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TOULOUSE SCHOOL OF ECONOMICS

Three Essays in Trade and Production Networks

by

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Abstract- English

The world around us has increasingly become integrated through the emergence of globalized trade and technology. My thesis lies on the intersection of international trade, macroeconomics and development and evaluate the implications of these increased interconnections and market institutions like-change in intermediaries or network structure. My work connects theory with detailed micro or country-level datasets to provide quantitative answers to these questions. I would now detail the two broad themes of my work:

Trade and Intermediaries

Gains from Agricultural Market Reform: Role and Size of Intermediaries: To what extent is agricultural output/efficiency limited by the non-competitive market structure in developing countries? And to what extent does market structure hinders intra-national trade within these countries? The recent work in quantitative trade literature has highlighted that the size of intra-national trade barriers is quite high and reduction of these barriers will lead to large welfare gains. It is fairly difficult to quantify the size of these intra-national trade barriers and it is even more challenging to identify their source- is it lack of infrastructure, information friction or inter-mediation (market structure)? The trade literature often uses spatial price gaps between different regions as a way to estimate trade costs, but since there are many factors generating this gap it does not allow to separately identify the contribution of intermediaries to these costs.

To circumvent these problems, I exploit a quasi-natural policy experiment, which changed the market structure in agricultural markets in one of the states in India. Prior to this policy change, the number of traders on local agricultural markets were fixed by the government. But after policy change the markets allowed free entry of traders. In order to estimate the welfare gains from this policy change, I build a Ricardian style comparative advantage model of intra-national trade in

agricultural crops with an additional layer of intermediaries. Using the model, I first derive an estimation equation based on no arbitrage condition which allows me to identify the change in margin charged by intermediaries, which also puts a lower bound on the size of intermediary markups. Since the market reform shifted only the market power of the intermediaries, while being orthogonal to other domestic frictions, a simple difference-in-difference (DD) strategy allows me to recover the size of margin charged by them. To implement this strategy I use daily-level farm-gate price data from these markets. In the case of groundnut, one of the major crops in Karnataka, I estimate 16% change in the intermediary margin due to this policy change. I then connect the model with rich micro datasets on land use and farm productivity to estimate other relevant parameters of the model to run counter-factual experiments. Under the assumption that the reform changes intermediary margin by 16% across crops and farmers can change their cropping decisions, I find that the policy change will lead to an average of 1.3% increase in welfare across regions. This is a significant welfare increase given that policy only impacts crops which account for 9% of the total state GDP.

This study is important because it highlights the important role of market structure in determining intra-national trade costs in developing countries, specially in the agricultural markets. This paper adds to the growing literature on intermediation in trade, where trade is conducted via intermediaries rather than by producers themselves. Finally, it shows that substantial welfare gains can be achieved through intra-national trade by reducing market power of these intermediaries. Understanding the role of market structure for trade is an important theme and I will continue to explore it in future research.

Network Structure and Input-Output Linkages

Shock diffusion: Does network structure matter? The aggregate economy is a dynamic system generated by interaction of various economic units. Can these micro units interact to generate aggregate fluctuations is an old debate in economics? Absent any interaction between sectors, the law of large number argument ensures that idiosyncratic shocks would die on the aggregate level. The recent literature in macroeconomic networks is trying to overturn this result by accounting for amplification of idiosyncratic sectoral shocks through sectoral interconnections. This study is important for at least two reasons. First, from a toolkit perspective, incorporating network features in macroeconomics both theoretically and empirically is a challenging task. So, it is important to know whether network structure matters and pin down the key characteristics. Second, if it really matters, it would generate new insights for business cycle literature due to increased understanding about how sectoral shocks can generate aggregate fluctuations.

Building on the recent work on this topic, (see Acemoglu et. al. (2012)), I introduce the concept of diffusion of shocks in a multi-sector economy through production frictions. I show that since sectors have different production horizons it leads to slow diffusion of idiosyncratic shocks and hence lower amplification of shocks on the aggregate level. This result is different from other recent papers which have single period models with contemporaneous production linkages and can generate aggregate fluctuations through sectoral shock amplification. I further argue that once we account for this diffusion rate, it is no longer sufficient to characterize the contribution of network structure to aggregate volatility by looking at summary statistics like degree distribution of the input-output matrix. I connect the model to the data by using lead time indicator from manufacturing as a proxy for diffusion rates of different sectors. In the end, I use factor models to get the contribution of aggregate and sector level shocks in aggregate volatility of US manufacturing sector. I find that contribution of sectoral shocks in case of diffusion adjusted network model is the same as that of a model without any network and much lower than standard network models without any diffusion. This result is in sharp contrast with other network papers which highlight higher contribution of sectoral shocks to aggregate volatility after accounting for amplification through production networks.

Employment in a Network of Input-Output Linkages (joint with Francois de Soyres): What is the consequence of a technological improvement in one sector on employment in sectors located downstream in the supply-chain? On the one hand, if material and labor are gross substitute in the production function, the price decrease for the former tends to reduce labor demand for the latter *per unit produced*. On the other hand, the upstream positive technological shock also increases the number of unit produced through a decrease in the marginal cost. The net effect on employment simply depends on the ratio between the elasticity of substitution in the production function and the price elasticity of demand.

While a positive technological shock to an upstream sector will always increase production or output in its downstream sector, labor employed can go up or down depending on two key parameters- the substitutability between intermediate inputs

and labor and price elasticity of its demand.We estimate those parameters at the sector level using detailed French data and show that employment sensitivity of sectors following a decrease in their material input price are very heterogeneous. Consequences for forecasting the effect of an increase in machine efficiency are discussed.

Abstract- French

Le monde qui nous entoure est de plus en plus intégré via la mondialisation des échanges commerciaux et de la technologie. Dans ce contexte, ma thèse se situe à l'intersection du commerce international, de la macroéconomie et de l'économie du développement et s'attache à évaluer l'impact de cette augmentation des interconnections et des structures de réseaux qui l'accompagnent ainsi que les institutions qui lui sont attachées. Mon travail fait le lien entre la théorie économique et les données – micro-économiques ou au niveau des pays – afin de répondre à ces questions. Mes recherches peuvent être regroupées selon deux grands thèmes que je développe ci-dessous:

Rôle des intermédiaires de vente dans le commerce

Les gains liés aux réformes du marché agraire : rôle et taille des intermédiaires de vente: Dans quelle mesure la production et la productivité agricole sont-elles limitées par l'absence de marché compétitif dans les pays en développement ? Et dans quelle mesure est-ce que les structures de marché entravent le commerce intra-national à l'intérieur de ces pays ? La littérature quantitative récente dans le domaine du commerce international a mis en avant l'importance décisive des barrières commerciales à l'intérieur des pays et les potentiels bénéfices que la société pourrait tirer de leur réduction. En règle générale, il est difficile de quantifier précisément la taille de ces barrières intra-nationales ainsi que d'identifier leur source – est-ce en premier lieu le manque d'infrastructure, les frictions liées à l'information ou le rôle des intermédiaires de vente et de la structure de marché ? Les travaux s'attachant à ces questions utilisent souvent les variations de prix observées dans l'espace pour recouvrer les coûts agrégés de transport, mais ces derniers recouvrent de nombreux facteurs distincts et une telle méthode ne permet pas d'identifier séparément la contribution des intermédiaires de vente dans les coûts totaux.

Pour dépasser ces problèmes, j'utilise une expérience quasi-naturelle via un changement de politique publique conduisant à une évolution de la structure des marchés agraires en Inde. Avant la mise en place de cette réforme, le nombre d'intermédiaires de vente sur les marchés agraires locaux était fixé par le gouvernement, tandis qu'après la réforme, l'entrée de nouveaux acteurs dans ce marché a été libéralisée. Afin d'estimer les gains pour la société issue de ce changement de réglementation, je construis un modèle théorique du commerce intra-national de biens agraires basé sur les avantages comparatifs de type Ricardien auquel j'ajoute un rôle spécifique pour les intermédiaires de vente. Dans un premier temps, ce modèle me permet de formuler une équation d'estimation basée sur des conditions d'absence d'arbitrage qui me permettent d'identifier la variation des marges des intermédiaires de vente, ce qui établit en même temps une borne inférieure du taux de marge de ces intermédiaires. Le changement règlementaire impactant seulement le pouvoir de marché des intermédiaires et étant orthogonal aux autres distorsions domestiques, j'utilise simplement une stratégie de différence des différences (DD) pour recouvrer le niveau des marges chargés par ceux-ci. L'implémentation de cette stratégie utilise des données quotidiennes pour les transactions opérées par les producteurs à la sortie de leur exploitation. Dans le cas des arachides, l'une des cultures principales de la région du Karnataka, mon estimation du changement de la marge des intermédiaires s'élève à 16% à la suite de la réforme de la réglementation. Dans un second temps, je fais le lien entre le modèle et les données micro-économiques d'utilisation des sols et de productivité de exploitations afin d'estimer les principaux paramètres du modèle et enfin de fournir des analyses contrefactuelles. Prenant l'hypothèse d'une diminution des marges des intermédiaires de 16% pour toutes les cultures et en permettant aux fermiers d'adapter leur choix de culture sur leur sol, j'estime les bénéfices de cette réforme à $1,3\%$ du bien être agrégé pour l'ensemble des régions. Une telle augmentation est particulièrement significative au regard d'une réforme qui touche des activités qui constituent seulement 9% du PIB total de l'état considéré.

Une telle étude est de première importance car elle met en lumière le rôle déterminant des structures de marché dans les pays en développement, et en particulier en ce qui concerne les marchés agraires. Ce travail contribue à la littérature en pleine essor étudiant le rôle des intermédiaires dans le commerce national et international. Finalement, ce travail montre que des gains substantiels de bien être peuvent être atteints dans le commerce intra-national en réformant la structure des marchés et ainsi le pouvoir des intermédiaires. La compréhension du rôle de ces structures est un thème de première importance et j'ai l'intention de poursuivre dans cette voix pour mes prochains projets de recherche.

La structure des réseaux de production

Diffusion des chocs:quel est le rôle de la structure du réseau? L'économie est un système dynamique dont l'évolution résulte de l'interaction de nombreuses entités. Le rôle de chacune de ces entités microéconomiques individuelles dans les fluctuations agrégées est un débat ancien en économie. Lorsque les secteurs n'interagissent pas les uns avec les autres, la loi des grands nombres conduit à l'effacement des chocs de chacune des entités qui n'ont ainsi pas d'impact individuel sur les agrégats économiques. La littérature récente en macroéconomie des réseaux tente de dépasser ce résultat en prenant en compte les effets d'amplification des chocs individuels pouvant résulter des liens de production entre entités. Un tel travail est important pour deux raisons. D'une part, dans la perspective de la production d'outils à l'usage des économistes, la prise en compte de ces effets de réseau en macroéconomie théorique et empirique constitue un challenge important. En ce sens, il est primordial de savoir si la structure précise des réseaux de production peut avoir un impact important sur les agrégats économiques et si tel est le cas quels sont les caractéristiques à prendre en compte. D'autre part, si de telles structures sont importantes, cela pourrait générer des avancées nouvelles dans l'étude des cycles économiques et permettre une meilleure compréhension du lien entre fluctuations sectorielles et agrégées.

Mon travail s'appuie sur les dernières avancées dans le domaine de l'étude des réseaux (Acemoglu et al. (2012)) et introduit le concept le concept de diffusion des chocs à travers les frictions de production dans une économie multisectorielle. Les secteurs ayant différents horizons de production, la diffusion des chocs idiosyncratiques est plus lente et moins sujette à des phénomènes d'amplification au niveau agrégé. Ce résultat diffère de la plupart des études sur le sujet qui modélisent une production uni périodique encourageant plus facilement l'amplification et où les liens de production conduisent les chocs sectoriels à impacter les fluctuations agrégées. De plus, mon travail montre que lorsque le temps de diffusion est pris en compte, les métriques simples développées par la littérature pour rendre compte de la capacité d'un réseau à générer de la volatilité agrégée, telle que la moyenne des degré sortant (weighted outdegree) ne sont plus suffisantes. Le modèle est ensuite relié aux données en utilisant les indicateurs lead time pour le secteur manufacturier comme reproduction du retard (ou avance) de propagation. Finalement, à l'aide d'un modèle de facteur, j'isole la contribution du secteur manufacturier dans la volatilité générale de l'économie américaine et montre que la contribution des chocs sectoriels dans un réseau avec diffusion retardée est équivalente à celle trouvée dans un modèle sans réseau, c'est-à-dire très faible comparée aux modèles de réseau à production contemporaine. Ce résultat établit un contraste important avec de nombreux papier traitant des réseaux de production qui mettent l'emphase sur e rôle important des fluctuations sectorielles dans la volatilité agrégée à travers les liens de production.

Emploi dans un réseau de production (co-écrit avec François de Soyres): Quelles sont les conséquences d'une innovation technologique dans un secteur sur le niveau d'emploi des autres secteurs situés plus loin dans la chaine de production. D'une part, si le travail et les facteurs intermédiaires de production sont substituts, alors une réduction de prix de ces derniers tend à réduire la demande pour le travail pour chaque unité produite. D'autre part, une innovation technologique dans secteur situé plus haut dans la chaine de production conduit à produire un plus grand nombre d'unités car le cout marginal de production décroît. L'effet total sur l'emploi dépend simplement du rapport entre l'élasticité de substitution de la fonction production et de l'élasticité de prix de la demande agrégée.

Ainsi, alors qu'une innovation technologique dans un secteur situe plus haut dans la chaine de production a inévitablement des effets positifs sur le niveau de production, l'effet sur l'emploi est plus nuancé et dépend des deux paramètres clefs que sont l'élasticité de substitution entre les emplois et les biens intermédiaires ainsi que l'élasticité-prix de la fonction de demande totale. Nous estimons ces deux paramètres pour un grand nombre de secteurs avec des données micro-économiques françaises. Les résultats montrent des sensibilités très différentes entre les secteurs. Nous discutons enfin les conséquences de cette hétérogénéité pour les prévisions sectorielles de l'automatisation.

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The time spent at Toulouse School of Economics (TSE) during my PhD has been one of the most exciting and intellectually stimulating phase of my life. The thesis that I present here has been made possible thanks to the contribution and support of various people here at TSE and outside.

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I would also take this opportunity to thank all the other Professors here at TSE and outside, who have helped me in refining and developing my research ideas both during personal interactions as well as through workshops and seminars. I have gained immensely through my discussions with Patrick Feve, Christian Hellwig, Marti Mestieri, Robert Ulbricht, Franck Portier, Tim Lee and Paul Scott.

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Also my research has empirical focus and would have been impossible without the various data sources that I used during this time. Firstly, I will thank the market authorities (ReMSL) and participants in India, who shared relevant information and data about the rollout of market reform in the agricultural markets. Secondly, I would also acknowledge the support from INSEE for sharing firm level data on French firms.

Finally, I would thank my whole family back in India, who have been an important source of motivation and support during all this time. This challenging work was made easy only through the good wishes and blessings of all my elders and ancestors.

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To my grandparents...

Chapter 1

Gains from Agricultural Market Reform: Role and Size of Intermediaries

Abstract

How does market structure and the presence of intermediaries impact the cropping pattern and agricultural trade within a country? The difference between farm-gate and consumer prices implies large intra-national trade costs but it is difficult to know the contribution of intermediary margins to these costs. This paper exploits a pro-competitive policy reform from India, that allowed free entry of intermediaries in the agricultural markets, to quantify the size of these margins. I develop a Ricardian style comparative advantage model of intra-national trade in agricultural crops, which embeds intermediaries and is suitable for this study of market structure change. The model gives a structural equation that allows me to estimate the change in intermediary margin due to this reform. I find that post reform the intermediary margin decreased by 16% for Groundnut, one of the major crops in this region. I then connect the model with rich micro datasets on farm productivity and land use to estimate relevant parameters to run counter-factual experiments which reveal that the reform will increase average welfare by 1.3% through changes in cropping pattern.

1.1 Introduction

Recent work in the quantitative trade literature has highlighted the importance of intra-national trade barriers. The welfare gains from the removal of these intra-national trade barriers are found to be as large or even larger than the gains from removing international trade barriers in the case of developing countries. Another important feature of these countries is their dependence on agriculture. Since a significant part of their population is dependent on agriculture[1], the performance of agricultural markets and policies has a direct impact on their livelihood and is a crucial component of poverty reduction programs.

While lack of physical infrastructure, adverse geography and market integration are common barriers to trade in these agricultural markets, scant attention has been paid to the presence of intermediaries and market structure in these countries, which can potentially have a huge impact on how different regions within these countries trade and what they trade[2]. While there has been some work on understanding the role of intermediaries, there is a gap on the quantitative side of the literature to assess the role of intermediaries, specially in the agriculture sector (see Atkin and Donaldson(2016)). It is already difficult to characterize the size of these intra-national trade costs, and it becomes even more challenging once one decides to break down these costs into different components such as lack of infrastructure, information friction or inter-mediation.

To circumvent the problems associated with any such empirical exercise, I use a quasi-natural policy experiment from India to estimate the margins charged by intermediaries on local agricultural markets and put a lower bound on the intermediation costs. The policy reform involved moving from a system with fixed number of government mandated intermediaries to a system with free entry of intermediaries. The reform was initiated in the beginning of February 2014 in the state of Karnataka in India and has been sequentially rolled out in different markets.

Other papers in the trade literature use spatial price gaps to put an upper bound on the size of trade costs between regions, but it lumps together the various factors

[1] Agriculture contributes roughly 20% to Indian GDP and around 65% of population is still rural according to 2011 census.

[2] Other than trade, there is large literature in development which points towards large surplus cornered by middlemen in developing countries.

contributing to this gap, e.g. trade costs and markups. In contrast, this paper leverages a natural experiment on market reform to directly measure the size of these costs associated with market power of intermediaries. A unique dataset containing daily farm-gate price data allows me to recover the margins charged by intermediaries on these markets. The presence of price data both before and after the policy is the crucial factor in determining the impact of this policy change. An important contribution of my paper is to use this high frequency price data from India. Previous papers either did not have the necessary data available or they did not exploit this feature of the data.

Using the minimal condition of price arbitrage across different regions, a common result in trade models, gives me a simple estimation equation to pin down the change in intermediary margin, which also corresponds to the lower bound of their market power. Since the market reform shifted only the market power, while being orthogonal to other domestic friction, a simple difference-in-difference (DD) strategy allows me to recover the size of the margin charged by these intermediaries. The daily price-data both before and after implementation of the policy allows me to control for market level unobserved heterogeneity by using the panel dimension of the data. In the case of groundnut, one of the major crops in Karnataka, I estimate this intermediary margin around 16%.

The remaining part of the paper then deals with evaluating the long run welfare impact of this policy change. I develop a Ricardian style comparative advantage model with multiple crops and multiple regions, with an added layer of intermediation on trade. The farmers grow multiple crops on different plots of land, which vary in quality. The average quality of land varies across regions as well as crops, thus giving comparative advantage to a given region in certain crops. Differences in land quality across regions, thus generate crop specialization, a regular feature of Ricardian style models. Farmers sell their crops to the intermediaries, who then sell it on the local, domestic and international markets. In case of trade, there exists transporters who charge transportation cost over and above the trader margins and ship the goods. The first important difference relative to standard trade models is that farmer choices are based on farm-gate prices in the region, which is different than the consumer prices in the same region. Since other papers do not deal with intermediaries, they use the same prices for both farming and consumer decision. However in my case, this difference is crucial as it generates a wedge between between farmer and consumer choices. In the end, I close the model by assuming that the economy acts as a small open economy and takes foreign prices as given.

The second difference relative to existing trade models is in the way I embed the intermediaries, who charge a fixed margin over and above the farm-gate prices. I do not have data on number of intermediaries before and after the reform, but the modelling choice circumvents this problem by capturing market power as a function of this margin charged by the intermediaries. The change in market structure leads to a change in the margin charged by these intermediaries, which gives an estimation equation for change in market power.

To quantify the model, I then combine data from different sources on Indian agriculture. The agricultural data consists of crop choices, production, land allocation and productivity across different regions and crops. The iceberg trade costs across different Indian districts are generated from the dataset prepared by Allen and Atkin (2016) on Indian highways and freight rates. Finally, I use disaggregated household level consumption data to estimate the elasticity of consumption across crops.

The market structure with fixed number of intermediaries is a common feature in agricultural markets all across India and the counter-factual analysis involves assessing the welfare impact of this policy if the restriction on number of intermediaries is relaxed across all these markets.

After estimation of relevant parameters, I use my model for evaluating two counter-factual scenarios under the assumption that the reform changes intermediary margin by 16% across a set of crops. Under the first scenario, farmers are not allowed to change their output decisions post market reform. This can be thought of as a short term response where farmers stick to old cropping pattern but change in market structure changes their incomes through changes in trade. The second counter-factual scenario gives freedom to farmers to change their cropping pattern in response to market reform. This scenario highlights the presence of misallocation across crops due to market structure. Under this scenario, I find that the policy reform will increase the average welfare by 1.3% in these regions. While there are negligible gains in the first case, the second scenario delivers heterogeneous but positive welfare gains for most regions. Since the set of crops affected by this reform accounts for approximately 9% of total GDP, the welfare gains from change in policy are sizable.

This paper is connected to a large body of literature on the size of intra-national trade costs, agriculture and inter-mediation. The most important contribution of the paper is in understanding the role of intermediaries and their size in intra-national trade costs. One strand of this literature looks at gains from trade under variable markup charged by the producers (see Melitz and Ottaviano (2008); Feenstra and Weinstein (2010); Edmond, Midrigan, and Xu (2011)). But here the focus is more on market power of producers rather than intermediaries.

The other and more closely related stream of literature explicitly models intermediaries and comes in two different shades. In case of Ahn, Khandelwal, and Wei (2011) and Antràs and Costinot (2011) intermediaries act as trade facilitators. The intermediaries in these models help in breaking into new markets (usually foreign) and are important for trade. On the other hand Chau, Goto, and Kanbur (2009) model intermediaries as middlemen who earn excessive profits in developing country markets, which is closer to the setting in this paper. In this case, intermediaries hurt local trade by charging high markups. Atkin and Donaldson (2015) come closest to the paper and they use detailed micro-data to quantify the share of intra-national trade costs which can be attributed to the presence of intermediaries. The main difference with their paper is that while I estimate a lower bound on the surplus captured by the intermediaries, they put an upper bound (since intermediaries might be playing an important role in supply chain by providing storage facility etc).

The theoretical model presented in the paper is similar to the studies on trade and agriculture literature (see Costinot, Donaldson and Smith (2016); Costinot and Donaldson (2011); Sotelo (2016)). All these papers use Ricardian style comparative advantage model of trade with crop choice and then use it to quantify welfare impact under counter-factual scenarios like climate change or improved infrastructure. My modelling choice is driven by the absence of intra-national trade data, which is usually present in the case of international trade. Thus it is similar to Sotelo (2016), who too uses information on land use data instead of trade for quantifying the model. The modelling innovation here is the inclusion of intermediaries in a tractable way which gives a direct method to evaluate the change in market power post policy reform.

More broadly, the paper also connects to the work on inefficiency in agriculture, mainly by Gollin, Lagakos, and Waugh (2013), Gollin and Rogerson (2014) and others. This paper highlights another source of inefficiency, which can arise due to high margins charged by the intermediaries, thus impacting overall trade and comparative advantage in developing countries. Lastly, the paper is also related to the work on telecommunication infrastructure and market performance (see Jensen(2007); Aker(2010); Steinwender(2015)). These papers too exploit a natural experiment, the expansion of mobile networks or telegraph, to study changes in price discovery mechanisms. In contrast, this paper focuses on estimating intermediary margins rather than changes in price dispersion.

The rest of the paper is organized as follows. Section 2 describes the agricultural market in India and the associated policy reform. It also gives reduced form evidence for increase in prices recieved by farmers due to this reform. Section 3 gives the theoretical framework with intra-national trade in presence of intermediaries. Section 4 describes the data used in the analysis. Section 5 explains the estimation procedure as well as give the parameter estimates. Section 6 provides welfare analysis under counterfactual scenarios. Section 7 concludes.

1.2 Agricultural Market in India and Policy Reform

The agricultural market in India is highly regulated through the institution called Agricultural Market Produce Committee(APMC), which regulate the local agricultural markets, both the number of markets as well as the number of intermediaries active on each market. Historically, APMCs were constituted around 1960s to support farmers and prevent their exploitation at the hands of money lenders and local traders. Thus the state governments regulated agricultural markets through APMCs, so that it can monitor marketing activities and help farmers get fair price for their produce. Although, given restricted entry of traders on these markets APMCs themselves evolved over time and became exploitative due to excessive power to the intermediaries.

