ESSAYS ON DYNAMIC ADJUSTMENT IN LABOR MARKETS

by

Ding Xuan Ng

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Abstract

The makeup of jobs in the United States has undergone significant changes from 1980 to the 2010's - in terms of occupation choice, wage structure and geography. Many of these changes have been attributed to low-frequency trends in production technology, market structure, and global demand. In these essays, we investigate three types of low-frequency changes in labor demand, and provide theoretical models, as well as empirical evidence, of how they are dynamically causing adjustments in the US labor market.

In the first essay, we study the effects of technological changes that can substitute for "routine" task intensive occupations on unemployment spells. Constructing and estimating a search and matching model of unemployment, we find that the rate of unemployed workers from routine occupations who search for routine jobs has increased from 1990-2012. In the same time period, the rate of technological mismatch between these unemployed workers and routine job vacancies has nearly doubled. Post mismatch, the rate of labor force exit has risen for males in the goods-producing sector since the mid 1990's. These results suggest that there are considerable adjustment costs for unemployed labor from technological change.

In the second essay, we investigate if automation technologies have caused rising market shares by the largest firms in the US, and the impacts on the labor share of aggregate income. We construct a model where automation technologies are made available to a small number of firms within industries, and analyze partial and general equilibrium effects on factor shares. We find that the rise of "superstar firms" may cause a rise in the share of income accruing to owners/shareholders at the expense of traditional labor and capital inputs at first, but that the labor share should eventually increase as long as labor remains essential to the production process.

In the third essay, we explore the implications of large firm entry on county wage and

employment outcomes up to ten years after initial entry. Constructing a spatial equilibrium model of large firm entry into local labor markets, we decompose the effects of large firm entry into agglomeration effects, where the new large firm causes further entry of firms into the county for greater productivity benefits, and crowding out effects, where the large firm pushes existing firms to exit the county due to new higher wages. Estimating the model on a sample of counties with large establishment entry form 1990-2005, we find that for most industries, crowding out effects slightly outweigh the agglomeration effects, and large firm entry has a small net negative effect on county employment growth. Entry of manufacturing and services establishments result in lower crowding out effects and thus produce better employment growth outcomes than other industries.

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Chapter 2, *The Macroeconomics of Superstars* was co-authored with my advisor Anton Korinek.

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Chapter 1

Technological Unemployment and Occupational Mobility

1.1 Introduction

The US employment share for occupations that are intensive in *routine* tasks has declined steadily since the 1980's. These routine task intensive occupations include factory production workers and operators, but also includes white-collar clerical occupations. Also since 1990, the US employment share for occupations that are intensive in *manual* tasks has increased. Examples of manual task intensive occupations include technicians and repairmen, as well as service sector jobs such as protective services and personal care occupations.[1] The leading explanation for these changes in employment share is the fall of labor demand for routine occupations, brought about by adoption of new technologies that can replace human labor in routine tasks. This is called Routine-Replacing Technical Change (RRTC), and has been the

[1]For details, see for example Acemoglu and Autor [2010], who use Census and American Community Survey data to track changes on occupation employment shares from 1959-2007.

subject of a burgeoning literature since the pioneering work of Autor, Levy, and Murnane [2003], Autor, Katz, and Kearney [2006], and others. Furthermore, RRTC has happened in conjunction with rising demand for manual service occupations, studied in Siegel and Barany [2014], Autor and Dorn [2013], and others.

As RRTC leads to permanent job destruction in routine occupations, unemployed workers previously employed in these jobs should increasingly switch to manual occupations experiencing rising labor demand. The data show that this is not the case. We build a dataset on unemployment spells for individual workers from 1984-2012 using 11 panels of the Survey of Income Participation (SIPP), allowing us to track worker transitions in labor force status and sector/occupation of employment. The data show that from 1984-2012, the proportion of unemployed workers from routine occupation jobs who transition to manual jobs in the service sector has barely risen, while the proportion who return to routine occupation jobs has remained high and stagnant.

We find another trend in the data that deserves attention: unemployment duration for workers who transition from routine to manual occupations has increased steadily in the 1990's and 2000's. Not only has the average duration risen, the distribution of unemployment duration for occupation switchers has also become increasingly increasingly heavy-tailed. We note that these trends are observed particularly acutely for routine occupation workers in the goods-producing sector. Finally, we find that unemployed workers who eventually switch from routine to manual occupations have been exiting the labor force during their unemployment spell at higher rates.

Standard models of RRTC suggest that as labor demand for routine occupations declines, routine job losers will transition to manual occupations.[2] Our empirical evidence suggests

[2]Standard models of RRTC, such as that in Autor et al. [2006], are frictionless, and therefore have no unemployment. Routine occupation job losers transition immediately to manual occupations.

that this view is too simplistic, and that we need to better understand the dynamics of unemployment in the face of RRTC. To do this, we construct a search-and-matching model of unemployment based on the standard Diamond Mortensen Pissarides (DMP) framework, with important modifications. The labor market is segmented into sector-occupations, each of which may be subject to labor replacing technology shocks. The model generates *technological mismatch* in the sector-occupation for workers of low ability, implying that jobs for low ability workers will be destroyed, and unemployed workers of low ability will not be able to find jobs.

With imperfect information on the probability of technological mismatch in each sector-occupation, unemployed workers of heterogeneous ability and switching costs optimally select one sector-occupation in which to search, following the intuition of a standard Roy model. Upon meeting a vacancy in their selected sector-occupation, workers who are not productive enough to be employed in their selected sector-occupation are technologically mismatched, and can decide whether to search in a different sector-occupation or exit the labor force.

Those who eventually search in a different sector-occupation are a group we label **Mismatched Switchers**. If the proportion of Mismatched Switchers among unemployment inflows increases, the model predicts that unemployment duration for occupation switchers increases.

Technologically mismatched unemployed workers may choose to exit the labor force rather than switch due to high costs of switching sector-occupations. We label this group of unemployed workers **Mismatched Labor Force (LF) Exiters**. The model implies that a rise in the proportion of Mismatched LF Exiters reduces occupational mobility, and increases outflows from the labor force.

We identify and estimate technological mismatch in different sector-occupations for unemployed workers of different gender, age, and education groups from 1984-2012 using the data

on unemployment spells. For each unemployment spell, we track unemployment duration and outcomes - whether workers stay in their sector-occupation, switch sector-occupations, or exit the labor force at the end of the unemployment spell. To identify sector-occupation mismatch in our model, we exploit variation in unemployment duration for unemployed workers who switch sector-occupations. Intuitively, high unemployment duration for switchers reflects a larger share of mismatched workers who only expanded their search after finding themselves mismatched in their old sector-occupations. We also exploit variation in unemployment outcomes for workers who differ in original sector-occupations and individual characteristics. Intuitively, high rates of staying in the same sector-occupation indicate that unemployed workers are able to return to similar types of jobs, and thus are correlated with lower probability of mismatch.

Estimating our model, we find that the rates of Mismatched Switching and Mismatched LF Exit have risen from 1990-2012 for both routine and manual occupations, but more quickly for routine occupations. This is driven by three structural forces. First, unemployed workers are increasingly self-selecting into the sector-occupation of their previous job. Second, the probability of technological mismatch for unemployed workers has increased steadily since about 1990. Third, technologically mismatched workers are increasingly exiting the labor force rather than searching in a different sector-occupation. Yet, there is substantial heterogeneity in the evolution of technological mismatch across unemployed workers of different origin sector-occupations and demographic characteristics, and our estimation produces some fruitful insights.

We find evidence that unemployed workers have been increasingly staying in the sector-occupation of their last job for their job search. Self-selection into their old sector-occupation by unemployed workers has grown significantly from 1984-2012. This is most true for routine workers in the goods-producing sector, where the fraction of workers choosing to search in

their old sector-occupation increased from 87% in 1984 to $>$ 95% in 2012. There is no evidence that RRTC has reversed this trend, which standard RRTC models imply should happen. Rising self-selection into the same sector-occupation among unemployed workers is an indication that switching costs have risen, reducing mobility across sector-occupations.

We estimate that the probability of technological mismatch for routine unemployed workers searching in their old sector-occupations more than doubled from 1990-2008, from 13% to 30%. That is, in 2008, 30% of routine occupation unemployed workers seeking to be re-employed in routine jobs were unsuccessful in their search. Somewhat surprisingly, we find that among routine unemployed, mismatch has grown more rapidly for service sector workers than goods-producing sector workers in the 2000's. This is a striking result: research on the labor-replacing effects of technological change have often focused on goods-producing industries such as manufacturing and construction. Our results show that routine workers in service industries such as customer service representatives in telecommunications and cashiers in retail have experienced more mismatch than their goods-producing counterparts in the 2000's. Equally surprising is our result that mismatch has also been rising for manual workers, both in the goods-producing and service sectors.

Higher rates of unemployed workers searching in their old sector-occupation, coupled with lower rates of successful job search in routine occupations for ex-routine occupation workers, have resulted in higher rates of mismatch between job seekers and jobs in the markets for routine and manual workers. Aggregating across sector-occupations, we estimate that the proportion of unemployment inflows that are technologically mismatched has risen from about 13% as a fraction of total US unemployment inflows in 1984 to around 35% in 2007, the eve of the Great Recession.

Worryingly, rates of labor force exit for mismatched *men* from the goods-producing sector have been rising. In the early 1990's, about 75% of mismatched unemployed men chose to

exit the labor force rather than switch sector-occupations. By 2008, this rate increased to about 80% by 2008 for men in the goods-producing sector, and decreased to about 70% for men in the services sector. In contrast, the rate of labor force exit among mismatched women has declined broadly from 19840-2008. Aggregating across sector-occupations, Mismatched LF Exit has grown more rapidly than Mismatched Switching from 1990 to 2012.

Our paper can be seen as an analysis of how technological change affects unemployment dynamics, and adds to the literature on technology's effects on wage levels, the wage distribution, and employment. Earlier work on Skill-Biased Technological Change (SBTC) by Katz and Murphy [1992] and Bound and Johnson [1992] investigates the effects of technological change on wage inequality, while more recent work by Acemoglu and Restrepo [2017] emphasize technology's effects on employment, by changing the set of tasks requiring human labor. Our work is more closely related to the Routine-Replacing Technical Change (RRTC) models of Autor et al. [2003] and Goos, Manning, and Salomons [2009]. However, this literature typically assume frictionless settings that abstract from the transition dynamics that underlie sector-occupation mobility. As a result, unemployment does not appear in these models. By adding search-and-matching labor markets and sector-occupation switching costs for unemployed workers, we are able to investigate how labor market imperfections may impede labor market transitions across sectors and occupations after technological change.

Our paper is also related to the literature on sector and occupational mobility. Early treatments such as Heckman and Sedlacek [1985] and Heckman and Honore [1990] simulated sector mobility dynamics using the sector-selection model of Roy [1951], focusing on the econometrics of self-selection but abstracting from switching costs and unemployed workers flows. The literature on sectoral shocks, starting with the work of Lucas and Prescott [1974] focuses on the labor mobility effects of sector-level demand shocks. In particular, Jovanovic and Moffitt [1990] attribute the bulk of inter-sector labor mobility in the US from 1968-1980

to self-selection across sectors by workers, rather than sector demand shocks. We engage a similar question, but focus on a time period where technology shocks have had powerful effects on labor demand not just on the sector level, but also on the occupation level. Lee and Wolpin [2010], also focusing on sector mobility of workers, find that sector switching costs have impeded worker transitions from manufacturing to the service sector, depressing total output in both sectors. Using a finer classification of occupations than we do, Moscarini and Thomsson [2006] find that occupational mobility peaked around 1995 and continued to fall until 2005, the end of their sample. They attribute the decline to cyclical reasons, highlighting that the 2001 recession precipitated a sharp decline in occupational mobility. We find that declining occupational mobility can be attributed to lower frequency increases in sector-occupation switching costs from 1990-2012.

Finally, our paper is related to the literature on mismatch unemployment. So far, this literature has conceived of mismatch unemployment as the additional unemployment arising from mobility costs for workers across segmented labor markets, and includes work by Sahin, Song, Topa, and Violante [2012], Herz and van Rens [2015], Barnichon and Figura [2013], and others.[3] Out paper can be seen as proposing and estimating two explanations for the rise of mismatch unemployment - rising barriers to occupational mobility and shifting occupational labor demand. We also demonstrate an important consequence of rising sector and occupational mismatch - rising labor force exit by prime age workers. In this way, we provide a new mechanism for explaining the secular decline in the labor force participation rate. This decline, documented by Aaronson, Cajner, Fallick, Galbis-Reig, Smith, and Wascher [2014] and many others, has led to serious investigation as to how non-participation in the labor force should feature into macroeconomic models of job search. In contrast to Alvarez

[3]In the words of Herz and van Rens [2015], mismatch unemployment is "[u]nemployment that results from deviations from the benchmark condition," the benchmark conditions being zero wage rigidities and zero mobility costs for workers (and jobs) across segmented labor markets.

and Shimer [2011]'s notion of 'rest unemployment', where discouraged workers exit the labor force to wait out cyclical dips, unemployed workers in our model exit the labor force either to accumulate human capital for a match upon re-entering the labor force, or to take up the outside option permanently. Our results show that this mechanism is important in explaining the persistent fall in labor force participation among routine unemployed males.

By estimating the evolution of sector-occupation mismatch for unemployed workers from 1984-2012, this paper provides a picture of technological change that significantly advances the RRTC view that workers in routine occupations should transition seamlessly to manual occupations. Switching sector-occupations has become increasingly costly, which has encouraged ever more routine job losers to search in their original sector-occupations, despite the increasing likelihood of mismatch. Further, mismatch has not been isolated to routine occupations; unemployed workers in manual occupations have faced similar rates of growth in technological mismatch in the 2000's. Somewhat surprisingly, mismatch has affected routine workers in the service sector significantly more than routine workers in the goods-producing sector. Finally, the increased mismatch coupled with increasing unwillingness to switch sector-occupations across the economy has resulted in rising labor force exit in all sector-occupations excepting high-skilled abstract occupations. Labor force exit is a margin that can no longer be ignored when investigating unemployment dynamics.

1.2 Empirical Motivations

In this section, we present evidence for three trends in the unemployment behavior of workers who switch broad occupation groups. Firstly, we show that there is no evidence of increasing rates of switching from routine occupations to manual occupations from 1984-2008. Instead, unemployed workers from routine occupations are increasingly likely to stay

in routine occupations. Secondly, the duration of unemployment spells of workers who switch from routine to manual occupations has increased substantially. Thirdly, unemployed workers who eventually switch from routine to manual occupations are increasingly likely to exit the labor force (stop searching for jobs) during the course of their unemployment spell.

We use 11 panels of the Survey of Income and Program Participation (SIPP) that covers the time period from 1984-2008 to construct a pooled dataset of unemployment spells.[4] Each SIPP is a longitudinal panel that tracks individuals on a monthly basis across 2-6 years, with the length of the panel varying by survey. To construct our sample of unemployment spells, we use individual worker transitions in labor force status between monthly observations. For their labor force status, individuals can be employed (E), unemployed (U), or out of the labor force (O). We denote nonemployment, which could mean U or O, as $\not E$. We define an unemployment spell as an episode in an individual panel that starts with $E\not E$.[5] We include both EU and EO transitions in our unemployment spells to avoid misclassification of job losers from measurement error in self-reported job search variables. For details on identifying labor force status transitions with SIPP data, refer to Appendix A.1.1.

We restrict our unemployment spells sample to workers who are ages 18-64 at the start of the panel, not on temporary layoff[6] and remain in the SIPP panel for its entire length.[7]

We categorize employment into jobs by major sector and major occupation group. Jobs are either in the Goods-Producing ($Prod$) or Services ($Serv$) sector.[8] The Goods-Producing

[4]We use the 1984, 1985, 1987, 1990, 1991, 1992, 1993, 1996, 2001, 2004 and 2008 panels of the SIPP.

[5]We use monthly SIPP data, similar to Fujita and Moscarini [2017], in order to make our estimates on labor market flows consistent with the CPS. However, using panel data at the monthly instead of the weekly frequency introduces time aggregation issues, which implies that we miss $E\not E$ episodes that occur between monthly observations.

[6]We exclude workers on temporary layoff from our unemployment spells, Fujita and Moscarini [2017] present evidence that workers on temporary layoff exhibit quite different unemployment behavior from unemployed *job searchers*, who are our group of interest.

[7]Attrition of participants between waves of interviews introduces a sample selection bias in making within-sample comparisons. We expand on this below.

[8]Using 2-digit 2012 NAICS codes, $Prod$ comprises codes $11, 21, 23, 31-33$, while $Serv$ comprises all other

sector include Mining/Extraction, Construction and Manufacturing industries, while the Services sector includes Food and Accommodation, Healthcare, and Education industries.[9]

Following Autor and Dorn [2013] and many others, we use a task-based approach to classify occupation groups into 3 coarse groups - Abstract (A), Routine (R) and Manual (M). Using data from the US Department of Labor's Dictionary of Occupation Titles (DOT), we measure each occupation on three aggregate measures of Abstract, Routine, and Manual task requirements.[10] Informally, R occupations require the performance of repetitive tasks, and include white-collar occupations such as typists as well as blue-collar occupations such as machine operators. M jobs require the performance of laborious tasks with significant variation in physical responses, and include jobs such as truck drivers and social workers. A jobs require a high degree of reasoning and planning, and include occupations such as engineers and managers. In sum, we classify jobs into six possible sector-occupations, and denote them as $Sect.Occ$, where $Sect \in \{Prod, Serv\}$ and $Occ \in \{A, R, M\}$: for example, $Prod.R \rightarrow$ Goods-Producing Routine jobs, etc.

Each unemployment spell that ends in employment can then be described as:

$$E_{\tau,j} \nearrow \searrow E_{\tau+s,j'}$$

τ denotes the calendar year-month in which the worker separates from her job, and s is thus the duration (in months) of the unemployment spell The j subscript denotes the sector-occupation of the worker's job, and so $j \in \{Prod, Serv\} \times \{A, R, M\}$. If $j = j'$, then the worker stays in the same sector-occupation, and is termed a "stayer". On the other hand, if $j \neq j'$, then the worker finds a job in a different sector-occupation, and is termed a

2 digit codes excluding 92 (Public Administration)

[9] We have excluded agricultural workers from the analysis due to the seasonality of the worker and poor quality of data on agricultural workers.

[10] For details on consistent occupation classification, see Appendix A.1.3.

"switcher".

To compare unemployment duration consistently within and between panels, we must deal with the problems of right-censoring that accompany the use of SIPP panel data. Namely, each SIPP panel is of a different length, which introduces a right-censoring problem as unemployment spells have different amounts of time to develop. Further, $E\backslash E$ transitions that happen late in a panel also introduces a right-censoring problem, for the same reason. We ensure comparability across panels by a trimming procedure, ensuring that all unemployment spells have exactly 12 months to develop ex-ante. We elaborate on the trimming procedure in Appendix A.1.2.[11]

1.2.1 Summary Statistics

Table 1.1: Sample Size by Panel

Panel	Inds	Spells	*Prod*			*Serv*		
			A	R	M	A	R	M
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1984	26953	3966	74	1447	308	293	1100	744
1985	18693	2599	67	878	199	240	725	490
1987	15693	1848	41	630	116	156	558	347
1990	35063	2334	52	920	150	218	611	383
1991	22392	1498	49	587	98	149	386	229
1992	31502	2294	49	805	172	260	643	365
1993	30971	2030	39	680	109	232	585	385
1996	58957	10831	253	2723	673	1483	3394	2305
2001	52778	6673	179	1598	336	1117	2134	1309
2004	66826	9154	219	2029	434	1212	2669	2591
2008	57905	12692	395	3152	606	1717	3330	3492

Notes: Number of individuals and $E\backslash E$ spells by SIPP Panel. Further decomposed into number of $E\backslash E$ spells by previous broad sector and occupation group.

[11] For all of our empirical work, we use weighted estimates so as to have a nationally representative sample of workers. This is important as some SIPP panels oversample from a segment of the US population, e.g. the 1996 panel oversamples low-income households.

We present some summary statistics from our unemployment spells data. Table 1.1 shows the number of distinct workers after restricting the sample as described above (Column 2), as well as the number of unemployment spells by panel (Column 3). Columns 4-9 further break down the unemployment spells by sector-occupation *of previous job*. Table 1 shows that the panels vary considerably in sample size and length of panel. Generally, earlier panels have fewer unemployment spells, but this is made up for by the fact that pre-1996, SIPP panels overlap in calendar time.[12] We also note that any estimates involving unemployment spells for *Prod.A* (abstract production) workers are somewhat unreliable due to small sample size.

Table 1.2: Unemployment Outcomes and Duration by Panel.

Panel (1)	Stay (2)	Switch (3)	Exit (4)	Unemp (5)	Duration (6)
1984	0.53	0.21	0.12	0.14	3.4 (2.8)
1985	0.51	0.23	0.14	0.12	3.3 (2.7)
1987	0.55	0.23	0.14	0.074	3.1 (2.5)
1990	0.73	0.21	0.064	0.0034	2.1 (1.5)
1991	0.74	0.19	0.062	0.002	2.2 (1.8)
1992	0.73	0.2	0.072	0.0031	2.2 (1.8)
1993	0.72	0.2	0.075	0.0015	2.1 (1.6)
1996	0.68	0.14	0.14	0.035	3 (2.5)
2001	0.62	0.15	0.17	0.062	3.4 (2.9)
2004	0.64	0.14	0.18	0.043	3.1 (2.6)
2008	0.58	0.13	0.14	0.14	4.5 (3.7)

Notes: Columns 2-5:Partitioning each SIPP panel's E-to-E spells by outcome. "Stay" denotes employment in the same sector-occupation as previous job, "Switch" denotes employment in a different sector-occupation from previous job, "Exit" denotes labor force exit, "Unemp" denotes right-censored unemployment. Column 6: Mean (std) duration of E-to-E spells.

Table 1.2 presents statistics for duration and outcome of unemployment spells by panel. Columns 2-5 decomposes unemployment spells into 4 mutually exclusive and comprehensive outcomes - employed stayers ($E_{\tau,j}$-to-$E_{\tau+s,j}$); employed switchers ($E_{\tau,j}$-to-$E_{\tau+s,j'}$); labor force

[12]The SIPP redesign in 1996 also increased the number of households in the survey considerably.

exit ($E_{\tau,j}$ to O); and continued unemployment ($E_{\tau,j}$ to U). Columns 6 and 7 report the mean and standard deviation for unemployment duration for by panel, only for E to E spells.[13]

Using monthly labor force variables to identify transitions results in time aggregation issues, where we miss E to E transitions that happen between monthly observations, biasing measured unemployment duration upwards. In other words, these short unemployment spells are observed as EE transitions between jobs, or job to job transitions. Nevertheless, the size of the bias remains constant throughout our time period, as we use labor force status in the second week of each month throughout our sample. This allows us to be consistent with unemployment duration measured in the CPS, that also uses monthly data of labor force status observed in the second week of each month.

Column 3 in Table 1.2 show that the rate of switching sector-occupations through unemployment has declined steadily from 1984 to 2012. These findings are in line with a growing literature investigating declining occupational mobility in the past 30 years. Moscarini and Thomsson [2006] find using CPS data that rates of occupational switching fell sharply in the 1990's, and especially after the 2001 recession. More recently, Xu (2017) finds, using SIPP data,that occupational switching has declined from the mid 1990's onward. While these studies use finer classifications of occupation groups, Table 1.2 shows that the decline in occupational mobility is true even when we use a coarse division of occupations into three groups - Abstract, Routine, and Manual.

1.2.2 Slow Reallocation

Here we present new evidence that specifically, rates of switching from $Prod.R$ to $Serv.M$ jobs through unemployment have remained persistently low from 1984-2012. In RRTC mod-

[13]See Appendix A.1 for several pertinent limitations of using unemployment duration data from the SIPP.

els such as that in Autor and Dorn [2013], reduced demand for human labor in occupations with high routine task content leads to rising employment in low skill service jobs as $Prod.R$ workers switch to $Serv.M$ jobs. We show that this has not been happening in the data on unemployed worker flows. On the contrary, the rate of switching from $Prod.R$ to $Serv.M$ has actually been declining.

Figure 1.1 displays hires from unemployment into $Serv.M$ jobs, or $UE_{\tau+s,Serv.M}$ transitions, decomposed by previous sector-occupation j. Each year from 1984-2012, we take all $UE_{\tau+s,Serv.M}$ transitions observed in SIPP data where $\tau + s$ falls within that year. We then decompose these transitions into sector-occupations of previous employment. The solid red line shows that the proportion of hires whose previous employment was in $Prod.R$ jobs stayed essentially constant at around 7% from 1984-2008, showing that hires of $Prod.R$ unemployed workers did not account for the rise in employment share in manual service jobs observed by Autor et al. [2003], among others. While hires from $Serv.R$ rose in the earliy 1990's, the rate stagnates in the late 1990's at around 15%. On the other hand, hires from the rest of the economy (RoE) spiked from 1984 to the early 1990's, and declined thereafter. Since the RoE group includes potentially new labor force entrants, this may be accounted for by rising female labor force participation and employment into $Serv.M$ jobs in this period. From the mid 1990's onwards, the proportion of hires who are stayers rose significantly, continues to rise in the 2000's.

Figure 1.2 presents the smoothed evolution of next sector-occupation for R unemployed workers from 1984-2008, with the left panel displaying trends for $ProdR$ unemployed and the right panel for $Serv.R$ unemployed. Each year, we take all $E_{\tau,Prod.R}UE_{\tau+s,j'}$ transitions where τ falls within that year and decompose them by sector-occupation j of next employment. The dashed green line shows that the proportion of $Prod.R$ workers switching to $Serv.M$ jobs has risen very slowly and remains low and throughout the time period,

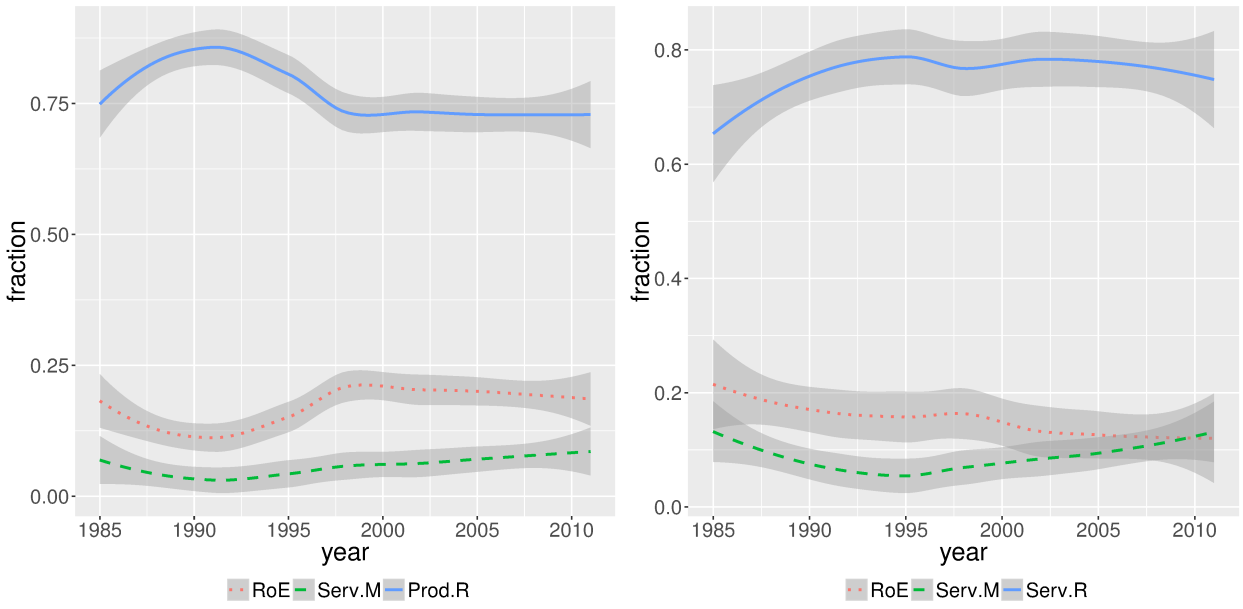


Figure 1.1: Hires into *Serv.M* by previous sector-occupation.
Notes: Each year, we take all observed hires into *Serv.M* in the combined weighted SIPP data. The lines are smoothed means over annual estimates using locally weighted smoothing using a quadratic polynomial and a bandwidth of 0.75. Error bounds are local asymptotic standard errors.

at around 7% from 2000-2012. Transitions to other sector-occupations from *Prod.R* jobs through unemployment has also been declining. The proportion of *Prod.R* unemployed who stayed in *Prod.R* jobs has remained stagnant since the late 1990's. The trends are very similar for *Serv.R* workers,who have also seen very gradual increase in transitions to *Serv.M* through unemployment, just slightly faster than for *Prod.*R workers.[14]

Taken together, the persistently high rate of *Prod.R* and *Serv.R* unemployed workers remaining in their sector-occupation in Figure 1.2 and the rise in hires into *Ser.M* jobs for workers who previously worked those jobs from the mid 1990's onwards shows that labor

[14]Complementary to our results are the findings reported in Cortes, Jaimovich, Nekarda, and Siu [2014], who find using CPS data that transitions from non-routine to routine occupations through unemployment has declined substantially since the 1980's.



(a) *Prod.R* (b) *Serv.R*

Figure 1.2: Job losers from R jobs, decomposed by sector-occupation of next job.
Notes: Each year, we take all observed job loss from *Prod.R* (left panel) and job loss from *Serv.R* (right panel) in the combined weighted SIPP data. The lines are smoothed means over annual estimates using locally weighted smoothing using a quadratic polynomial and a bandwidth of 0.75. Error bounds are local asymptotic standard errors.

market fluidity may be falling along a sector-occupation dimension.

We show that these trends in sector-occupation transitions for unemployed workers are robust to two common issues with using SIPP data to measure labor force transitions - seam bias and attrition bias. Seam bias refers to the phenomenon where labor force status changes are observed much more often between two waves of interviews (at the 'seam') than between two months within a wave. Seam bias should affect the timing of labor force transitions in and out of unemployment, but should not affect the eventual employment outcome observed. As such, we should not expect our Figure 1.2 results to be significantly affected by seam bias. As a further robustness check, we repeat this analysis removing labor force transitions that are observed at the seam from our sample, and find similar trends to those in Figures

1.1 and 1.2.

Attrition bias refers to sample selection problems that result from restricting our sample only to interviewees to remain in the survey through the entire length of the panel. If labor force transition behavior is correlated with the likelihood of attrition from the sample, our results may be affected by attrition bias. Prior research suggests that this might indeed be the case.[15] To check that our results in Figures and 1.1 1.2 this observation is robust to attrition bias, we repeat our analysis also using workers who leave the panel before its conclusion in our sample.

1.2.3 Unemployment Duration for Switchers Rising

We present evidence that unemployment durations for workers who switch occupations have increased from 1984-2012. In particular, this has been true for routine to manual occupations switchers.

Figure 1.3 shows the smoothed evolution of mean unemployment durations (by month) for unemployed workers who stayed in the same occupation group, and for those who switch. In the left panel, we plot the trend from 1984-2012, and note that the mean unemployment duration for occupation stayers, indicated by the red, gold, and green lines (for A,R,M occupation stayers respectively) has increased slowly since the mid 1990's. Unemployed durations for occupation switchers, indicated by the pink line, has increased more rapidly in the same time period. Plotting the trend for $Prod.R$ and $Serv.R$ workers who switch to manual jobs in the light blue and dark blue lines respectively, we find that $Prod.R$ to M switchers have consistently seen the highest unemployment durations.

