). These weights are based on the all India Consumer Expenditure Survey conducted in 2011-12. The products in our dataset are classified into 10 different product groups by matching each item with the corresponding group in CPI to which the item belongs. Throughout this chapter, I report duration estimates converted to monthly frequency to make comparison across reference periods and studies undertaken in other countries easier.

2.3 Features of Food Price Behaviour in India: Stylised facts

This section provides a set of stylised facts about the nature of price setting within food sector in India. Since this study is the first attempt to characterise nature of price setting in India specific context, documenting these are important. Also, the patterns that emerge from these stylised facts throw light on the underlying factors conditioning price flexibility. These facts are reported in terms of: (1) degree and price flexibility across products, (2) extent of downward flexibility, (3) size of price change, (4) spatial dispersion of price levels, (5) variation in price flexibility across time, (6) seasonality of price flexibility and (7) regional variation in price flexibility. Table 2.1 summarises major indicators based on which these stylised facts are documented. I have also checked the sensitivity of these estimates to missing data and has found that they are robust to missing data problem as stated above (Appendix A.1).

2.3.1 Food prices are flexible but with a significant level of heterogeneity

On a weekly basis, the weighted median frequency of price change is about 18% which corresponds to a duration of 1.2 months. However, there is considerable heterogeneity across product groups. For example, vegetable prices on an average change about two times in a month whereas milk prices changes only once in five months. Appendix table A.3 gives details of price behaviour across all the items covered in the study.

Variance decomposition of product level frequency of price change indicates that between-

[12]For a detailed discussion on methodology of computing duration see Gouvea (2007) and Bils and Klenow (2004).

group variation accounts for 76% of the total variation.[13] This indicates that product group specific characteristics are more important in driving heterogeneity in price stickiness. Greater importance of product group level characteristics in conditioning price stickiness as against specific product level factors could be on account of a number of reasons. Supply or sector specific demand shocks could have similar effects on price stickiness of products within the same product group. Also, given the substitutability of products within the same product group, there could also be spillover effects among products in a group creating similar effect. Which of these channels dominates this phenomenon is an important question, but is beyond the scope of this study.

These results also throw some light into the different factors at play in explaining heterogeneity of price stickiness.[14] First is the role of market structure. For example, in the case of milk, we see that the prices are relatively sticky and anecdotal evidence suggest that the milk market in India is dominated by the co-operatives. Similarly, for finished products like biscuit and bread we see a large duration of price spell. This is also indicative of the fact that at higher end of the value chain prices tend to be more sticky. Apart from differences in market power across different product groups, the nature of shocks faced could also be different across different items contributing to heterogeneity in degree of price stickiness. Items like vegetables are usually subject to more frequent supply shocks owing to their short crop cycles and dependence on weather. We see that vegetables exhibit largest price flexibility among our product groups. Therefore the observed heterogeneity in degree of price stickiness could be a combined outcome of sector specific supply shocks, market structure as well as the size of cost of changing prices.

2.3.2 Prices are flexible downwards for most products

Most of the literature on price setting emphasises the role of downward price rigidity as a key driver of price stickiness. I find that prices are flexible downwards with an average 57% of the price changes being price increases and 43% price decreases (56 and 44% respectively, if we use weighted median estimates). These estimates are similar to the ones derived for food prices in advanced economies (see Klenow and Kryvtsov (2008) for US, Dhyne et al. (2006) for euro area and Berka et al. (2011) for Switzerland).

As in the case of change frequency, we see considerable variation in this ratio across products. For select vegetables (tomato, onion and brinjal), decreases are more frequent relative to increases (Appendix table A.3). With average aggregate inflation remaining positive for each of these over the sample period, this implies that the magnitude of price increases, on an average, was larger than decreases for these items, leading to such a pattern. Milk and products, mutton

[13] I used the Bartlett's test to check whether the variance within product groups are the same and the results confirmed that the equality of variance can not be rejected (χ^2 value of 12.31 with $Prob > \chi^2$=0.196.

[14] These observations are descriptive in nature as data limitations does not allow us a more formal analysis.

and processed food items like biscuit and bread exhibited most downward rigidity with more than 60% of the price changes being price increases.

There exists a significant negative association between price flexibility (frequency of price change) and ratio of price increases to total changes (correlation coefficient of -0.79 between the two). Those food items which exhibit a longer duration of price spells are, therefore, the ones which have prices which are relatively downward rigid. This, in fact, brings about the role of downward price rigidity in generating price stickiness.

2.3.3 Price change magnitudes are relatively large

Column 5 of Table 2.1 gives the average size of absolute change in percentages, conditional on observing a price change. The average absolute size of a price change is about 10% whereas the median price change is about 6% on account of the positively skewed distribution of absolute size of price changes. Vegetables and fruits have a high level of absolute price change of 18% and 14%, respectively indicating that these prices are extremely volatile across time with the amplitude of price changes being very large. On an average, the absolute size of price decreases are marginally higher than that of price increases. At the product group level, however, we see a significant divergence in this pattern with 6 of the 11 product groups having higher absolute size of price decrease.

2.3.4 There is considerable spatial variation in price levels across centres

I computed the standard deviation of log of prices at the product level across all centres for each week. This was averaged for the entire time period to generate product level statistics. This was further aggregated by using a weighted sum within each product category using CPI weights and is reported in Column 6 of Table 2.1. On an average, for beverages and most of the relatively perishable items like vegetables, fruits, meat, fish and spices, prices show much more cross-sectional variability as compared with more durable items like pulses, sugar and edible oils. Cereals and milk are, however, an exception to this general pattern.

2.3.5 Frequency of price change co-moves more with inflation than size of price change

To gauge the link between food price inflation and frequency of price changes, I look at the trends in change frequency (overall, increase and decrease; weighted average across products) against inflation in CPI for food items over the time period. To abstract from volatility in frequency of price changes on a week to week basis and also to make sure that there are enough samples in each time period, I define quarter as the unit of analysis. For each quarter, the frequency of price changes and the absolute size of change are estimated at the product level and then arrive at weighted average for each of the product category.

Figure 2.1 plots the trends in frequency of price changes over time. Overall frequency of price change remained range-bound between 15-20% for most of the time period, barring the latest few quarters (2017 onwards) when it fell below that range. The trend in annual inflation based on food category CPI[15] is plotted in the secondary axis. The variability in frequency of price change across high and low inflation episodes is of a lower magnitude than that of the change in inflation. The frequency of price increases and decreases move in opposite direction to changes in inflation. A higher inflation is associated with a higher frequency of price increase whereas frequency of price decreases co-moves negatively with inflation. Since overall frequency of price change is a sum of these, they cancel out each other leading to lower variability in frequency of price change. Period since 2017, however is marked by a decline in frequency of price increase leading to a fall in overall frequency of price change, something which can be expected in a low inflation environment. I also checked whether the observed trends were broad based by looking at the product categories and found that the frequency of price change across product groups generally move in the same direction (Appendix figure A.2).

I also looked at the trends in average absolute size of price change (both increase and decrease separately) over the sample period. Figure 2.2 indicates that size of absolute change remained volatile but in a very narrow range of between 10-12% for most of the time period up to 2015. There has been a gradual moderation in the size of price change since then and the average size of price change moved to about 7% in the latest period. The CPI food inflation, however, ranged between -0.1 to 16.3% during the same period. A combined look at the movements of frequency of price change and size shows that inflation is associated more with frequency of price change than size.

2.3.6 There are Seasonal Variations in Price Changes

Food prices in India exhibit significant seasonal pattern largely following the crop cycle. The co-movement of frequency of price change with inflation that we observed above is translated into seasonal pattern in price change frequency too. In Figure 2.3, I plot the average frequency of price increases and decreases across quarters. We see that largest frequency of price increase and smallest frequency of price decrease occur in April-June quarter. From thereon, there is a gradual decrease in frequency of increase over successive quarters and for frequency of price decreases, the trend is opposite. This is largely driven by the seasonal pattern where the arrival of crop usually leads to a fall in prices during the winter season and prices rebounding during

[15] I use CPI for Industrial Workers (IW) for period between 2005-2011 as all India CPI is available only from 2011.

the summer.

The seasonal pattern, however, is not uniform across different product group categories. I estimated the seasonal effects on price change frequency as follows. For each of the product group in the dataset I ran regressions of frequency of increase and decrease on dummy variable for each of the month keeping August as the base. Data was aggregated at the centre level with centre fixed-effects incorporated in the regression. The coefficient of each month gives us an idea about whether the price increase/decrease frequency was significantly different in that month as compared with the base month (August). I report the coefficients from individual regressions for each product category in Appendix tables A.4 and A.5 for both frequency of price increases and decreases. The key takeaway is that as compared to August, frequency of price increases were generally lower for vegetables, pulses and sugar during the period December to March. All of these also had higher frequency of price decreases during December to March. Cereals and Milk, two of the product groups with largest weight in CPI, however, does not exhibit much seasonality in frequency of price changes.

2.3.7 Price stickiness vary across regions

The literature on price stickiness and spatial dispersion largely focus on the role of sticky prices on generating price dispersion across the outlets in a homogeneous location (Kaplan and Menzio 2015; Sheremirov 2015). I look at the dispersion in price stickiness across different regions in India. Different regions in India could be expected to have different characteristics in terms of price setting behaviour owing to its diversity in level of economic development as well as other factors like institutions and infrastructure. I divided the country into five different regions, North, South, East, West and North East.[16] The overall frequency of price increases and decreases are reported in figure 2.4. We see that frequency of price changes is lower in Northern and North-Eastern region as compared with the other regions.

There could be a host of factors that influence varying degree of price stickiness across regions. Within the limited scope of this study, I focus on two important economic characteristics and its association with level of price stickiness across regions. Per-capita income can impact demand elasticity of food and also stand for the level of economic development. I worked out the correlation coefficient between average per-capita income in 2018-19 across 28 states for which data was available and the degree of price flexibility. I find that per capita income at state level and frequency of price changes do not exhibit any significant co-movement (correlation coefficient of 0.10).

Another important factor which could have a role in shaping the degree of price could be the level of infrastructure. If a region is well connected with the rest of the country, it could have a less

[16]This follows the classification used by Price Monitoring Cell, Government of India.

severe impact from supply shocks. Also, in a region with poor connectivity changes in transport costs would have an impact on inflation as well as frequency of price change. I calculated the correlation between price change frequency and road density per thousand population across various states in 2018. I find that there exists a negative and significant correlation between price change frequency and road density (coefficient of -0.56 with a 'p' value of 0.02).

The take away from these stylised facts is that the price setting in food sector has a lot of heterogeneity and are conditioned by the type of the product, level of aggregate food price inflation, seasonal effects as well as spatial factors. All these indicate that the price setting is influenced by underlying economic conditions.

2.4 Price stickiness in low *versus* high frequency price movements

Estimating an appropriate degree of price stickiness is also dependent on the selection of time frame. Initial works on empirical estimation of price stickiness, however, ignored this question. Bils and Klenow (2004) estimated price stickiness in the US taking into account all the price changes by arguing that even the magnitude and duration of temporary price changes are driven by shocks and therefore a realistic estimation of price flexibility should include those changes as well. Nakamura and Steinsson (2008) countered this and argued that some part of the sales could be orthogonal to underlying macroeconomic conditions and therefore needs to be excluded while estimating price stickiness. The result was that while Bils and Klenow (2004) found the duration of price spells to be 4.3 months, Nakamura and Steinsson (2008) estimated it to be at much higher level of 7-11 months.

This debate initiated a number of subsequent works which tried to reconcile the simultaneous existence of differential price stickiness at low and high frequencies. Kehoe and Midrigan (2008) showed that firms could set prices separately for shorter and longer horizon, under the assumption that temporary price changes are less costly than more permanent price changes. Eichenbaum et al. (2011) examined the impact of this on macroeconomic policy and concluded that the monetary policy have substantial real effects in the presence of differential price setting between temporary and reference prices. Kehoe and Midrigan (2015) extended both the standard Calvo pricing and menu cost models by adding separate frictions to show that low frequency price movements do respond to monetary policy shocks. The empirical estimates for other countries also support the hypothesis of different price stickiness at high and low frequency (for example see Berka et al. (2011) for Switzerland). The case for looking at a low frequency movement of prices, therefore, is stronger in the debate on the appropriate measure of price stickiness.

Identifying the temporary price changes from the data and defining an appropriate time frame for low frequency price movements are the two important challenges in estimating low frequency price stickiness. Those studies which used the official CPI data from the US had the advantage of data collection agency recording a separate identifier for sales price. In those datasets which do not have an explicit identification of the sales price, some studies have excluded price changes which revert to the original price in the next period while estimating frequency of price changes. The other approach is to define a time frame for which a reference price could be set and then use the price which is recorded most number of times within the reference period (modal price) as the reference price and recalculate frequency of price changes with respect to reference prices instead of posted prices.

The literature is rather ambiguous on selection of time frame for calculating the reference price. Eichenbaum et al. (2011) justified the choice of quarter as a reference time frame by stating that most macroeconomic models are calibrated on a quarterly basis and the nature of price movements are similar between monthly and quarterly reference time frames. Kehoe and Midrigan (2015) selected annual time frame as the reference period, which was justified by the fact that even at annual frequency, about 73% of the posted prices were equal to the reference prices. Moreover, they also found that this ratio is consistent with the moments generated by calibrated menu-cost model in their study.

There is no identification of sales prices in our dataset and therefore defining a time period for calculating the reference price is the first challenge. Using a simple method of excluding price changes which revert within one period does not allow us to clearly identify the temporary price changes, given the level of flexibility that we observed in posted prices. For example, prices may rise by 10% and subsequently fall by 2% for five consecutive weeks for it to reach the original level. Excluding mean reverting price changes would therefore be difficult in such a scenario. I rely upon both patterns emerging from the data as well as arguments from the literature for the selection of appropriate time frame for calculating the reference price.

Changing the reference period may lead to a different estimate of duration of price changes but the ranking of products in terms of degree of price flexibility should be more or less similar irrespective of the time frame. I calculated frequency of price changes at weekly, monthly, quarterly and annual time frames. For each of the time frame, the reference price is defined as the price which prevailed the most number of times during the time period (modal price). Subsequently, I calculated the Spearman rank correlation of duration estimated across each of these reference prices at the product level (Table 2.2). We see that the ranking of products according to the degree of price flexibility is maintained almost the same up to the quarterly frequency, whereas in annual frequency, the rank correlation coefficient falls markedly. Additionally, I calculated the fraction of prices that are equal to the reference prices in each of the time frame. For monthly and quarterly time frames, these fractions were 87 and 75%, respectively, while for annual frequency it fell to 58%. These indicate that annual frequency may not be a true representation of the low frequency price movements. Intuitively, agricultural price cycles in India could be expected to have less than annual frequency as many crops have a shorter than annual crop cycle. Even many annual crops are cultivated more than once in a year (during *kharif* and *rabi* seasons). In view of these, I select quarterly time frame as the period for calculating the reference price which is also informed by the fact that the fraction of prices at mode prices in quarterly estimates matches with the results from Kehoe and Midrigan (2015).

We see that the duration increases significantly with quarterly reference prices. It increases from 1.3 months in the posted prices to 4.6 months with reference prices. Table 2.3 compares the duration estimated with quarterly reference price data with that of posted price (weekly) estimates across all the major food product categories. The large dispersion in duration across products continues to persist with the standard deviation of duration measured on quarterly reference prices being 1.77. The duration of reference prices in the case of cereals, spices and milk are in the range of 7-10 months, which is not in conformity with the notion of perfectly flexible food prices. Except for vegetables and pulses, posted prices are equal to reference prices for more than two third of the sample indicating that for most product group categories such reference prices are indeed relevant. We can therefore, conclude that the notion of food prices being extremely flexible needs to be re-looked as there is evidence of much higher level of price stickiness at low frequency.

How far our results align with evidence from other countries? Studies undertaken in different country contexts indicate that, generally food prices are much more flexible than non-food prices (Table 2.4). Also, in all the countries, food prices are more flexible in posted prices than in reference prices. Our estimate of posted price duration is lower than most studies in the literature. Estimates of reference price level duration in food prices in India, however, is higher than the corresponding number for US reported by Nakamura and Steinsson (2008).

Another important question is how relevant are these estimated levels of price stickiness for macroeconomic policy? I look at the literature to provide a comparative perspective on how these results line up with the theoretical postulates. The first generation of New-Keynesian macroeconomic models were in a single sector framework with one price stickiness parameter and most calibrated models used/estimated it to be in the range of 6-9 months. Smets and Wouters (2007) use 6 months while Christiano et al. (2005) and Gertler and Leahy (2008) estimate it to be 7.5 months. Median estimate of this study for food prices is lower than these. Smets and Wouters (2007), however, show that a reduction of price stickiness weakens the strength of nominal rigidities through increase in persistence of mark-up shocks and price indexation but does not eliminate it. Therefore, the real effects of nominal shocks in food sector could still be relevant, though not as strong as the benchmark models.

With respect to heterogeneity across product groups and difference between stickiness in posted and reference prices, Golosov and Lucas Jr (2007) showed that in the presence of menu costs and strong state-dependency in pricing monetary non-neutrality becomes small and transient, which questioned the foundation of New-Keynesian macroeconomic policy. In response, Nakamura and Steinsson (2010) calibrated a multisector menu cost model with heterogeneity in frequency and size of price change and showed that accounting for heterogeneity in price setting would increase the monetary non-neutrality by a factor of three. Further, Midrigan (2011) showed that distinguishing between temporary and permanent price changes would make the models in line with Golosov and Lucas Jr (2007) produce similar level of monetary non-neutralities as in a standard Calvo pricing model. Our results show that both these factors are at work in food sector in India and therefore there is a non-negligible role for food price stickiness in policy.

2.5 Models of Price Stickiness and Behaviour of Food Prices in India

This section is devoted to understanding how far the observed characteristics of price setting in food sector in India are driven by the identified reasons for price stickiness in the literature. Understanding this is important as the macroeconomic policy framework of inflation targeting is based on the assumptions of presence of price rigidities working through the channels identified in the literature.

Macroeconomic literature on price setting is broadly divided into time-dependent and state-dependent pricing models. In a time-dependent pricing model, the timing of price change is exogenous. If we assume that the underlying process is approximated by a Taylor (1980) set up, firms get to change price in every n^{th} period. Therefore, the proportion of firms changing their prices is constant across time. In a Calvo (1983) formulation, only a fraction of firms are able to reset their prices at any point of time and the probability of price adjustment is random. Even under Calvo model of price setting, under the assumption of independent decision of price change by each firm, the expected value of proportion of firms changing their prices is constant over time (noted by Klenow and Kryvtsov (2008)). This implies that frequency of price change would be perfectly staggered under a pure time-dependent pricing with the expected value of fraction of sellers changing their price being constant over time.

In state-dependent pricing models, firms face a cost of changing the price (menu cost) and the decision to change price is dependent on the size of the marginal cost or demand shock and the extent of menu cost. One way to look at the empirical validity of state-dependent pricing is to see the relationship between frequency of price change and its size in cross section. This relationship could either be positive or negative conditional on the specifications/assumptions about the underlying process for menu costs and shocks to demand or cost faced by the firms. If menu cost differs across firms and they face mean zero iid shocks to cost/demand, we would expect a negative relationship between size and frequency of price change in cross section. This is because, firms with large menu cost will wait longer to change their price (implying lower frequency) and accumulated costs would imply larger size of price change (Berka et al. 2011). In the presence of large idiosyncratic shocks with a fat tail distribution, firms frequently hit their upper bound of price change and they change their price more often and by a larger amount which generates a positive relationship between frequency and size of price change (Klenow and Kryvtsov 2008). Also in terms of the dichotomy between behaviour of posted price and reference price, Kehoe and Midrigan (2015) calibrate the model with both permanent and transitory idiosyncratic shocks to productivity. This enables them to match the differential response of posted and reference prices to the shocks. If the permanent shocks are large and persistent we can expect the sellers to pass it on by raising both the frequency and size of price change leading to a positive relationship between the two in case of reference prices.

Regression of size and frequency of price change on marginal cost over time is another way to identify the extent of state-dependency. The literature, however, does not have a consensus on either the magnitude of impact or on the relative importance of frequency and size of price change. For example, in response to a monetary shock, the average size of change responds in the model of Golosov and Lucas Jr (2007) whereas in Dotsey et al. (1999) it is the fraction of firms who changes their price which responds to the shock. I now examine how these predictions are borne out by our data.

2.5.1 Staggering versus Synchronisation in Price Changes

One of the ways by which time-dependent pricing can be tested is to look at whether price changes are synchronised or staggered across products/locations. An empirical test for staggering versus synchronisation in price changes was proposed by Fisher and Konieczny (2000) while studying the price setting behaviour of Canadian newspapers. They proposed the following measure:

$$FK = \sqrt{\frac{1}{T}\frac{\sum_{t=1}^{T}(p_t - \tilde{p})^2}{\tilde{p}(1-\tilde{p})}} \tag{2.5}$$

where p_t is the proportion of firms changing their price in period t and $\tilde{p}$ is the proportion of firms changing prices estimated from the whole sample (across all the periods). Under perfect synchronisation, the measure FK would have a value of 1. In every period either all the sellers change their prices or none change their price which would mean that p is a binary variable with variance equal to $\tilde{p}(1-\tilde{p})$. On the other hand, if price setting is completely staggered, $p_t = \tilde{p}\ \forall t$ leading to $FK = 0$. The authors proposed a χ^2 test for testing the null hypothesis that price setting is completely staggered. Dias et al. (2005) provided a structural interpretation to the FK index and interpreted it as a method of moments estimator of degree of synchronisation. They showed that the null hypothesis of perfect staggering could be tested using a test statistic which takes the form

$$Q = (NT)FK^2 \tag{2.6}$$

where N is the number of cross-section observations and T is the total time period which follows a χ^2 distribution with $(T - 1)$ degrees of freedom. I use the same measure to test for perfect staggering in price setting. As price setting could be synchronised/staggered both across centres and products, I conduct the test for perfect staggering both at the commodity level and at the centre level.

I reject the null hypothesis of perfect price staggering both at the product level and at the centre level. Appendix tables A.6 and A.7 give the results of the test. The evidence of synchronisation at the centre level (prices of different commodities at the same centre) point towards centre specific state variables having a significant role in shaping price stickiness. Similar argument can be made with product level synchronisation i.e., prices of same product across different centres show evidence of synchronisation indicative of importance of product level state variables too. If we take the value of FK index as the degree of price synchronisation, on an average, the value at centre level is higher than the value at product level.

2.5.2 Relationship Between Duration and Size of Price Change

As discussed earlier, conditional on the nature of menu costs and magnitude of cost or demand shocks, the relationship between size and frequency of price change could be either positive or negative. How this relationship is manifested in our data is tested by estimating the following regression in a cross section set up.

$$Y_{ic} = \alpha + \beta X_{ic} + \gamma_c + \gamma_p + \epsilon_{ic}. \tag{2.7}$$

where Y_{ic} is the absolute size of change and X_{ic} is the frequency of price change for product i at centre c averaged across all time periods. γ_c and γ_p are centre level and product category level fixed effects. Since we have documented that there is significant heterogeneity in price setting behaviour across different product categories, I also ran separate regressions on each of the product groups with the same specification but with only centre level fixed effects.

We see that there exists a significant and negative relationship between frequency and size of price change at the aggregate level for posted prices (Table 2.5). At the product category level, beverages, cereals, fruits milk, oils and pulses exhibit this negative and significant relationship indicating that for posted prices variability in menu costs is likely the major contributor to differences in frequency of price changes in these items. Meat, spices, sugar and vegetables, however, does not show any significant relationship between size and frequency of price change.

In case of reference prices, we see that at the aggregate level there is no significant relationship between the size of price change and frequency of price change (Col 4 of Table 2.5). At the product category level, however, we see a dichotomy with cereals, milk, oils pulses and spices exhibiting a negative and significant co-efficient whereas vegetables and meat exhibiting a positive relationship. For vegetables and and meat, weather related and other supply shocks are large and very frequent, creating large shocks to marginal costs impacting both frequency and size of price changes. If we follow the argument of Kehoe and Midrigan (2015) reference prices adjust to permanent component of shocks and therefore both the size and frequency of price changes respond to more permanent changes in marginal cost or demand in these items. Posted prices showing a negative relationship when reference prices have an ambiguous relationship indicates that for posted prices transitory shocks lead to differential response across sectors depending on the size of the menu cost.

2.5.3 Response of Frequency and Size of Price Change to Inflation

In a state-dependent pricing model, the response of frequency and size of price changes to marginal cost shocks is the major channel through which how price stickiness vary over time can be identified. Empirical identification of this relationship is difficult as marginal cost is not directly observable in most cases. Eichenbaum et al. (2011) is the only exception where they could explicitly get the data on movement of marginal cost as well as prices from the same dataset. Most of the other studies used some measure of aggregate inflation as a proxy for changes in marginal cost. Nakamura and Steinsson (2008) used aggregate level of inflation while Dhyne et al. (2006) as well as Berka et al. (2011) used the regional and sectoral level inflation respectively as proxy for marginal cost.

Following the identification strategy in the literature, I use the CPI product category inflation as the proxy for marginal cost. All India CPI is available only from 2011, which restricts the analysis to only the period 2011-2021. Figure 2.5 plots the trends in both year-on-year and month-over-month CPI inflation for food during this period which shows that our sample period had considerable variability in inflation. As compared with the other studies in the literature, our empirical setting provides the scope for better identification as the period under our analysis is characterised by significant variability in CPI food price inflation. Also from a methodological point of view, in most of the studies, annual inflation (log difference of 12 month) was used as a proxy for marginal cost. Changes in annual inflation, however, could be driven by base effect as much as price change in the latest period. For example, if there was a sudden fall in prices in last year in the same month, when we calculate the annual inflation, inflation could go up even when prices in the current period remain constant (European Central Bank 2017). To overcome this potential bias, I use the first difference in log CPI. The basic specification is as follows,

$$Y_{it} = \alpha + \beta \Delta log(CPI)_{pt} + \gamma_t + \gamma_p + \epsilon_{it}. \tag{2.8}$$

where Y_{it} is the variable of interest averaged across weeks and centres for a product i in a month/quarter t. There are five estimates with different dependent variables; frequency of price change, frequency of price increase, frequency of price decrease, absolute size of increase and absolute size of decline. $\Delta log(CPI)_{pt}$ is the first difference of log of CPI for product group p in period t. γ_t are time fixed effects and γ_p are product category level fixed effects. Presence of a large number of centres in our dataset enables us to follow such an identification strategy. I run the regressions both on posted prices are well as reference prices (quarterly mode).

Table 2.6 reports the results for posted prices. The coefficient of regression of inflation on frequency of price change is insignificant which may suggest that the price change frequencies do not respond to marginal cost shocks. However, under state-dependent pricing, the cost of changing price is compared with size of marginal cost and the seller changes the price when marginal cost is above menu cost. Therefore, when inflation is high, more producers are likely to revise their prices upwards and vice versa. Likewise, when there is an increase in marginal cost, the proportion of price decreases will fall. Therefore, we need to look at the frequency of price increases and decreases separately. The results reported in column 2 and 3 of Table 2.6 show that frequency of price increases respond positively to changes in inflation while frequency of price decreases respond negatively. Thus it cancels out in the aggregate change frequency, which is a sum of these two, as the magnitude of response of both price increases and decreases are similar.

Turning to the absolute size of price increases and decreases, absolute size of price increases do not respond to inflation whereas that of price decreases declines. This is intuitive as the sellers would not want to increase the size of price increase and thereby lose customers whereas they can easily reduce the size of price decline to accommodate the shock.

If we look at the reference prices, the overall frequency of price change responds positively to inflation (Table 2.7). The pattern of frequency of price increases responding positively to inflation and price decreases responding negatively is maintained in the reference prices. The magnitude of coefficient increases significantly in both the cases, but more so for price increases. In terms of the size of price changes, now the size of price increases respond positively to inflation while the size of price decreases continues to respond negatively to inflation. Thus, in terms of response of frequency and size of price change, reference prices show much more alignment with the predictions of a standard state-dependent model.

The reduced form empirical results, thus gives us the idea that food prices in India exhibit properties that match predictions of state-dependent pricing models and therefore they can not be excluded altogether while framing macroeconomic policy.

2.6 Behaviour of Sticky Component of Food Prices and Non-food Prices

What are the implications of our results for macroeconomic policy, especially monetary policy? Should monetary policy pay attention to the developments in the sticky component of food prices? If movements in prices of excluding food and fuel category mirrors the trends in sticky component in food prices, the latter would be a sufficient statistic for the trends in sticky food prices. In that case, a policy focusing on excluding food and fuel component would also take into account the dynamics of sticky food prices. Therefore, to make an explicit case for directly focusing on sticky component of food prices, its underlying dynamics should not necessarily coincide with that of the non-food prices.

I undertake the following exercise to test whether sticky food prices co-move with core inflation (underlying inflation which is generally approximated by inflation in excluding food and fuel category). I construct a reweighed CPI for each of the major food groups by multiplying the consumption weight with duration estimated from reference prices. This approach follows the empirical literature on estimating core inflation by re-weighting the CPI using inverse of historical volatility or estimated persistence parameter (see Silver (2007) for a detailed discussion on alternate methodologies). The difference between the conventional measures and my approach is that while the literature use statistical properties of the CPI, I explicitly use the estimated price stickiness as the weighting parameter. This approach is more aligned with micro-foundations of role of nominal distortions. For example, Eusepi et al. (2011) showed that targeting a measure of inflation which assigns the largest weight for price stickiness leads to minimum welfare loss.

First, I obtain CPI data on food prices at the product group level. For each of the product category, after multiplying the CPI weights with the duration estimates derived from reference prices I normalise them to 100. Using these new weights, I generate an aggregate stickiness weighted food price index. I compare the trends in this measure with non-food component of CPI as well as the CPI food prices (official). The analysis was carried out on a monthly basis by estimating year-on-year inflation based on all the three measures and the period covers from 2012-2021, the time span for which inflation based on a national CPI is available in India. Overall CPI food inflation is much more volatile during the period as compared with the stickiness re-weighted food price inflation (Figure 2.6). Also, sticky food inflation and excluding food and fuel inflation does not coincide all the time. For example, the CPI excluding food and fuel inflation (conventional core inflation) declined during 2013-17 a phase where the sticky food inflation remained consistently above the conventional core inflation. Similarly since mid 2017, we see the excluding food and fuel inflation remaining firm rising whereas the sticky food inflation remaining low except for the initial months of the pandemic shock.

Given that food accounts for nearly half of weight in CPI in India, this has significant implications for macroeconomic policy. For example, if the central bank uses excluding food and fuel measure of inflation in a Taylor rule, under-prediction of inflation in core on account of exclusion of sticky food prices can lead to lower than desired changes in interest rate and vice-versa. The bottom line is that macroeconomic models have to explicitly account for sticky component of food prices in such an environment.

2.7 Conclusion

In this chapter, I provide evidence of extent of price stickiness in food sector in India using a newly constructed dataset for the period 2005-2021. I document that there exists heterogeneity in degree of price stickiness within food products and duration of price spell goes up from 1.3 to 4.1 months if we use the reference prices (quarterly mode). Stylised facts about price setting behaviour indicate that, frequency of price change is synchronised across products and regions, co-move with inflation and exhibit strong seasonality in select products. Regression results show that both in posted as well as reference prices, frequency of price increases and decreases are significantly impacted by marginal cost shocks (proxied the inflation at the product group level). At the aggregate, both frequency and size of price change respond to marginal cost shocks in the case of reference prices. These empirical findings are in alignment with the predictions of a state-dependent pricing model with menu cost. Finally, I show that trends in a stickiness re-weighted CPI food inflation does not perfectly align with CPI excluding food and fuel inflation and therefore the latter can not fully capture the dynamics of sticky component of food prices.

The findings of this study brings forth a number of issues which provides the scope for further research. A natural extension of this study would be to compile data on non-food items and undertake a similar exercise depending on data availability. Also, given our finding of large heterogeneity across the country, spatial dimensions of price setting is another important dimension to which this study can be extended to. It would be interesting to study whether the law of one price holds across regions, how prices respond to shocks across regions with different characteristics in terms of economic development and institutions. Finally, given that food prices are usually informally set, what contributes to the observed price stickiness could be an interesting question. The next chapter of the thesis explores one of such mechanisms.