APMCs are controlled by the state governments, which divide each state into different geographical locations, which then constitute a local *Mandi* (or market). Farmers are allowed to sell their produce only at their local government approved

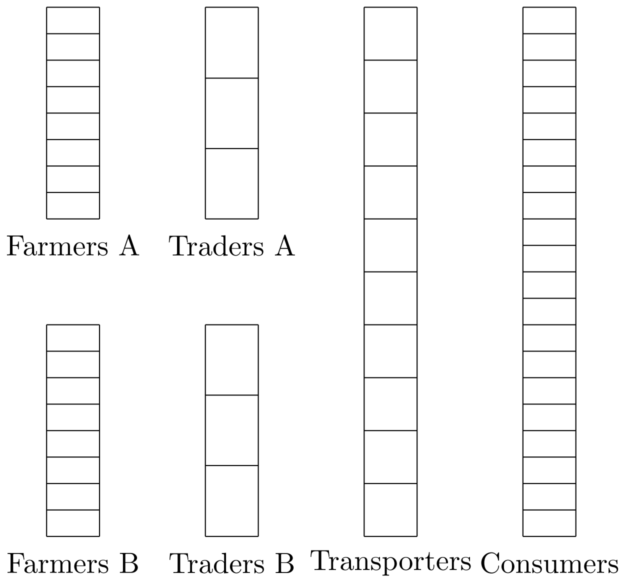

FIGURE 1.1: Market Structure: Before Integration

market and only to government approved traders [3]. This setup reduces the flexibility of the farmers and gives market power to the local intermediaries who get their license renewed once every 5 or 10 years, depending on the state. Whole sale and retail traders, even if they wish to, are not allowed to purchase directly from the farmers. This restriction coupled with the fact that number of intermediaries on the market are pre-decided by the government, makes these markets uncompetitive. Although, the local produce is sold off through auctions on these local markets but given the small number of intermediaries, it is easier for them to collude and suppress the prices paid to the farmers. The market power of these intermediaries is reported as a big problem in the agricultural market and also gets reflected in the big difference between retail vs farm gate prices paid to the farmers.

Figure 1.1 describes the structure of the market before policy change. The markets are segmented because farmers in market A are allowed to sell their only produce to the intermediaries active in market A. Similar is the case for market B. The number of blocks at each level represents the number of players on each level. So, farmers are much more numerous than intermediaries, who form the second layer

[3] Although farmers can sell small amounts locally to each other in their village but big harvests have to go through these markets. Thus, intra or inter-national trade in agricultural commodities has to go through these markets due to restrictions imposed by the state. Also retail chains are not allowed to directly procure from farmers but have to buy indirectly through the same intermediaries. In 2012, Walmart was denied to sign a contract directly with the farmers, which would have meant bypassing the APMCs.

FIGURE 1.2: Market Structure: After Integration. The orange block corresponds to the new traders due to free entry.

of this market. After buying from farmers, intermediaries sell their goods to other wholesalers or retailers who form 3rd layer and I call them transporters in the rest of the paper. They ship the goods around before selling them to the final consumer. The number of transporters and final consumers are also larger than the number of intermediaries, who are limited and fixed by the government.

1.2.1 Unified Market Platform: Karnataka

The state of Karnataka in South India has been a forerunner in agricultural market reforms and has been taking advantage of modern technology to bring reforms in the agricultural sector. The Unified Market Platform (UMP) is part of this initiative to connect different agricultural *Mandis* in the state through an online auction platform for agricultural commodities. The reform is called market integration because it brings together the intermediaries and farmers from different markets. The scheme was formally launched on 22 February 2014.

The reform intends to develop a transparent and integrated e-auction mechanism to connect farmers with intermediaries in order to improve competitiveness and thus fetch higher prices for farm produce. Figure 1.2 represents the market structure in Karnataka post integration reform.

There are two immediate changes which can be seen from figure 1.2. All farmers are now shown together under level 1, because they can technically sell their produce to any intermediary on the online auction platform. The intermediaries in level 2 are now constituted by the old intermediaries, white blocks, plus the additional intermediaries (in orange) who are added due to free entry condition. The free entry of new traders is the most important block of this reform. Post reform, given the ease of registration anyone with basic knowledge of internet can register himself as an intermediary on this platform.

Currently, there are very few intermediaries who trade on multiple markets, which essentially means that this market reform has increased the number of intermediaries on each local market, thus increasing the competitiveness for buying farm produce. Given last estimates there were approximately 35,000 intermediaries active on some 100 markets. The other two layers i.e. 3 and 4 of transporters and consumers are unaffected by this reform and would see no change [4].

Present Structure: Since the project is named Unified Market Platform, one gets an impression that many intermediaries are trading on multiple markets at the same time. But there are few traders active on multiple markets as came out of discussions with the authorities who are implementing this program. The main reason behind fewer traders active on multiple markets is that quality testing facilities are not available on most markets. This means that online traders have no way to find out the quality of the farm produce, without being physically present on the market. During my visit to these markets in August 2016, only five markets had such a quality testing feature.

Not only such quality labs are expensive to setup but the ones which have been established are also not used by the farmers. Since the testing requires farmers to part with a sample of their produce and most farmers are marginal, they prefer to sell it without getting tested rather than lose part of their produce to testing. Another reason for farmer disinclination to quality testing comes from the fact that testing usually takes few days to a week and in most cases the farmer is not ready to wait and is happy to receive the payment on same day.

This means that physical presence on the *Mandi* is essential for gauging quality of the produce and an intermediary sitting hundreds of kilometres away on his computer would not engage on the markets sans quality certificate. Even a big trading firm which might think of getting active on multiple markets would need physical presence on the markets it wants to buy from. Given this background, the

[4] Although this might change in long run as new supply chains will be formed to reflect the changed market structure. Since this paper deals with short term changes, it is safe to assume that the basic structure of layers 3 & 4 of remains unchanged

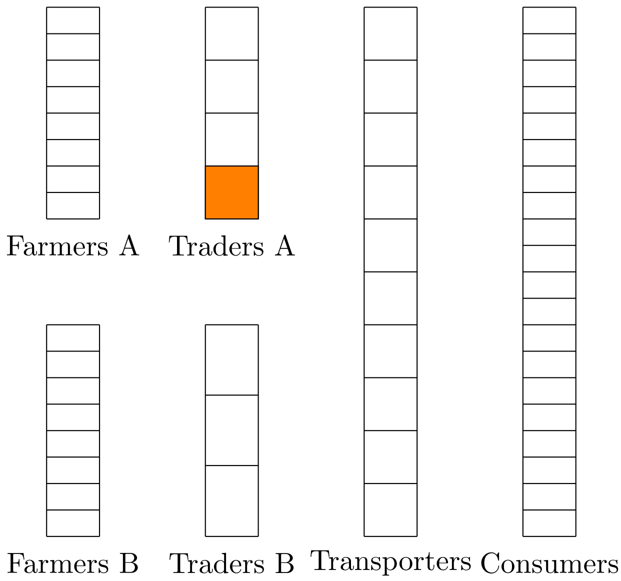

FIGURE 1.3: Market Structure: After Integration. The orange block corresponds to the new traders due to free entry.

unification of markets can be seen as an increase in the number of intermediaries on each market due to free entry condition as represented in figure 1.3. The above details support the assumption that this reform only changed the bargaining power of the local intermediaries vis-a-vis the farmers. I will use this assumption both in the model and estimation.

Market functioning: Farmers and intermediaries who want to sell/buy on the market need to get themselves registered on the e-platform. Intermediaries who want to be active on this market need to pay a nominal fee and keep some pledged money or security with the platform. Once a market is integrated, all the intermediaries on this market have to get themselves registered.

The farmers are still required to bring their crop to the local *Mandi* and cannot directly enter into contract with others outside the *Mandi*. Once the farmer brings the crop to the *Mandi*, each lot of the farmer is given an identification number with physical parameters like weight, crop and variety at the entry gate of the market.

Once the characteristics of the lot are determined it is put up for auction on the e-platform with all details. The prospective buyers can bid for any of these lots till the stipulated cutoff time, which is usually 3 pm in the afternoon after which the bidding closes. After the auction closes, the winning bids are flashed on the local market TV screens. The farmer also receives a message about the price for his lot on his mobile phone. Thereafter, the farmer is required to give his acceptance for the bid price. In case he rejects the offer there is second round of auctions on the same day which is executed in similar fashion.

Implementation details: The state of Karnataka has 155 major markets, out of which some 71 were integrated till September 2015 and have been included in the period of study. The roll out of reforms was not immediate and markets were integrated on the unified platform over time. The coverage of the program is shown in figure 1.5, which shows the distribution of integrated markets in the state.

Figure 1.6 shows the rollout of the reform and gives the number of markets integrated on the e-platform every month. The first three markets were integrated in February 2014 and then the rest were integrated in waves, with maximum markets being integrated in November 2014. This paper covers markets which were integrated till September 2015.

1.2.2 Reduced form evidence

Given the pro-competitive nature of policy reform described above, it is expected that the farmers in the integrated regions will get higher farm-gate price for their produce. Since all the markets did not get integrated at the same time, it allows us to compare markets which did not get integrated against those which got integrated and see if the farmers really got a higher price.

Before evaluating the gains to farmers from this policy, it is important to look at the market characteristics of the integrated and non-integrated markets. There were 71 integrated markets as of September 2015 and another 84 non-integrated ones. The observable market characteristics are shown in table 3.1. The first level gives the mean and standard deviation of annual expenditures of these markets. The average spending of all the markets is equal to Rs 75.5 Million and there is no significant difference between integrated and non-integrated markets. The other observable characteristics annual income, number of villages covered and number of traders active on each market are also similar for the two sets of markets. Also, the median market size (not reported in this table) is also very close to the mean. Given these figures, one can conclude that size characteristics do not govern early selection of a market into this program. A logit regression for selection of markets into the program over market level observables gave insignificant coefficients on market level observables, thus ruling out the possibility of selection of markets on observables.

The most important parameter which changed post policy reform is the number of traders on each of these markets. The integrated markets have on average 171 traders. Although, I could not get the number of registered traders on each of these markets separately for post reform period, but the authorities informed me that there were roughly $30,000$ traders registered on the UMP platform as of September 2015. Since, all the previous traders had to also get registered on the platform for trading, this gives an average of 257 new traders on each market. This is more than 100% increase in the number of traders and enough to break the market power of the previous intermediaries.

This policy reform should result in higher farm-gate prices for the farmers. To test this prediction I use daily level farm-gate price data from June '13-July '15. I show the impact of this policy on groundnut prices by running the following regression:

$$Y_{it} = \beta * \text{Integration}_{it} + \delta_i + \nu_t + \epsilon_{it} \tag{1.1}$$

where Y_{it} correspond to the price of groundnut in region i at time t. I observe three moments of price in the data- mode, maximum and minimum, which are all reported. The Integration$_{it}$ variable captures the integration status of market i at time t and is equal to 1 if integrated and otherwise 0. The specification in equation 1.1 underlines the difference-in-difference strategy because we are comparing increase in farm-gate price of groundnut in integrated market after integration vis-a-vis non-integrated markets, which act as the control group.

The panel dimension of the data allows us to control for the unobserved market level heterogeneity, which otherwise might have caused the change in outcomes. The identifying assumption here is that the only market characteristic which changes post reform is the market power of intermediaries, which is captured by the Integration$_{it}$ variable. The remaining market characteristics remain the same and are filtered out by the term δ_i, the market fixed effect. The term ν_t filters out the time fixed effects from the regression.

The results from the estimation of equation 1.1 are given in table 1.2. Integration results into an increase of Rs 148 in the modal price of 100 kg of groundnut, which is approximately 4% of the average modal price of groundnut in 2015. The results for all crops do not go into same direction. For example- there is no impact on prices of maize, which is also reported in the appendix.

The next section will now outline the theoretical model which would be used for deriving estimation equations and simulating the counter-factuals.

1.3 Theory

1.3.1 Environment

To study the impact of change in market structure on farmer choices and welfare, I develop an intra-national trade model based on comparative advantage between different regions. Each region is endowed with some agricultural productivity over different crops which will lead to specialization of different regions in different crops. This is the underlying reason for trade between different regions, just like in any other Ricardian model. Finally, I use the model to study the impact of change in market structure on the change in this comparative advantage of different regions.

Geography: The world is divided into Home and Foreign. Home is a small open economy divided into regions indexed $i = 1, .., I$ and Foreign $i = F$. Each region can also grow agricultural crops indexed by $k = 1, .., K$. The crops are homogeneous and can be traded across different regions. Other than agricultural crops, manufacturing good denoted by M captures rest of the consumption. Each region i also consists of set of plots Ω_i, with individual plots indexed by ω, each of size one. The total land in region i is then denoted by $H_i = \int_{\Omega_i} d\omega$.

Agents: Each region i consists of three different agents. A representative consumer who supplies labor, takes farming decisions, receives factor payments and buys consumption goods on the local market. A representative intermediary who buys farm production. The trader in i buys goods from the intermediaries and sells them to the final consumer in all regions in Home and Foreign.

Preferences: The representative consumer in region i spends a fraction b of his income on agricultural goods, $C_{i,A}$ and rest on manufactured goods, $C_{i,M}$.

$$U_i \quad = \quad C_{i,A}^{b} C_{i,M}^{1-b} \tag{1.2}$$

where

$$C_{i,A} = \left(\sum_{k=1}^{K} a_k^{\frac{1}{\sigma}} C_{i,k}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

σ is the elasticity of substitution between different agricultural goods. Also a_k corresponds to crop specific taste shifters and are normalized to add up to one i.e. $\sum_{k=1}^{K} a_k = 1$. Since Home is small compared to Foreign and does not have any impact on Foreign prices, we do not have to specify Foreign preferences as it can be summarized by just a vector of prices.

The CES consumption bundle on agricultural crops is standard across most trade models. Since we do not observe intra-national trade data, we would estimate σ directly from consumption data. Thus we do not use region dependent taste shifters and assume a_k are similar across regions.

The household in each region i also supplies labour inelastically to the agricultural and manufacturing sector, given by $L_{i,A}$ and $L_{i,M}$ respectively. As the model is restricted to short term predictions, we keep labor immobile across regions as well as across sectors. The households receives payments from labor and inter-mediation.

Technology: The manufacturing good is produced using constant returns to scale technology in labor and given by $y_{i,M} = T_i l_{i,M}$ where T_i is the labor productivity coefficient. On the agricultural side, we assume land and parcels of land are perfect complements. By combining $\phi_{i,k}(w)$ share of plot ω with $l_{i,k}(w)$ amount of labor, a representative farmer can produce:

$$q_{i,k}(\omega) \quad = \quad \Lambda_{i,k}(w) \min\{\phi_{i,k}(w), l_{i,k}(w)\} \tag{1.3}$$

where $q_{i,k}(\omega)$ is the output of crop k if share $\phi_{i,k}(w)$ of plot ω is allocated to k. Another important parameter is $\Lambda_{i,k}(w) \geq 0$, which denotes the total factor productivity of plot ω if allocated to crop k in region i. [5] Also, in Indian context most farmers are marginal which means plot sizes are small and the labor is tied to the plot. A similar production function can be derived from Cobb-Douglas technology as in Sotelo(2016) by restricting the size of plot associated with each unit of labor. [6] Further, to keep the land choices tractable we impose assumption on the productivity distribution.

The vector of land productivity, $\Lambda_{i,k}(w)$, for producing different crops k in region i and plot ω has a Frechet distribution with parameters $(\bar{\gamma}A_{i,k}, \theta)$:

$$P[\Lambda_{i,k}(w) < \Lambda] = e^{-\bar{\gamma}^{\theta} A_{i,k}^{\theta} \Lambda^{-\theta}} \tag{1.4}$$

where $\bar{\gamma}$ is a normalization parameter.[7] The parameter $A_{i,K} \geq 0$ captures the average productivity of land for growing k in region i and is thus shared by all plots ω. A high $A_{i,K}$ implies that on average all plots in region i have high productivity for growing crop k. On the other hand, the dispersion in land quality across the plots in region i is captured by θ, which decreases with increase in θ. Thus a higher value of θ will imply higher specialization across different regions.

1.3.2 Market Structure

Intermediary: The farmers sell their farm produce to their local representative intermediary. The farmer in region i gets a farm gate price $f_{i,k}$ for crop k, over which the intermediary then charges a mark-up $\mu_{i,k}$ before selling it to the trader, who then sells it to consumers locally or in other regions. [8] Thus the final consumer price is given by $p_{i,k} = \mu_i f_{i,k}$, in case where crop k is sourced locally. This is a parsimonious representation of the market structure in India and the market integration reform can be captured by change in this mark-up $\mu_{i,k}$ charged by the

[5] Costinot et al(2014) use a similar production technology with an additional parameter to capture different labor intensities across different countries. Since, this model is restricted to India, labor intensity of agricultural production will be same across different regions.

[6] Sotelo(2016) uses a constant returns to scale production function in labor, land and intermediate inputs and allows for different factor intensities across different crops. Similar choice can be used here as well.

[7] Γ is a normalization parameter.

[8] You can think of it as a bargaining solution between trader and farmer with bargaining weights β and $1-\beta$ respectively. This $\mu_{i,k}$ can be derived as a solution to simple bargaining problem and is shown in the Appendix.

intermediaries. Post market reform, the intermediaries will see decrease in their bargaining power, which can be captured by decrease in $\mu_{i,k}$.

Trade: Trade is costly between regions and subject to iceberg trade costs, $d_{ni,k} \geq 1$, charged by the transporters. It means the trader in i need to ship $d_{ni,k}$ units of good k in order to sell one unit in region n. Also, $d_{nn,k} = 1$, for all n and k i.e. trade is costless within a region and $d_{ni,k}$ satisfies the triangle inequality, $d_{ni,k} \leq d_{nj,k} \times d_{ji,k}$. Manufactured goods are traded costlessly within Home, but cannot be traded between Home and Foreign.

Prices: The farmer gets price $f_{i,k}$ for his produce while final consumers have to pay $p_{i,k}$ for good k in region i. So, the farmer and consumer decisions are based on different prices. There is no iceberg cost for shipping manufacturing good within Home so it has same price P_M across all regions.

Home is small open economy so its trading decisions do not change prices in Foreign. Also, region i in Home bears all iceberg cost for trade with Foreign, i.e. both to and from the port. Given this assumption, i buys one unit of crop k from Foreign at $d_{iF,k}p_{F,k}$, while sells it at $p_{i,k}/d_{Fi,k}$.

1.3.3 Decisions

Consumption The representative consumer uses income from all the sources to maximize his utility given in (1.2) by purchasing consumption goods. The budget constraint of this consumer is given by:

$$E_i \geq p_M C_{i,M} + \sum_{k=1}^{K} p_{i,k} C_{i,k} \tag{1.5}$$

where E_i is the household income and is given by:

$$E_i = \omega_{i,M} L_{i,M} + \sum_{k=1}^{K} f_{i,k} q_{i,k} + \sum_{k=1}^{K} (\mu_{i,k} - 1) f_{i,k} q_{i,k} \tag{1.6}$$

Given the CES assumption on the household utility from agricultural goods, we get shares spent on each good as:

$$s_{i,k} = ba_k \left(\frac{p_{i,k}}{P_i}\right)^{1-\sigma} \tag{1.7}$$

There are a few assumptions embedded in the household income as written above. The households receive the wage payments from the manufacturing sector as well as get all the income from the agricultural production. If production technology in agriculture also required intermediate input, then final consumer would have subtracted that cost from the final revenue. In the model, farmers and intermediaries are separate entities, so we can also consider a case where representative consumer only receives income by selling crops at farm gate prices i.e. $\sum_{k=1}^{K} f_{i,k} q_{i,k}$. We will revisit this question again during welfare calculations.

Production: The representative farmer in region i allocates the land to maximize his revenue. We fix the reservation wage for agricultural labor equal to zero, so that all labor is employed as well as it is always profitable to grow some crop rather than leave the land idle. Given the production technology in (1.3), land allocation in region i can be solved as a discrete choice problem. Let

$$\eta_{i,k} = \Pr\{f_{i,k}\Lambda_{i,k}(\omega) = \max\{f_{i,1}A_{i,1}, ..f_{i,K}A_{i,K}\}\} \tag{1.8}$$

denote the probability of assigning plot ω to crop k. Since there is continuum of plots on Ω_i, $\eta_{i,k}$ also corresponds to the share of land allocated to crop k in region i. Given the Frechet assumption on the productivity distribution, we can solve for land shares to get:

$$\eta_{i,k} = \frac{(f_{i,k}A_{i,k})^{\theta}}{\sum_{l=1}^{K} (f_{i,l}A_{i,l})^{\theta}} \tag{1.9}$$

The land share allocated to crop k goes up with the marginal product of land, $f_{i,k}A_{i,K}$, in crop k. So, amount to land allocated to given crop k rises both in its farm-gate price $f_{i,k}$ as well as productivity $A_{i,k}$. Also, θ captures the sensitivity of land allocation to different crops. A higher θ makes land allocation more sensitive to changes in both prices as well as productivity, also leading to more specialization across regions. Again, the prices used here for decision making are farm-gate prices, $f_{i,k}$, because the representative farmer bases his decision on farm gate prices he receive and not on final consumer prices.

The total production of crop k in region i is then given by, $q_{i,k} = \int_{\Omega} q_{i,k}(\omega)d\omega$. Using law of iterated expectations and given production technology (1.3), we can write:

$$q_{i,k} = H_i \eta_{i,k} \mathrm{E}[\Lambda_{i,k}(\omega) | f_{i,k}\Lambda_{i,k}(\omega) = \max\{f_{i,1}A_{i,1}, ..f_{i,K}A_{i,K}\}] \tag{1.10}$$

where the term $H_i\eta_{i,k}$ is the total land in region i devoted to crop k. This follows from the assumption that each plot is measure one and the total land is equal to H_i. The last term is equal to the expected productivity of crop k in region i conditional on crop being produced in region i. Again, given Frechet assumption this can be solved to give:

$$\mathrm{E}[\Lambda_{i,k}(\omega) | f_{i,k}\Lambda_{i,k}(\omega) = \max\{f_{i,1}A_{i,1}, ..f_{i,K}A_{i,K}\}] = A_{i,k} \times \eta_{i,k}^{-1/\theta} \tag{1.11}$$

The above equation directly tells that average productivity conditional on a crop being produced is strictly higher than unconditional average productivity i.e. $A_{i,k} \times \eta_{i,k}^{-1/\theta} > A_{i,k}$. Using the above two equation, we then get production of crop k in region i:

$$q_{i,k} = H_i A_{i,k} \eta_{i,k}^{(\theta-1)/\theta} \tag{1.12}$$

Trade The transporters in i have access to technology to transport goods to all other regions in Home as well as both import and export to Foreign. The transporters maximize their profits from trade although they would earn zero profit in equilibrium. The transporter problem is given by:

$$\max_z \sum_{n=1}^{I}\sum_{k=1}^{K} z_{ni,k}\left(p_{n,k} - d_{ni,k}p_{i,k}\right) + \sum_{k=1}^{K}\{z_{Fi,k}\left(p_{F,k} - d_{Fi,k}p_{i,k}\right) + z_{iF,k}\left(p_{i,k} - d_{iF,k}p_{F,k}\right)\} \quad (1.13)$$

where $z_{ni,k}$ are domestic trade flows of good k from i to n. $z_{iF,k}$ and $z_{Fi,k}$ are imports and exports of good k to Foreign respectively. In case of Foreign trade, iceberg cost $d_{iF,k}$ is paid by the transporter at the port. Again, it is important to mention here that the transporters buy the goods from the intermediary in region i at price $p_{i,k}$ which is then sold to the consumers in all regions. A simple way to think about this setup is the following. Transporters buy the final crops from intermediaries and pay them price $p_{i,k}$ which clears the market. Then in market i, the intermediaries pay back farm gate price $f_{i,k} = (1/\mu_i)p_{i,k}$ to the farmer. The transporters in Home take prices in Foreign as given and the amount of trade does not have any impact on Foreign prices.