Taking into account that changes in SIPP survey design (surveyed in detail in Appendix

[15]Investigating attrition bias in labor force status, McArthur (1988) found that the interviewees who respond throughout the panel have a lower unemployment rate than those who drop out.



(a) 1984-2012 (b) 1996-2012

Figure 1.3: Mean Unemployment Duration for Sector-Occupation Switchers and Stayers.

A.1.1) may affect the reliability of our results pre-1996, we plot the trend in mean unemployment duration post-1996 in Figure 1.3b. We observe that *Prod.R* workers who switch to *M* jobs still experience the highest mean unemployment duration. Further, their mean unemployment accelerated during the Great Recession, in contrast to *Serv.M* workers. This is not surprising, as we know that the early years of the Great Recession disproportionately affected the *Prod* sector.

To gain deeper insight into changes in the distributions of unemployment durations for occupation switchers, we plot unemployment duration densities for *R* to *M* occupation switchers in Figure 1.4. The left panel shows unemployment duration distributions for *Prod.R* to *M* switchers in three time intervals - 1984-1995 (red), 1996-2003 (green), and 2004-2012 (blue), and the right panel shows the same for *Serv.R* to *M* switchers. Each of these three intervals includes a period of economic expansion and a period of economic contraction. We



(a) *Prod.R* to *M* Occupation Switchers

(b) *Serv.R* to *M* Occupation Switchers

Figure 1.4: Unemployment Duration Densities for occupation switchers, from 1984-1995, 1996-2003, and 2004-12

immediately notice that for both groups, the right tail for unemployment duration is growing larger in later time periods. The growth of the right tail is especially large in the left panel, for *Prod.R* to *M* switchers.

Further, we note that from 1984-1995, the mode for unemployment duration is 1-2 months. In the 1996-2003 period, the distributions are clearly double model, with the first mode at 1-2 months and the second mode at 4-5 months. By the third interval, from 2004-2012, the first mode has almost completely disappeared, and the mode for unemployment duration is 4-5 months.

Longer unemployment durations for occupation switchers adds another dimension to the picture of declining labor market fluidity in the US, suggesting that routine unemployed workers are facing increasing barriers to switching occupations (especially to manual occu-

pations). In particular, how can we explain the increasing prominence of a second, higher mode in unemployment duration distributions for occupation switchers? It suggests that there are perhaps two distinct groups of unemployed workers who switch occupation groups, who differ by the nature of the frictions they face in their job search. In the rest of this paper, we investigate if the rise of the second mode for switchers can be explained by the rise of sector-occupation mismatch.

1.2.4 Labor Force Exit for Switchers

We find that R to M occupation switchers are dropping out of the labor force during the course of their unemployment spells at rising rates. Specifically, this means that unemployed workers reported that they stopped searching for jobs after losing their jobs, before eventually switching to M occupations. Figure 1.5 shows the rate of labor force exit during the unemployment spell for unemployed workers from 1984-2012. The red line represents routine to manual occupation switchers, the blue line represents all other occupations switchers, while the green line represents all stayers. The rate of labor force exit for routine to manual switchers has been significantly higher than all other switchers since the 1980's. From 1984 to the early 1990's, the rate of labor force exit during unemployment rises for routine to manual switchers from 1984-1990, while that of all other unemployed workers declined. By 2005, 30% of routine to manual switchers exited the labor force during unemployment, compared with 20% for all other switchers.

Higher labor force exit rates for routine to manual switchers is another indication that unemployed routine occupation workers are facing rising barriers to occupational mobility, particularly to manual jobs. These workers may be discouraged by their inability to find jobs in their origin sector-occupations, and exit the labor force rather than switch sector-

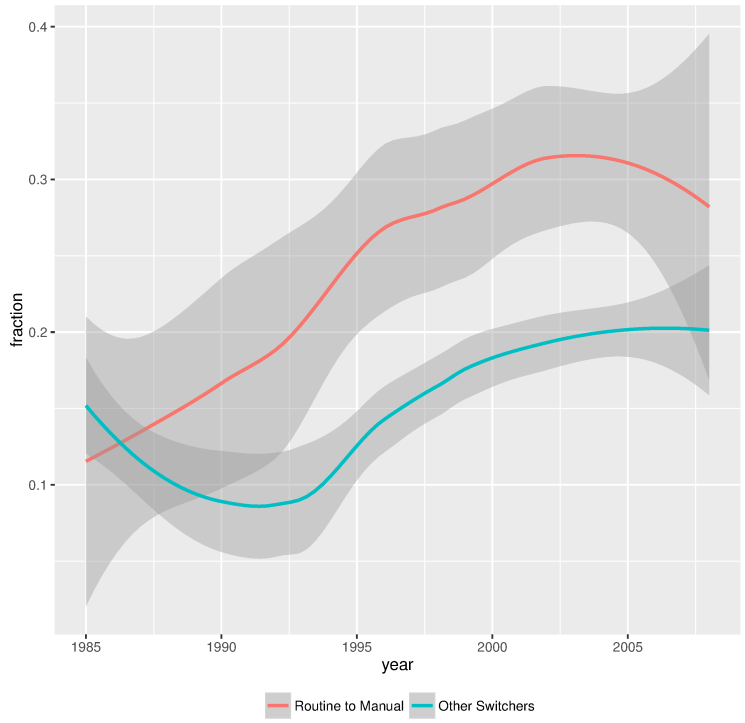


Figure 1.5: Labor Force Exit during Unemployment Spell.

occupations. Alternatively, workers may be exiting the labor force to accumulate the human capital necessary to gain employment in their final sector-occupations. In either case, rising labor force exit rates for switchers indicate that sector-occupation switching is becoming more costly.

1.2.5 Interpretations

In light of these empirical observations, this paper proposes the following unifying explanation that rests on the concurrent rise of two labor market trends. First, costs to sector-occupation mobility have risen, prompting unemployed workers to increasingly self-select into their origin sector-occupations. The literature cites several potential drivers - Lee and Wolpin [2010] find high non-pecuniary costs of mobility between goods and ser-

vices sectors, while Kambourov and Manovskii [2009] find that occupational mobility causes large destruction of occupation-specific human capital. Second, mismatch has increased for routine unemployed searching in their origin sector-occupations, due to reduced demand for routine labor driven by rising RRTC and offshoring of routine jobs. The net effect is that rising numbers of unemployed are not productive enough to be employed in the jobs they are searching for.

Unemployed workers self-select into their origin sector-occupations without realizing that the probability of mismatch is high, leading to time spent searching that does not result in employment. Upon realizing that they are mismatched, workers then redirect their search to other sector-occupations. This implies that among unemployed workers who eventually switch, a rising fraction only begin searching in their final sector-occupation after realizing they are mismatched in their origin sector-occupation, manifesting in longer unemployment durations for switchers, observed in Figure 1.4.

Higher rates of searching in the origin sector-occupation combined with higher rates of mismatch implies that more unemployed workers have to either search in other sector-occupations or exit the labor force. The high costs of sector-occupation mobility that induced higher rates of searching in the origin sector-occupation also lead to higher rates of labor force exit among mismatched workers, resulting in the observations in Figure 1.5.

As fewer unemployed workers self-select into different sector-occupations, and more workers are deciding to exit the labor force after mismatch, gross flows of unemployed workers across sector-occupations also declines. This results in the persistently low rates of switching into manual service jobs observed in Figure 1.2. Both mobility costs and mismatch constitute inefficiencies in the labor market, as they retard and prevent efficient reallocation of labor across sector-occupations. We construct a model that features both mechanisms, and estimate the relative contributions of each to dynamic and static labor market inefficiencies.

1.3 Model

We build an equilibrium search and matching model of the labor market segmented by sector-occupation. Newly unemployed workers optimally choose to either search in a sector-occupation for employment, or exit the labor force. Firms in each sector-occupation endogenously destroy jobs and create vacancies, subject to labor-replacing technological shocks. The model generates equilibrium worker flows in and out of unemployment, in and out of the labor force, and across sector-occupations. Within a sector-occupation's labor market, unemployed workers may be mismatched with vacancies if their skills are not demanded by job vacancies, generating mismatch unemployment in the model.

We first describe the search-and-matching architecture of our labor markets, each of which is based on a standard Diamond-Mortensen-Pissarides (DMP) model. The model is in discrete time, and we omit time subscripts for brevity in this section, denoting one period ahead versions of an object by the standard $'$ superscript. There is a finite number of sector-occupations indexed by $j \in \mathcal{J}$ in the economy. For each j, there is a search-and-matching labor market where firms and unemployed workers meet to fill sector j jobs. A matching technology represented by the matching function $m_j(\cdot, \cdot)$ takes the measure of unemployed workers searching in j ($u_j \in \mathbb{R}_+$), and the measure of vacancies opened by firms ($v_j \in \mathbb{R}_+$) as arguments. The assumption that labor markets are segmented means that meetings can only happen between vacancies in j and unemployed (who have decided to search) in j. [16]

We assume that the matching function is standard Cobb-Douglas for all $j \in \mathcal{J}$. Labor market tightness in each j is defined as $\theta_j = \frac{v_j}{u_j}$, job finding probability for workers defined as $f_j = \frac{m_j}{u_j}$, and job filling probability for firms defined as $q_j = \frac{m_j}{v_j}$.

[16] There is considerable empirical support for the assumption of segmented labor markets, for example, Barnichon and Figura [2013] argue that segmented labor markets fits labor market flow data better than the aggregate labor market approach.

Vacancies are costly to create and maintain, and an open vacancy incurs a fixed cost of κ to firms each period. There is a continuum $\mathcal{I}$ of workers in the economy, where $\mathcal{I}$ is of positive measure, and workers are indexed by i. Upon becoming unemployed, worker i is endowed with a vector of observable characteristics $\mathbf{x}$, which includes the sector-occupation of her previous job. She also draws from an ability distribution for each j, denoted $G_{j\mathbf{x}}(\alpha)$, and which has support $\mathbb{R}_+$. Note that $G_{j\mathbf{x}}(\alpha)$ varies by worker characteristics $\mathbf{x}$. [17] We denote as $\alpha_i = \{\alpha_{ij}\}_{j\in\mathcal{J}}$ unemployed worker i's vector of idiosyncratic sector-occupation specific abilities. We further assume that $\mathbb{E}[\alpha_{i\mathbf{x}}] = 1$, where $\mathbb{E}[\alpha_{i\mathbf{x}}]$ is the expectation of the ability random variable α_i, conditional on characteristics $\mathbf{x}$. This implies that conditional on $\mathbf{x}$, α_i can be interpreted as a multiplicative error term for productivity.

1.3.1 Labor Demand

Production

There is a representative firm in each sector-occupation j with the following production technology.

$$\mathbf{Y}_j = F_j(O_j)$$

$F_j(\cdot) \geq 0$, and has a positive first derivative and a negative second derivative. Each j takes as factor input O_j, aggregate efficient units of labor employed in j. j can be expressed as the integral:

$$O_j = \int_0^\infty \eta g_j(\eta) d\eta \tag{1.1}$$

[17] Thus, these distributions have a similar interpretation to the *skill to task mapping* used in Heckman and Sedlacek [1985] - a worker's ability in j depends on her skills $\mathbf{x}$.

In the above, $g_j(\eta)$ is the density function for η, the efficient units of labor employed in j.[18] [19] $\int_0^\infty \eta g_j(\eta) d\eta$ is its mathematical expectation, and is interpreted as the measure of efficient labor in j.

When employed, worker i's efficient units of labor in j can be expressed as:

$$\eta_{ij\mathbf{x}} = y_{j\mathbf{x}} \alpha_{i\mathbf{x}}$$

where $\eta_{ij\mathbf{x}}$, her j-specific efficiency units of labor, consists of a piece that is constant across workers of skills x in j ($y_{j\mathbf{x}}$), and a piece that measures idiosyncratic match-specific productivity ($\alpha_{i\mathbf{x}}$). [20] Each period, the marginal product to firm j of employing her is:

$$p_j F_j^1 y_{j\mathbf{x}} \alpha$$

F_j^1 is the first derivative of the production function $F_j(\cdot)$, which we have assumed to be positive and decreasing in aggregate efficient labor employed O_j, which we can interpret as the price of skill in j. $y_{j\mathbf{x}}$ can be interpreted as a skill-biased technological change parameter, and p_j is the price of the output good in sector-occupation j, which is taken as given by the firm.

Upon meeting worker i, firm j observes her type, $\mathbf{x}$, as well as her idiosyncratic ability in j, α_{ij}. The value function for firm j of employing unemployed worker i in Bellman equation form is:

$$J_{j\mathbf{x}}(\alpha_{ij}) = p_j F_j^1 y_{j\mathbf{x}} \alpha_{ij} - w_{jx}(\alpha_{ij}) + \delta \mathbb{E}[(1-\lambda) J'_{j\mathbf{x}} + \lambda V'_j] \tag{1.2}$$

[18] Note that we have not assumed that $\int_0^\infty \eta g_j(\eta) d\eta = 1$. $g_j(\eta)$ is an equilibrium object, determined each period by the distribution of η for employed workers in j. In other words, $g_j(\eta)$ is not a probability density.

[19] We assume $g_j(\cdot)$ is absolutely continuous in η, $\forall j$, and that it takes nonzero values only for $\eta > 0$, and furthermore, that $g_j(\eta) \geq 0 \forall \eta \in \mathbb{R}$.

[20] Since $\mathbb{E}[\alpha_{j\mathbf{x}}] = 1$, it follows that $\mathbb{E}[\eta_{ij\mathbf{x}}] = y_{j\mathbf{x}}$.

Again, the superscript $'$ indicates the one period ahead iteration of the object. In Equation 1.2, $w_{jx}(\cdot)$ is the wage function in j for $\mathbf{x}$ workers, that depends only on the worker's ability α_{ij}. λ is the probability of exogenous job destruction. Note that we have assumed here that λ is constant $\forall j$. Aside from the expression for the worker's marginal product, equation 1.2 is entirely standard for DMP models with exogenous job separation, so $J'_{j\mathbf{x}}$ and $V'_{j\mathbf{x}}$ are just the next period's value functions for employing the worker and having a vacancy in j respectively.

Technological Mismatch

Our model contains a technological mismatch mechanism, where a worker is not productive enough to be employed by the firm. Firms do not employ workers for whom the value from the employment relationship is negative. That is, for workers such that $J_{j\mathbf{x}}(\alpha_{ij}) < 0$, existing jobs are destroyed and potential workers are not employed. It is pinned down by solving, for each j and for each $\mathbf{x}$, the equation:

$$J_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}}) = 0 \ \ \forall j, \mathbf{x} \tag{1.3}$$

This condition for endogenous job destruction similar to that in Mortensen and Pissarides [1994]. Equations 1.2 and 1.3 imply:

$$p_j F^1_j y_{j\mathbf{x}} \alpha^*_{j\mathbf{x}} - w_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}}) = -\delta \mathbb{E}[(1-\lambda) J'_{j\mathbf{x}}] \ \ \forall j, \mathbf{x} \tag{1.4}$$

We make some immediate comments about equilibrium $\alpha^*_{j\mathbf{x}}$. First, firms will accept a current period loss from employing the marginal worker in anticipation of increasing productivity in future periods. Thus, the LHS of Equation 1.4 can be negative if $\delta \mathbb{E}[(1-\lambda) J'_{j\mathbf{x}}]$ is positive. The existence and uniqueness of $\alpha^*_{j\mathbf{x}}$ is ensured by the following condition.

Assumption 1.3.1. $\frac{d}{d\alpha}\left(MP_{j\mathbf{x}}(\alpha) - w_{j\mathbf{x}}(\alpha)\right) > 0$

That is, firm j's flow surplus from employing workers of type $\mathbf{x}$ are increasing in worker idiosyncratic ability α. Under Assumption 1.3.1, which holds under many standard sticky wage settings, including fixed wage and Nash Bargaining wages, there exists a unique $\exists\alpha^*_{jx} \in \mathbb{R}_+$.[21]

Imposing Assumption 1.3.1, $\alpha^*_{j\mathbf{x}}$ is thus a *technological productivity threshold* for workers of type $\mathbf{x}$ in sector-occupation j. Workers i such that $\alpha_{ij} < \alpha^*_{j\mathbf{x}}$ are technologically mismatched, and will not be employed in j.

Labor-Replacing Technical Change We now introduce labor-replacing technical change to our model. This takes a similar form to assumptions in models of RRTC, including those in Acemoglu and Autor [2010] and Restrepo [2016]. Specifically, it is assumed that a machine factor input is perfectly substitutable with human labor in the production of certain tasks. This is equivalent to assuming a task production function that is linearly additive in human and machine inputs. We thus model such a shock as a permanent positive additive shock to the measure of efficient factor inputs in j, O_j. In the presence of labor-replacing technical change, O_j is modified from Equation 1.1.

$$O_j = \int_0^\infty \eta g_j(\eta) d\eta + K_j, \tag{1.5}$$

The labor-replacing technology shock, K_j, has a direct impact on $\alpha^*_{j\mathbf{x}}$. By increasing the total quantity of efficient factor inputs for firm j, a postive K_j shock results in a a decline in F^1_j for present and future periods, reducing the skill price for labor in j. If Assumption 1.3.1

[21] We immediately see that in perfectly competitive labor markets, where marginal product is equated to wages in every period and no economic rents are made, Assumption 1.3.1 does not hold and the threshold α^*_{jx} does not exist.

holds, then lower ability workers become unprofitable for firms to employ. The threshold productivity $\alpha^*_{j\mathbf{x}}$ increases. This argument contains the intuition for the following partial equilibrium proposition:

Proposition 1. *Assume that sector-occupation j is in an initial steady state equilibrium. If Assumption 1.3.1 holds, a positive labor-replacing technology shock K_j in j results in an immediate increase in $\alpha^*_{j\mathbf{x}}$, $\forall \mathbf{x}$.*

The above proposition implies that a labor-replacing technical shock results in job destruction for existing workers i with $\alpha_{ij} < \alpha^*_{j\mathbf{x}}$. Further, more unemployed workers searching for jobs in j would be technologically mismatched. Both these implications are formal manifestations of a *labor-saving motive* in our model.

Our model can incorporate other types of shocks, including simple Skill-Biased Technical Change (SBTC), trade shocks, and sector demand shocks. Briefly, an increase in import competition and a negative demand shock are equivalent in our model, and both result in a rise in $\alpha^*_{j\mathbf{x}}$. SBTC results in rising $\alpha^*_{j\mathbf{x}}$ for type $\mathbf{x}$ workers that the shock was biased against, while having ambiguous impact on worker types the shock was biased towards. We formally discuss these shocks in Appendix A.2.1.

Vacancy Creation

The value of a vacancy in j is represented by the following Bellman equation:

$$V_j = -\kappa + \delta \mathbb{E}[q_j J'_j + (1 - q_j) V'_j] \tag{1.6}$$

Recall that κ is the per period cost of having a vacancy and q_j is the probability of filling the vacancy. The new feature in our model is the term $\mathbb{E}[J'_j]$ in Equation 1.6, the expected value of a future match in j. This term is defined as:

$$\mathbb{E}[J'_j] = \sum_{\mathbf{x}\in\mathbf{X}} \frac{u_{jx}}{u_j} \int_{\alpha^*_{j\mathbf{x}}}^{\infty} J_{j\mathbf{x}}(\alpha) dG_{j\mathbf{x}}(\alpha)$$

The expected value of a future match is the weighted average firm surplus from matching with an unemployed worker searching in j. As such, it depends on the distribution of $\mathbf{x}$ among unemployed workers searching in j, $\frac{u_{j\mathbf{x}}}{u_j}$, and also the expected value supplied by a match with a type $\mathbf{x}$ worker, characterized by $\int_{\alpha^*_{j\mathbf{x}}}^{\infty} J_{j\mathbf{x}}(\alpha) dG_{j\mathbf{x}}(\alpha)$. Note that firms internalize the probability of technological mismatch for each type of worker due to $\alpha^*_{j\mathbf{x}}$.

We adopt the standard assumption that free entry determines job creation for each j. That is,

$$V_j = 0 \tag{1.7}$$

Equation 1.7 implies that for each j, vacancies are created until the expected surplus from a vacancy is equal to the marginal cost of creating/maintaining a vacancy κ. Given $\alpha^*_{j\mathbf{x}}$ (determined by Equation 1.4) and $u_{j\mathbf{x}}$for each $\mathbf{x}$, Equation 1.7 implies that vacancy creation each period must satisfy:

$$\begin{aligned} \frac{\kappa}{\delta q_j} &= \mathbb{E}[J'_j] \\ &= \sum_{\mathbf{x}\in\mathbf{X}} \sigma_{j\mathbf{x}}(1 - G_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}}))\mathbb{E}[J'_{j\mathbf{x}}|\alpha_{ij} > \alpha^*_{j\mathbf{x}}] \end{aligned} \tag{1.8}$$

In the above, $\sigma_{j\mathbf{x}} = \frac{u_{j\mathbf{x}}}{u_j}$, the share of type $\mathbf{x}$ workers within the pool of unemployed in j. Intuitively, vacancy creation increases in the expected value from employing a worker in the next period, which depends on three components. First, firm j creates more vacancies if the

share of productive workers among unemployed workers is high. Second, more vacancies are created if there is low probability of technological mismatch (low $G_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}})$). Third, more vacancies are created if the surplus from employing a non-technologically mismatched worker is high, represented by the term $\mathbb{E}[J'_{j\mathbf{x}}|\alpha > \alpha^*_h]$.

To see how technological change may affect vacancy creation, we focus on the role of the technological mismatch parameter $G_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}})$. An RRTC shock that results in a rise in $\alpha^*_{j\mathbf{x}}$ (Proposition 1) reduces vacancy creation by increasing $G_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}})$, the probability of technological mismatch. Intuitively, vacancy creation is low if the unemployed pool searching in j are unlikely to be productive enough to be employed.

1.3.2 Labor Supply

We model the labor supply decisions of unemployed workers. To focus on the labor market transitions of unemployed workers, we do not consider on-the-job search (OJS) in our model. Only workers who become unemployed optimally decide on a sector-occupation to search in. To introduce mismatch unemployment to the model, we make the following assumptions. Workers know their skill type $\mathbf{x}$ and their abilities α_i in each j when they first become unemployed.However, they do not observe the ability thresholds $\alpha^*_{j\mathbf{x}}$ set by firms for any j. This is important so that in equilibrium, some workers do decide to search in sector-occupations where they are technologically mismatched ($\alpha_{ij} \leq \alpha^*_{j\mathbf{x}}$).

We also assume that all newly unemployed workers who transition into unemployment from a job in j draw a cost $c_{ij'}$ from distribution function $C_{j'\mathbf{x}}(\cdot)$, representing the costs of switching to a different sector-occupation $j' \in \mathcal{J}$. We can think of these flow costs as psychic costs of working in an unfamiliar job, in addition to retraining and relocating costs. Workers have full knowledge of these switching costs. Additionally, we assume that $c_{ij} = 0$ for the

worker's previous sector-occupation j. We denote the vector of sector-occupation switching costs for each unemployed worker i as $\mathbf{c}_i$.

Finally, each newly unemployed worker has information on the wage schedule for each sector $w_{jx}(\alpha)$, and can observe labor market tightness in each sector θ_j.

Newly unemployed workers make a sector-occupation search decision by maximizing the value of unemployed search, which we can express as the following Bellman equation:

$$U_{\mathbf{x}}(\alpha_i, \mathbf{c}_i) = b_x + \delta \max_{j' \in \mathcal{J}} \{\mathbb{E}[f_{j'} W'_{j'\mathbf{x}} + (1 - f_{j'}) U'_{\mathbf{x}}]\} \tag{1.9}$$

The unemployed worker receives a flow benefit $b_{\mathbf{x}}$ from unemployment, which we interpret as unemployment benefits. Equation 1.9 reflects the assumption that newly unemployed workers of type $\mathbf{x}$ choose to search for employment in some sector-occupation j by maximizing the surplus value from employment. The worker then enters the pool of unemployed in the chosen sector-occupation at the start of the next period. Once she has decided to search in a sector, she continues searching in that sector until she meets a vacancy.[22]

The value function for a worker who is employed in a job in j is:

$$W_{j\mathbf{x}}(\alpha_{ij}, c_{ij}) = w_{j\mathbf{x}}(\alpha_{ij}) - c_{ij} + \delta \mathbb{E}[\lambda U' + (1 - \lambda) W'_{j\mathbf{x}}] \tag{1.10}$$

Equation 1.10 is standard in DMP models with no OJS, except for the additional term c_{ij}, which is the flow cost to the worker of working in j.[23]

[22] Since we are modeling events that last a relatively short time (unemployment spells) at relatively high (monthly) frequencies, we think that assuming that unemployed workers do not re-optimize j each period is reasonable.

[23] We have specified c_{ij} as a flow cost instead of a one time fixed cost to simplify the analysis.

Unemployed Sector-Occupation Choice

Equation 1.9 implies that worker i chooses to search in sector-occupation j such that $f_j\mathbb{E}[W'_{jx}(\alpha_{ij}, c_{ij})]$ is highest.[24] To represent this decision, we define $\phi_{\mathbf{ix}}$ as the following:

$$\phi_{i\mathbf{x}} = j \text{ iff } f_j\mathbb{E}[W'_{j\mathbf{x}}(\alpha_{ij}, c_{ij})] > f_k\mathbb{E}[W'_{k\mathbf{x}}(\alpha_{ik}, c_{ik})]\forall k \neq j$$

$\phi_{i\mathbf{x}} = j$ if the worker self-selects into j.[25] The fraction of type $\mathbf{x}$ workers who self-select into j is then expressed as:

$$P(\phi_{i\mathbf{x}} = j) = P(\mathbb{E}[f_j W'_{j\mathbf{x}}] \geq \mathbb{E}[f_k W'_{k\mathbf{x}}]), \ \ \forall k \neq j \tag{1.11}$$

From the above, it is clear that unemployed worker sector-occupation decisions is an extension of the standard Roy model, for example, in Heckman and Honore [1990]. The main innovation in our model is that workers also take into consideration f_j, the probability of meeting a vacancy in each j, in their sector-occupation decision. In the standard Roy model, a key determinant of $P(\phi_{i\mathbf{x}} = j)$ is the covariance structure of ability distributions and switching cost distributions across sector-occupations. We do not impose assumptions on the joint distributions α_i and $\mathbf{c}_i$.

Mismatch and Labor Force Exit

Once a newly unemployed worker enters the pool of unemployed workers searching in some j, Equation 1.9 implies that each period, she meets a vacancy in j with probability f_j.

[24] To see this, note that $U'_{\mathbf{x}}$ is invariant to next period's sector-occupation choice.

[25] In our model, the value of employment in worker i's previous sector-occupation is always greater than the value of remaining unemployed. This ensures that a newly unemployed worker will always search in some j instead of exiting the labor force immediately. As such, our model is best suited to approximate the behavior of unemployed workers with significant attachment to the labor force.

Once she meets a vacancy, if $\alpha_{ij} \geq \alpha^*_{j\mathbf{x}}$, the worker makes a $UE_{\tau+s,j}$ transition. On the other hand, if $\alpha_{ij} < \alpha^*_{j\mathbf{x}}$,the worker is *mismatched* in j, and can either transition to searching in some other sector $k \neq j$, or exit the labor force. To represent the switching/labor force exit decision of mismatched workers, we define the variable $\psi_{i\mathbf{x}}$ as the following:

$$\psi_{i\mathbf{x}} = \begin{cases} 0 & \text{if } \mathbb{E}[U'_{\mathbf{x}}] > \mathbb{E}[W'_{k'\mathbf{x}}(\alpha_{ik'}, c_{ik'})] \ \ \forall k' \in \mathcal{J} \\ k & \text{if } \mathbb{E}[W'_{k\mathbf{x}}(\alpha_{ik}, c_{ik})] \geq \mathbb{E}[U'_{\mathbf{x}}] \\ & \text{and if } f_k \mathbb{E}[W'_{k\mathbf{x}}(\alpha_{ik}, c_{ik})] > f_{k'} \mathbb{E}[W'_{k'\mathbf{x}}(\alpha_{ik'}, c_{ik'})] \ \ \forall k' \neq k \end{cases}$$

Unemployed workers who self-select into j ($\phi_{i\mathbf{x}} = j$) but find themselves mismatched in j ($\alpha_{ij} < \alpha^*_{jx}$) choose $\psi_{i\mathbf{x}} = 0$ if the value of being unemployed exceeds that of being employed in any other sector-occupation. In this case, the worker stops searching and exits the labor force. The fraction of type $\mathbf{x}$ unemployed workers who exit the labor force can therefore be expressed as:

$$P(\psi_{i\mathbf{x}} = 0) = P\left(\mathbb{E}[W'_{k\mathbf{x}}] < \mathbb{E}[U'_{\mathbf{x}}] | \left\{\phi_{i\mathbf{x}} = j, \alpha_{ij} < \alpha^*_{j\mathbf{x}}\right\}\right) \ \ \forall k \neq j. \tag{1.12}$$

Otherwise, mismatched workers re-optimize in their sector-occupation search and search in that sector-occupation at the start of the next period.

1.3.3 Wage Determination

In our baseline model, we assume a simplified version of Nash Bargaining. In particular, we assume that the wage schedule is:

$$w_{j\mathbf{x}}(\alpha_{ij}) = \beta\left(p_j F_j^1 y_{j\mathbf{x}} \alpha_{ij}\right) + (1-\beta) b_{\mathbf{x}} \tag{1.13}$$

In the above, β is the standard Nash Bargaining parameter, interpreted as the bargaining power of workers. In our baseline model, we assume this to be constant across the economy. We observe immediately that the wage determination schedule satisfies Assumption 1.3.1, which guarantees the existence and uniqueness of $\alpha^*_{j\mathbf{x}}$.

Our functional form assumption for the wage schedule enables us to find a recursive equilibrium that has the analytically tractability required for estimating the model. Assuming Nash Equilibrium wage determination does not alter the implications of our model.

1.3.4 Worker Flows

The inflows to unemployment of type $\mathbf{x}$ workers is the sum of Employment to Unemployment (EU) flows and Out of Labor Force to Unemployment (OU) flows. EU flows, in turn, are the sum of exogenous and endogenous job destruction. Recall that exogenous job destruction is simply a constant share λ of employment, and endogenous job destruction is equal to the measure of employed workers i such that $\alpha_{ij} < \alpha^*_{j\mathbf{x}}$. We do not model OU flows, and take it as an exogenous variable.[26] Flows of type $\mathbf{x}$ unemployed workers searching in sector-occupation j, can be expressed as:

[26]We do not need to impose assumptions on OU flows in our estimation. OU flows will only be important in the characterization of steady state equilibrium, which we do not focus on.

$$
\begin{aligned}
u'_{j\mathbf{x}} = & \underbrace{(1-f_j)u_{j\mathbf{x}}}_{\text{No meeting with vacancy}} \\
& + \underbrace{P(\phi_{i\mathbf{x}}=j)\left(EU_{\mathbf{x}}+OU_{\mathbf{x}}\right)}_{\text{Self-selected into } j} \\
& + \underbrace{\sum_{k\neq j} P(\psi_{i\mathbf{x}}=j) f_k G(\alpha^*_{k\mathbf{x}}) u_{k\mathbf{x}}}_{\text{Mismatched switchers from } k \text{ to } j}
\end{aligned} \tag{1.14}
$$

Equation 1.14 is the law of motion for u'_j, and it clarifies worker flows in our model. The first component consists of unemployed workers who do not meet a vacancy in the current period, and they continue to search in j in the next period. The second component are the fraction of type $\mathbf{x}$ inflows to unemployment who self-select into j. The third component consists of unemployed workers who are searching in a different sector-occupation in the current period, meet a vacancy, realize that they are technologically mismatched, and decide to switch to searching in j.