2.8 Tables

Table 2.1: Behaviour of Food Prices in India: A Snapshot

Product Category	Frequency of Price Change (%)	Duration (Months)	Proportion of Price Increases (%)	Size of Change(%)	Size of Increase(%)	Size of Decrease(%)	Std. Dev. of Log Prices	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Milk & products	4.31	5.2	68.31	8.0	7.8	8.3	0.16	1,45,379
Non-alcoholic beverages	6.05	3.7	62.37	7.8	7.8	7.9	0.53	1,10,453
Spices	8.88	2.5	56.79	12.0	12.2	11.9	0.30	1,86,204
Cereals & products	12.22	1.8	58.06	6.4	6.4	6.5	0.32	4,61,258
Oils & fats	19.84	1.0	57.49	4.5	4.6	4.5	0.17	1,65,914
Meat & fish	20.42	1.0	55.77	9.2	9.0	9.4	0.27	1,35,871
Sugar & confectionary	20.51	1.0	51.51	4.9	5.2	4.6	0.10	1,55,455
Egg	22.34	0.9	53.74	9.0	8.9	9.1	0.17	38,117
Fruits	23.83	0.8	53.12	13.7	13.5	14.0	0.35	1,40,809
Pulses & products	27.59	0.7	53.39	5.1	5.2	5.0	0.13	2,76,302
Vegetables	41.65	0.4	50.39	18.4	18.6	18.2	0.31	1,64,158
All Products (Mean)	18.30	1.1	57.26	9.8	9.6	10.0	0.25	19,79,920
All Products (Median)	17.87	1.2	55.54	6.5	6.5	6.5	0.21	19,79,920

Table 2.2: Spearman Rank Correlation Between Duration Estimates

Time	Weekly	Monthly	Quarterly	Annual
	(1)	(2)	(3)	(4)
Weekly	1			
Monthly	0.985	1		
Quarterly	0.957	0.985	1	
Annual	0.787	0.841	0.888	1

Table 2.3: Duration Estimates Based on Weekly and Quarterly Reference Prices

Duration based on	Weekly	Quarterly	% at Reference Price (Quarter)
	(1)	(2)	(3)
Vegetables	0.44	1.98	52.5
Pulses and products	0.74	2.56	63.7
Egg	0.91	3.40	67.7
Fruits	0.96	3.85	74.5
Oils and fats	1.05	3.33	72.7
Meat and fish	1.12	4.39	74.3
Sugar and confectionery	1.64	4.36	80.4
Spices	2.57	6.92	82.7
Cereals and products	3.42	7.15	79.7
Non-alcoholic beverages	3.70	8.51	89.2
Milk and products	5.30	9.84	88.9
All Products	1.29	4.64	75.19

Table 2.4: Estimates of Duration of Price Spells (Months): Select Countries

		Food Prices		Overall	
Country	Study	Posted	Reference	Posted	Reference
	(1)	(2)	(3)	(4)	(5)
US (Offline)	Nakamura and Steinsson (2008)	2.1	3.5	4.6	11.0
US (Online)	Cavallo (2018)		-	4.3	-
Euro Area	Dhyne et al. (2006)	3.0	-	10.6	-
Switzerland	Berka et al. (2011)	2.2	37	-	-
Brazil	Gouvea (2007)	1.6	-	1.9	-
India	This study	1.3	4.6	-	-

Table 2.5: Regression of Size of Price Change on Frequency
Dependent Variable: Average Absolute Size of Log Price Change

	Posted Prices		Reference Prices	
Category	Coeff	Std. Error	Coeff	Std. Error
	(1)	(2)	(3)	(4)
All Products	-0.05***	(0.01)	-0.02	(0.01)
Beverages	-0.55***	(0.14)	0.27	(0.17)
Cereals	-0.07**	(0.03)	-0.07***	(0.02)
Fruits	-0.11**	(0.05)	0.03	(0.09)
Meat	-0.02	(0.02)	0.08***	(0.03)
Milk	-0.14**	(0.06)	-0.10**	(0.05)
Oils	-0.13***	(0.03)	-0.15***	(0.03)
Pulses	-0.06***	(0.01)	-0.03*	(0.02)
Spices	-0.03	(0.06)	-0.18***	(0.05)
Sugar	-0.09	(0.06)	-0.01	(0.04)
Vegetables	-0.01	(0.03)	0.14**	(0.07)

*, ** and *** indicate significance at 10, 5 and 1%, respectively.

Explanatory variable is the frequency of price change in all the regressions.

For all products, the regression includes centre and product category level fixed effects. Standard errors are clustered at product category level. Estimates for egg is not reported as there is only one product in the category.

Table 2.6: Regression of Frequency and Size of Price Change: Posted Prices

	(1)	(2)	(3)	(4)	(5)
	chf	incf	decf	abinc	abdec
$\Delta logCPI$	0.02	0.88***	-0.86***	-0.00	-0.15***
	(0.10)	(0.16)	(0.15)	(0.03)	(0.03)
_cons	0.17***	0.09***	0.08***	0.09***	0.09***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Product Category FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N	7182	7182	7182	7045	6873
adj. R^2	0.627	0.491	0.536	0.289	0.260

DataPeriod: 2011-2021

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

chf: Frequency of Price Change, incf: Frequency of Price Increase

incf: Frequency of Price Increase, abinc/abdec: Mean (absolute) size of increase/decrease

Table 2.7: Regression of Frequency and Size of Price Change: Reference Prices

	(1)	(2)	(3)	(4)	(5)
	chf	incf	decf	abinc	abdec
$\Delta logCPI$	0.12*	1.76***	-1.64***	0.50***	-0.50***
	(0.06)	(0.22)	(0.18)	(0.14)	(0.11)
_cons	0.48***	0.27***	0.21***	0.14***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Product Category FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N	2394	2394	2394	2371	2289
adj. R^2	0.463	0.348	0.426	0.355	0.261

DataPeriod: 2011-2021

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

chf: Frequency of Price Change, incf: Frequency of Price Increase

incf: Frequency of Price Increase, abinc/abdec: Mean (absolute) size of increase/decrease

2.9 Figures

Figure 2.1: Price Change Frequency Over Time

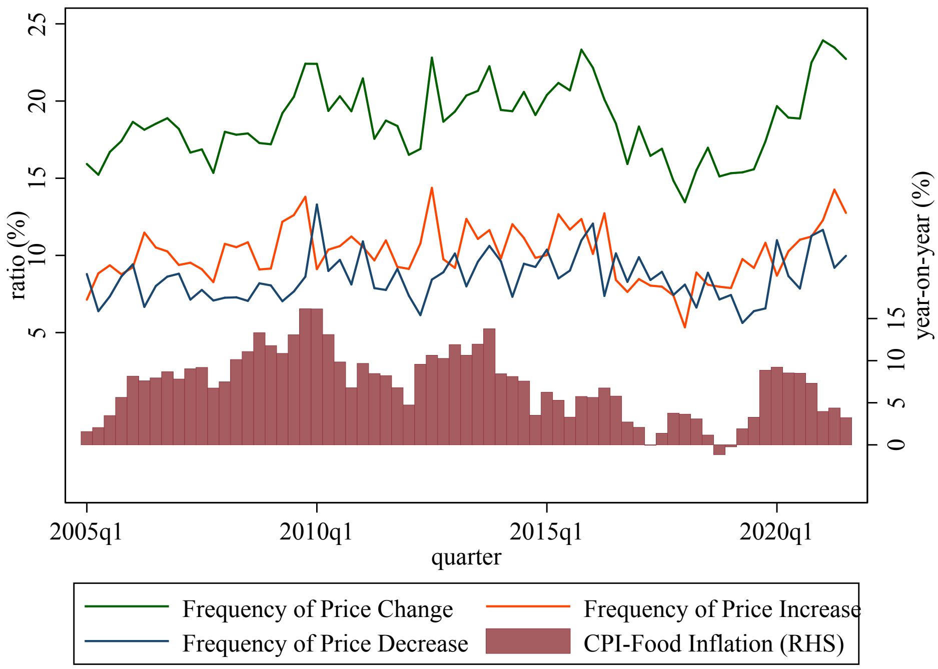


Figure 2.2: Trends in Magnitude of Price Change Over Time

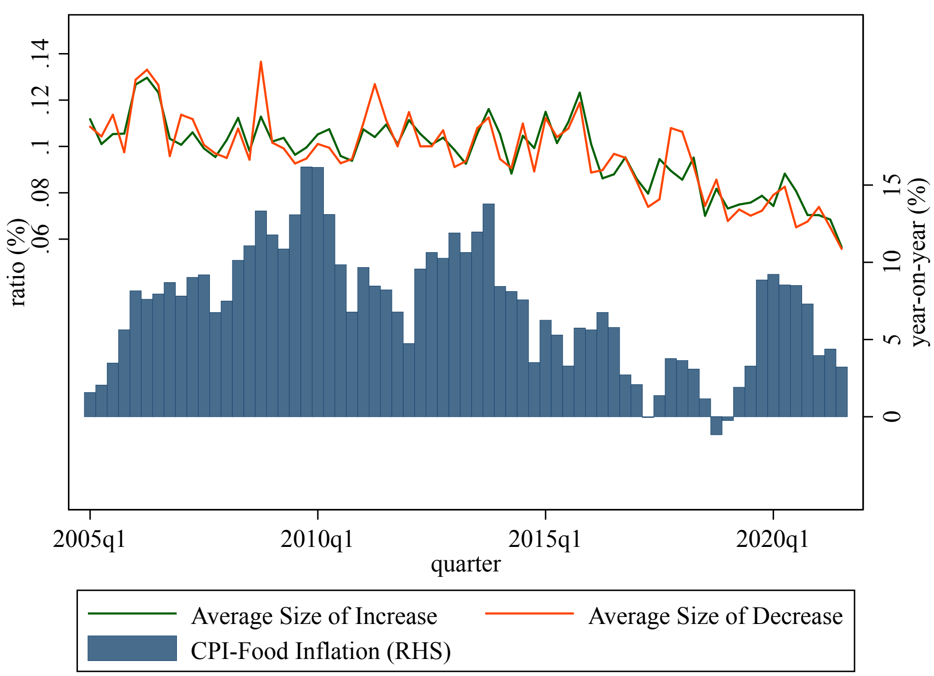


Figure 2.3: Price Change Frequency Across Quarters

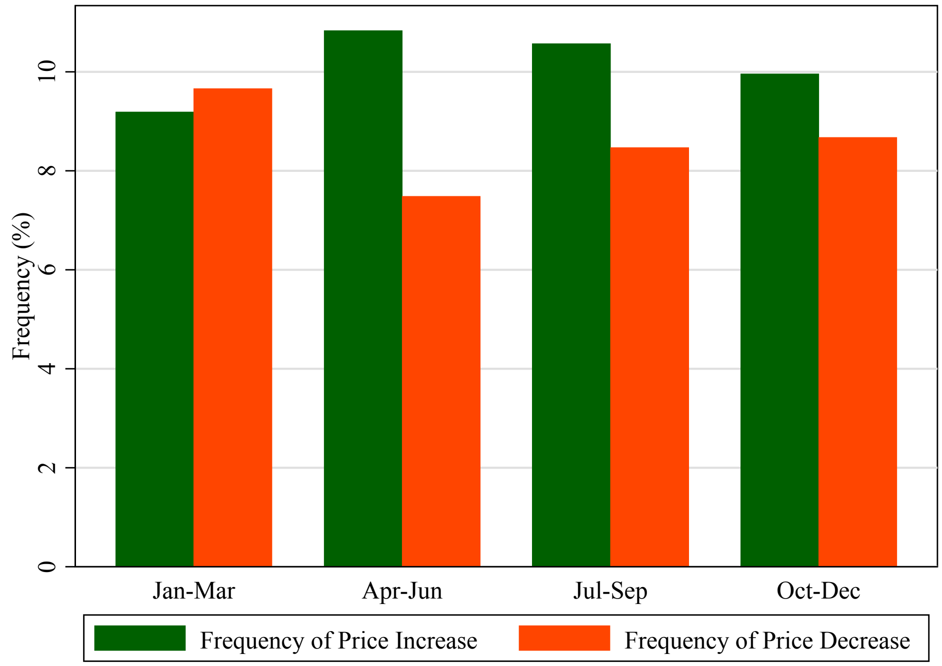


Figure 2.4: Food Price Changes Across Regions

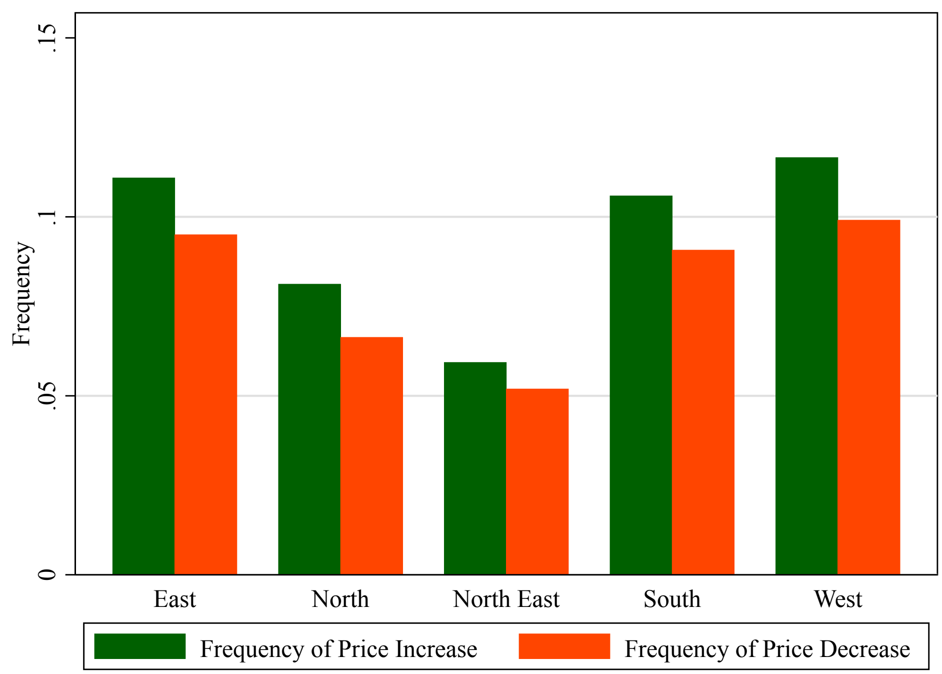


Figure 2.5: Trends in overall CPI Food inflation 2011-21

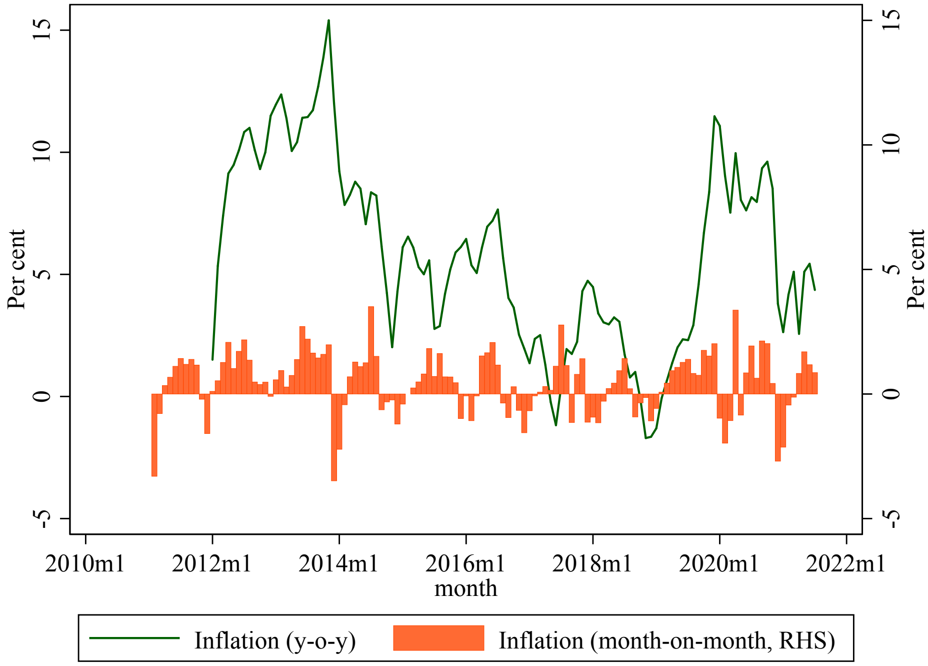
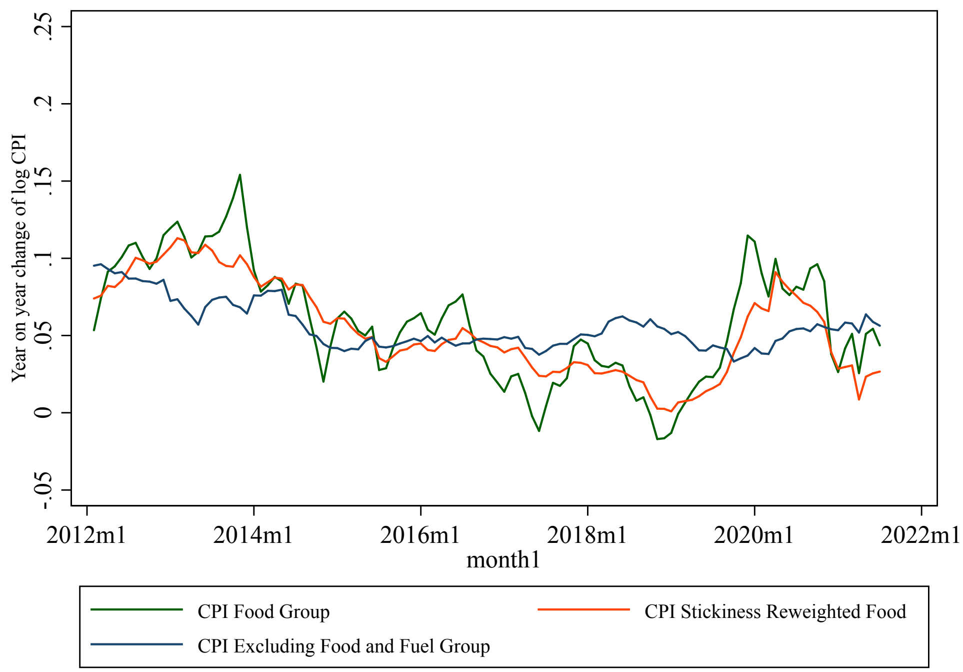


Figure 2.6: Trends in Sticky Food Inflation vs. Food and Non-food components



Chapter 3

Price Setting in a Cash Dominant Economy

3.1 Introduction

Understanding the nature of price setting and sources of price rigidity has been one of the areas of active research in macroeconomic literature in recent years. A number of studies attempted to estimate the cost of changing prices known as menu costs to see how much of price stickiness could be attributed to the menu costs (e.g., Levy et al. (1997), Anderson et al. (2015), Eichenbaum et al. (2011)). Apart from menu costs, a growing body of literature has been focusing on behavioural and other reasons that could explain stickiness of prices. For example, there is evidence that the producers' attempt to take advantage of consumers' left digit bias leads to prices becoming more sticky at 9 and .99 ending digits (Levy et al. 2011). Also, price setting prices at digits which are convenient for transactions could contribute to price rigidity (Knotek 2008). In this chapter, we look at the nature of price setting in food prices in India and show that when most of the transactions are done using cash, there is a strong incentive for prices to be rounded in order to ease transactions. This in turn generates price stickiness. We also show that the such rounding off is much less in the case of online transactions and prices are much more flexible. By embedding the friction on account of non-divisibility of currency into a standard menu cost model, we further show that the extent to which the currency non-divisibility influences price stickiness is conditioned by the magnitude of distance between price points, level of prices as well as the size of menu costs.

The chapter begins by documenting the existence of bunching at round digits which matches the currency denominations available in India. For this, we use a novel data compiled from the Price Information System set up by the Indian Government to monitor the prices of essential food items on a weekly basis which was discussed in detail in chapter 2. We also validate the existence of bunching at round digits by looking at the pattern of bunching in implied prices from consumer expenditure data. Then we look at the bunching behavior in an online grocery shop prices in India to show that in an online setting bunching in rounded digit reduces significantly and that prices become much more flexible.

In the case of offline prices, we show that nearly half of all prices are set in digits ending 0 or 5. The bunching at 0 and 5 ending digits are larger at higher levels of prices. By looking at the probability of price being constant, we show that 0 ending prices, on an average, are twice more likely to remain constant as compared with odd digit ending prices whereas 5 ending prices are 50% more likely to remain constant. Conditional on a price change, the transition probabilities indicate that the price transitions are mostly dominated by movements between the 0 and 5 ending prices. This is also reflected in the distribution of price changes in absolute values where we see that the magnitude of price change maps currency denominations.

Using web scraped data on online prices for fruits and vegetables we then show that the bunching in round digits reduce substantially when we look at online prices. At the aggregate level, online prices are much more flexible than their offline counterparts with prices changing almost once in every three days for fruits and vegetables as compared with about two to three weeks in case of offline prices. The 0 and 5 ending prices constitute less than one third of all prices and we see a significant bunching of prices at 9 ending digits, especially at higher level of prices. However, we do not find evidence of 0 and 5 bunched prices being more sticky, as the probability of price remaining constant is nearly the same for 0 and 5 ending prices as compared with odd digit ending prices. In order to check whether 9 ending prices now become the bunching point in online setting, we estimate the probability of price remaining constant, conditional on it being a 9 ending price and show that 9 ending prices are indeed more sticky than the non-9 ending prices, but the magnitude of stickiness is much lesser as compared with 0 and 5 ending prices in offline setting. The transitional probabilities also fail to bring forth any particular pattern to show that price transitions are between bunched price points.

These results show that when transactions are using physical currency, it acts as a friction that contributes to price stickiness. We incorporate this friction into a menu cost model by allowing discontinuity in price setting to account for discrete currency denominations. Specifically, we use distance between two price points in which prices can be set as the tool to embed this friction. Our simulations show that in the presence of small menu costs, prices become more sticky when the distance between price points becomes larger. However, in the presence of high menu costs, price points become less binding as a constraint. This is because if a seller has to wait for a long time to change the price, and the consequent accumulated desired price change is large, the price discontinuity would not matter. Also, we show that if the distance between price points are linear across price levels, the effect of price points on price stickiness is much larger for low level of prices. In other words, faced by a common shock, lower denominated prices would find it harder to adjust as compared with higher denominated prices.

We calibrate this model to the key moments of price setting in the case of offline food price data. We show that neither menu costs, nor price points in its own is able to generate the key moments of the data. Therefore a suitable approach is an augmented hybrid model with simultaneous existence of price points and menu costs. In order to understand the contribution of price points to price stickiness, we run a counterfactual and show that the menu costs would have to be 30 per cent higher to generate the same level of price stickiness once we remove the friction induced by price points. Therefore, we can conclude that both price points and menu costs contribute to price stickiness.

The rest of the chapter is organised as follows. Section 3.2 looks at price bunching in case of food prices from the survey data on offline prices and examines its' role in generating price stickiness. Section 3.3 examines the same issue in an online setting using web scraped data from a large retail chain. Section 3.4 introduces the menu cost model with embedded price points and Section 3.5 shows calibration results and extent to which price points contribute to price stickiness. Implications of existence of price points for price setting and its interaction with menu cost and price levels is explored through the lens of the model in Section 3.6. Section 3.7 discusses conclusions and policy implications and emerging issues for further research.

3.2 Price Setting in Offline Prices

3.2.1 Data

This study uses a newly constructed dataset using information on prices available from the Price Information System set up by the Department of Agriculture and Co-operation, Government of India.[17] The system was set up for monitoring the retail prices of essential commodities in different parts of the country on a weekly basis. Retail prices - defined as the price which the ultimate consumer pays when buying from a retailer - are collected in respect of 46 food items which cover the broad spectrum of consumption basket. Some of the items have prices quoted for more than one variety leading to a total number of 56 products/varieties for which prices are available. In terms of coverage, the data includes prices of items which comprise of 30% of all India Consumer Price Index (CPI) and 65% of the items covered within the food category within CPI. The geographical coverage of this data is extensive with data reported from 85 centres spread all over the country.

Prices are collected by using a proforma where a single price quote is obtained for each of the product from each centre. Various nodal agencies work as the agents of price collection which includes Market Intelligence Units, State Government's Bureau of Economics and Statistics, Agriculture Producing Market Committee (APMCs), District Supply Offices, Agriculture Marketing agencies *etc.* Each week, the proforma is received by the central agency. Consistency is ensured by making sure that the prices are received for the identical item from all the centres by specifying the exact variety for which the price is collected.[18] The agency also makes sure that

[17] This is managed by the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India.

[18] For example, for Apple, it is defined as delicious, medium size in Kilograms; for biscuit as Glucose biscuit,

the reporting is regular by sending fortnightly reminders in case of missed reporting and also seeking clarifications from the data supplying agencies if the received data has a variation of more than 10%. The data is compiled and disseminated in the "Retail Bulletin of Food Items" which is published every week. Part of this data is also hosted in the Ministry of Agriculture, Government of India website.

We compiled this data using both the Weekly Bulletin and data hosted in the government website. Although the data is available from 2001, the reporting was quite irregular and data is available only for a few centres. Observation of the compiled data as well as discussions with the government officials revealed that the regular reporting of data started from 2005. Therefore, for the purpose of analysis, we use the data from first week of January 2005 to last week of October 2021 (a total of 890 weeks). The total number of price records are 1.9 Million, spread across 46 products and 85 centres. Data consistency was ensured by manually checking for reporting errors like zero coding of missing observations as well as errors in decimal points. Since the database is survey based, there could be a possibility of reporting error which could remain even after the checks are carried out. To make sure that we do not include minor errors in data entry as price changes, we exclude all price changes which are denominated as less than 50 paise[19] for price levels below 100 rupees and below 1 rupee for prices above 100. This filtering leads to dropping of a marginal amount of price changes from the data (about 2500 from 1.19 million change observations).

3.2.2 Bunching and Price Stickiness

In this section, we attempt to establish the micro evidence for price rigidity. Firstly, we examine whether there is bunching of prices at any particular digits and how that is related to the price levels and product categories. Secondly, we test whether the prices are more sticky at levels where they are bunched which could establish the link between bunching and stickiness. Then we look at the transition probabilities, conditional on a price change, between price points to see whether there exists any discreteness in price change pattern. Finally we also look at the size distribution of price change frequencies at the product level to see whether such discreteness in price changes result in concentration of change magnitudes.

First, we divide the entire sample into three groups according to the average of prices observed (those with average price less than Rupees 25, between 25-100 and greater than 100). We then calculate the share of prices observed with digits ending for each of the single digits and of decimals. Overall, 49% of the prices were set in denominations with last digit ending at 0 or 5 (Figure 3.1). The share of prices set with 0 as ending digit goes up substantially with increase in price levels whereas that of ending at 5 remain almost at the same level. The share of prices

80 gram packet and for banana it is fair average quality per dozen.

[19] 50 paise is the smallest denomination of coin in circulation.

reported in decimal points is less than 5% even for the small ticket items. This is in contrast with the results observed by Levy et al. (2011) for US where prices were set with digits ending at 9 and in decimal points in most number of cases with only 20% of the prices set in whole digits. Thus, we see that there is considerable bunching at 0 and 5 ending digits with some mass also in even digits.

Bunching of prices at any specific level, however, does not necessarily lead to price rigidity. For bunching to generate stickiness in prices, the probability of price remaining constant at a bunched digit would have to be higher than other points. To test this, we adapt the empirical strategy used by Levy et al. (2011) to our setting to estimate the probability of price remaining constant. We use a binomial logit model to estimate the probability of price remaining constant at different price levels ending at different digits. Unlike in Levy et al. (2011) where they tested only for price change probability between 9 ending and other digits, we look at probability of price remaining constant over a range of values ending in decimal points, even numbers, 5 and 0 against odd digits. With substantial variation across product category groups in price levels, it is likely that price rigidity at bunched digits can be different across product groups. Therefore, in departure from Levy et al. (2011), we also test for the probability of price remaining constant at each of the bunching point for every product category. we estimate the following regression by way of maximum likelihood using equation 3.1.

$$ln\big(p_t/(1-p_t)\big) = \alpha + \beta_d Digit_{ict} + \gamma_c + \gamma_p + \gamma_m + \epsilon_{ict} \tag{3.1}$$

where p is the probability of price remaining constant in period t. $Digit_{ict}$ represents a set of dummy variables representing prices set at decimal points, even digits, 5 and 0. γ_c, γ_p and γ_m are centre level, product category level and monthly fixed effects, respectively. For each of the 10 product categories in our data set, separate estimates of the above specification excluding the product category fixed effects are also attempted. Estimated coefficients are reported in Table 3.1. The table also reports odds ratios, calculated as $e^{coefficient}$, which gives idea about likelihood of price changes as compared with baseline category (prices set in odd digits).

Prices set at digits ending 0 are twice likely to remain constant as compared with prices set at odd digits at the aggregate. Odds ratios vary from 1.6 in the case of oils and fats to 2.7 for cereals and products. For prices ending at digit 5, the odds ratio at the aggregate is 1.48 implying almost a 50% higher likelihood of keeping prices constant as compared with prices ending at odd digits. For even digit ending prices, odds ratio is 1.35. In the case of decimals, however, the ratio is 0.41 indicating that prices set with decimal points are almost 60% less likely to remain constant as compared with prices set at odd digits. This pattern of high stickiness in bunched prices is not driven by level effects which is evident from product category level analysis. For example, both vegetables and spices have odds ratios of around 1.9 for prices ending at 0 to remain constant as compared with prices set at odd digits, though their average levels of prices are significantly different (Rs.18.7 for vegetables and Rs.91.2 for spices).

If bunching contribute to price stickiness, it would also reflect in the way price changes occur. If some price points are preferred over others, there would be more number of price transitions occurring between them. In order to see whether such a pattern is supported by our data, we estimate the transition probability across each of the price digits in a 10 state Markov Chain. We ignore the decimal points in this exercise as they are less than 5% of our sample and only look at the last whole digit of price. The transition probability matrix is worked out as percentage of price changes occurring between two values ending at each of the single digits to total number of price changes in the dataset. For example, the movement of price from 10 to 20 is recorded as a move from digit ending at 0 to 0, from 10 to 12 as 0 to 2 and so on. The transition probability matrix shows that movement from one 0 ending price to another 0 ending price dominate the transitions with 12% of all changes (Table 3.2). The next two highest probabilities are movement from 0 to 5 and 5 to 0 at around 6% each. Of a total of 100 possible changes, 25% of the price changes are between the two bunched points 0 and 5. It is also striking to note that conditional on a change, 2, 5 and 8 ending prices are most likely to change to a 0 ending price.

So far, we have evidence of bunching at 0 and 5 ending prices, greater price stickiness at those points and higher likelihood of movement of prices between the preferred price points. How do these patterns translate to stickiness in prices at the product level? If prices are sticky on account of these, we can expect discrete changes in prices. Assuming that marginal cost shocks are normally distributed, if we see spike in mass points at certain specific denominations of price change, it is an evidence of frictions in setting the optimal price. In order to see whether such friction is prominent in our case, we look at the frequency of price changes across products.

For each product, we generate a frequency distribution of price change magnitudes in absolute levels. For convenience of presentation, we plot 4 products with different characteristics in terms of level and flexibility of prices. We choose apple and mutton, with an average price of Rs.90 and 270 as the items with relatively high level of prices. Apple represents a relatively flexible price item whereas mutton is from the stickier end of the spectrum. Similarly from the low price category we plot onion and bread, with average price of Rs.15 and 19 respectively; onion being a flexible price item and bread being sticky.

In Figure 3.2 frequency of price change is plotted against magnitude of change in levels for these products. For products with high level of prices (apple and mutton), most of the changes occur in values of Rs. 5, 10 and 20, irrespective of increase or decrease. Similarly for low level of prices, changing prices by Rs. 1 and 2 dominates over the changes in other denominations. Even though this amount appear to be small, as a percentage of average prices, these turn out to be more than 5% and 10% respectively. As a robustness check, Appendix B.1 plots the frequency of price changes against magnitude of change in percentages. The discreteness found in absolute amounts is not reflected in percentages as most frequencies are below 5% and spread out over a range of values. Thus, the discreteness is not on account of sellers changing price by any specific value in percentage terms.

This pattern is in fact repeated over all the products in the sample. We calculated the share of top denominations (say like 5, 10 and 20 for apple) in overall change magnitudes for all the products. Conditional on a price change, 60% of the time, it changes by either one of the two most preferred denominations, say 5 or 10 and 72% of the time, by either of the three most preferred denominations. As the product's average price increases this pattern does not disappear rather the values by which price change occurs moves up. For example, once the average product price reaches near three digit figures, the price change pattern shifts to 5, 10 and 20 and stays the same for all the products with price above 100.

Now the question is why do such a preference pattern exist where both price levels and changes have a discrete pattern? One possible reason for this could be the role of cash. India is predominantly a cash driven economy and most of the transactions behind the prices reported in our data are carried out in cash. While deciding on by how much the prices should change, the transaction cost involved with dealing in cash could, therefore, become an important determinant. Prices could be set in such a way that the cost of transaction in terms of making available the exact change denominations is minimised. The availability of denominations of currency and coin in India exactly matches these change frequency pattern.[20] 70% of all price changes reported in our data are in denominations of 1,2,5 or 10.