1.3.4 Competitive Equilibrium

The competitive equilibrium of the economy defined above is given by:

Definition A competitive equilibrium consists of, for each region $i = 1, .., I$ (a) consumer prices $p_{i,k}$, farm-gate prices $f_{i,k}$ for all crops $k = 1, .., K$ and p_M for manufactured goods; (b) final good consumption $C_{i,M}$ and $C_{i,k}$ for all crops $k = 1, .., K$; (c) inputs $\{l_{i,k}(\omega), \phi_{i,k}(\omega), \omega \in \Omega_i\}$ and outputs $q_{i,k}$ for all crops k and labor input $l_{i,M}$ and $y_{i,M}$ for manufactured good M; (d) trade flows, (i) domestic $z_{ni,k}$ for all regions $n = 1, .., I$ and international (ii) $z_{iF,k}$ and $z_{Fi,k}$, for all crops $k = 1, .., K$, such that:

1. quantities in (b) solve the consumer's problem given income and prices;
2. inputs and outputs in (c) solve manufactured goods producer's problem, given prices;
3. inputs and outputs in (c) solve the problem of representative farmer, given farm gate prices;

4. agricultural goods prices in (a) are consistent with profit maximization by traders

$$p_{n,k} \leq d_{ni,k} p_{i,k} \tag{1.14}$$

with equality if $z_{ni,k} \geq 0$, for all regions $n, i \in \{1, .., I, F\}$ and all crops $k = 1, .., K$; and with intermediaries giving farmers price $f_{i,k}$ such that

$$p_{i,k} = \mu_{i,k} f_{i,k} \tag{1.15}$$

and the law of one price holds in manufactured good;

5. Local markets clear for all labor, land and crops:

$$L_{i,A} = \sum_{k=1}^{K} \int_{\Omega_i} l_{i,k}(\omega) d\omega \tag{1.16}$$

$$L_{i,M} = l_{i,M} \tag{1.17}$$

$$1 = \sum_{k=1}^{K} \phi_{i,k}(\omega), \text{ for all } \omega \in \Omega_i \tag{1.18}$$

$$C_{i,k} = q_{i,k} - \sum_{n \in W} d_{ni,k} z_{ni,k} + \sum_{n \in W} d_{in,k} z_{in,k}, \text{ for all } k \tag{1.19}$$

where $W = \{1, .., I, F\}$

6. The domestic market for manufactured goods clear:

$$\sum_{i=1}^{I} C_{i,M} = \sum_{i=1}^{I} y_{i,M} \tag{1.20}$$

7. Balanced trade with Foreign; value of exports is equal to value of imports

$$\sum_{k=1}^{K} p_{F,k} \sum_{i=1}^{I} \frac{z_{Fi,k}}{d_{Fi,k}} = \sum_{k=1}^{K} p_{F,k} \sum_{n=1}^{I} d_{nF,k} z_{nF,k} \tag{1.21}$$

where domestic traders pay the iceberg cost both in case of imports as well as exports

I also normalize the price of manufactured good $p_M = 1$, which completes the characterization of the competitive equilibrium.

1.4 Data

This section gives information on the datasets I have collected for this paper. I use the top 12 crops by area sown in Karnataka between 2000-2011. The region i in all cases will correspond to a district and is equal to 18 in case of Karnataka while 340 in case of India. The different datasets that I use are:

1. **Integration details:** ReMSL(Rashtriya e-Market Services Pvt. Limited) [9] is the nodal organization responsible for rolling out the Unified Market Platform policy across Karnataka. I collected information on the launch dates of the program in different markets from this agency.
2. **Farm Gate Prices:** Agmarket portal run by the Directorate of Marketing & Inspection[10], Government of India collects information on the wholesale markets, *Mandis*, across India. Around $2,700$ *Mandis* from across the country report data to the above portal on around 350 commodities and $2,000$ varieties. I scraped the data from the above website to get information on characteristics of *Mandis* as well as data on daily prices. The *Mandis* report three movements of prices- Max, min and modal price for the day as well as quantities. While the prices are well reported, the quantities of arrival on the market are not available for more than 80% of the observations.
3. **Crop Choices:** Data on cropping pattern, crop prices and crop yields is collected by ICRISAT VDSA (Village Dynamics in South Asia) and covers information on major crops from 1960s to 2011 at district level. I use information from VDSA both for Karnataka and India to estimate relevant parameters in the simulation.
4. **Crop Productivity:** VDSA provides information on realized crop yields, which is higher than the potential crop yields in a region. To correct for it and measure potential crop yield, I use data from GAEZ (Global Agro-Economic Zones) from FAO, which gives estimates of crop yields in a grid of 5 arc-minute cells. The crop specific potential yields are calculated based on various geological and weather parameters as well as the intensity of input (high or low). For a detailed discussion on this dataset, see Costinot and Donaldson (2014).

[9] Official website of the organization: http://www.remsl.in/. I would also thank Mr. Manoj Rajan, CEO ReMSL for discussing relevant information related to the rollout of this policy.

[10] Official website of the organization: http://agmarknet.gov.in

5. **Consumer Preferences:** Data on consumer preferences comes from NSS (National Sample Survey) 2011-12. The household level dataset contains detailed information on major commodities & expenditures.

6. **Trade Costs:** I use the travel time data between different districts as combined by Allen and Atkin(2016) in their recent paper as a measure of trade costs. I use the information corresponding to 2011 Road Maps of India. I combine it with freight data to estimate iceberg trade costs. [11]

1.5 Estimation

This sections gives details on how to estimate the various parameters needed to simulate the model and estimate welfare gains. The first subsection gives details on estimating the change in margin charged by the intermediaries. The remaining part of this section deals with estimating the other two parameters- heterogeneity in productivity θ and consumer elasticity σ.

1.5.1 Change in markup due to integration

Theory: The markup, $\mu_{i,k}$ is the parameter which changed due to the policy reform. I use the no arbitrage condition between different markets to estimate the change $\Delta\mu_{i,k}$. Let's say two markets i and j supply non-zero quantity of a good k to market l, both before and after the integration and only market i gets integrated. The price arbitrage condition before integration in period t_1 requires:

$$p_{l,kt_1} = \mu_{1i,k} d_{li,k} f_{i,kt_1} = \mu_{1j,k} d_{lj,k} f_{j,kt_1} \tag{1.22}$$

while post-integration in period t_2:

$$p_{l,kt_2} = \mu_{2i,k} d_{li,k} f_{i,kt_2} = \mu_{1j,k} d_{lj,k} f_{j,kt_2} \tag{1.23}$$

[11] I have collected freight rates data from an emerging portal which matches truckers with potential customers: http://www.truckbhada.com/, and provides information on freight rates between different cities and is a good measure of transportation costs.

where $\mu_{1i,k}$ and $\mu_{2i,k}$ correspond to the markups in market i at time t_1 and t_2 respectively, while in market 2 the markup remains the same i.e. $\mu_{2i,k}$ in both periods.

Assumption: *Markups in market j do not change due to change in market structure in i in period t_2.*

Since, the policy was rolled out over a period of time, it is possible to identify change in μ by using the two equations given above and the assumption on change in markup. Dividing equation 1.23 by 1.22, we can write down change in $\mu_{i,k}$ in market i by:

$$\frac{\mu_{2i,k}}{\mu_{1i,k}} = \left(\frac{f_{i,kt_1}}{f_{j,kt_1}}\right) / \left(\frac{f_{i,kt_2}}{f_{j,kt_2}}\right) \tag{1.24}$$

The above equation allows us to estimate change in mark-up by directly looking at the farm gate prices both before and after the integration. Since market i gets integrated, we expect $\mu_{2i,k}$ to go down post integration. This is captured by the higher farm gate prices ratio in post integration period i.e. $\frac{f_{i,kt_2}}{f_{j,kt_2}}$ is higher than the price ratio $\frac{f_{i,kt_1}}{f_{j,kt_1}}$ in period t_1. This equation allows us to estimate changes in μ separately for each of the different markets i. For the rest of this exercise I would assume that markups are the same across markets and depend only on their integration status i.e. μ_1 before integration and μ_2 after integration.

The assumption on change in markup would definitely be a concern in estimations over a longer horizon where the other layers of transporters and consumers change in response to policy reform. But since we are restricting our empirical estimations to immediately after the implementation of policy, it is safe to assume that there is no change in behavior of agents in other markets due to change in market structure just in market i. This is not a very restrictive assumption in short run as the layers of transporters and consumers are fairly competitive and would take a long time to change. But if we wait for the change in these other layers we would identify not just change in margin of intermediaries but also the change in whole market structure.

Another concern with the above assumption is related to the anticipation of the policy in other markets. If the traders in unintegrated markets feel that they would soon be integrated, they might decide to charge higher markups for the remaining few months to get a higher profit. Even if this concern were true, we would expect that markets which get integrated later on will show lower change in markup due to them charging higher markups just before integration. This would bias our estimator for change in markups downwards and under-estimate the impact of the policy. Also I am using Bangalore as an unintegrated market, which remain unintegrated for the whole duration, and is a bigger market than all others so this should be less of a concern.

While it is directly possible to estimate the change in markups μ from consumer price data $p_{i,k}$, but I use only farm-gate price data for this exercise. There are two reasons for it. Firstly, I only have access to farm gate price data both before and after the policy change. There is no consumer survey data right before or after the policy change. Secondly, consumer price data is less precise and noisy as it is calculated from the household surveys using backward calculations from self-reported household expenditure and consumption. Due to these problems, I stick to using only farm-gate price data for this estimation. Although theoretically it is possible to use price arbitrage conditions to back out the changes in μ even from consumer price data.

Estimation: To estimate the change in markups as described above, I use Bangalore as the base market for comparison with other integrated markets. Bangalore is the capital city of Karnataka and did not get integrated till September 2015, the time period for which I have collected the data. Bangalore being the capital city is a good benchmark for this exercise, since being the capital city a lot of trade flows through this market and it is also used by other traders for gauging state wide market prices. We will focus on groundnut as it is one of the main crops in Karnataka and has high trade volumes on the Bangalore market.

Figure (1.9) shows the impact of integration on the modal farm gate price ratio between market i and Bangalore market i.e $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$. The plot shows the evolution of residuals of price ratio after filtering out the market and time fixed effects. The top two rows correspond to the markets that got integrated during this period i.e. before 30 June 2015. The vertical line in these two panels corresponds to the date of integration. The third row shows the three markets that did not get integrated during this period to show the impact on control group.

The residuals in the top two columns clearly show that integration leads to increase in price ratio $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$ due to change in policy. The control markets in the third row do not show any similar increase when compared to their historical levels. Another point to notice here is that the residuals are fairly close to zero and bundled up together before the policy change both in the integrated and non-integrated markets. But post policy change, the residuals in integrated markets are much more dispersed, highlighting that the new intermediaries are driving this change and price discovery became more noisy. There is no similar change in non-integrated markets.

Instead of looking at figure (1.9), a similar exercise can be done by looking at average price ratio both before and after integration as shown in table . While the average modal price ratio across markets is 1.03 before integration, it jumps to 1.46 after integration. Similar result holds for ratio of maximum price in these markets. The minimum price ratio although increases from the initial value but it does not increase as much as the other two ratios.

Instead of looking at full sample, we can also look at how the price ratio changed just for the integrated markets. Here we again see that the modal price ratio has jumped up from around 1 to around 1.5 i.e. by almost 50 percent. This same exercise can be done in the spirit of regression discontinuity exercise by comparing price ratios just before and after the integration where the last panel in table 1 computes the same ratio for 2 months before and after the integration and once again we can see that price ratio jumps up. The only difference in the last case being that here the price ratio jumps up from 1.17 to around 1.8. Since there is seasonality in these price ratios with an yearly cycle, taking ratio just before and after the policy change will give a biased measure of ratio change. As many markets get integrated around September 2014, the two months prior and after belong to two different seasonal cycles as can be seen from figure (1.9). To get correct estimate for change in price ratio, we need to filter out seasonal noise, which can be done by including time fixed effects.

To estimate the impact of market integration policy on price ratio $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$, we run the following regression:

$$\left(\frac{f_i}{f_{Bangalore}}\right)_t = \beta^*\text{Integration}_{it} + \delta_i + \nu_t + \epsilon_{it} \tag{1.25}$$

where β captures the impact of integration on price ratio, while δ_i and ν_t denote market and time fixed effects respectively. Since the data has panel dimension, using the above estimation equation (1.25) also allows us to control for unobserved market heterogeneity through δ_i. The underlying identification assumption in the above equation is that the dummy variable Integration is the only change in market level characteristics and it captures the change in market power of traders.

This assumption also means that integrating market i does not change markup decisions by traders in another market j. This applies to both integrated as well as unintegrated markets. It is good assumption for the unintegrated market since farmers are still captive on such a market without any other outside option. Also, if traders by looking at prices in integrated markets change their markups, they would have to pay increased prices to the traders, thus downward biasing our estimate for β. On the other hand, if traders are active on multiple integrated markets it can potentially change the information flow in the whole market, thereby generating dependence among the integrated markets[12]. But since very few traders are active on multiple markets, the major thrust of policy change comes through increasing the number of local traders on each market, thus changing only the market power μ of traders.

The results of running regression equation (1.25) are shown in table 2. The market integration policy, changes the modal price ratio $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$ by 0.2. Since the average modal price ratio was almost 1, this implies a change of 20% in the modal price ratio or a 16.66% change in value of μ. So, an average integrated market gets 20 percent higher modal price as compared to Bangalore market post integration. The ratio of maximum price also shows similar increase and is 25 percent higher than pre-integration maximum price ratio.

As a robustness measure for the validity of DD strategy, I also check for divergence in trends of price ratios in the integrated vs non-integrated markets. This is done

[12] See Allen(2015) on information value of trade. In the short run we do not expect big changes to take place on this dimension. Also, market prices did not differ too much in the pre-integration period to expect huge change from information flow across regions. Most of the traders on these markets had access to daily price movements across all markets available through internet and local newspapers

by including pseudo treatment indicators for periods before the true treatment. The coefficients on pseudo treatment dummies (two, four and six months before treatment) are close to zero and insignificant and are shown in figure 1.7.

1.5.2 Demand Elasticity, σ

The demand elasticity parameter σ can be recovered by using equation (1.7), which gives the share of consumer spending on each of the agricultural goods. Taking log of equation (1.7) gives us the following estimation equation:

$$ln\,(s_{n,k}) = (1-\sigma)lnp_{n,k} - (1-\sigma)lnP_n + loga_k \tag{1.26}$$

Here, the elasticity parameter can be recovered by regressing log expenditure share $s_{n,k}$ on price $p_{n,k}$ of crop k. Including terms on area fixed effects in the regression will filter out the term corresponding to aggregate price index in region n, while fixed-effect term on crop will give us the crop specific demand shifters a_k.

To estimate demand elasticity, I use 2011-12 NSS data which gives detailed information on household consumer expenditure. The consumer prices are recovered using information on expenditure and quantities which requires correction for measurement errors. Also, there are potential endogeneity issues with the above regression. To correct for these problems, I instrument $p_{n,k}$ by district level median prices with the identification assumption being that supply shocks can be spatially correlated but not the demand shocks. The IV estimate gives an value 2.3 for σ, which is higher than the OLS estimate.

1.5.3 Heterogeneity in Productivity, θ

The equation (1.9) on land shares gives us a way to estimate θ by combining information on district level productivity $A_{i,k}$, farm-gate prices $f_{i,k}$ and land shares $\eta_{i,k}$. Log linearizing equation (1.9) gives us:

$$\log\, A_{i,k}f_{i,k} = \frac{1}{\theta}\log\, \eta_{i,k} + \pi_i + \rho_k + \epsilon_{i,k} \tag{1.27}$$

A high value of $\eta_{i,k}$ points to high value of productivity $A_{i,K}$ in region i for crop k. But farmers can also decide to grow more of crop k if the farm-gate prices $f_{i,k}$ are high. I assume that GAEZ productivity is a noisy measure of productivity and is measured with some error, $\epsilon_{i,k}$. This assumption along with π_i and ρ_k, i.e. region and crop fixed effects respectively, allows me to filter out the supply side shocks. For estimating the above equation, I take mean value of land shares, $\eta_{i,k}$, and farm-gate prices, $f_{i,K}$, from the year 2000-2011, as present in VDSA dataset at the district level. Running the above regression with fixed-effects gives me an estimate of 2.2 for θ.

1.5.4 Other parameters

For the counter-factual exercise, I need to estimate other parameters which I explain here. The spending on crops is available on aggregate level for Karnataka, which is given by $b = 0.2$. The ROW price $p_{F,k}$ for crop k, is measured as average price of these crops across India.

I also estimate the iceberg trade costs $d_{ni,k}$ by using data on freight costs and travel time between region n and i from Allen and Atkin (2016) and freight data which I have collected. The regression of freight costs on travel times gives an estimate for iceberg costs. Lastly, I cannot estimate the margin charged on each crop $u_{i,k}$ separately for each of the regions due to lack of observations on consumer price, so I assume that margin charged on each crop is same across regions and equal to u_k, which I then estimate as mean ratio of consumer price to farm-gate price $p_{i,k}/f_{i,k}$ for regions which produce crop k. Since the iceberg costs satisfy triangle equality, it implies that a region which produces crop k also sells it on its local market.

1.6 Welfare analysis

Having estimated the relevant parameters in the last section, we can now use the model for studying counter-factual scenarios. Although there are 155 separate agricultural *Mandis* in Karnataka, but land use and other data is only available at the district level. So, for the counter-factuals we will restrict model simulation to only 17 markets or districts. Also I include top 11 crops from Karnataka which contribute 85% to the total farm revenue in the state. Also, for foreign trade I assume that it is routed through the capital city of Bangalore. So, iceberg trade cost for international trade from region i will be a product of iceberg cost from region i to Bangalore and then to the ROW.

In the remaining part of this section, we will evaluate two different counter-factual exercises under the assumption that margin charged by intermediaries goes down by 16% across half of the crops. The next two subsections give detail on these two different scenario.

Partial adjustment: In this case, farmers are not allowed to change their cropping decision in the aftermath of policy reform. This can be thought of as a short-term impact of reform, where farmers are stuck with their cropping pattern but reduced margins change the comparative advantage of different regions.

Full adjustment: In the long run farmers would be able to change their cropping decisions to take into account the changed environment. Under full adjustment we solve for competitive equilibrium for new values of μ_k.

The welfare change is calculated from the absolute change in utility of representative consumer in each region. The change under two scenarios is shown in figure 1.8. The first thing to notice from the figure is that under full adjustment all but one region see a positive change in its welfare. Although some regions gain more than others, but on average the welfare gains in this case are 1.3%. The partial adjustment case is not so stark with some regions losing while others gaining on overall welfare. The regions which lose in this case are primarily productive in crops for which μ_k does not change post reform. This means that welfare gains in short run are cornered by regions which grow crops that stand to gain from the change in policy reform.

1.7 Conclusion

The paper has highlighted the important role of market structure in determining intra-national trade costs. It exploits a policy reform, which limited the market power of these intermediaries to estimate the size of margins charged by the intermediaries in agricultural markets in India, thus giving an idea on the size of surplus cornered by intermediaries in developing countries. The presence of such high margins gives another policy tool to reduce intra-national trade barriers, similar to transportation or other infrastructure development.

Using a Ricardian style comparative advantage model of trade in agricultural goods, I also quantify the welfare gains from this policy reform. The counterfactual scenario in the paper was used to evaluate the gains from reducing intermediary margin for different crops. I show that it would lead to an average 1.3% welfare gains in Karnataka in the long run through production adjustments.

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1.9 Appendix

1.9.1 Bargaining

Although μ encompasses a large number of wedges, but can be rationalized as a Nash bargaining problem between farmer and intermediary over total surplus. Let's say:

- Trader's share β and farmer's share $1-\beta$
- Sunk production cost for farmer so bargaining only over final output.
- Nash Bargaining over total surplus pq, which is defined by:

$$max_a \; a^{\beta}(pq-a)^{(1-\beta)}$$

- Trader's share $a = \beta pq$
- Farmer's share $pq-a = (1-\beta)pq = fq$, and he gets paid in terms of farm-gate price, $(1-\beta)p = f$.
- Or, final consumer price $p = \frac{1}{(1-\beta)}f$ and markup- $\mu = \frac{1}{(1-\beta)}$

1.9.2 Equilibrium in algorithm

The equilibrium in the algorithm consists of solving the following equations for prices $p_{i,k}$ and trade $z_{ni,k}$:

Market Clearing:

$$C_{i,k} - q_{i,k} + \sum_{I-i} z_{ij,k} + \sum_{I-i} d_{ji} z_{ji,k} = 0 \;,\; \forall i, k$$

No arbitrage:

$$\begin{aligned} p_{n,k} \leq d_{ni} p_{i,k} \text{ with } z_{ni,k} \geq 0 \;,\; \forall i, j, k \\ \text{and } p_{n,k} = d_{ni} p_{i,k} \text{ iff } z_{ni,k} = 0 \end{aligned}$$

Both $C_{i,k}$ and $q_{i,k}$ are already be solved in terms of other deep parameters and prices, which are directly fed into the algorithm.

1.10 Tables and Figures

Table 1.1: Market Summary

	Non-integrated	Integrated	All
Annual Expenditure (Million Rs)	76.81	73.91	75.5
	(45.23)	(41.46)	(43.44)
Annual Income (Million Rs)	72.14	79.54	75.4
	(43.86)	(42.91)	(43.44)
Area Served (Villages)	65.88	63.93	64.98
	(39.46)	(37.71)	(38.55)
Traders	165	171	166
	(105)	(93)	(103)
Total Markets	84	71	155

Note: Till Sep '15 and all crops — Mean and (standard deviation)

Table 1.2: Change in Groundnut prices

	Dependent variable:		
	modal	max	min
	(1)	(2)	(3)
Integration	148.688**	108.058	−33.697
	(78.352)	(107.455)	(105.529)
Observations	9,912	9,912	9,912
R^2	0.800	0.758	0.727
Adjusted R^2	0.777	0.731	0.696
Residual Std. Error (df = 8917)	289.338	332.456	321.080

Note: Std errors clustered at market-time.

Table 1.3: Change in Maize Prices

	Dependent variable:		
	modal	max	min
	(1)	(2)	(3)
Integration	21.613	12.933	5.008
	(20.370)	(30.052)	(20.254)
Observations	20,473	20,473	20,473
R^2	0.802	0.614	0.753
Adjusted R^2	0.778	0.568	0.724
Residual Std. Error (df = 18306)	61.795	163.665	67.996

Note: Std errors clustered at market-time.

Table 1.4: Mean $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$ for Groundnut

	Full Sample		
	modal	maxP	minP
	(1)	(2)	(3)
Before integration	1.03	1.04	0.91
After integration	1.46	1.52	1.02
Observations	6,618	6,618	6,618
	Only integrated markets		
Before integration	0.96	0.96	0.84
After integration	1.51	1.55	1.10
Observations	5,626	5,626	5,626
	2 months around Integration		
Before integration	1.17	1.20	1.03
After integration	1.80	1.89	1.36
Observations	670	670	670
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 1.5: $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$ on full Sample for Groundnut

	Dependent variable:		
	modal_R	maxP_R	minP_R
	(1)	(2)	(3)
Integration	0.198**	0.252***	−0.023
	(0.081)	(0.071)	(0.079)
Market FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	6,618	6,618	6,618
R^2	0.392	0.413	0.366
Adjusted R^2	0.384	0.406	0.358
Residual Std. Error (df = 6537)	0.502	0.472	0.503
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 1.6: Value of μ

crop	μ
chickpea	1.16
fmillet	1.36
groundnut	2.65
maize	2.52
pigeonpea	2.23
pmillet	1.40
sorghum	1.43
soybean	2.42
sunflower	2.52
rice	2.01
wheat	1.45

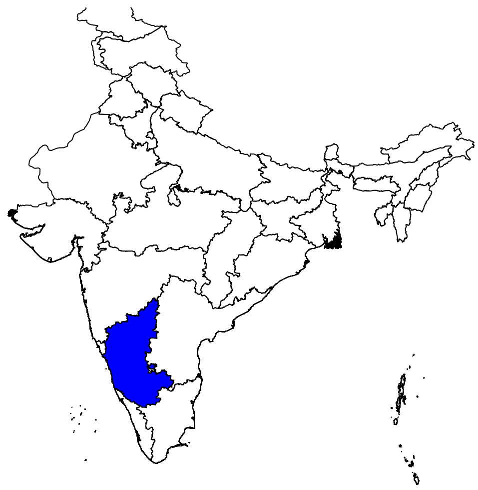

Figure 1.4: Map of India. State of Karnataka (in blue) where reform was implemented

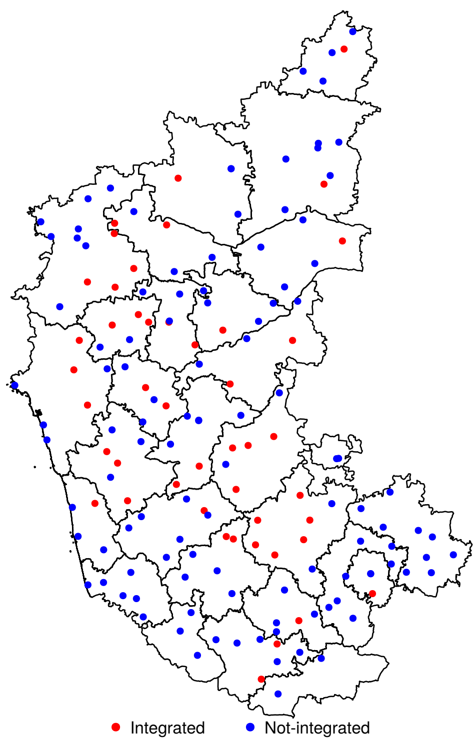

FIGURE 1.5: Integrated Markets in Karnataka

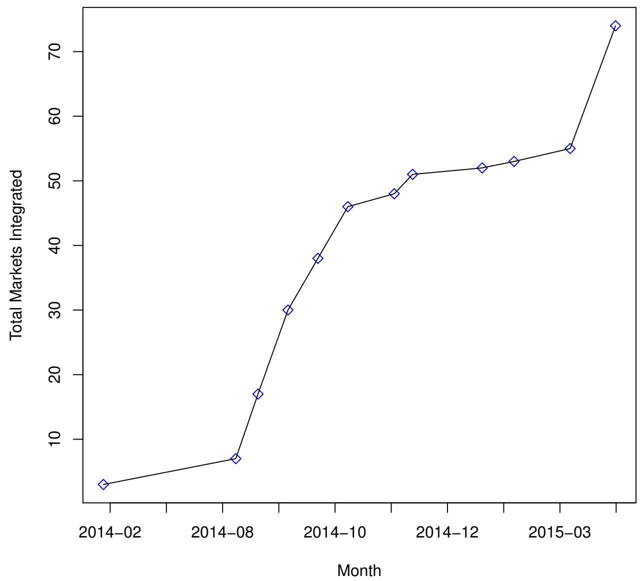

FIGURE 1.6: Cumulative number of markets integrated on the platform over time

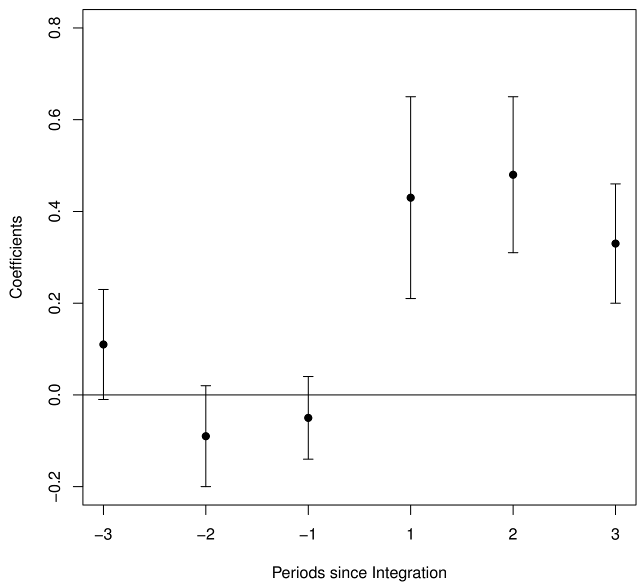

FIGURE 1.7: Testing for parallel trends between integrated and non-integrated markets. Each point on x-axis corresponds to 60 days before/after integration. The y-axis is the coefficient during this period.