For completeness, we also state the following laws of motion for employment and OLF in Appendix A.2.

1.3.5 Equilibrium

For each $j\mathbf{x} \in \mathcal{J} \times \mathbf{X}$, we have the following state variables: endogenous unemployed worker flow quantities O_j, $u_{j\mathbf{x}}$, $EU_{\mathbf{x}}$, $OU_{\mathbf{x}}$, and exogenous objects $y_{j\mathbf{x}}$ (skill-biased technological parameter), $g_{j\mathbf{x}}(\cdot)$ (density function for ability distribution), $c_{j\mathbf{x}}(\cdot)$ (density function for sector-occupation switching costs), and p_j (output price).

We then define a recursive equilibrium in our model as the following. For each $j\mathbf{x} \in \mathcal{J}\times\mathbf{X}$,

equilibrium in each period is the set of value functions $\{J_{j\mathbf{x}}, V_j, U_{\mathbf{x}}, W_{j\mathbf{x}}\}$, a labor demand vector $\{\alpha^*_{j\mathbf{x}}, v_j\}$, labor supply distribution functions $\phi_{i\mathbf{x}}$ and $\psi_{i\mathbf{x}}$, and unemployment worker flows $u_{j\mathbf{x}}$ such that:

- (Bellman Equations) $\{J_{j\mathbf{x}}, V_j, U_{\mathbf{x}}, W_{j\mathbf{x}}\}$ satisfying Equations 1.2, 1.6, 1.9, and 1.10.
- (Threshold Technological Productivity) $\alpha^*_{j\mathbf{x}}$ satisfies Equation 1.3,
- (Job Creation) θ_j satisfies Equation 1.7,
- (Sector Choice) $P(\phi_{i\mathbf{x}} = j)$ satisfies Equation 1.11,
- (Participation Choice) $P(\psi_{i\mathbf{x}} = 0)$ satisfies Equation 1.12,
- (Worker Flows) $u'_{j\mathbf{x}}$ satisfies Equations 1.14.

The timing of the model follows the order prescribed above, and can be summarized as follows. At the start of each period, firms in j decide on the technological productivity threshold for each $\mathbf{x}$, $\alpha^*_{j\mathbf{x}}$. This determines EU flows for next period. Firms then create vacancies v_j. Search-and-matching then occurs between unemployed workers and vacancies, which determines meetings ($m_{j\mathbf{x}}$), UE flows, and mismatched workers. At the end of the period, newly unemployed workers make their sector-occupation choices, determining the distribution of $\phi_{i\mathbf{x}}$, and technologically mismatched workers make sector-occupation/labor force exit choices, determining the distribution of $\psi_{i\mathbf{x}}$. This determines UO flows and cross sector-occupation flows. The laws of motion for worker flows than determine O_j and $u_{j\mathbf{x}}$ recursively for next period. We characterize our model's dynamic and steady state equilibrium in Appendix A.2.

1.4 Econometric Model

1.4.1 Decomposition of EU Flows

Our model implies that flows into unemployment from jobs in some sector-occupation k can be decomposed into distinct unemployment categories. For the rest of our paper, we employ the notation that type $\mathbf{x}$ workers come from sector-occupation $k \in \mathcal{J}$. That is, $E_k U_{\mathbf{x}}$ denotes flows from employment in k to unemployment. Figure 1.6 illustrates the decomposition of unemployment inflows implied by our model many periods after entry into unemployment.[27]

Upon entry into unemployment, workers optimally decide on a sector-occupation to search in, with full information on current labor market conditions f_j, their own ability α_{ij}, the wage schedule for their skills $w_{j\mathbf{x}}(\cdot)$, and their switching costs c_{ij}, for all $j \in \mathcal{J}$. However, they have no information on firms' ability thresholds $\alpha^*_{j\mathbf{x}}$ for any $j \in \mathcal{J}$. They self-select into some $j \in \mathcal{J}$, with this distribution denoted by $\phi_{i\mathbf{x}}$.

A fraction $P(\phi_{i\mathbf{x}} = k)$ of workers self-select into k, that is, they self-select into the sector-occupation of their previous job, while $P(\phi_{i\mathbf{x}} \neq k)$ of workers self-select into a different sector-occupation. We make the following simplifying assumption for identification: Those who self-select into a different sector-occupation from their previous employment are never technologically mismatched in that sector-occupation. We think this is a reasonable assumption, as workers who self-select into a different sector-occupation are likely to do so because of knowledge of their own comparative advantage there. As a result, a fraction $P(\phi_{i\mathbf{x}} \neq k)$ of workers make the $E_k U_{\mathbf{x}} E_j$ transition having self-selected into $j \neq k$. We call them **Self-Selected Switchers**.

Among the fraction $P(\phi_{i\mathbf{x}} = k)$, a fraction $1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ are matched successfully and

[27] As $t \to \infty$, the probability of meeting a vacancies in any sector j go to 1.

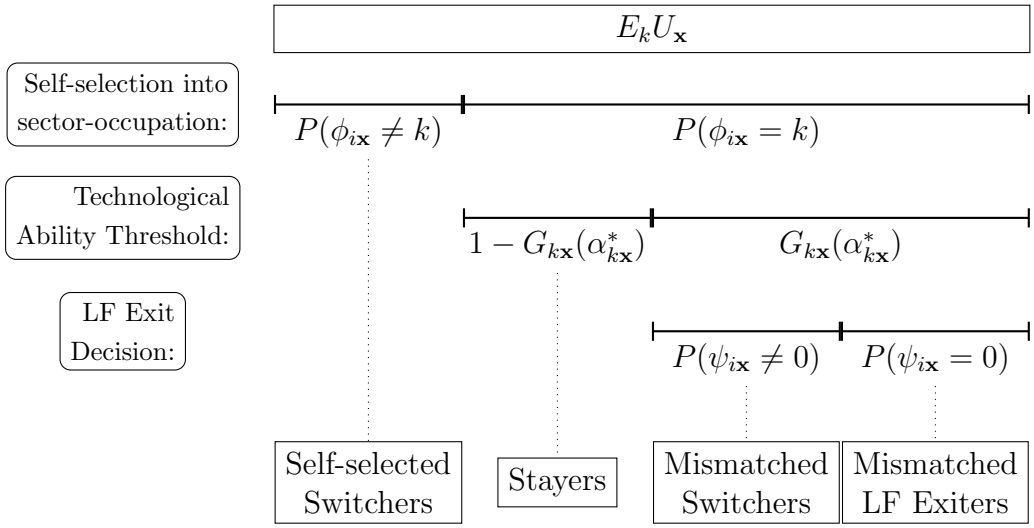


Figure 1.6: Decomposition of EU flows of type $\mathbf{x}$ workers from sector-occupation k

become employed in their previous sector-occupation k. These workers make the $E_kU_{\mathbf{x}}E_k$ transition, gaining employment in their previous sector-occupation. We call them **Stayers**.

The remaining fraction $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ of workers who self-selected into k find out that they are mismatched in k. For these workers, the probability of employment in k is 0, and optimally decide to switch to some other $j \neq k$, or exit the labor force.[28] A fraction $P(\psi_{i\mathbf{x}} \neq 0)$ decide to switch after mismatch in k, and eventually make the $E_kU_{\mathbf{x}}E_j$ transition for some $j \neq k$. We call them **Mismatched Switchers**.

Finally, a fraction $P(\psi_{i\mathbf{x}} = 0)$ of workers decide to exit the labor force after mismatch, and make the $E_kU_{\mathbf{x}}O$ transition. We call them **Mismatched LF Exiters**.

This model implies that many time periods after the initial inflow to unemployment, as the probability of meeting a vacancy goes to 1, EU flows from some sector-occupation k can be decomposed into four distinct groups: Self-selected switchers, mismatched switchers, stayers, and mismatched LF exiters. Figure 1.6 depicts this.

Of these four groups, self-selected switchers and stayers are appropriately classed under

[28] Formally, $\mathbb{E}[W'_{k\mathbf{x}}] = 0$.

conventional definitions of *frictional unemployment*, as their unemployment spells are simply due to having to wait for a meeting with a vacancy. On the other hand, mismatched switchers and mismatched LF exiters represent inefficiencies in labor force transitions across sector-occupations. Mismatched switchers self-select into their old sector-occupations, and spend time during unemployment searching for a job that they are not demanded for. High mismatch not only causes longer unemployment durations for mismatched workers, bringing about potential deleterious effects of longer unemployment, but also retards the rate of worker flows across sector-occupations. Mismatched LF Exiters are no longer employable in k, but cannot or will not switch into different sector-occupations. High numbers of mismatched LF exiters increases UO flows, and leads to higher *technological unemployment*, leading to lower labor force participation.[29]

1.4.2 Duration Model of Unemployment

Our model from Section 1.3 gives rise to a parametric duration model of unemployment, which will form the basis of our estimation. The implied distributions for the unemployment durations allow us to identify the structural parameters of the model. In particular, we have a variant of a proportional hazard model for unemployed workers who switch sector-occupations, a particular case in the class of models studied in Heckman and Singer [1984].

We can now state the unemployment duration distributions for *conditional on unemployment spell outcome*. Let the random variable for unemployment duration of worker i's unemployment spell beginning in period τ be denoted as $U_{i\tau}$. We also define as $out_{i\tau}$ the random variable for the outcome of the unemployment spell for worker i beginning in period

[29]We use the term technological unemployment rather than structural unemployment to emphasize that technological mismatch in their previous sector-occupation leads to the exit of these workers from the labor force.

τ. $out_{i\tau}$ can take four possible values - from the set $\{st, sw, ex, cu\}$. These represent staying in the same sector-occupation (st), switching to a different sector-occupation (sw), labor force exit (ex), and continued unemployment (cu), respectively.

Stayers

Unemployment spells that satisfy $out_{i\tau} = st$ experience $E_{k,\tau}U_{\mathbf{x}}E_{k,\tau+s}$ transition - they lose a k job at time τ, then return to a k job after s periods. Referring to Figure 1.6, they are **Stayers** in our model, and their unemployment duration is characterized by the distribution

$$(U_{i\tau}|out_{i\tau} = st) \;=\; U^s_{k\tau} \tag{1.15}$$

The random variable $U^s_{k\tau}$ characterizes the distribution of unemployment duration workers who self-select to search in k at time τ, with the superscript s denoting self-selection. In our model, the pmf for $U^s_{k\tau}$ is:

$$P(U^s_{k\tau} = s) = \left(\prod_{t=1}^{s-1}(1 - f_{k\tau+t})\right) f_{k\tau+s} \tag{1.16}$$

Note that the pmf resembles that of a geometric density, except that the hazard rate $f_{k\tau+t}$ varies across periods. Note also that the hazard rate for Stayers does not depend on worker type $\mathbf{x}$.

Switchers

Referring again to Figure 1.6, switchers from k to j can be either self-selected switchers or mismatched switchers. Conditional on switching, the distribution for unemployment duration is described by:

$$(U_{i\tau}|out_{i\tau} = sw) \;=\; U^{s}_{j\tau}\mathbb{1}(\phi_{i\mathbf{x}\tau} \neq k) + U^{m}_{kj\tau}\mathbb{1}(\phi_{i\mathbf{x}\tau} = k) \tag{1.17}$$

The unemployment duration distribution for a k to j switcher is $U^{s}_{j\tau}$ if she is a self-selected switcher, and $U^{m}_{kj\tau}$ if she is a mismatched switcher, where the superscript m for the latter denotes mismatch. The pmf for $U^{s}_{j\tau}$ is analogous to that for Stayers in Equation 1.16. The pmf for $U^{m}_{kj\tau}$ is:

$$P(U^{m}_{kj\tau} = s) = \sum_{s'=1}^{s}\left[\prod_{s''=1}^{s'-1}(1 - f_{k\tau+s''})f_{k\tau+s'}\prod_{s'=1}^{s-1}(1 - f_{j\tau+s'})f_{j\tau+s}\right] \tag{1.18}$$

$U^{m}_{jk\tau}$ denotes the random variable for unemployment duration for mismatched unemployed workers who first search in j, and then switch to searching in j' after they are mismatched. We assume that the worker is guaranteed a successful match in j' once she meets a vacancy. Equation 1.18 reflects this simplifying assumption, specifying that mismatched unemployed workers search in at most two sector-occupations. Equation 1.18 also reflects our model's implication that the lower bound for the unemployment duration for a mismatched unemployed worker is two periods. For $U^{m}_{jj'\tau} = 2$, she must meet a vacancy in j in period $\tau + 1$ and be mismatched, before meeting a j' vacancy in period $\tau + 2$ and gaining employment.

Using Equation 1.17, and given the distributions for $U^{s}_{j\tau}$ and $U^{m}_{kj\tau}$, we then have the following conditional expectation for unemployment durations of switchers:

$$\mathbb{E}[U_{i\tau}|out_{i\tau} = sw, \mathbf{x}] = \mathbb{E}[U^{s}_{k\tau}]P(\phi_{i\mathbf{x}\tau} \neq k|out_{i\tau} = sw) + \mathbb{E}[U^{m}_{k\tau}]P(\phi_{i\mathbf{x}\tau} = k|out_{i\tau} = sw)$$

For brevity, we define $p^{m}(\mathbf{x}) = P(\phi_{i\mathbf{x}\tau} = k|out_{i\tau} = sw)$. Intuitively, $p^{m}(\mathbf{x}) =$ is the probability that a worker was mismatched in k, conditional on eventually switching from

k to j. Since $P(\phi_{i\mathbf{x}\tau} \neq k|out_{i\tau} = sw) = 1 - P(\phi_{i\mathbf{x}\tau} = k|out_{i\tau} = sw)$, we can express the conditional expectation for the unemployment duration of switchers as:

$$\mathbb{E}[U_{i\tau}|out_{i\tau} = sw, \mathbf{x}] = \mathbb{E}[U^s_{k\tau}] + p^m(\mathbf{x}) \left(\mathbb{E}[U^m_{k\tau}] - \mathbb{E}[U^s_{k\tau}]\right) \tag{1.19}$$

Note that within a reasonable range of values for f_{jt}, $U^s_{j\tau}$ is resembles a geometric distribution. On the other hand, $U^m_{kj\tau}$ resembles the sum of two geometric distributions, which gives a negative binomial distribution counting the number of periods before two meetings. We make two observations. First, $\mathbb{E}[U^m_{kj\tau}] > \mathbb{E}[U^s_{j\tau}]$. Second, $mode(U^m_{jk\tau}) > mode(U^s_{j\tau})$. That is, the expectation and mode of unemployment duration for a mismatched switcher are higher than those of a self-selected switcher. These facts become intuitive when we note that self-selected switchers search immediately in the sector-occupation of their eventual employment j, while mismatched switchers search first in their last sector-occupation k, and only begin searching in j after realizing that they are mismatched in k.

We now make some observations on the unemployment duration distribution for switchers implied by our model. Given the distribution of unemployment duration for switchers (aggregating Equation 1.17 across i) is a weighted combination of the distributions $U^s_{k\tau}$ and $U^m_{kj\tau}$. As $p^m(\mathbf{x})$ rises for some $\mathbf{x}$, that is, the share of mismatched switchers relative to self-selected switchers rises, the mean and mode of the unemployment duration for switchers rises.[30] For values of $p^m(x)$ close to half, the unemployment duration of switchers of type $\mathbf{x}$ is bimodal. In Section 1.2, we noted that the unemployment duration distribution for switchers has seen two developments since the mid 1990's - it has developed a fat right tail, and it has developed a second mode. Viewed from the lens of our model, this reflects the

[30]The hazard rate for k to j switchers at time t depends on f_{kt}, f_{jt}, and $p^m(\mathbf{x})$. The resemblance to a proportional hazard model similar to Cox (1975) studied in Heckman and Singer [1984] derives from the dependence of the hazard rate on $p^m(\mathbf{x})$.

rise in number of mismatched switchers relative to self-selected switchers.

1.5 Identification

The key empirical exercise of our paper to use unemployment spell data to identify and estimate a decomposition of unemployment inflows into the four groups delineated in Figure 1.6. We wish to draw conclusions on whether mismatched switching and mismatched LF exit have been rising for unemployed workers in aggregate, and note trends for various demographic groups. Further, we also identify the structural parameters in our model - $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, $P(\phi_{i\mathbf{x}} = k)$, and $P(\psi_{i\mathbf{x}} = 0)$. The first of these, the probability of technological mismatch, should be interpreted as labor-demand drivers of sector-occupation mobility. The latter two, the probability of self-selecting into the same sector-occupation, and the probability of exiting the labor force upon mismatch, should be interpreted as labor-supply drivers of occupation mobility.

1.5.1 Data

We use the database of unemployment spells pooled from 11 SIPP panels from 1994-2012. The details of sample construction are laid out in Section 1.2. Each unemployment spell starts with a $E_{k,\tau}U_{\mathbf{x}}$ transition, where τ is the calendar month-year of the start of the unemployment spell, and $\mathbf{x} \in \mathbf{X}$ is a vector of characteristics which describe the unemployed worker's age, education, year of the start of the unemployment spell, and sector-occupation of the worker's last held job.

$$\mathbf{X} = \{gender, educ, age, year, k\}$$

$$gender \in \{M, F\}$$

$$educ \in \{\leq HS, SC, \geq BA\}$$

$$age \in \{17-30, 31-45, 46-64\}$$

$$year \in \{1984, 1985, ..., 2012\}$$

$$k \in \mathcal{J} \times \mathcal{N}, \quad \mathcal{J} = \{Prod, Serv\}, \mathcal{N} = \{A, R, M\}$$

We also observe the duration and outcome of the unemployment spell, which we denote by $U_{i\tau}$ and $out_{i\tau}$ respectively.

$$U_{i\tau} \in \{1, 2, ..., 12\}$$

$$out_{i\tau} \in \{st, sw, ex, cu\}$$

Our unemployment spells have durations that range from 1-12 months, since we restrict our unemployment spells to last a maximum of 12 months, to overcome problems with right-censoring in unemployment spells that start later in the panel. Outcomes can take four values - staying in the same sector-occupation (st), switching to a different sector-occupation (sw), labor force exit (ex), and continued unemployment (cu).

1.5.2 Identification of Labor Mobility Parameters

Identification of f_{jt}

We first show identification of job finding probabilities f_{jt} for each sector-occupation, during each month, ie $\forall jt \in \mathcal{J} \times \mathcal{T}$, where $\mathcal{T}$ includes all the months in our panels. We use a non-parametric strategy in the spirit of the Kaplan-Meier estimator for hazard rates.

Proposition 2. *Let N_{jt} be the number of unemployed in period t who are eventually Stayers in j. Let $E_{j,\tau \nearrow \mathbf{x}} E_{j,t}$ ($\tau < t$) be the number of unemployed whose last job was in j, and transition to employment in j in period t. Then, we have*

$$f_{jt} = \mathbb{E}\left[\frac{E_{j,\tau \nearrow \mathbf{x}} E_{j,t}}{N_{jt}}\right] \tag{1.20}$$

We use Equation 1.20 from Proposition 2 to estimate f_{jt}. The hazard rate for Stayers in j at time t can in turn be estimated by the rate of exit from unemployment in time t among all eventual stayers. While we do not observe the sector-occupation of search in any time t for eventual switchers (they may be Self-selected Switchers or Mismatched Switchers), our model implies that Stayers are always searching in the sector-occupation of last employment. In addition, Stayers are not technologically mismatched, because they are by definition successfully employed eventually. The meeting probability f_{jt} is thus equivalent to the hazard rate for Stayers. Since we can observe hazard rates for Stayers using a Kaplan-Meier estimator as described in Proposition 2, we can then identify f_{jt} for all jt.

f_{jt} allow us to identify $U^s_{j\tau}$, the unemployment duration distributions for self-selected searchers, for all $j\tau$, using Equation 1.16. We also identify $U^m_{kj\tau}$, the unemployment duration distributions for all mismatched searchers, for all $kj\tau$, using Equation 1.18.

Identification of $P(\phi_{i\mathbf{x}\tau} = k), G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}), P(\psi_{i\mathbf{x}\tau} = 0)$

We first prove identification for an intermediate parameter, $p^m(\mathbf{x})$, using Equation 1.19. Since we observe $U_{i\tau}$ and $out_{i\tau}$, we can construct the LHS of Equation 1.19. Given the full distributions $U^s_{k\tau}$ and $U^m_{kj\tau}$, we also identify $\mathbb{E}[U^s_{k\tau}]$ and $\mathbb{E}[U^m_{kj\tau}]$.

Equation 1.19 can be formulated as the following:[31]

$$\mathbb{E}\left[\frac{(U_{i\tau}|out_{i\tau} = sw) - U^s_{k\tau}}{U^m_{kj\tau} - U^s_{k\tau}} \;\middle|\; \mathbf{x}\right] = \frac{\mathbb{E}[U_{i\tau}|out_{i\tau} = sw, \mathbf{x}] - \mathbb{E}[U^s_{k\tau}]}{\mathbb{E}[U^m_{kj\tau}] - \mathbb{E}[U^s_{k\tau}]}$$
$$= p^m(\mathbf{x})$$

The first equality follows from the conditional independence of $U^s_{k\tau}$ and $U^m_{kj\tau}$ from $\mathbf{X}$, which also implies mean independence so that $\mathbb{E}[U^s_{k\tau}|\mathbf{x}] = \mathbb{E}[U^s_{k\tau}]$ and $\mathbb{E}[U^m_{kj\tau}|\mathbf{x}] = \mathbb{E}[U^m_{kj\tau}]$. [32] The second equality comes directly from manipulating 1.19. We can thus non-parametrically identify $p^m_\tau(\mathbf{x})$ as the conditional expectation (given $\mathbf{x}$) of the variable $\frac{(U_{i\tau}|out_{i\tau}=sw,\mathbf{x})-\mathbb{E}[U^s_{k\tau}]}{\mathbb{E}[U^m_{kj\tau}]-\mathbb{E}[U^s_{k\tau}]}$.

Conditioning on $\mathbf{w}$, we observe $P(out_{i\tau} = st|\mathbf{x})$ and $P(out_{i\tau} = sw|\mathbf{x})$ using their sample analogs from our data on unemployment spells. We now use $p^m(\mathbf{x})$, $P(out_{i\tau} = st|\mathbf{x})$, and $P(out_{i\tau} = sw|\mathbf{x})$ to identify our model's structural parameters.

Our model implies that Stayers self-selected into their previous sector-occupation k, and are technologically not mismatched. From our decomposition of unemployment inflows in Figure 1.6, we know that the fraction of stayers is:

$$P(out_{i\tau} = st|\mathbf{x}) = P(\phi_{i\mathbf{x}} = k)(1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})) \tag{1.21}$$

[31] This falls under the class of Additive Index Models, as studied in a large literature on Nonparametric Identification. See, for example, Matzkin [2007]. $p^m(\mathbf{x})$ is the index function we wish to identify.

[32] This is again based on the our model's implications (assumptions) that the meeting probabilities in each sector-occupation are only a function of labor market conditions, and are independent of worker type $\mathbf{X}$.

The share of Self-selected Switchers, as shown in Figure 1.6, is the fraction of switchers who are not technologically mismatched. Wer therefore have:

$$P(\phi_{i\mathbf{x}} \neq k) = (1 - p^m(\mathbf{x}))P(out_{i\tau} = sw|\mathbf{x}) \tag{1.22}$$

Equation 1.22 follows immediately from the fact that we defined $p^m_\tau(\mathbf{x}) = P(\phi_{i\mathbf{x}} = k|out_{i\tau} = sw)$.

Finally, we can express $P(\psi_{i\mathbf{x}\tau} = 0)$ as the fraction of unemployed who self-select into k, are mismatched, and *do not* switch to another sector-occupation. Formally, this can be expressed as:

$$P(\psi_{i\mathbf{x}} = 0) = 1 - \frac{p^m(\mathbf{x})P(out_{i\tau} = sw|\mathbf{x})}{G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})P(\phi_{i\mathbf{x}} = k)} \tag{1.23}$$

Equations 1.21-1.23 give us three equations in three unknowns - $P(\phi_{i\mathbf{x}} = k), G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}), P(\psi_{i\mathbf{x}} = 0)$. Proving identification for these three functions of $\mathbf{x}$ is straightforward. Identifying these structural parameters then allows us to perform the decomposition of *EU* flows into Self-Selected Switchers, Mismatched Switchers, Stayers, and Mismatched LF Exiters, by using the expressions for each component in Figure 1.6.

1.6 Estimation

We use kernel based regressions for our estimations for $p^m(\mathbf{x})$, $P(out_{i\tau} = st|\mathbf{x})$, and $P(out_{i\tau} = sw|\mathbf{x})$. Note that we have defined $\mathbf{X} = \{gender, educ, age, year, j\}$, where there are 2 gender groups, 3 education groups, 3 age groups,and 6 sector-occupations, over 29 years (from 1984-2012) of unemployment spells. We treat gender, education, age, and sector-occupation as discrete variables, and year as a continuous variable. As such, we have 5

regressors and $2*3*3*6 = 108$ discrete cells. Table 1.3 gives additional summary statistics by our chosen regressors for our unemployment spells data..

Table 1.3: Summary Statistics for unemployment spells data used in kernel regressions.

		All Spells	Switchers
N		54,000	10,344
Gender	M	0.56	0.59
	F	0.44	0.41
Age	18-30	0.39	0.48
	31-45	0.36	0.33
	46-64	0.26	0.19
Educ	$\leq HS$	0.52	0.52
	SC	0.33	0.34
	$\geq BA$	0.15	0.14
Sect-Occ	$Prod.A$	0.03	0.04
	$Prod.R$	0.27	0.23
	$Prod.M$	0.06	0.07
	$Serv.A$	0.13	0.14
	$Serv.R$	0.29	0.30
	$Serv.M$	0.23	0.22

To estimate $p^m(\mathbf{x})$, we use the regression implied by Equation 1.19, derived from our duration model of unemployment.

$$\mathbb{E}\left[\frac{(U_{i\tau}|out_{i\tau} = sw) - \mathbb{E}[U^s_{k\tau}]}{\mathbb{E}[U^m_{jk\tau}] - \mathbb{E}[U^s_{k\tau}]}|x\right] = p^m(x) \tag{1.24}$$

The regression in Equation 1.24 is the conditional expectation of a transformed variable of unemployment duration for *switchers*. To create the transformed LHS variable, we first estimate the full unemployment duration distributions for self-selected switchers and mismatched switchers, $U^s_{k\tau}$ and $U^m_{kj\tau}$, using Equations 1.16 and 1.18 respectively.

To do this, we need to estimate f_{jt} for each $t = \tau$ and $j \in \mathcal{J}$. We rely on the result in Proposition 2, to non-parametrically estimate $\hat{f}_{jt} = \frac{E_{j,\tau}\cancel{E_{\mathbf{x}}}E_{j,t}}{N_{jt}}$. We can then form the

transformed LHS duration variable in Equation 1.24 for regression estimation.

Equation 1.24 has an appealing intuitive interpretation. Recall that by construction, $\mathbb{E}[U^m_{kj\tau}] > \mathbb{E}[U^s_{j\tau}]$, $\forall j \in \mathcal{J}$ for a given k, implying that the denominator is always > 0. This implies that $p_m(\mathbf{x})$ is increasing in the conditional expectation for unemployment durations for switchers $\mathbb{E}\left[U_{i\tau}|out_{i\tau} = sw, \mathbf{x}\right]$. That is, the probability that switchers are mismatched rather than self-selected increases in the mean unemployment duration for unemployed workers of any given type $\mathbf{x}$. The closer the numerator $\mathbb{E}\left[U_{i\tau}|out_{i\tau} = sw, \mathbf{x}\right] - \mathbb{E}[U^s_{k\tau}]$ is to the model-implied value of $\mathbb{E}[U^m_{jk\tau}] - \mathbb{E}[U^s_{k\tau}]$, the larger the share of mismatched switchers among switchers of type $\mathbf{x}$.

A second thing to note is that the transformed LHS variable controls for labor market conditions in origin and destination sector-occupations. Switchers who switch to j with a loose labor market and (equivalently) low probability of meeting a vacancy face longer unemployment durations even if they are not mismatched. This increases both $\mathbb{E}[U^m_{kj\tau}]$ and $\mathbb{E}[U^s_{j\tau}]$, resulting in declines in the transformed LHS duration variable. Estimating the regression in Equation 1.24 will then imply lower $p^m(\mathbf{x})$. We can make a similar argument for how labor market tightness in the origin sector-occupation affects the LHS variable in the regression, which then has analogous interpretations for $p^m(x)$. In this sense, we estimate $p^m(x)$ using unemployment durations controlling for labor market conditions in the origin and destination sector-occupations.

We also estimate $P(out_{i\tau} = st|\mathbf{x})$ and $P(out_{i\tau} = sw|\mathbf{x})$. These are the probabilities that, conditional on $\mathbf{x}$, an unemployment spell results in staying and switching sector-occupations respectively. We use kernel-based regressions to non-parametrically estimate these functions of $\mathbf{x}$, which we denote $o^{st}(\mathbf{x})$ and $o^{sw}(\mathbf{x})$.

$$P(out_{i\tau} = st|\mathbf{x}) = \mathbb{E}[\mathbb{1}(out_{i\tau} = st)|\mathbf{x}] = o^{st}(\mathbf{x}) \tag{1.25}$$

$$P(out_{i\tau} = sw|\mathbf{x}) = \mathbb{E}[\mathbb{1}(out_{i\tau} = sw)|\mathbf{x}] = o^{sw}(\mathbf{x}) \tag{1.26}$$

For the regression in Equation 1.25, we form a binary variable for unemployment spell outcomes $\mathbb{1}(out_{i\tau} = st)$, that takes a value of 1 if unemployed stays in the same sector-occupation as her last job, and 0 if they do not. For the regression in 1.26, the binary variable $\mathbb{1}(out_{i\tau} = sw)$ takes the value 1 if the worker switches to a different sector-occupation. Taking as our sample all unemployment episodes, we estimate Equations 1.25-1.26 as separate kernel regressions, regressing binary dependent variables on $\mathbf{X} = \{gender, educ, age, year, k\}$.

In all, we estimate three kernel regressions, Equations 1.24-1.26. The choice of the non-parametric regression was made to retain complete flexibility over the shapes of $p^m(x)$, $o^{st}(\mathbf{x})$, and $o^{sw}(\mathbf{x})$, since theory gives us no guide as to how the components of $\mathbf{X}$ should influence the probability of mismatch. We have imposed some parametric restrictions on the in our duration model of unemployment, and do not wish to impose further parametric assumptions not implied by our model. Undoubtedly, this comes with tradeoffs, most notably the problem of dimensionality associated with all kernel methods, which restricts the number of variables we could include in $\mathbf{X}$.[33] Nevertheless, we have a large enough sample of unemployment spells from the pooled SIPP panel (as reported in Table A.1) to achieve reasonable standard errors. We expand on the details of our kernel regressions, including bandwidth selection and kernel choice in Appendix A.3.