What are the implications of such a pattern for aggregate price stickiness? We could argue that those products which are subject to more frequent cost shocks reach their preferred price change magnitudes more often, therefore changes prices more often. On the other hand, those products where the shocks are relatively benign, sellers would have to wait for costs to accumulate for them to reach the preferred denomination of price change, or front load the changes, thereby creating a low frequency of price change. Also, depending on the level of prices, the ability of a seller to change price could change. At lower level of prices, it is much less likely that you will find a convenient denomination to change the price into for a small change in marginal cost. However, as prices goes up, the availability of such price points also increases. The size of menu cost could be another factor conditioning price response. A complete understanding of the channels through which these play out in generating price stickiness would require developing a full fledged model based on the premises set above. We explicitely address this issue in section 3.4 where we introduce a menu cost model with price points.

[20]various coin/currency denominations available are at Rs.0.5, 1, 2, 5, 10, 20, 50, 100, 500 and 2000.

3.2.3 Cash Friction Across Price Levels

While we observe that there is bunching of prices at round digits, the link to availability of cash is not directly established. Rounding could also be caused by agents trying to minimise the mental cost of calculation or any other behavioural reasons. However, such behavioural patterns would generate the situation where the rounding will be in percentage terms and not in absolute values. To illustrate, if an optimal price of 9.5 would be rounded to next round digit 10, the same agents would round off 95 to 100. In such a situation, we would see that the distance between pricing points are multiplied with levels of prices which is referred to as constant relative distance. In other words as the price levels goes up, the distance between price points would also increase proportionally.

To test this we look at whether the digit distribution of price is level invariant. As a prior, we should expect that the digit distribution should be more discrete at lower price levels where it is a binding constraint. Suppose we take items which are priced with average price between 10 to 25 and compare it with the same at a level of multiple between 100 to 250 in terms of digit distribution. If rounding off is also scaled up as price levels go up, percentage of prices with 5 as ending digit in price range of 10-25 should match the percentage of prices set with 50 as ending digit in price range 100-250. Basically, the digit distribution would also be scaled up with level of prices. Using our data, we test whether this holds true. Table 3.3 presents the results.

Nearly 23 per cent of prices are set at multiples of 10 in range of 10-25 whereas only 11 per cent of prices are set at multiples of 100 in price range 100-250. Also, only 4% of prices are set in decimal places for price range in 10-25 whereas single digits prices are 29% of the total prices recorded in the price range of 100-250. This indicates that as price levels go up, rounding off is not scaled up by the same extent. One implication from this pattern is that in terms of magnitudes, rounding as a friction is more binding for prices which are denominated at lower levels. If all prices are rounded off to the multiples of 5 and 10, lower denomination prices are further away from their optimal price (in percentage terms) as compared with higher denominated prices.

3.2.4 Evidence of Bunching from Consumption Expenditure Data

One of the potential issues with our data is that the observed bunching could be on account of the errors in survey reporting. If the survey respondents round prices while reporting, this could potentially bias our estimates. As a cross check we use the consumption expenditure data to look at the bunching. The Household Consumption Expenditure Survey undertaken by the National Sample Survey Office (NSSO) for 2011-12 records data on overall consumption expenditure by households in India. The data records both value and quantity of consumption.

Using this, we can derive implicit prices (unit values) of these items. It is much less likely that the survey respondents would report an implied price in round digits as they only report the total value of consumption and not the price.

From the NSSO expenditure data, we estimated the implied prices for the same items for which we have the food price data. Digit distribution of those imputed prices are reported against the same from the food price data is reported in Table 3.4.

Our results show that the implied prices show a much higher concentration on digits ending 0 as compared with survey data. Prices designated in decimal points are also much higher than the survey data. If we were to assume that the implicit prices are reported correctly, the rounding in survey data seems to have happened more at the decimal level. However, the bunching at round digits in the survey data is replicated in implicit prices which validates our assertion that the round digits at 0 and 5 are not on account of a survey reporting bias.

If bunching across round digits observed in our data is on account of a behavioural response to cost of handling cash, we should expect that the bunching should be less prominent in administered prices which are fixed by the Government. In India, the Government supplies essential items through the Public Distribution System (PDS) at subsidised prices. In the consumption expenditure data, we have information about purchases of households from PDS shops for rice, wheat and sugar. We now check the bunching in digits in PDS prices for these items as against the market price for the same items. Both are taken from the implicit prices available from the consumption expenditure data. Figure 3.3 shows that the administered PDS prices did not exhibit the bunching that we see in market price for the same products. Close to a third of all PDS prices were set in decimals whereas for the same items, about one third of the market prices were set in either 0 or 5 ending digits.

One argument against such a strict comparison could be that the price levels are not the same and PDS prices are much lower in levels and therefore the level effects could be driving this difference. In order to make sure that the observed difference is not on account of level effects (prices in PDS being lower than the market prices and therefore), we also compare the price bunching between market price of wheat and PDS price of sugar, both of which has almost similar average prices. The difference between bunching continues to remain even when we compare items at the same price levels (Table 3.5).

Another implication of this difference between PDS and non-PDS prices in terms of bunching is that the observed bunching in the data is not likely to be driven by the survey reporting error. If the bunching was on account of respondents rounding prices and then using quantity number to multiply to arrive at the value reported, there is no reason to believe that the respondents would report it differently across the two sets of prices (administered and non-administered). As we know *a priori* that PDS prices are administratively set and as such non-rounded.

3.3 Price setting pattern in Online Prices

In the previous section, using the food price data from physical shops, we showed that there is significant bunching at round digits. Bunching of prices also matched the currency denominations indicating that use of cash for transactions could be a major reason behind bunching. If bunching of prices is driven by currency availability, in an environment where the physical use of cash is minimal such bunching of prices should be absent. We therefore look at an environment where the use of cash is minimal; online grocery shopping. We collected data on prices of select grocery items offered by one of the India's leading online retail chains in the city of Bangalore. The data was collected on a daily basis from March 2020 to October 2021 for about 32 categories which mostly included fruits and vegetables. Unlike the offline food price data which covers a larger number of products/items, the online data is restricted to these two product groups and one location mostly on account of resource constraints. The data is characterized by detailed product identification and at the item level we have 719 unique product identifiers with 86,112 unique price observations.

Though the data is at daily frequency, there are discontinuities in the data.[21] There are a number of reasons for this. First, there were dates when the product was not available in the online grocery store at all for some periods of time. The period under our study has been one where the COVID related supply disruptions have been significant. Mahajan and Tomar (2021) found that product availability fell by 10% for vegetables and fruits for the same online grocery retailer during COVID supply disruptions. Second, there have been many products for which appeared in the sample for a while and then subsequently disappeared. The median duration of presence of an item in our sample is 218 as against a total of 586 days in our sample.[22] Finally, there have also been dates when the data retrieval was not possible which created some discontinuity in the data. The impact of data discontinuities on account of all the reasons mentioned above is expected to be minimal for the purpose of our analysis as we mainly focus on the price bunching and not on comparison of price movements across time. However, in order to maintain consistency, as in the case with the offline price data, we restrict our analysis to only those observations where there are two continuous data points whenever we look at any measure which is comparing the movements over time.

Before looking at the bunching across digits and its implications for price stickiness in online setting, we compare the overall price setting pattern in both offline and online cases. For comparability, in case of offline prices we only use data from March 2020. However, we include all the centres in our calculations though online data is available only in the case of Bangalore.[23] We see that prices change much more frequently in the online case as prices change once every

[21] Overall the number of continuous observations is 65,179 which is about 76% of the total data points.

[22] We define duration of presence as the difference between the first and last day for which a price observation is recorded in our sample.

[23] This is due to data constraints as keeping only Bangalore would reduce sample size to just 420.

two days for vegetables and once in three days for fruits (Table 3.6). The corresponding figures for offline prices are about 14 and 24 days, respectively. Also, the absolute size of price change is smaller in case of online prices as compared with our offline price data. The proportion of price increases, however is marginally higher in the case of online prices. These descriptive statistics are indicative of the fact that prices on an average are much more flexible in online price setting in food prices in India. These results are not in alignment with literature on offline and online price changes in the developed world. Cavallo (2017) showed that both the frequency and size of price change are similar across online and offline stores by looking at 56 multilateral retail chains in 10 countries.

3.3.1 Bunching in Online Prices

In order to understand bunching behaviour in online prices, we first look at the the distribution of prices according to the last digit of price set, same as in the offline scenario. About 13% of the prices were set in 5 and 0 ending each (Figure 3.4). Thus as compared to offline prices, 0 and 5 ending prices have a much less share in overall price distribution (26% overall as compared with 55% in the case of offline prices). Also, the share of prices ending at 9 is much higher in online prices (18%) as compared with offline prices (2%). Another important feature is that unlike in the case of offline prices, decimal ending prices constitute a much larger share irrespective of price levels (about 12%).

Next, we look at the distribution of last digit of prices across different price levels. Same as in the case of offline prices we group the prices into three broad categroies; below 25, 25-100 and above 100. Figure 3.4 shows that as the price level goes up we see that the 9 ending prices becomes the dominant category with about 40% of all prices above Rs.100 being set in 9 ending digits. This is in contrast with the offline price case where the 0 and 5 ending price became the dominant prices in digit distribution at price levels above Rs.100. The share of prices ending in decimals declined as the price levels increased in the case of offline prices (Table 3.1) whereas it remained nearly constant in the case of online prices.

Next, we look at the probability of price being kept constant, conditional on being at a specific last digit by using the following specification.

$$ln\big(p_t/(1-p_t)\big) = \alpha + \beta_d Digit_{it} + \gamma_i + \gamma_m + \epsilon_{id} \tag{3.2}$$

where p is the probability of price remaining constant in period t. $Digit_{it}$ represents a set of dummy variables representing prices set at decimal points, even digits, 5 and 10. γ_i, and γ_m are product level and monthly fixed effects. This specification is identical to the one in the case of offline data (equation 3.1). We estimate this by way of Maximum Likelihood and the results are presented in Table 3.7. We see that in case of both fruits and vegetables, compared to the odd digit prices the 5 and 0 ending prices are almost as much likely to remain constant. Even though the coefficients are significant in most cases, the he odds ratio ranges between 0.89 to 1.08 which is in sharp contrast with the prices in offline case where we saw that the 0 ending prices were more than twice more likely to remain constant (with odds ratio of above 2) as compared with the same baseline category. So the marginal bunching that we see in 0 and 5 ending in online prices do not necessarily translate to higher price stickiness.

Online prices exhibited bunching in 9 ending digits which is in line with the strategic price setting behaviour studied in the literature. We would like to see whether the bunching in 9 ending digits indeed contribute to price stickiness. Therefore, we use the same specification as in equation 3.2 but modify the indicator variable as

$$ln\big(p_t/(1-p_t)\big) = \alpha + \beta Digit9_{it} + \gamma_i + \gamma_m + \epsilon_{id} \tag{3.3}$$

where p is the probability of price remaining constant in period t. $Digit9_{it}$ represents a dummy variable which takes the value 1 if a price is set at a digit ending 9. γ_i, and γ_m are product level and monthly fixed effects. The results are presented in Table 3.8. 9 ending prices are more likely to be kept constant as compared with non-9 ending prices. In the case of fruits, the odds ratio is 1.43 while for vegetables it is 1.12. These magnitudes are significantly smaller than the case for 0 and 5 ending prices in the case of offline prices.

We also look at the transition probabilities between price digits conditional on price change in the online data. We find that the transition probabilities are much more dispersed in online prices (Table 3.9). About 10% of the time, price transitions are between prices set at decimals. The next highest transition probability is from 0 ending to 9 ending (2.8%) and from 5 ending to 6 ending (2.4%). This as compared with the offline price data shows that the transition between bunched prices do not dominate the transition probability matrix in an online setting.

Price setting pattern in the online case indicates that prices are much more flexible as compared with offline prices. The bunching in 0 and 5 ending prices decline significantly in online setting though we observe large bunching at 9 ending prices. Although 9 ending prices are more likely to remain constant as compared with non-9 ending prices, the extent of price stickiness that we observe in 9 ending prices is much lesser than in offline prices. We also see that the transition probabilities are not dominated by movement between bunched prices. Thus our empirical evidence points to significant relaxation of constraints faced in terms of rounding of prices to ease transaction in offline setting when we move to an online environment.

3.4 A Menu Cost Model with Price Points

As we have seen in the empirical exercise, the presence of pricing points has a major role in determining the extent of price stickiness. Studies so far have either documented the existence of price points (Knotek 2008) where prices tend to bunch at certain points or have shown that such bunching indeed contributes to stickiness in prices. By how far the presence of price points are important for the overall price stickiness and whether price points can explain observed price setting pattern is an important issue. In the literature, Knotek (2016) incorporated price points in a standard menu cost model by adding an additional cost parameter to prices which are set not at price points. He showed that in the presence of price points, menu costs have a negligible effect on price stickiness. Hahn and Marenčák (2020) used a combination of price points and sticky information to match properties of price setting observed in the data. However, the impact of distance between two price points on price stickiness and it's interplay with menu costs is not well explored in the literature.

Our primary objective in this section is to calibrate a model which would help us to to match the data moments in terms of bunching as well as other price setting attributes. We explore this issue within the framework of a standard menu cost model in line with Nakamura and Steinsson (2008). We augment the standard menu cost model of price setting by incorporating discontinuity in prices that are available to be set by the seller. In a world where there are no digit frictions in setting the price, optimal price should be able to change by any small increment in response to shocks. However, digit frictions could create discontinuity in price setting. This could be either on account of pricing technology constraints or on account of behavioural reasons. In a currency system where money is not fully divisible, prices can only change by the magnitude of lowest denomination currency in circulation. Additionally in some cases, non-availability of lower denominational currency or coins could also mean that distance between two price points could be greater than the lowest denomination of currency. Furthermore, preferences over pricing points like the 9 and 0.99 as pointed out by Basu (1997) would also mean that pricing points could exist independent of the currency denominations. Also, such a specification allows us the flexibility to analyse the impact of change in pricing technology on overall price stickiness. Following from our empirical exercise where we show that prices are much more flexible in an online price setting environment where cash no longer a binding constraint, we can approximate it as a reduction in the distance between two price points.

In terms of model strategy, first we extend the menu cost model set out in Nakamura and Steinsson (2008) by introducing two agents; a producer and a retailer instead of a single firm. This helps us to better represent the food supply chain in India. In order to keep the model tractable, we have combined all the agents in the supply chain as one entity which enjoys market power (retailer) and assumes that the producer faces a perfectly competitive market. While this is a simplification of the real-world supply chain network, the idea is to incorporate all the frictions in the entire supply chain as one entity and show how it matters for price stickiness.

In order to account for existence of price points, along with conventional menu costs, Knotek (2016) incorporated an additional cost for setting prices at price points. Hahn and Marenčák (2020) introduced price points restrictions by allowing firms to set prices only in discrete set of price points but they did not include menu costs in their specification. We follow an approach where both price point restrictions and menu costs are present. This helps us study the dynamic interaction between the two. Also, unlike Hahn and Marenčák (2020) where they used constant relative distance wherein distance between price points remain fixed as a ratio of prices,[24] we use constant absolute distance between price points. As we showed in the empirical section, the distance between price points do not get scaled up in case of food prices in India and therefore such a specification would better capture the dynamics in our case. We define a constant d_i as the distance between any two adjacent price points in the price vector.

3.4.1 Model Outline

We have two agents; a producer and a retailer. The producer produces a single good $y_t(z)$ using technology

$$y_t(z) = A_t(z)L_t(z) \tag{3.4}$$

where $A_t(z)$ is the aggregate productivity conditional on realisation of state z and $L_t(z)$ is the unit of labour used in production. Productivity follows an AR(1) process viz.,

$$log(A_t(z)) = \rho log(A_{t-1}(z)) + \epsilon_t(z) \tag{3.5}$$

Where ρ is the autoregressive coefficient of productivity and $\epsilon_t(z)$ is the shock to productivity realised each period. We assume that $\epsilon_t(z) \sim N(0, \sigma_\epsilon^2)$

Farmer faces a perfectly competitive market and his revenue is

$$P_t y_t(z) = W_t L_t(z) \tag{3.6}$$

Where P_t is the price received and W_t is the nominal wages paid. The economy is characterised by constant real wages which is related to the elasticity of demand θ in the following way.[25]

$$\frac{W_t}{P_t} = \frac{\theta - 1}{\theta} \tag{3.7}$$

The second agent is a retailer who buys the good from the farmer and sells it with a markup

[24] Distance between 5 & 10 and 50 & 100 are treated as the same.

[25] See Nakamura and Steinsson (2008) for a discussion on this relationship.

over cost. The retailer faces the following demand function

$$C_t(z) = \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} \tag{3.8}$$

Where $C_t(z)$ is the consumption demand, $p_t(z)$ is the nominal price and P_t is the general price level.

Aggregate price level evolves in the following manner:

$$log(P_t) = \mu + log(P_{t-1}) + \eta_t \tag{3.9}$$

Where μ is the average rate of inflation in the economy and η_t is the shock inflation t. We assume $\eta_t \sim N(0, \sigma_\eta^2)$

The firm hires K unit of labour to change its price when it changes the price.

Deviating from the standard model where the retailer can choose any price as the optimal price, we assume that the choice of prices are constrained by the existence of pricing points which are separated by a distance of d. Let $\mathbb{P}$ be the universe of prices that a retailer can set in a frictionless world. With the presence of pricing points, the set of prices that a retailer set are;

$p_t \in \mathbb{P}$ such that

$$mod(\frac{p_t}{d}) = 0 \tag{3.10}$$

where $mod(\frac{p_t}{d})$ is the reminder of division of p_t by d. In other words, prices can be set only in multiples of d which determines the distance between two price points.

Under market clearing, profits when price p_t is changed is

$$\pi_t(z)^c = \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta}\Big(\frac{p_t(z)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(z)}\Big) - \frac{\theta-1}{\theta}K \tag{3.11}$$

Profits when price is kept constant is

$$\pi_t(z)^{nc} = \Big(\frac{p_{t-1}(z)}{P_t}\Big)^{-\theta}\Big(\frac{p_{t-1}(z)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(z)}\Big) \tag{3.12}$$

Value function for a firm changing price is:

$$V^c(p_{t-1}(z)/P_t, A_t(z)) = \underset{p_t}{max}\big[\pi_t(z)^c + \beta\mathbb{E}V(p_t(z)/P_{t+1}, A_{t+1}(z))\big] \tag{3.13}$$

Value function for a firm not changing price is:

$$V^{nc}(p_{t-1}(z)/P_t, A_t(z)) = \pi_t(z)^{nc} + \beta\mathbb{E}V(p_{t-1}(z)/P_{t+1}, A_{t+1}(z)) \tag{3.14}$$

Bellman equation is therefore

$$V(p_{t-1}(z)/P_t, A_t(z)) = max\big[V^c(p_{t-1}(z)/P_t, A_t(z)), V^{nc}(p_{t-1}(z)/P_t, A_t(z))\big] \tag{3.15}$$

This problem is solved numerically through value function iteration over a grid. For approximating the evolution of shock processes over time, we discretize the autoregressive process and their innovations using the methodology proposed by Tauchen (1986). In order to incorporate price points into our simulations we adopt the following numerical strategy. Given the space between two price points defined by d we discretize the policy function using the formula.

$$N = \frac{p_{max} - p_{min}}{d} \tag{3.16}$$

Suppose that given the shocks to productivity and aggregate inflation, the range of prices that a retailer can set is between 0-10 with $d = 1$. In this case, we would have N=10. If we reduce d to 0.1, the N would increase to 100. Thus N is decreasing in d.

3.5 Model Calibration and Results

3.5.1 Benchmark Calibration

We calibrate this model to match the properties of price setting observed in the offline food price data. For calibration of the model, we use a set of moments from the data which are the key statistics discussed in chapter 2 to characterise price setting dynamics. Our targeted moments include frequency of price changes, average size of price changes, fraction of price increases as well as proportion of prices which are ending at 0 or 5. We look at absolute size of price increases, size of price decreases as well as proportion of transition between bunched prices as the non-targeted moments to check for robustness of calibration. Also we look at the difference in size of price change between top and bottom decile of price range as a non-targeted moment. Since we have four targeted moments, we internally calibrate four parameters. These are: ρ (AR coeffcient of productivity process), variance of productivity shock σ^2_ϵ, size of menu cost K and distance between price points d. Externally calibrated parameters include discount factor β and elasticity of demand θ for which we use standard values from the literature. The two other parameters which are calibrated externally are μ (average inflation) and σ_{μ}^2 (variance of inflation). For this, we use CPI for food inflation in India for the period of 2006-2021. We estimated the value of μ and σ_{μ}^2 on monthly CPI data and worked out the corresponding weekly values. ρ, σ_{ϵ}^2 and K helps us to pin down the first three targeted moments whereas d helps us to target the bunching and the value of d was calibrated accordingly. We restrict our analysis to prices in the range of 5-250 which corresponds to 92% of the price observations in our sample. Our baseline parameter values are set out in Table 3.10.

Table 3.11 compares the moments from the data with the same from the model. The model is able to generate moments that match the data moments in all the targeted moments. While matching the frequency of price changes, the model also generate features such as a larger proportion of price increases in targeted moments and higher absolute value of average size of price decreases in non-targeted moments. In terms of bunching it also tracks the proportion of prices set at round prices and transition between bunched price points. There is a small discrepancy between the bunching observed in the data and the model as distance- the structural parameter that targets this moment- is calibrated at discrete values of multiples of 0.5.[26]

One of the implications of constant absolute distance between price points is that price points would be more binding at lower levels of prices. This would mean that in percentage terms, the average size of price change would be larger at lower price levels as compared with higher price levels. When we compare the average size of price change at the top and bottom decile in the data, we find that the average size of price change at the bottom decile of price distribution at 13.8 per cent is significantly higher than the top decile (7.8 per cent). Our hybrid model matches this difference directionally (Table 3.11). Therefore, apart from matching the bunching moments, a hybrid model enables us to track the asymmetry in size of price change across price levels.

In our model, we have two types of frictions; a menu cost and a price point. How important are these type of frictions in generating price stickiness is the next issue we explore. For this, we undertake the following exercise. First we recalibrate the model by shutting down the price points friction while keeping the menu cost channel active. We look at by how far the model is able to match data moments in the absence of price points. Then we again recalibrate the model, this time setting the menu cost parameter to zero and keeping only the price point as the active friction.

[26] 0.5 corresponds to the lowest denomination of currency in circulation.

3.5.2 Case Without Pricing Points

In this exercise, we calibrate the model without the presence of price points as a friction. Here the firms are allowed to set prices at any value with any last digit. Since we do not have price points friction, we can not target proportion of 10 or 5 ending prices as a moment and therefore we have included that as a non-targeted moment. In trying to make the model with only menu cost and no price points match the data moments, we also recalibrate the other structural parameters. The parametrisation of the model is detailed in Table 3.12 and the comparison of moments between data and model is presented in Table 3.13.

A comparison of the structural parameter values of the benchmark model and the model with only menu costs throws up some interesting results (Table 3.10 and Table 3.12). We see that in order to generate the same magnitude of price stickiness, the menu cost parameter has to be about 30% higher in a model with menu cost alone as compared with a hybrid model. Similarly the persistence of productivity parameter is double in the menu cost only model. These indicate that in the the presence of price points in the hybrid model contribute significantly in generating price stickiness apart from helping us in matching the bunching moments in the data. In other words, we would need much higher values of menu cost and productivity persistence to see the kind of price stickiness that we see in the data if price points were absent. In that sense, this could be seen as a counterfactual exercise.

Table 3.13 shows that the model matches key stickiness moments of the model. Even without the price points, the model is able to match frequency and size of price changes and proportion of price increases. It also tracks the non-targeted moments fairly well. However, the proportion of rounded prices that the model generates is only 10% whereas in the data it is much higher at 53%. This indicates that a standard menu cost model would fail to replicate the actual price setting behaviour in terms of bunching even though the other moments of data are well matched. Also, the average size of price change is same across price levels in a menu cost model and therefore it fails to replicate the difference in size of price change between lower and higher level of prices. In sum, while a model with only menu costs can approximate the price setting behaviour with a much higher value for menu cost as compared with a model with price points, it fails to match bunching as well as asymmetry in size of price change. Therefore the role of price points can not be overlooked in trying to understand nature of price setting in our case.

3.5.3 Case with Price Points and no Menu Costs

On the other hand, if price points were the only source of price stickiness, we should be able to generate the key moments of the data in a model even when we set menu cost to zero and keep only price points as the source of friction. As was discussed in the benchmark calibration, presence of menu costs can influence the frequency of price change, size of price change and proportion of price increases but not the bunching. Therefore, if we set menu cost to zero, we fail to target all the four moments at the same time as we have now restricted one of the structural parameter to zero. Our attempts with calibration show that we can either target the frequency or size of price change in our calibration and not both at the same time when menu cost is zero but not both together.

We present results based on targeting frequency of price change, proportion of price increases and proportion of rounded prices as a targeted moments. The structural paramametrs used for calibration are given in Table 3.14 and the comparison of model generated moments with that of data is presented in Table 3.15. We see that once we target the frequency of price change, the size of change required to match the frequency goes up significantly higher than what is observed in the data. In terms of non-targeted moments, the standard deviation of prices as well as the size of price increases and decreases required to match frequency are much higher as compared with what is observed in the data. Higher magnitude of size of price change at lower deciles is matched directionally in the price points model. We also present calibration results with size of price change as the targeted moment in Appendix B.2. Appendix Table B.2 shows that if we target the size of price change, the frequency of price change as well as the standard deviation of prices needed to match the frequency turn out to be much smaller than what is observed in the data. Thus while having price points alone can help in match the bunching moment in the data, simultaneous matching of other key parameters are not possible. Therefore, price points alone cannot replicate the key stickiness moments in the data. Our approach of using a hybrid model as set out int the benchmark version, therefore seems to be the appropriate choice.

3.6 Robustness Checks and Dynamic Interactions between Price Points, Menu Cost and Price Levels

In the previous section, we presented the hybrid model with both menu costs and price points and showed that such an approach helps us to match key moments in the data. Here we attempt to study the impact of dynamic interaction between menu costs, price points and price levels through the lens of our model. We first look at the impact of price points on price stickiness looking at the policy function across different values of distance between price points d. Then we explore whether this relationship is conditioned by the size of the menu cost. Finally, we look at the relationship between price points and price levels as in our model we incorporate a constant absolute distance as compared with constant relative distance in Hahn and Marenčák (2020). For all the following exercises, we keep our baseline parametrisation in Section 3.5.

3.6.1 Pricing points and Price stickiness

Using the baseline parametrisation, we first simulate the model for different number of pricing points. we plot the policy function from 4 different values of d which generates the number of pricing points as 10, 50, 100 and 500. As expected, the policy function is much more discrete when the number of price points are less (Figure 3.5) . We see that the prices remain constant over a range of state variables and then exhibit discrete large changes. There also is an indication of a non-linear relationship between price stickiness and price points. When number of points increased from 10 to 50, policy function turned out to be much smoother. The marginal effects of price points on optimal price beyond a point seem to be limited. This of course follows from the fact that there are menu costs in changing prices.

3.6.2 Pricing Points and Menu Costs

Price points are often used as a behavioural explanation for prices to exhibit stickiness behaviour which mimics the menu cost model properties. However, how far price points impact price setting behaviour under different pre-existing menu cost conditions is not explored in the literature. In other words, whether price points matters in environments where there are already significant stickiness of prices on account of menu costs is an issue worth examining. We look at this by re-simulating our model with a very high menu cost increasing it by a factor of 10. Then we compare the policy functions under restrictive number of price point (10) and a more relaxed number of price points (100). The associated policy functions are presented in Figure 3.6.

We can see that the shape of policy functions are similar in both cases of high and low number of pricing points. What is also interesting to note in the shape of policy functions is that for the range of state variable where prices do not change, the policy functions look almost identical. This could imply that in the presence of menu costs, pricing points may not be an additional friction in price setting and therefore the role of pricing points in generating price stickiness is more pronounced only when menu costs are low.

The economic argument for pricing points to be less influential in generating price stickiness under high menu costs is as follows. When menu costs are high, prices do not change often and when they change, they do by a large magnitude. If the average size of desired price change is higher than the distance between two price points, price points do not add extra stickiness in terms of frequency of price changes. However, if the menu costs are low, the optimal price responds to even small change in underlying state variables. If the distance price points is higher, the prices can not adjust and therefore price points act as a friction generating price stickiness. This is a result also observed by Knotek (2016) wherein he found that introducing pricing points with 9 cents ending prices over a range of prices \$0.50 to \$3.00 reduced the role of menu costs in explaining price stickiness to almost negligent levels.

3.6.3 Price Points and Stickiness: Level effects

As noted above, our model incorporates a constant absolute distance specification wherein the distance between two price points are kept the same all along the price grid. The intuition is that in a world where most of the transactions are carried out in cash, price points would be determined by the availability of denominations of currency and therefore distance should remain the same across price levels. However, a constant absolute distance would imply that the relative distance would be a declining function of level of prices. This would mean that the distance would be much larger as a ratio of price for lower denomination price. If we look at price points as a friction, this in turn would imply that such a friction is more binding at lower price levels as compared with higher price levels owing to the constant absolute distance property.

This has important implications for price responses to aggregate shocks. Ideally, in response to a common shock like the aggregate inflation, adjustments of individual prices should be level neutral i.e., all prices should adjust in the same manner. If prices that are denominated at the lower levels have lower number of price points available, prices could be sticky at lower levels as compared with higher level of prices. In order to verify whether such a mechanism is in operation in our model, we simulate our calibrated model to first generate optimal price in a frictionless world (no price points) and then again a case where the price points are binding. Price stickiness in the presence of such a restriction should not create a difference in frequency of price change, if frictions from price points are scale neutral. We look at the frequency of price change in 2 levels of prices. These include prices which are set between 5-25 and 230-250 which corresponds to both end of the spectrum of our simulations (5-250). Table 3.16 presents the results from our exercise.

We see that in the case of lower level of prices, price points generate significant difference in frequency of price change. The presence of price points reduce the overall frequency of price change from 16.8 % to 9.4% for prices in the range of 5-25. For higher level prices (230-250), the frequency of price change remains almost the same. Therefore, low denomination prices could be more distorted in an environment where pricing points are more binding. Given an aggregate shock to the economy, lower denomination prices would remain relatively sticky whereas higher denomination price would be adjusting more instantly. This could have implications for monetary non-neutrality across different price levels.

3.7 Conclusion

In this chapter, we studied the role of bunching in generating price stickiness and its interplay with use of cash. We show that in case of food prices in India, offline prices exhibit bunching in round digits and bunched prices are more sticky than non-bunched prices. In case of online prices we show that bunching in round digits fall significantly and bunching does not generate stickiness as in the case of offline prices. A menu cost model augmented with price points is then used to generate implications of price points and bunching on price stickiness. We show that the size of the menu cost, level of prices and distance between price points are critical factors in determining the role of price points in price rigidity. The study also shows that in the case of Indian offline food prices, in the absence of price points menu costs would have to be 30% higher to generate the same level of price stickiness we see in the data.

The study points to a number of emerging research issues. One of the major findings of the study is that if cash is a binding constraint defining price price points, the effect of price points on price rigidity would be conditional on level of prices. This would mean that in economies where cash is prevalent, lower denomination prices would find it difficult to adjust to optimal level as compared with higher denomination prices. Thus, response of prices to aggregate shocks would also be influenced by the level of prices. This would mean that monetary non-neutrality would be influenced by price levels. Studying the implications of such non-neutrality would be an interesting area of future research.

If prices set in a cash based economy are more sticky, movement to a cashless world would have important implications for policy. As more and more prices are digitally set, prices could turn out to be more flexible. Also, we see that the lower denomination prices are more likely to face cash as a binding constraint. If there is a difference in composition of consumption in terms of level of prices across the income distribution, we could expect that removal of cash constraint will lead to asymmetric welfare effects. If the consumption basket of the poor consists of more low denomination priced items as compared with rich, moving from a cash to cashless economy would benefit the poor more as now they will face prices which are more optimally set. How these play out in transition from a cash to cashless economy is an important issue that can be explored further.