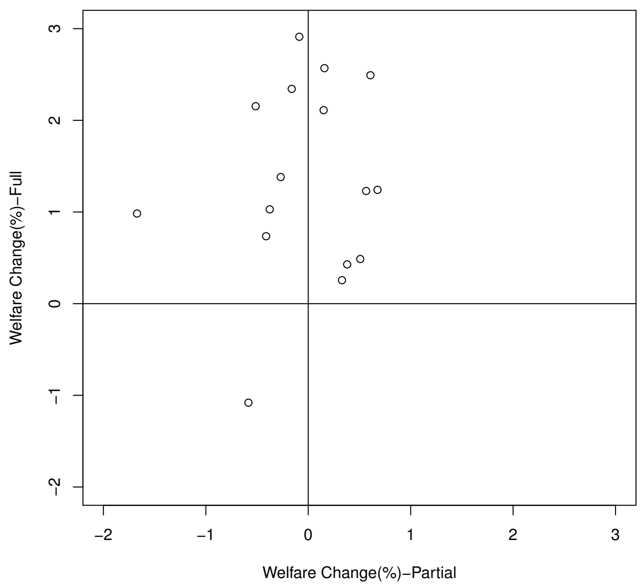

FIGURE 1.8: Comparison of absolute welfare change due to 16% change in markup of six crops: fmillet, groundnut, pigeonpea, pmillet, sunflower and soybean

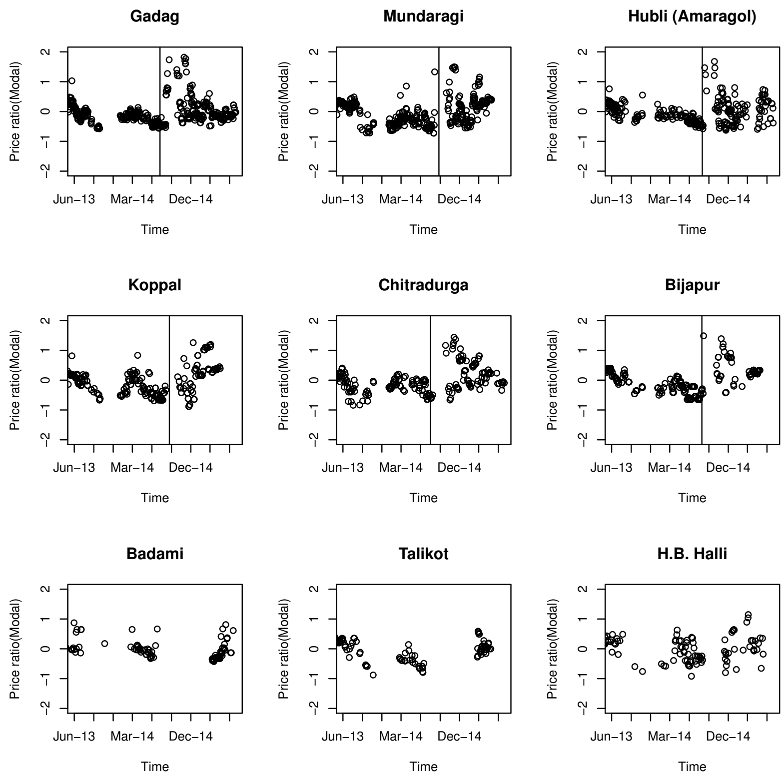

FIGURE 1.9: Each panel shows modal price ratio $\left(\frac{f_{i,k}}{f_{Bangalore,k}}\right)$ after filtering out time and market fixed effects for each market. The vertical line in each panel corresponds to the date of integration for this market in case it got integrated.

Chapter 2

Shock Diffusion: Does inter-sectoral network structure matter?

Abstract

This paper introduces the concept of diffusion of shocks in a macroeconomic network consisting of inter-sectoral production linkages. I show that if sectors have different reaction horizons it would lead to diffusion of shocks through the network over time which prevents the inter-sectoral linkages to form the feedback loop structure essential to generate aggregate volatility. This result is different from other recent papers which have single period model with contemporaneous production linkages between different sectors thus generating sectoral shock amplification as one sector reacts to another contemporaneously resulting in bigger aggregate fluctuations. In contrast if sectors have different production horizons due to varying complexity of their production process or supply chain, it would break down the feedback architecture present in single period models. I further show that if the diffusion rate is varied for different sectors, the contribution of network structure to aggregate volatility can be insignificant. Also, it is no longer sufficient to characterize this contribution of inter-sectoral production network to aggregate volatility by just looking at input-output matrix or its summary statistics like degree distribution. The paper thus highlights the stark difference between the study of financial and inter-sectoral production networks because of the possibility of contemporaneous amplification and hence cascades in the case of financial networks. In the end, I propose lead time indicator as a possible proxy for measuring differential sectoral diffusion rates.

2.1 Introduction

It is one of the oldest debates in economics whether idiosyncractic shocks to individual sectors can generate aggregate volatility in the economy. Beginning with Lucas (1977), who argued that such shocks to individual sectors would die down in the aggregate economy due to diversification, it has been further analyzed in Dupor (1998) and Horvath (1999). With the development of new tools that are available to analyze networks now, there has been a renewed interest in revisiting this old question. This debate has been carried forward in the recent paper by Acemoglu et al(2012) who uses a network argument to show that in the presence of input-output linkages, small idiosyncratic shocks can generate aggregate fluctuations depending on the structure of the network. According to their argument, it is possible to generate such aggregate volatility from idiosyncratic shocks if the input-output network is highly asymmetric and a few big sectors provide input to a large number of other sectors .

Most of the papers with argument in favor of this hypothesis have a static production framework where the productivity shocks propagate contemporaneously through the whole economy in just one period. Due to static nature of the production setup the general equilibrium effects create a feedback loop in their model which allows them to generate big fluctuations on the aggregate level. In contrast, if we allow shocks to diffuse through the network with a certain lag, this feedback loop can break down and can substancially attenuate the amplification of shocks. This paper shows how we can think about diffusion in a production economy and then highlights two aspects associated with inclusion of diffusion and allowing for different diffusion rates between different sectors.

The first part of the paper highlights the difference generated by allowing for a one period diffusion lag in the economy. Here I compare the model presented in Long and Plosser (1983), which is a one period diffusion model, with a zero period diffusion model of Acemoglu et al (2012). Due to contemporaneous production linkages between sectors in case of zero period diffusion model, the aggregate volatility due to sectoral shocks is higher in such an economy. This fact has been shown empirically in the paper by Sarte et al (2011). I further show that in a zero period diffusion model not only the aggregate volatility is higher but the contribution of network linkages to aggregate volatility is also higher. Actually this increase in aggregate volatility is achieved through the hightened role of sectoral linkages, which amplify the shocks due to the contemporaneous production function.

But the actual production economy is far from this contemporaneous production function that is normally used in zero-period models. In the real economy, output from one sector does not act as an input to another sector in the same period. The different sectors in economy have different production horizons and there is a significant time lag between initialization and completion of production. This fact is well presented in the paper by Humphreys et al (2001) where they discuss the importance of input inventories for firms. This idea is captured in the supply chain management and inventory literature by the concept of lead time. Figure 2.1 shows the density plot of average lead time for different sectos at the 3-digit NAICS level. The lead time is measured from M3 database of US census and is the ratio of unfulfilled shipments to value of shipments every month. This ratio can then be converted into weeks to capture production horizon. For eg. the ratio of 1 gives a lead time of one month because the unfulfilled shipments is equal to value of shipments. Now looking at figure 2.1 we can see that average production horizon for sectors is approximately ten weeks but there are significant number of sectors which have to plan their production much far ahead. This clearly highlights the presence of some kind of friction in the sectoral production system and takes us away from the contemporaneous production function. This same effect is further highlighted in figure 2.2 as a response of durable and non-durable goods sector to the Lehman crisis. The non-durable goods have a lower lead time and their production can be adjusted very quickly. The non-durable goods reacted sharply to the 2008 crisis and hit their lowest levels in four months. In contrast, the durable goods have longer production horizon and it took much longer for these sectors to cut their production. Thus it took almost more than a year before the shipments and inventory level of durable goods touched their lowest level.

The second part of the paper builds on this fact about difference in lead times across sectors. Since the sectors have different lead times, they plan their production at different times and thus react to the shock in period t at different times. I subsequently develop a multi-sector model where different sectors have different production horizons and use inputs from different time periods. This eventually gives a model with different diffusion rates for different sectors and further attenuates the amplification of shocks. Now a shock to a given sector i in time period t affects its downstream sectors at different period of time. This creates a

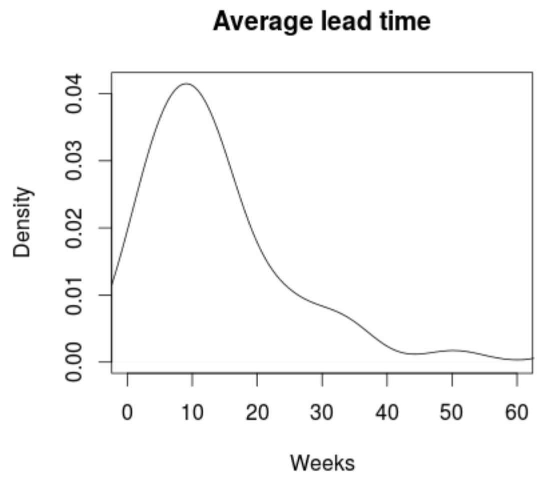

FIGURE 2.1: Average lead time across sectors (3-digit NAICS)

diversification in response of different sectors at any given time. Thus even if a sector has large out-degree i.e. it provides intermediate input to a large number of downstream sectors, the chances of this sector generating aggregate volatility would go down as its downstream sectors have different production horizons and would react to the same shock in different periods.

I finally show that input-output matrix is not a sufficient statistic to understand whether sectoral shocks can generate aggregate volatility. As shown in Acemoglu et al (2012), if the weighted out-degree of sectors has a heavy tailed distribution, it is sufficient to generate aggregate fluctuations from sectoral shocks. In the presence of unequal diffusion rates for different sectors it depends on another measure which I call diffusion adjusted weighted out-degree. This measure in contrast depends both on input-output matrix and diffusion rate of different sectors in the economy. As I would later show the sum of these diffusion adjusted out-degrees for a given sector is equal to the out-degree measure present in zero-period diffusion model. This in turn makes it difficult to generate a heavy tailed distribution for adjusted out-degree measure. So, it is possible but increasingly difficult to generate aggregate volatility from idiosyncratic shocks when sectors have different diffusion rates.

The rest of the paper is organized as follows. In section 2, I develop and compare the two canonical zero-period and one-period diffusion models. This is then used to illustrate the difference in aggregate volatility generated due to this change in assumption. Section 3 provides a sketch of micro-founded production model for

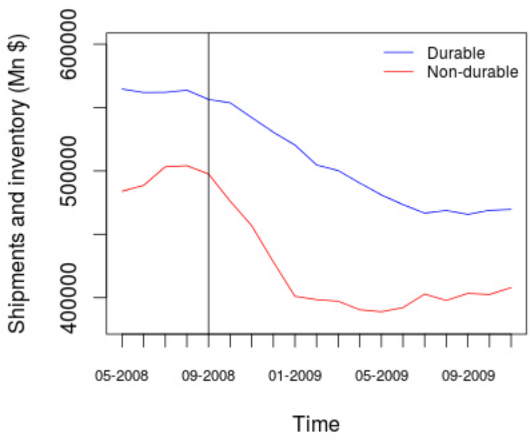

FIGURE 2.2: Reaction of durable and non-durable sectors after Lehmann crisis

sectors with unequal diffusion rates and extend it to a n sectors. This model is then used to highlight the diversification impact of unequal diffusion over time on aggregate volatility. Section 4 concludes.

2.2 Diffusion: Two canonical models

The phenomenon of shock diffusion can be illustrated by comparing two basic models which have been used frequently and interchangably in the literature. The first class consists of models where shocks diffuse in the same period and affect other sectors contemporaneously. This in turn impact their own production decision in the same period and generate a feedback loop. I would call these models as zero period diffusion(0PD) models. Some of these models are presented in Carvalho(2008), Acemoglu et al(2012), Dupor(1998) etc. The second class consists of primarily one period diffusion(1PD) model as presented in Long and Plosser(1983) where firms use inputs from the previous period for production.

In this section, I would present the basic and comparable 0PD and 1PD models as presented in Carvalho(2008) and Long and Plosser(1983). I would then use these models to highlight the difference in contribution of network interconnectivity to aggregate volatility that one can generate from considering the speed of diffusion of shocks.

2.2.1 0PD- Acemoglu et al (2012)

Consider a multisector economy consisting of N different sectors indexed by $i = 1, .., N$. Each sector i produces a different good of quantity Y_{it} at date t using labor L_{it} and input X_{ijt} from other sectors $j = 1, .., N$. The Cobb-Douglas production technology used for production is given by:

$$Y_{it} = Z_{it} L_{it}^{\alpha} \prod_{j=1}^{N} X_{ijt}^{(1-\alpha)\gamma_{ij}} \tag{2.1}$$

$$\triangle Z_{it} = log(\varepsilon_{it}), \varepsilon_{it} \sim N(0, \sigma_i) \tag{2.2}$$

where Z_{it} is the productivity shock to sector i in period t. $\triangle Z_{it}$ is log-normal and i.i.d across sectors and time unless otherwise stated. X_{ijt} is the input from sector j used in the production by sector i.

The production linkages provide the source of interconnectedness between the sectors and is present in the exponent $\gamma_{ij} \geq 0$. This inter-sectoral connectivity can be completely captured by $N \times N$ matrix $\Gamma = [\gamma_{ij}]_{N \times N}$ where element ij corresponds to the share of input j for production in sector i. This matrix Γ would be referred to as input-output matrix in the rest of the paper. For now I assume that share of labor $\alpha \in (0, 1)$ in production is constant across all sectors. The column sums of Γ capture the importance of a sector as an intermediate input for production in other sectors. This is defined as weighted out-degree in Acemoglu et al(2012). I further assume that the production functions exhibit constant returns to scale which is captured by:

Assumption (A1): $\sum_{j=1}^{N} \gamma_{ij} = 1$, for all $i = 1, .., N$

On the consumption side there is a representative agent who derives utility by consuming the above mentioned N goods produced in the economy and supplies one unit of labor inelastically. The utility of this agent is given by:

$$U(C) = E_t \sum_{t=0}^{\infty} \beta^t \overset{[}{i}= 1]N \sum \theta_i ln\, C_{it} \tag{2.3}$$

$$\sum_{i=1}^{N} \theta_i = 1 \quad and \quad \theta_i > 0, \forall i \tag{2.4}$$

Since, there is no inter-temporal decision making involved in production, the above problem can be solved as a set of static problems corresponding to each time period, t. Finally, we can close the model by defining the set of resource constraints:

$$\sum_{i=1}^{N} L_{it} = 1 \tag{2.5}$$

$$C_{it} + \sum_{j=1}^{N} X_{jit} = Y_{it} \quad , \forall i = 1, .., N \tag{2.6}$$

Let $y_{it} = log\, Y_{it}$ and y_t be the vector of log sectoral output. Then, Acemoglu et al(2012) show that the competitive equilibrium of the above economy can be given by:

$$y_t = \mu_0 + [I - (1-\alpha)\Gamma]^{-1} z_t \tag{2.7}$$

where μ_0 is a N-dimensional vector of constants depending on the model parameters. Since, we are interested in aggregate growth volatility we can look at:

$$\triangle y_t = [I - (1-\alpha)\Gamma]^{-1} \varepsilon_t \tag{2.8}$$

Using the fact that all eigenvalues of $(1-\alpha)\Gamma$ are strictly less than one, we can express the above equation as a power series:

$$\triangle y_t = \sum_{k=0}^{\infty} [(1-\alpha)\Gamma]^k \Bigg] \varepsilon_t \approx [I + (1-\alpha)\Gamma]\, \varepsilon_t \tag{2.9}$$

I have ignored the second order interconnections in the above equation because it would make it easier to compare it with one period diffusion model. Although it is well documented that in a network economy second order interconnections can also matter. As I will show later, the ignored second order terms would be present in case of 1PD model as well, so we do not loose much in terms of comparison. Using the above equation, Acemoglu et al(2012) later show how aggregate volatility of economy would depend on weighted out-degree of sectors. This captures the relative importance of a sector as input to all other sectors. Given a fat-tailed distribution of weighted out-degrees one will obtain that aggregate volatility does not decay at rate $\sqrt{n}$. For now, lets look at the aggregate volatility from a practical point of view:

$$Var_{0PD}(\triangle y_t) = \Sigma_{\varepsilon\varepsilon} + (1-\alpha)^2 \Gamma \Sigma_{\varepsilon\varepsilon} \Gamma' + (1-\alpha)\Sigma_{\varepsilon\varepsilon}\Gamma' + (1-\alpha)\Gamma\Sigma_{\varepsilon\varepsilon}$$

Since we are interested in aggregate volatility, we can use an aggregate statistic:

$$Vol_{0PD}(\triangle y) = \frac{1}{N^2}\mathbf{1}' Var_{0PD}(\triangle y_t)\mathbf{1} \tag{2.10}$$

This aggregate volatility statistic is based on giving equal weight to all sectors, but it is possible to use a more realistic weighted measure when taking the model to the data. For volatility analysis, this statistic has been used frequently in the literature (see Horvath, 1998, or Dupor, 1999 or Carvalho, 2008). But comparison of the 0PD and 1PD model would be the same even if we were to consider any other sectoral weights.

2.2.2 1PD- Long and Plosser (1983)

The 0PD model is very similar to the classic Long and Plosser (1983) model. Now, the production in sector i in period t depends on the inputs purchased in period $t-1$. The production is given by:

$$Y_{it} = Z_{it} L_{it-1}^{\alpha} \prod_{j=1}^{N} X_{ijt-1}^{(1-\alpha)\gamma_{ij}} \tag{2.11}$$

The problem of the representative household remains the same as in the previous 0PD model. The resource constraint also remains the same except that the input X_{ijt} from sector j to i is used for production in period $t+1$:

$$C_{it} + \sum_{j=1}^{N} X_{jit} = Y_{it} \quad , \forall i = 1, .., N \tag{2.12}$$

We can again denote the log sectoral output as y_t and solve for planner's problem. Long and Plosser (1983) show that the solution to planner's problem is given by:

$$y_t = \mu_1 + (1-\alpha)\Gamma y_{t-1} + z_t \tag{2.13}$$

where μ_1 is a N-dimensional vector of constants depending on the model parameters. Since, we are interested in aggregate volatility we can work with demeaned output:

$$\triangle y_t = \left[I - (1-\alpha)\Gamma \boldsymbol{L}\right]^{-1} \varepsilon_t \tag{2.14}$$

where $\boldsymbol{L}$ is the lag operator. We can again express the above equation as a power series:

$$\triangle y_t = \left[\sum_{k=0}^{\infty} [(1-\alpha)\Gamma \boldsymbol{L}]^k \right] \varepsilon_t \approx [I + (1-\alpha)\Gamma \boldsymbol{L}] \, \varepsilon_t = \varepsilon_t + (1-\alpha)\Gamma \varepsilon_{t-1} \tag{2.15}$$

Similar to 0PD model, now we can write sectoral and aggregate volatility terms for 1PD diffusion model:

$$Var_{1PD}(\triangle y_t) = \Sigma_{\varepsilon\varepsilon} + (1-\alpha)^2 \Gamma \Sigma_{\varepsilon\varepsilon} \Gamma'$$

$$Vol_{1PD}(\triangle y) = \frac{1}{N^2} \mathbf{1}' Var_{1PD}(\triangle y_t) \mathbf{1} \tag{2.16}$$

One key point to differentiate 1PD model from 0PD is the timing for usage of inputs. In 0PD model, the shock from sector i immediately propagates to other sector and then affects sector i production through general equilibrium effect. This generates a feedback loop and amplification of shocks. In 1PD model on the other hand, shocks do affect other sectors but only with a lag of one period due to the time constraint on production. Now a shock to a sector i has a contemporaneous effect on itself but only a lagged one on all others, therefore there is no feedback from the other sectors to the sector i and in turn again on other sectors. This partially closes down the amplification channel as present in 0PD model.

It is a common practice to treat all these models interchangeably but as shown above they are very different in their amplification potential. This point has been ignored in other papers where the models can have extended framework involving capital and labor but inputs are produced and used in the same period. For eg. the model in Horvath (1998) solves infinite horizon problem for the social planner but still uses inputs produced in the same period. The output dependence on previous period comes only through the capital market. In terms of production linkages it is still a 0PD model and allows for contemporaneous feedback and amplification of shocks in production. On the other hand, the 1PD model uses inputs from previous periods and do not allow contemporaneous amplification of shocks through network structure.

2.2.3 0PD vs 1PD models

Proposition 1: The aggregate volatility in case of 0PD model is always higher than 1PD model:

$$Vol_{0PD}(\triangle y) > Vol_{1PD}(\triangle y) \tag{2.17}$$

The result here follows directly from the definition of aggregate volatility for the two models. The result will hold even if we include higher order terms in the power series expansion due to the fact that 0PD model will always include the volatility terms present in 1PD model. The reason for different aggregate volatility is due to production lag in case of 1PD model which leads to dropping out the variance term involving cross product of ε_t and $(1-\alpha)\Gamma\varepsilon_{t-1}$. Under the assumption of no auto-correlation of shocks across sectors, this cross product term is completely dropped out. But the result would hold even if there is small auto-correlation between shocks over time.

Definition : Network contribution to aggregate volatility(NC) is the fraction of volatility contributed by the terms involving network structure parameters. It can be defined as:

$$NC = 1 - \frac{\mathbf{1}'\Sigma_{\varepsilon\varepsilon}\mathbf{1}}{Vol(\triangle y)} \tag{2.18}$$

Network contribution is an important metric because it shows the importance of inter-sectoral linkages in generating aggregate volatility. If there were no intersectoral linkages, the aggregate volatility will just be the sum of sector level variances and is captured by the term $\mathbf{1}'\Sigma_{\varepsilon\varepsilon}\mathbf{1}$. The other terms in aggregate volatility contain Γ, which captures the increase in aggregate volatility due to inter-sectoral linkages.