[33] In our selection of the set $\mathbf{X}$, we initially included race and region, and excluded them in our final regressions after finding them to be insignificant.

1.6.1 Estimating Structural Parameters

In Section 1.5.2, we showed that for any $\mathbf{x}$, knowing $p^m(\mathbf{x})$, $o^{st}(\mathbf{x})$, and $o^{sw}(\mathbf{x})$ allows us to identify some of our model's structural parameters. Specifically, Equations 1.21-1.23 is a system of 3 equations in 3 unknowns.

We estimate these functions in the following order.

$$P(\phi_{i\mathbf{x}} \neq k) = (1 - p^m(\mathbf{x}))o^{sw}(\mathbf{x}) \tag{1.27}$$

Intuitively, $P(\phi_{i\mathbf{x}\tau} \neq k)$ is the portion of total switchers who are not mismatched. Using our kernel regression estimates for $p^m(\mathbf{x})$ and $o^{sw}(\mathbf{x})$, we use Equation 1.27 to estimate $P(\phi_{i\mathbf{x}\tau} \neq k)$.

$$G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}) = 1 - \frac{o^{st}(\mathbf{x})}{P(\phi_{i\mathbf{x}} = k)} \tag{1.28}$$

Noting that $P(\phi_{i\mathbf{x}} \neq k) = 1 - P(\phi_{i\mathbf{x}\tau} \neq k)$, the intuition for the above is that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ is simply the fraction of type $\mathbf{x}$ unemployed who self-select to search in k, the same sector-occupation as their previous job, and who are successful at gaining employment. We use our kernel regression estimates for $o^{st}(\mathbf{x})$ and our estimates of $P(\phi_{i\mathbf{x}} \neq k)$ from Equation 1.27 to estimate $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ using Equation 1.28.

$$P(\psi_{i\mathbf{x}} = 0) = 1 - \frac{p^m(\mathbf{x})o^{sw}(\mathbf{x})}{P(\phi_{i\mathbf{x}} = k)G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})} \tag{1.29}$$

Intuitively, the fraction of mismatched labor force exits $P(\psi_{i\mathbf{x}\tau} = 0)$ is the fraction of total mismatched who do not choose to switch sectors. We use our kernel regression estimates for $o^{sw}(\mathbf{x})$ and our estimates of $P(\phi_{i\mathbf{x}\tau} \neq k)$ and $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ to estimate $P(\psi_{i\mathbf{x}\tau} = 0)$ using Equation 1.29.

For our estimates of all three of the above, we use a parametric bootstrap procedure to estimate standard errors - we take iid draws from the asymptotic distributions of our kernel regression estimates to construct bootstrap samples. We estimate standard errors for our structural parameter estimates as:

$$s_z^2 = \left(\frac{1}{N} \sum_{i=1}^{N} \left(z(y_i) - z(\hat{y}) \right)^2 \right)^{1/2} \quad y_i \sim N(\hat{y}, \sigma_y^2)$$

where $z(y)$ denotes the structural parameter which is a function of parameters y, with the functional forms specified in Equations 1.27-1.29. We denote $\hat{y}$ as the estimated conditional mean of parameter y, and y_i a bootstrap sample drawing from the estimated distribution of y. Finally, σ_y^2 is the asymptotic variance of y, and N the number of bootstrap draws, In each case, we take $N = 999$.

1.7 Estimation Results

1.7.1 Kernel Regression Results

We first report our estimates for our kernel regressions for $p^m(\mathbf{x})$, $o^{st}(\mathbf{x})$, and $o^{sw}(\mathbf{x})$, with the regressors $\mathbf{X} = \{gender, educ, age, year, k\}$. In this section, we report our regression estimates as a function of $year$, for $1984 \leq \ year \ \leq 2012$, and selected $k \in \mathcal{J}$. In general, we omit estimates for abstract occupations and only report results for routine and manual occupations, because results for abstract occupation unemployed workers are largely insignificant due to smaller sample sizes. To get *composition-adjusted* estimates, we weight our estimates using *gender*, *age*, and *educ* shares at the beginning of the sample, in year

1985.[34] This implies that our results do not reflect the changing gender, age, and education composition in our sample.

In Figure 1.7, we report the evolution of $p^m(\mathbf{x})$ for workers of different origin sector-occupations k. We find that $p^m(\mathbf{x})$ increased substantially for workers from both routine and manual occupations in the 1990's and 2000's, from about 0.25 to 0.6. Recall that $p^m(\mathbf{x})$ is the probability of mismatch in the last sector-occupation among switchers. This means that from 1984-2008, the share of eventual switchers who were mismatched in their last sector-occupation rose from one quarter to greater than half.

Looking closer at Figure 1.7, we note that the $p^m(\mathbf{x})$ rise in the 1990's was steepest for $Prod.R$ workers, routine occupations in the goods-producing sector. From 2000 onward, however, other routine and manual occupations catch up to $Prod.R$ workers, and there is convergence by 2005, when about 50% of switchers were mismatched in their original sector-occupations for all routine and manual categories.

We report the full results for $p^m(\mathbf{x})$ conditional on gender, age, and education in Appendix A.3. Most notably, while middle-aged workers (aged 30-45) experience lower $p^m(\mathbf{x})$ than older workers (aged 46-64) in the 1990's, the gap disappears by around 2005. Also, while lower educated ($\leq HS$) workers experience higher $p^m(\mathbf{x})$ than higher educated workers in the 1980's and 1990's, the gap again declines by the mid 1990's. An overall theme seems to be convergence between workers of different groups in terms of probability of mismatch among switchers from 2000-2008.

Figure 1.8 plots the composition-adjusted regression estimates for $o^{st}(\mathbf{x})$, the probability of re-employment in the same sector-occupation for unemployed workers, again conditional on *year* and j. Figure 1.8 shows that $Prod.R$ workers consistently display higher $o^{st}(\mathbf{x})$ than

[34] We use the 1985 sample to estimate our weights because of the large sample size from that year compared to 1984.

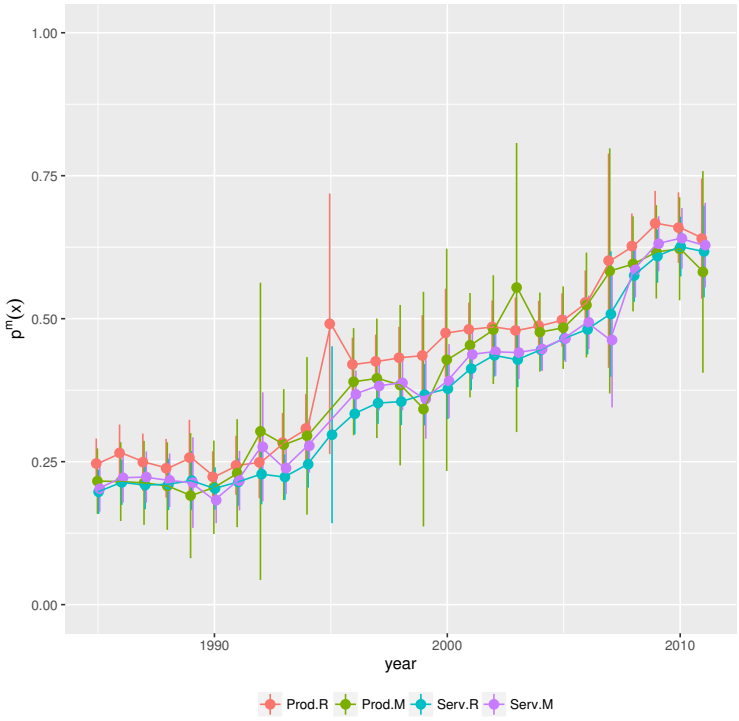


Figure 1.7: Estimates for $p^m(\mathbf{x})$ - probability of technological mismatch among sector-occupation switchers

Notes: Estimates derived from kernel regression with age, gender, education, and year regressors. Estimates are adjusted to match age, gender, and education composition of 1985 unemployment spells in pooled SIPP panel.

other routine and manual occupations. That is, $Prod.R$ unemployed workers experience higher rates of successfully staying in $Prod.R$.

In the 1990's, there was a steady decline in $o^{st}(\mathbf{x})$ for all sector-occupation groups, and the decline for $Prod.R$ workers was steepest. By 2000, the gap between $Prod.R$ workers and the other groups has almost completely disappeared. However, from 2000-2005, $Prod.R$ workers experienced a substantial bump in $o^{st}(\mathbf{x})$, with $Prod.M$ workers registering a small increase as well. On the other hand, $o^{st}(\mathbf{x})$ for $Serv.R$ and $Serv.M$ workers continues to decline, suggesting that there may be a sector effect for the goods-producing sector operative in this period, enabling more unemployed workers to stay in the same sector-occupation.

Examining results for $o^{st}(\mathbf{x})$ across gender, age, and education groups (reported in Appendix A.3) reveals some complementary conclusions. While lower and middle educated workers ($\leq HS$ and SC) experienced steady declines in $o^{st}(\mathbf{x})$ in the 1990's, highly educated ($\geq BA$) workers saw increases in $o^{st}(\mathbf{x})$ for most of the 1990's. The bump in $o^{st}(\mathbf{x})$ for $Prod.R$ workers from 2000-2005 was also observed for $\geq BA$ and to a smaller extent for $\leq HS$ workers, but not for middle educated SC workers. This bump was also observed for males, but not for females.

Figure 1.9 shows estimates for $o^{sw}(\mathbf{x})$,the probability of finding employment in a different sector-occupation.[35] Again, we report composition-adjusted estimates conditional on $year$ and j. For all routine and manual occupations, $o^{sw}(\mathbf{x})$ has declined throughout the time period. $Prod.R$ workers have consistently shown the lowest probability of switching among routine and manual workers, while $Prod.M$ workers display the highest. Interestingly, $o^{sw}(\mathbf{x})$ has declined rapidly among $Serv.M$ workers, while $Serv.R$ workers have experienced nearly stagnant $o^{sw}(\mathbf{x})$ since the mid 1990's.

[35]Recall that $o^{sw}(\mathbf{x}) \neq 1 - o^{st}(\mathbf{x})$, as unemployment spells can also end in labor force exit or continued unemployment.

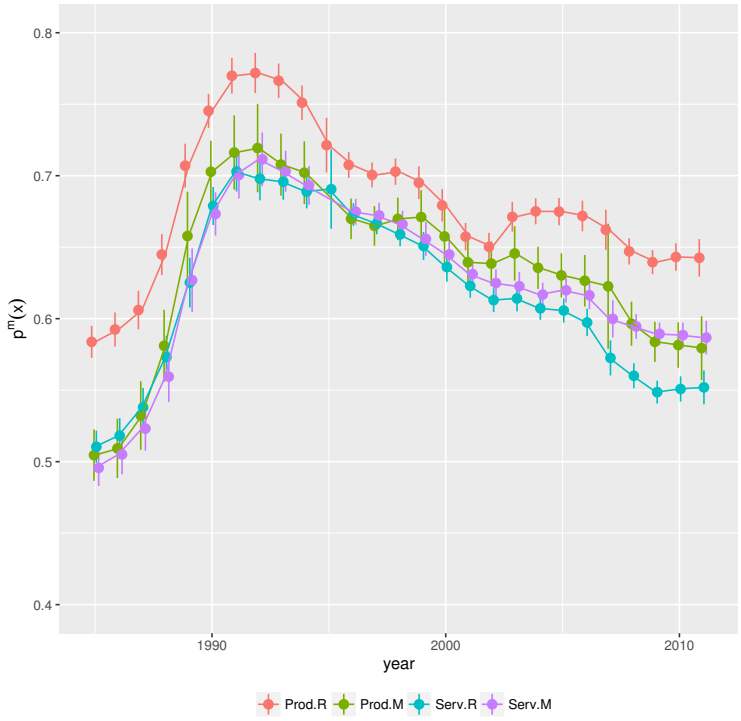


Figure 1.8: Estimates for $o^{st}(\mathbf{x})$ - probability of unemployed staying in same sector-occupation

Notes: Estimates derived from kernel regression with age, gender, education, and year regressors. Estimates are adjusted to match age, gender, and education composition of 1985 unemployment spells in pooled SIPP panel.

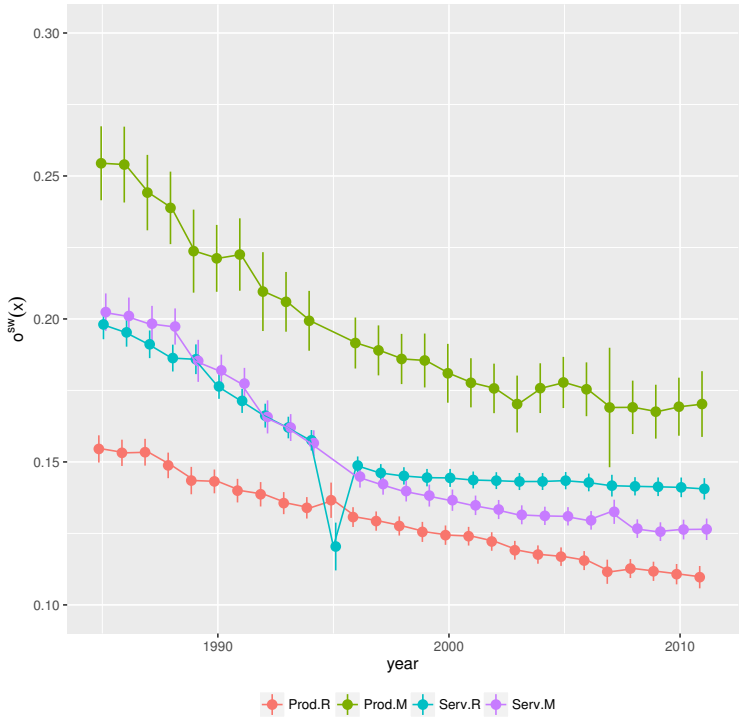


Figure 1.9: Estimates for $o^{sw}(\mathbf{x})$ - probability of unemployed switching sector-occupations
Notes: Estimates derived from kernel regression with age, gender, education, and year regressors. Estimates are adjusted to match age, gender, and education composition of 1985 unemployment spells in pooled SIPP panel.

1.7.2 Self-selected Switching - $P(\phi_{i\mathbf{x}} \neq j)$

We use our kernel regression estimates in our estimation of the model's structural parameters - $P(\phi_{i\mathbf{x}} \neq k)$, $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, and $P(\psi_{i\mathbf{x}} = 0)$.

Figure 1.10 shows estimates for $P(\phi_{i\mathbf{x}} \neq k)$ conditional on year and sector-occupation. Recall that $P(\phi_{i\mathbf{x}} \neq k)$ is the probability that unemployed workers self-select into a different sector-occupation. Once again, we omit estimates for abstract occupations because results are insignificant. For all 4 sector-occupations, $P(\phi_{i\mathbf{x}} \neq k)$ has declined significantly and continuously from 1984-2012. On average, in 1984, about 18% of routine and manual *EU* flows self-select into different sector-occupations from their last job. By 2007, only about 7% of *EU* flows do so. The Great Recession somewhat arrested this downward trend, with the share of self-selected switchers leveling off at about 5% of job losers from 2008-2012. This implies that $P(\phi_{i\mathbf{x}} = k) \approx 95\%$,that is, 95% of job losers self-select into the same sector-occupation as their last job. In particular, $Prod.R$ workers have demonstrated consistently lower probabilities of self-selected switching than other manual and routine workers. These results are observed across education and age groups.

What is implied by the result that $P(\phi_{i\mathbf{x}} \neq k)$ has been declining for routine and manual occupations? Recall that in our model, $\phi_{i\mathbf{x}}$ is determined in Equation 1.11 by expected wages and switching costs across sector-occupations. According to the basic Roy model, worker reallocation should decline between k and j if $Var(\alpha_{ij} - \alpha_{ik})$ declines, that is, if $Cov(\alpha_{ij}, \alpha_{ik})$ rises. Intuitively, if $Cov(\alpha_{ij}, \alpha_{ik})$ has risen over the past three decades, job losers are less likely to receive relative wage increases by switching sector-occupations, and so are less likely to self-select into a different sector-occupation. Rather more straightforwardly, switching costs across sector-occupations could also have risen. As explained in our model, c_{ij} could represent psychic costs of working in an unfamiliar work environment, or required retraining

costs.

Both explanations put downward pressure on $P(\phi_{i\mathbf{x}} \neq k)$, and could account for the result that $P(\phi_{i\mathbf{x}} \neq k)$ has declined for $Prod.R$ workers in the past three decades, which is counterintuitive considering the declining employment share of routine-intensive occupations in the same period.

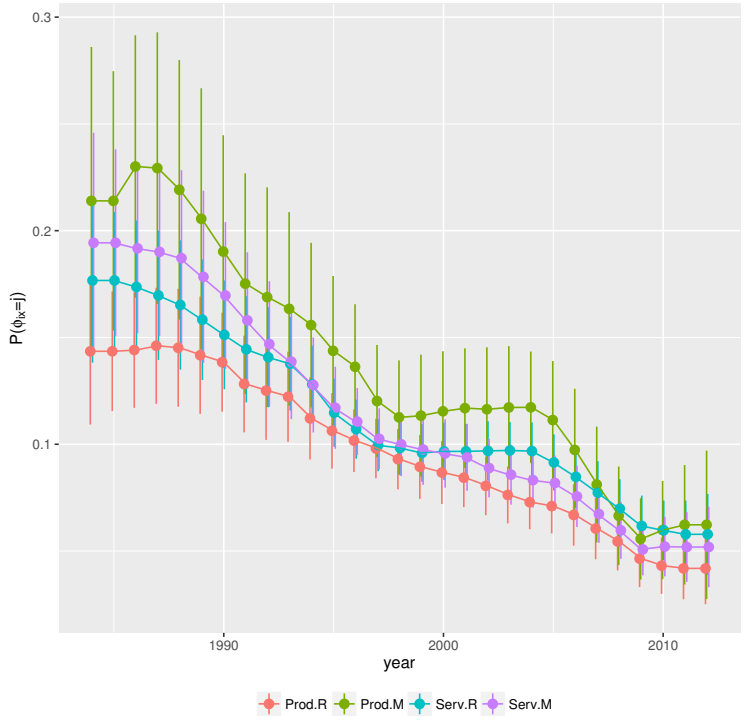
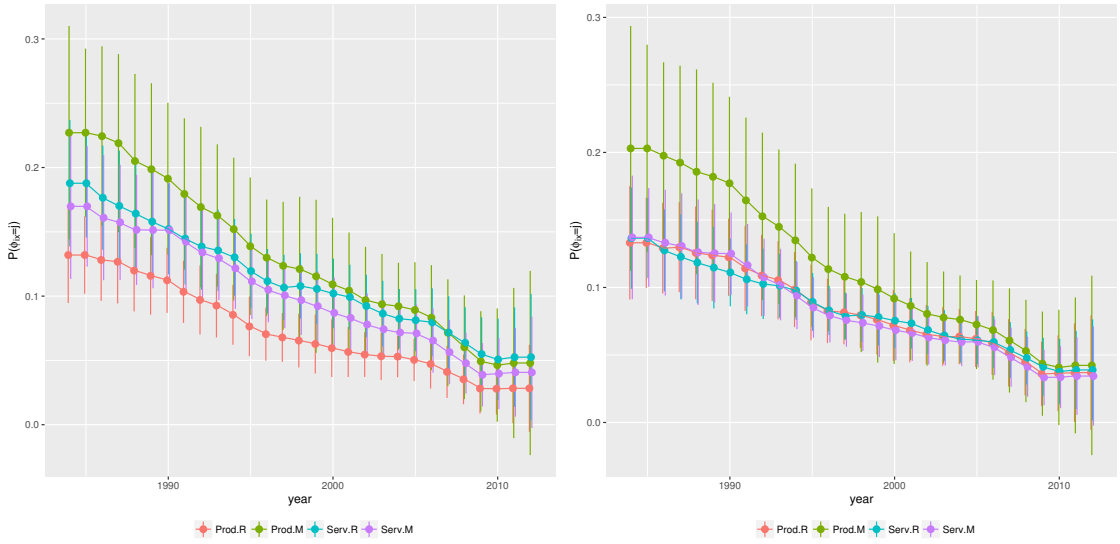


Figure 1.10: Kernel Regression Estimates for $P(\phi_x \neq j)$

Notes: Probability of Self-Selected Switching - conditional on origin sector-occupation from 1984-2012.

Recall that we have estimated $P(\phi_{i\mathbf{x}} \neq k)$ using Equation 1.27, where $P(\phi_{i\mathbf{x}} \neq k)$ is derived as a function of $p^m(\mathbf{x})$ and $o^{sw}(\mathbf{x})$. We can deduce from the results presented in Section 1.7.1 that declining $P(\phi_{i\mathbf{x}} \neq k)$ is driven by rising $p^m(\mathbf{x})$ and falling $o^{sw}(\mathbf{x})$. Intuitively, overall switching has declined steadily, while the share of mismatched switchers among switchers has risen. Consequently, both forces imply falling shares of self-selected



(a) Male (b) Female

Figure 1.11: Kernel Regression Estimates for $P(\phi_{i\mathbf{x}} \neq k)$

switchers. The result that *Prod.R* workers display a consistently lower $P(\phi_{i\mathbf{x}} \neq k)$ than other sector-occupations is clearly also a consequence of higher $p^m(\mathbf{x})$ and lower $o^{sw}(\mathbf{x})$ for *Prod.R* workers.

Gender Effects on $P(\phi_{i\mathbf{x}} \neq j)$

Figure 1.11 shows the estimates for $P(\phi_{i\mathbf{x}} \neq k)$ differentiated by gender. We first note that on average, males have higher rates of self-selected switching than females. Among males, however, *Prod.R* workers display the lowest $P(\phi_{i\mathbf{x}} \neq k)$, meaning that they are less willing to search in different-occupations than male job losers from other routine and manual jobs. This is not observed among female *Prod.R* workers. Thus, while unemployed males have higher rates of self-selected switching than females, this is not true for *Prod.R* men, who consistently have lower $P(\phi_{i\mathbf{x}} \neq k)$ than their male peers in other routine and manual occupations.

1.7.3 Technological Mismatch - $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$

Figure 1.12 shows estimates for $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, conditional on *year* and k. Recall that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ is the probability of mismatch in the sector-occupation of workers' last jobs. We first note that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ declined for all routine and manual occupation groups up to 1990, followed by consistent increases thereafter. The probability of mismatch more than doubles from about 13% in 1990 to almost 30% in 2008. Unsurprisingly, rates of technological mismatch continued to rise (along with spikes in job destruction) at the beginning of the Great Recession before some leveling off in the recovery.[36]

Broadly, $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ increased at about the same rate for all routine and manual occupations in the 1990's. In the 2000's, $Serv.R$ workers displayed the steepest increases in probability of technological mismatch,[37], while $Prod.R$ workers experienced the smallest increases, even experiencing a decline in mismatch in the mid 2000's. This has led to $Serv.R$ workers being the most mismatched group, and $Prod.R$ workers being the least mismatched group by 2008, and this has continued during the Great Recession.

Recall that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ rises in our model if labor demand for workers of type $\mathbf{x}$ decline. Our results reflect that for both routine and manual occupation groups, firms have been hiring unemployed workers previously employed in the same sector-occupation at lower rates since 1990.[38] In particular, labor-replacing technical change should lead to rising $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$.

Equation 1.28 shows that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ is estimated as a function of $P(\phi_{i\mathbf{x}} = k)$ and $o^{st}(\mathbf{x})$. Intuitively, the probability of *not* being mismatched is the probability of successfully finding re-employment in k ($o^{st}(\mathbf{x})$), conditional on self-selecting into k. The steep fall in $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$

[36] From the lens of our model, the Great Recession registers as a negative shock to output price p_{jt}, which Proposition 1 tells us leads to increases in $G_{jx}(\alpha^*_{jx})$, ceteris paribus. A recovery, by increasing future z_{jt} reduces $G_{jx}(\alpha^*_{jx})$.

[37] We find that this is true especially for young $Serv.R$ workers, aged 18-30.

[38] This is in line with findings by MOLLOY, SMITH, TREZZI, and WOZNIAK [2016] on declining aggregate hires by firms in the US.

in the late 1980's (rise in $1-G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$) is driven by the rise in of $o^{st}(\mathbf{x})$. From 1990 onwards, however, there is a reversal, with $o^{st}(\mathbf{x})$ declining for routine and manual workers. At the same time, self-selecting into their previous sector-occupations ($P(\phi_{i\mathbf{x}} = k)$ continues to rise). A larger pool of self-selected stayers and lower rates of successful stayers drive our result that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ rose since the 1990's.

Mismatch for $Serv.R$ vs $Prod.R$

The differences in rate of technological mismatch for $Prod.R$ and $Serv.R$ workers in the 2000's is a somewhat surprising result. If RRTC is driving rise in mismatch probability for routine unemployed workers, as predicted by our model in Proposition 1, $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ should have risen for both $Serv.R$ and $Prod.R$ workers. The decline in $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ for $Prod.R$ workers from 2000-2005 suggests that the rate of RRTC may actually have declined for $Prod.R$ workers in this period, while continuing apace for $Serv.R$ workers.

What is driving the decline in probability of mismatch for $Prod.R$ unemployed workers from 2000-2005? From our results in Section 1.7.1, we observe that this is associated with the rise in $o^{st}(\mathbf{x})$ for $Prod.R$ workers (also observed in $\leq HS$ and $\geq BA$ males), which was not observed in $Serv.R$ workers. Instead, $Serv.R$ workers experienced steadily declining $o^{st}(\mathbf{x})$ throughout the 2000's, resulting in steeply rising $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ for these workers in that period.

1.7.4 Labor Force Exit after Mismatch - $P(\psi_{i\mathbf{x}} = 0)$

Figure 1.13 shows our estimates for $P(\psi_{i\mathbf{x}} = 0)$, which is the probability labor force exit among technologically mismatched unemployed workers. Overall, the probability of labor force exit upon mismatch declined from 1984-1990 from about 90% to 80%, rose in the

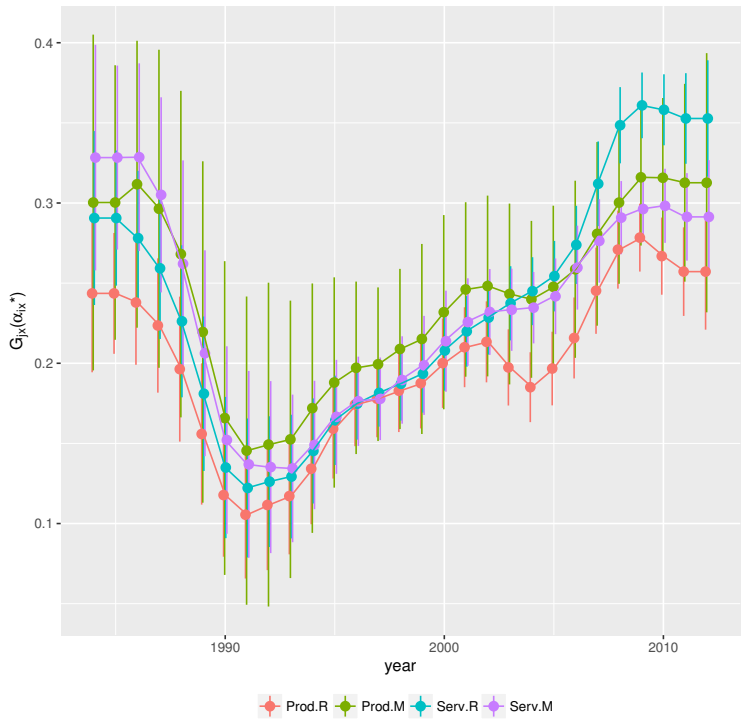


Figure 1.12: Kernel Regression Estimates for $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$

Notes: Probability of sector-occupation mismatch - conditional on origin sector-occupation from 1984-2012Non-Parametric Regression Estimates for $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ - probability of technological mismatch - from 1984-2012.

1990's and has declined gradually in the 2000's. Since 1990, the rate of labor force exit for mismatched workers has increased in $Prod.R$ and $Prod.M$, but declined for $Serv.R$ and $Serv.M$ workers. The rise in the 1990's was most prominent for $Prod.R$ workers, rising from about 72% in 1990 to 80% in the early 2000's. By 2000, mismatched $Prod.R$ workers are about as likely as those in other sector-occupations to exit the labor force.

From Equation 1.29, we note that that $P(\psi_{i\mathbf{x}} = 0)$ is estimated as a function of $P(\phi_{i\mathbf{x}} = k)$, $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, $p^m(\mathbf{x})$, and $o^{sw}(\mathbf{x})$. Intuitively, $P(\psi_{i\mathbf{x}} = 0)$ is the fraction of total mismatched workers (the denominator in Equation 1.29) who do not switch to other sector-occupations (the numerator in Equation 1.29). The decline in $P(\psi_{i\mathbf{x}} = 0)$ in the 1980's was driven by the decline in mismatch probability $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, and higher rates of mismatched switchers in that period (declines in $o^{sw}(\mathbf{x})$ offset by rising $p^m(\mathbf{x})$). In the 1990's however, $P(\psi_{i\mathbf{x}} = 0)$ increased due to the rise in mismatched workers (caused by lower $P(\phi_{i\mathbf{x}} = k)$ and higher $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$). For $Prod.R$ and $Prod.M$ workers, higher numbers of mismatched workers coupled with declining switching rates, implies that more mismatched workers are dropping out of the labor force in these sector-occupations.

Gender effects on $Prod.R$ $P(\psi_x = 0)$

Further conditioning on gender, Figure 1.14 gives us more insight into the rise of $P(\psi_{i\mathbf{x}} = 0)$ for mismatched $Prod.R$ workers in the 1990's. In 1990, $P(\psi_{i\mathbf{x}} = 0)$ was significantly lower for $Prod.R$ and $Prod.M$ females than $Serv.R$ and $Serv.M$ females. This reflects that in 1990, females in the goods-producing sector were more attached to the labor force than females in the services sector. From 1990-2007, while $P(\psi_{i\mathbf{x}} = 0)$ remains steady for $Prod.R$ and $Prod.M$ females, it declines steadily for $Serv.R$ and $Serv.M$ females. This reflects rising attachment to the labor force among service sector females, even controlling for age and education composition of the sample.