3.8 Tables

Table 3.1: Results of Logit Regression: Probability of No Price Change on Price Digits

Price Ending at	Decimal Points			Even Digits (2,4, 6 and 8)			5			10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Product Category	Coeff	Std. error	Odds Ratio	Coeff	Std. error	Odds Ratio	Coeff	Std. error	Odds Ratio	Coeff	Std. error	Odds Ratio
All Products	-0.90	(0.02)	0.41	0.30	(0.01)	1.35	0.39	(0.01)	1.48	0.73	(0.01)	2.08
Cereals and products (21.4)	-1.81	(0.29)	0.16	0.37	(0.09)	1.45	0.67	(0.09)	1.95	1.01	(0.09)	2.75
Egg (40.6)	-0.57	(0.08)	0.57	0.36	(0.02)	1.43	0.49	(0.02)	1.63	0.76	(0.02)	2.14
Fruits (58.8)	-2.26	(0.09)	0.10	0.38	(0.04)	1.46	0.38	(0.05)	1.46	0.89	(0.05)	2.44
Meat and fish (181.4)	-0.59	(0.09)	0.55	0.33	(0.03)	1.39	0.48	(0.03)	1.62	0.89	(0.03)	2.44
Milk and products(29.3)	-1.20	(0.10)	0.30	0.30	(0.03)	1.35	0.63	(0.03)	1.88	0.94	(0.03)	2.56
Oils and fats (135.1)	-0.89	(0.03)	0.41	0.25	(0.02)	1.28	0.34	(0.03)	1.40	0.48	(0.02)	1.62
Pulses and products (60.4)	-1.00	(0.05)	0.37	0.28	(0.03)	1.32	0.32	(0.03)	1.38	0.70	(0.03)	2.01
Spices (91.2)	-0.85	(0.06)	0.43	0.35	(0.04)	1.42	0.30	(0.04)	1.35	0.65	(0.04)	1.92
Sugar and Confectionery (32.4)	-0.69	(0.05)	0.50	0.30	(0.03)	1.35	0.29	(0.04)	1.34	0.53	(0.04)	1.70
Vegetables (18.7)	-0.97	(0.06)	0.38	0.34	(0.04)	1.40	0.28	(0.05)	1.32	0.64	(0.04)	1.90

Figures in parentheses in column (1) are average price of products in the product category.
Reference Category is prices set at digits ending 1, 3, 7 and 9. Odds ratio is calculated as $e^{coefficient}$.
All the coefficients are significant with $p<0.01$.

Table 3.2: Transition Probability Matrix Conditional on a Price Change:Offline Prices

Current	Next Period Ending Digit									
Ending Digit	1	2	3	4	5	6	7	8	9	0
1	0.01	1.21	0.20	0.14	0.09	0.05	0.04	0.12	0.13	1.09
2	1.01	0.08	1.56	1.95	1.15	0.57	0.13	0.65	0.11	3.33
3	0.17	1.24	0.01	1.37	0.57	0.17	0.07	0.12	0.04	0.36
4	0.11	1.60	1.07	0.06	2.43	1.36	0.16	0.58	0.06	1.20
5	0.08	1.09	0.51	2.02	0.77	2.66	0.52	1.17	0.09	**5.94**
6	0.04	0.58	0.16	1.14	2.30	0.08	1.47	1.93	0.13	1.37
7	0.06	0.14	0.07	0.14	0.43	1.14	0.02	1.68	0.22	0.45
8	0.13	0.68	0.13	0.54	1.09	1.77	1.40	0.10	1.28	3.84
9	0.17	0.18	0.04	0.08	0.09	0.12	0.18	1.01	0.01	1.35
0	1.29	3.73	0.34	1.20	**6.06**	1.23	0.33	3.56	1.13	**12.15**

Each cell contains percentage of price change to total price change observations (215,399).
The highest three values are indicated in bold.

Table 3.3: Distribution of Prices according to Digits

Average Price (10-25)		Average Price (100-250)	
(1)	(2)	(3)	(4)
Price ending	Per cent	Price ending	Per cent
Decimals*	0.47	Single digits**	13.77
0.5	3.64	5	15.41
1	3.67	10	3.05
2	12.00	20	8.94
3	4.64	30	4.35
4	9.29	40	6.00
5	12.02	50	8.54
6	9.89	60	8.99
7	5.05	70	5.78
8	12.15	80	9.32
9	3.80	90	4.76
10	23.38	100	11.09

*: Except 0.5, **: Except 5.

Table 3.4: Price Bunching in Implied Price versus Survey Data

Price Ending	Survey	NSSO Implied Price
1	2	3
decimal	2.51	10.86
1	2.27	0.8
2	9.31	9.54
3	3.5	1.02
4	7.95	6.53
5	14.28	8.05
6	8.07	6.31
7	3.77	0.87
8	10.18	6.22
9	2.48	0.52
10	35.69	49.27

Table 3.5: Price Bunching in PDS Sugar versus Market Wheat

	Non-PDS Wheat	PDS Sugar
Avg price (Rs)	16.2	15.1
Digit ending		
0	19.18	3.04
1	6.16	0.15
2	16.58	1.52
3	4.46	1.75
4	8.23	26.39
5	10.97	10.08
6	10.30	10.60
7	4.88	2.04
8	9.91	3.97
9	2.61	0.23
Decimals	6.73	40.23

Table 3.6: Basic Properties of Price Setting: Online vs.Offline

	Duration (Days)	% of Price Increase	Average Size of Inc (%)	Average Size of Dec (%)
Vegetables (Offline)	14.2	51	19.7	19.6
Fruits (Offline)	24.3	53	14.8	15.6
Vegetables (Online)	2.2	54	11.9	13.7
Fruits (Online)	2.8	55	8.0	10.4

Table 3.7: Probability of No Price Change on Price Digits: Online Prices

Digit ending	Fruits			Vegetables		
	Coefficient	Std Error	Odds Ratio	Coefficient	Std Error	Odds Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Even	-0.15***	0.04	0.86	-0.09***	0.02	0.92
Five	-0.11*	0.04	0.89	-0.03	0.03	0.97
Zero	-0.08***	0.04	0.92	0.08***	0.03	1.08
Decimals	-0.23***	0.05	0.79	-0.23***	0.04	0.80

Reference Category is prices set at odd digits except 5
Odds ratio is calculated as $e^{coefficient}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8: Probability of no-price change 9 ending prices: Online

Digit ending	Fruits			Vegetables		
	Coefficient	Std Error	Odds Ratio	Coefficient	Std Error	Odds Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Nine Ending	0.36***	0.03	1.43	0.12***	0.03	1.12

Reference Category is prices set at digits other than 9
Odds ratio is calculated as $e^{coefficient}$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.9: Transition Probability Matrix Conditional on a Price Change:Online Prices

Current Ending Digit	Next Period Ending Digit 0	1	2	3	4	5	6	7	8	9	Decimals
0	0.55	1.74	1.21	0.69	0.54	1.39	0.67	0.47	1.05	2.22	1.06
1	1.29	0.04	1.49	0.50	0.26	0.41	0.24	0.23	0.28	0.64	0.39
2	1.13	0.89	0.10	1.58	0.72	0.82	0.42	0.18	0.46	0.76	0.47
3	0.75	0.49	1.10	0.08	1.15	1.03	0.45	0.20	0.32	0.49	0.44
4	0.48	0.23	0.59	0.90	0.11	1.50	0.66	0.34	0.38	0.45	0.52
5	1.21	0.40	0.63	0.86	1.20	0.64	**2.38**	0.62	0.88	2.13	0.87
6	0.71	0.26	0.48	0.44	0.56	1.71	0.14	1.48	0.88	0.85	0.52
7	0.49	0.23	0.25	0.29	0.25	0.65	0.95	0.03	1.17	0.75	0.43
8	1.04	0.30	0.45	0.38	0.38	0.67	0.77	0.97	0.20	1.89	0.49
9	**2.79**	0.68	0.83	0.42	0.46	2.09	0.66	0.62	1.43	2.19	0.95
Decimals	0.99	0.39	0.45	0.45	0.45	0.95	0.46	0.39	0.61	0.82	**10.11**

Each cell contains percentage of price change to total price change observations (22218).
The highest three values are indicated in bold.

Table 3.10: Selection of Parameters for Calibration: Benchmark Model

Parameter	**Value**	**Choice Benchmark**
β	$0.96^{(1/52)}$	Literature
θ	3	Lower bound in the literature
μ	0.00139	Estimated from CPI Food in India during 2006-21
σ_μ	0.0061	Estimated from CPI Food in India during 2006-21
ρ	0.3	Calibrated
σ_ϵ	0.054	Calibrated
K	0.0101	Calibrated
d	2.5	Calibrated

Table 3.11: Comparing moments between the Data and Model

Variable	Data	Benchmark Model
Targeted Moments		
Frequency of Price Change (%)	18.3	18.2
Average Size of Price Change (abs) (%)	9.8	9.8
Fraction of Price Increases (%)	55.5	55.3
Proportion of 10 or 5 ending prices (%)	53.2	50.1
Non-targeted moments		
Std.Dev of Log Prices	0.24	0.25
Size of Price Increases (%)	9.6	9.7
Size of Price Decreases (%)	10.0	10.1
Transition Prob. betw 0 & 5 Prices	29.7	24.3
Size of price change at lowest decile (%)	13.8	13.0
Size of price change at highest decile (%)	7.4	9.4

Table 3.12: Selection of Parameters for Calibration: No Price Points

Parameter	Value	Choice Benchmark
β	$0.96^{(1/52)}$	Literature
θ	3	Lower bound in the literature
μ	0.00139	Estimated from CPI Food in India during 2006-21
σ_μ	0.0061	Estimated from CPI Food in India during 2006-21
ρ	0.5975	Calibrated
σ_ϵ	0.0538	Calibrated
K	0.01365	Calibrated

Table 3.13: Comparing moments between the data and the model

Variable	Data	Menu Cost Model
Targeted Moments		
Frequency of Price Change (%)	18.3	18.4
Average Size of Price Change (abs) (%)	9.8	9.7
Fraction of Price Increases (%)	55.5	55.4
Non-targeted moments		
Std.Dev of Log Prices	0.24	0.29
Size of Price Increases (%)	9.6	9.4
Size of Price Decreases (%)	10.0	10.1
Proportion of 10 or 5 ending prices (%)	53.19	10.20
Size of price change at lowest decile (%)	13.8	9.7
Size of price change at highest decile (%)	7.4	9.7

Table 3.14: Selection of Parameters for Calibration: Only Price Points

Parameter	**Value**	**Choice Benchmark**
β	$0.96^{(1/52)}$	Literature
θ	3	Lower bound in the literature
μ	0.00139	Estimated from CPI Food in India during 2006-21
σ_{μ}	0.0061	Estimated from CPI Food in India during 2006-21
ρ	0.3	Calibrated
σ_{ϵ}	0.447	Calibrated
K	0.0	Calibrated

Table 3.15: Comparing moments between the data and the model

Variable	**Data**	**Price Points Model**
Targeted Moments		
Frequency of Price Change (%)	18.3	18.2
Fraction of Price Increases (%)	55.5	53.5
Proportion of 10 or 5 ending prices (%)	53.2	50.1
Non-targeted moments		
Average Size of Price Change (abs) (%)	9.8	19.3
Std.Dev of Log Prices	0.24	0.49
Size of Price Increases (%)	9.6	20.6
Size of Price Decreases (%)	10.0	17.7
Size of price change at lowest decile (%)	13.8	19.3
Size of price change at highest decile (%)	7.4	7.7

Table 3.16: Frequency of Price Change (%) Across Price Levels (d=2.5)

Price Range	10-25	235-250
With Price Points	9.45	18.88
Without Price Points	16.81	18.37

3.9 Figures

Figure 3.1: Frequency of Prices Ending with Digits: Offline

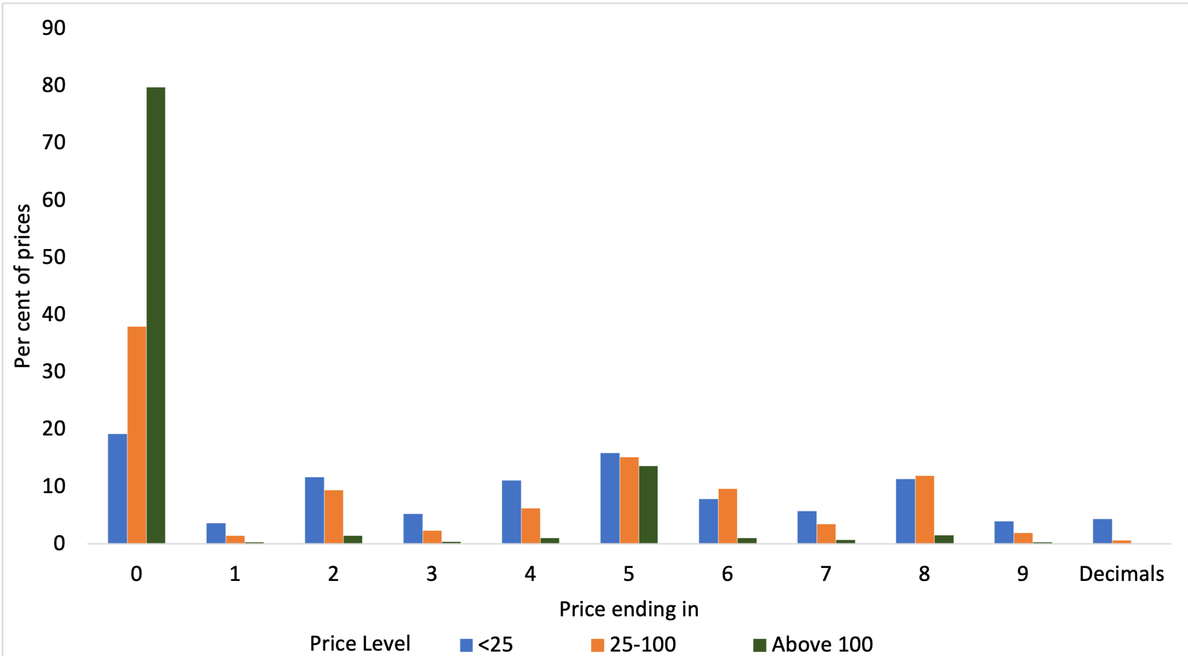


Figure 3.2: Frequency Across Magnitude of Price Change

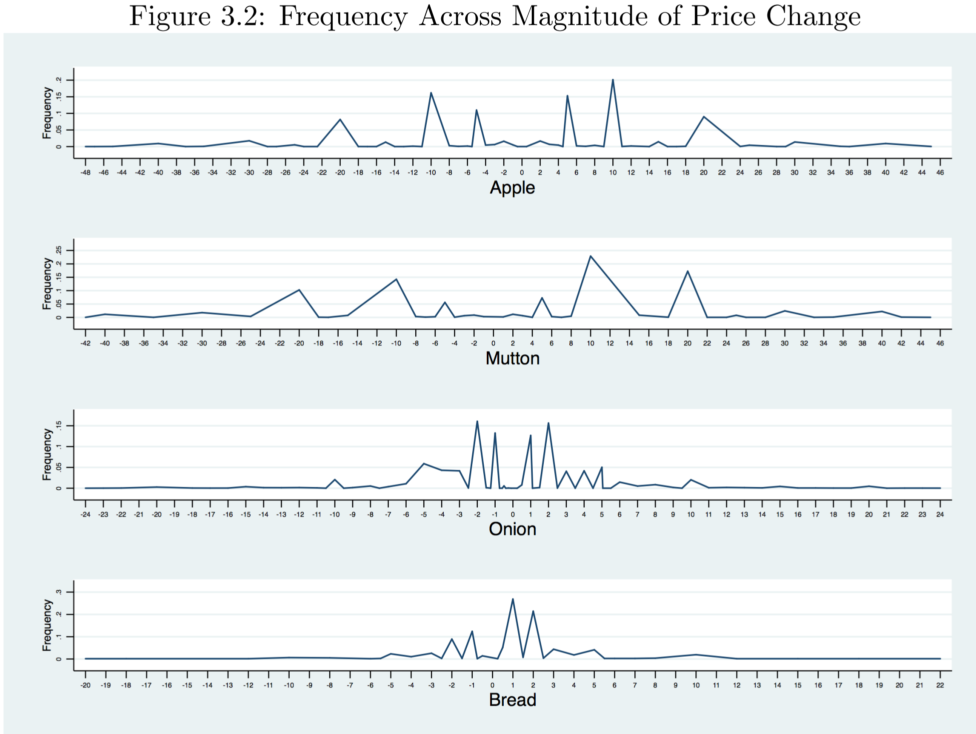


Figure 3.3: Digit distribution of prices: Administered (PDS) versus Market

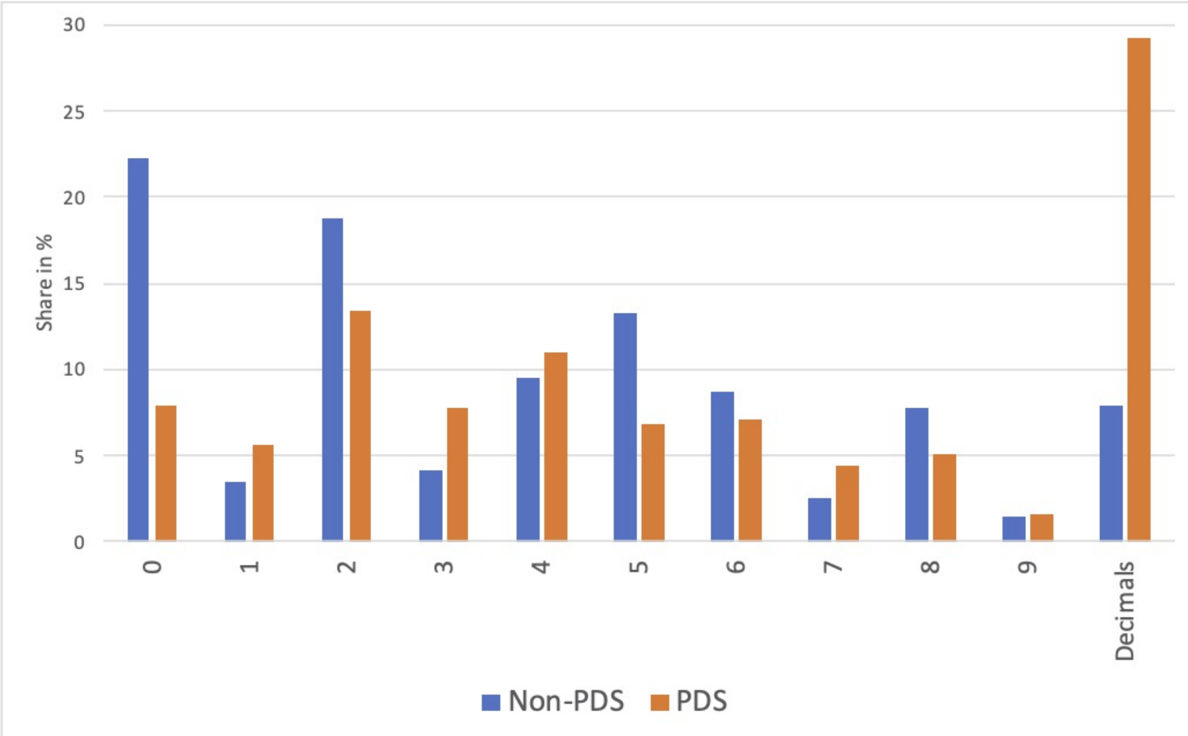


Figure 3.4: Frequency of Prices ending in Digits: Online

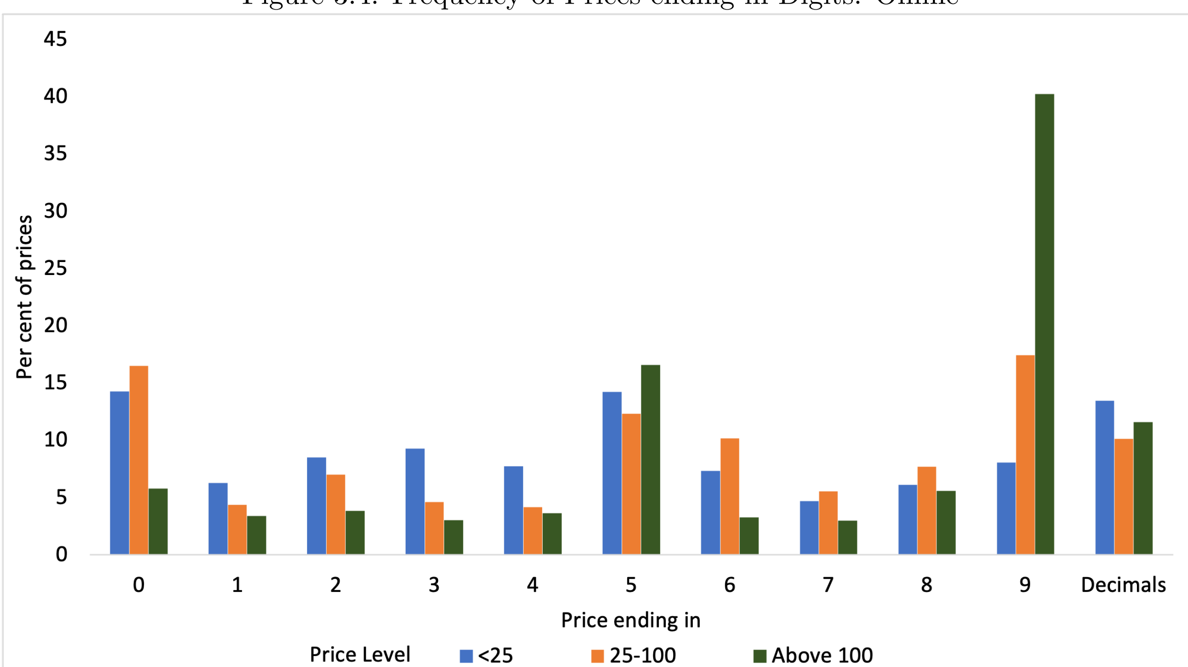


Figure 3.5: Policy Function and Price Points (N)

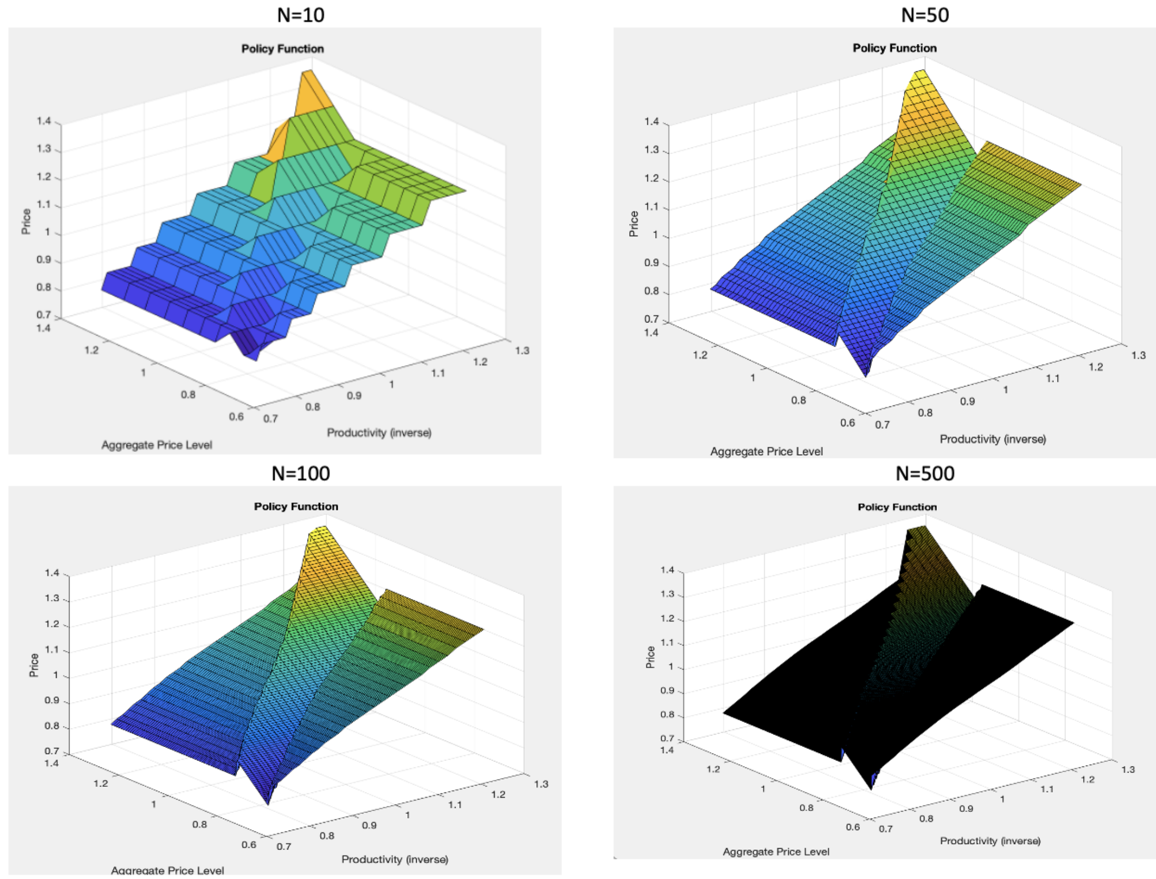
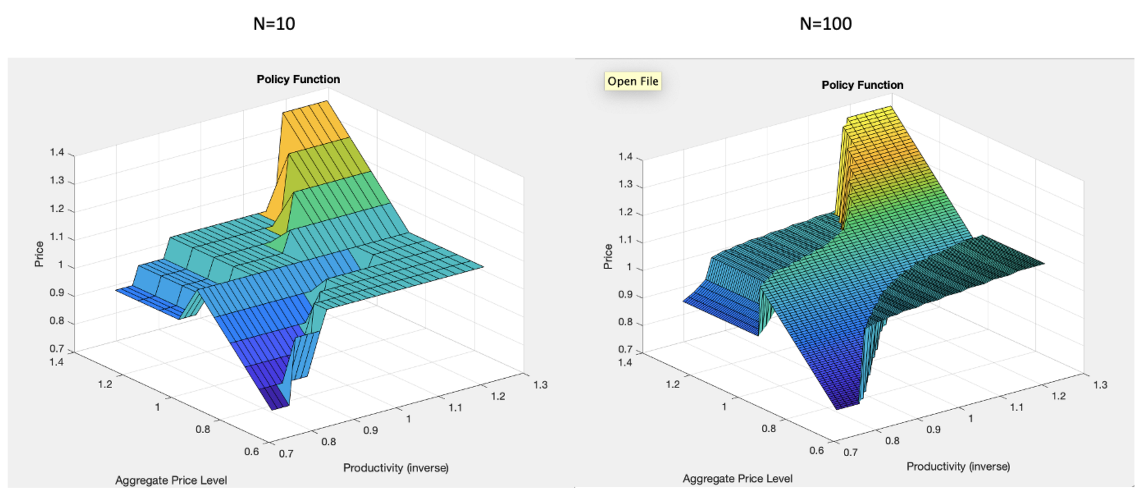


Figure 3.6: Policy Function and Price Points with High Menu Costs



Chapter 4

India's Food Supply Chain During the Pandemic

4.1 Introduction

Since the COVID-19 pandemic began, one concern has been that lockdowns might be especially damaging in the poorest countries – in these places lockdowns may reduce the spread of coronavirus, but only by simultaneously leaving poor families without cash to spend, and without food to eat. In this chapter, we shed light on a particular aspect of this concern: can food supply chains remain functional in the face of a national lockdown, and a growing burden of coronavirus cases? We address this question by documenting the breakdown and subsequent recovery of India's food supply chain during the first three months of India's national lockdown.

On March 24, 2020, India announced a strict lockdown for 21 days in response to a surge in COVID-19 cases. According to the World Bank, India's lockdown was the largest implemented by any country.[27] The lockdown was extended in three additional phases of 14 days each, with each phase accompanied by relaxations in lockdown rules. Following these three additional phases, the central government announced a staggered lifting of the lockdown. Using web-scraped daily data on wholesale volumes and prices for 271 food varieties traded at 1,804 agricultural markets in 24 states of India, we document trends in the supply and prices of food during these phases. Specifically, we estimate the size of the initial shock to food supply and wholesale prices following the lockdown announcement, the extent of the recovery, and the correlation of the shock and the recovery with the spread of the virus.

We describe four findings. First, food arrivals in wholesale markets dropped by 69% in the three weeks following the lockdown, but subsequently recovered, reaching similar levels to those in 2019 by early-May. Second, we estimate dynamic effects of the lockdown on wholesale prices that are similar to the effects on volumes. In particular, while wholesale prices initially increased by 8%, they quickly returned to a downward trend. Third, the initial state-level food supply shock was highly correlated with exposure to COVID-19 – states with more COVID-

[27] Karaban and Mozumder (2020). The Oxford COVID-19 Government Response Tracker (https://covidtracker.bsg.ox.ac.uk) also shows that the initial lockdown in India was one of the strictest.

19 suffered larger drops to food arrivals after the lockdown relative to previous years – but this correlation disappeared during the recovery phase, suggesting that food supply volumes recovered irrespective of the incidence of the virus spread. Fourth and finally, we use within-state variation to unpack the correlation between COVID-19 exposure and the initial supply shock. We find evidence that the correlation is driven by state-level policies, rather than local responses of those in the food supply chain. In particular, districts more exposed to COVID-19 *did not* have larger food supply disruptions than less-exposed districts belonging to the same state. In addition, using state-level declines in mobility as a proxy for policy responses to the pandemic, we demonstrate a strong positive relationship between state-level declines in mobility and the severity of the food supply shock.

The rest of this chapter is organized as follows. In the next section, we give an overview of the COVID-19 situation in India, the policy response of both the central and state governments, and the labor supply response of individuals. Thereafter, we describe our data sources. We then present our four empirical findings. Finally, we give concluding observations.

4.2 Background and Data

4.2.1 COVID-19 in India

The COVID-19 virus spread rapidly across the globe in the early months of 2020, forcing the World Health Organisation to declare it a pandemic by early-March. India reported its first case on January 30, 2020, though the initial spread remained contained, with only 500 cases reported by March 23.[28] Despite the low reported caseload, India responded to the rapid global spread of the virus by announcing a nationwide lockdown on March 24. In an effort to preserve the functioning of the food supply chain, most of the agricultural sector and food markets were exempted from the lockdown. Nevertheless, frictions in inter-state travel and labor shortages posed significant obstacles for the food supply chain.

As the virus began to spread rapidly within the country, the lockdown was extended on April 14 until May 3. The intensity of the lockdown was, however, eased partially. Areas with large COVID-19 outbreaks were designated as hotspots, and within hotspots, containment zones were demarcated where the intensity of virus spread was the highest. Strict lockdowns were implemented in hotspots while non-hotspot areas were allowed to open up necessary activities from April 20. The lockdown was further extended by two-week periods beginning May 3 and May 17, along with more relaxations in non-hotspot areas. Apart from the containment zones, the government started opening up the country from June 1. The virus, however, continued to spread, and by June 30 India had the fourth highest number of positive cases reported (over

[28] See https://coronavirus.jhu.edu/map.html.

585,000) with over 17,000 deaths.[29] In terms of cases per capita, however, India had a relatively low rate of confirmed cases, with 0.4 per one thousand population as compared with 7.8 per one thousand in the US (the country with the highest number of confirmed cases as of June 30).[30]

The distribution of confirmed cases was very uneven, with more than half of the confirmed cases reported in six major cities: Mumbai, Delhi, Ahmedabad, Chennai, Pune, and Kolkata. As a result, the response of state-level governments to COVID-19 has varied, with some states, e.g. Punjab and Telangana, extending the lockdown until June 30th, and many beginning their lockdown several days prior to the national lockdown. State-level policies varied on other dimensions as well. For instance, in Delhi, mandis (local agricultural markets) were restricted to operate at half capacity, with vendors operating on alternate days.[31] The government of Tamil Nadu placed restrictions on the timings at which trucks could unload deliveries in mandis.[32] And the government of Maharashtra enforced mandi closures in response to pandemic surges.[33]

One of the major responses to the government measures was a large exodus of migrant laborers from urban centers to rural areas. 40% of India-born men in urban India live in a place different to their birthplace (versus 14% in rural India, Census 2011). Because opportunities to work were scarce, many migrant laborers returned to their locations of origin at the onset of the lockdown. Estimates place this exodus at about 6.7 million people by June 2020 across just the six states of Bihar, Uttar Pradesh, Rajasthan, Madhya Pradesh, Odisha, and Jharkhand,[34] and 11.4 million people by February 2021 across all states.[35] This reduced available labor for the food supply chain, often leaving wholesale markets and traders with insufficient workers, especially in the initial days of the lockdown.[36] Since most of the supply chain in India is informal and labor intensive, the repercussions of such a labor shortage can be substantial. Our analysis of the food supply chain is set in this background.

[29] https://www.mohfw.gov.in/# accessed on August 30, 2020.

[30] https://ourworldindata.org/ accessed on August 31, 2020.

[31] The Economic Times (2020).

[32] The New Indian Express (2020).

[33] Srivastava (2020). For a more thorough discussion of state-level policy variation, see Narayan and Saha (2020).

[34] Mathew (2020).

[35] This data was provided by Shri. Santhosh Kumar Gangwar, Minister of State for Labour and Employment in Indian parliament on February 8, 2021 as an answer to Lok Sabha unstarred question No. 1056.

[36] In principle, laborers who returned to their native villages could supply labor in their nearby mandis, reducing the labor supply shock to rural mandis. But frictions due to the lockdown may have made it difficult to establish relationships in new markets. Indeed, in Section 4.3.1 we find that the food supply shock was similarly severe in rural and urban districts.