Proposition 2: The network contribution to aggregate volatility is always higher for 0PD model:

$$NC_{0PD} > NC_{1PD} \tag{2.19}$$

Proof: The result follows directly from proposition 1. Since, the non-network term, $\mathbf{1}'\Sigma_{\varepsilon\varepsilon}\mathbf{1}$ in aggregate volatility is the same for both 0PD and 1PD models and aggregate volatility is higher for 0PD model. So we get:

$$\frac{\mathbf{1}'\Sigma_{\varepsilon\varepsilon}\mathbf{1}}{Vol_{0PD}(y)} < \frac{\mathbf{1}'\Sigma_{\varepsilon\varepsilon}\mathbf{1}}{Vol_{1PD}(y)} \tag{2.20}$$

2.2.4 Irrelevance of higher order diffusion process

The 1PD Long and Plosser (1983) model can be written similarly for a n-period diffusion model, with production lag of n periods. This model would seem to correspond to a slower rate of diffusion of shocks in the economy. But any such model would have no fundamental difference with 1PD model in terms of aggregate volatility. This can be summarized by:

Definition : The vector of sectoral growth rates for an n-period diffusion model will be given by:

$$\triangle y_t = \left[I - (1-\alpha)\Gamma \boldsymbol{L}^n\right]^{-1} \varepsilon_t \approx \varepsilon_t + (1-\alpha)\Gamma\varepsilon_{t-n} \tag{2.21}$$

Proposition 3: The aggregate volatility or NC do not depend on production lag i.e.:

$$Vol_{1PD}(\triangle y) = Vol_{2PD}(\triangle y)... = Vol_{nPD}(\triangle y) \tag{2.22}$$

$$NC_{1PD}(\triangle y) = NC_{2PD}(\triangle y)... = NC_{nPD}(\triangle y) \tag{2.23}$$

The above proposition shows that all production lags give the same value for aggregate volatility as well as the network contribution to aggregate volatility. This follows from the fact that demeaned output vector depends on two terms; current shock, ε_t and a lagged shock, ε_{t-n} times the network term $(1-\alpha)\Gamma$. In terms of diffusion process the nPD is no different than 1PD because period, t output only depends on lagged output from one other period. In case of 1PD, this input comes from period $t-1$ and in case of nPD it comes from $t-n$. So it does not have any additional dampening effects. In contrast if firms were allowed and find it optimal to smoothen their response to shock from period $t-n$ for n periods, then the results could be different.

But at the same time, the above proposition also highlights the difference between contemporaneous production process as in 0PD model and a lagged production process in any nPD model. So for the case where firms are not allowed to smoothen their response over n periods, proposition 3 would apply and considering a production processes with more than one period lag will not change any results. For all practical purposes, one can use 0PD and 1PD models to highlight the difference caused by diffusion rate.

2.3 Model: Unequal diffusion rate(UDR)

Since different sectors have different production horizons, it makes sense to study a model where all sectors do not react to shocks at the same time. As discussed in the introduction and explained through figure 2.1, average lead time varies significantly for different sectors and determines their production horizon. The sector with small production horizon would buy its input just preceding production, while another sector with a longer production horizon might contract its inputs multiple periods before production can begin.

This difference in production horizon would create a difference in how sectors react to shocks. A sector with longer production horizon would react with a delay to the shock to its upstream sectors. Consider a sector which buys its inputs in period $t-2$ for production in period t. Since the sector is unable to tinker or change its production quickly, the shock to its supplier in period $t-2$ can affect it only in period t. In comparison, a sector which purchases its input in period $t-1$ for production in period t would react in period t if there is any shock to its suppliers in period $t-1$. In a multi-sector setting this would lead to slow diffusion of shocks through a sector with longer production horizon. Thus a multi-sector model with sectors having different production horizons would generate unequal diffusion rate of shocks in different parts of the economy.

2.3.1 3-sector economy

Consider a 3-sector model with the restrictions discussed above. The setting is similar to Long and Plosser (1983) with one change. Sector 1 and 2 have a small production horizon and use inputs from period $t-1$ for production in period t. On the other hand, sector 3 has a longer production horizon and uses inputs from period $t-2$ for production in period t. The production in the economy is given by:

$$Y_{it} = Z_{it} L_{it-1}^{\alpha} \prod_{j=1}^{N} X_{ijt-1}^{(1-\alpha)\gamma_{ij}} \quad \forall i = 1, 2 \tag{2.24}$$

$$Y_{3t} = Z_{3t} L_{3t-2}^{\alpha} \prod_{j=1}^{N} X_{3jt-2}^{(1-\alpha)\gamma_{ij}} \tag{2.25}$$

where Z_{it} is the productivity shock to sector i in period t and ε_t is log-normal and i.i.d. as before. The representative agent wants to maximize life-time utility and his per period utility is given by:

$$U(C_t) = \sum_{i=1}^{N} \theta_i ln\, C_{it} \tag{2.26}$$

The restrictions on the utility are same as in section 2. The resource constraint is also same, except that now sector 3 buys input in period t and uses it in period $t+2$:

$$C_{it} + \sum_{j=1}^{N} X_{jit} = Y_{it} \quad , \forall i = 1, .., N \tag{2.27}$$

Now, we can solve the planner's problem for this economy. The planner wants to maximize the expected lifetime utility of the agent subject to production functions given in (3.1) and (3.2), resource constraint (3.4) and labor market clearing conditions. This can be expressed as a value function problem:

$$V(S_t) = max \quad \{U(C_t) + \beta V(S_{t+1}|S_t) \tag{2.28}$$

where $S_t = (Y_t, Z_t)$ is the set of state variables. This problem can be solved by "guess and verify", which gives the following solution:

$$V(S_t) = k_1 ln\, Y_{1t} + k_2 ln\, Y_{2t} + k_3 ln\, Y_{3t+1} + J(Z_t) + K \tag{2.29}$$

where k_i is a set of constants given by:

$$k_i = \theta_i + \beta \sum_{j=1}^{3} k_j \gamma_{ji}, \quad \forall i = 1, 2, 3 \tag{2.30}$$

$J(Z_t)$ depends on production uncertainty parameters while K is also constant and do not depend on Y_t or Z_t. This finally gives us the consumption and input quantities at time t as given in the appendix.

Given the solution above, we can now focus on output in different sectors. It would help us compare the solution obtained here with that in the previous section. The log output for unequal diffusion rate (UDR) model is given by:

$$y_{1t} = \mu_{udr1} + (1-\alpha)\left[\gamma_{11}y_{1t-1} + \gamma_{12}y_{t-2} + \gamma_{13}y_{t-3}\right] + z_{1t} \tag{2.31}$$

$$y_{2t} = \mu_{udr2} + (1-\alpha)\left[\gamma_{21}y_{1t-1} + \gamma_{22}y_{t-2} + \gamma_{23}y_{t-3}\right] + z_{2t} \tag{2.32}$$

$$y_{3t} = \mu_{udr3} + (1-\alpha)\left[\gamma_{31}y_{1t-1} + \gamma_{32}y_{t-2} + \gamma_{33}y_{t-3}\right] + z_{3t} \tag{2.33}$$

where μ_{udr} terms are constants that depend on model parameters. The above solution can be better summarized in matrix form below:

$$y_t = \mu_{udr} + (1-\alpha)\left[\Gamma_1 y_{t-1} + \Gamma_2 y_{t-2}\right] + z_t \tag{2.34}$$

$$\triangle y_t = (1-\alpha)\left[\Gamma_1 \triangle y_{t-1} + \Gamma_2 \triangle y_{t-2}\right] + \varepsilon_t \tag{2.35}$$

where

$$\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ 0 & 0 & 0 \end{bmatrix} \quad and \quad \Gamma_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix} \tag{2.36}$$

$$\Gamma = \Gamma_1 + \Gamma_2 \tag{2.37}$$

The above equation 2.34 captures the dynamics of the economy. The input-output matrix Γ still governs how sectoral outputs affect future production but it now gets split up in two matrices Γ_1 and Γ_2. Sectors 1 and 2 which have a production horizon of 1 period gets directly affected through Γ_1 where subscript 1 corresponds to 1-period production horizon. Sector 3, since it has a different production horizon of 2 periods gets directly impacted through Γ_2 from shocks that hit the economy in period $t-2$.

2.3.2 n-sector economy

Given the mechanism in the last sub-section we can easily get a reduced form solution for any n-sector economy with production linkages. Any such economy where sectors can have up to p-periods of production horizon will have a solution of VAR(P) form given by:

$$y_t = \mu_{udr} + (1-\alpha)\left[\Gamma_1 y_{t-1} + ... + \Gamma_p y_{t-p}\right] + z_t \tag{2.38}$$

$$\triangle y_t = \left[I - (1-\alpha)\left[\Gamma_1 \boldsymbol{L} + ... + \Gamma_P \mathbf{L^P}\right]\right]^{-1} \varepsilon_t \tag{2.39}$$

$$\triangle y_t \approx \left[I + (1-\alpha)\left[\Gamma_1 \mathbf{L} + ... + \Gamma_P \mathbf{L^P}\right]\right] \varepsilon_t \tag{2.40}$$

$$\Gamma = \Gamma_1 + .. + \Gamma_P \tag{2.41}$$

The solution to n-sector and P period production horizon economy has an easy reduced form as shown in equation 2.38. Since the economy now has sectors with P different production horizons, the input-output matrix Γ gets split up into P components.

2.3.3 1PD vs UDR models

Proposition 4: The aggregate volatility in case of 0PD and 1PD models is always higher than UDR model:

$$Vol_{0PD}(y) > Vol_{1PD}(y) > Vol_{UPR}(y) \tag{2.42}$$

Proof: It follows from the definition of $Vol_{1PD}(y)$ and $Vol_{UDR}(y)$as below:

$$Vol_{1PD}(y) = \frac{1}{N^2}\mathbf{1}' \left[\Sigma_{\varepsilon\varepsilon} + (1-\alpha)^2 \Gamma \Sigma_{\varepsilon\varepsilon}\Gamma'\right]\mathbf{1}$$

$$= \frac{1}{N^2}\mathbf{1}' \left[\Sigma_{\varepsilon\varepsilon} + (1-\alpha)^2 \left[\Gamma_1 + .. + \Gamma_p\right] \Sigma_{\varepsilon\varepsilon} \left[\Gamma_1 + .. + \Gamma_p\right]'\right]\mathbf{1}$$

$$> \frac{1}{N^2}\mathbf{1}' \left[\Sigma_{\varepsilon\varepsilon} + (1-\alpha)^2 \left[\Gamma_1 \Sigma_{\varepsilon\varepsilon}\Gamma_1' + .. + \Gamma_p \Sigma_{\varepsilon\varepsilon}\Gamma_p'\right]\right]\mathbf{1} = Vol_{UPD}(y)$$

This proposition establishes the decreases in aggregate volatility caused due to unequal diffusion rates over different sectors. The unequal diffusion rates spread the impact of a shock to sector i in period t across different periods for its different downstream consumers. It is essential for all the downstream sectors to react contemporaneously to one shock to generate substantial aggregate volatility. But unequal diffusion rates close down this amplification channel and do not allow for contemporaneous reaction for all sectors. I will further show in next subsection below how this addition of time dimension to shock propagation can affect asymptotic properties.

The mechanism is better explained by looking at figure 2.3. Sector 1 is the only input supplier in the economy and supplies to all other sectors in the economy. The upper half of the figure corresponds to 1-period diffusion model. Here, a shock hits sector 1 in period t and then affects all the downstream sectors together in period $t+1$. Now compare this to the bottom half of the figure which represents an unequal diffusion rate economy where sectors 2 and 3 buy their input with 1 period production lag while 4 and 5 buy with 2 period production lag. In this second

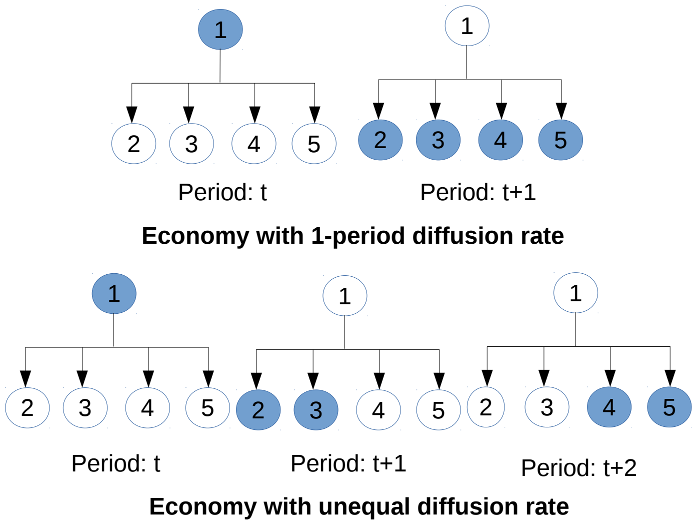

FIGURE 2.3: Shock propagation through the economy. Blue color correspond to sectors currently affected by shock that hit sector 1 in period t.

economy, the shock to sector 1 affects different parts of economy at different times. Thus on the aggregate the contribution of this shock that hits sector 1 in period t to aggregate volatility is diminished as all sectors do not react at the same time. So, even if a sector is supplier to a large number of downstream sectors its impact on aggregate volatility is diminished due to this spread of shock over time.

Proposition 5: The network contribution to aggregate volatility is also lower for UDR model:

$$NC_{0PD}(y) > NC_{1PD}(y) > NC_{UDR}(y) \tag{2.43}$$

Proof: The result follows the proof as given in Proposition 2.

Since the aggregate volatility goes down in case of UDR model, it also has a negative impact on network contribution to aggregate volatility. The diversification of the impact of period t shocks over time leads to smaller amplification of shocks due to network. This in turn decreases the contribution of network structure to aggregate volatility.

2.3.4 Asymptotic properties

Definition : Diffusion adjusted out-degree of a sector is the weighted out-degree measure adjusted for diffusion:

$$d_{pi} = \sum_{j=1}^{N} w_{ji}^{p} \quad where \quad w_{ji}^{p} \in \Gamma_p \tag{2.44}$$

The adjusted out-degree, d_{pi} measures the contribution of sector i as an input for period t production in other sectors which use input factors from period $t-p$. This adjusted out-degree is closely related to the weighted out-degree measure, d_i:

$$d_{pi} \leq d_i \quad \forall p, i \tag{2.45}$$

$$\sum_{p=1}^{P} d_{pi} = d_i \quad \forall i = 1, .., N \tag{2.46}$$

So, in an economy populated by sectors with P different production horizons, we would have $P \times N$ adjusted out-degree measures, d_{pi}, corresponding to lag p and sector i. The above two equations 2.45 and 2.46 follow directly from the fact that input-output matrix $\Gamma = \Gamma_1 + .. + \Gamma_P$. Since $d_{pi} \leq d_i$, it highlights the fact that sector i can be a big input supplier in the whole economy, but if sectors have different production horizons, on average the contribution of sector i production in period t an an input to other sectors can be small in subsequent periods. Thus unequal diffusion rate forces us to make the distinction between weighted out-degree, d_i and adjusted out-degree, d_{pi}.

Assumption 2(A2): The sectoral growth volatility is same across all sectors i.e. $\sigma_i = \sigma \quad \forall i = 1, .., N$.

The asymptotic results can be shown to hold for any general case where the sectoral volatility σ_i are bounded above by a finite constant. Here I have considered a simple case for illustration purpose, but can be extended as in Acemoglu et al (2012). Given assumption 3 we can now write:

Proposition 6: Under A3 and considering first order-interconnections the volatility for different diffusion models can be given by:

$$Vol_{0PD}(\triangle y)^{1/2} = Vol_{1PD}(\triangle y)^{1/2} = \Omega\left(\frac{1}{n}\sqrt{\sum_{i=1}^{n} d_i^2}\right) \tag{2.47}$$

$$Vol_{UDR}(\triangle y)^{1/2} = \Omega\left(\frac{1}{n}\sqrt{\sum_{i=1}^{n}\sum_{p=1}^{P} d_{pi}^2}\right) \tag{2.48}$$

If a few sectors provide large fraction of input supplies in the economy, this asymmetry between sectors can force the aggregate volatility to decay at a rate slower than $\sqrt{n}$. As shown in Acemoglu et al (2012), a heavy tailed distribution for d_i is enough to show that aggregate volatility decreases at a rate slower than the usual diversification argument. This result is reiterated in equation 2.47, where the zero-period output growth volatility is bounded below by average sum of squares of weighted out-degree, d_i. In contrast for an economy with unequal diffusion rates, the volatility has a different lower bound given by average sum of squares of adjusted weighted out-degree, d_{pi}.

Thus the above proposition establishes the difference in asymptotic properties that can arise depending on whether we consider shock diffusion in the economy or not. Depending on the distribution of d_i and d_{pi}, these two economies can have different decay rates for aggregate volatility. So, when we take unequal diffusion rates for different sectors into consideration it can possibly change the asymptotic properties of aggregate volatility in the economy. Also given equation 2.46, we know that the sum of d_{pi} over p periods is equal d_i. Given sufficient difference in diffusion rates across sectors, this could imply a substantial difference in distributions of d_i and d_{pi}. If d_{pi} turns out to be not so heavy tailed, then sectoral shocks would fail to generate aggregate volatility.

Another important implication of the above proposition is that input-output matrix is no longer a sufficient statistic for characterizing the role of idiosyncratic sectoral shocks in generating aggregate volatility. The aggregate volatility now depends on d_{pi} which in turn depends on both input-output structure and diffusion rate across sectors. It is possible to get the empirical counterpart of the above measure d_{pi}. The input-output matrix is usually available from national accounts, while lead time indicator can be used as a proxy for different production horizon or diffusion rate of sectors. I would explore this empirical dimension in the future version of this paper.

2.4 Application

In this section, I look at the structure of US economy and study whether we can find some evidence for variable diffusion of shocks in the economy. The first part provides preliminary evidence in this regard while the second section will look at the implication of different diffusion rates in the economy.

2.4.1 Reaction to Lehmann Crisis

To highlight the different reaction times, we can look at the reaction rates of different sectors in the aftermath of Lehmann crisis. The sectors which allowed

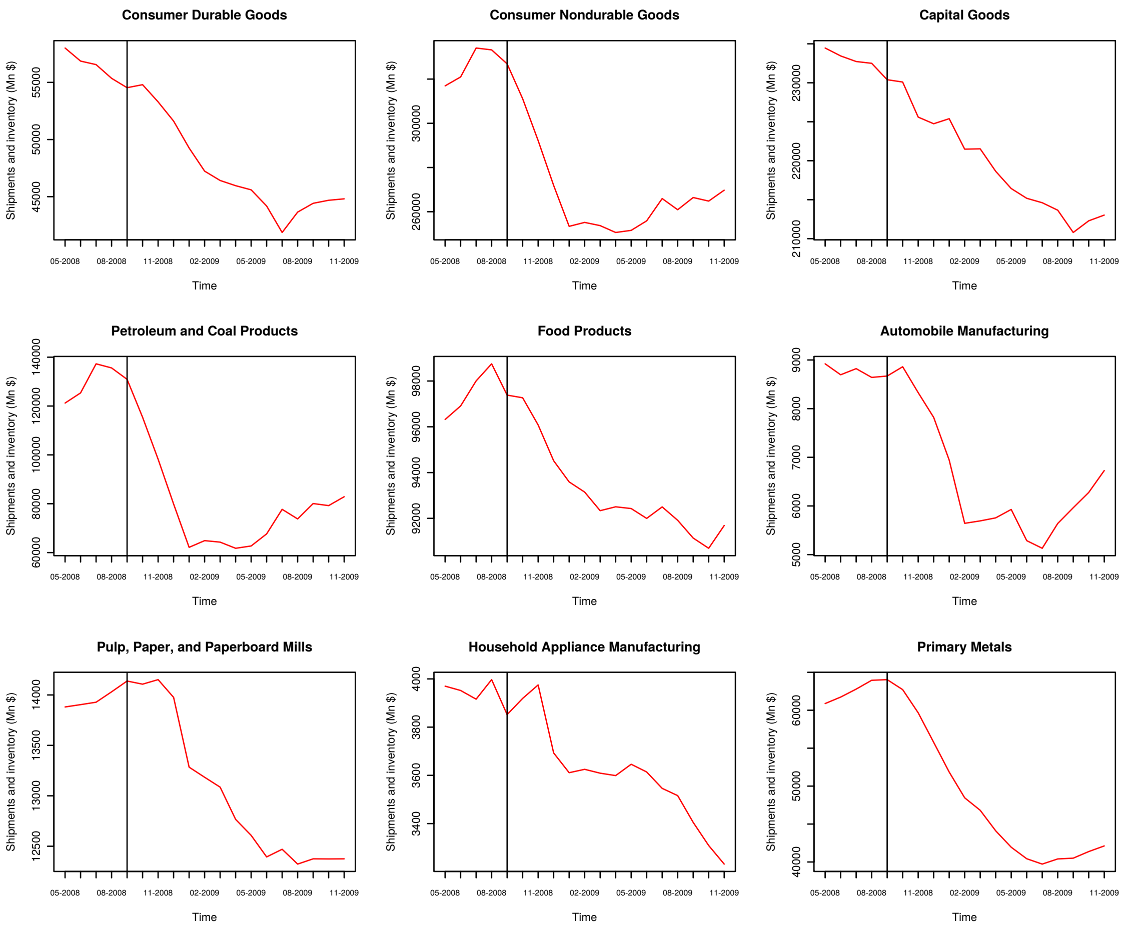

FIGURE 2.4: Movement of shipments plus inventory in different sectors to Lehmann crisis

quick adjustment would react quickly to the shock and adjust their production decisions. This would then be reflected in their shipment levels and inventory.

For this purpose, I use shipments and inventory data from Bureau of Economic Analysis and plot the reaction of different sectors in the months following the Lehmann crisis. The plots in figure 2.4 and figure 2.5 show the reaction times of different sectors.

Figure 2.4 gives the reaction of shipments plus inventory for different sectors after Lehmann went bankrupt in September 2008. The sum of shipments and inventory is a proxy for production of the sector. The vertical line on the graph corresponds to the cut-off month for Lehmann bankruptcy. The first thing to notice from these graphs is that not all sectors reacted to this shock at the same rate. Some sectors like consumer non-durables and petroleum and coal products reacted more by instantaneously cutting down their production and reached their lowest levels

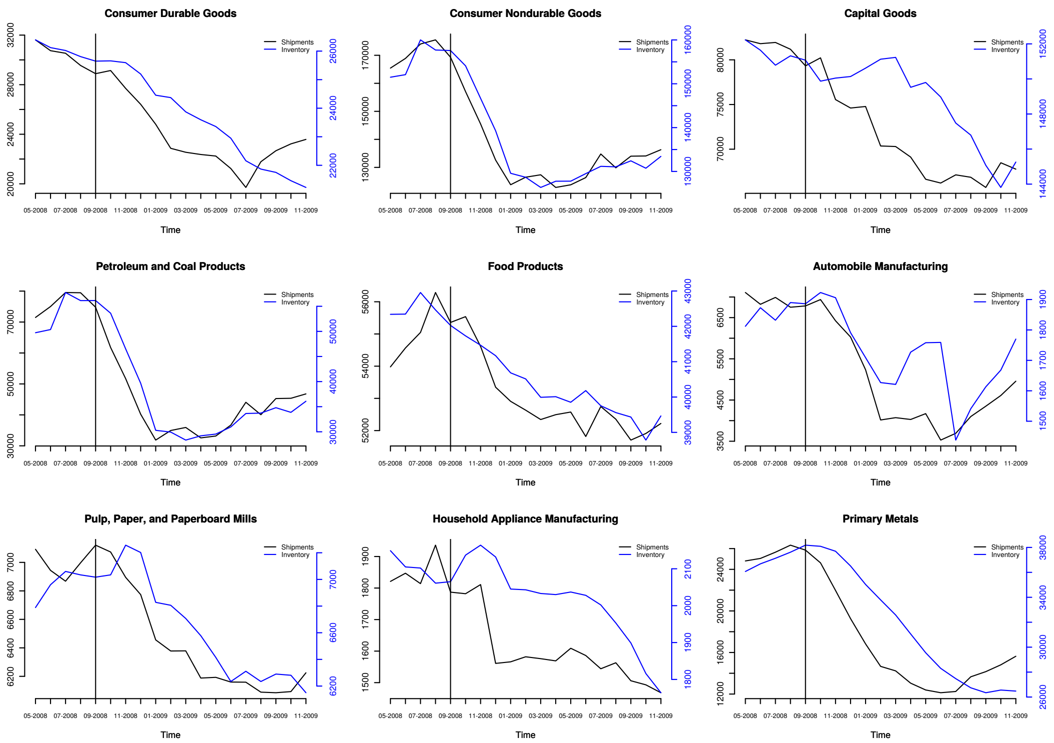

FIGURE 2.5: Movement of shipments and inventory in different sectors to Lehmann crisis

in the following three to four months. On the other hand, some other sectors like consumer durables and capital goods took much longer to reach their lowest output levels which happened in almost one year. This gives evidence for the fact that shock propagation through the macro economy depends on sectoral diffusion rates.

Although in the above plot, all the sectors start reacting to the shock more or less at the same time but they still differ in their adjustment rate- some cut down their production relatively quickly compared to others. This factor is not captured in the model presented in the previous section but can be included in a richer model with inventory which allows for some forward looking adjustment by different sectors. But the plots in figure 2.4 need some more analysis about sectoral shock propagation because the above plots actually show sectoral reaction to an aggregate shock (Lehmann bankruptcy was a major event and triggered the reactions on a national level). Since the reaction rates for different sectors are so different for an aggregate level shock, we can expect that sectors would react with different lags for TFP shock to an individual sector, the main assumption of this paper.