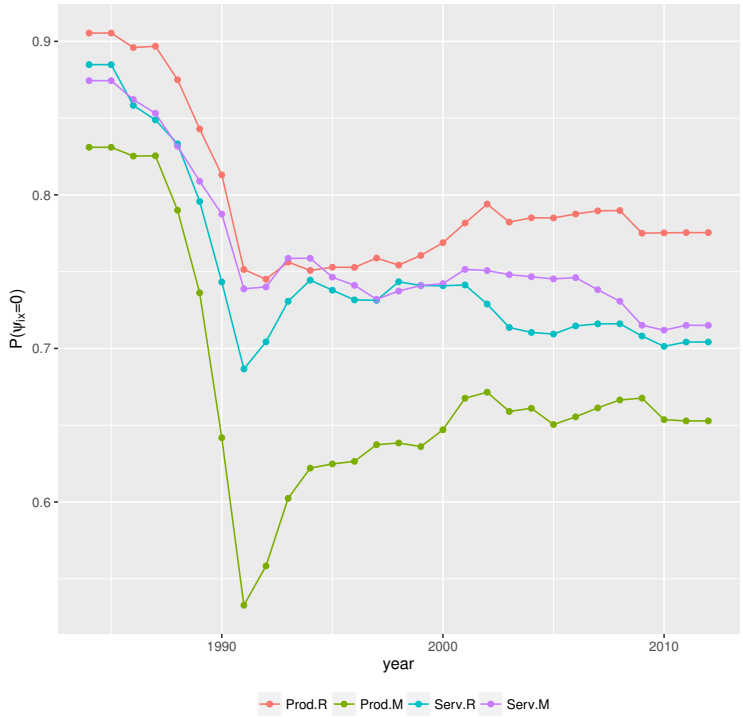
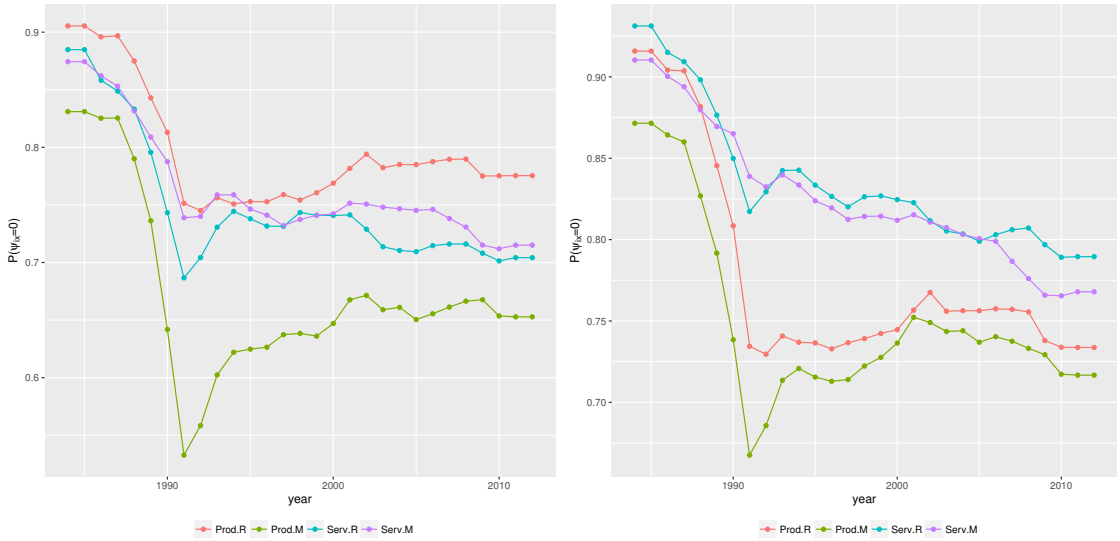


Figure 1.13: Kernel Regression Estimates for $P(\psi_x = 0)$
footnotesize: Notes: Probability of labor force exit after mismatch - conditional on origin sector-occupation from 1984-2012.

Prod.R and *Prod.M* males, on the other hand, see rising $P(\psi_{i\mathbf{x}} = 0)$ from 1990-2007. Instead of switching to other sector-occupations, in particular manual task intensive occupations, *Prod.R* males are exiting the labor force at higher rates after technological mismatch. Strikingly, $P(\psi_{i\mathbf{x}} = 0)$ for *Prod.R* males surpasses that of *Prod.R* females by around 2000.

$P(\psi_{i\mathbf{x}} = 0)$ during the Great Recession

All routine and manual workers experienced significant declines in $P(\psi_{i\mathbf{x}} = 0)$ during the Great Recession. To understand why, we note that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ increased across the board as seen in Figure 1.12. The rise in $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ results in job destruction even for workers with higher ability, and implies that workers with higher ability α_{ij} are mismatched from their



(a) Male (b) Female

Figure 1.14: Kernel Regression Estimates for $P(\psi_x = 0)$

original sector j. If $Cov(\alpha_{ij}, \alpha_{ik}) > 0$, workers with higher α_{ij} are likely to switch sectors instead of exiting the labor force after mismatch. Thus, increasing mismatch of higher ability workers drives the decline in $P(\psi_{i\mathbf{x}} = 0)$

1.7.5 Summary of Structural Parameter Results

We list some notable results from our structural estimation.

1. Rates of unemployed routine and manual workers self-selecting out of their last sector-occupations have fallen steadily from 1984-2012.

2. On average, male unemployed are more likely to self-select out of their old sector-occupations than females.

3. Among male workers, *Prod.R* workers are less likely to self-select out of their last sector-occupation than males from other sector-occupations.

4. Mismatch among unemployed who self-select into their last sector-occupations has been rising for both routine and manual occupations since 1990.

5. From 2000 onwards, $Serv.R$ workers experienced steeply rising rates of mismatch while $Prod.R$ workers saw declines in the mid 2000's. Since 2008, $Serv.R$ workers have faced highest rates of mismatch, while $Prod.R$ workers have faced the lowest.

6. Since 1990, the rate of labor force exit after mismatch has increased for $Prod.R$ and $Prod.M$ unemployed males, but declined for $Serv.R$ and $Serv.M$ unemployed males.

7. Labor force exit among mismatched workers has continued to decline from 1990-2012 for service sector females, and has been declining from 2000-2012 for goods-producing sector females.

8. Rates of labor force exit after mismatch has been greater among $Prod.R$ men than men and women from all routine and manual sector-occupations since the mid 2000's.

1.8 Aggregate Mismatch

We now use our structural parameter estimates to construct time series for the decomposing EU flows into the components in Figure 1.6. In particular, we are interested in the evolution of mismatched switchers and mismatched LF exiters, who represent two measures of labor market frictions that inhibit unemployed worker flows across sector-occupations. For clarity, we recount the elements of this decomposition.

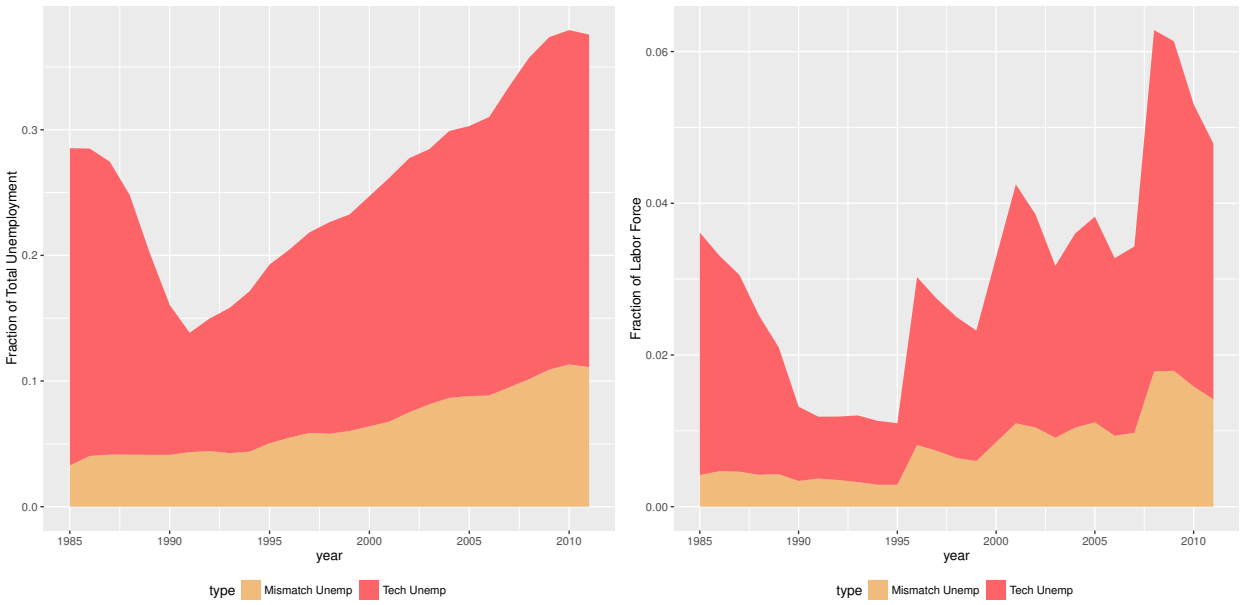
$$\begin{aligned}
\text{Self-selected switchers:} &\quad P(\phi_{i\mathbf{x}} \neq k) \\
\text{Mismatched switchers:} &\quad P(\phi_{i\mathbf{x}} = k) G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}) P(\psi_{i\mathbf{x}} \neq 0) \\
\text{Mismatched LF exiters:} &\quad P(\phi_{i\mathbf{x}} = k) G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}) P(\psi_{i\mathbf{x}} = 0) \\
\text{Stayers:} &\quad P(\phi_{i\mathbf{x}} = k) \left(1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})\right)
\end{aligned}$$

Note that the sum of the mismatched switchers and mismatched LF exiters is simply $P(\phi_{i\mathbf{x}} = k) G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, the fraction of *EU* flows per year who are sector-occupation mismatched. To find aggregate mismatch and technological unemployment for the US, we weight our estimates, which are conditional on $x \in \mathbf{X}$, by the share of x in yearly flows into unemployment. To construct these weights, we match the joint $\mathbf{X}$ distribution in each year to those in our unemployment spell dataset.[39] In effect, we 'integrate out' gender, age, education, and sector-occupation to find the rate of mismatch unemployment and technological unemployment each year for the US.

We report the results of this exercise in Figure 1.15a, which decomposes total sector-occupation mismatch into mismatched switching (at the bottom in orange) and mismatched LF exit (on top in red). These are depicted as a percentage of total flows into unemployment. We note that mismatched switching has grown steadily from 1985-2012, while mismatched LF exit declined from 1990-1995, but has been on a steady upward trajectory since.

We also form time series for the rates of mismatched switching and mismatched LF exit as a share of annual average employment. Again, we derive total numbers of each $x \in \mathsf{X}$ from weighted SIPP data, apply our estimation results, and aggregate across X to find aggregate numbers. We report the results in results in Figure 1.15b. Again, these follow broadly similar low-frequency patterns as in Figure 1.15a, except that cyclical changes in job destruction are more clearly reflected. As expected, spikes in both mismatch and

[39] We apply SIPP weights for individuals, which should make our dataset a nationally representative sample.



(a) Mismatch and Technological Unemployment as a fraction of Aggregate *EU* flows

(b) Mismatch and Technological Unemployment as a fraction of Employment

Figure 1.15: Aggregate Technological Mismatch

technological unemployment are observed during the dot com crash and at the start of the Great Recession, following spikes in job destruction rates.

1.8.1 Mismatched Switching

Mismatched switching has steadily risen from 1984-2012. This can be attributed to two major drivers. First, the declining rates of self-selected switching across sector-occupations. As shown in Figure 1.11, $P(\phi_{i\mathbf{x}} \neq k)$ has declined consistently for routine and manual sector-occupations, but Figure 1.11a shows that male $Prod.R$ workers have been especially disinclined to self-select into different sector-occupations. Second, the rising rates of sector-occupation mismatch for stayers. Figure 1.12 shows that $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ has been rising for routine and manual stayers since around 1990. Figure 1.12 also shows that $Serv.R$ workers have

experienced the steepest increases in mismatch in the 2000's. The combination of these two effects implies that workers have been increasingly choosing to search in their old sector-occupations where their skills are no longer demanded, since around 1990.

1.8.2 Mismatched LF Exit

Mismatched LF Exit fell from 1984-1990, but has grown steadily since 1990 as a fraction of flows into unemployment, at a higher rate than mismatch unemployment. Our estimation results suggest that these can be viewed as two distinct periods.

From 1984-1990, the fall in mismatched LF exit can be attributed to the steep fall in $P(\psi_{i\mathbf{x}} = 0)$ during this period, reflected in 1.13. Figure 1.14b further shows that this decline was strongest for production sector workers, especially females. We interpret this as showing that increasing attachment of women to the workforce, especially in goods-producing industries, contributed strongly to the fall in labor force exit even for mismatched workers in this period. $P(\psi_{i\mathbf{x}} = 0)$ continues to decline for women in the service sectors, which puts downward pressure on aggregate mismatched LF exit, but this effect has been dominated by other factors after 1990, the period of rising aggregate mismatched LF exit.

From 1990 onward, the rise in mismatched LF exit is driven by the same combination of factors that fostered increasing mismatch unemployment. Falling $P(\phi_{i\mathbf{x}} \neq k)$, combined with rising $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ - in words, lower rates of self-selected switching coupled with higher mismatch in origin sector-occupations. The fact that mismatched LF exit has continued to grow at faster rates than mismatched switching is due to the fact that on average, $P(\psi_{i\mathbf{x}} = 0)$ has stayed consistently high post-1990, after significant declines in the 1980's. As Figure 1.14b shows, $P(\psi_{i\mathbf{x}} = 0)$, has actually been rising for production sector males since 1990, further contributing to the rise in aggregate rates of technological unemployment.

1.9 Conclusion

In this paper, we have derived estimates for rates of sector-occupation mismatch out of *EU* flows, and further decomposed mismatched unemployed workers into those who eventually switch sector-occupations, and those who exit the labor force. We label these unemployed workers mismatched switchers and mismatched LF exiters respectively, and estimated the evolution of these rates from 1984-2012. To investigate the effects of RRTC, offshoring, and import competition on unemployment for routine versus manual workers, we have further estimated effects of sector-occupation on mismatched switching and mismatched LF exit.

Throughout this paper, we have understood sector-occupation mismatch to mean that unemployed workers are searching for jobs in sector-occupations where their skills are not demanded by firms, and so are unemployable there. Mismatched workers either have to redirect their search to another sector-occupation, or exit the labor force. We construct a search-and-matching model segmented by sector-occupation, where each sector-occupation can be subject to RRTC shocks. These shocks create dynamic effects in occupational mobility and labor force exit decisions for unemployed workers. The model allows us to form identifying assumptions about the unemployment durations and outcomes of mismatched workers.

Estimating the model using non-parametric techniques, we find that mismatched switching has been rising steadily from 1984-2012, while mismatched LF exit has also been rising since 1990 after declines from 1984-1990. Driving these results are structural dynamics that deserve independent interest. On the whole, self-selection into different sector-occupations by unemployed workers has declined steadily throughout the time period, while mismatch in their last sector-occupation has increased substantially. In particular, male routine workers in the production sector have consistently displayed the lowest rates of self-selected sector-

occupation switching. Yet, their disinclination to switch is somewhat justified by their lower increases in mismatch, relative to manual occupations. Routine workers in *service* sectors, however, have seen steep increases in sector-occupation mismatch in the 2000's. Finally, labor force exit after mismatch has been rising for males in production sector routine and manual jobs, which is contributing substantially to higher mismatched LF exit for these groups.

Chapter 2

The Macroeconomics of Superstars

2.1 Introduction

Technological progress in the digital arena and in machine intelligence has greatly accelerated in recent years and has triggered large societal changes. One of the implications of this type of progress has been to transform an increasing number of sectors into so-called superstars sectors. This makes it of critical importance to understand the forces at work and examine lessons for how to design public policies to deal with the superstar phenomenon and the resulting increase in inequality.

This paper studies the macroeconomic implications of the superstar phenomenon for factor prices, factor shares, inequality and overall economic efficiency. We describe an economy in which there is a large number of sectors served by traditional competitive firms that have a constant returns production technology. A traditional sector turns into a superstar sector when an entrepreneur comes up with a *digital innovation* – characterized as an innovation that requires a fixed cost and automates a fraction of the tasks involved in production, thereby lowering the marginal cost.

Digital innovations are information goods that are *non-rival* but *excludable*. In our setup, the non-rival nature of digital innovation implies that, although it requires a fixed cost, it can be reproduced widely at zero marginal cost, which generates a form of increasing returns to scale. To cite a simple example, once an online travel agency has programmed its website, it can easily displace tens of thousands of traditional travel agents without much additional effort – since the website just needs basic computing resources, it scales almost costlessly. The excludable nature of innovation implies that the innovator gains market power. The trade-off between the cost savings from digital innovation and the resulting market power is one of the major themes of our paper.

We identify three channels through which the introduction of a digital innovation in one sector affects the economy: First, there is a *factor- (or labor-)saving effect* since a fraction of production tasks in the sector is made redundant, and the demand for labor and capital declines in proportion. Second, the innovator uses her newly-gained market power to charge a markup and earn a monopoly rent, which we term the *superstar profit share*. If the innovator's cost reductions are relatively small, this mark-up is bounded by competition from traditional firms – the innovator does not cut prices but instead absorbs the entire cost savings as markup, i.e. the losses of traditional factor owners equal the gains of superstars. If the cost reductions are larger, then the innovator can charge her optimal monopoly price while still undercutting the firms using traditional technologies, and a third effect arises, the *output scale effect*: given lower prices, demand for the superstar's output rises, which increases both factor demand for capital and labor and superstar profits. The additional wealth created by superstars creates extra demand for all goods in the economy, including goods from traditional sectors. This effect increases the demand for traditional labor and partly offsets the labor-saving effect described earlier.

Our model implies that in the initial stages of digital innovation, a firm that has exclu-

sionary access to cost-saving technology will rapidly increase its market share. In general equilibrium, digital innovations across a range of sectors always lead to an increase in output. As long as the cost reductions are relatively small, however, the entire increase in output is absorbed by a rising superstar profit share, and the labor and capital share decrease. The decline in labor and capital share in general equilibrium is due to declining demand for labor and capital inputs in aggregate, leading to declines in nominal wages and capital rental rates. Income inequality between those who earn wage labor and those who earn returns from ownership of share in superstar firms will therefore increase.

Once cost reductions from digital innovation crosses a critical threshold, however, the labor, capital and superstar profit shares should stabilize in general equilibrium. As the aforementioned output scale effect dominates the factor-saving effect, market demand created by a combination of falling prices and rising wealth (of superstars) rises rapidly. Consequently, as long as labor and traditional capital remain essential factor inputs to the production technology, they become increasingly scarce, which puts upward pressure on their factor prices. This ensures that real wages and the labor share eventually stop falling.

We also use the model framework to study the described superstar phenomenon from a normative perspective and describe its efficiency properties. Compared to the first best, superstar entrepreneurs in our model under-innovate and under-produce since they inefficiently restrict supply to charge a monopoly premium. We propose three alternative ways of improving efficiency: first, to finance digital innovations using public funds and provide them to as free public goods to all; this would make the superstar phenomenon disappear, and the effects of digital innovation would simply show up as productivity increases. Secondly, to undo the monopoly markups using a subsidy; this would restore efficient quantities but (except if taxation can be targeted solely at superstars) lead to even larger superstar profits and greater inequality. Third, price regulations that would leave sufficient profits

to superstar firms to recoup fixed costs but increase quantities and reduce the monopoly distortions.

We explore various extensions of our framework to show that it can account for important real world features, including allowing for oligopolistic markets, and allowing for the elasticity of substitution between factor inputs to change across time. We show that a rise in cost-saving digital innovations by one firm can quickly lead to a reduction of the number of firms and eventually to a monopoly, if other firms are prevented from adopting the same digital innovations. Allowing for other firms to share in cost-saving digital innovations will allow more firms to survive, and will increase both consumer and producer surplus in the aggregate. On the other hand, propping up insufficiently productive firms through subsidies, and preventing a monopoly by a single firm that has adopted digital innovation, can be welfare decreasing.

Relationship to the literature We innovate on the existing body of economic literature in two main respects. First, we contribute a macroeconomic perspective to a strand of literature that describes the "economics of superstars" [e.g. Rosen, 1981] from a microeconomic dimension, without analyzing the implications for the rest of the economy, including the implications for those left behind. We are the first to study the broader macroeconomic implication of the superstar phenomenon in an increasing number of sectors of the economy, we link it to the increase in income inequality that has occurred in recent decades, and we make predictions on the future path of inequality. The second related strand of literature describes recent increases in inequality as resulting from phenomena such as skill-biased technological change, which changes e.g. the share of income earned by the top-quartile vs. the bottom-quartile of the income distribution, but does not specifically consider the role of superstars (see e.g. Autor, 2013). However, most data sources on inequality show that it is

really the top 0.01% (or even smaller percentiles) of the income distribution that amass the vast majority of gains – this relates much more closely to superstars than to highly-skilled workers.

Since Rosen [1981], economists have entertained the view that certain types of technological change can significantly enhance the productivity advantages of talented workers. In Rosen's view, new technology reduces the marginal costs of production for these 'superstar' individuals, which enables them to increase production and, by virtue of their greater ability (or quality of output), win larger market shares and extract greater rents. Rosen had in mind such technological changes as the television for comedians, and the radio for musicians. A common feature of these examples is that they allowed the production of a single 'unit' of services to be rendered to a larger pool of consumers. With the rise of the internet and rapidly improving communications technologies, the past 20 years have seen advancements in exactly the types of technologies that Rosen envisioned would lead to 'superstar' effects. While Rosen focused primarily on the positive effects of such technological changes on equilibrium prices and market shares, his model has obvious implications on the distribution of income and wealth in jobs affected by advances in superstar technology. More recent work has investigated these distributional effects. Gabaix and Landier [2008] and Garicano and Rossi-Hansberg [2006], among others, have used versions of this same mechanism to explain the rapid growth of income share in the far-right tails of CEO's and managers. Gabaix and Landier [2008] model the matching of the best CEOs to the largest firms, while Garicano-Rossi and Hanberg (06) model the rise in wages for the most productive managers as communication costs decline.

On a macroeconomic level, there is abundant evidence that these distributional changes are indeed in effect. Piketty and Saez [2001] documented that the income share for the top 0.1% of earners in the US has increased rapidly in the 1990's and 2000's, and that trend has

continued since the publication of their paper. Investigating the occupational composition of the top 0.01% of earners over time using IRS data, Kaplan and Rauh [2010] find that the share of financial executives, lawyers and athletes has increased substantially. Bakija, Cole, and Heim [2012], using more complete IRS data, find additionally that even within the upper percentiles of these occupations, income inequality has increased substantially.

Beyond the income distribution of earners, technology that enables superstar earners has also been associated with a small number of firms acquiring high market concentration (see Brynjolfsson, Hu, and Smith [2010]). Evidence collected by Mueller, Ouimet, and Simintzi [2015] shows that the average size of the largest firms has increased very significantly in fourteen of the fifteen countries they study between the mid-1980s or mid 1990s and 2010. The average size of the top 50 (100) firms in the US grew by 55.8% (53.0%) between 1986 and 2010.

Finally, technological change has also been investigated as a cause of the declining labor share. Karabarbounis and Neiman [2013] and Alvarez-Cuadrado, Long, and Poschke [2014] document that the labor share of income has declined steadily from the 1970's to the 2000's. Autor, Dorn, Katz, Patterson, and Reenen [2017] show that the labor share of income has also been declining at the firm and establishment level, and show that industries that have seen the largest rise in market concentration have also tended to see the starkest declines in labor share.

Thus far, work on superstars has largely concentrated on modeling the effects of superstar technology on the distribution of earnings within occupations (of managers and CEOs, for example), or on the market structure in an industry (e.g. Noe and Parker [2005] investigate how the web-based sector produces a "winner-take-all" market). By contrast, we examine the macroeconomic effects of superstar technologies and ask how superstar technologies lead to rising income inequality, rising market concentration and a declining labor share. Secondly,

we investigate the welfare effects of the introduction of superstar technologies. In particular, do the returns from implementing superstar technology occur as a result of rising monopoly rents accruing to owners of the superstar technology, or rather as a result of compensation for increased productivity from new technology? This question hits at the heart of a topic of contention in the literature on superstar CEO compensation. Edmans and Gabaix (2008), among others, construct assignment models that suggest that rising superstar compensation is efficient, in line with rising individual productivity. On the other hand, Bebchuk and Fried (2004), among others, argue that increased ability to extract rents by superstar managers accounts for their rising earnings.

We provide a model that introduces the superstar entrepreneur as a factor of production who implements superstar technology in production, and owns the new technology. Our model articulates how the introduction of the superstar entrepreneur can lead to inequality along three dimensions - income inequality, declining labor share of income, and increasing market share of superstar firms. The model does this through through two main mechanisms. First, adoption of superstar technologies allows entrepreneurs to extract greater rents from monopoly power and increasing scale. This provides incentives for these firms to adopt superstar technologies, and provides high returns to the entrepreneurs behind those firms. Secondly, superstar firms lead to increasing market concentration as traditional firms need to scale down production. At first, demand for labor declines in aggregate, while labor supply is unchanging. Wages stagnate and employment declines, leading to a decline of the labor share. Later, wages increase again as

Existing explanations for rising income inequality and the declining labor share include Autor and Dorn [2013] and Karabarbounis and Neiman [2013] who posit that the decline in the relative price of computer capital to labor is an important explanation. Elsby, Hobijn, and Sahin [2013] argue for the importance of trade and international outsourcing, and they

present evidence indicating that the labor share declines the most in U.S. industries that were strongly affected by increasing imports (e.g., from China). Piketty (2014) also stresses the role of social norms and labor market institutions, such as unions and the real value of the minimum wage. Nevertheless, we show that the adoption of superstar technologies, by increasing firm size and promoting higher market concentration, is a distinct and very plausible explanation for these macroeconomic phenomena.

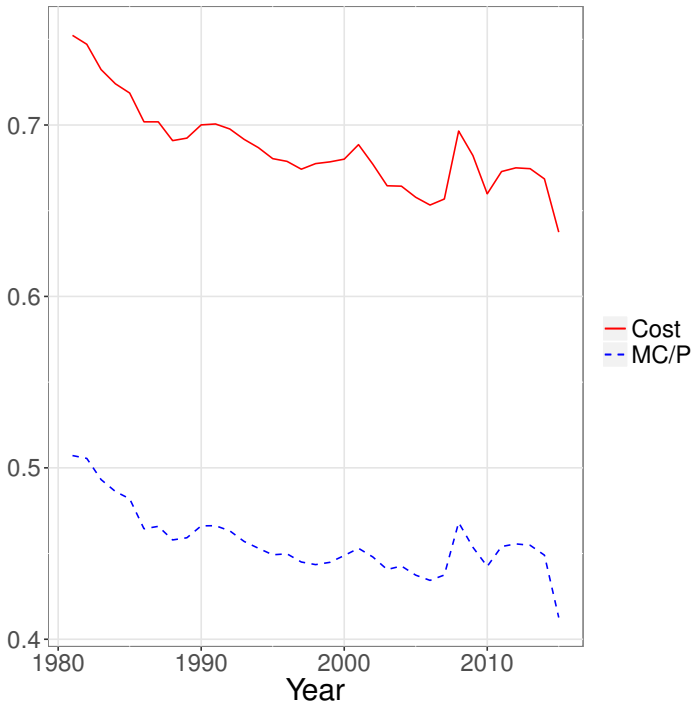


Figure 2.1: Average revenue share of variable inputs (red line) and $\frac{MC}{P}$ (blue line)
Notes: Average revenue share of variable inputs is measured as Cost of Goods Sold divided by Sales. $\frac{MC}{P}$ is calculated using method of finding markups in DeLoecker and Eeckhout [2017]. Both series are calculated as sales-weighted average of all Compustat firms, from 1980-2014.

2.1.1 Empirical Motivation

The macroeconomic relevance of digitization and the resulting superstar phenomenon is underlined by a number of trends in the data. These are the falling labor share of aggregate income, accompanied by the rising income share of firm profits. We discuss two sets of evidence suggesting that these trends are associated with the rise of superstar firms. First, the rising market concentration of the largest firms within industries, observed across major sectors of the US economy, and second, the rise in markups of price over marginal cost for the largest firms. Combined, these two trends suggest rising economic profits accruing to the largest firms. Finally, we discuss some evidence that suggest that the rise in superstar firms may be due to the adoption of new automation technologies.

In this section, we use Compustat data on all publicly listed firms in the US, similar to DeLoecker and Eeckhout [2017].

Falling Revenue Share of Variable Inputs Recent work by Karabarbounis and Neiman [2013], Alvarez-Cuadrado et al. [2014] and others have documented the broad secular decline of the labor share of income in the US as well as internationally. Relatedly, a strand of literature including Barkai (2017) and DeLoecker and Eeckhout [2017] have noted a concurrent rise in the profit share of income in the US, primarily from around 1980 to 2014. In other words, the share of aggregate income going to owners and shareholders has been on the rise. Barkai (2017) estimates the profit share as a residual after netting out labor and capital shares, while DeLoecker and Eeckhout [2017] measure profits as markups of price over marginal cost. The particular method of DeLoecker and Eeckhout [2017] essentially captures the falling revenue share of variable inputs, as Figure 2.1 shows. The dashed blue line reproduces DeLoecker and Eeckhout [2017]'s time series of sales-weighted average markups across US publicly listed firms using the same Compustat data and inverts it, so that we

have marginal cost as a fraction of price, or $\frac{MC}{P}$. The solid red line simply plots the cost of variable inputs as a fraction of sales revenue, or $\frac{COGS}{REV}$, again as a weighted average across publicly listed US firms. Specifically, we use the Cost of Goods Sold series in Compustat as a measure of cost of variable inputs, which includes intermediate inputs and direct labor (excluding labor and other for advertising or marketing, as well as idle plant expenses). The revenue share of variable inputs, including labor has fallen to just slightly over 0.6 in 2014. The mirror image is that gross profits – the fraction of revenues that does not pay for cost of goods sold – have risen.

We note some heterogeneity across major US sectors in the time trend of revenue share of variable inputs. The revenue share of variable inputs has fallen for most major US sectors, except for Retail and Wholesale sectors, where the variable input share has remained relatively constant since 1980. For details, refer to Figure B.5 in the Appendix.

The Rise of Superstar Firms What empirical trends underlie the rising aggregate share of gross profits? Looking at firm level data, Autor et al. [2017] and Brynjolfsson et al. [2010] both find that industry market concentration in the US has risen significantly at least since the mid-1990s, and Autor et al. [2017] in particular find that this is observed across major sectors in the US economy. With market shares of the largest firms within US industries rising, large and growing firms earning greater monopoly rents could be a driver of the rising aggregate profit share.

Recent work by Autor et al. [2017], DeLoecker and Eeckhout [2017], and Hall [2018] find mixed empirical evidence relating the rise firms with large market share and the rise of markups. DeLoecker and Eeckhout [2017] find that the average of firm markups weighted by sales has been rising less rapidly than the unweighted average of markups. This implies that the covariance between firm market share (as a share of the aggregate sample) and markup

is negative, and increasingly so.[1] This is an interesting finding, as it implies that markups of small publicly traded firms have been higher than that of larger firms throughout the time period. On the other hand, Autor et al. [2017] find that the covariance between market share and labor share of existing firms is negative, suggesting that the fall in the average labor share among US firms is primarily due to the increasing market shares of existing low labor share firms. If there is an inverse relationship between labor share and markups at the firm level, as standard monopoly models imply, then their results suggest that there should be a positive covariance between firm market share and markups, which is the opposite of what DeLoecker and Eeckhout [2017] find.