4.2.2 Data

Our main source of data is the online database set up by the central government's Ministry of Agriculture. As part of an initiative to enhance transparency and improve price discovery, the Ministry of Agriculture created a network of mandis by connecting them through an integrated scheme for agricultural marketing. The volume of arrivals of each food variety, along with price information (maximum, minimum, and modal traded price), is reported by each mandi to the Agricultural Marketing Network which is consolidated and uploaded to its portal, agmarknet.gov.in, on a daily basis. The data covers 307 varieties (e.g. coconut, beans, tomato), with each variety belonging to one of 15 broad categories.[37]

Our initial dataset includes all varieties reported to the Agmarknet portal during January 1 to June 30 of 2018, 2019, and 2020. To enable aggregation of volumes across varieties, we include only those products that are measured in tonnes, meaning we exclude those measured in numbers. While all 15 broad categories remain represented, this sample restriction excludes 31 of the 307 varieties. Nevertheless, these 31 varieties constitute only 4.1% of the total number of mandi-variety-day-level observations. For our analysis of wholesale prices we use the modal price, which better reflects the general price level than the minimum or maximum price.

Though 2,905 markets have reported products measured in tonnes to Agmarknet at some point during January to June of 2018 to 2020, the number of markets reporting at any one time has varied year-to-year (Figure C.1). To get closer to a balanced panel, we restrict our sample only to those mandis that reported arrivals in tonnes at least once during the month of March 2020. This sample restriction leads us to drop a handful of large states, including Bihar and Maharashtra (Table C.1). Our final dataset consists of 271 varieties traded at 1,804 markets in 24 states of India.

Despite our sample restrictions, our geographic coverage is representative of India as a whole. Districts with mandis ever reporting data to the Agmarknet portal are remarkably similar on average observables to Indian districts overall (columns 2 and 3, Table C.2) – most notably, the 640 Indian districts have a rural share of households of 73% on average, and so do the 508 districts represented by mandis on Agmarknet. More importantly, the 391 districts represented by our 1,804 analysis sample mandis are also similar. Only two exceptions stand out. First, our analysis sample districts are on average slightly more populous than Indian districts overall (2.1 versus 1.9 million people). Second, our analysis sample districts have a lower share of Scheduled Tribes (13 versus 18%). Given that even these two differences are small, our results likely generalize to agricultural markets nationwide.

[37]The categories are: Cereals, Spices, Fibre Crops, Oil Seeds, Fruits, Pulses, Forest Products, Other, Vegetables, Dry Fruits, Drug and Narcotics, Oils and Fats, Live Stock and Poultry and Fisheries, Beverages, and Flowers. Except where explicitly mentioned, all groups are included in our analysis.

Importantly, we note that a key limitation of our dataset is that it does not capture food that is traded outside of the mandi supply chain network (e.g. through the direct selling of produce by farmers to customers). Nevertheless, a significant fraction of India's food supply appears to be traded at the 1,804 markets that comprise our analysis sample. For the 18 varieties (among cereals, oil seeds, and commercial crops) for which we have compiled production data, our analysis sample markets covered an average of 25% of nationwide production during 2019/20 (Figure C.2). Furthermore, this number is a lower bound on sales coverage, given that not all production is marketed – for example, the marketed surplus ratio (the ratio of marketed output to total output) was 74% for wheat and 84% for rice in 2014/15, the most recent year with data available (Government of India 2019). An overall marketable surplus of 80% would suggest that our mandis cover 31% of India's agricultural sales.

To link supply shocks with variation in COVID-19 exposure, we use data from api.covid19india.org on the number of confirmed cases of coronavirus at the state- and district-level as of April 14, 2020 (the end of Phase 1 of the lockdown) and as of June 30, 2020 (the end of Phase 5). covid19india.org aggregates COVID-19 numbers in real-time across state bulletins, official handles (e.g. Chief Ministers, Health Ministers) and press reports, and uses a team of volunteers to validate the data. We note that *confirmed cases* differ from the true case count given underreporting and insufficient testing.[38] Nevertheless the relationship between confirmed cases and the health of the food supply chain is informative given that confirmed cases are likely an important input into policy decisions. We return to this point in Section 4.3.4.

Finally, to link supply shocks with declines in mobility we use Google mobility data.[39] Google infers mobility from users of its applications who allow it to track their location. The data reports aggregate mobility patterns without revealing the travel data of individual users.

[38] Related, Anand et al. (2021) estimates that the true number of deaths from COVID-19 in India exceeds the confirmed deaths by an order of magnitude.

[39] From https://www.google.com/covid19/mobility/

4.3 The Lockdown and the Response of India's Food Supply Chain

4.3.1 Food Arrivals Fell Immediately But Subsequently Recovered

Among the sample of mandis that reported at least once in March 2020, aggregate food arrivals were similar prior to March 24 in 2018 and 2019 as compared with 2020 (Figure 4.1).[40][41] Following the lockdown on March 24, 2020, arrivals dropped dramatically as compared with levels in 2018 and 2019, and gradually recovered from Phase 2 of the lockdown onwards. This core pattern is similar for each of six major food groups (Figure C.5), suggesting that the recovery was not driven by product-specific government procurement.

To quantify the aggregate patterns in Figure 4.1 we use variants of the following difference-in-difference specification:

$$ln\left(\text{Volume}\right)_{yd} = \alpha_y + \alpha_d + \sum_{t=1}^{5} \beta_t \text{Phase}_{yd}^{t} + \epsilon_{yd} \tag{4.1}$$

where $ln\left(\text{Volume}\right)_{yd}$ is the log of the total volume of food arrivals in tonnes on calendar date d (e.g. January 1) during year y (either 2019 or 2020). α_y and α_d are year and calendar date fixed effects, respectively, making this a difference-in-difference design where we are comparing the volume change before and after the lockdown began in 2020 with the volume change before and after March 24 in 2019.[42] We include only data from March 1 to June 30 in these regressions, making the "before" period March 1 to 24. To estimate separate effects for each phase of the lockdown, we include a set of dummy variables for the five phases. Phase_{yd}^{1} is a dummy variable equal to one for the period March 25, 2020 to April 14, 2020, and equal to zero otherwise. The remaining dummies are switched on for April 15 to May 3 (Phase_{yd}^{2}), May 4 to May 17 (Phase_{yd}^{3}), May 18 to May 31 (Phase_{yd}^{4}), and June 1 to June 30 (Phase_{yd}^{5}), with all of these dates in 2020 only. For specifications at the day-level, we use robust standard errors, while for specifications

[40] Wheat accounts for 30.7% of total food volume in our data, and exhibits considerable volatility from year to year (see Figure C.3). To confirm that wheat does not drive our results, we replicate all the main tables and figures involving total food volumes in Appendix C.3, excluding wheat. None of our core results are affected by the exclusion of wheat. We do not replicate our analysis of price trends without wheat, as these analyses are at the product-day level, so wheat does not have an outsized influence.

[41] We plot the seven-day moving average to smooth weekly fluctuations in arrivals, given notable dips on Sundays (Figure C.4).

[42] With only data for 2020 we could estimate a pre-post (or before-after) specification, in which we compare volumes before and after March 24, 2020. The key drawback with such a specification is that changes after March might reflect seasonality in volumes, rather than the causal effect of the lockdown and associated COVID-19 shocks. By including the 2019 data, we "difference out" this seasonality (formally by including calendar date fixed effects), making our estimates difference-in-difference estimates. These estimates essentially ask how much bigger the volume drop was after March 2020 when compared with that after March 2019, and attribute this difference to the effects of the pandemic. Put another way, we implicitly estimate the counterfactual volumes (in the absence of the pandemic) after March 24, 2020 to be those implied by applying the seasonality in 2019 to the levels of volumes at the start of 2020.

at the mandi-day-level, we cluster standard errors at the mandi-level.

Phase 1 of the lockdown reduced nationwide food arrivals by 69%[43] (column 1, Table 4.1), with a nearly identical estimated drop when we also include data from 2018 in the "control group" (column 2). Volumes subsequently recovered – the Phase 2 fall is only 20% (column 1), while each of the coefficients for Phase 3 to 5 are actually positive, though not significant, in both columns 1 and 2 (with the exception of Phase 5 in column 2, significant at the 10% level). These regression results show that aggregate volumes fully returned to normal levels by early-May, and even somewhat exceeded normal levels by June.

The large volume reduction during Phase 1 could reflect two margins: mandis closing completely (the extensive margin) or mandis remaining open but at lower capacity (the intensive margin). We find evidence for both margins. The number of functional mandis fell by 39 to 42% during Phase 1 (columns 3 and 4, Table 4.1, and visualised in Figure 4.2), showing that the extensive margin drove some of the volume reduction.[44] These extensive margin effects are potentially more damaging than intensive margin effects – extreme food insecurity is presumably less likely if all markets remaining functioning, though at lower capacity, than if markets in some locations shutdown completely, with other locations functioning at normal levels.

To isolate intensive margin effects, we aggregate food arrivals to the mandi-day-level, and re-run the difference-in-difference specification with mandi fixed effects. Given that the outcome is the natural logarithm of arrivals, any non-functional mandi-days are dropped from the regression. As a result, the coefficients can be interpreted as the effects on mandi-level volumes conditional on the mandi remaining open. When considering only the intensive margin, volumes fell by 44% during Phase 1 (columns 5 and 6, Table 4.1), with a similar pattern of recovery, including significantly higher volumes than normal during Phases 3 to 5.

While we see effects at both the extensive and intensive margins, we might expect effects to vary spatially. Given that high population density facilitates the transmission of COVID-19, one hypothesis would be that the volume shock is more severe at mandis in more urban districts. In fact, the phase-wise patterns of shock and recovery are similar in urban and rural districts (Figure 4.3). If anything, we estimate a slightly larger Phase 1 volume shock in the more *rural* districts, though we cannot reject that the Phase 1 effects are equivalent in rural and urban districts at conventional levels (Table C.3). These results suggest that local COVID-19 risk,

[43]The Phase t volume fall in % is estimated as $100 \times \left(1 - e^{\beta_t}\right)$.

[44]One important assumption we make here is that effects on the number of functioning mandis are given by our estimated effects on the number of *reporting* mandis. If the reporting itself (holding constant whether the mandi was functioning) was negatively impacted by the lockdown, we would overestimate the fall in functionality that followed the lockdown. We think our assumption is reasonable given two pieces of evidence that non-reporting mandis are likely non-functioning. First, other experts (e.g. Rawal and Verma 2020) and Government of India officials themselves report the number of functional mandis as the number of mandis reporting data to Agmarknet. Second, the Ministry of Agriculture states that mandis that are part of the Agmarknet scheme are fully computerized and the dataflow is nearly automatic, suggesting that reporting is straightforward conditional on having data to report.

which is higher in urban areas, may not be a key driver behind supply disruptions – a theme we return to more systematically in Section 4.3.4.

4.3.2 Drivers of the Volume Shock

To understand what drove the initial volume shock we draw on a set of qualitative interviews with wholesale traders in Delhi, and information from publicly available sources.

A sudden fall in the volume of arrivals could be due to a fall in demand or issues pertaining to the supply chain. Supply-side issues appear to have been important contributors. First, uncertainty about the rules on inter-state travel made it cumbersome to transport produce across state borders. Border closures, extra layers of inspection and documentation requirements, and a lack of clarity on the rules regarding the transport of agricultural produce created uncertainty for truck drivers.[45] Inability to find paid work to transport produce added to these frictions. Secondly, at the market level, a sharp fall in the supply of labor, driven by the exodus of migrant laborers from urban areas to their native places, reduced the pace at which trucks could be loaded and unloaded. A shortage of ancillary workers, e.g. book keepers, also impacted the daily functioning of the markets.[46]

Constraints faced at the last mile of the supply chain by retail vendors also played a part in reducing transaction volumes. Rules on social distancing made many retail markets non-functional in urban areas, and retail vendors had to resort to alternative business models – e.g. selling in multiple neighborhoods in the same day – which increased effort costs and reduced volumes. Many other retail vendors decided not to operate at all.

The recovery of wholesale volumes since mid-April 2020 is significant given these supply-side vulnerabilities. After the initial hiatus, inter-state movement of agricultural goods recovered as policies to ease restrictions on the cross-state movement of agricultural goods were put in place.[47] The central government issued directives to free the inter-state movement of vehicles carrying essential commodities and worked in coordination with State Agricultural Marketing Boards to ensure the smooth movement of agricultural goods across state borders.[48] In addition, wholesale markets adapted by resuming operations with physical distancing and other measures to limit the spread of the virus. For example, in Asia's largest wholesale fruit and vegetable market in Delhi, Azadpur mandi, traders with odd- and even-numbered sheds ran business on alternate days, vegetables and fruits were sold at separate times, and limits on the number of trucks that could be operated by each individual trader were introduced.[49]

[45] Hussain (2020).
[46] Mishra and Pillai (2020).
[47] See https://pib.gov.in/PressReleseDetail.aspx?PMO=3&PRID=1608009 accessed on July 20, 2020.
[48] See https://pib.gov.in/PressReleseDetailm.aspx?PRID=1616771 accessed on July 20, 2020.
[49] The Economic Times (2020).

4.3.3 Wholesale Prices Increased and Then Returned to a Downward Trend

A return to pre-lockdown food volumes may still be consistent with a threat to food security if prices are higher. To explore this, we use an event study approach to compare the evolution of wholesale prices in 2020 with 2018 and 2019. This year-by-year event study approach differs from the analysis in Table 4.1 in that we do not explicitly estimate a difference-in-difference effect of the pandemic. We change the approach when considering prices because the strong autocorrelation in prices makes the parallel trends assumption unreasonable. As a result, our analysis of prices is more descriptive in nature than our analysis of volumes.

We estimate the following specification separately for each of the three years:

$$ln\,(\text{Modal Price}_{smfd}) = \alpha_{smf} + \sum_{t=-11}^{-1} \beta_t^{\text{pre}} \text{Week}_d^t + \sum_{t=1}^{14} \beta_t^{\text{post}} \text{Week}_d^t + \epsilon_{smfd} \tag{4.2}$$

where $ln\,(\text{Modal Price}_{smfd})$ is the natural logarithm of the modal price of food variety f in mandi m in state s on calendar date d. α_{smf} are state-by-mandi-by-food variety fixed effects. Week_d^t is a dummy variable equal to one if date d belongs to the t^{th} week after March 24 – for example, Week_d^1 is equal to one for March 25 to 31, while the first and last weeks are January 1 to 7 (Week_d^{-11}) and June 24 to 30 (Week_d^{14}), respectively. The omitted category is Week_d^0, covering March 18 to 24. From this specification we estimate pre-lockdown trends in prices (β_t^{pre}) and post-lockdown trends (β_t^{post}), holding constant the food variety and location, and implicitly conditioning on availability of the variety.[50] We can then compare these estimated trends with the trends estimated for 2018 and 2019.

Wholesale prices did not change noticeably around March 25 in 2018 or 2019, while in 2020 prices jumped sharply by 8% (Figure 4.4). The increase suggests that the sudden fall in supply was not matched by a commensurate fall in demand. This price spike was however short-lived – four weeks after the lockdown began, price levels were similar to those immediately prior to the lockdown. Following this, wholesale prices returned to a downward trend, such that prices were 5 to 10% lower than pre-lockdown levels toward the end of Phase 5.[51] In short, prices were affected similarly to volumes (Figure 4.1) – an initial shock during Phase 1 followed by a return to normality during the subsequent lockdown phases.[52]

[50] One caveat is that with non-functional markets (Figure C.1), sometimes food was not available at all during the lockdown, making the prices of some food varieties effectively infinite. This means that our analysis here understates the effective lockdown-induced increase in wholesale prices, given that we study only the effects on prices conditional on availability.

[51] One possible explanation for the lower price level by Phase 5, other than that of a return to trend, could be that while supply rebounded, demand remained low, placing downward pressure on prices.

[52] The pattern of rising wholesale prices at the onset of the lockdown holds for most of the major commodity groups (Figure C.6), with the exception of spices, which did not see a lockdown-induced price increase at all. One possible explanation is that the non-perishability and relative non-necessity of spices meant that demand

While our analysis considers wholesale prices, evidence for urban areas from Narayanan and Saha (2021) suggests that our findings may also hold for retail prices – they find that the retail price markup over wholesale prices remained fairly constant during the lockdown period.

4.3.4 State-Level Food Supply Disruptions Versus Coronavirus Spread

An important question is whether the supply chain disruption was driven more by state-level lockdown policies or by local behavioral responses. If the latter, continued virus transmission would disrupt supply chains even in the absence of state-mandated lockdowns. We approach this question in two main steps. First, we correlate the evolution of food arrivals at the state-level with the state-level coronavirus caseload. We will show that the initial disruption was highly positively correlated with coronavirus at the state-level. Second, we use *within*-state variation to unpack the correlation, and find the correlation between district-level COVID-19 incidence and food supply disruption is neither economically nor statistically significant, indicating that the relationship is not driven by local responses to COVID-19 exposure. Finally, utilizing the decline in state-level mobility as a proxy for state-level policy, we show a strong positive relationship between decline in mobility and the food supply disruption. We conclude that state-level policy responses are more likely responsible for the food supply shock rather than voluntary individual responses.

It is important to note that the confirmed COVID-19 case counts differ from the true COVID-19 case counts due to underreporting and insufficient testing, and that the extent of undercounting may differ by state. Nevertheless, confirmed COVID-19 case counts represent the best information about the severity of the pandemic available to policymakers and market participants. Thus the analysis to follow can be viewed as investigating the relationship between (potentially mistaken) views about the severity of the pandemic and the health of the food supply chain.[53]

To analyze the relationship between food supply and confirmed COVID-19 cases at the state level, we first estimate the size of the volume shock for each state, separately for the first phase of the lockdown versus the subsequent four phases of the lockdown. This way we broadly split the post-lockdown period into the "shock" phase and the "recovery" phase (as is clear in Figure 4.1 and Table 4.1). We use the following specification for each state s:

$$ln\,(\text{Volume})^s_{yd} = \alpha^s_y + \alpha^s_d + \gamma^s \text{Phase}^1_{yd} + \theta^s \text{Phase}^{2-5}_{yd} + \epsilon^s_{yd} \tag{4.3}$$

which differs from equation 4.1 in two ways. First, the s super-scripts indicate that this regres-

was more elastic than it was for other commodity groups and therefore a supply disruption did not lead to major changes in prices. However, we do not find strong evidence for heterogeneity in the lockdown-induced price increase by perishability overall (Figure C.7). While the 2020 wholesale price trends for (manually-classified) perishables are more volatile than those for non-perishables, both product categories see a similar short-term spike in prices after the lockdown.

[53]For a discussion of related issues, see Abay et al. (2021).

sion is run state-by-state for state-specific coefficients. Second, we replace the dummy variables for each of the Phases 2 to 5 with Phase^{2-5}_{yd}, a dummy variable equal to one for the entire post-Phase 1 period (April 15 to June 30). Importantly, the outcome is now the natural logarithm of *state*-level food arrivals on a particular day, rather than that of nationwide food arrivals. We again use data only from March 1 to June 30, in 2019 and 2020, and estimate effects for 17 states with consistent data – those with at least 10 mandis on average reporting daily data during each of the months from March to June in 2019, and from January to March in 2020. These 17 states cover 885 million people, or 73% of India's population as of the 2011 census.[54]

The Phase 1 volume fall at the state-level ($100\times\left(1-e^{\hat{\gamma^s}}\right)$) is strongly positively correlated with the log number of confirmed cases of coronavirus as of the end of Phase 1 ($\rho = 0.72$, $p = 0.001$, Figure 4.5). In fact, the log number of confirmed cases of coronavirus alone explains over half of the variation in the state-level volume shocks ($R^2 = 52\%$). While the lockdown was national, the impact on essential food supply was more severe in regions which had a higher incidence of the virus.

The picture that emerges in the period starting in Phase 2 is, however, quite different. The state-level volume fall during Phases 2 to 5 is uncorrelated with the coronavirus caseload as of the end of Phase 5 ($\rho = 0.07$, $p = 0.8$, Figure 4.6). This shows that the nationwide supply recovery visualized in Figure 4.1 does not mask heterogeneity across states with more versus less coronavirus – in essence, volumes recovered regardless of the spread of coronavirus.

4.3.5 Is the Supply Disruption-COVID-19 Relationship Due to State-Level Policies or Local Responses?

There are two main factors that would lead to a correlation between the initial food supply disruption and the state-level incidence of coronavirus. First, states with more coronavirus introduced stricter lockdown policies with greater efforts at enforcement. These policies could have disrupted the supply chain.[55] Second, even holding state-level policies constant, people could voluntarily change their behavior in response to a high local incidence of coronavirus. For example, rather than being deterred by state-level policies, people might voluntarily restrict their labor supply out of fear of contracting the disease. Distinguishing between the two factors matters – if voluntary individual responses are most important, the lifting of lockdown policies would not reliably restore the functioning of food supply chains.

[54] These 17 states are Andhra Pradesh, Chattisgarh, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Tripura, Uttar Pradesh, Uttrakhand, and West Bengal. The seven states (or union territories) that are dropped relative to our previous 24-state analyses are: Goa, Jammu and Kashmir, Jharkhand, Meghalaya, Nagaland, NCT of Delhi, and Pondicherry (Table C.1).

[55] While we do not directly observe state-level lockdowns in our data, we utilize declines in state-level mobility, measured via Google mobility data, to proxy for state-level lockdowns. Figure C.8 demonstrates a strong relationship between state-level COVID-19 incidence and mobility reductions as of April 14 (Phase 1 of the national lockdown).

We look at this question by examining within-state variation in food supply and COVID-19 intensity. If state-level policy variation alone is responsible for the correlation between COVID-19 intensity and the disruption of the food supply, then the relationship should disappear in a within-state analysis. However, if the disruption is driven by voluntary behavioral responses, then the correlation should persist even using within-state variation. In what follows we demonstrate that there is no economically or statistically significant correlation between the food supply shock and COVID-19 intensity at the within-state level and therefore the food supply shocks are most likely due to state-level policy variation.[56] At the close of this section we provide a more direct form of evidence that state-level policy is responsible for the food supply shock. Namely, we demonstrate that declines in mobility, measured using Google mobility data, are strongly correlated with food supply shocks at the state level.

We begin with our analysis of district-level data to estimate the evolution of food supply in districts with more versus less coronavirus exposure. Earlier, we used a difference-in-difference specification (equation 4.1) to estimate the effect of the lockdown as the additional fall in volumes post-March 24 in 2020 relative to 2019. Now we test whether this difference-in-difference effect is larger in districts with more exposure to COVID-19. This amounts to a triple-difference approach, in which the triple interaction term is between (i) post-March 24, (ii) the year 2020, and (iii) confirmed COVID-19 cases at the district-level. More formally, we estimate:

$$\begin{aligned} arcsinh\left(\text{Volume}_{xyd}\right) = \alpha_{xd} + \alpha_{xy} + \alpha_{dy} \\ + \phi_1\left(arcsinh\left(\text{COVID-19 Cases}_x\right) \times \text{Phase}^1_{yd}\right) \\ + \phi_2\left(arcsinh\left(\text{COVID-19 Cases}_x\right) \times \text{Phase}^{2-5}_{yd}\right) + \epsilon_{xyd} \end{aligned} \tag{4.4}$$

where Volume_{xyd} is the total quantity of food arrivals in tonnes to district x during year y on calendar date d. Here we take the inverse hyperbolic sine, rather than the natural logarithm, of Volume_{xyd}, given that 18% of our analysis sample observations at the district-day-level are zero-valued. As is standard with triple-difference specifications, we include all possible two-way interactions: α_{xd} are district-by-calendar date fixed effects, α_{xy} are district-by-year fixed effects, and α_{dy} are date fixed effects.[57] These two-way interactions fully absorb the overall difference-in-difference effect of the lockdown, meaning our focus in this specification is only on estimating the *differential* effect of the lockdown in high- versus low-exposure districts.

COVID-19 Cases_x is the number of confirmed coronavirus cases in district x by the end of Phase 1 (April 14, 2020). Given that 166 of our 399 analysis sample districts had zero confirmed cases of COVID-19 by April 14, we again take the inverse hyperbolic sine of this variable. Phase^1_{yd} and Phase^{2-5}_{yd} are as defined earlier. We cluster standard errors at the district-level.

[56] We note that policy can vary at the district-level as well. Nevertheless, the fact that we find no evidence of a relationship between district-level COVID-19 incidence and the food supply shock indicates that neither district-level policy nor voluntary individual withdrawal of labor supply are responsible for the shocks.

[57] Equivalent to calendar date-by-year fixed effects.

$\hat{\phi}_1$ is our estimate of the *additional* effect of Phase 1 of the lockdown on volumes in COVID-19 affected districts relative to unaffected districts, while $\hat{\phi}_2$ is the estimate for Phases 2 to 5. Given the inverse hyperbolic sine transformations on the left- and right-hand-side, these coefficients can be interpreted as elasticities for large enough values of Volume and COVID-19 Cases (Bellemare and Wichman 2020).

We estimate three variants of this specification. First, we replace $arcsinh\,(\text{COVID-19 Cases}_x)$ with $arcsinh\,(\text{COVID-19 Cases}_s)$ where s denotes the state that district d belongs to. This initial specification aims to replicate the strong positive correlation in Figure 4.5 – showing that districts that belong to states with more COVID-19 suffered a larger supply shock during Phase 1. In the second variant we estimate equation 4.4 itself. In doing so, we test whether districts with more COVID-19 themselves suffered a larger supply shock. In the third variant, we add state-date fixed effects (α_{sdy}), fully absorbing any time-varying state-level policy (or even non-policy) variation. This specification allows us to estimate the different effects of the pandemic on affected versus unaffected districts while only making comparisons within the same state.[58]

Before turning to the three specifications described, we first replicate the negative effects of the lockdown on supply (e.g. as in column 1, Table 4.1) using the district-day-level data.[59] Consistent with our earlier results, food arrivals to districts dropped by 86% during Phase 1 of the lockdown (column 1, Table 4.2, compared with a 69% drop in column 1, Table 4.1), and recovered fully during Phases 2 to 5.

The Phase 1 disruption was larger in COVID-19-affected states ($p < 0.01$, column 2, Table 4.2), consistent with the strong positive correlation between caseload and state-level supply shocks in Figure 4.5. Specifically, the point estimates imply that a doubling of state-level cases by April 14 is associated with a negative supply shock that is 33% larger.

Strikingly, the correlation between COVID-19 exposure and supply disruption disappears when we instead define exposure at the district-level (column 3, Table 4.2), and remains small and not statistically significant when we exploit only within-state variation (column 4). These results suggest that the strong relationship between supply disruptions and COVID-19 exposure is not driven by local reactions – for example, the withdrawal of labor due to local fears of catching coronavirus. Instead, the pattern of results is most consistent with supply disruptions being driven by state-led reactions, with states with more COVID-19 reacting more aggressively.[60]

[58]In support of the key assumption for a triple-difference specification, pre-trends are parallel for each of these three variants of our core specification (Table C.5).

[59]Note that our district-level estimates need not coincide with our India-level estimates given that our district-level regressions are unweighted.

[60]Phase 2 to 5 district-level supply disruptions are also not mediated by COVID-19 exposure (columns 3 and 4, Table 4.2). These Phase 2 to 5 results are similar if we instead define COVID-19 exposure as of the end of Phase 5, i.e. June 30, paralleling Figure 4.6 (Table C.6).

We note that, much as in the case of state-level confirmed COVID-19 cases, district-level COVID-19 cases are very likely to be measured with error, and this error may vary systematically across districts. For instance, some districts may not have testing facilities, and people may cross district boundaries to get tested. As in the case of state-level confirmed COVID-19 cases, if people utilize district-level confirmed COVID-19 case statistics to inform their decisions, then our analysis demonstrates that voluntary responses to perceived COVID-19 intensity are not a significant contributor to the food supply shock. However, people may have also used other sources of information about the pandemic's intensity, which were only imperfectly correlated with confirmed cases. In this event the lack of district-level correlation between confirmed cases and the food supply shock may in part be due to our imprecise measurement of perceived COVID-19 intensity at the district level.

To provide more direct evidence that state-level policy is a primary driver of the food supply shock, we turn to Google mobility data. In the absence of a comprehensive list of state-level policy responses to the pandemic, declines in mobility may be a good proxy for policy responses. Namely, states with more stringent lockdowns should see a larger decline in mobility. In Figure C.9 we replicate the analysis of Figure 4.5, but rather than confirmed COVID-19 cases, the x-axis measures the decline in state-level mobility during Phase 1 of the lockdown. Indeed, there is a strong positive correlation ($\rho = 0.54$, $p = 0.03$) between declines in state-level mobility and the food supply shock. Table C.4 confirms this conclusion in a regression framework. Every 1% decrease in mobility at the state-level corresponds to a 2.6% decrease in food volumes ($p < 0.01$), though this relationship disappears once controlling for COVID-19 intensity. Echoing Figure 4.6, the unconditional relationship also disappears in Phases 2 - 5 ($\rho = 0.15$, $p = 0.56$, Figure C.10).

4.4 Conclusion

This chapter documents how India's food supply chain responded following the national lockdown. Aggregate volumes dropped by 69% during the first few weeks of the lockdown, but subsequently fully recovered. Similarly, wholesale prices rose by 8% initially, but then returned to a downward trend. Exploiting regional variation, we also show that the initial volume shock was closely correlated with local exposure to COVID-19, and we demonstrate that this was more likely driven by state-level policy variation than by voluntary responses of those within the food supply chain. These facts provide some comfort with regard to the concerns of food security in large emerging economies like India's in the wake of the pandemic.

Policymakers around the world, and especially in the developing world, face an important tradeoff in reacting to a pandemic. The more stringent their initial lockdown the less the pandemic can spread, but also the worse is the potential damage to the economy's most critical functions. That India's food supply chain began recovering immediately following the strictest phase of the lockdown was not a forgone conclusion. Shutting the country down for three weeks – and then beginning a staggered reopening – could have introduced a coordination breakdown along the many components of the supply chain, hampering its recovery even far after the lockdown was lifted. Though it is only a single case study, the fact that India's food supply chain recovered so quickly and completely suggests that strict lockdown measures at the onset of pandemics need not cause long-term economic damage.

4.5 Tables

Table 4.1: The Lockdown's Impact on Food Arrivals

	ln(Food Arrivals)		ln(Functioning Mandis)		ln(Food Arrivals)	
	(1)	(2)	(3)	(4)	(5)	(6)
Phase 1 (Mar 25-Apr 14)	-1.17***	-1.18***	-0.54***	-0.51***	-0.58***	-0.59***
	(0.30)	(0.24)	(0.14)	(0.12)	(0.04)	(0.04)
Phase 2 (Apr 15-May 3)	-0.22	-0.20	-0.07	-0.02	-0.17***	-0.16***
	(0.26)	(0.23)	(0.14)	(0.13)	(0.04)	(0.04)
Phase 3 (May 4-May 17)	0.17	0.16	-0.12	-0.13	0.18***	0.21***
	(0.32)	(0.28)	(0.19)	(0.17)	(0.04)	(0.04)
Phase 4 (May 18-May 31)	0.30	0.29	-0.10	-0.11	0.27***	0.31***
	(0.33)	(0.28)	(0.19)	(0.16)	(0.04)	(0.04)
Phase 5 (Jun 1-Jun 30)	0.40	0.40*	0.06	0.08	0.21***	0.31***
	(0.26)	(0.22)	(0.14)	(0.12)	(0.04)	(0.03)
Observations	240	360	240	360	260181	388382
Sample Period	2019-20	2018-20	2019-20	2018-20	2019-20	2018-20
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mandi Fixed Effects	No	No	No	No	Yes	Yes

Notes: The unit of observation is a day in columns 1 to 4, and a mandi-day in columns 5 and 6. The regressions include data from March 1 to June 30 for each year (either 2019-2020 or 2018-2020), with the exception of national holidays (Republic Day and Holi). Robust standard errors in columns 1 to 4, standard errors clustered at mandi-level in columns 5 and 6. The outcome for columns 1 and 2 is the natural logarithm of the tonnes of nationwide food arrivals to mandis that reported at least once in March 2020. The outcome for columns 3 and 4 is the natural logarithm of the number of functional (i.e. reporting) mandis among the sample relevant for columns 1 and 2. The outcome for columns 5 and 6 is same as that for columns 1 and 2, though measured at the mandi-day-level. $***p < 0.01, **p < 0.05, *p < 0.1$.