This fact becomes more clear when we look at the breakdown of inventory and shipments in figure 2.5. The two sectors which stand out in this figure are capital goods and household appliance manufacturing. Due to the shock their shipments fall relatively quickly when compared to their inventory levels. Infact, the inventory levels in these two sectors remain fairly constant for few months as compared to other sectors which means these sectors did not rapidly cut down their production levels, thus leading to an accumulation of inventory. It is only after six or eight months that these sectors reduced their output levels enough to bring down the levels of their inventory.

For most other sectors both inventory and shipments fall at the same rate. So, in general shipments plus inventory seems a good proxy for sectoral prodution and can potentially be used to quantify diffusion rates. But again what comes out of this figure 2.5 is that sectors react differently to an aggregate shock. So in case of a sectoral shock they would probably react even more slowly, which can be due to lack of contemporaneous information about the shock or production frictions as argued in the previous section.

2.4.2 Outdegree distribution

In this section, we do the same exercise as in Acemoglu et al(2012) and look at the out-degree distribution in the context of US economy. The difference in this case is that we also plot the out-degrees after accounting for different diffusion rates of different sectors. The diffusion rates are proxied by lead time of different sectors. Since the different sectors in economy have different production horizons, there is a time lag between initialization and completion of production and this is captured by lead time indicator. The different lead times for different sectors can be inferred from the Figure 2.1 in the introduction. Unlike Acemoglu, here I restrict my attention to the manufacturing sector of the US economy because I do not have any lead time style proxy for other sectors.

I use the detailed benchmark input–output accounts from 2007, compiled by the Bureau of Economic Analysis for the exercise in this section. BEA provides commodity-by- commodity direct requirements tables, where the typical (ij) entry captures the value of spending on commodity i per dollar of production of commodity j. As detailed above, I restrict my attention only to the manufacturing

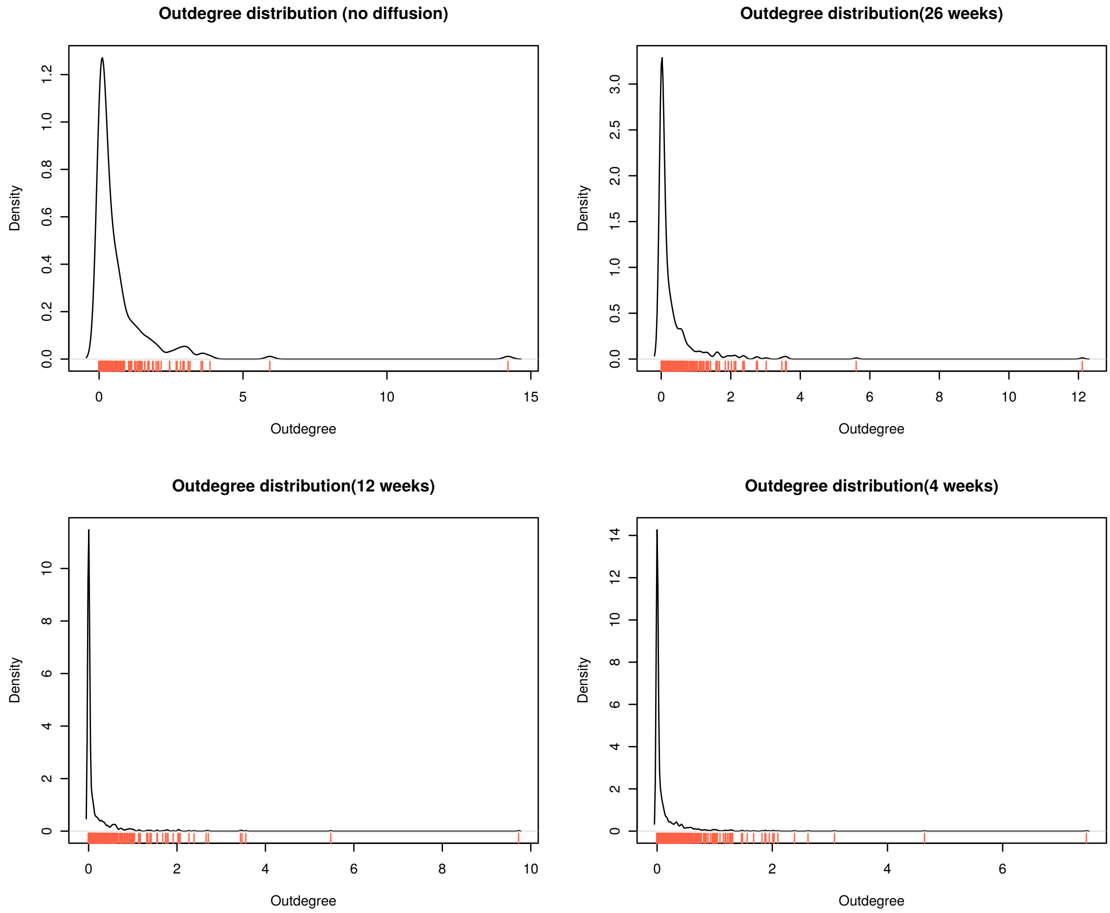

FIGURE 2.6: Distribution of diffusion adjusted out-degrees for different lead-time cutoffs

sector which gives me 237 sectors that roughly correspond to four-digit NAICS level.

As argued before, I use lead time as a proxy for diffusion rates of different sectors. The lead time of different sectors is calculated by dividing unfulfilled orders by value of shipments in a given month. I use the monthly average lead time value over the period 1991-2008 for the calculations in this section. The lead time values are not available at 4-digit level and I can only calculate it for 42 distinct sectors. These 42 sectors are both at 3 or 4-digit NAICS level. This means that lead time is not available at the same disaggregated level as input-output table which has 237 sectors. The 4-digit NAICS sectors in the direct requirements that do not have a corresponding 4-digit lead time indicator, I assign them the lead time value for 3-digit NAICS. This would give me similar diffusion rates for many sectors and would thus lead to less differentiated diffusion rates on a finer sectoral level.

Figure 2.6 shows the density plots of weighted out-degree for different diffusion rates depending on how we split up the economy based on sectoral lead times. The top-left panel in this figure corresponds to the case where we do not account for different diffusion rates. It is similar to the case presented in other network models like in Acemoglu et al(2012). The top right panel corresponds to dividing sectors into two categories, those with lead time less than 26 weeks and others with lead time more than 26 weeks. This gives us two different diffusion rates for the sectors in this economy where the diffusion adjusted weighted out-degree are calculated from Γ_1 and Γ_2 as in equation 2.38. The bottom left panel similarly corresponds to the case when we split sectors by lead time cutoffs 12, 24, 36 and above weeks. Finally, the bottom right panel corresponds to the case with bins created using 4, 8, 12, 24 and above week slices of lead time.

What the results in the above graphs show is that once we start accounting for differential diffusion rates, the sectors with very high weighted out-degree starts to fall. This makes it difficult to generate heavy tailed distribution of the diffusion adjusted weighted out-degree of these sectors. As compared to the top left panel where the highest outdegree was roughly 15, the bottom right panel has the highest out-degree of 8. What is more important is that the entire density shifts to the left and thus making it even less likely to generate heavy-tailed distribution.

Another important point to notice here is that these plots are generated with limited information in lead time values for many sectors. Since, the lead time data was available for only 42 sectors, a lot of sectors get assigned to the same diffusion bin corresponding to the parent NAICS level. Due to this problem a large number of sectors are present in the first bin and hence inflate the diffusion adjusted out-degrees to a certain level. But overall the diffusion mechanism decreases the likelihood of generating a heavy tailed distribution of outdegrees and thus also decreases the chances that a sectoral shock can generate aggregate fluctuations.

2.5 Sectoral shock decomposition

In this section, I do similar exercise as performed in Foerster, Sarte and Watson (2012) and use factor methods to decompose the industrial production (IP) into components arising from aggregate and sector specific shocks. I use structural factor analysis and see how incorporation of diffusion channel into multi-sector growth model attenuates the contribution of sector specific shocks to aggregate volatility.

2.5.1 Overview of the data

I use IP data for the years 1984-2007 for the analysis in this section. The data is restricted to the above time period to keep the results comaparable to the exercise performed in Foerster, Sarte and Watson (2012). The data corresponds to 3-digit industry level NAICS classification and reported for 26 sectors. It is possible to extend the analysis and use 117 sectors i.e. 4-digit industry classification as in Foerster, Sarte and Watson (2012) instead of current 26 sectors but we are restricted by data on lead time indicator as it is reported only at 3-digit level.

The IP data is reported on a monthly frequency level but we restrict ourselves to quarterly level. The quarterly value for IP indices are constructed by taking average over the monthly values in that quarter. IP_t denotes the aggregate IP value in time period t while IP_{it} denotes the IP value for sector i in period t. We will be working with growth rates of different sectors which are denoted by g_t for the aggregate IP and as x_{it} at the sectoral level. The growth rates are then defined by $g_t = 400 \times ln\ (IP_t/IP_{t-1})$ and $x_{it} = 400 \times ln\ (IP_{it}/IP_{it-1})$.

2.5.2 Setup: Factor Analysis

In this section, we perform both statistical as well as structural factor analysis to decompose the aggregate fluctuations into aggregate and sectoral shocks. Let us first begin with the statistical factor analysis. Let X_t denote the vector of sectoral growth rates x_{it} in period t, then the factor model can be written as:

$$X_t = \Lambda F_t + u_t \tag{2.49}$$

where F_t is a $k \times 1$ vector of latent factors, Λ is $N \times k$ matrix of factor loadings and u_t is $N \times 1$ vector of sector specific idiosyncratic disturbances. As in classical factor analysis F_t and u_t are assumed to be mutually uncorrelated and i.i.d. with a diagonal covariance matrix for u_t. This allows us to express the covariance matrix of growth rates, X_t as $\Sigma_{XX} = \Lambda\Sigma_{FF}\Lambda' + \Sigma_{XX}$, where Σ_{FF} and Σ_{XX} are covariance matrices of F_t and u_t respectively. Since, by construction, Σ_{XX} is assumed to be diagonal, all covariance between different sectors is explained by the common factos F_t. We can use principal components to consistently estimate the factors as discussed in Stock and Watson (2000) and then use penalized least-square criterion to further select the number of factors. In the current exercise, I restrict the number of factors to two to simplify the analysis and deliver comparable results. Although the results are similar if we use just one common factor.

Now having estimated the common factors, we can use them to construct a measure for importance of aggregate shocks. We can define $R^2(F) = \bar{w}'\Lambda\Sigma_{FF}\Lambda'\bar{w}/\sigma_g^2$ as the contribution of common factors to aggregate volatility where σ_g^2 is the variance of growth rate of aggregate IP. The above formula comes from the assumption that aggregate growth rate $g_t \simeq \bar{w}'X_t$, where we have further assumed that sectoral weights $\bar{w}$, i.e. vector of contributions of sectors to overall IP, is constant over time.

The above described statistical factor analysis misses one important point that sectoral shocks can be amplified through sectoral linkages as shown in Long and Plosser (1983), Horvath (1998), Carvalho (2007) and other related papers. What this implies is that in the absence of a structural model, idiosyncratic sectoral shocks amplified through inter-sectoral linkages would appear as common shocks under statistical factor analysis. But we can use the structural models presented in the Section 3 to separate the network contribution of sectoral shocks from common shocks as done in Foerster, Sarte and Watson (2012).

We have to look at the one-period diffusion model or Long and Plosser (1983) model for carrying out structural factor analysis. The sectoral growth rate X_t is given by:

$$X_t = \left[I - (1-\alpha)\Gamma_1 \boldsymbol{L}\right]^{-1} \varepsilon_t \tag{2.50}$$

Now, sectoral innovations ε_t consist of both aggregate as well as sectoral shocks, given by:

$$\varepsilon_t = \Lambda_S S_t + \nu_t \tag{2.51}$$

where S_t is a $k \times 1$ vector of latent factors and correspond to aggregate shocks, Λ_S is $N \times k$ matrix of factor loadings while ν_t is $N \times 1$ vector of sector specific idiosyncratic disturbances. We further assume that S_t and ν_t are mutually uncorrelated and i.i.d and the idiosyncratic shocks, ν_t are uncorrelated i.e. the covariance matrix $\Sigma_{\nu\nu}$ is diagonal.

The evolution of sectoral output growth can now be expressed as a factor model:

$$X_t = \Lambda(L)F_t + u_t \tag{2.52}$$

where

$$\Lambda(L) = [I - (1-\alpha)\Gamma_1 \boldsymbol{L}]^{-1} \Lambda_S \tag{2.53}$$

and $F_t = S_t$, and

$$u_t = [I - (1-\alpha)\Gamma_1 \boldsymbol{L}]^{-1} \nu_t \tag{2.54}$$

From the above equation, one can see that sectoral shocks are amplified through inter-sectoral linkages captured by the term $[I - (1-\alpha)\Gamma_1 \boldsymbol{L}]^{-1}$. Ignoring the above term is the main reason for over-estimation of contribution of aggregate shocks in aggregate volatility. To overcome this problem, one can apply factor model to ε_t, instead of X_t. The only problem is that one does not observe ε_t but it is possible to apply factor decomposition on its empirical counterpart given by:

$$\varepsilon_t = [I - (1-\alpha)\Gamma_1 \boldsymbol{L}]\, X_t \tag{2.55}$$

A similar analysis as listed above is done in Foerster, Sarte and Watson (2012). The additional exercise in this paper is is to perform a similar analysis for diffusion adjusted model. In case of diffusion adjusted model, we decompose:

$$\varepsilon_t = \left[I - (1-\alpha)\left[\Gamma_1 \boldsymbol{L} + ... + \Gamma_P \mathbf{L^P}\right]\right] X_t \tag{2.56}$$

Table 2.1: Contribution Aggregate shocks

	Data (1)	1PD (2)	UDR (3)
R^2(S)	72%	63%	73%

2.5.3 Results

The results of the different models discussed above are presented in table 1. The contribution of aggregate shocks is captured by the value $R^2(S)$. Column 1 corresponds to the case where we apply factor analysis to raw data. In this case, the sectoral inter-linkages do not play any role and we see that common shocks have a 72% contribution to overall volatility.

The second column in the same table corresponds to one period diffusion model or Long and Plosser (1983) model. Since this model takes into account the inter-sectoral linkages, the contribution of common shocks goes down and now only contribute 63% to the aggregate volatility. Although, the contribution of common shocks has gone down in this case but not as much as reported in Foerster, Sarte and Watson (2012). The reason being that the shocks affect downstream sectors one period later and hence attenuates some of the amplification mechanism present in their paper.

The third column needs some explanation because I have used unequal diffusion rate model in this case. I have divided the sectors into two- one with lead time less than a quarter and another with lead time more than one quarter i.e. Γ is split into Γ_1 and Γ_2. Then I applied factor method to decompose ε_t constructed using the filter $I - (1-\alpha)\left[\Gamma_1 \boldsymbol{L} + \Gamma_2 \mathbf{L^2}\right]$. In this case, the contribution of common shocks goes up due to the fact that sectoral shocks affect few sectors in one time period. To compensate this and achieve higher correlation between sectors, the common shocks now need to be larger to achieve the same aggregate volatility.

2.6 Conclusion

This paper started out to explore the idea of shock diffusion in a multi-sector economy. Using two canonical models, I showed how a lagged production function can be used to model shock diffusion in the context of a production economy. I then showed that 1-period diffusion models generate less aggregate volatility when compared to 0-period diffusion models that use contemporaneous production linkages.

I then developed a more realistic diffusion model where different sectors have different production horizons and thus different diffusion rates. Under this setup, I find that introduction of shock diffusion partially closes down the important channel for shock amplification as present in the single period models with contemporaneous production linkages. Since different sectors have different shock diffusion rates, the shock to sector i at time t affects different sectors at different periods of time, thus reducing the impact of this shock on aggregate volatility in any single period. I later use this model to pin down the asymptotic properties of aggregate volatility as the number of sectors goes to infinity and again ask the question- whether idiosyncratic sectoral shocks can generate aggregate volatility in the economy after controlling for differential shock diffusion? The short answer is yes, but with a much stricter requirement. The requirement is that the diffusion adjusted weighted out-degree measure should have a heavy tailed distribution where this adjusted weighted out-degree depends on both the network structure and diffusion rates of different sectors.

In the end, the paper presents quantitative evidence to show that accounting for diffusion channel reduces the importance of inter-sectoral networks in amplifying idiosyncratic sectoral shocks. The contribution of sectoral shocks in aggregate volatility is not as high as argued in some of the recent papers. This gives important reason to further examine the diffusion channel in greater detail as it will have important implications for the direction of this literature.

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Appendix

Optimal quantities

The problem in section 3.1 gives the following optimal consumption and input quantities:

$$C^*_{it} = \left(\frac{\theta_i}{k_i}\right) Y_{it}, \quad \forall i = 1, 2, 3$$

$$X^*_{ijt} = (1-\alpha)\left(\frac{\beta k_i \gamma_{ij}}{k_j}\right) Y_{jt}, \quad \forall i, j = 1, 2, 3$$

Now using the production function we can get log-output for sector 1 as below:

$$Y_{it} = Z_{it} L^{\alpha}_{it-1} \overset{[}{j} = 1]N \prod X_{ijt-1}^{(1-\alpha)\gamma_{ij}} \quad \forall i = 1$$

which gives:

$$y_{1t} = \mu_{udr1} + (1-\alpha)\left[\gamma_{11} y_{1t-1} + \gamma_{12} y_{t-2} + \gamma_{13} y_{t-3}\right] + \varepsilon_{1t}$$

Chapter 3

Employment in a Network of Input-Output Linkages

joint work with **Francois de Soyres**

Abstract

What is the consequence of a technological improvement in one sector on employment in sectors located downstream in the supply-chain? On the one hand, if material and labor are gross substitute in the production function, the price decrease for the former tends to reduce labor demand for the latter *per unit produced*. On the other hand, the upstream positive technological shock also increases the number of unit produced through a decrease in the marginal cost. The net effect on employment simply depends on the ratio between the elasticity of substitution in the production function and the price elasticity of demand. We estimate those parameters at the sector level using detailed French data and show that employment sensitivity of sectors following a decrease in their material input price are very heterogeneous. Consequences for forecasting the effect of an increase in machine efficiency are discussed.

3.1 Introduction

Recent developments in the network literature have highlighted the important role of input-output linkages in amplification of sector level shocks. In an interconnected economy, an increase in the efficiency of one sector yields benefits for all other sectors, the magnitude of which depends on the detailed network structure. While those sectoral spillovers are always positive when one looks at gross output production, this is not necessarily the case for usage of one particular input such as labor, or for value added production in general.[1] Following a decrease in the price of a material input, firms and sector re-optimize their input mix in production as well as their production scale.

In this paper, we start by showing in a simple theoretical framework that the consequence of a technological innovation for labor demand in downstream sectors depends on two key elasticities: (i) the elasticity of substitution between labor and material input and (ii) the price elasticity of demand. The first parameter captures the change in the input mix due to a change in relative prices, while the second captures the size of increased sales attracted by the sector following the decrease in marginal cost. Indeed, if total sales is fixed, the employment consequences of a decrease in the price of intermediate input depends solely on the gross substitutability or complementarity between labor and material inputs in the production function. However, when firms increase the share of the cheaper input in their production basket, they also decrease their production costs and hence their price, hereby attracting new customers. Such a change in the scale of production counteracts the reduced labor share per unit produced, so that the overall direction of labor demand is ambiguous. We show that the two elasticities described above are the only parameters one needs to estimate in the data in order to make prediction for employment changes.

We then exploit a very detailed dataset of French firms and estimate those elasticities separately for each sector. Using a panel of French firms matched with employee level data, we can estimate the value of those two parameters using within firms variations and construct a value for the sector level elasticities. Finally, we put together our theoretical and empirical results together and compute

[1] Acemoglu and Restrepo (2016) study "the race between machine and man" and the consequences of automation (which could be seen as a technological improvement in the sector producing robots) for labor share.

the degree of sensitivity of employment in each sector with respect to technological improvements.

Our paper is related to several strands of literature on production networks. First, on the theoretical side, after the seminal contribution by Long and Plosser (1983) on business cycles in a network economy, many papers have been interested in the sectoral origin of aggregate volatility in output, diluting the original "diversification" argument, according to which idiosyncratic sectoral or firm-level shocks should wash out in the aggregate due to law of large numbers. Carvalho (2011), Acemoglu et al. (2012) and others have provided necessary conditions under which a networked economy with input-output linkages is able to amplify sectoral shocks to create aggregate fluctuations. While many studies focus on volatility or gross output, we are specifically interested in the employment consequences of technological shocks in the context of input-output linkages.

On the empirical side, Atalay (2015) and Foerster et al. (2011) have tried to test the predictions of these theoretical models and estimate the contribution of sectoral shocks to aggregate volatility. Giovanni et al. (2014) use detailed firm level data from France for this decomposition exercise. More recently Barrot and Sauvagnat (2016) use natural disaster as a proxy for firm level idiosyncratic shocks to study the propagation of these shocks from one firm to another and understand the impact on downstream *output* growth rates and spillovers.

Our paper is also closely related and contributes to the literature on estimating production elasticities. Oberfield and Raval (2016) use cross-sectional firm level balance sheet data to estimate sector level substitution elasticity in the production function. In the absence of precise firm level efficiency wage information, they had to use area level efficiency wages for their estimations. We improve upon their methodology by using detailed firm level data which allows us estimation of firm level efficiency wage, which can be directly used in the estimation of production elasticity. There is another important contribution in the empirical section, which is estimation of substitution elasticity between material inputs and capital-labor. A large part of the previous literature has primarily focused on estimating substitution elasticity between capital and labor but we document the other elasticity as well. Our results highlight substantial heterogeneity in elasticity of substitution between material inputs and capital-labor across sectors.

The rest of the paper is organized as follows. In the next section, we lay down our theoretical framework and derive a prediction for the employment change in a sector following a decrease in the price of its material input. This elasticity depends on two key elasticities for which we derive estimation equations. In section three, we present our dataset and empirical strategy and derive estimated value for the production and the demand elasticities for many sector. We also present consolidated result for sector's sensibility to upstream shocks. Section four offers concluding remarks and avenues for future research.

3.2 Theoretical Framework

This section develops a simple theoretical framework of firms and sectors employment decisions which forms the basis of our empirical work.

3.2.1 Basics

We consider a sector k populated by a large number of identical firms producing a good Y_k using three inputs: labor L_k, capital K_k and material inputs M_k bought from other firms. Since all firms within sector k are symmetric, there is no need for firm specific index and we simply write the generic production function for all firms in sector k as:

$$Y_k = \left[\mu^{\frac{1}{\epsilon_P}} V_k^{\frac{\epsilon_P - 1}{\epsilon_P}} + (1-\mu)^{\frac{1}{\epsilon_P}} M_k^{\frac{\epsilon_P - 1}{\epsilon_P}}\right]^{\frac{\epsilon_P}{\epsilon_P - 1}} \tag{3.1}$$

where $V_k = K_k^{\alpha} L_k^{1-\alpha}$ is a Cobb-Douglas aggregate of labor and capital and $\epsilon_P > 0$ is the elasticity of substitution between basic factors of production and material inputs. μ is a weight that controls for the spending share of basic production factors vis-a-vis material input. As will be clear later, assuming that those weights are constants means that we do not need to estimate them as we use time differences in order to relate changes in relative input prices to changes in relative input usage. Sector k faces an aggregate demand curve characterized by a price elasticity of ϵ_D, such that:

$$D(p_k) = D_0(p_k)^{-\epsilon_D} \tag{3.2}$$

where p_k is the price of sector k's good and ϵ_D is the price elasticity of demand. We do not model further the demand side in the market for goods produced by sector k but rather posit the existence of an aggregate demand function with a (locally) constant price elasticity. Such demand can potentially come from other industries of from final consumers. Sector k is monopolistic and choses its price in order to maximize profit. Since it faces a demand with a constant price elasticity ϵ_D, standard derivations lead to a price at a constant markup over marginal cost:

$$p_k = \frac{\epsilon_D}{\epsilon_D - 1} MC_k = \left(\mu v_k^{1-\epsilon_P} + (1-\mu) q_k^{1-\epsilon_P}\right)^{\frac{1}{1-\epsilon_P}} \tag{3.3}$$

where MC_k is the marginal production cost of sector k which is equal to the price index dual to the CES aggregation in the production function (3.1). We denote by q_k is the price of material inputs and v_k is the price of the $K-L$ bundle which is defined by:

$$v_k = \frac{r_k^{\alpha}}{\alpha^{\alpha}} \cdot \frac{w_k^{1-\alpha}}{(1-\alpha)^{1-\alpha}} \tag{3.4}$$

Let us now invert the demand curve (3.2) to get:

$$p_k = D_0^{-\frac{1}{\epsilon_D}} \times Y_k^{-\frac{1}{\epsilon_D}} \tag{3.5}$$

Firms in sector k take input price as given and chose L_k, K_k and M_k in order to maximize their profit, given the demand they are facing.[2] We first model the optimal choice of material input and the capital labor bundle and we will characterize separately the demand for labor and capital below. In this context, total profits in sector k are equal to total revenues minus total costs which can be written:

$$\Pi = p_k Y_k - v_k V_k - q_k M_k = D_0^{-\frac{1}{\epsilon_D}} \times Y_k^{\frac{\epsilon_D - 1}{\epsilon_D}} - v_k V_k - q_k M_k \tag{3.6}$$

where we replace the price using the inverse demand curve (3.5), implying that firms do not take their output price as given. The associated first order conditions are:

$$\{V_k\}: \qquad D_0^{-\frac{1}{\epsilon_D}} Y_k^{-\frac{1}{\epsilon_D}} \frac{\partial Y_k}{\partial V_k} = v \tag{3.7}$$

$$\{M_k\}: \qquad D_0^{-\frac{1}{\epsilon_D}} Y_k^{-\frac{1}{\epsilon_D}} \frac{\partial Y_k}{\partial M_k} = q \tag{3.8}$$

[2] It is equivalent to solve the problem in two step, wherein the first step firms chose inputs to minimize their production price and in a second step they chose their price to maximize profit.