To reconcile these empirical observations, we look directly at the evolution of markups for a sample of the largest firms within industries in 2014. Specifically, we take the sample of publicly listed firms in Compustat that are in the top 4 in market share within 4 digits NAICS industries in 2014, which we call our sample of superstar firms. Figure 2.2 displays the rise in average market share for our superstar firms. Superstar firms saw increasing average (sales) market share from 1990-2014. For most sectors, the growth in market share was positive in the 1990's, accelerated in the late 1990's and continued at a rapid rate into the 2000's. Using the DeLoecker and Eeckhout [2017] method of calculating markups, we then plot the evolution of markups for this sample of firms in the left panel in Figure 2.2 shows the sector-level evolution of mean markups for superstar firms, while right panel in Figure 2.2 shows the weighted average of markups for non-superstar firms.

Beneath these aggregate trends, we note that there is substantial sector heterogeneity in the evolution of market shares and markups for superstar firms. We plot mean market shares and markups for superstar firms across 6 major sectors of the economy (excluding Finance

[1]They use an Olley-Pakes decomposition of the rise in weighted average into within and between firm components.

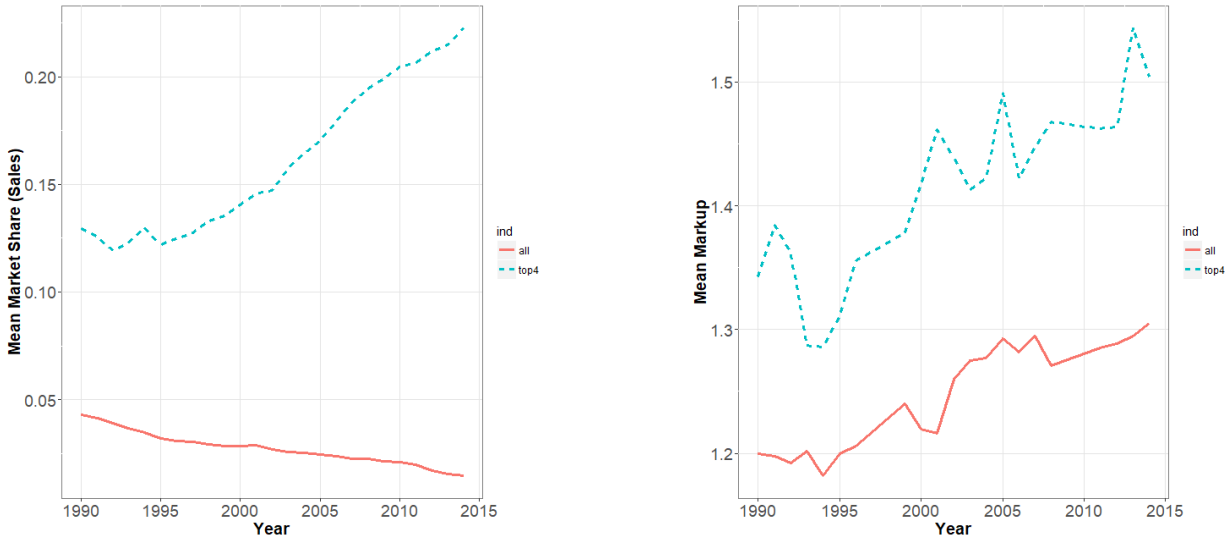


Figure 2.2: Mean Markup by major sector. Left Panel: Top 4 firms by market share growth from 1990-2014. Right Panel: All other firms.

Sector firms due to unreliable sales data for financial firms) in Appendix B.1. Appendix Figure B.2 shows that there are sectors that buck the aggregate trends; for example, in the Retail sector, market share for superstar firms rose consistently even in the 1990's. Also, markups for superstar firms declines relative to non-superstar firms for several sectors in the 2000's, such as Manufacturing and Services sectors.

Another revealing way to view the data on superstar markups is to distinguish between hi-tech and non hi-tech sectors. Using the Census list of 6-digit NAICS industries that they consider most likely to be technology intensive,we repeat the analysis on market shares and markups of superstar firms in hi-tech industries, which we present in Appendix B.1. Figure B.4 shows that while the non hi-tech sector saw rising superstar markups relative to non-superstar markups in the 2000's, this is reversed in the hi-tech sector. This observation may imply that the determinants behind markups may be different for hi-tech industries versus non hi-tech industries.

These observations generate several pertinent takeaways

1. The mean market shares of superstar firms rose in the 1990's and accelerated for some sectors in the 2000's.
    - The acceleration in the 2000's is true of Manufacturing and Services sectors, while the rise in superstar firm market share was much more steady for Retail and ACUT sectors.
2. In 1990, markups for superstar firms were higher than the weighted average of markups of all other firms, across all sectors.
3. From 1990-2014, markups for superstar firms remained relatively higher than the weighted average within their industries, as their market shares increased.
    - There is substantial sector heterogeneity in the the ratio of superstar markups to non-superstar markupsfrom 1990-2014.
    - The hi-tech sector saw superstar markups decline relative to non-superstar markups in the 2000's, while the non hi-tech sector saw superstar markups rise relative to non-superstar markups in the same period.
4. From 1990-2014, markups for superstar firms had lower markups than the unweighted average of markups within their industry.

These observations allow us to go some way towards reconciling the disparate observations in DeLoecker and Eeckhout [2017] and Autor et al. [2017]. In 1990, today's superstar firms were relatively small and charged higher markups than their industry average. As they have grown larger, they have maintained high markups. Relative to small firms in their industry however, in several sectors, their markups have declined as their market shares have risen in

several sectors. Thus, while the rise in superstar firms has been responsible for the rise in weighted average markups, the negative covariance between market share and markups has continued to hold in aggregate. Further, while the aggregate data suggest that the rapid rise in market share for superstar firms in the 2000's may indeed be the primary force behind the rise in average markups in the non hi-tech sector, the particularly rapid rise of markups for superstar firms in the non hi-tech sector suggests that the "within-firm" rise in markups for superstar firms has been substantial as well.

Technology and Intangible Capital Although there is clear correlation between the rise of superstar firms and the rise of the profit share, and economic theories on market structure uniformly predict rising profits as a result of rising monopoly power, rising fixed costs of production could also drive the rise in observed gross profit share. Underlying the observation of the rising profit share is the falling share of traditional variable inputs, as observed in Figure 2.1. The cost of variable inputs, or Cost of Goods Sold, does not include the cost of research and development,as well as advertising and marketing. These costs go into generating technologies that may be codified in blueprints and patents.

In the data, a small literature has emerged showing the rise in the role of intangible assets for firms. Intangible assets are firm assets that are not traditional physical capital (in the form of property, plants, and equipment). Intangible assets include copyrights, patents, software, and more generally, assets that are potentially not directly part of the production process. OECD [2013] find that most advanced economies have seen increasingly intensive use of intangible assets, while Alexander and Eberly [2018] find that at the industry level, intangible assets have risen as a share of total assets for most industries in the US, since around 1990. We show that for the US, the largest firms account for the lion's share of growth in intangible assets within industries. Figure 2.3 shows the share of intangible assets

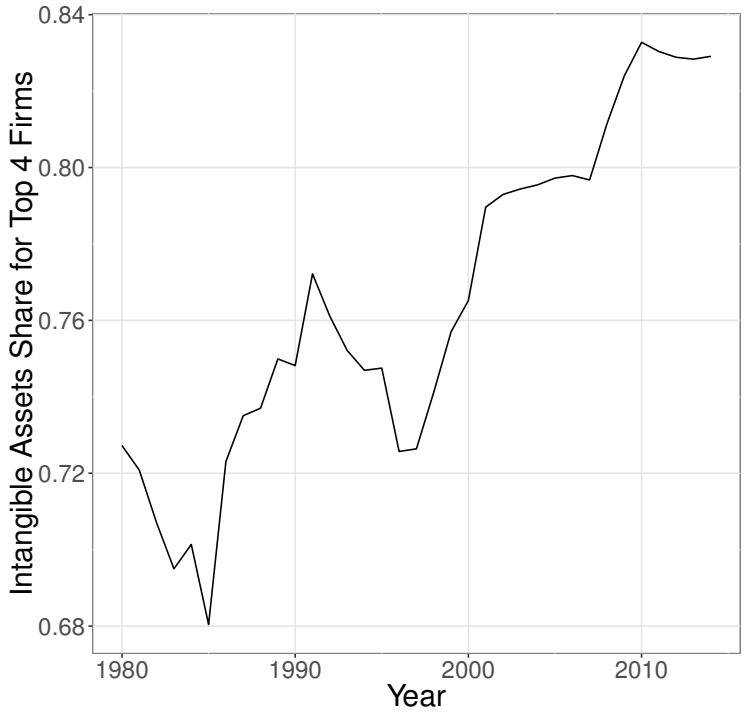


Figure 2.3: Intangible Asset Share

Notes: Combined share of intangible assets excluding goodwill by top 4 firms within 4 digit NAICS industry codes, by sales share in industry. (Left) Average across all 4 digit industries.

owned by the top four firms by total sales within 4 digit industries. The concentration of intangible assets in top firms rises almost 12% from 72% -84% from the mid-1990s to 2015, while market concentration (measured as a fraction of sales) by the same firms rises less than 5% in the same period. In Figure B.6 in the Appendix, we show that the rising concentration of intangible assets in the largest firms is observed across all major sectors in the US, except for the wholesale sector.

Alexander and Eberly [2018] find that intangible assets have been increasingly used to substitute for investment in traditional capital inputs. Since intangible capital includes patents for new technology and software that may be able to substitute for labor inputs as well, the rise of intangible capital may indicate rising potential to substitute for the tradi-

tional direct labor and capital inputs in general. Considering this, the rise in concentration of ownership of intangible assets suggests that the largest firms are owning increasing shares of assets that have the potential to replace traditional factor inputs in the production process. Firm owners of the largest firms can then reap the yields on intangible assets, to the exclusion of traditional factor inputs and smaller firms. Next, we provide a framework that shows how automation technologies may lead to owners of a small number of firms garnering larger shares of income.

2.2 Baseline Model

Our baseline model is set in a static economy in which there is a unit mass of consumers who are homogeneous, except that a variable fraction θ may also be active as superstar entrepreneurs. There are two traditional factors of production, capital and labor, as well as a unit mass of differentiated intermediate goods and a final good which serves as numeraire. Each consumer inelastically supplies an endowment of labor $L = 1$ and capital $K > 0$ which fully depreciates in production, earning competitive wage W and rental rate R. Furthermore, consumers also earn profits Π^T from the activities of traditional firms, which we will describe below. They consume their total income in terms of final goods

$$C = W + RK + \Pi^T$$

and obtain utility from consumption according to the neoclassical utility function $u(C)$. Consumers who are also active as superstar entrepreneurs earn and consume in addition the superstar profits Π^S described below.

Final Goods are obtained by combining a unit mass of differentiated intermediate goods indexed $i \in [0,1]$ in a Dixit-Stiglitz production function

$$Y = \left(\int_0^1 Y_i^{1-\frac{1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{2.1}$$

where we assume that the elasticity of substitution $\epsilon > 1$. Given that the price of final goods serves as numeraire, the relative prices of intermediate goods satisfy the usual price index equation $P = \left(\int P_i^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}} \equiv 1$. The demand function for each good i is

$$Y_i = (P_i)^{-\epsilon} Y$$

which can easily be inverted into an inverse demand function $P_i(Y_i; Y) = (Y_i/Y)^{-1/\epsilon}$.

Traditional Firms There is a large number of competitive firms in the each sector i who have access to what we call a *traditional* production technology. Firms using this technology produce output by hiring labor and capital in a competitive factor market and combining them according to the Cobb-Douglas production technology

$$Y_i = F_i(K_i, L_i) = A_i K_i^{\alpha} L_i^{1-\alpha}$$

The optimal factor demands of traditional firms are $K_i^T(Y_i; R, W) = \left(\frac{\alpha}{1-\alpha} \cdot \frac{W}{R} \right)^{1-\alpha} / A_i$ and $L_i^T(Y_i; \cdot) = \left(\frac{1-\alpha}{\alpha} \cdot \frac{R}{W} \right)^{\alpha} / A_i$, where the superscript T refers to *traditional* firms. The resulting total cost function $TC^T(Y_i)$ for firms employing traditional technology, and the

corresponding unit cost UC_i^T, which both depend on factor prices R and W, are

$$TC_i^T(Y_i) = \left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\frac{Y_i}{A_i}$$
$$UC_i^T = \left(\frac{R}{\alpha}\right)^{\alpha}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}/A_i$$

As long as only firms employing the traditional technology are active in sector i, competitive behavior implies that the price of the intermediate good i is pinned down by the unit cost function of traditional firms,

$$P_i = UC_i^T \tag{2.2}$$

giving rise to a quantity demanded and produced of

$$Y_i^T = \left(UC_i^T\right)^{-\epsilon} Y$$

Superstar Firms When a firm invents a new digital innovation that allows it to automate a fraction of the tasks required to produce output and the firm can exclude others from using this innovation, it turns into a superstar firm. In our baseline model, we assume that there is at most a single superstar firm in each sector. (We will generalize this below in section 2.4.1). More specifically, we assume that a superstar firm has the option to spend a fixed user cost ξ_i to automate a fraction γ_i of the tasks involved in production, enabling it to produce output at marginal cost $MC_i^S = (1-\gamma_i)\,UC_i^T$, where the superscript S refers to the *superstar* firm. For reasons of analytic simplicity, we denote the user cost ξ_i w.l.o.g. in terms of units of the traditional technology UC_i^T, leading to a total cost function

$$TC_i^S(Y_i) = \xi_i \cdot UC_i^T + UC_i^S \cdot Y_i = [\xi_i + (1-\gamma_i)\,Y_i] \cdot UC_i^T$$

One of the most natural interpretations of this setup is that the firm replaces a fraction γ_i of the tasks involved in production using digitization and information technology that can be scaled at close-to-zero cost. The fixed cost ξ_i in our example can be interpreted as the sum of the annualized value of any initial investment in establishing the superstar technology plus any fixed platform cost that accrues per time period to run the technology.

This captures that a large number of sectors can automate a fraction of the tasks involved in producing or providing their product by creating digital innovations that reduce the marginal cost of providing their product to one more customer. Many practical examples arise in the service sector, in which firms provide their products digitally and/or interact with their customers over the Internet, cutting down significantly on costs. This includes the music, entertainment and sports sectors, which stream their products (or, in earlier days, produced digital or analog copies) instead of performing live in front of their customers, as was necessary in the 18th century, producing a number of well-known superstars; the office work sector, in which a large fraction of secretarial work has been replaced by personal computers and office suites that are provided by superstar firms like Microsoft; the travel industry, in which the majority of travel agents have long been replaced by websites that perform the same function at zero marginal cost, producing superstar online travel companies that intermediate the vast majority of travel services; the financial sector, in which customers increasingly interact with their institutions via expensive digital platforms that create a strong impetus to merge into superstar firms. In the retail sector, online shopping superstars such as Amazon have made significant inroads in replacing regular brick-and-mortar stores that provide retail services. According to many experts, the transportation sector is at the cusp of a revolution after which its services will be performed by driverless cars and trucks, programmed by a handful of superstar providers. Even in manufacturing, an increasing number of firms employ digital innovations to automate significant parts of the production

process. For example, Nike, one of the superstars in athletic wear, recently announced that it is working on a proprietary robot technology to automate the production of footwear, cutting its unit labor costs in half (FT, 2017).

A superstar firm that deploys its automation technology chooses a level of output to maximize profits,

$$\max_{P_i, Y_i} \pi^S(Y_i) = P_i Y_i - TC_i^S(Y_i) \qquad \text{s.t.} \qquad P_i = P(Y_i; Y) \leq UC_i^T \tag{2.3}$$

The constraint captures that the superstar firm internalizes its market power, i.e. that the market price of its goods $P_i(Y_i; \cdot)$ depends on the quantity produced, and that the superstar firm cannot set a higher price than the price at which traditional firms would compete with the superstar firm. If this constraint is binding, then the superstar firm will simply set $P_i = UC_i^T$. For simplicity, we assume that all output is produced by the superstar firm in that case (the superstar firm would push any competing traditional firms out of the market by lowering the price by an infinitesimal amount). Otherwise, if the constraint is slack, the superstar firm's output is determined by the optimality monopoly pricing condition

$$\underbrace{P_Y(Y_i; \cdot) Y_i + P_i(Y_i; \cdot)}_{\text{Marg Rev.}} = \underbrace{(1 - \gamma_i) UC_i^T}_{\text{Marg Cost}}$$

Given the Dixit-Stiglitz production function for final goods, the optimality condition can be simplified and combined with the constraint imposed by competitive traditional firms into the markup pricing rule

$$P_i^S = \mu_i \cdot (1 - \gamma_i) \cdot UC_i^T \qquad \text{where} \qquad \mu_i = \min\left\{ \frac{1}{1 - \gamma_i}, \frac{\epsilon}{\epsilon - 1} \right\} \tag{2.4}$$

Intuitively, when the cost savings from automation are small ($\gamma_i < 1/\epsilon$), the superstar firm is constrained by the potential competition from traditional firms and charges the competitive price of firms using the traditional technology, satisfying all the demand that prevails at that price. In that region, superstar firms absorb all their cost savings as rent. When automation has proceeded sufficiently far in comparison to the demand elasticity that the superstar firm can charge its optimal monopoly markup and still undercut traditional firms ($\gamma_i \geq 1/\epsilon$), then the monopoly price prevails, and competition from traditional firms is irrelevant for the superstar firm.

The quantity demanded from the superstar firm is accordingly

$$\begin{aligned} Y_i^S &= \left(P_i^S\right)^{-\epsilon} Y = \left[\mu_i \cdot (1-\gamma_i) \cdot UC_i^T\right]^{-\epsilon} Y \\ &= \left[\mu_i \cdot (1-\gamma_i)\right]^{-\epsilon} Y_i^T = \max\left\{1, \left(\frac{\epsilon\,(1-\gamma_i)}{\epsilon - 1}\right)^{-\epsilon}\right\} \cdot Y_i^T \end{aligned}$$

The superstar firm always produces at least as much as the traditional sector.

It is only profitable to deploy the superstar technology if the markups plus cost savings from automation that the firm can obtain allow it to recoup the fixed cost ξ_i,

$$(\mu_i - 1)\,(1-\gamma_i)\,Y_i^S \geq \xi_i \tag{2.5}$$

2.2.1 Digital Innovation and the Superstar Effect

This section analyzes how progress in digital innovation, captured by increases in the cost-saving parameter γ_i from zero to close to one, affect the equilibrium of a given sector i of the economy. In particular, we focus on the implications for factor demand and monopoly rents in sector i.

Proposition 3 (Digital innovation and the superstar effect)**.** *(i) As long as the cost savings from digital innovation are small relative to the inverse demand elasticity, $\gamma_i < 1/\epsilon$, a superstar firm entering the market charges the traditional price P_i^T because of competition from traditional firms and produces the traditional firm quantity Y_i^T. In this region, increases in automation linearly reduce demand for capital and labor and linearly increase superstar profits, since all cost savings are absorbed in the form of monopoly profits.*

(ii) Once innovation exceeds the threshold $\gamma_i > \frac{1}{\epsilon}$, a superstar firm entering the market charges a lower price $P_i^S < P_i^T$ than the price of traditional firms, given by the optimal monopoly markup $\frac{\epsilon}{\epsilon-1}$ over its costs, and output rises above the output of traditional firms, $Y_i^S > Y_i^T$. Increases in automation reduce the price charged by the superstar firm linearly, but raise demand for capital and labor as well as output and superstar profits in a convex fashion. If $\gamma_i \to 1$, the sector reaches a singularity at which output goes to infinity.

(iii) The superstar firm finds it optimal to enter the market and displaces all firms using the traditional technology once automation has reached a threshold $\gamma_i \geq \hat{\gamma}_i$.

Proof. For point (i), observe that the threshold $\hat{\gamma}_i$ implies that superstar firms break even. At the threshold, the superstar profit is just sufficient to cover the fixed cost of operating the superstar technology.

For point (ii), observe that our earlier discussion implies the price charged $P_i^S = UC_i^T$ and output level $Y_i^S = Y_i^T$. Given constant output, factor demand is $L_i^S = (1-\gamma_i) L_i^T$ and $K_i^S = (1-\gamma_i) K_i^T$, which is linearly decreasing in γ_i, and superstar profits $\pi_i^T = \gamma_i Y_i^T$, which are linearly increasing.

For point (iii), observe that superstar output is given by $Y_i^S = \left[(1-\gamma_i)\frac{\epsilon}{\epsilon-1}UC_i^T\right]^{-\epsilon} Y \simeq (1-\gamma_i)^{-\epsilon}$, which satisfies

$$\frac{dY_i^S}{d\gamma_i} \simeq \epsilon\,(1-\gamma_i)^{-\epsilon-1} > 0$$
$$\frac{d^2Y_i^S}{d\,(\gamma_i)^2} \simeq \epsilon\,(\epsilon+1)\,(1-\gamma_i)^{-\epsilon-1} > 0$$

Given the Cobb-Douglas production function for the variable component of the superstar technology, factor demand is

$$L_i^S\left(Y_i^S;Y\right) = \left(\frac{1-\alpha}{\alpha}\cdot\frac{R}{W}\right)^{\alpha}\frac{(1-\gamma_i)\,Y_i^S}{A_i} \simeq (1-\gamma_i)\,Y_i^S \simeq (1-\gamma_i)^{-\epsilon+1}$$

which satisfies

$$\frac{dL_i^S}{d\gamma_i} \simeq (\epsilon-1)\,(1-\gamma_i)^{-\epsilon} > 0$$
$$\frac{d^2L_i^S}{d\,(\gamma_i)^2} \simeq (\epsilon-1)\,\epsilon\,(1-\gamma_i)^{-\epsilon-1} > 0$$

and similar for capital demand $K_i^S\left(Y_i^S,\cdot\right)$.

The revenue of the superstar firm is given by $R_i^S = P_i^S\cdot Y_i^S = \left[(1-\gamma_i)\frac{\epsilon}{\epsilon-1}UC_i^T\right]^{-\epsilon+1} Y \simeq (1-\gamma_i)^{-\epsilon+1}$ with derivatives w.r.t. γ_i of identical signs as for factor demands. Superstar profits are given by a constant share of revenue, which satisfies the same inequalities. □

The intuition for points (ii) and (iii) of the Proposition 3 is also illustrated in Figure 2.4, in which we assume for simplicity that $\xi_i = 0$. As we start from low levels of automation, the superstar's cost savings compared to traditional firms are at first relatively small, and its optimal monopolistic pricing strategy (green diamonds) is constrained by the threat of competition from traditional firms, inducing superstar firms to charge the price that would

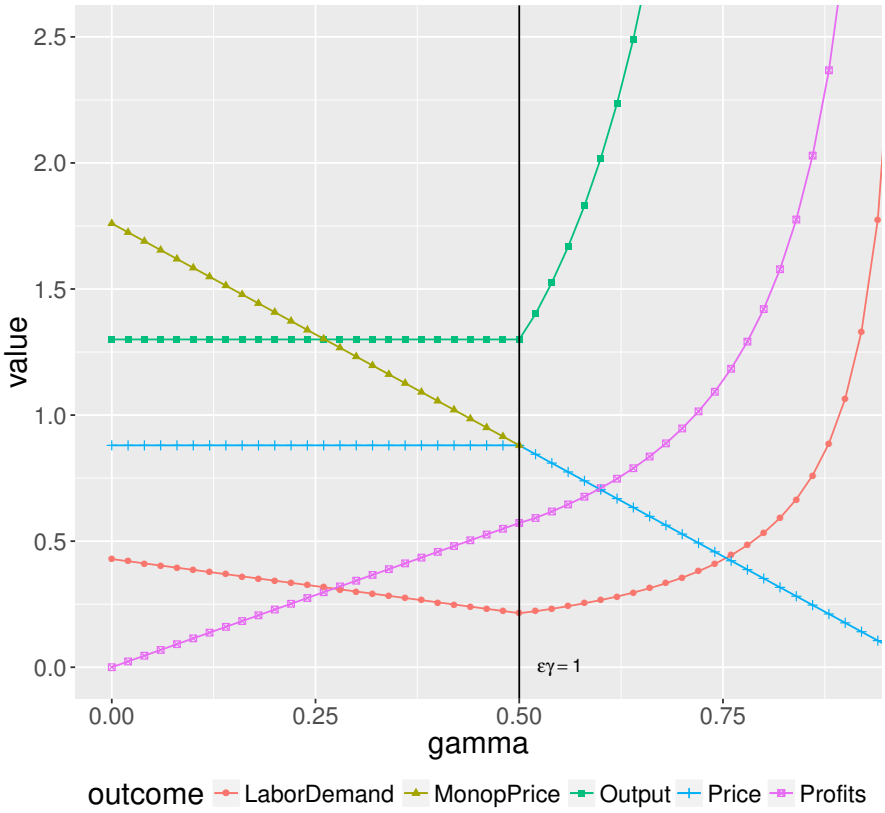


Figure 2.4: Automation and the superstar effect

be charged by traditional firms (blue crosses). In this region, increasing digital automation induces the superstar firm to absorb any cost savings via increased markups and profit margins (pink boxes), without increasing output (green squares). And given that output remains constant, rising levels of digital automation imply that the superstar firm reduces its demand for the traditional factors capital and labor in that region (red circles). As a result, only the *labor- (or factor-)saving effect* of technological progress is present.

However, once the cost savings of the superstar firm are larger than the desired monopoly markup, indicated by the vertical line, the superstar firm passes any additional cost savings on to consumers via lower prices in order to boost demand for its output, benefiting consumers. In this region, improvements in the automation technology induce the superstar firm to lower prices (blue crosses) but increase production (green squares). Given that we assumed the demand for the firm's output is relatively elastic ($\epsilon > 1$), lower prices induce a sufficient increase in demand and production so that total revenue increases, of which the superstar firm absorbs a fixed share in monopoly rents (pink boxes). By the same token, the increase in quantities also outweighs the lower factor requirements per unit produced so that total factor demand by the superstar firm increases (red circles). As a result, the factor-saving effect of technological progress is outweighed by what we may call an *output scale effect* of technological progress.

Superstars and factor shares

We next focus on factor shares in the economy and on how technological progress among superstars, captured by a marginal increase in the cost savings parameter γ_i, affects these factor shares. The following results hold for an individual sector in the economy, taking aggregate factor prices as given:

Corollary 1 (Increasing automation and factor shares)**.** *(i) An individual sector i in which a superstar has entered exhibits a superstar profit share of*

$$\sigma = \min\left\{\gamma_i, \frac{1}{\epsilon}\right\} \tag{2.6}$$

as well as a capital share of $\alpha(1-\sigma)$ and a labor share of $(1-\alpha)(1-\sigma)$.

(ii) As long as $\gamma_i < \frac{1}{\epsilon}$, a marginal increase in γ_i leaves output unchanged but reduces the labor and capital shares while commensurately increasing the superstar profit share. When $\gamma_i \geq \frac{1}{\epsilon}$, further marginal increases in γ_i raise output but leave the labor, capital and superstar profit share constant.

Proof. The result follows from Proposition 3. □

The intuition for the corollary is that as long as automation is in its early stages and $\gamma_i < \frac{1}{\epsilon}$, superstars simply absorb all their cost savings γ_i since their price charged remains at the level of traditional firms. Once the inequality is reversed, superstars can increase their profits by charging the optimal monopoly (gross) markup $\frac{1}{\epsilon}$ and increasing the quantity supplied. This implies a ceiling for the profit share of superstar monopolists that is determined by consumer preferences, i.e. by consumers' elasticity of substitution among intermediate goods.

The superstar factor So far we have analyzed the economic changes arising from digital innovation and the superstar phenomenon by describing the effects of replacing a fraction γ_i of the tasks involved in producing sector i output with a perfectly scalable digital technology. In the following, we illustrate that the introduction of a superstar technology can equivalently be described as introducing a new "superstar factor" into the production function of the economy.

Corollary 2 (The Superstar Factor)**.** *The allocations chosen by a superstar sector i are equivalent to what would be chosen by a competitive firm that employs $S_i = 1$ units of a superstar factor in the production technology*

$$\tilde{Y}_i = \tilde{F}_i(K, L, S) = \begin{cases} \frac{(1-\gamma_i)^{\gamma_i}}{1-\gamma_i} \left(K_i^{\alpha} L_i^{(1-\alpha)} \right)^{1-\gamma_i} S^{\gamma_i} & \text{if } \epsilon\gamma_i < 1 \\ \left(\frac{1}{1-\gamma_i} K_i^{\alpha} L_i^{(1-\alpha)} \right)^{\frac{\epsilon-1}{\epsilon}} S^{\frac{1}{\epsilon}} & \text{if } \epsilon\gamma_i \geq 1 \end{cases}$$

Proof. □

Intuitively, the formulation in Corollary 2 implies that a competitive firm that has access to the indicated production function will choose the same levels of capital, labor and produce the same level of output as the superstar firm described in Proposition 3. Furthermore, the Cobb-Douglas structure implies that the capital, labor and superstar profit shares are given by $\alpha(1-\sigma)$, $(1-\alpha)(1-\sigma)$ and σ, respectively.