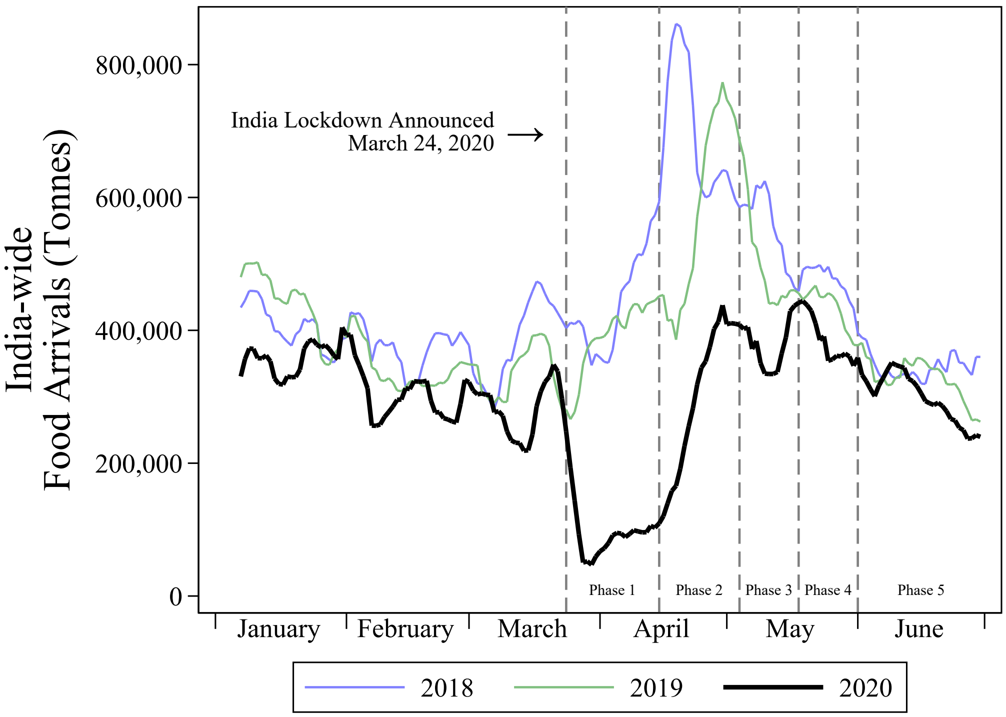
Table 4.2: District-Level Supply Disruptions by COVID-19 Exposure

	arcsinh(Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.96***			
	(0.10)			
Phases 2-5 (Apr 15-Jun 30)	0.15**			
	(0.06)			
arcsinh(COVID-19 Cases in State) × Phase 1		-0.40***		
		(0.05)		
arcsinh(COVID-19 Cases in State) × Phases 2-5		0.05**		
		(0.03)		
arcsinh(COVID-19 Cases in District) × Phase 1			-0.00	0.02
			(0.06)	(0.05)
arcsinh(COVID-19 Cases in District) × Phases 2-5			0.04	0.04
			(0.04)	(0.05)
Observations	94164	94164	94164	93928
Number of Districts	399	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	No	Yes	Yes	No
State-Date Fixed Effects	No	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from March 1 to June 30 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the inverse hyperbolic sine (arcsinh) of the number of tonnes of food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of April 14, 2020. $***p < 0.01, **p < 0.05, *p < 0.1$.

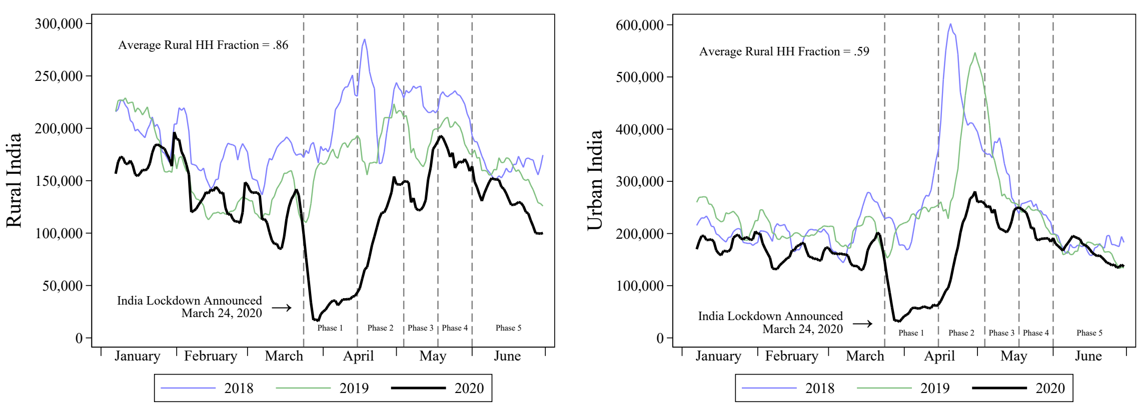
4.6 Figures

Figure 4.1: The Lockdown Caused Wholesale Volumes to Plummet



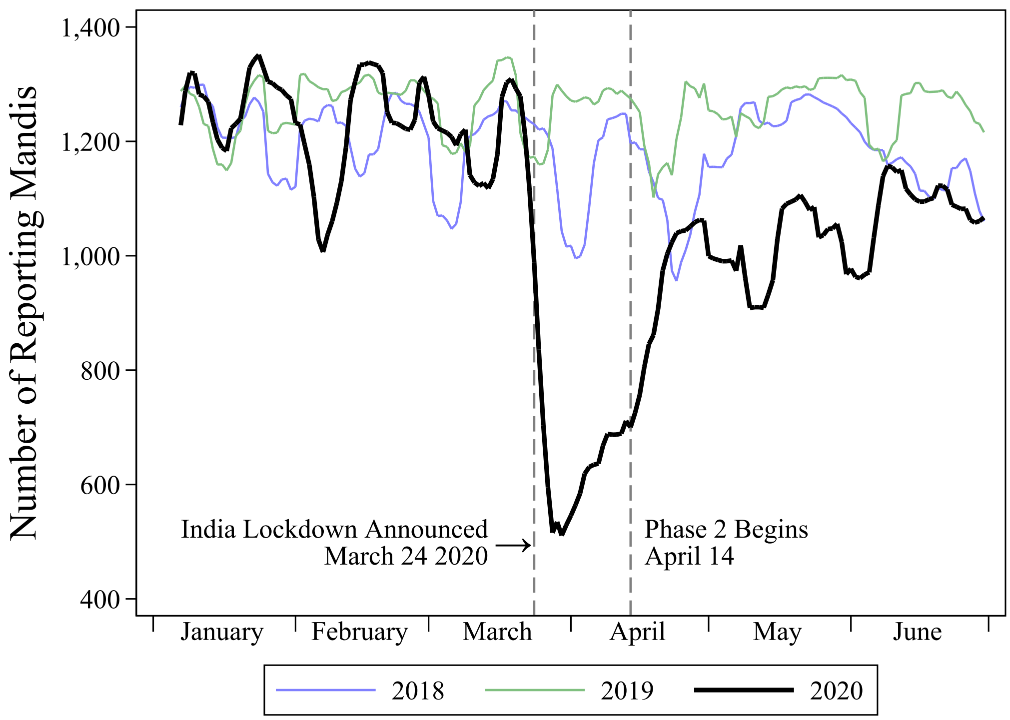
Notes: The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Source: agmarknet.gov.in.

Figure 4.3: Food Arrivals to Urban vs. Rural India



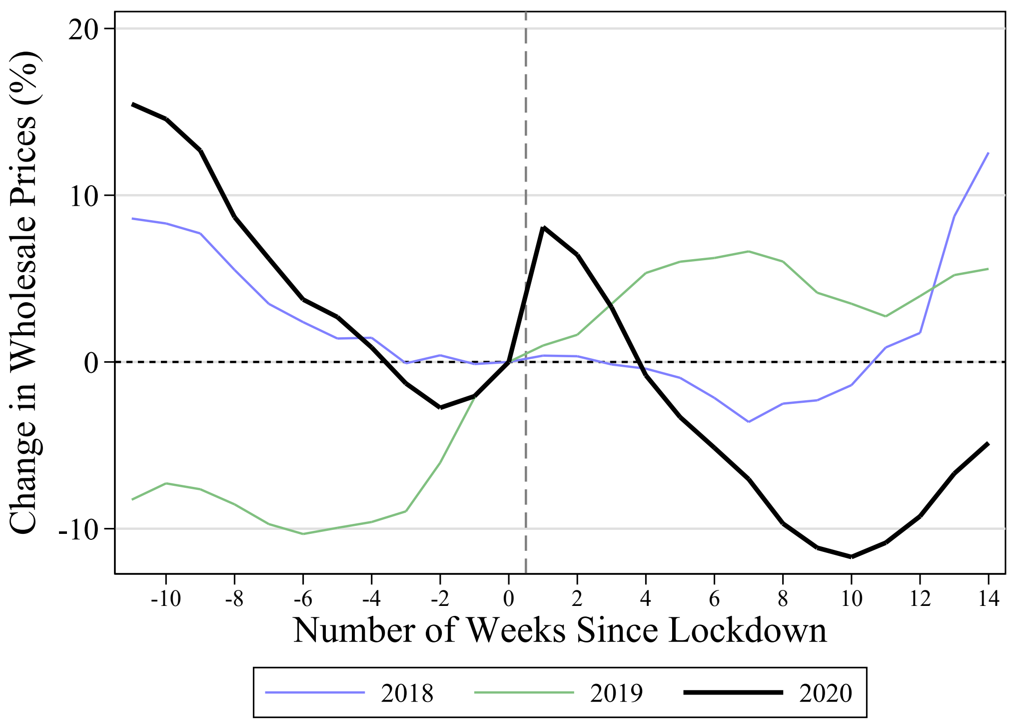
Notes: The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. Rural India includes any mandis residing in a district with an above-median share of rural households in the 2011 Census, with Urban India including all other mandis. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Source: agmarknet.gov.in.

Figure 4.2: The Number of Functioning Mandis Plummeted and Then Recovered



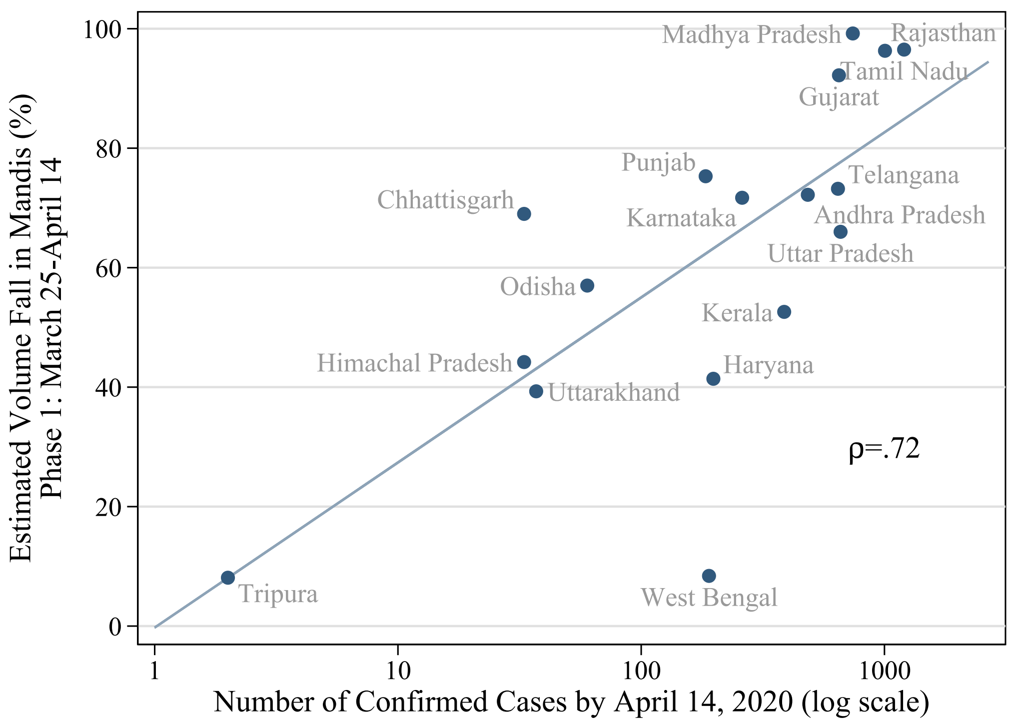
Notes: The y-axis variable is a seven-day moving average of the number of mandis that reported any data to Agmarknet on each date, among the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average number of reporting mandis for January 1 to 7). Source: agmarknet.gov.in.

Figure 4.4: After an Initial Increase in Wholesale Prices, Prices Returned to Trend



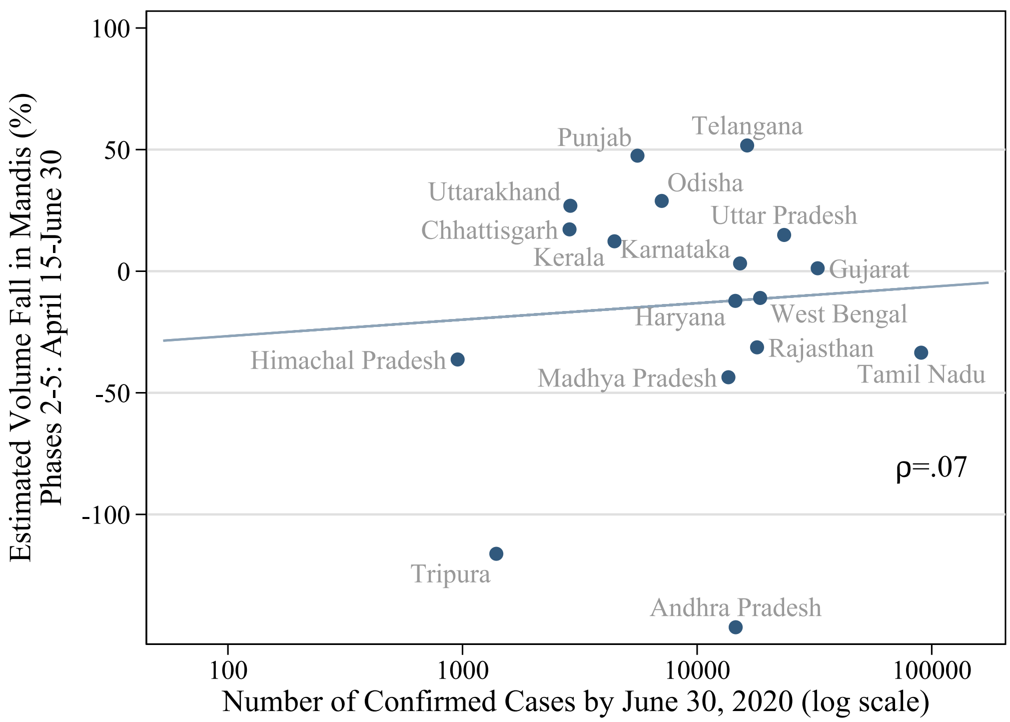
Notes: The figure plots the percentage change in wholesale prices implied by the year-by-year estimates from equation 4.2. Specifically, the pre-lockdown y-axis variable is $100 \times \left(e^{\hat{\beta_t^{pre}}} - 1\right)$ for $t \in \{-11, -10, ..., -2, -1\}$, while the post-lockdown variable is $100 \times \left(e^{\hat{\beta_t^{post}}} - 1\right)$ for $t \in \{1, 2, ..., 13, 14\}$. The sample comprises only those mandis that reported data at least once in March 2020.

Figure 4.5: States With More Coronavirus Cases Had Bigger Supply Chain Disruptions During Phase 1



Notes: The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\gamma}^s}\right)$ using estimated coefficients from equation 4.3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 1 (April 14), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 1 volume fall and the natural logarithm of the number of confirmed cases by April 14, 2020.

Figure 4.6: Volume Shocks Were Not Correlated With Coronavirus Cases After Phase 1



Notes: The y-axis is the estimated Phase 2-5 volume fall for each of 17 states, where the estimate is $100\times\left(1-e^{\hat{\theta^s}}\right)$ using estimated coefficients from equation 4.3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 5 (June 30), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 2-5 volume fall and the natural logarithm of the number of confirmed cases by June 30, 2020.

Chapter 5

Conclusion

Previous three chapters of this thesis dealt with different but related issues on inflation in India with the common theme of exploring the role of food prices and its dynamics. Focus of these chapters has been on identifying some of the relevant questions which are not explored in detail in the literature and shedding light on some of those issues to better inform policy.

Chapter 2 examines nature of price setting within food sector in India. Compiling a novel dataset we present a set of empirical facts which characterise food prices in India to be of having varying degree of price stickiness which contest the traditional notion that food prices are mostly flexible. We highlight the role of product group level factors in generating this heterogeneity. We then present a set of reduced form evidence to show that food prices in India exhibit properties that match predictions of a state-dependent pricing model with menu costs. We also show that the sticky component of food prices does not necessarily coincide with the conventional measures of core inflation like that of excluding food and fuel.

These findings throw light into interesting policy questions. One issue that is of immediate policy relevance would be: how much should monetary policy respond to changes in food prices? In India, within the inflation targeting framework, monetary policy reaction function incorporates both headline and core inflation (Benes et al. 2017). The relative weights assigned to core and headline inflation in monetary policy reaction function could be a policy concern emerging from findings of this study. Our findings also raise another important question of whether food prices also respond to monetary policy. Khundrakpam and Das (2011) showed that wholesale food prices do respond to money supply changes in India. Further investigation into retail food price dynamics and the role of monetary policy would be an interesting issue worth pursuing.

While chapter 2 aimed at providing evidence of existence of price stickiness in food sector in India, chapter 3 further investigates the role of bunching in prices in generating price stickiness. We show that prices are set in round digits which are easy to transact using cash in the case of physical stores and such rounded prices are much more likely to remain constant as compared with non-rounded prices. Using web-scraped data, we also show that bunching in round digits decreases a lot when we look at online prices and prices become much more flexible. Embedding discontinuities in prices that can be set by producers in a menu cost model, we show that existence of such price points significantly contributes to price stickiness as menu costs would have to be 30% higher to generate the same level of price stickiness in the absence of price points. We also show that size of menu costs and levels of prices are important factors in determining the extent to which price points contribute to price stickiness.

Rapid advancements in payment technologies have reduced the use of cash for transactions in recent years. Findings of our study, therefore, has a lot of importance in terms of policy. If moving from a physical cash environment to a digital cash world changes the way prices are set and prices become more flexible, role of monetary policy in such an environment would be an interesting policy question. Also, such a shift to digital payments in emerging economies could have welfare effects in terms of efficiency gains as well as who in the income distribution benefits from such a shift.

Chapter 4 is the final core chapter in this thesis which documents the response of food supply and prices to COVID-19 pandemic and lockdowns in India. We show that food arrivals dropped sharply in the wake of the initial lockdown to contain the virus but recovered swiftly. Wholesale prices also witnessed a spike which was short lived. The initial response of food supply was highly correlated with intensity of virus spread whereas such correlation disappeared during the recovery phase. We use variation in food supply and intensity of virus spread at district level to show that the fall in food supply was driven by state level policies as against economic agents' response to risk of virus spread. Our findings suggest that the food supply chains in India remained resilient to disruptions caused by temporary lockdowns.

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Appendix A

Appendix to Chapter 2

A.1 Robustness Check for Missing Data

In this section, I look at the sensitivity of key results to the issue of missing observations. Out of the total of 865 weeks in the dataset, we do not have data on a continuous basis for all the centres. Discontinuities in reporting are caused by both missing observations as well as the data collection day being a holiday leading to no data collection in that week. Additionally, some of the centres were added to the dataset over the years while some other centres stopped reporting. This has made the data an unbalanced panel. Therefore, I check whether the discontinuities in data reporting drive our results.

Since the primary interest of the study is to examine frequency of price changes and not calculating inflation *per se*, availability of price data for any two consecutive weeks is sufficient to calculate a change observation. I have made the assumption that results are unaffected by the presence of missing observations and carried out the analysis incorporating all the change observations that can be generated from the data.

I calculate key summary statistics on two restricted versions of sample and compare the results with that available from the full data set. In the first restricted sample, I drop those centres which did not report price observations for more than 25% of the total number of weeks. This reduced the total number of centres to 70 as against 85 in our full sample. Further, I define a narrow set of centres, which recorded most consistent reporting. I select only those centres which, in each month have reported at least 3 price observations in 90% of the months in our data. Applying this criteria reduced the total number of centres to 20. In many centres, some of the products were not traded at all owing to different consumption pattern across the country. Therefore, applying this criterion uniformly across all the products was not possible. The reporting pattern suggests that once a centre reports price data for a week, it does report for all the commodities that are traded in that centre. Therefore, I filter the centres by applying the criteria that the centre has reported at least one price point for any of the items.

Table A.1 reports the frequency of price change as well as the average size of absolute change across all the major product groups. At the aggregate level, there is almost no change in the estimated frequency of price change across the filtered samples. If we look at the product level characteristics, we see that absolute size of change does not vary much across different sample sets (the maximum being variation of 0.01 in the case of vegetables). In case of frequency of price change, while the results are almost identical between all centres and 70 centres,. However, there are exceptions like vegetables and meat and fish and pulses where the restricted sample frequency is higher by about 5-7 percentage points when we use at the most restrictive sample selection which includes only 20 centres. It needs to be, however, noted that the centres which are reporting more consistently are more urbanised and therefore we may not be able to establish a direct pattern of bias from the differences. Figure A.1 reports the results at product level where I have plotted the change, increase and decrease frequencies as well as size of absolute change across different sample sets at the item level. Diagonal alignment of scatter plots indicate that even at product level the frequencies computed from different samples do not vary much.

Table A.1: Change Frequency and Absolute Size of Change: Truncated versus Full Sample

	Change Frequency			Absolute Size of Change		
Product group	Full Sample	70 centres*	20 centres**	Full Sample	70 centres*	20 centres**
	(1)	(2)	(3)	(4)	(5)	(6)
Milk and products	0.04	0.04	0.05	0.08	0.08	0.07
Non-alcoholic beverages	0.06	0.06	0.07	0.08	0.08	0.07
Spices	0.09	0.09	0.11	0.13	0.12	0.10
Cereals and products	0.14	0.14	0.15	0.09	0.08	0.08
Sugar and confectionery	0.20	0.20	0.21	0.06	0.06	0.06
Oils and fats	0.20	0.20	0.23	0.05	0.05	0.04
Meat and fish	0.20	0.20	0.27	0.09	0.09	0.09
Fruits	0.21	0.21	0.25	0.13	0.13	0.12
Egg	0.22	0.22	0.25	0.09	0.09	0.09
Pulses and products	0.28	0.28	0.33	0.05	0.05	0.05
Vegetables	0.42	0.42	0.48	0.18	0.18	0.17
All Commodities (Mean)	0.16	0.16	0.19	0.09	0.09	0.08
All Commodities (Median)	0.15	0.16	0.17	0.09	0.09	0.08

* These centres reported data for more than 25% of the weeks in the sample.
** These centres reported data for at least 3 weeks in more than 90% of the months in our database.

I also check for the sensitivity of estimates of change frequency over time to missing data. Figure A.2 gives trends in frequency of price change across major product groups over different sample sets as defined above. Overall, the trends observed in all the product groups are similar. Therefore, we can conclude that our results are largely robust to missing data, though estimates at individual product levels may contain some bias.

Figure A.1: Product Level Key Summary Statistics: Full versus Truncated Sample

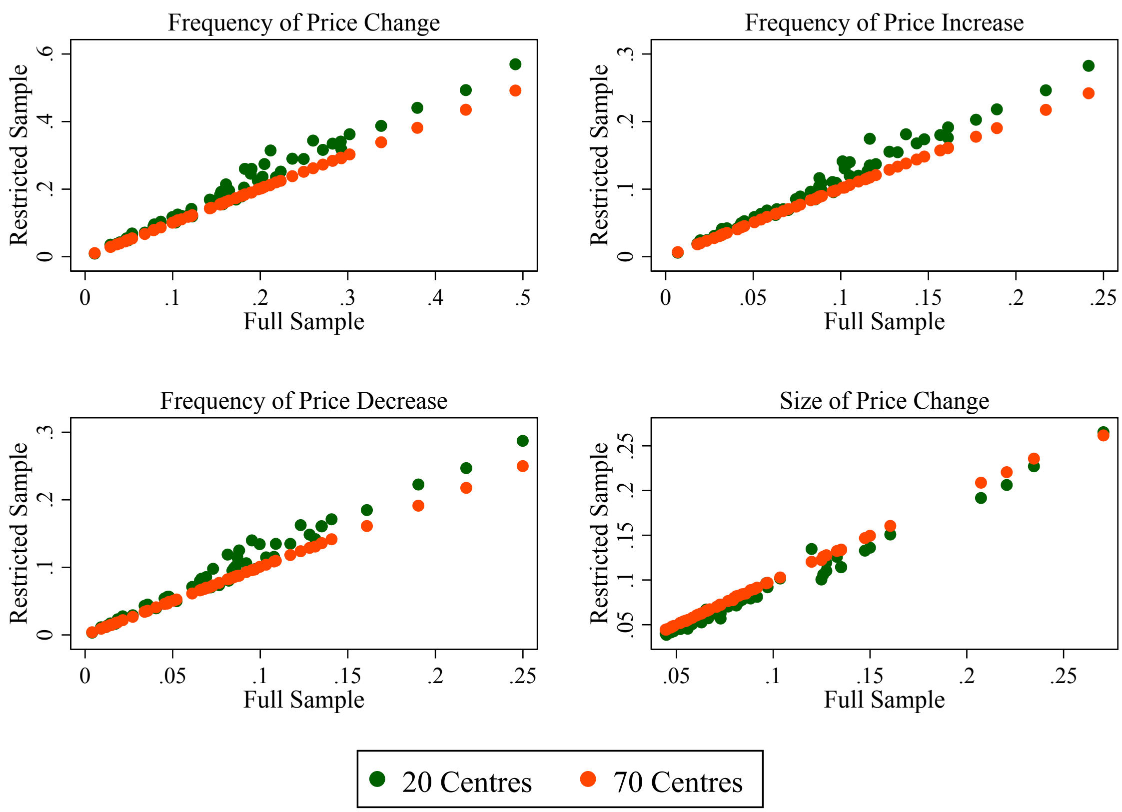
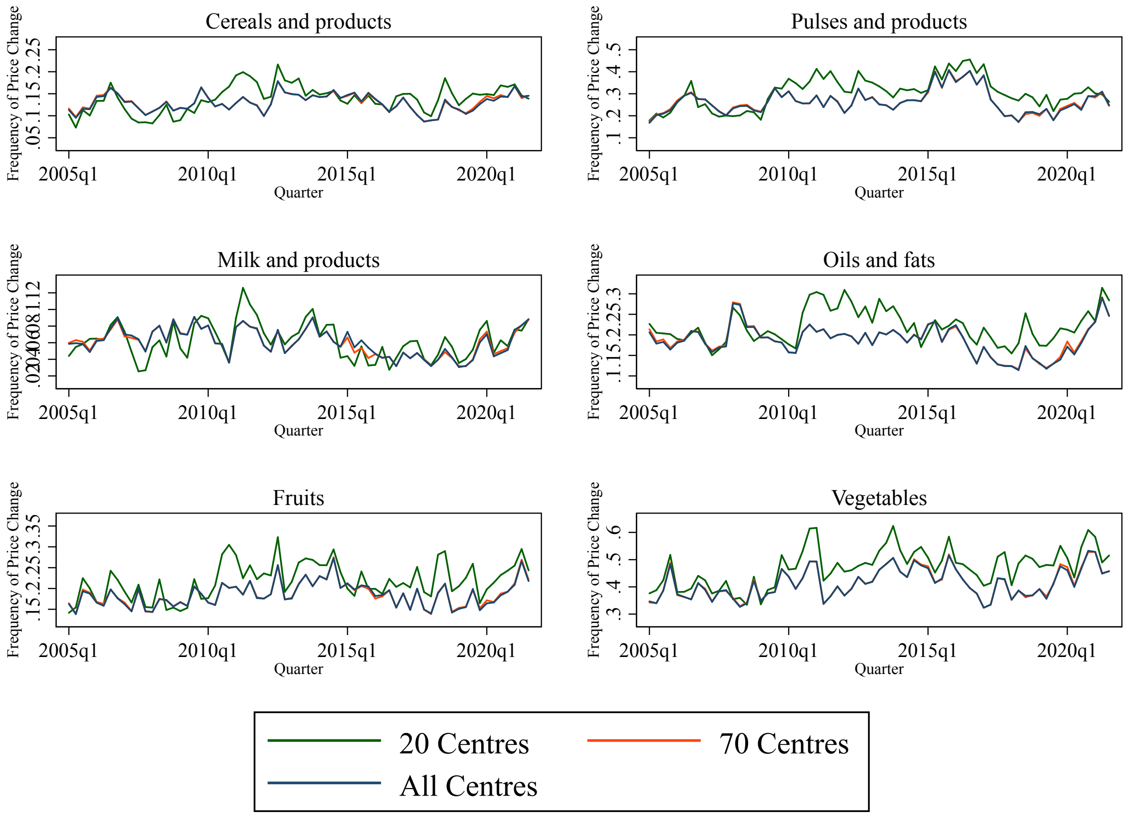


Figure A.2: Trends in Change Frequency Across Full and Truncated Samples



A.2 Additional Tables

Table A.2: List of Items Covered and Weight in All India CPI

Product	Weight in CPI	Category
1	2	3
Atta	0.85	Cereals and products
Bajra	0.11	Cereals and products
Biscuit	0.88	Cereals and products
Bread	0.11	Cereals and products
Jowar	0.23	Cereals and products
Maida	0.03	Cereals and products
Maize	0.06	Cereals and products
Ragi	0.05	Cereals and products
Rice	4.38	Cereals and products
Suji	0.10	Cereals and products
Wheat	1.70	Cereals and products
Eggs	0.43	Egg
Apple	0.47	Fruits
Banana	0.56	Fruits
Coconut	0.31	Fruits
Chicken	1.23	Meat and fish
Fish	1.26	Meat and fish
Meat	0.79	Meat and fish
Butter	0.01	Milk and products
Ghee	0.01	Milk and products
Milk	6.42	Milk and products
Coffee	0.05	Non-alcoholic beverages
Tea	0.95	Non-alcoholic beverages
Coconut Oil	0.08	Oils and fats
Gingelly Oil	0.01	Oils and fats
Groundnut Oil	0.33	Oils and fats
Mustard Oil	1.33	Oils and fats
Vanaspati	0.07	Oils and fats
Arhar	0.80	Pulses and products
Besan	0.16	Pulses and products
Gram	0.29	Pulses and products

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Product	Weight in CPI	Category
1	2	3
Masur	0.30	Pulses and products
Moong	0.34	Pulses and products
Urad	0.27	Pulses and products
Black Pepper	0.13	Spices
Coriander	0.33	Spices
Cummin Seed	0.01	Spices
Red Chillies	0.57	Spices
Turmeric	0.50	Spices
Gur	0.10	Sugar and confectionery
Salt	0.16	Sugar and confectionery
Sugar	1.13	Sugar and confectionery
Brinjal	0.28	Vegetables
Onion	0.98	Vegetables
Potato	0.64	Vegetables
Tomato	0.57	Vegetables

Table A.3: Behaviour of Food Prices in India: Product level

Product Category	Frequency of Price Change (%)	Duration (Months)	Proportion of Price Increases	Average Size of Absolute Change	Standard Deviation of Log Prices	Number of Observations
1	2	3	4	5	6	7
Tomato	49.14	0.3	49.15	0.23	0.41	41,218
Onion	43.48	0.4	49.94	0.16	0.26	41,536
Brinjal	37.95	0.5	49.85	0.22	0.34	39,823
Potato	33.81	0.6	52.42	0.15	0.29	41,581
Arhar	30.20	0.6	53.40	0.05	0.10	41,114
Apple	29.26	0.7	55.09	0.13	0.32	37,784
Moong	29.20	0.7	53.71	0.05	0.12	41,449
Urad	28.27	0.7	52.26	0.05	0.16	40,288
Gram	26.07	0.8	52.92	0.06	0.17	78,312
Chicken	26.04	0.8	52.72	0.10	0.24	37,494
Masur	23.67	0.9	53.99	0.05	0.14	37,878
Eggs	22.34	0.9	53.74	0.09	0.17	38,117
Sugar	21.80	0.9	50.52	0.05	0.08	41,110
Jowar	21.09	1.0	54.05	0.08	0.24	24,846
Banana	20.48	1.0	51.33	0.15	0.33	39,807
Groundnut Oil	20.27	1.0	57.53	0.04	0.19	33,521
Mustard Oil	20.04	1.0	57.58	0.04	0.15	37,811
Gur	19.72	1.1	53.33	0.07	0.19	40,928
Fish	19.56	1.1	54.30	0.10	0.49	59,789
Coconut Oil	18.24	1.1	55.40	0.06	0.29	33,424
Besan	18.15	1.2	53.65	0.06	0.17	37,261
Bajra	17.87	1.2	54.11	0.08	0.22	26,075
Wheat	16.61	1.3	55.54	0.06	0.28	56,759
Vanaspati	16.44	1.3	57.97	0.05	0.14	36,041
Black Pepper	16.09	1.3	54.58	0.07	0.32	37,640
Maize	15.73	1.3	54.33	0.09	0.28	31,268
Gingelly Oil	15.70	1.4	56.83	0.06	0.28	25,117
Ragi	15.44	1.4	55.61	0.08	0.27	16,079
Rice	15.09	1.4	57.22	0.06	0.41	1,16,989
Cummin Seed	14.24	1.5	53.97	0.07	0.29	34,453
Atta	12.23	1.8	57.31	0.07	0.21	38,765
Meat	12.14	1.8	61.30	0.06	0.19	38,588
Maida	11.77	1.8	57.09	0.07	0.15	38,194
Suji	11.00	2.0	57.69	0.07	0.19	38,552
Ghee	10.34	2.1	60.76	0.05	0.20	36,878
Coconut	10.25	2.1	54.62	0.11	1.03	63,218
Red Chillies	8.64	2.6	58.67	0.12	0.33	38,365