As is usual, firms use production inputs until the marginal revenue product associated with each input equals their price they are paying for those inputs. It is apparent from the above equations that the price elasticity of demand is an important parameter in shaping input demand, stemming from the fact that the marginal revenue product associated with hiring an additional unit of any input is governed by (i) the impact this additional input has on production cost and (ii) the impact this change in marginal cost and hence on pricing has on final revenue. Using the production function (3.1), we can have an expression for the partial derivative of Y_k with respect to each input. In particular, we have:

$$\frac{\partial Y_k}{\partial V_k} = \left[\mu^{\frac{1}{\epsilon_P}} V_k^{\frac{\epsilon_P - 1}{\epsilon_P}} + (1-\mu)^{\frac{1}{\epsilon_P}} M_k^{\frac{\epsilon_P - 1}{\epsilon_P}}\right]^{\frac{1}{\epsilon_P - 1}} \times \mu^{\frac{1}{\epsilon_P}} \times \frac{\epsilon_P - 1}{\epsilon_P} \times V_k^{\frac{-1}{\epsilon_P}}$$

Using this expression as well as the corresponding equation for $\frac{\partial Y_k}{\partial M_k}$), we can combine the first order conditions and obtain an expression of the ratio of basic input to material demand:

$$\frac{V_k}{M_k} = \frac{\mu}{1-\mu} \times \left(\frac{v_k}{q_k}\right)^{-\epsilon_P}$$

Note that we can also rewrite this equation in terms of factor payment rather than quantity, which will prove useful when we estimate the elasticity of substitution in the next section. Multiplying the above equation on both sides by the ratio of factor prices, yields:

$$\frac{v_k V_k}{q_k M_k} = \frac{\mu}{1-\mu} \times \left(\frac{v_k}{q_k}\right)^{1-\epsilon_P} \tag{3.9}$$

Finally, replacing v_k by its expression in (3.4) and using the fact that total payment to the bundle V_k is simply equal to payment to labor and capital, we obtain:

$$\frac{r_k K_k + w_k L_k}{q_k M_k} = \frac{\mu}{1-\mu} \cdot \left(\alpha^{-\alpha}(1-\alpha)^{\alpha-1}\right)^{1-\epsilon_P} \times \left(\cdot\frac{r_k^{\alpha} w_k^{1-\alpha}}{q_k}\right)^{1-\epsilon_P} \tag{3.10}$$

3.2.2 Hat algebra

We want to get closed form solutions for the percentage changes of variables when there is a positive technological shock in sector located upstream to sector k. In our framework, such a shock would affect sector k's input choice and sales through its impact on the price of material input q_k and ultimately on the marginal production cost. Our goal is to show that the change in employment in sector k depends on two key elasticities, ϵ_P and ϵ_D, which we will then estimate for many sectors using detailed French data.

We denote $\widehat{x}$ the percentage change of any variable x ($\widehat{x} = \frac{dx}{x} = d\log(x)$). Starting with the FOCs in sector k, we first substitute the expression of Y_k using the production function and then log-linearize (3.8) and obtain (assuming that D_0, μ and all elasticities are parameters that do not change): -2cm0cm

$$\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)\cdot\frac{\epsilon_P-1}{\epsilon_P}\cdot\left(\frac{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}}{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}\widehat{V_k}+\frac{(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}\widehat{M_k} \tag{3.11}$$

where we used the usual formula: $\widehat{(x+y)} = s_x\widehat{x} + s_y\widehat{y}$, with $s_x = \frac{x}{x+y}$. The equivalent holds for the first order condition relative to V_k. Let us denote $s_V = \frac{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}}{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}$ and equivalently for s_M. Combining the log linear transformations of first order conditions yields the following expressions for $\widehat{V_k}$:

$$\widehat{V_k} = \frac{\epsilon_P^2}{1-(\epsilon_P-1)\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)}\cdot \left[\left(\frac{\epsilon_P-1}{\epsilon_P}\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)s_M-\frac{1}{\epsilon_P}\right)\widehat{v_k}-\frac{\epsilon_P-1}{\epsilon_P}\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)s_M\widehat{q_k}\right] \tag{3.12}$$

We further assume that changes in wage and rental rate of capital are uncorrelated to shocks to the price of material inputs.[3] Taking the expectation over all possible realizations of shocks to upstream sectors, the above expression then simplifies to:

$$\mathbb{E}\widehat{V_k} = \frac{-\epsilon_P^2}{1-(\epsilon_P-1)\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)}\cdot\frac{\epsilon_P-1}{\epsilon_P}\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)\cdot s_M\mathbb{E}\widehat{q_k}$$

Furthermore, using the Cobb-Douglas nature of the $K-L$ bundle, total spendings on labor is simply equal to a share $(1-\alpha)$ of total spendings for the bundle V_k. In turn, this yields a simple relationship between proportional changes in L_k and

[3]This approach is similar to what is done in Amiti et al (2013). Alternatively, we could assume that shocks to the price of material input are small and the rest of the economy is large enough so that both wages and rental rate of capital are fixed exogenously. In such a case, we would not need to take expectations to get rid of wages and rental rate changes.

proportional changes in V_k:

$$w_k L_k = (1-\alpha) v_k V_k \qquad \Longrightarrow \qquad \widehat{L_k} = \widehat{V_k}$$

Finally, after rearranging and considering a positive technological shock upstream, triggering a decrease in the associated price price $\widehat{q_k} = -1$, the change in K and L usage is given by:

$$\widehat{L_k} = \frac{\epsilon_P(\epsilon_P - 1) \cdot \left(\frac{\epsilon_P(\epsilon_D - 1)}{(\epsilon_P - 1)\epsilon_D} - 1\right)}{1 - (\epsilon_P - 1)\left(\frac{\epsilon_P(\epsilon_D - 1)}{(\epsilon_P - 1)\epsilon_D} - 1\right)} s_M \tag{3.13}$$

As can be shown numerically, the expression above is strictly positive if and only if

$$\epsilon_D > \epsilon_P$$

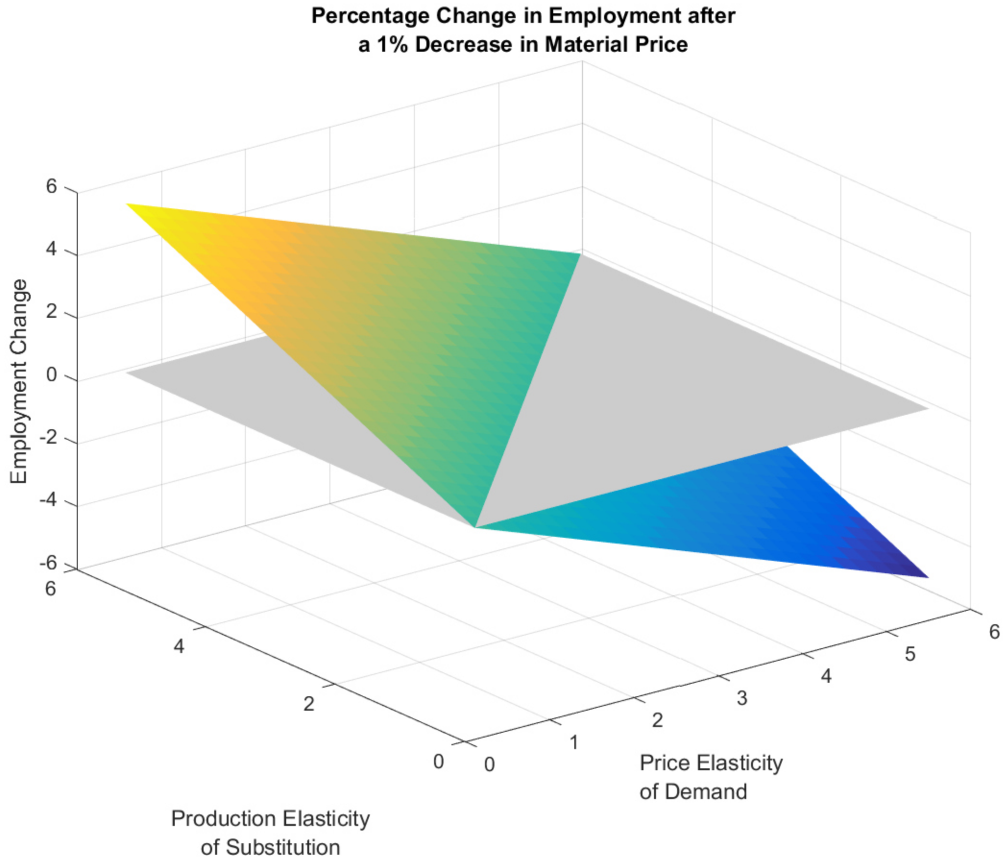
Proposition 1
In our partial equilibrium analysis,[4] a technological improvement in a sector k' located upstream to k in the supply chain leads to an increase in employment in k if and only if the elasticity of substitution between the $K-L$ bundle and material inputs ϵ_P is lower than the price elasticity of aggregate demand faced by sector K, ϵ_D.

3.2.3 Numerical Explorations

In this section, we quantitatively investigate the consequences of varying the values of the two key parameters: the demand elasticity ϵ_D and the production elasticity ϵ_P. We consider the partial equilibrium model described above with a fixed wages and rental rate of capital, and compute the value of the proportional change in employment after a decrease in material price using equation (3.13). The graph below plots the value of $\widehat{L_k}$ in the vertical axis as a function of both ϵ_P and ϵ_D. We added in grey the reference surface defined by $z = 0$. We see that whenever $\epsilon_D > \epsilon_P$, employment in sector k *increases* when the price of material input *decreases*, even when labor is gross substitute with materials in the production function.

[4] with fixed wages and rental rate of capital

FIGURE 3.1: Numerical explorations for the elasticity of employment



When $\epsilon_P > 1$, the $K - L$ is gross substitute with materials in the production function. A decrease in material price gives incentives to firms in sector k to demand more material inputs relative to labor and capital for each unit produced and the spending *share* of labor decreases which triggers a decrease in marginal cost and hence in the price p_k. Moreover, when $\epsilon_D > \epsilon_P > 1$, the decrease in price leads to an increase in sales that more than overturns the decrease in labor demand. Even though the share of spending devoted to labor decreases, total spendings on all inputs increases more strongly so that the net effect is an increase in total demand for labor. Hence, employment in sector k increases as a result of the positive technological shock upstream. The result is obviously reversed when $\epsilon_D < \epsilon_P$ and the sales increase does not compensate the decrease in labor share, resulting in a net decrease in employment.

When $\epsilon_P < 1$, labor is gross complement with materials in the production function. In such a case, the drop in material price triggers an increase in the labor and capital share in spendings.

3.2.4 Estimation Equations

Before presenting our empirical section, we simply lay down the estimation equations delivered by our theoretical framework. We start by presenting the equations tat enable us to estimate the production elasticity in two different framework and then turn to the demand elasticity.

Looking first at the nested CES production function described above, profit maximization in sector k yields the usual relationships relating relative spending and relative prices:

$$\frac{r_k K_k + w_k L_k}{q_k M_k} = \frac{\mu}{1-\mu} \cdot \left(\alpha^{-\alpha}(1-\alpha)^{\alpha-1}\right)^{1-\epsilon_P} \times \left(\cdot \frac{r_k^{\alpha} w_k^{1-\alpha}}{q_k}\right)^{1-\epsilon_P}$$

Taking the logarithm and considering differences over time within a firm in sector k yields the relationship between *changes* in relative spending and *changes* in relative prices:

$$\Delta \log\left(\frac{r_k K_k + w_k L_k}{q_k M_k}\right) = (1-\epsilon_P)\left(\alpha \Delta \log\left(\frac{r_k}{q_k}\right) + (1-\alpha)\Delta \log\left(\frac{w_k}{q_k}\right)\right) \quad (3.14)$$

Alternatively, positing a production function in which labor and material inputs are directly aggregated in a CES form (without a first step aggregating labor and capital), firms' optimization problem leads to a slightly different realtionship. In particular, without a $K-L$ bundle, the share of labor relative to capital disappears from the relative forst order conditions for labor and material, leading to the following estimation equation:

$$\Delta \log\left(\frac{w_k L_k}{q_k M_k}\right) = (1-\epsilon_P)\Delta \log\left(\frac{w_k}{q_k}\right) \quad (3.15)$$

Finally, in order to get an indirect measure of the price elasticity of demand, we measure the price cost margin (PCM) in each sector and invert it to get a measure of ϵ_D using

$$\epsilon_D = \frac{PCM}{PCM-1}$$

3.3 Empirics

The consequence of positive technological shocks in sector i for any sector k located downstream of i in the supply chain is governed by two key elasticities. The goal of this section is to use detailed data on French firms in many industries in order to estimate those elasticities at the sector level. We focus on manufacturing sector corresponding to 1-digit level "C" under NAF nomenclature used by French statistical agency INSEE. This gives us 24 sectors at 2-digit level.

3.3.1 Data

There are two main sources of firm level datasets that we use for this exercise. Our first source of firm level data is the BRN which comes from the French fiscal administration.[5] It contains balance-sheet information collected from the firms' tax fillings as well as detailed information on the firms' balance sheets, including the value of total capital stock, the total wage bill, the average firm level wage rate. Our dataset also contains the sectors and the region in which the firm operates which is an important information given our estimation strategy.

We focus our analysis on the 7 years period stretching from 2003 to 2009 where all variables are labeled in Euro (and not French Francs). Initially, the dataset contains more than 500,000 firms per year. We get rid of firms employing less than 5 employees, which reduces the sample to about 300,000 firms per year.[6] The number of observation per year can be found in table 3.1 and the number of observation per sector can be found in appendix, table **??**. Sectors are unevenly represented in our sample and some sectors contain a very low number of observation. We concentrate our analysis on sectors gathering at least 2,200 observations in total and hence do not use sectors 11, 12, 19 and 30.

The second dataset is DADS (Déclaration annuelles de données sociales), which collects matched employer-employee information and specifically wage information, which is important for our analysis. The data is collected from mandatory

[5] BRN stands for Benefice Reel Normal, the normal tax regime for French firms.

[6] There are two reasons why we believe small firms should not be used in our estimation. First, firms employing a small number of employees have a "discretionary problem" as adjusting their labor force by one person can constitute a sizable adjustment in their total wage payment, implying a non-continuous adjustment in their input mix. Second, small firms also experience a higher average growth rate and might expand their input base in a non optimal way based on recruitment opportunities.

Table 3.1: Total Observations

	All	More than 5 employees	More than 10 employees
2003	$51,424$	$49,116$	$35,345$
2004	$50,977$	$48,421$	$34,476$
2005	$50,081$	$47,757$	$34,034$
2006	$49,187$	$46,999$	$33,573$
2007	$48,100$	$45,959$	$33,004$
2008	$45,560$	$42,611$	$31,722$

Note: From BRN and DADS merge (Only NAF "C" sectors)

reporting of gross earnings by each firm to the French tax authority. The DADS is a subset of this income tax data, covering all individuals employed in French enterprises and who were born in October of even-numbered years. Each observation in DADS dataset corresponds to a matched employer-employee pair and contains information like number of days worked, total wage, occupation and other employee related information like age, sex etc. Each observation also contains employee id which allows for matching an individual across years as well as firm identifier (SIREN), which allows for matching DADS with BRN data. For the eight years of our analysis, the resulting dataset has roughly 200 million matched employer-employee observations.

In the end we merge the two sources of datasets, BRN and DADS, to get final dataset with approximately $50,000$ observations per year as shown in table 3.1. This is the final merged data we use for running firm level regressions to estimate effect of wages on input choice of firms.

3.3.2 Estimation: Elasticity of substitution

In order to identify elasticity of substitution between various inputs of the firm we use the log-linearized equation (3.14) and (3.15), which come from solving firm's profit maximization problem in the case of a nested CES or full CES production function respectively. Accordingly, we will use two different specifications as baseline estimates of elasticity of substitution. The first comes directly from equation (3.14), which we call nested CES specification, where labor and capital as a bundle are substitutable with intermediates, and it gives us the following regression equation:

$$\log\left(\frac{rK+wL}{qM}\right)_{kjt} = (1-\epsilon_P)(1-\alpha_j)\log{(w)}_{kjt} + \gamma_k + \delta_t + CONTROLS + \epsilon_{kjt} \tag{3.16}$$

where LHS of equation (3.16) gives the ratio of capital and labor spending to intermediates for firm k in sector j at time t. The variable of interest here is the regression coefficient on firm level wage w_{kjt}. The wage used here is the efficiency wage for the firm after controlling for observable measures of skill and worker level characteristics. To estimate the efficiency wage for each firm we use matched employer-employee DADS data to construct residual wage for the the firms. [7] Since, we have firm level panel we can control for firm level heterogeneity by using firm fixed effects γ_k. The time fixed effects δ_t allow us to control for yearly variations across all firms. Lastly, all the regressions that we report controls for firm level variables like age, region, number of employees etc. It is important to note here that we are using firm level data here instead of plant level data because BRN reports capital and intermediate usage at the firm level and not plant level.

The identification in the above equation comes from exploiting the changes in within firm wages as well as across firms over time. Since we have observations for the same firm over multiple periods, we can get rid of bias coming from firm level skill differences or other observable and non-observable factors. Also, this specification allows for firms to have different rental rates of capital which will be captured by firm fixed effects γ_k, under the assumption that this rental rate does not change over time for a given firm.

As a second baseline, we use full (non-nested) CES specification, where capital, labor and intermediates enter the same CES production function with same elasticity of substitution ϵ_P across the three inputs. Log-linearizing profit maximizing condition for non-nested CES production function gives the following regression equation:

$$\log\left(\frac{qM}{wL}\right)_{kjt} = -(1-\epsilon_P)\log{(w)}_{kjt} + \gamma_k + \delta_t + CONTROLS + \epsilon_{kjt} \tag{3.17}$$

[7]The details of residual wage construction are given in Appendix B.

where equation (3.17) is similar to (3.16) with the only difference in LHS coming due to different specification for the production function. The identification strategy in this non-nested case is similar to the one used for nested production function. Since we are interested in difference between ϵ_P across different sectors, we run the above regressions separately for all 2-digit sectors belonging to the "C" category, under 1-digit NAF industry classification. The results of our regressions are reported in the next sub section.

Using the French firm level dataset has many advantages and helps us overcome many of the problems persistent with the estimation of production elasticities. Firstly, it gives us information on matched employer-employee data with detailed worker characteristics. This helps us filter out skill and other worker level differences and get precise residuals at the firm level to calculate efficiency wage. Also, since we can match this information with balance sheet data of firms, we can run regressions as stated in equations (3.16) and (3.17) with firm level wages. Otherwise, the lack of individual worker level wage information in balance sheet data does not allow for precise measurement of efficiency wage. So, unlike Oberfield and Raval (2016) who use area level efficiency wage to circumvent this problem, we can directly use efficiency wage at firm level. Our approach thus improves upon their estimation method because we use precise firm level information rather than aggregated area level wages. Secondly, the panel dimension of the dataset allows us to control for individual firm level unobservable heterogeneity. Having firm fixed effects thus allows us to control for differential rental rate of capital across firms and thus we do not have to make strict assumption that capital is completely mobile across firms as in the case of Oberfield and Raval (2016). Thirdly, since we do not use area level wages in our primary regression, we can also control for regional heterogeneity. Oberfield and Raval (2016) instead had to use an IV to control for this regional heterogeneity. In our case, on the other hand we can already control for regional heterogeneity in firm location choice by including region fixed effects.

Endogeneity

The equations (3.16) and (3.17) allow us to estimate firm level elasticity of substitution using both within and across firm variation in wages over time. Since we have a panel dimension it allows us to control for firm level unobserved characteristics but there are various sources for endogeniety bias in these regressions.

For example- due to adjustments costs to capital or labor, firm's input choices can deviate from the static cost minimization problem which can also have an impact on the efficient wages paid by the firm.

To solve potential endogeneity bias, we follow the approach developed in Oberfield and Raval (2016) and use area level efficiency wages instead of firm level wages. Since most firms are small and cannot impact area level wages, using area level wages corrects for the bias arising from firm's deviation from its cost minimization problem as area level wages will be orthogonal to such deviation. Having said that, it is important to highlight that such bias in our case is much smaller than in case of Oberfield and Raval (2016). Indeed, the panel dimension of our dataset allows us to control for any time invariant firm level unobserved heterogeneity through firm fixed effects. Moreover, since Oberfield and Raval (2016) use a single cross-section of area level wages, they could not control for regional differences using region fixed effects. In our case, having access to a panel provides significant improvements regarding such problems.

As a robustness check for our OLS results, we thus run two more specifications for each of the nested and non-nested CES case. The first specification is similar to Oberfield and Raval (2016) where we use area level efficiency wage w_{jt} in equations (3.16) and (3.17) instead of firm level wage w_{kjt}. [8] As a second robustness check, we use area level wage w_{jt} as an instrument for firm level wage w_{kjt}. The area level wage w_{jt} satisfies both the conditions necessary for being a good instrument. One, it is highly correlated with firm level efficiency wages once filtering out individual worker level characteristics and other skill level differences. Two, it also satisfies the exclusion restriction since using the panel dimension allows us to capture effects like firm location choice through firm fixed effect and hence error terms are much less likely to be correlated with the instrument.

Estimation Results

Overall, we report three different estimates for each of the two cases corresponding to the nested and non-nested estimation equations (3.16) and (3.17).

1. The first set of estimates is called OLS and correspond to a set of panel regressions for each sector with firm and year fixed effects for equations (3.16)

[8] The area level wages are constructed by taking average across the residuals, across all workers in a given area, from the wage equation.

and (3.17). In this case we use firm level wages as independent variable in the right hand side of the equations.

2. The second set of estimates is called Area and it corresponds to the estimates similar to the ones reported in Oberfield and Raval (2016). Here, instead of using firm level wages, we use area level wages, computed by taking average wage over all firms in a given area. Oberfield and Raval argue that such a specification is attractive because firms may find it costly to adjust capital or labor. Deviations of a firm's capital or labor from static cost minimization due to adjustment costs would then be in the residual, but should be orthogonal to the area level wage rate.

3. The third set of estimates is called IV. In this case, we use area level wages as an instrument for firm level wages.

The point estimates for different sectors in each of these six cases (2 production function assumption $\times$ 3 empirical specification for wages) are reported in table 3.4. Interestingly, there is very large heterogeneity across sectors for these point estimates. Moreover, point estimates and resulting elasticities are quite sensitive to the estimation procedure as well as the assumption about the production function.

Calculation: Elasticity of substitution in production

Equipped with these point estimates PE_j as reported in table 3.4 as well as the value of capital share α_j as reported in table 3.2 for each sector j, we back out the value of the elasticity of substitution in production for each sector. First, assuming a *full CES* aggregation of all factors of production in the production function,[9] the elasticity of substitution is simply given by

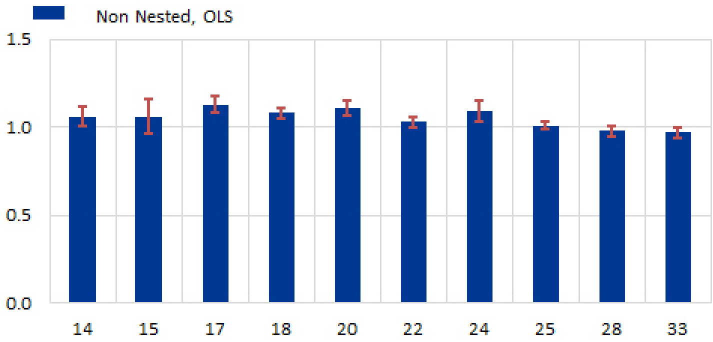
$$\epsilon_{P,j} = 1 - PE_j \tag{3.18}$$

with the variance of $\epsilon_{P,j}$ and PE_j being equal. Moreover, positing a nested CES form in the production function yields the following relation between point estimates and $\epsilon_{P,j}$:

$$\epsilon_{P,j} = 1 - \frac{PE_j}{1 - \alpha_j} \tag{3.19}$$

[9] Meaning that there is no $K - L$ bundle that is aggregated as a first step.