2.2.2 General equilibrium results

Let us now consider the general equilibrium of our static benchmark economy. In the following, we assume w.l.o.g. a symmetric equilibrium in which all sectors share the same baseline technology $A_i = A$ and automation parameter $\gamma_i = \gamma$. In such a symmetric equilibrium, (2.1) implies that aggregate output is given by

$$Y = \frac{A}{1-\gamma} K^{\alpha} L^{1-\alpha} \tag{2.7}$$

At the same time, equation (2.6) indicating the share of output accruing to superstars continues to apply, which implies that wage and capital income are given by

$$w = (1-\alpha)(1-\sigma)Y \tag{2.8}$$

$$RK = \quad \alpha \ (1-\sigma)Y \tag{2.9}$$

Proposition 4 (Output in general equilibrium)**.** *(i) Aggregate output is a convex function of* γ*.*

(ii) As long as $\gamma < \frac{1}{\epsilon}$*, an increase in* γ *linearly reduces labor and capital shares while commensurately raising the superstar profit share. Wages and the return on capital remain constant and superstars absorb all the increase in output.*

(iii) When $\gamma \geq \frac{1}{\epsilon}$*, further increases in* γ *raise output but leave the labor, capital and superstar profit share constant. Wages and the rental rate of capital increase in line with output.*

(iv) As $\gamma \to 1$*, the economy reaches a singularity at which output and all factor income go to infinity.*

Proof. Result (i) is obtained by observing that equation (2.7) is a convex function of γ. For (ii), we observe that the superstar factor share satisfies $\sigma = \gamma$ in this region. We substitute this together with (2.7) into equations (2.8) and (2.9) to obtain the result. For (iii), we use instead the superstar factor share $\sigma = \frac{1}{\epsilon}$, which is relevant in the described region. Point (iv) is a straightforward limit result. □

Our general equilibrium results differ in important aspects from the partial equilibrium results of Proposition 3, as is also illustrated in Figure 2.5 for the case of $\xi_i = 0 \forall i$:

As long as $\gamma_i < \frac{1}{\epsilon}$, individual firms in partial equilibrium do not increase output, but

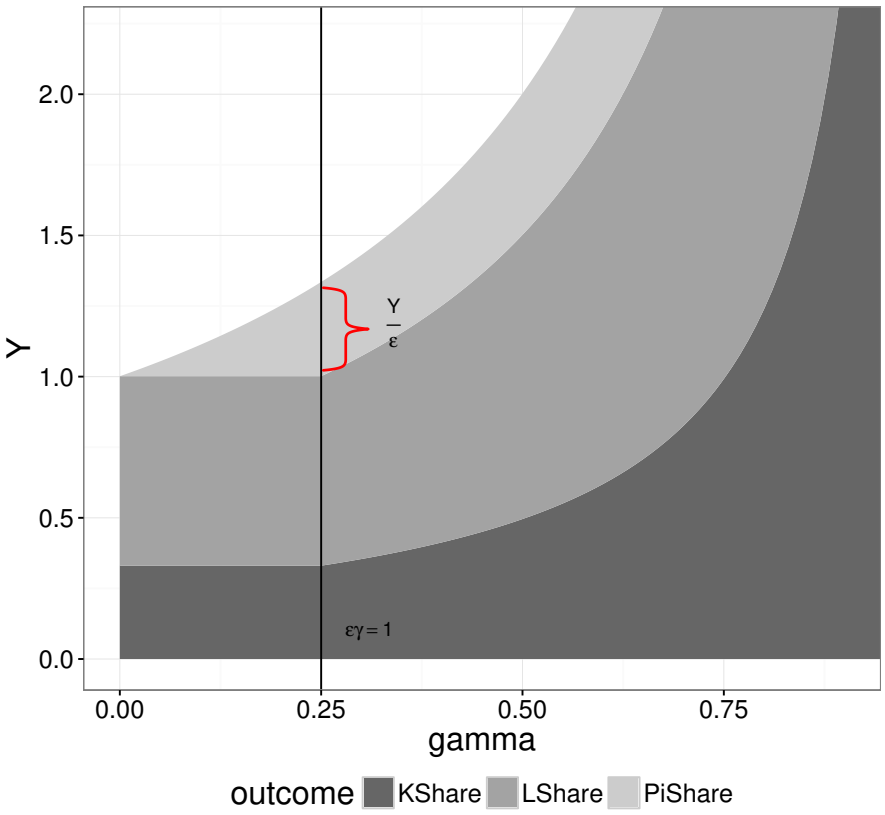


Figure 2.5: Factor shares as a function of automation

reduce their factor demand. However, in general equilibrium, this decline in factor demand reduces wages and the return on capital, lowering all firms' unit costs – no matter if they use the traditional or superstar technology – sufficiently so that they increase output and absorb the available factor supply. As a result, output in general equilibrium goes up, although all the gains accrue to the superstars (see the blue top area).

Once digital automation exceeds the threshold $\gamma_i \geq \frac{1}{\epsilon}$, monopolist superstars set a constant price markup over their costs in all sectors. Further increases in digital automation γ_i lead to price declines of the intermediate goods across all sectors, triggering an increase in aggregate demand and output – due to the scale effect of Proposition 3. The mechanism through which the rise in output is shared among all three factor owners is that greater demand for labor and capital pushes up wages and the interest rate. As a result, the share of superstar profits and the factor shares of labor and capital remain constant, as shown in the figure.

One important point to remember is that the described results compare the allocations of different static one-period economies, in which the supply of the factors capital and labor is taken as exogenous. Our results on wages and the rental rate of capital in points (ii) and (iii) of the proposition suggest that incentives to supply labor and capital are unaltered in the early stages of automation but are increased once the threshold $\bar{\gamma} = \frac{1}{\epsilon}$ is surpassed. This implies that when factor supplies are endogenous, labor supply and capital accumulation will lag behind output growth in the early stages of digital automation, but additional capital accumulation and growth in capital and labor supply will occur once the threshold $\gamma_i \geq \frac{1}{\epsilon}$ is crossed, as we will explore in further detail when we analyze macroeconomic dynamics in Section 2.5.

2.3 Welfare Analysis

The main inefficiency from the emergence of superstars is monopoly power that arises because superstars can exclude others from employing the innovation that they have developed. In our baseline model, the resulting monopoly rents at first compensate superstars for the cost ξ_i of developing the innovation and then generate windfall gains for the superstars.

This section evaluates the welfare properties of the described superstar economy. We start with a first-best perspective to analyze how a planner would employ superstar technologies under idealized circumstances. Then we consider what policy measures can be employed in a second-best world to mitigate the inefficiencies arising from the superstar phenomenon.

2.3.1 First best

In the first best, a social planner would choose the optimal mix of traditional and superstar technologies (captured by the indicator function $1_i^S = 1$ when the superstar technology in sector i is active), in order to maximize total output net of the total user costs of the superstar technology,

$$\max_{\{K_i,L_i,Y_i\}} \left(\int_0^1 Y_i^{1-\frac{1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} \qquad \text{s.t.} \qquad Y_i = \max_{1_i^S} \left\{ \frac{A_i K_i^\alpha L_i^{1-\alpha} - 1_i^S \xi_i}{1 - 1_i^S \gamma_i} \right\} \forall i,$$
$$\int_0^1 K_i = K$$
$$\int_0^1 L_i = L$$

Proposition 5 (First Best and Monopoly Distortions from Digital Innovation)**.** *The decentralized equilibrium exhibits (i) insufficient digital innovation and (ii) inefficiently low quantities in superstar sectors compared to traditional sectors.*

Proof. See appendix.

□

The intuition behind our result is that private superstar firms charge a markup upon developing digital innovations, which – unsurprisingly – leads to inefficiently low quantities. This also implies that they do not generate the full social surplus that could be obtained from the superstar technology. As a result, the threshold $\hat{\gamma}_i$ at which they decide to innovate is insufficiently low. A first-best planner would employ the superstar technology to produce larger output and generate more social surplus, and therefore has greater incentive to innovate.

The inefficiencies described in the proposition refer to superstar sectors in comparison to traditional sectors. In our static setup, the monopoly power of superstar firms does not distort the aggregate level of capital but only its allocation across different industries. In our dynamic setup in Section 2.5, monopolistic superstar firms also distort the level of the capital stock downwards because they reduce the returns earned by traditional capital.

Corollary 3 (Correcting Monopoly Distortions)**.** *The inefficiency described in Proposition 5 can be corrected in the following ways:*

(i) by financing the fixed cost ξ_i of socially desirable digital innovations using public funds and making them freely available to competitive traditional firms;

(ii) by employing non-linear pricing schemes whereby superstars charge a fixed cost and satisfy the demand for their product at marginal cost;

(iii) by providing a subsidy $s_i = \sigma P_i$ on the output of superstar firms to offset their monopoly markups.

Although the described policy options make production more efficient and implement the first best, not all of them generate Pareto improvements because the distribution of surplus

changes. Option (i) implies that superstar profits disappear since anybody can use the efficient new technologies. Option (iii) increases demand for the output of superstar firms to the socially efficient level, but implies that superstar firms earn even larger monopoly profits, unless some of their profits can be taxed away in lump sum fashion. However, if transfers are feasible, all three policies can generate Pareto improvements.

Naturally, all three proposed policies also come with important caveats in practice:

Option (i), public financing of digital innovation, requires large amounts of fiscal revenue. Furthermore, it requires that innovation can be performed without additional agency costs, i.e. that researchers do not need to earn additional rents to be incentivized to perform. Moreover, it requires that the information underlying the innovation is fully non-rival and can indeed be freely distributed without generating bottlenecks in its use (for example, because only a small number of experts can use it).

Option (ii), charging a fixed cost and satisfying demand at marginal cost, supposes detailed information about the structure of demand, including the ability to appropriately discriminate between heterogeneous consumers who have different demand curves, derive different surplus and should therefore optimally be charged different fixed costs. In principle, any fixed cost between ξ_i and $\xi_i + \pi_i$ can support the first-best level of output, with the distribution of the surplus π_i to be determined by bargaining (in a decentralized equilibrium) or policy.

Option (iii), subsidizing monopolistic firms requires large amounts of fiscal revenue, and raising this revenue may introduce large distortions of its own. Furthermore, it may be politically quite undesirable to provide subsidies to firms that are already earning large monopoly rents.

2.4 Extensions

2.4.1 Market share dynamics

This subsection extends our baseline model to incorporate multiple superstar firms in a given sector vying for sectoral dominance. In our baseline model, we made the extreme assumption that there was at most a single superstar firm per sector so as to focus on clear and simple results. We now relax this assumption to examine the robustness of our analysis. We consider a sector i with a superstar firm $j = 1$ that has variable cost savings γ_{i1} and assume that a second superstar firm $j = 2$ can enter the sector by paying a fixed cost ξ_i and produce sector i goods with variable cost savings γ_{i2}.

The entrant and the incumbent engage in Cournot competition. This is thus a model of Cournot duopoly where firms have heterogeneous cost functions. The total output in sector i is the sum of the output of the two firms, $Y_i^D = Y_{i1} + Y_{i2}$, where we use the superscript D to indicate that it refers to the duopoly case. Each firm ij takes the output of the other firm as given and solves

$$\max_{P_{ij}, Y_{ij}} P_{ij} Y_{ij} - (1 - \gamma_{ij}) \, UC_i^T Y_{ij} - \xi_{ij} \qquad \text{s.t.} \qquad P_{ij} = P\left(Y_{i1} + Y_{i2}; Y\right) \leq UC_i^T$$

The optimality condition for firm j equates marginal revenue and marginal cost, $P_Y Y_{ij} + P_i = (1 - \gamma_{ij}) \, UC_i^T$, as in our baseline model.

Pricing Constrained by Traditional Technology When competition from traditional firms constrains the pricing of superstar firms, then they charge the price given by the unit cost of traditional firms $P_{ij} = UC_i^T$ and jointly produce the output that would be

produced by traditional firms, $Y_i^D = Y_{i1} + Y_{i2} = Y_i^T$.[2] Each superstar firm earns profits of $\pi_{ij=} (\gamma_{ij} Y_{ij} - \xi_{ij}) \cdot UC_i^T$. This region is analogous to the $\epsilon\gamma \leq 1$ region in our baseline model with a single superstar firm.

Unconstrained Duopoly Pricing When competition from traditional firms does not constrain pricing and both superstar firms find it optimal to participate in the market, their optimality conditions in a Cournot duopoly are

$$P_i\left(Y_i^D\right)\left[1 - \frac{1}{\epsilon}\left(\frac{Y_{ij}}{Y_i^D}\right)\right] = (1 - \gamma_{ij}) UC_i^T \text{ for } j \in \{1, 2\} \tag{2.10}$$

which implies market shares that we denote by

$$\lambda_{ij} = \frac{Y_{ij}}{Y_i^D} = \epsilon\left[1 - \frac{(1 - \gamma_{ij})\, UC_i^T}{P_i\left(Y_i^D\right)}\right] \tag{2.11}$$

Observing that the two market shares must satisfy $\lambda_{i1} + \lambda_{i2} = 1$, we obtain the Cournot duopoly price

$$P_i^D = \frac{2\epsilon}{2\epsilon - 1}\left(1 - \frac{\sum_j \gamma_{ij}}{2}\right) \cdot UC_i^T \tag{2.12}$$

and, substituting the inverse demand function $P_i\left(Y_i, Y\right)$, total output for the duopoly

$$Y_i^D = \left[\frac{2\epsilon}{2\epsilon - 1}\left(1 - \frac{\sum_j \gamma_{ij}}{2}\right) UC_i^T\right]^{-\epsilon} \cdot Y$$

Compared to the superstar monopoly solution described in our baseline setup, the duopoly acts as if demand was twice as elastic and charges a price that depends on the average cost savings of the two firms. This captures the standard intuition that prices decline as more

[2]The distribution of output between the two superstar firms is indeterminate in this case. One natural way of resolving this is e.g. to assign market shares according to the unconstrained Cournot equilibrium between the two firms, as derived below in equation (2.11).

firms enter a market in Cournot competition. For example, if both superstar firms have the same cost savings γ_i, they charge half of the markup that a monopoly superstar firm would charge.

We can now establish the condition that guarantees that the duopoly price is not constrained by competition from traditional firms:

Condition 1 (Unconstrained Duopoly Pricing)**.** *The duopoly is not constrained by competition from traditional firms if and only if*

$$\epsilon \sum_j \gamma_{ij} > 1$$

Proof. The proof follows from re-arranging the inequality $P_i^D < UC_i^T$ using the optimal duopoly pricing condition (2.12). □

Condition 1 provides an analogous condition to $\epsilon\gamma_{i1} \geq 1$ in our baseline model. When two superstar firms participate in the market, we enter the phase of optimal pricing earlier than under monopoly since the markup charged by duopolistic firms is lower.

Conditions for Existence of Duopoly We now wish to analyze the conditions under which a superstar duopoly will prevail in the market. Profits of each of the two firms in a duopoly would be

$$\pi_{ij}^D = \lambda_{ij} Y_i^D \left[P_i^D - (1-\gamma_{ij})UC_i^T\right] - \xi_i \text{ for } j \in \{1,2\}$$

It can be seen that a firm will not find it desirable to enter if either its cost savings γ_{ij} are too low compared to the market price (which will be the case if the other firm has considerably higher cost savings) or if its fixed cost ξ_i are too high.

For simplicity, we consider the case $\xi_i = 0$ in the following. Let us consider a superstar firm with cost savings γ_{i1} and assume a second firm with γ_{i2} that considers whether to enter. The new entrant earns positive profits and finds it desirable to enter if and only if $\pi_{i2}^D > 0$. If pricing behavior in the duopoly equilibrium is constrained by competition from traditional firms, i.e. if Condition 1 is violated, then a duopoly equilibrium is always possible for any $(\gamma_{i1}, \gamma_{i2})$, and both superstar firms charge the price of traditional firms P_i^T.

If Condition 1 is met and the duopoly equilibrium is unconstrained, then substituting the equilibrium duopoly values into the market share function implies a market participation threshold of

$$\gamma_{i2} \geq \hat{\gamma}(\gamma_{i1}) = \frac{\epsilon\gamma_{i1} - 1}{\epsilon - 1}$$

This condition simultaneously guarantees that $\pi_{i2}^D \geq 0$. By symmetry, an analogous expression determines the threshold at which the first superstar firm $i1$ will exit the market.

We summarize the market share dynamics with two superstar firms in the following proposition, which considers a market with an existing superstar firm with γ_{i1} and examines what happens as we vary the cost savings parameter γ_{i2} of a potential entrant from zero to one:

Proposition 6 (Market Share Dynamics under Unconstrained Duopoly)**.** *For a given γ_{i1}, as we increase the cost savings γ_{i2}, a potential entrant $i2$*

- *does not enter the market as long as $\gamma_{i2} < \hat{\gamma}(\gamma_{i1})$;*
- *enters the market at $\gamma_{i2} = \hat{\gamma}(\gamma_{i1})$, where $P_i^M = P_i^D$, Y_i^M=Y_i^D, and $\lambda_{i2} = 0$;*
- *lowers the market price P_i^D, raises total sector output Y_i^D, and increases its own market share λ_{i2} as γ_{i2} rises further;*

- *takes over the entire market at the point* $\gamma_{i1} = \hat{\gamma}(\gamma_{i2})$ *so the incumbent superstar firm exits, and monopoly pricing takes over, resulting in steeper declines in price and increases in quantity as* γ_{i2} *increases further.*

Proof. Most of the proposition is clear from the discussion above. The only thing to verify is that $\gamma_{i2} = \hat{\gamma}(\gamma_{i1})$ is a kink, where $P_i^M = P_i^D$ but $\lim_{\gamma_{i2} \to \hat{\gamma}(\gamma_{i1})^-} \frac{dP_i}{d\gamma_{i2}} \neq \lim_{\gamma_{i2} \to \hat{\gamma}(\gamma_{i1})^+} \frac{dP_i}{d\gamma_{i2}}$, but the left hand derivative differs from the right hand derivative. First, note that from equation 2.12, we can express

$$\begin{aligned} \frac{P_i^D}{P_i^M} &= \kappa_i \\ &= \frac{(\epsilon - 1)(1 - \gamma_{i1}) + (\epsilon - 1)(1 - \gamma_{i2})}{(\epsilon - 1)(1 - \gamma_{i1}) + \epsilon(1 - \gamma_{i1})} \end{aligned}$$

At $\gamma_{i2} = \hat{\gamma}(\gamma_{i1})$, $\kappa_i = 1$. From our previous discussion, for any $\gamma_{i2} < \hat{\gamma}(\gamma_{i1})$, $\frac{dP_i}{d\gamma_{i2}} = \frac{dP_i^M}{d\gamma_{i2}}$, while for any $\gamma_{i2} > \hat{\gamma}(\gamma_{i1})$, $\frac{dP_i}{d\gamma_{i2}} = \frac{dP_i^D}{d\gamma_{i2}}$. We can explicitly show that $\left|\frac{dP_i^D}{d\gamma_{i2}}\right| < \left|\frac{dP_i^M}{d\gamma_{i2}}\right|$ for all γ_{i2}. By substituting our expression for duopoly price (equation 2.12) into our expression for λ_{i2} (equation 2.11), we also see that $\lambda_{i2} = 0$ at $\gamma_{i2} = \hat{\gamma}(\gamma_{i1})$. A symmetric argument can be made for the takeover of monopoly pricing at $\gamma_{i1} = \hat{\gamma}(\gamma_{i2})$. □

Intuitively, a second superstar firm will enter the market if its cost savings are sufficiently high that it can compete with the existing superstar firm. The additional competition pushes down the market price. If the new entrant is sufficiently more productive, she pushes out the existing superstar firm and equilibrium reverts to a monopoly. Accounting for positive costs ξ_{i1} and ξ_{i2} adds additional inequality constraints to the entry and exit conditions of firms without affecting the main intuition of the result.

From the lens of our model, the emergence of winner-take-all markets thus has several implications. We can envision a market structure where instead of having a pool of tra-

ditional competitors, existing firms have heterogeneous γ_{ij}, and engage in unconstrained monopsony pricing. To fix ideas, we revert to our simple case of the duopoly, even though this analysis is robust to n-firm oligopoly under Cournot competition. From Proposition 6, a duopoly becomes a monopoly if one firm's cost savings from γ_{ij} substantially exceed its competitors' cost savings. Formally, if $\gamma_{i1} < \hat{\gamma}(\gamma_{i2})$ holds, where firm 1's cost savings are too low, a monopoly naturally forms. Further, our model implies that if $\gamma_{i1} < \hat{\gamma}(\gamma_{i2})$holds, a monopoly would ensure lower(partial) equilibrium prices and greater equilibrium output than under a duopoly. If a winner-take-all market emerges because one firm has far exceeded its competitors in variable cost savings, the monopoly may be welfare improving rather than decreasing.

However, using Equation 2.12, we can show that if $\gamma_{i1} \geq \hat{\gamma}(\gamma_{i2})$, and the two firms are relatively close in variable cost savings, a duopoly results in lower equilibrium prices and higher output than under a monopoly, and increases both consumer and producer surplus. Conversely, the superstar share of income also declines. Thus, there are welfare advantages to having many firms in the industry, as long as they are relatively competitive in terms of γ_{ij}. In practical terms, subsidies for uncompetitive firms are welfare decreasing, but avoiding monopoly control of variable cost saving technologies and making them available to many firms can be welfare improving. Of course, this simple analysis takes γ_{ij} as exogenous, and does not consider incentives required for γ_{ij} production.

2.4.2 Elasticity of Substitution

This section consider the case that the elasticity of substitution between different varieties of intermediate goods in final production satisfies $\epsilon \leq 1$ to analyze how superstar firms would act in such an environment. In our baseline model, we assumed that $\epsilon > 1$, which generated

an optimal monopoly (gross) markup of $\frac{\epsilon}{\epsilon-1}$. After superstar innovation had generated sufficient cost savings so that they could charge this markup in the face of competition from traditional firms, they passed on any additional cost savings to consumers who expanded demand for the respective variety of intermediate goods to such an extent that the total revenue of superstar firms increased.

When $\epsilon \leq 1$, price reductions in an intermediate variety do not generate sufficient demand so as to increase revenue and profits. In fact, a monopolist who faces the demand function $Y_i = (P_i)^{-\epsilon} Y$ with $\epsilon \leq 1$ would find it optimal to charge a price $P_i \to \infty$ in order to maximize profits. In our setting, competition from traditional firms prevents price increases, but monopolist superstars do not find it optimal to pass on cost savings to their customers even if $\gamma_i \to 1$. This implies that our results in Proposition 3 and its Corollaries 1 and 2 continue to apply, although the inequality $\gamma_i < \frac{1}{\epsilon}$ is always satisfied by default. For example, when $\epsilon \leq 1$, superstar firms always earn the superstar profit share $\sigma = \gamma_i$.

Whereas the case of $\epsilon > 1$ offered the perspective that digital innovation in the form of increases in γ_i will only temporarily reduce the labor share and ultimately (as soon as $\gamma_i > \frac{1}{\epsilon}$) lead to growth that is evenly spread across factors, an elasticity of substitution of unity or below raises the dismal specter of all the gains from innovation going to the superstars, with traditional factor owners being clear losers. This would make the competition policies described in Section 2.3 even more urgent.

2.5 Macroeconomic Dynamics

We now embed our model of superstar firms into a dynamic setting in order to analyze the effects of increasing automation for capital accumulation and macroeconomic dynamics.

Consider an infinite horizon discrete time economy with time denoted by $t = 0, 1, \ldots,$

in which production in each sector and period occurs according to either a traditional or a superstar technology, as described in the baseline model of Section 2.2. We add a subscript t to our notation to denote the time period of each variable. Consumers inelastically supply one unit of labor each period, earning wage W_t, and choose a path of consumption C_t and investment I_t in traditional capital to maximize utility described by the function

$$U = \sum_{t=0}^{\infty} \beta^t u\left(C_t\right)$$

subject to individual period budget and capital accumulation constraints

$$C_t + I_t = W_t + R_t K_t + \Pi_t$$
$$K_{t+1} = \left(1 - \delta\right) K_t + I_t$$

where $R_t K_t$ is the return on traditional capital in period t and δ is the depreciation rate on traditional capital.

Steady State We compare the steady states of an economy for different levels of digital automation $\gamma_i = \gamma \forall i$ while assuming that $\xi_i = 0 \forall i$. Steady state variables are denoted without the subscipt t. In steady state, the household's Euler equation pins down the equilibrium net interest rate $r = \frac{1}{\beta} - 1$ and the associated rental rate of capital $R = r + \delta$. For given γ, the steady state capital share of the economy satisfies

$$RK = \alpha\left(1 - \sigma\right) Y = \frac{\alpha\left(1 - \sigma\right) A K^{\alpha} L^{1-\alpha}}{1 - \gamma} = \alpha A K^{\alpha} \cdot \max\left\{1, \frac{\epsilon - 1}{\epsilon\left(1 - \gamma\right)}\right\}$$

Substituting the equilibrium rental rate R, we obtain the steady state level of capital

$$K = \left[\frac{\alpha(1-\sigma)A}{(1-\gamma)R}\right]^{\frac{1}{1-\alpha}} L = \left[\frac{\alpha A}{R}\right]^{\frac{1}{1-\alpha}} \cdot \max\left\{1, \frac{\epsilon-1}{\epsilon\,(1-\gamma)}\right\}^{\frac{1}{1-\alpha}}$$

This implies that the capital stock is unchanged as long as digital innovation remains below the threshold $\gamma < \frac{1}{\epsilon}$, but then rises in γ in a convex fashion. Output, wages and superstar profits follow immediately from the steady-state level of capital,

$$\begin{aligned}
Y &= \frac{AK^{\alpha}L^{1-\alpha}}{1-\gamma} = \frac{A}{1-\gamma} \cdot \left[\frac{\alpha A}{R}\right]^{\frac{\alpha}{1-\alpha}} \cdot \max\left\{1, \frac{\epsilon-1}{\epsilon\,(1-\gamma)}\right\}^{\frac{\alpha}{1-\alpha}} \\
w &= (1-\alpha)\,(1-\sigma)\,Y = \frac{(1-\alpha)\,(1-\sigma)\,AK^{\alpha}L^{1-\alpha}}{1-\gamma} \\
&= (1-\alpha)\,A\left[\frac{\alpha A}{R}\right]^{\frac{\alpha}{1-\alpha}} \cdot \max\left\{1, \frac{\epsilon-1}{\epsilon\,(1-\gamma)}\right\}^{\frac{1}{1-\alpha}} \\
\Pi &= \sigma Y = \frac{\sigma AK^{\alpha}L^{1-\alpha}}{1-\gamma} = \frac{A}{1-\gamma} \cdot \left[\frac{\alpha A}{R}\right]^{\frac{\alpha}{1-\alpha}} \cdot \min\left\{\frac{1}{\epsilon}, \gamma\right\} \max\left\{1, \frac{\epsilon-1}{\epsilon\,(1-\gamma)}\right\}^{\frac{\alpha}{1-\alpha}}
\end{aligned}$$

For low levels of digital innovation $\gamma < \frac{1}{\epsilon}$, output rises in a convex manner in γ because of the greater productivity generated by the innovation, but wages remain constant, and all the gains are absorbed by rising superstar profits. After the threshold, output, wages and superstar profits all rise at the same rate, given by the term $\left(\frac{1}{1-\gamma}\right)^{\frac{1}{1-\alpha}}$. These findings are also illustrated in Figure 2.6, which depicts the comparative statics of steady state output as a function of digital automation γ, split into the three components capital share, labor share, and superstar profit share.

Level of Asset Prices It is also instructive to observe the implications of digital innovation for asset prices: we distinguish between the market value of traditional capital K and the market value of capitalized superstar rents $Q^S = \frac{\Pi}{r}$. In practice, asset prices traded in

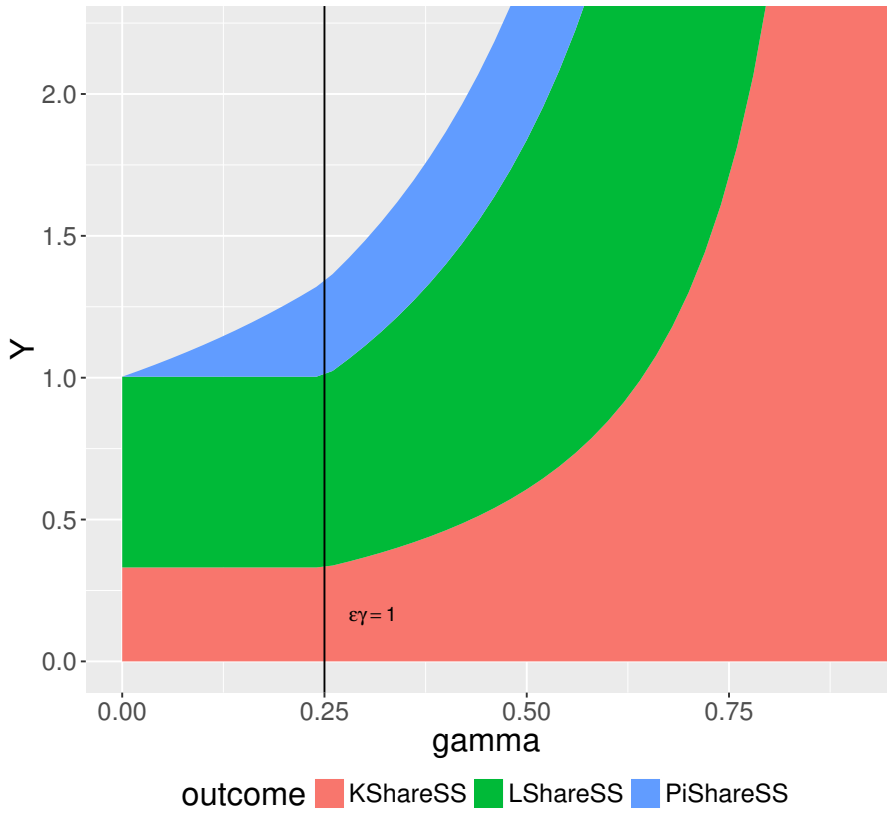


Figure 2.6: Comparative statics of steady state as a function of digital innovation

financial markets comprise both components, $Q = K + Q^S$. Substituting the steady state values from above, we find that

$$Q^S = \frac{\sigma}{\alpha(1-\sigma)} \cdot \frac{r+\delta}{r} \cdot K$$

This relationship illustrates that the capitalized value of superstar rents can easily reach levels that are of equal or higher magnitude than the value of traditional capital.

Transitional Dynamics We now examine the dynamics of the system as it converges to a new steady state. We assume for simplicity that the economy starts out without superstar technologies and experiences a shock that raises digital innovation to $\gamma_i = \gamma \forall i$ in period 0.

For low levels of digital innovation $\gamma < \frac{1}{\epsilon}$, the dynamics are simple: since all the benefits of the innovation are captured by superstars, output rises but the capital stock and wages remain constant. This implies that there are no transitional dynamics and the economy jumps immediately to the new steady state.

If digital innovation rises above the threshold $\gamma > \frac{1}{\epsilon}$, the capital stock will rise to a higher level, and the transition is determined by the Euler equation

$$\frac{u'(c_{t+1})}{u'(c_t)} = \frac{1}{\beta\left[R_{t+1}(K_{t+1}) + 1 - \delta\right]}$$

where $R_t = \frac{\epsilon-1}{\epsilon}\frac{\alpha A}{1-\gamma}K_t^{\alpha}$. Since $\frac{dR_t}{d\gamma} > 0$, a positive shock to γ results in lower consumption and higher saving on impact, i.e. c_0 jumps downwards at time 0, but the system evolves in a smooth way thereafter to the new steady state of higher capital stock, higher wages, and higher consumption.

2.6 Conclusion

Our paper describes how the introduction of digital technologies leads to winner-takes-all markets and the creation of superstars. Digital innovation imposes up-front fixed costs that allow firms to reduce the marginal cost of serving additional customers. Since the digital innovations typically come with a considerable extent of excludability, they also confer monopoly power to the innovators, enabling them to turn into superstars in the market that they are serving. We argue that this represents one of the fundamental driving forces behind the rise in inequality in recent decades.

We show that increasing digital automation entails a complex trade-off: at first, automation lowers production costs but induces superstar firms to absorb the cost savings via higher markups and to extract increasing monopoly rents whereas the labor share in the economy declines. Once the optimal markup is reached, further progress in automation is passed on to consumers via cost savings, leading to economic growth with a constant (but depressed) labor share and constant monopoly profit share accruing to superstars. Although monopoly rents for superstars support their investment in digital technologies, the overall level of such rents is socially excessive. Furthermore, the rising role of fixed costs also requires changes in macroeconomic management, for example due to a flattening of the Phillips curve.

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Chapter 3

Crowding Out versus Agglomeration after Large Firm Entry

3.1 Introduction

When a firm opens a large establishment in a county, the literature on local labor markets gives us several ways to interpret the effects. Firstly, the presence of agglomeration economies imply that that wage and employment may rise more than the direct impact of firm entry. On the other hand, the denser labor market that results from large firm entry may result in a crowding out of existing local firms. A large body of literature provides both theory and empirical evidence on a large number of different sources of positive effects of agglomeration on firm productivity. These can be separated into two coarse categories. The first predicts agglomeration of firms from different industries as the entering firm, possibly due to access to higher density of market demand, or easier access to common input suppliers.[1] The second

[1]For example, see Davis and Weinstein [2001], who use data on Japanese firms to show that market demand is positively correlated with firm productivity, or Edward L. Glaeser and Saiz [2001], who provide some empirical evidence that agglomeration happens in cities due to access to consumers facilitated by urban

strand of literature emphasizes that agglomeration effects derive from co-location of firms of the same industry, due to proximity to a common pool of labor and technology.[2] On the other hand, the empirical literature that studies the effects of large firm openings on local earnings and employment provides evidence of possible crowding out effects on existing local firms.[3]

This paper provides a framework to empirically parse agglomeration effects from crowding out effects, in response to a labor demand shock in the form of large establishment entry. To do so, we construct a model where large establishments select into counties, and entry results in the generation of agglomeration economies, as well as crowding out of existing firms. We identify the magnitudes of these opposing effects by firstly estimating general functional forms for each, depending on county characteristics, labor market conditions, and the industry of the entering firm. This enables us to simulate counterfactual county responses to large establishment entry in our structural model, without encountering endogeneity problems faced by reduced-form estimation methods.