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Product Category	Frequency of Price Change (%)	Duration (Months)	Proportion of Price Increases	Average Size of Absolute Change	Standard Deviation of Log Prices	Number of Observations
1	2	3	4	5	6	7
Coriander	7.89	2.8	56.96	0.14	0.32	36,927
Turmeric	7.81	2.8	55.17	0.14	0.26	38,819
Tea	6.09	3.7	62.40	0.08	0.52	66,569
Coffee	5.19	4.3	61.80	0.08	0.84	43,884
Butter	4.73	4.8	69.47	0.08	0.21	35,130
Milk	4.29	5.3	68.33	0.08	0.16	73,371
Salt	3.31	6.9	63.31	0.16	0.40	73,417
Bread	2.89	7.9	68.44	0.13	0.20	37,332
Biscuit	1.09	21.0	63.32	0.27	0.38	36,399

Table A.4: Estimates of Seasonal Effects on Frequency of Price Increase

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Beverages	Cereals	Egg	Fruits	Meat	Milk	Oils	Pulses	Spices	Sugar	Vegetables
January	0.00	-0.00	0.00	0.02**	0.02**	0.00	-0.00	-0.00	-0.01*	-0.01	-0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
February	-0.00	-0.01*	-0.01	0.02***	0.02**	-0.00	-0.00	-0.01*	-0.01**	-0.03***	-0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
March	-0.01	-0.01**	-0.04***	0.04***	0.02**	0.01	-0.01	-0.01	-0.01**	-0.02***	-0.02**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
April	0.00	-0.01**	-0.01	0.05***	0.03***	0.01	0.01*	0.04***	-0.00	-0.00	0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
May	-0.00	-0.01***	0.02*	0.04***	0.03***	-0.00	-0.01	0.03***	-0.01	-0.02***	-0.00
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Jun	0.01	-0.01**	0.05***	0.02***	0.03***	0.00	-0.00	-0.01	-0.00	-0.01	0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
July	0.00	-0.00	0.01	0.02**	0.02***	0.00	-0.00	0.02***	-0.00	0.01	0.05***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
September	0.00	-0.00	0.01	-0.00	0.00	0.02***	-0.01	0.01*	0.00	-0.01**	0.02**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
October	-0.00	-0.01	0.02*	0.01	0.02**	0.01	-0.01	0.03***	-0.00	-0.02**	0.04***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
November	-0.00	0.00	0.06***	-0.01	0.01	0.00	-0.00	0.02***	-0.01*	-0.02***	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
December	0.00	-0.01*	0.04***	-0.00	0.03***	-0.00	0.01	-0.02***	-0.01***	-0.03***	-0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.02**	0.06***	0.08***	0.09***	0.12***	0.03***	0.09***	0.10***	0.05***	0.08***	0.21***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	1857	9363	956	2895	2855	2862	4539	5797	4755	2911	3880
Adjusted R^2	0.203	0.176	0.453	0.192	0.248	0.156	0.290	0.393	0.304	0.157	0.293

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Estimates of Seasonal Effects on Frequency of Price Decrease

	(1) Beverages	(2) Cereals	(3) Egg	(4) Fruits	(5) Meat	(6) Milk	(7) Oils	(8) Pulses	(9) Spices	(10) Sugar	(11) Vegetables
January	-0.00	-0.01**	0.03***	-0.08***	-0.01	-0.00	0.00	0.02***	0.00	0.03***	0.09***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
February	-0.00	-0.00	0.06***	-0.09***	-0.01	0.00	0.01	0.03***	0.01*	0.03***	0.07***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
March	0.00	-0.00	0.08***	-0.09***	0.02**	-0.00	0.02***	0.02***	0.00	0.02***	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
April	-0.01*	-0.00	0.04***	-0.10***	-0.01*	0.00	-0.00	-0.01	-0.00	0.01	-0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
May	-0.00	-0.01**	-0.01	-0.10***	-0.02**	-0.00	-0.01	-0.01**	-0.01**	0.01	-0.03***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Jun	-0.00	-0.00	-0.03***	-0.08***	-0.02***	-0.00	0.01	0.01***	0.00	0.01	-0.07***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
July	-0.00	-0.00	0.01	-0.06***	-0.00	0.00	0.00	0.00	0.00	0.00	-0.03***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
September	0.00	-0.01**	-0.01	-0.01	-0.01	0.00	0.00	-0.01	-0.00	0.01	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
October	-0.00	-0.01**	-0.03**	-0.06***	-0.02**	-0.00	-0.00	-0.02***	-0.01*	0.00	-0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
November	-0.00	-0.01***	-0.03***	-0.06***	-0.02**	-0.00	-0.01	-0.01	-0.01**	0.01**	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
December	-0.00	-0.01*	-0.00	-0.08***	-0.02***	0.00	-0.01**	0.02***	-0.01	0.04***	0.13***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.01*	0.05***	0.05***	0.15***	0.14***	0.02***	0.06***	0.09***	0.03***	0.04***	0.19***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	1857	9363	956	2895	2855	2862	4539	5797	4755	2911	3880
Adjusted R^2	0.266	0.186	0.534	0.219	0.234	0.213	0.239	0.374	0.304	0.145	0.350

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: FK Measure of Synchronisation and χ^2 test values: Products

No.	Product	FK_measure	Dias_Q	No	Product	FK_measure	Dias_Q
1	Apple	0.23	1816.1	24	Gur	0.20	1503.0
2	Arhar	0.26	2526.9	25	Jowar	0.21	999.1
3	Atta	0.19	1292.9	26	Maida	0.19	1277.3
4	Bajra	0.22	1173.3	27	Maize	0.20	1106.5
5	Banana	0.19	1372.9	28	Masur	0.22	1736.4
6	Besan	0.22	1739.4	29	Meat	0.20	1426.8
7	Biscuit	0.18	1105.9	30	Milk	0.17	1863.2
8	Black Pepper	0.19	1290.8	31	Moong	0.22	1791.3
9	Bread	0.18	1083.9	32	Mustard Oil	0.23	1870.0
10	Brinjal	0.17	1091.1	33	Onion	0.31	3655.7
11	Butter	0.20	1313.8	34	Potato	0.24	2161.6
12	Chicken	0.21	1521.1	35	Ragi	0.27	1102.9
13	Coconut	0.15	1388.0	36	Red Chillies	0.18	1186.1
14	Coconut Oil	0.20	1174.0	37	Rice	0.14	2267.7
15	Coffee	0.19	1482.0	38	Salt	0.16	1637.3
16	Coriander	0.18	1163.6	39	Sugar	0.29	3317.0
17	Cummin Seed	0.18	1052.6	40	Suji	0.19	1225.4
18	Eggs	0.21	1549.1	41	Tea	0.16	1563.1
19	Fish	0.16	1356.2	42	Tomato	0.21	1765.1
20	Ghee	0.19	1238.4	43	Turmeric	0.19	1356.9
21	Gingelly Oil	0.21	1013.1	44	Urad	0.23	1956.4
22	Gram	0.22	3574.3	45	Vanaspati	0.21	1487.9
23	Groundnut Oil	0.20	1192.5	46	Wheat	0.18	1680.0

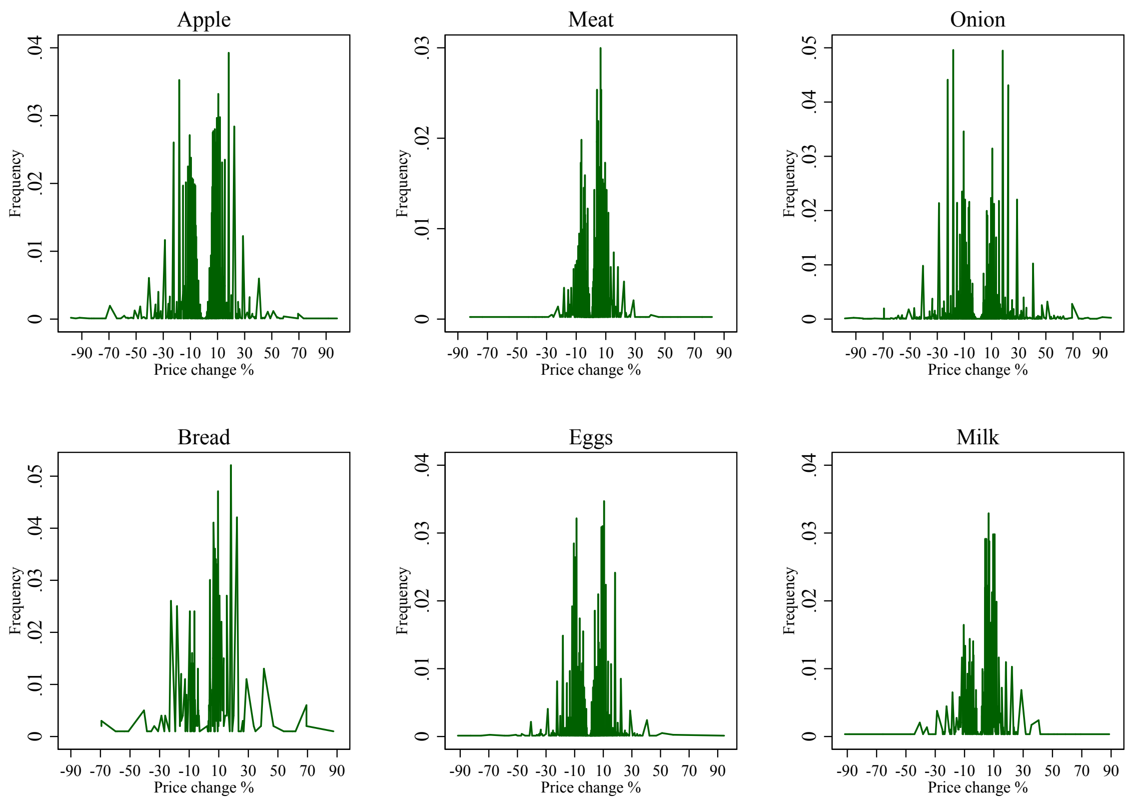
All the Q values are significant at 1% with degrees of freedom (T-1)

Table A.7: FK Measure of Synchronisation and χ^2 test values: Centres

No.	Centre	FK_measure	Dias_Q	No.	Product	FK_measure	Dias_Q
1	2	3	4	5	6	7	8
1	Agartala	0.35	3341.5	43	Jalpaiguri	0.30	1351.3
2	Agra	0.23	1255.1	44	Jammu	0.29	2733.6
3	Aizwal	0.28	2450.1	45	Jodhpur	0.26	2111.3
4	Allahabad	0.28	2366.0	46	Kanpur	0.23	1319.6
5	Amritsar	0.26	751.9	47	Karnal	0.35	1881.0
6	Asansol	0.35	3032.5	48	Khozhikode	0.49	9434.2
7	Aurangabad	0.29	932.9	49	Kohima	0.25	525.7
8	Bangalore	0.39	4292.1	50	Kolkata	0.37	4424.1
9	Bhatinda	0.32	1435.7	51	Kurnool	0.37	4958.9
10	Bhawanipatna	0.35	1118.0	52	Lucknow	0.31	3982.9
11	Bhillai	0.32	1353.8	53	Ludhiana	0.23	978.4
12	Bhopal	0.33	4591.1	54	Madurai	0.30	1975.8
13	Bhubneshwar	0.36	5170.4	55	Malda	0.36	2164.6
14	Bijapur	0.21	1029.7	56	Mandi	0.34	2688.6
15	Chandigarh	0.27	219.2	57	Mumbai	0.26	2414.3
16	Chennai	0.39	5579.1	58	Muzaffarpur	0.54	90.8
17	Chittoor	0.42	6651.7	59	Nagpur	0.31	1835.5
18	Coimbatore	0.37	4610.2	60	Nasik	0.28	1109.3
19	Cuttack	0.37	3135.5	61	Panaji	0.30	2237.9
20	Dausa	0.29	3275.5	62	Patna	0.38	5887.2
21	Delhi	0.39	4725.9	63	Pondicherry	0.54	992.0
22	Dhanbad	0.33	2615.3	64	Pune	0.27	572.0
23	Dibrugarh	0.24	1584.3	65	Rajkot	0.41	1461.7
24	Dispur	0.28	1531.7	66	Ranchi	0.30	3136.2
25	Ernakulam	0.47	8279.0	67	Rewa	0.32	1362.8
26	Gandhi Nagar	0.46	6196.9	68	Saharanpur	0.25	1451.9
27	Gangtok	0.28	259.8	69	Salem	0.39	3895.3
28	Gaya	0.47	2133.5	70	Sehore	0.31	1554.3
29	Gorakhpur	0.25	2099.6	71	Shillong	0.28	2825.5
30	Guntur	0.36	3942.2	72	Shimla	0.30	394.9
31	Guwahati	0.21	1295.1	73	Shrinagar	0.29	179.5
32	Gwalior	0.40	1456.0	74	Silchar	0.29	1120.2
33	Hajipur	0.44	64.1	75	Srinagar	0.26	235.5
34	Haldwani	0.42	134.1	76	Surat	0.32	878.3
35	Hissar	0.39	3453.0	77	Swaimadhopur	0.32	2884.5
36	Howrah	0.35	2576.1	78	Tambram	0.60	112.2
38	Hyderabad	0.44	7790.8	80	Trivandrum	0.39	5476.8
39	Imphal	0.41	4040.6	81	Tumkur	0.26	1547.7
40	Indore	0.35	1060.1	82	Udaipur	0.23	1399.1
41	Itanagar	0.17	315.4	83	Vadodra	0.28	820.4
42	Jaipur	0.32	3665.4	84	Vishakhapatnam	0.40	5295.7

A.3 Additional Charts

Figure A.3: Appendix C: Frequency Across magnitude of Price Change in Percentages

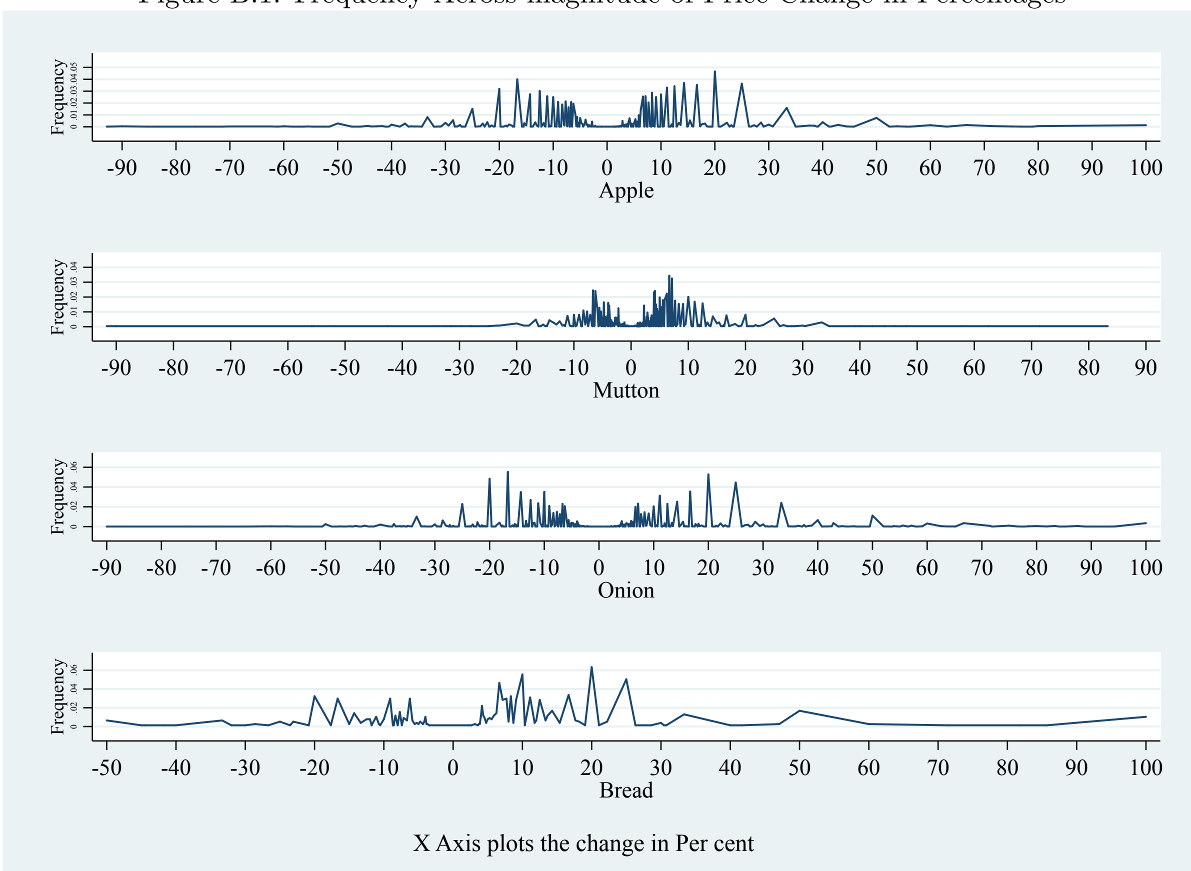


Appendix B

Appendix to Chapter 3

B.1 Additional Charts

Figure B.1: Frequency Across magnitude of Price Change in Percentages



B.2 Calibration of Model with Price Points only: Alternate Targeted Moments

Table B.1: Selection of Parameters for Calibration: Only Price Points

Parameter	**Value**	**Choice Benchmark**
β	$0.96^{(1/52)}$	Literature
θ	3	Lower bound in the literature
μ	0.00139	Estimated from CPI Food in India during 2006-21
σ_μ	0.0061	Estimated from CPI Food in India during 2006-21
ρ	0.2	Calibrated
σ_ϵ	0.175	Calibrated
K	0.0	Calibrated
d	2.5	Calibrated

Table B.2: Comparing moments between the data and the model

Variable	**Data**	**Model**
Targeted Moments		
Average Size of Price Change (abs) (%)	9.8	10.1
Fraction of Price Increases (%)	55.5	51.4
Proportion of 10 or 5 ending prices (%)	53.19	50.1
Non-targeted moments		
Frequency of Price Change	18.3	7.45
Std.Dev of Log Prices	0.24	0.06
Size of Price Increases (%)	9.6	10.8
Size of Price Decreases (%)	10.0	9.4
Size of price change at lowest decile (%)	13.8	19.2
Size of price change at highest decile (%)	7.4	3.7

Appendix C

Appendix to Chapter 4

C.1 Additional Tables

Table C.1: Coverage of States

State	All Mandis	March Mandis
Andaman And Nicobar	3	0
Andhra Pradesh	138	14
Arunachal Pradesh	1	0
Assam	22	0
Bihar	2	0
Chandigarh	1	0
Chattisgarh	150	136
Goa	7	7
Gujarat	215	148
Haryana	113	57
Himachal Pradesh	35	22
Jammu And Kashmir	19	8
Jharkhand	23	1
Karnataka	158	145
Kerala	105	95
Madhya Pradesh	286	276
Maharashtra	327	0
Manipur	5	0
Meghalaya	16	5
Mizoram	3	0
Nagaland	19	17
Nct Of Delhi	8	3
Odisha	104	71
Pondicherry	3	3
Punjab	231	110
Rajasthan	163	144
Tamil Nadu	201	121
Telangana	162	63
Tripura	32	27
Uttar Pradesh	256	243
Uttrakhand	21	18
West Bengal	76	70
TOTAL	2905	1804

Notes: The Table shows the number of mandis per state in the full sample versus in our analysis sample. The full sample ("All Mandis") includes any mandi that reported any arrivals (in tonnes) during January to June, 2018 to 2020. Our analysis sample ("March Mandis") includes only the subset of mandis that reported arrivals (in tonnes) at least once during March 2020.

Table C.2: Representativeness at the District-Level

	All Districts	Mandi Districts	March-Mandi Districts
Population	1891961	2051330	2086947
Fraction of Rural Households	.73	.73	.73
% Aged 0 to 6	14	14	13
Male Population/Female Population	1.1	1.1	1.1
% Scheduled Caste	15	16	17
% Scheduled Tribe	18	15	13
% Literate	62	63	63
% of Male Population Working	53	54	54
% of Female Population Working	28	28	28

Notes: Each cell gives the district-level mean for a variable from the 2011 Indian Census. The second column reports the India-wide mean (640 districts). The third column reports the mean for districts in which at least one mandi reported arrivals in tonnes during January to June, 2018 to 2020 (508 districts). The fourth column is the same, but only for the subset of districts with mandis that reported during March 2020 (391 districts), as per our analysis sample.

Table C.3: The Lockdown's Impact on Food Arrivals: Rural vs. Urban

	ln(Food Arrivals)			
	Rural	Rural	Urban	Urban
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.38***	-1.38***	-1.05***	-1.05***
	(0.27)	(0.22)	(0.33)	(0.27)
Phase 2 (Apr 15-May 3)	-0.15	-0.09	-0.26	-0.27
	(0.25)	(0.22)	(0.29)	(0.26)
Phase 3 (May 4-May 17)	0.17	0.16	0.17	0.17
	(0.30)	(0.26)	(0.34)	(0.31)
Phase 4 (May 18-May 31)	0.27	0.27	0.35	0.33
	(0.29)	(0.25)	(0.37)	(0.31)
Phase 5 (Jun 1-Jun 30)	0.26	0.30	0.54*	0.50*
	(0.21)	(0.19)	(0.31)	(0.26)
Observations	240	360	240	360
Sample Period	2019-20	2018-20	2019-20	2018-20
Average Rural HH Fraction	.86	.86	.59	.59
Phase 1: p(Rural=Urban)	.44	.34		
Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes

Notes: The unit of observation is a day. The regressions include data from March 1 to June 30 for each year (either 2019-2020 or 2018-2020), with the exception of national holidays (Republic Day and Holi). Robust standard errors used throughout. The outcome for columns 1 and 2 is the natural logarithm of the tonnes of food arrivals to mandis in rural districts that reported at least once in March 2020. The outcome for columns 3 and 4 is the same, but for mandis in urban districts. Rural districts are those with an above-median fraction of rural households as per the 2011 Census. Urban districts are all remaining districts. Average Rural HH Fraction is the average (across districts) fraction of rural households among the districts included in the sample for that column. P-values to test the equality of the Phase 1 effect in rural vs. urban districts come from a pooled specification in which all right-hand-side variables are interacted with an indicator variable for rural district. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table C.4: Predicting State-Level Supply Disruptions

	Estimated Volume Fall in Mandis (%) Phase 1: March 25-April 14		
	(1)	(2)	(3)
ln(Number of Confirmed Cases by April 14, 2020)	12.00***		11.12***
	(1.66)		(2.66)
Fall in Mobility by April 14, 2020 (%)		2.60***	0.37
		(0.85)	(0.77)
Observations		17	

Notes: The unit of observation is a state. Robust standard errors. Constant included but not shown. The outcome is the estimated Phase 1 volume fall for each of 17 states, using the estimates from equation 3. Number of Confirmed Cases by April 14, 2020 is the number of confirmed cases of coronavirus by the end of Phase 1, from api.covid19india.org. Fall in Mobility is the percentage fall in mobility from pre-pandemic to April 14, 2020, from google.com/covid19/mobility, averaged across six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential (reverse-coded). $***p < 0.01, **p < 0.05, *p < 0.1$.

Table C.5: Pre-Trends Check for District-Level Analysis

	arcsinh(Arrivals to District)		
	(1)	(2)	(3)
arcsinh(COVID-19 Cases in State) × March 1-24 2020	-0.03		
	(0.02)		
arcsinh(COVID-19 Cases in District) × March 1-24 2020		-0.01	-0.03
		(0.03)	(0.03)
Observations	38304	38304	38208
Number of Districts	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	No
State-Date Fixed Effects	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from February 1 to March 24 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the inverse hyperbolic sine (arcsinh) of the number of tonnes of food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of April 14, 2020. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table C.6: District-Level Supply Disruptions by COVID-19 Exposure as of June 30, 2020

	arcsinh(Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.96***			
	(0.10)			
Phases 2-5 (Apr 15-Jun 30)	0.15**			
	(0.06)			
arcsinh(COVID-19 Cases in State) $\times$ Phase 1		-0.34***		
		(0.07)		
arcsinh(COVID-19 Cases in State) $\times$ Phases 2-5		0.02		
		(0.04)		
arcsinh(COVID-19 Cases in District) $\times$ Phase 1			0.17**	0.02
			(0.07)	(0.05)
arcsinh(COVID-19 Cases in District) $\times$ Phases 2-5			0.01	0.02
			(0.04)	(0.05)
Observations	94164	94164	94164	93928
Number of Districts	399	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	No	Yes	Yes	No
State-Date Fixed Effects	No	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from March 1 to June 30 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the inverse hyperbolic sine (arcsinh) of the number of tonnes of food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of June 30, 2020. $***p < 0.01, **p < 0.05, *p < 0.1$.

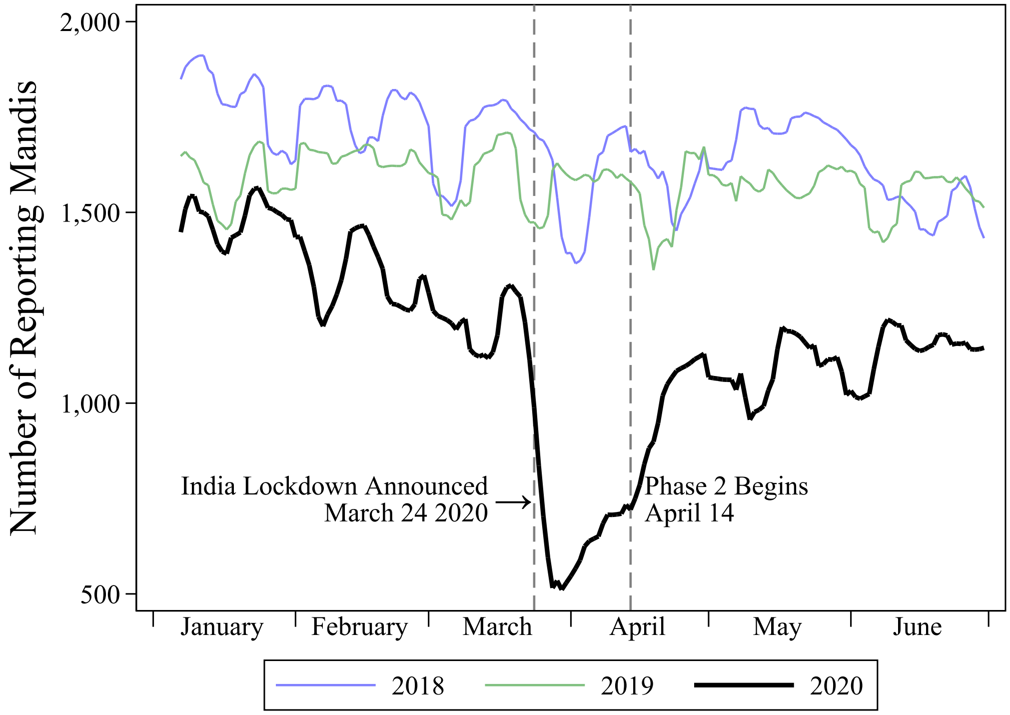
Table C.7: District-Level Supply Disruptions by COVID-19 Exposure

	arcsinh(Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.82***			
	(0.09)			
Phases 2-5 (Apr 15-Jun 30)	0.13**			
	(0.06)			
arcsinh(COVID-19 Cases in State) × Phase 1		-0.34***		
		(0.04)		
arcsinh(COVID-19 Cases in State) × Phases 2-5		0.05**		
		(0.03)		
arcsinh(COVID-19 Cases in District) × Phase 1			-0.01	0.02
			(0.06)	(0.05)
arcsinh(COVID-19 Cases in District) × Phases 2-5			-0.00	-0.02
			(0.04)	(0.05)
Observations	94164	94164	94164	93928
Number of Districts	399	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	No	Yes	Yes	No
State-Date Fixed Effects	No	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from March 1 to June 30 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the inverse hyperbolic sine (arcsinh) of the number of tonnes of non-wheat food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of April 14, 2020. $***p < 0.01, **p < 0.05, *p < 0.1$.

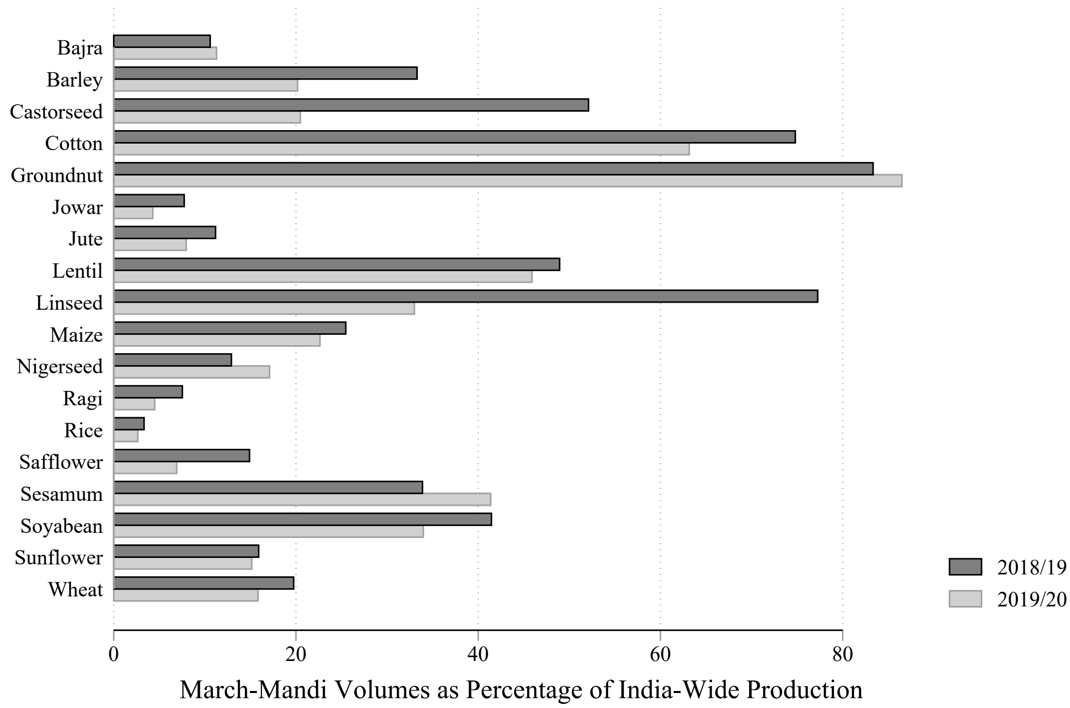
C.2 Additional Figures

Figure C.1: Reporting Mandis From 2018 to 2020



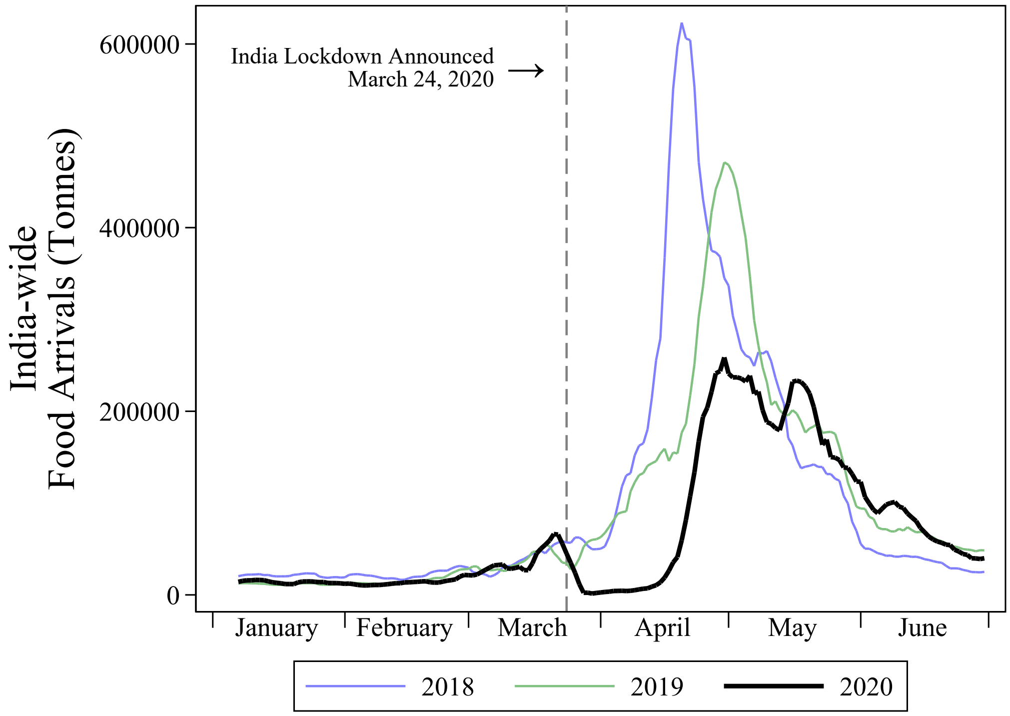
Notes: The y-axis variable is a seven-day moving average of the number of mandis that reported any data to Agmarknet on each date. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average number of reporting mandis for January 1 to 7). Source: agmarknet.gov.in.