FIGURE 3.2: Production Elasticity for 10 2-digits sectors
Non-Nested Production, OLS



We then need to compute standard deviation for this variable. For a ratio $R = X/Y$ where X and Y are independent variables, we use the following formula[10] to compute the variance of R

$$V(R) = \frac{V(X)}{Y^2} + V(Y)\frac{X^2}{Y^4}$$

Hence, noting $\sigma_{\alpha,i}$ and $\sigma_{PE,i}$ the standard errors of α_i and PE_i respectively, the standard error of the production elasticity for sector i is given by

$$\sigma_{\epsilon_P,j} = \sqrt{\frac{\sigma^2_{PE,j}}{(1-\alpha_j)^2} + \sigma^2_{\alpha,j}\frac{PE_j^2}{(1-\alpha_j)^4}} \tag{3.20}$$

As a result, our OLS estimates for the production elasticity are presented in graph ??. The first important result to notice here is that sectors are fairly heterogeneous in their elasticity of substitution. Second, many sectors feature a gross substitution between labor and material inputs with a value for the elasticity above one as is apparent from the graph. These two features together imply that sectors are heterogeneous in their response to shocks to material inputs. Interestingly, imposing a full CES functional form or a nested CES one (where capital and labor are first aggregated into a K-L bundle which is then combined in a second CES form to material input) yields different results.

[10]See in “Sampeling Techniques”, 3rd Ed. by Cochrane (1977), page 183 for a proof

FIGURE 3.3: Production Elasticity for 10 2-digits sectors
Nested Production, OLS

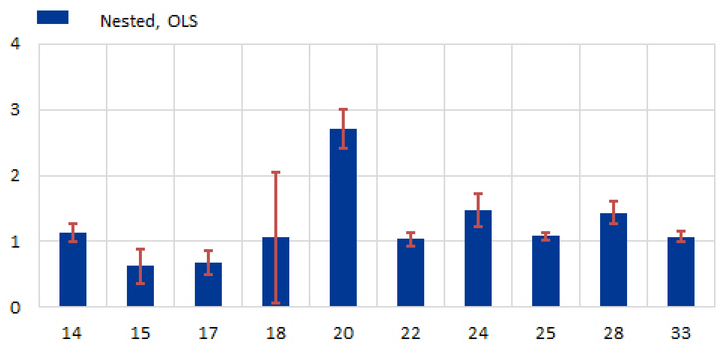
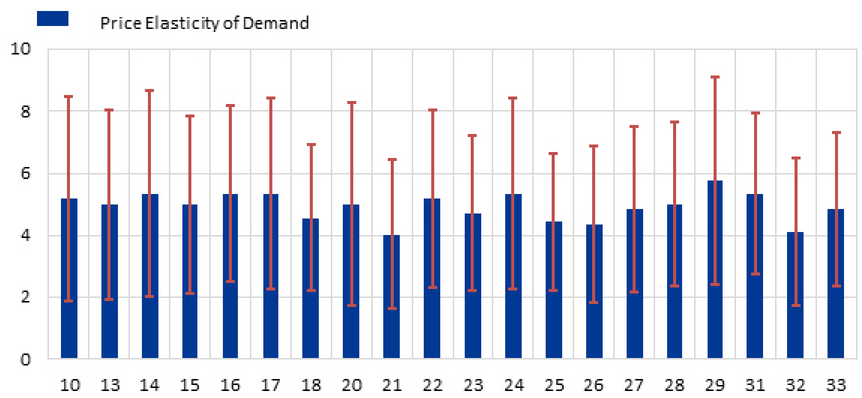


FIGURE 3.4: Price Elasticity of Demand for 20 2-digits sectors



3.3.3 Estimation: Price elasticity of demand

To estimate the demand elasticity faced by each sector, we assume optimal price setting behavior under monopolistic competition where firms maximize their profits. Under this assumption, the markup of the firm is given in terms of its demand elasticity as $\epsilon_D/(\epsilon_D - 1)$. We estimate the markup across sector by ratio of firm level revenue to cost averaged across all firms in a given sector. To do this we only take firms whose markup lies in $(1, 2)$ and ignore the outliers. The results of this exercise are shown in figure 3.4 and table 3.5. Most of the sectors have a demand elasticity between 4 and 5. This way of measuring demand elasticity is in line with other recent work in the literature.

3.4 Sectoral sensitivity to upstream shocks

The sensitivity of employment in sector i with respect to a shock to any sector k located upstream in the supply chain is governed by equation (3.13). As exposed in proposition 1, a positive shock upstream leads to an increase in employment in sector j if and only if:

$$\frac{\epsilon_P}{\epsilon_D} < 1$$

Panel Fixed Effects Regressions

In figures 3.5 and 3.6, we present our estimates of the above ratio for 10 sectors, revealing that the level of this employment elasticity is not constant across sectors under both the baseline estimates of nested and non-nested production function. In terms of *direction*, our OLS estimation yields the prediction that all sectors would increase employment following a positive technological shock upstream.[11] This results stems primarily from the fact that the demand elasticity for most of these sectors lie between 4 and 5 which implies a significatnt increase in the production scale for associated with a decrease in price and marginal cost.

In terms of *magnitude*, however, sectors present significant differences. The chemical industry (sector 20) presents a higher ratio of elasticity in the production function to price elasticity of demand than other industries, revealing a lower employment reaction. On the other hand, the leather and shoes industry (sector 15) or the wood industry (sector 16) seems to be particularly sensitive to upstream technological shock with an employment reaction associated with upstream technological shock significantly higher than other industries.

Panel with Area Level wages

Using area level wages in lieu of firm level wages has a significant impact on the results, as presented in figure 3.7 for the non nested case and 3.8 for the case of a nested CES production function. In particular, the nested CES case feature several industries with a ratio of elasticities high enough that the threshold value of one lies in the confidence interval. According to our results, the chemical (sector

[11] Note that this is no longer true in our other specifications where we use area-level wages, see below

FIGURE 3.5: Ratios of production elasticity to demand elasticity
Non Nested Production, OLS

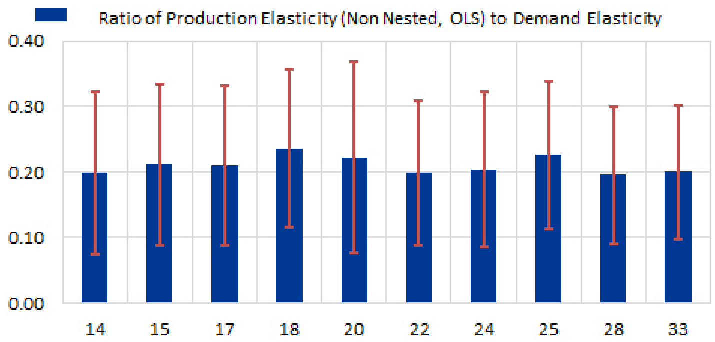


FIGURE 3.6: Ratios of production elasticity to demand elasticity
Nested Production, OLS

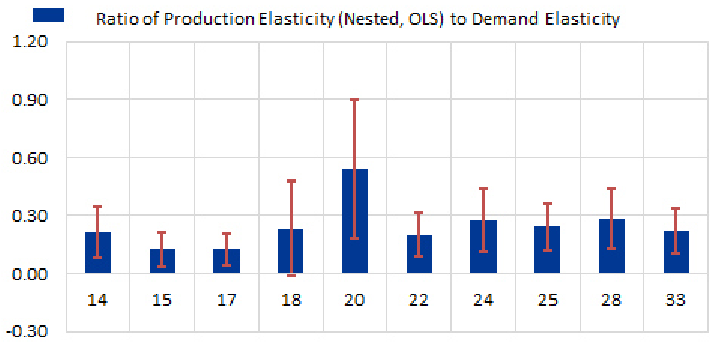
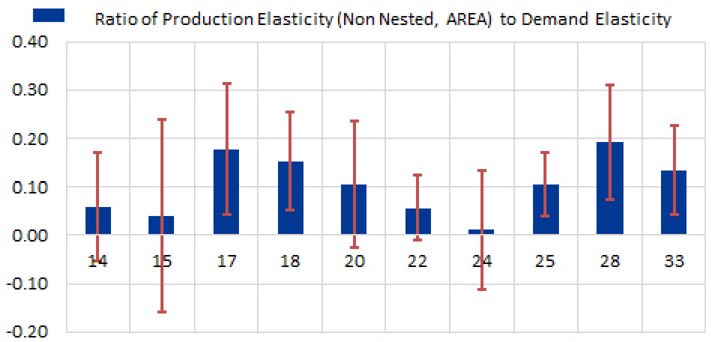


FIGURE 3.7: Ratios of production elasticity to demand elasticity
Non Nested Production, Area



20) and metallurgy (sector 24) industries would then *decrease* their employment in response to a positive shock in the upstream sector.

Panel with Area Level wages as Instruments

Finally, figures 3.9 and 3.10 present our estimated ratio of elasticities when the

Figure 3.8: Ratios of production elasticity to demand elasticity
Nested Production, Area

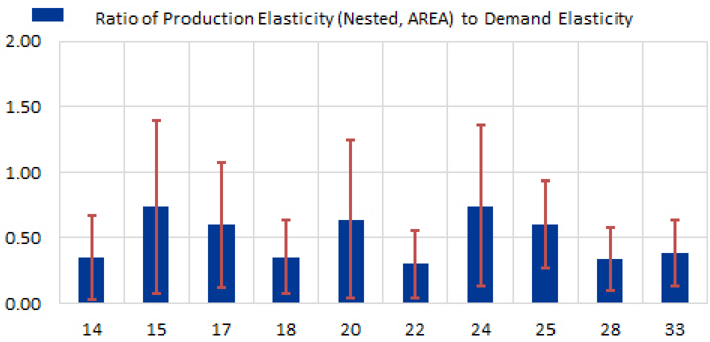
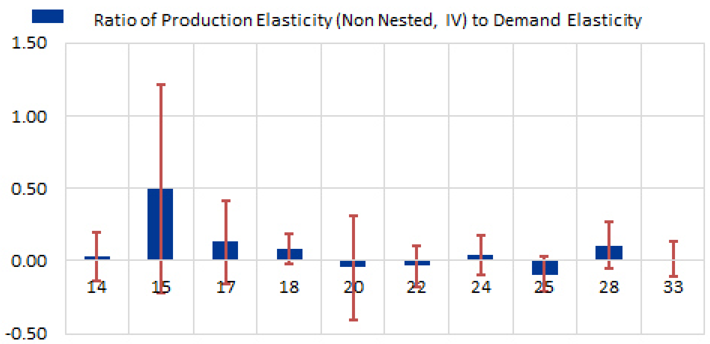


Figure 3.9: Ratios of production elasticity to demand elasticity
Non Nested Production, IV

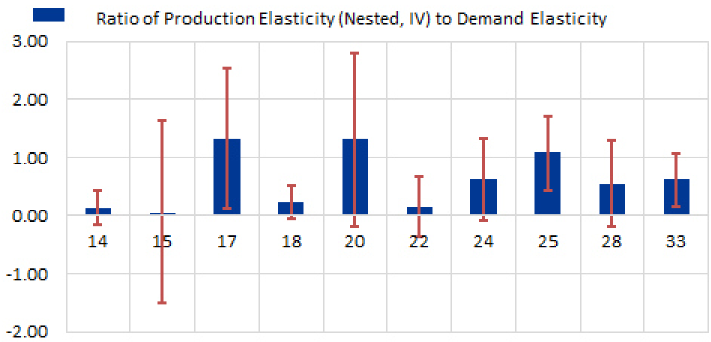


elasticity of substitution in the production function is computed using area level wages as instruments. The result is even more striking in this case as the ratio can take values as low as 0.1 for the clothing industry (sector 14) and as high as 1.2 for the chemical industry (sector 20). Those differences illustrate the fact that assuming identical production and demand elasticities across industries can potentially impose an important bias on the sensitivity of several sectors to upstream technological shocks.

3.5 Conclusion

This paper adds to our understanding on propagation of shocks within the network of interconnected sectors. In contrast to other papers in the literature, we highlight how a positive shock in an upstream sector does not always result in hiring more labor in downstream sectors. Using a theoretical model of production with labor,

Figure 3.10: Ratios of production elasticity to demand elasticity
Nested Production, IV



capital and material inputs, we show that the labor response can be summarized by the combination of two crucial elasticities, overall demand elasticity and elasticity of substitution in production, for a given sector.

Using detailed firm level data on French firms, we then estimate these elasticities separately for different industrial sectors. We find a high degree of heterogeneity across sectors for both demand and production elasticities. Interestingly, some sectors feature production elasticities that are high enough that a positive shock in an upstream sector would lead to a decrease in their labor usage. Intuitively, a decrease in the price of material inputs relative to labor triggers an important shift in the optimal input mix chosen by firms in those sectors, depressing labor demand for each unit produced. The associated increase in sales (due to a price decrease) and production is not large enough to compensate this negative force, leading to an overall decrease in employment while total revenues and gross output increase.

Using micro data on French firms in many industrial sectors allows us to take a highly disaggregated view and reveals a high degree of heterogeneity in both production and demand elasticities, leading to different sectoral responses to technological shocks. Such a result sheds a new light on the important debate on the consequences of automation and the digital revolution.[12] Abstracting for changes in the demand side of the economy, an increase in the relative efficiency of machines compare to labor would trigger different consequences across sectors. While textile, chemical or metallurgy might increase employment due to a strong reaction in the production scale, others would experience a contraction of labor usage.

[12]This theme is an important part of the 2017 French presidential campaign. See the excellent book "Le Monde est Clos et le Desir Infini" by Daniel Cohen for an analysis on this phenomenon.

3.6 References

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3.7 Theoretical Appendix

3.7.1 Log-Linearization

The log-linear transformation of the first order condition with respect to V_k in firms' profit maximization can be written -2cm0cm

$$\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)\cdot\frac{\epsilon_P-1}{\epsilon_P}\cdot\left(\frac{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}}{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}\widehat{V}_k\right)+$$

$$\left(\frac{\epsilon_P(\epsilon_D-1)}{(\epsilon_P-1)\epsilon_D}-1\right)\cdot\frac{\epsilon_P-1}{\epsilon_P}\cdot\left(\frac{(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}{\mu^{\frac{1}{\epsilon_P}}V_k^{\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}}\widehat{M_k}\right)-\frac{1}{\epsilon_P}\widehat{V_k}=\widehat{v}_k(3.21)$$

3.7.2 Nested-CES derivation

In this appendix, we relax the assumption of Cobb-Douglas aggregation between labor and capital and consider a nested CES production function as:

$$Y_k=\left[\mu^{\frac{1}{\epsilon_P}}\left(\alpha^{\frac{1}{\epsilon_V}}K_k^{\frac{\epsilon_V-1}{\epsilon_V}}+(1-\alpha)^{\frac{1}{\epsilon_V}}K_k^{\frac{\epsilon_V-1}{\epsilon_V}}\right)^{\frac{\epsilon_V}{\epsilon_V-1}\cdot\frac{\epsilon_P-1}{\epsilon_P}}+(1-\mu)^{\frac{1}{\epsilon_P}}M_k^{\frac{\epsilon_P-1}{\epsilon_P}}\right]^{\frac{\epsilon_P}{\epsilon_P-1}} \tag{3.22}$$

3.8 Empirical Appendix

3.8.1 Wage residuals

This section describes the calculation of wage residuals used in the main regressions throughout the paper. The wage residuals are generated by using DADS matched employer-employee dataset as described in detail in the data section. The DADS gives information on wages as well as other characteristics such as age, gender, occupation etc. of the individual in a given year.

The first step is to estimate a wage equation before aggregating the residuals at the firm or area level. We use the following regression to filter out the different effects:

$$\log w_{ikjt} = CONTROLS + O_i + F_k + R_{ikj} + \epsilon_{ikjt} \tag{3.23}$$

where we control for various individual level characteristics. Also, we control for occupation O_i of the individual to filter out the skill bias, as well as firm fixed effects F_k and region dummies R_{ikj}.

After running the above regression, we filter out the residuals to be further used in regressions reported in table 2. We back out the individual level residuals and then calculate average wage residual for each firm by averaging across workers from same firm. Similarly, for area level wage residual we average over all workers in a given geographical area.

TABLE 3.2: Capital share α_j for different sectors

Sector	Mean	Standard Deviation
10	0.67	0.14
11	0.77	0.14
12	0.79	0.12
13	0.59	0.20
14	0.49	0.19
15	0.49	0.17
16	0.62	0.17
17	0.65	0.17
18	0.56	0.17
19	0.71	0.13
20	0.67	0.18
21	0.71	0.17
22	0.62	0.18
23	0.64	0.18
24	0.66	0.18
25	0.56	0.17
26	0.51	0.19
27	0.52	0.19
28	0.51	0.18
29	0.56	0.17
30	0.56	0.18
31	0.52	0.17
32	0.52	0.17
33	0.44	0.17

Table 3.3: Point estimates from regressions in equations (3.16) and (3.17)

	Non-nested			Nested		
Sector	(OLS)	(Area)	(IV)	(OLS)	(Area)	(IV)
10	-0.16***	-0.04	-0.47	0.05	0.75**	3.71*
	(0.020)	(0.181)	(0.950)	(0.028)	(0.255)	(1.749)
11	-0.263***	-0.28	-0.88	0.26*	-0.63	-0.86
	(0.082)	(0.861)	(1.109)	(0.111)	(1.144)	(1.507)
12	-1.11	19.27	-11.86	0.41	-22.32*	14.12
	(1.191)	(10.26)	(25.16)	(1.030)	(7.571)	(31.12)
13	-0.03	-1.74**	-7.66	-0.18*	1.37*	6.41
	(0.046)	(0.556)	(6.068)	(0.057)	(0.672)	(5.681)
14	-0.06	0.69	0.84	0.00	-1.23*	-1.46
	(0.055)	(0.568)	(0873)	(0.061)	(0.620)	(1.006)
15	-0.06	0.80	-1.48	0.01	-1.43	-0.54
	(0.098)	(0.992)	(3.285)	(0.114)	(1.145)	(3.613)
16	-0.11***	-0.74*	-1.90	0.00	1.07*	3.34
	(0.039)	(0.353)	(1.700)	(0.047)	(0.423)	(2.372)
17	-0.127**	0.05	0.30	0.17**	-.29	-1.08
	(0.048)	(0.476)	(1.481)	(0.063)	(0.617)	(2.019)
18	-0.08**	0.30	0.63	0.03	0.33	0.44
	(0.028)	(0.298)	(0.452)	(0.036)	(0.380)	(0.568)
19	0.98*	4.09	10.29	1.01*	6.81	14.00
	(0.417)	(4.726)	(15.07)	(0.482)	(5.128)	(20.07)
20	-0.11*	0.47	1.22	-0.10	0.45	1.33
	(0.04)	(0.551)	(1.774)	(0.065)	(0.730)	(2.323)
21	-0.24**	-0.71	12.44	0.26	3.42	-35.67
	(0.118)	(1.124)	(32.33)	(0.151)	(1.433)	(87.62)
22	-0.03	0.71*	1.18	-0.04	-0.48	-0.33
	(0.029)	(0.304)	(0.700)	(0.040)	(0.404)	(0.881)
23	-.02	0.51	0.99	-0.04	-0.38	-0.46
	(0.053)	(0.505)	(1.020)	(0.067)	(0.645)	(1.278)
24	-0.09	0.94	0.80	-0.14	-2.09*	-1.92*
	(0.06)	(0.658)	(0.713)	(0.086)	(0.848)	(0.949)
25	-0.01	0.53**	1.40**	-0.06**	-0.40*	-1.12*
	(0.018)	0.177)	(0.505)	(0.020)	(0.200)	(0.548)
26	-0.05	-0.86	-0.72	0.02	0.54	-0.24
	(0.052)	(0.590)	(0.923)	(0.061)	(0.689)	(1.071)
27	0.12*	-0.21	-0.38	-0.29***	0.45	0.87
	(0.050)	(0.553)	(1.067)	(0.060)	(0.641)	(1.305)
28	0.02	0.04	0.46	-0.17***	0.00	-0.50
	(0.03)	(0.300)	(0.775)	(0.035)	(0.351)	(0.905)
29	-.09	0.58	6.68	-0.01	-0.95	-8.75
	(0.059)	(0.592)	(15.42)	(0.070)	(0.690)	(18.15)
30	-0.03	1.89	1.93	-0.21	-0.14	0.23
	(0.111)	(1.147)	(1.691)	(0.134)	(1.391)	(1.870)
31	-0.06	0.57	39.17	-0.04	0.49	14.35
	(0.042)	(0.402)	(227.6)	(0.051)	(0.473)	(86.76)
32	-0.06	-0.20	-2.12	-0.02	0.49	5.21
	(0.036)	(0.394)	(5.034)	(0.044)	(0.466)	(9.048)
33	0.03	0.35	0.95	-0.07*	-0.16	-0.77
	(0.028)	(0.290)	(0.578)	(0.031)	(0.314)	(0.626)

Table 3.4: Number of observations in above regressions

Sector	(1)	(2)	(3)	(4)	(5)	(6)
10	30085	37,326	30,084	30,890	37,331	30,089
11	1841	2,126	1,841	1,842	2,127	1,842
12	22	23	22	22	23	22
13	7,417	8,411	7,417	7,418	8,412	7,418
14	6,771	8,014	6,771	6,772	8,015	6,772
15	2,285	2,617	2,285	2,286	2,618	2,286
16	7,679	9,503	7,679	7,685	9,509	7,685
17	5,157	5,766	5,157	5,159	5,768	5,159
18	13,077	15,935	13,077	13,081	15,939	13,081
19	263	272	263	263	272	263
20	6,941	7,631	6,941	6,941	7,631	6,941
21	1,799	1,907	1,799	1,799	1,907	1,799
22	13,660	15,349	13,660	13,662	15,351	13,662
23	9,410	11,102	9,410	9,413	11,105	9,413
24	3,400	3,667	3,399	3,400	3,667	3,399
25	42,566	50,550	42,565	42,573	50,557	42,572
26	7,155	8,214	7,154	7,158	8,217	7,157
27	5,616	6,322	5,616	5,617	6,323	5,617
28	16,044	18,570	16,044	16,047	18,574	16,047
29	4,880	5,504	4,880	4,882	5,506	4,882
30	2,103	2,415	2,103	2,103	2,415	2,103
31	7,277	8,741	7,277	7,278	8,742	7,278
32	7,907	9,628	7,909	7,907	9,628	7,907
33	20,474	24,870	20,473	20,479	24,876	20,478

Table 3.5: Demand Elasticity ϵ_D

Sector	Markup(Mean)	Markup(SD)	ϵ_D(Mean)	ϵ_D(SD)
10	1.24	0.15	5.16	3.28
13	1.25	0.15	5.00	3.05
14	1.23	0.14	5.34	3.31
15	1.25	0.14	5.00	2.85
16	1.23	0.12	5.34	2.83
17	1.23	0.13	5.34	3.07
18	1.28	0.14	4.57	2.33
20	1.25	0.16	5.00	3.26
21	1.33	0.19	4.03	2.39
22	1.24	0.13	5.16	2.85
23	1.27	0.14	4.70	2.49
24	1.23	0.13	5.34	3.07
25	1.29	0.14	4.44	2.20
26	1.3	0.17	4.33	2.52
27	1.26	0.14	4.84	2.66
28	1.25	0.13	5.00	2.65
29	1.21	0.12	5.76	3.34
31	1.23	0.11	5.34	2.60
32	1.32	0.18	4.12	2.38
33	1.26	0.13	4.84	2.47

TABLE 3.6: Sector codes under NAF 1-digit "C"

Sector Code	Sector Name
10	Industries alimentaires
11	Fabrication de boissons
12	Fabrication de produits à base de tabac
13	Fabrication de textiles
14	Industrie de l'habillement
15	Industrie du cuir et de la chaussure
16	Travail du bois et fabrication d'articles en bois et en liège, à l'exception des meubles;
17	Industrie du papier et du carton
18	Imprimerie et reproduction d'enregistrements
19	Cokéfaction et raffinage
20	Industrie chimique
21	Industrie pharmaceutique
22	Fabrication de produits en caoutchouc et en plastique
23	Fabrication d'autres produits minéraux non métalliques
24	Métallurgie
25	Fabrication de produits métalliques, à l'exception des machines et des équipements
26	Fabrication de produits informatiques, électroniques et optiques
27	Fabrication d'équipements électriques
28	Fabrication de machines et équipements n.c.a.
29	Industrie automobile
30	Fabrication d'autres matériels de transport
31	Fabrication de meubles
32	Autres industries manufacturières
33	Réparation et installation de machines et d'équipements