Figure C.2: Mandi Volumes as Percentage of India-Wide Production



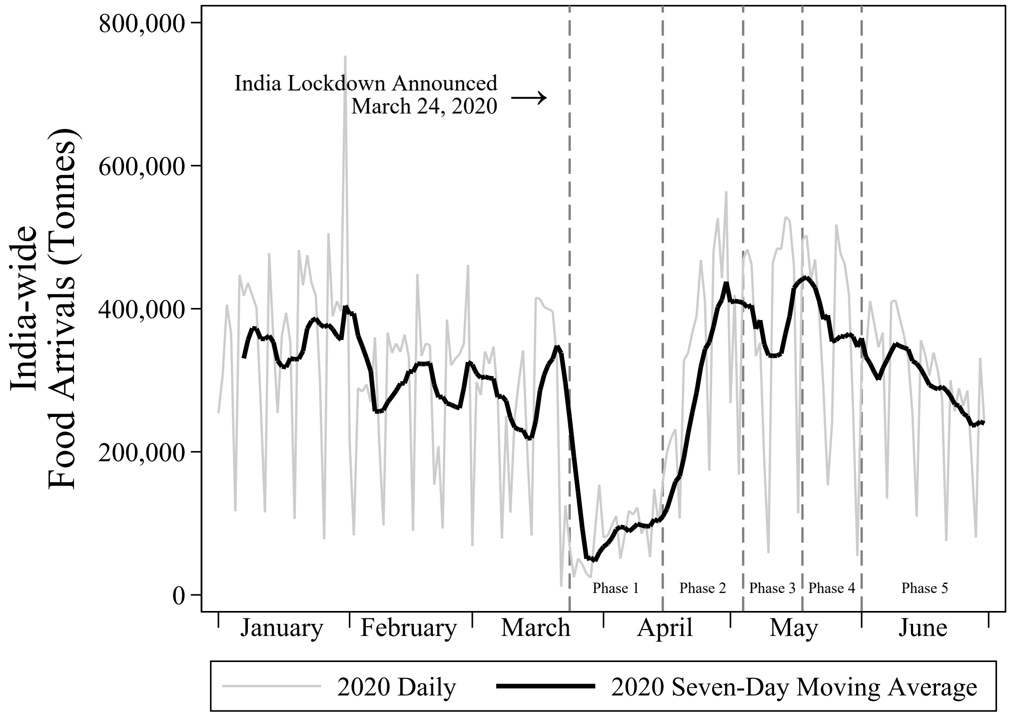
Notes: The x-axis variable is the aggregate tonnes of food arrivals to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020, as a percentage of total food production in India. This percentage is shown separately for two agricultural seasons (July 2018 to June 2019 and July 2019 to June 2020) and for the 18 food varieties coded similarly (and thus mergeable) in the two datasets (all either cereals, oilseeds, or commercial crops). The mean percentage coverage across the 18 varieties is 32% for 2018/19 and 25% for 2019/20. Each percentage is a lower bound of food sold in India given that not all production is sold. Sources: agmarknet.gov.in; Directorate of Economics and Statistics, Department of Agriculture, Cooperation and Farmers Welfare, https://eands.dacnet.nic.in/APY_96_To_06.htm.

Figure C.3: The Lockdown and Wheat Arrivals



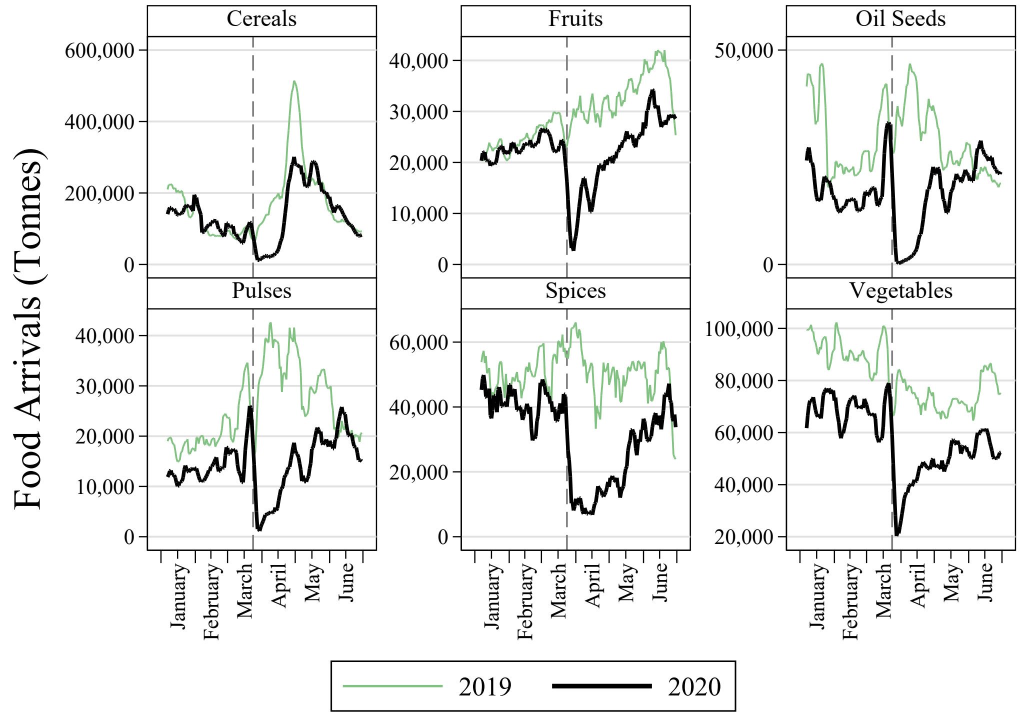
Notes: The y-axis variable is a seven-day moving average of aggregate tonnes of wheat arrivals to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Source: agmarknet.gov.in.

Figure C.4: Daily Trend in Arrivals, 2020



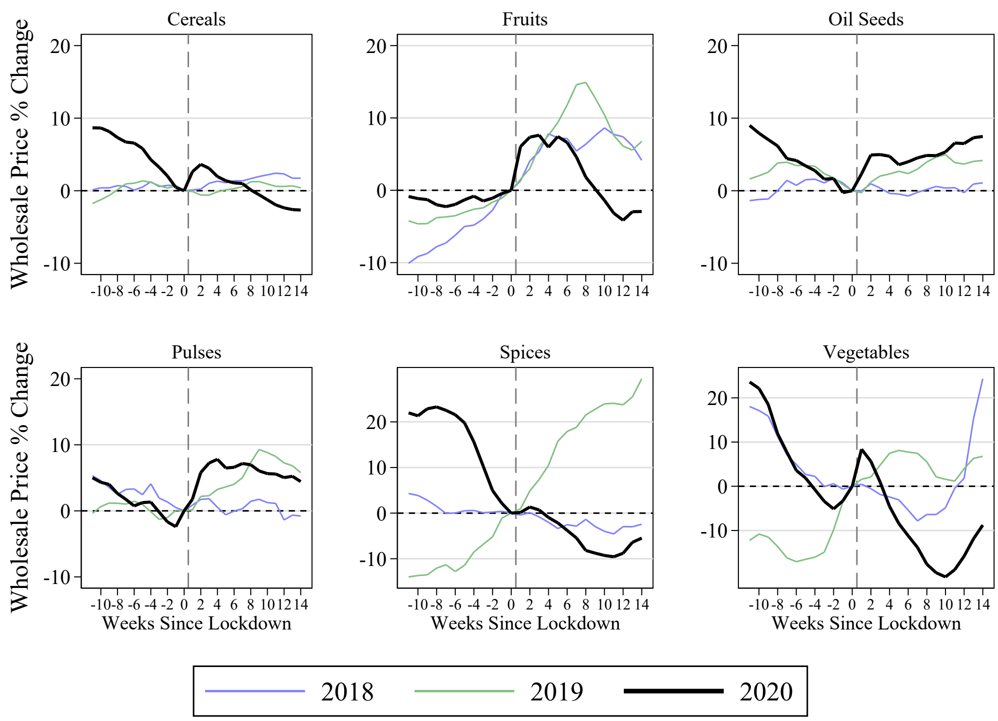
Notes: The figure plots the raw daily trend and seven-day moving average of aggregate tonnes of food arrivals to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Source: agmarknet.gov.in.

Figure C.5: The Lockdown's Impact by Food Group



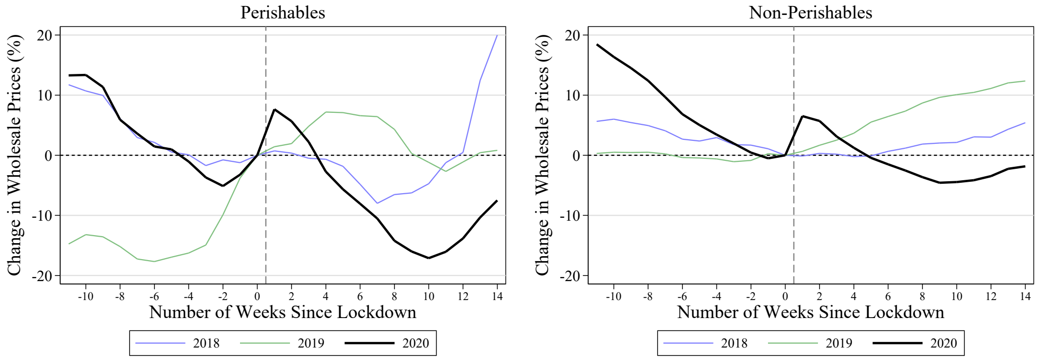
Notes: The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals, separately for each of six major product groups, to the 1,804 mandis that reported data to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Each of the six product groups contains multiple food varieties: Cereals (20), Fruits (32), Oil Seeds (19), Pulses (28), Spices (19), and Vegetables (81). The top-10 varieties by tonnage per group are: (1) Cereals: wheat, paddy (dhan) (common), maize, rice, paddy (dhan) (basmati), barley, bajra, sorghum, ragi kodo millet, and foxtail millet; (2) Fruits: tender coconut, banana, mango, watermelon, apple, papaya, pomegranate, sweet lime, grapes, and orange; (3) Oil Seeds: mustard, soya bean, groundnut, castor seed, copra, sesamum, linseed, coconut seed, cotton seed, and sunflower; (4) Pulses: bengal gram, arhar, lentil, kabuli chana, black gram, green gram, peas (dry), arhar dal, kulthi, and green peas; (5) Spices: coconut, garlic, dry chillies, coriander seed, cumin seed, turmeric, soanf, methi seeds, ginger (dry), and aijwan; (6) Vegetables: potato, onion, tomato, cauliflower, green chilli, cabbage, brinjal, ginger (green), carrot, and banana-green. The vertical dashed line denotes March 24, 2020, the date of the announcement of India's national lockdown. Source: agmarknet.gov.in.

Figure C.6: Wholesale Prices Evolved Similarly for Most Commodity Groups



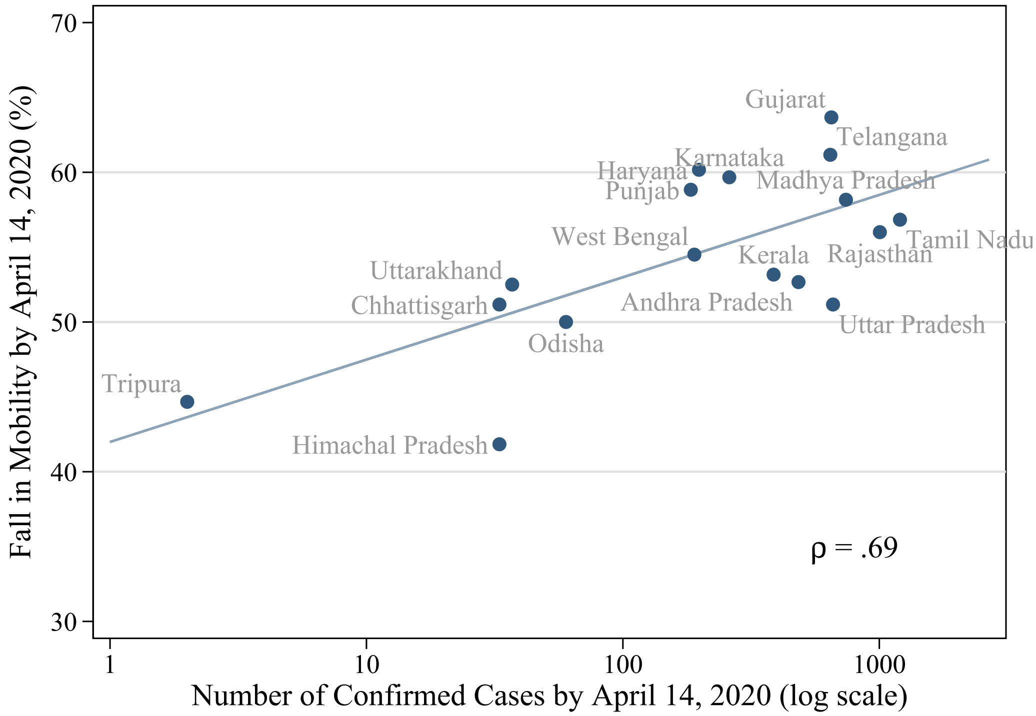
Notes: The figure plots the percentage change in wholesale prices implied by the year-by-year estimates from equation 4.2, separately for six major commodity groups. Specifically, the pre-lockdown y-axis variable is $100 \times \left(e^{\hat{\beta_t^{pre}}} - 1\right)$ for $t \in \{-11, -10, ..., -2, -1\}$, while the post-lockdown variable is $100 \times \left(e^{\hat{\beta_t^{post}}} - 1\right)$ for $t \in \{1, 2, ..., 13, 14\}$. The sample comprises only those mandis that reported data at least once in March 2020. Source: agmarknet.gov.in.

Figure C.7: Wholesale Prices Increased in the Short Term for Both Perishables and Non-Perishables



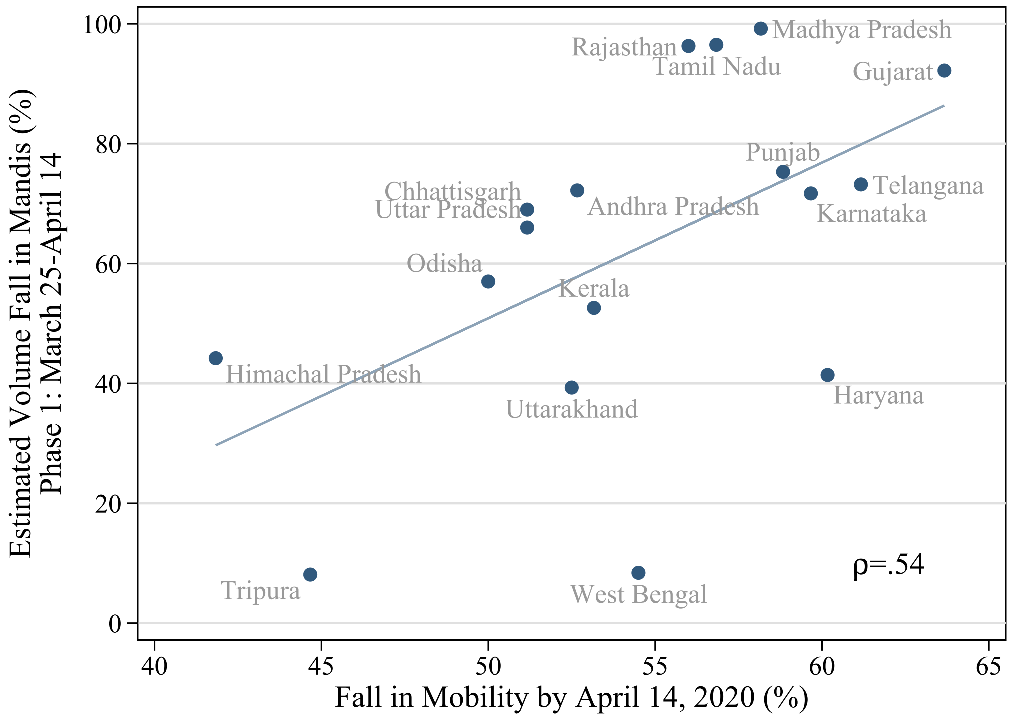
Notes: The figure plots the percentage change in wholesale prices implied by the year-by-year estimates from equation 4.2, separately for perishable (left) and non-perishable items (right). Specifically, the pre-lockdown y-axis variable is $100 \times \left(e^{\hat{\beta_t^{pre}}} - 1\right)$ for $t \in \{-11, -10, ..., -2, -1\}$, while the post-lockdown variable is $100 \times \left(e^{\hat{\beta_t^{post}}} - 1\right)$ for $t \in \{1, 2, ..., 13, 14\}$. The sample comprises only those mandis that reported data at least once in March 2020. We manually coded items as either perishable or non-perishable. Of the 15 broad product categories, 2 are coded as perishable (flowers and fruits), 11 are coded as non-perishable (beverages, cereals, drug and narcotics, dry fruits, fibre crops, forest products, oil seeds, oils and fats, other, pulses, and spices), and 2 are mixed (live stock, poultry, fisheries, and vegetables). In the live stock, poultry, and fisheries category, all items are coded as non-perishable except egg and fish. In the vegetables category, all items are coded as perishable except elephant yam, onion, potato, sweet potato, tapioca, and yam. Source: agmarknet.gov.in.

Figure C.8: States With More Coronavirus Cases Had Larger Falls in Mobility During Phase 1



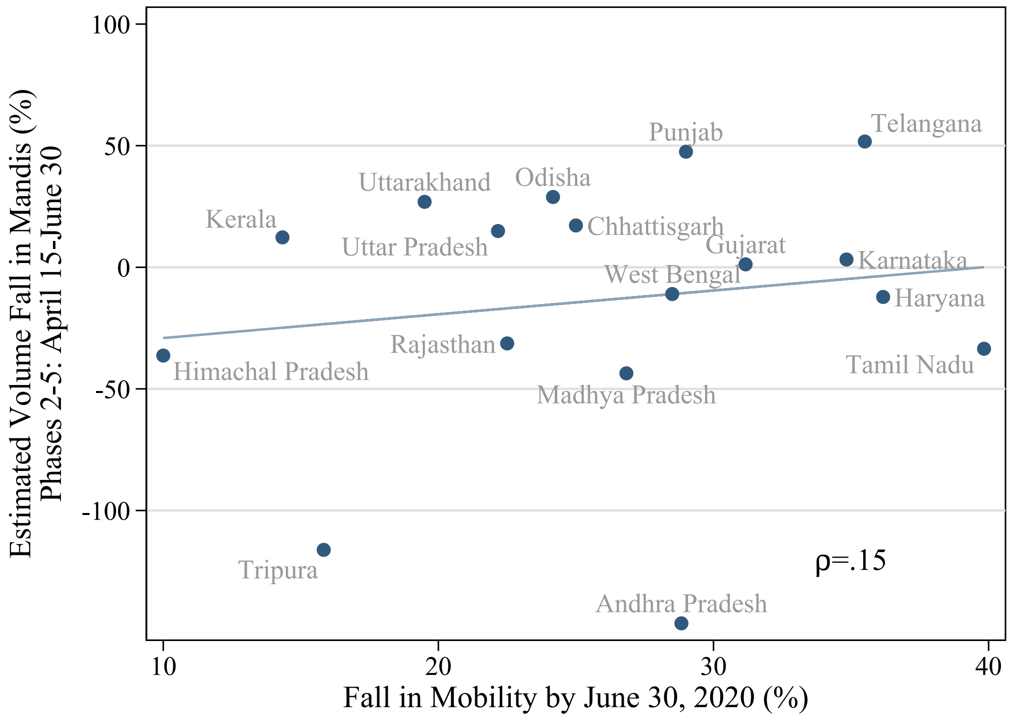
Notes: The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\gamma}_s}\right)$ using estimated coefficients from equation 4.3. The x-axis is the percentage fall in mobility from pre-pandemic to April 14, 2020, from google.com/covid19/mobility, averaged across six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential (reverse-coded). ρ is Pearson's correlation coefficient between the y- and x-axis variables.

Figure C.9: States With Larger Falls in Mobility Had Bigger Supply Chain Disruptions During Phase 1



Notes: The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\gamma}^s}\right)$ using estimated coefficients from equation 4.3. The x-axis is the percentage fall in mobility from pre-pandemic to April 14, 2020, from google.com/covid19/mobility, averaged across six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential (reverse-coded). ρ is Pearson's correlation coefficient between the y- and x-axis variables.

Figure C.10: Mobility Shocks Insignificantly Related To Supply Chain Disruptions Following Phase 1



Notes: The y-axis is the estimated Phase 2-5 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\theta}^s}\right)$ using estimated coefficients from equation 4.3. The x-axis is the percentage fall in mobility from pre-pandemic to June 30, 2020, from google.com/covid19/mobility, averaged across six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential (reverse-coded). ρ is Pearson's correlation coefficient between the y- and x-axis variables.

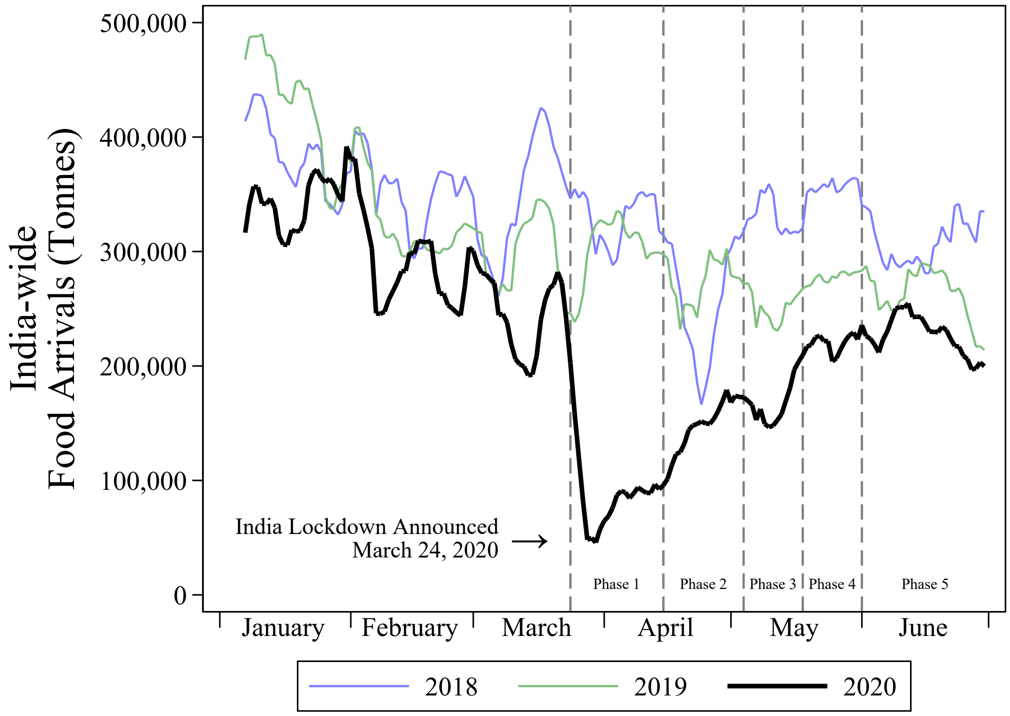
C.3 Arrivals Analysis Excluding Wheat

Table C.8: The Lockdown's Impact on Food Arrivals

	ln(Food Arrivals)		ln(Functioning Mandis)		ln(Food Arrivals)	
	(1)	(2)	(3)	(4)	(5)	(6)
Phase 1 (Mar 25-Apr 14)	-0.96***	-0.92***	-0.54***	-0.50***	-0.48***	-0.44***
	(0.28)	(0.23)	(0.15)	(0.12)	(0.04)	(0.04)
Phase 2 (Apr 15-May 3)	-0.14	-0.01	-0.10	-0.04	-0.12***	-0.06*
	(0.26)	(0.23)	(0.14)	(0.14)	(0.03)	(0.03)
Phase 3 (May 4-May 17)	0.07	-0.02	-0.12	-0.14	0.13***	0.12***
	(0.31)	(0.26)	(0.19)	(0.17)	(0.04)	(0.03)
Phase 4 (May 18-May 31)	0.20	0.12	-0.10	-0.11	0.24***	0.24***
	(0.32)	(0.26)	(0.19)	(0.17)	(0.04)	(0.03)
Phase 5 (Jun 1-Jun 30)	0.37	0.33	0.07	0.08	0.24***	0.31***
	(0.25)	(0.21)	(0.14)	(0.12)	(0.04)	(0.03)
Observations	240	360	240	360	252626	377749
Sample Period	2019-20	2018-20	2019-20	2018-20	2019-20	2018-20
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mandi Fixed Effects	No	No	No	No	Yes	Yes

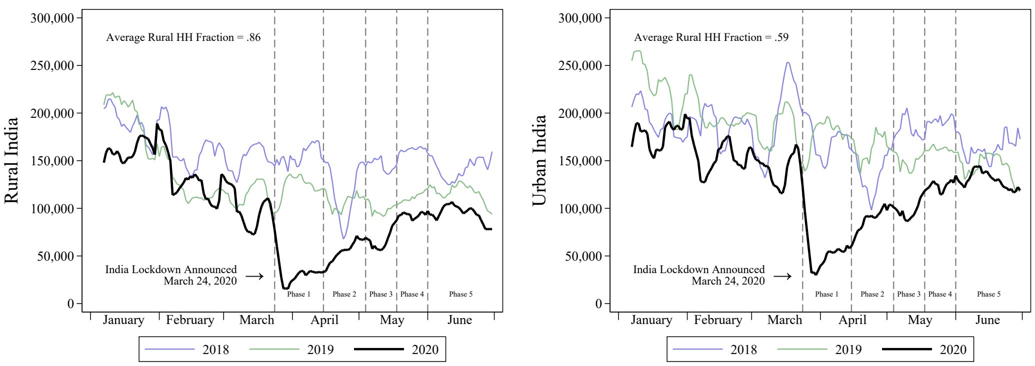
Notes: The unit of observation is a day in columns 1 to 4, and a mandi-day in columns 5 and 6. The regressions include data from March 1 to June 30 for each year (either 2019-2020 or 2018-2020), with the exception of national holidays (Republic Day and Holi). Robust standard errors in columns 1 to 4, standard errors clustered at mandi-level in columns 5 and 6. The outcome for columns 1 and 2 is the natural logarithm of the tonnes of non-wheat nationwide food arrivals to mandis that reported at least once in March 2020. The outcome for columns 3 and 4 is the natural logarithm of the number of functional (i.e. reporting) mandis among the sample relevant for columns 1 and 2. The outcome for columns 5 and 6 is same as that for columns 1 and 2, though measured at the mandi-day-level. $***p < 0.01, **p < 0.05, *p < 0.1$.

Figure C.11: The Lockdown Caused Wholesale Volumes to Plummet



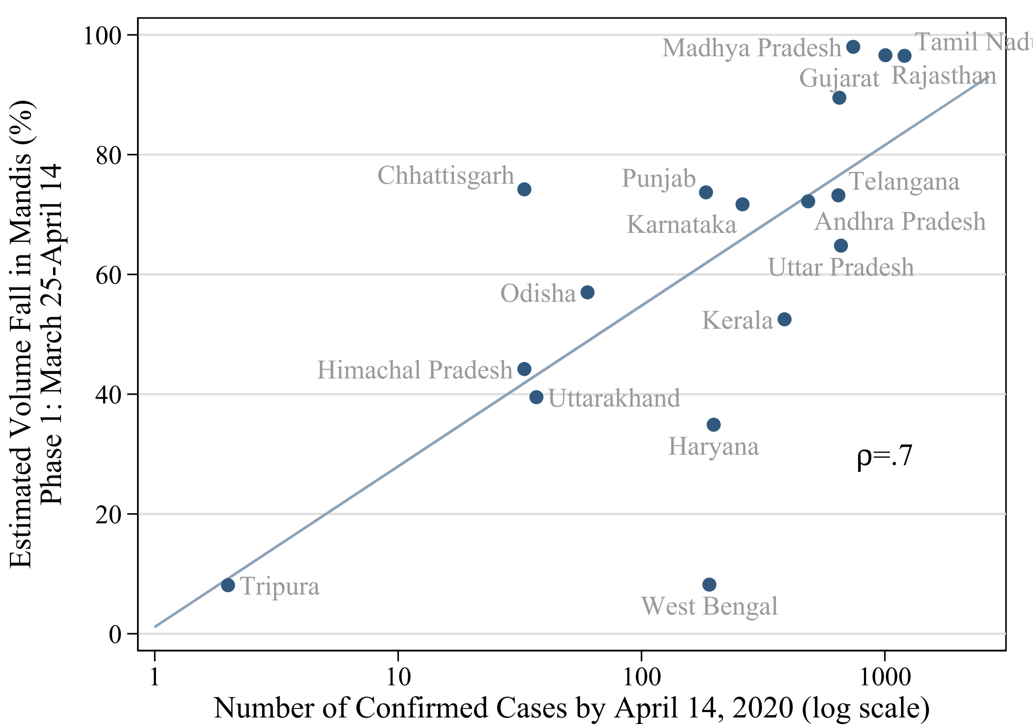
Notes: This figure parallels Figure 4.1, but excludes wheat arrivals. The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals, excluding wheat, to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Source: agmarknet.gov.in.

Figure C.12: Food Arrivals to Urban vs. Rural India



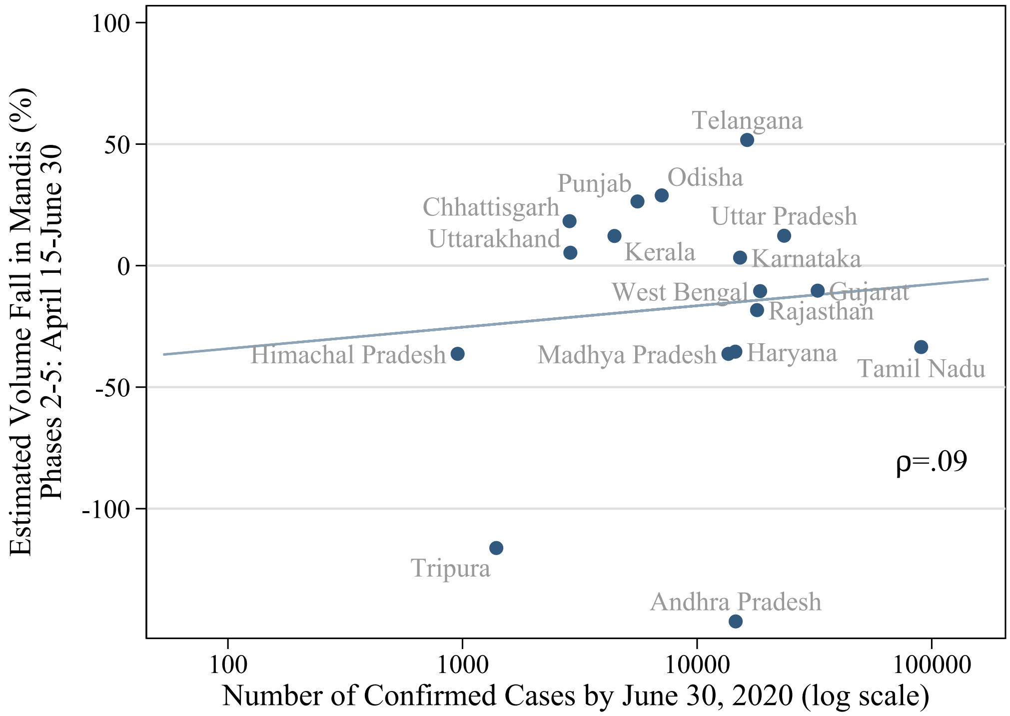
Notes: This figure parallels Figure 4.3, but excludes wheat arrivals. The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals, excluding wheat, to the 1,804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. Rural India includes any mandis residing in a district with an above-median share of rural households in the 2011 Census, with Urban India including all other mandis. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7). Source: agmarknet.gov.in.

Figure C.13: States With More Coronavirus Cases Had Bigger Supply Chain Disruptions During Phase 1



Notes: This figure parallels Figure 4.5, but excludes wheat arrivals. The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\gamma^s}}\right)$ using estimated coefficients from equation 4.3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 1 (April 14), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 1 volume fall and the natural logarithm of the number of confirmed cases by April 14, 2020.

Figure C.14: Volume Shocks Were Not Correlated With Coronavirus Cases After Phase 1



Notes: This figure parallels Figure 4.6, but excludes wheat arrivals. The y-axis is the estimated Phase 2-5 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\theta^s}}\right)$ using estimated coefficients from equation 4.3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 5 (June 30), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 2-5 volume fall and the natural logarithm of the number of confirmed cases by June 30, 2020.