We study the labor market effects of large establishment openings in counties where there are no incumbent large firms. Specifically, we identify a sample of US counties where an establishment that accounts for over 20% of total county employment opens between 1990 and 2005. In effect, immediately after large establishment entry, these counties become "one company towns". A plurality of these towns are located in the South and in the Appalachian belt, they tend to be nonmetro areas far from the closest metro area, and they tend to score lower than average on amenities metrics. Conducting naive difference-

amenities.

[2]For example, see Ellison, Glaeser, and Kerr [2010] who find that clustering occurs for industries that use the same type of labor, and Greenstone, Hornbeck, and Moretti [2010], who find positive effects of large manufacturing plant entry on similar plants in the locality.

[3]See Neumark, Zhang, and Ciccarella [2008], who find the Wal-mart openings reduce county-level employment and wages in retail.

in-differences (DID) analyses for wage and employment growth in these counties suggest that on average, there are small declines in employment and wage growth in the ten years after large establishment entry, after initial positive shocks to growth in the year of entry. We also find that these counties tend to remain one firm towns. On average, there is very little evidence of agglomeration, either in the industry of the entering large establishment or in other industries. However, there is substantial industry heterogeneity in wage and employment growth after large establishment entry. Mining, construction, wholesale trade and retail trade establishment are associated with large declines in employment and wage growth after entry, while manufacturing and services establishments are associated with slight increases in employment and wage growth, although growth is still slower than the average US county without large establishment entry.

Our DID results of substantial industry heterogeneity are in line with the disparate empirical literature on local labor market effects of plant openings, that generally concentrate on estimating the effects of establishment openings from a single industry. Neumark et al. [2008] and Basker [2007], using a mixture of DID and Instrumental Variable (IV) methods, find that Walmart openings have slightly negative impacts on county employment and earnings. Examining the entry of financial firms, Weinstein [2017]) uses a matching procedure with towns in bordering states to find persistent positive effects on wages and employment. Exploiting the recent shale boom in the US, Feyrer, Mansur, and Sacerdote [2017] find that new oil/gas extraction generates large and positive direct employment and wage effects, although their data does not allow them to study persistent labor market effects. Our reduced form results are not directly comparable to these studies, in that we focus on towns that become "one company towns" after the opening of a large establishment. Still, at the basic level, we advance on these strands of literature by generalizing them into a framework capable of accommodating and explaining industry heterogeneity in labor market outcomes after

establishment entry.

More fundamentally, we go further than the reduced form literature in explaining the mechanisms underlying county labor market outcomes after establishment entry. In particular, we construct a spatial-equilibrium model deriving from the pioneering work of Rosen (79) and Roback [1982], the workhorse model in studying flows of workers and firms across local labor markets, to explain our reduced form results. In line with other work that have used spatial-equilibrium models to investigate agglomeration economies, our model predicts that the entry of a large establishment into a county potentially generates two sources of agglomeration: (i) a rise in number of establishments of the same industry as the entering firm, (ii) and a rise in number of establishments in the non-tradeable sector. At the same time, our model implies that large establishment entry will raise wages, crowding out existing establishments.

Our model thus predicts that the effects of large establishment entry depends on the net effect from the preceding three mechanisms. A county may receive positive employment and wage impacts upon entry, but if crowding out effects dominate non-tradeable agglomeration, large establishment may have negative employment effects on the non-tradeable sector. If further entry of firms from the same industry produces large crowding out effects, these can dominate productivity benefits from agglomeration. These counties then persist as one-firm towns.

Using our model's structure, we propose a method for estimating the counterfactual treatment effect of large establishment entry on county employment and wage growth. We identify the size of non-tradeable agglomeration and crowding out effects for each county by estimating two general functions in the first stage. The first is a general function for the labor demand function for non-tradeable sector, which our model implies depends on total county employment. The second is a general wage response function, which summarizes information

on the slopes of county labor demand and supply curves. We then simulate county responses to a labor demand shock, conditioning on each county's pre-entry conditions. This allows us to avoid using outcome variables in the the contemporaneous and post-entry periods in our estimation, avoiding the problem of using dependent variables that are correlated with large establishment entry.

Estimating our model on our sample of counties, we find that on average, crowding out effects on non-tradeable labor employment approximately cancel out local demand agglomeration effects from large establishment entry. Further, there are minimal industry agglomeration effects after the entry of the initial large establishment. Therefore, the net effect of large establishment entry are, on average, limited to the positive direct impact on wages and employment from the entering firm. This explains our reduced form finding that aside from initial positive effects on wages and employment upon entry, no sustained growth is observed in the ten years after initial entry.

Our structural estimates suggest a few explanations for these results. First, crowding out effects are especially high in our sample are high due to several characteristics of the average county in our sample. These counties tend to be rural and far away from urban centers, have low natural amenities, and have tight housing rental markets. All three characteristics lead to high wage responses to labor demand shocks, in line with intuition from our structural model.[4] Relative large increases in wages lead to high crowding out of non-tradeable labor after large establishment entry.

Second, local labor demand agglomeration effects are small in our sample of counties because our average county has relatively low wage levels before large establishment entry. According to the intuition of our structural model, low wages imply that demand for non-tradeable consumption, and thus demand for non-tradeable labor, should not see large

[4]Note that we have not restricted the signs or magnitudes of our estimates.

increases after a rise in employment. This is an important reason for why the local labor demand agglomeration effects are relatively small in our sample.

Thirdly, our estimates suggest that the wage responses from further large establishment entry increase in our average county after initial large establishment entry. Our model does not predict further entry from establishments in the same industry as the productivity benefits from colocation with similar firms are not sufficient to outweigh high wages after entry.

Our results also offer some explanations as to why counties with manufacturing and services establishments experience some sustained growth in wages and employment after initial entry, in contrast with counties with entry from industries like agriculture or mining, that show no evidence of sustained growth after entry. Firstly, manufacturing and services establishments tend to enter counties that are less rural (lower crowding out effect), and have higher pre-entry wages (higher local agglomeration effect). Secondly, Services industries in particular seem to experience larger productivity benefits from colocating with other service industry establishments, and so experience some industry agglomeration.

Our results suggest that in order for large establishment entry to foment sustained wage and employment growth, policy intervention to reduce crowding out effects upon large establishment entry are important. Formally, these can enable counties to move up to higher equilibrium wages and employment, even after the cessation of subsidies. These can take the form of temporary subsidies to non-tradeable firms to buffer against rising wage costs after initial large establishment entry. These subsidies ensure that local agglomeration effects outweigh crowding out effects, providing larger gains to overall employment. Once county wages have risen enough to support a large enough non-tradeable sector, the subsidies can cease. We estimate the size of subsidies to the non-tradeable sector required to generate sustained employment and wage growth.

3.2 Large Firm Entry

3.2.1 Data

We use County Business Patterns (CBP) data from the Census Bureau to form an annual panel dataset on employment, wages, and establishments at the county level. Importantly, the CBP data contains the industry and size class breakdown of each county's establishments. The CBP is a comprehensive dataset of all US counties.

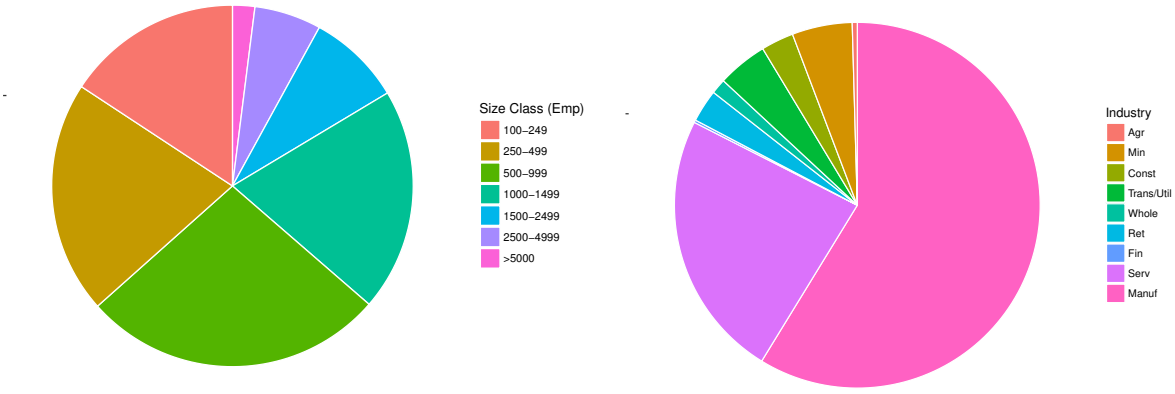
We look for instances of large firm entry into counties - specifically, the opening of an establishment accounting for $\geq 20\%$ of the county's employment. To do this, we look for county-year observations where there is exactly one establishment in an employment size class with $\geq 20\%$ of county employment, where in the previous year there were zero establishments in that same size class. There are several potential problems with this method: (i) We may be capturing a growing existing establishment (ii) As with all exercises that tries to measure flows from panel data, this analysis suffers from potential time aggregation issues. That is, multiple large establishments may enter and exit the county between yearly data collection dates. This is not critical for our purposes, as by restricting observations to counties that have exactly one new large firm, we are only capturing effects of the entry of the sole surviving large establishment. (iii) We do not capture large establishment entry when there is already an existing establishment in that size class operating in the county. This is perfectly acceptable for our analysis, as we are looking for the first observed entry of a large establishment in each county. The entry of subsequent large establishments may be correlated with the entry of the first large establishment, as would any observed labor market effects from the subsequent entry. To avoid these potential effects, we concentrate on observations where the entering large establishment is the county's first observed.

We then match the new large establishment to its 2-digit SIC code. Since there is exactly one such establishment in its size class in the county, there is no ambiguity in matching the entering large establishment to its 2-digit industry.

3.2.2 Summary Statistics

Figures 3.1-3.3 display some summary features of our data. Our sample consists of 351 large establishments, which should account for all large establishment entries into US counties from 1990-2005, according to our criteria. Figure 3.3a shows that that most of our observations occur in nonmetro rural areas with relatively low population, which is not surprising as our method excludes counties with existing large establishments, and our total employment threshold of 20% is high enough that no large urban areas would be included in our establishment entry data. Figure 3.3b shows that there is a leftward skew in the natural amenities distribution for these counties. That is, counties with large establishment entry are tend to score lower than average in the US Department of Agriculture's Natural Amenities Scale. This is a measure combining scores for climate, topography, and water area features, reflecting that counties with large establishment entry tend to score lower than average in these amenities. In Figure 3.2, we also note that large establishment entry occurs most often in the South and the Appalachian states, with Georgia leading the way with large establishment entry in 49 counties. Kentucky (37), Texas (30), and Virginia (28) follow in the rankings. This is perhaps less surprising when we consider that the South has a large concentration of rural counties with medium population sizes. However, Northeastern states sch as Vermont and New Hampshire, which also have many rural counties with low populations, experienced almost no large establishment entry from 1990-2005.

Figure 3.1b shows that the Manufacturing and Services establishments account for the



(a) Employment Size Class (b) Industry

Figure 3.1: Composition of Entering Large Establishments by Employment Size Class and 2 digit SIC Industry.

major part of large establishment entry in the US from 1990-2005, with manufacturing (265 establishment entries) accounting for over half of all our observations. Mining, Transport/Utilities, and Retail Trade establishment entries follow.

We report mean annual growth in county employment, wages, and total number of establishments before large establishment entry, during the year of entry, and in the years after entry in Table 3.1. Column 1 in Table 3.1 shows mean annual growth from years $t^* - 5$ to $t^* - 1$, where t^* is the year of entry, averaged across counties with large establishment entry. We note that employment and wage growth generally robust in our sample pre-entry, with employment growing at 2.3% and wages growing at 5.7% on average before entry. Unsurprisingly, employment and wage growth in the year of entry are strong, at 11.6% and 16.8% on average. In the first five year interval post entry, from $t^* + 1$ to $t^* + 5$, employ-

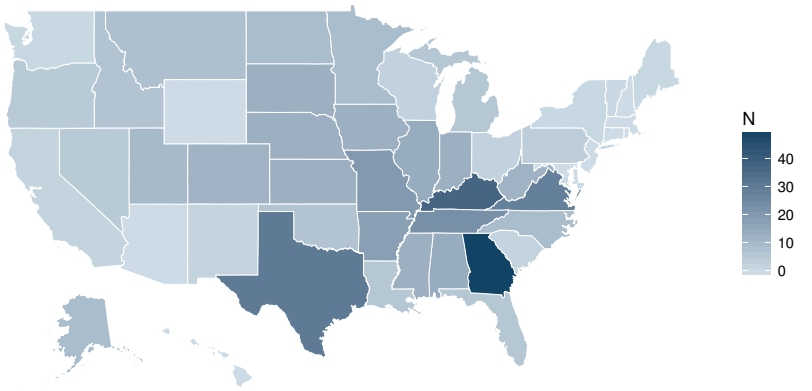
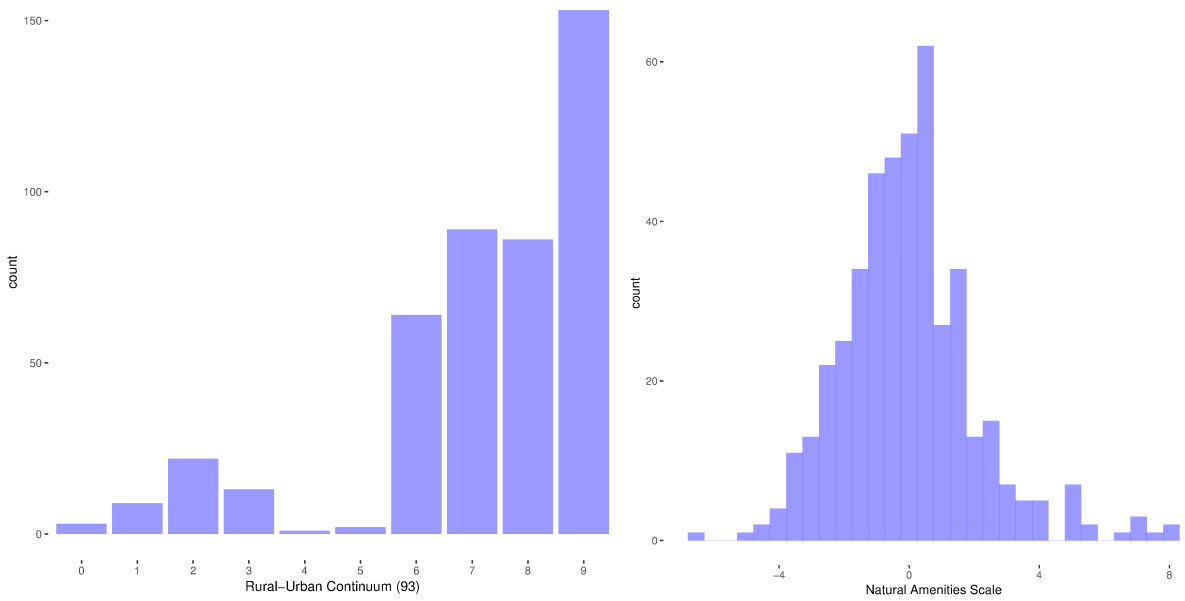


Figure 3.2: Concentration of Entering Large Establishments by U.S. State.

ment growth declines to 0.2% per year, and wage growth to 3.6%, both lower than pre-entry growth rates. In the second post-entry five year interval, from $t^* + 6$ to $t^* + 10$, employment growth becomes negative, while wage growth declines further to 2.1%. Post-entry wage and employment growth are significantly lower than pre-entry rates.

We also observe heterogeneity in employment and wage outcomes by industry of entering establishment. In particular, we note that employment and wage growth are lowest pre-entry in manufacturing counties, and highest in retail trade counties. We also find that establishment count growth pre-entry is also highest for retail trade counties. This suggests that retail trade establishments select into faster growing counties, relative to other industries.



(a) Rural-Urban Continuum (93) (b) Natural Amenities Scale

Figure 3.3: County Characteristics Densities for counties with Large Establishment Entry.
Notes: Rural-Urban Continuum (93) is a county classification from US Department of Agriculture. Codes 1-3 are for urban metro areas, with 1 having highest population. Codes 4-9 are for nonmetro areas, with higher numbers signifying smaller populations and longer distance to nearest urban metro area. Natural Amenities Scale classification from US Department of Agriculture. NAS combines measures of weather, topography, and water area, with high scores reflecting proximity to natural features that most people prefer.

We observe that wholesale trade, retail trade, and services establishments make the largest direct impact on wage and employment on average. This could be due to the larger size of establishments from these industries.

In the first five years after entry, agriculture, mining, and construction experience declining employment and below average wage growth. Manufacturing counties see above average wage and employment growth, while services counties see average employment growth but stronger than average wage growth. Transport/Utilities counties see the strongest wage and employment growth in the first five years post-entry. From years six-ten post-entry, all industries see negative employment growth and weak wage growth.

Table 3.1: Mean Annual Growth

Industry	Δy_{-5}	Δy_0	Δy_5	Δy_{10}
A: Employment				
Total	0.023	0.116	0.002	-0.008
Agriculture	0.055	0.023	-0.035	-0.048
Mining	0.031	0.092	-0.002	-0.000
Construction	0.023	0.115	-0.019	-0.028
Transport/Utilities	-0.004	0.080	0.011	-0.027
Wholesale Trade	0.040	0.224	-0.006	-0.017
Retail Trade	0.058	0.165	0.005	-0.004
Services	0.026	0.175	0.002	-0.007
Manufacturing	0.020	0.081	0.004	-0.007
B: Wage				
Total	0.057	0.168	0.036	0.021
Agriculture	0.085	-0.024	-0.025	-0.044
Mining	0.074	0.199	0.004	0.034
Construction	0.068	0.139	0.014	-0.008
Transport/Utilities	0.008	0.140	0.059	0.011
Wholesale Trade	0.079	0.348	0.004	0.014
Retail Trade	0.096	0.224	0.034	0.027
Services	0.063	0.210	0.043	0.024
Manufacturing	0.052	0.136	0.037	0.020
C: Establishment Count				
Total	0.009	0.005	0.008	-0.002
Agriculture	0.006	0.032	0.062	-0.002
Mining	0.022	-0.027	0.022	0.006
Construction	0.009	-0.037	0.008	-0.011
Transport/Utilities	0.002	-0.007	0.009	-0.007
Wholesale Trade	0.004	-0.004	0.011	-0.004
Retail Trade	0.023	0.047	0.009	0.010
Services	0.008	0.003	0.004	-0.004
Manufacturing	0.009	0.011	0.008	-0.001

Notes: Mean Annual Growth among counties with Large Establishment entry in Employment, Wage, and Number of Establishments by industry of entering establishment reported in Panels A,B, and C respectively. Column 1 shows mean annual growth for years $t^* - 5$ to $t^* - 1$, column 2 for year of entry $t^* - 1$ to t^*, column 3 for years $t^* + 1$ to $t^* + 5$, column 4 for years $t^* + 6$ to $t^* + 10$.

3.2.3 Evidence of Agglomeration Effects

We look for evidence of agglomeration effects after large establishment entry in our sample. Greenstone et al (10) find evidence of positive network effects on productivity for similar manufacturing plants in the same county. If this is true, we should see a rise in the number of same-industry establishments following large establishment entry, to take advantage of the network effects.

Table 3 shows the average growth rate of the number of same-industry establishments from pre-entry $(t^* - 1)$ to 5 years post entry $(t^* + 5)$. We find that there is no evidence of agglomeration other than in the services industry. In every other industry, the average number of same-industry establishments in the county actually declines. This suggests that agglomeration effects may be heterogeneous across industries, and that crowding out effects may be important in our sample.

3.2.4 Difference-in-Difference

We wish to estimate the effect of large establishment entry on county i's employment, wage bill, and establishment number growth. That is, for some county i, and with y_{it} denoting a dependent county-year variable, we wish to estimate the average treatment on the treated (ATT) effect of large establishment entry on Δy_{it}, the growth of variable y in county i in year t. The ATT can be expressed as:

$$\mathbb{E}[\Delta y_{it} | \Delta D_{ijt^*} = 1] - \mathbb{E}[\Delta y_{it} | \Delta D_{ijt^*} = 0] \tag{3.1}$$

D_{ijt^*} is a dummy for entry by a large industry j firm into county i in time t^*. We can estimate the above naively using a difference-in-differences (DID) estimator: [5] It is well

[5] This is equivalent to estimating the above by standard OLS with D_{ijt} representing dummy variables for

known that as long as there are unobserved county-year variables correlated with both y_{it} and D_{ijt}, estimating the ATT by DID is generally inconsistent, even if we control for county characteristics and year effects. In our specific case, selection effects of large establishment entry into counties render reduced form regression estimates inconsistent. Nevertheless, a naive DID estimation can be usefully interpreted as the average increase in Δy_{it}, controlling for linear county and year effects. For our DID estimation, we assume the following model of y_{it} growth:

$$\Delta y_{i(t^*+s)} = \alpha_i + \tau_{(t^*+s)} + \sum_j \sum_{s=0}^{t} \gamma_{js} \Delta D_{ijt^*} + \epsilon^y_{i(t^*+s)} \tag{3.2}$$

$\Delta y_{i(t^*+s)}$, which is growth in y s periods after t^*, depends on α_i, a county fixed effect, $\tau_{(t^*+s)}$, a time fixed effect, and $\epsilon^y_{i(t^*+s)}$, a mean 0, iid shock. Large establishment entry from industry j at time t^* affects $\Delta y_{i(t^*+s)}$ through the coefficient γ_{js}. Thus, γ_{js} is thus the ATT of large establishment entry s years after entry, which we allow to vary by entering industry j. For some year of entry t^*, our model implies that:

$$\begin{aligned}
\gamma_{js} &= \mathbb{E}[\Delta y_{i(t^*+s)} | \Delta D_{ijt^*} = 1] - \mathbb{E}[\Delta y_{i(t^*-1)} | \Delta D_{ijt^*} = 1] - (\tau_{t^*+s} - \tau_{t^*-1}) \\
&= \mathbb{E}[\Delta y_{i(t^*+s)} | \Delta D_{ijt^*} = 1] - \mathbb{E}[\Delta y_{i(t^*-1)} | \Delta D_{ijt^*} = 1] \\
&- \big(\mathbb{E}[\Delta y_{i(t^*+s)} | \Delta D_{ijt^*+s} = 0 \; \forall j, s] - \mathbb{E}[\Delta y_{i(t^*-1)} | \Delta D_{ijt^*+s} = 0 \; \forall j, s]\big)
\end{aligned} \tag{3.3}$$

The first equality of Equation 3.3 exploits the fact that in our model, $\mathbb{E}[\Delta y_{it} | \Delta D_{ijt^*} = 0] = \mathbb{E}[\Delta y_{it'} | \Delta D_{ijt^*} = 0] - (\tau_{t'} - \tau_t)$ for any t, t'. The second equality exploits the assumption that ΔD_{ijt} is mean independent of the error term ϵ_{it}. Using Equation 3.3, for each t^*, the

entry by an industry j establishment in county i in some year t.

DID estimator for $\Delta\gamma_{js}$ is:

$$\frac{1}{I_j}\sum_{i=1}^{I_j}\left(\Delta y_{i(t^*+s)} - \Delta y_{i(t^*-1)}\right) - \frac{1}{K}\sum_{k=1}^{K}\left(\Delta y_{k(t^*+s)} - \Delta y_{k(t^*-1)}\right) \tag{3.4}$$

The first term in the above expression is the simple average of the difference between post-entry growth and pre-entry growth, across I_j counties with large establishment entry from industry j in t^*. The second term is the simple average of difference between growth in year t^*+s and year t^*-1, across K firms that did not experience large establishment entry in any industry for all s. We then estimate $\hat{\gamma_s}$ as the weighted mean of expression 3.4 across $t^* \in (1990, 2005)$, using as weights the proportion of large establishment entries in each year of our sample.

We report the results of this exercise in Table 3.2. Column 1 reports $\hat{\gamma_{j0}}$, the effect of large firm entry on employment (Panel A), wages (Panel B), and number of establishments (Panel C) in the year of entry. These results are consistent with those from Table 3.1. Averaged across, $\hat{\gamma_{j0}}$ is large, positive, and significant for employment and wages, and insignificant for number of establishments. For individual industries, there is quite a bit of heterogeneity in estimated $\hat{\gamma_{j0}}$. Again consistent with Table 3.1, wholesale trade, retails trade, and services establishments had the greatest positive impact on county employment and wages in the year of entry.

Our estimates for $\hat{\gamma_{j1}}$ in column 2 show that in the first five years post-entry, large firm entry has a negative effect on employment and wage growth. Broken down by industry of entering establishment, $\hat{\gamma_{j1}}$ is positive only for Transport/Utilities establishments. Among other industries, the negative effect on employment and wage growth is smallest in magnitude for manufacturing establishments, followed by services establishments.

We report $\hat{\gamma_{j6}}$, the effect of large establishment entry six to ten years after entry, in

column 3. We find that the negative effects on employment and wage growth persist and increase in magnitude.

Table 3.2: Difference-in-Difference Estimates

Industry	$\Delta\gamma_{j(t^*)}$	$\Delta\gamma_{j(t^*+1)}$	$\Delta\gamma_{j(t^*+6)}$
A: Employment			
Total	0.090	-0.019	-0.021
Agriculture	-0.025	-0.088	-0.097
Mining	0.060	-0.031	-0.022
Construction	0.088	-0.040	-0.042
Transport/Utilities	0.081	0.018	-0.012
Wholesale Trade	0.176	-0.047	-0.045
Retail Trade	0.106	-0.054	-0.051
Services	0.145	-0.023	-0.022
Manufacturing	0.058	-0.015	-0.017
B: Wages			
Total	0.101	-0.020	-0.032
Agriculture	-0.103	-0.108	-0.129
Mining	0.112	-0.070	-0.039
Construction	0.060	-0.053	-0.074
Transport/Utilities	0.118	0.054	0.008
Wholesale Trade	0.257	-0.077	-0.058
Retail Trade	0.121	-0.067	-0.066
Services	0.138	-0.020	-0.033
Manufacturing	0.073	-0.016	-0.029
C: Establishment Count			
Total	-0.009	-0.000	-0.004
Agriculture	0.024	0.059	-0.006
Mining	-0.053	0.002	-0.011
Construction	-0.049	-0.000	-0.013
Transport/Utilities	-0.012	0.007	-0.002
Wholesale Trade	-0.014	0.007	0.002
Retail Trade	0.018	-0.012	-0.006
Services	-0.010	-0.003	-0.005
Manufacturing	-0.002	0.000	-0.003

Notes: Difference-in-differences estimates of coefficient on dummy for large establishment entry on log employment, wages, and establishment number growth. First-differencing is applied to control for county effects and DID estimation controls for year effects on growth. Columns 2 and 3 show estimates of average annual growth in the first and second 5 year intervals after large establishment entry.

3.2.5 Discussion

There are three main results from our reduced form exercises. First, aside from positive immediate impacts in the year of entry, large establishment entry leads to declining wage and employment growth in the ten years after entry. Second, there is little evidence of a rise in the number of establishments either in the industry of the initial large establishments, or in other industries in the ten years after entry. Third, there is substantial industry heterogeneity in the effects of large establishment on county employment and wages in the ten years after entry. Services and manufacturing counties experience stronger wage and employment growth than other industries, while wholesale, retail, and agricultural counties see the largest negative wage and employment declines. We also note that the services sector is the only one to see evidence of same industry agglomeration in the ten years after large establishment entry.

However, our reduced form estimates are problematic to interpret for several reasons. Firstly, it is well known within the empirical literature on local labor demand that estimating γ_{js} as the ATT is inconsistent due to endogeneity of ΔD_{ijt}. Econometrically, $\mathbb{E}[\epsilon^{y}_{i(t+s)}|\Delta D_{ijt}] \neq 0$, for all $s \in \mathbb{N}$. That is, the error terms for our dependent variables are not mean independent of all past and current values of ΔD_{ijt}, and weak exogeneity does not hold.

Looking to economic theory, the literature gives us several explanations for why weak exogeneity may not hold. Topel [1986] presents a model where a inward migration caused by a positive local labor demand shock produces a concurrent positive labor supply shock that reduces current wages. Bartik [2014] presents a model where a positive labor demand shock has a larger effect on wages if unemployment is higher at the time of initial firm entry. In other words, the distribution of $\epsilon^{W}_{i(t)}$ and $\epsilon^{E}_{i(t)}$ are both dependent on ΔD_{ijt}, depending

on initial labor market conditions and contemporaneous labor supply responses to large establishment entry.

Further, large establishment entry may affect the evolution of wages and employment years after initial large establishment entry through agglomeration effects. As argued in Glaeser and Gottlieb [2009], agglomeration effects may derive from various sources,[6], but models of agglomeration economies generally predict that firms gain productivity benefits by either co-locating with firms of the same industry, or co-locating with firms of different industries, within the same locality. These models predict that wage and employment processes after initial large establishment entry are fundamentally different from those before large establishment entry, due to agglomeration catalyzed by large establishment entry.

Finally, Kline and Moretti [2014] find evidence of industry heterogeneity in agglomeration effects after initial labor demand shocks, where manufacturing towns experience more persistent agglomeration effects than agricultural towns.

To explain our reduced form results, we seek to identify the effects of local labor market conditions on agglomeration after initial large plant openings. This requires us to impose structure on our estimation[7] for two main reasons. Firstly, as argued in Glaeser and Gottlieb [2009], the effects of agglomeration are highly dependent on the assumed source of the network effects of agglomeration. We articulate the sources of agglomeration that we can accommodate by writing down a structural model. Secondly, we think of agglomeration as a general equilibrium effect, requiring the relocation of geographically disperse firms in response to large establishment entry in a county. Imposing structure to our estimation

[6]Examples include reduced transport costs for firms to access suppliers and customers, a denser labor market for workers of the appropriate skills, and faster growth in firm productivity from learning in high human capital cities.

[7]For example, Notowidigdo [2011] uses a structural approach to estimate the effects of worker mobility costs on local labor demand shocks, and Kline and Moretti [2014] impose structure to estimate the effects of subsidies by the Tennessee Valley Authority (TVA) on local labor markets. See Chauvin (17) and Donaldson and Hornbeck (12) for other examples of structural estimation of local labor market shocks.

based on general equilibrium predictions will help us identify agglomeration effects. In the next section, we construct a model with general equilibrium agglomeration effects of large establishment entry.

3.3 Model

To explain our reduced form results, this section presents a spatial equilibrium model based on the Rosen-Roback framework, with innovations that capture the selection of large establishments into counties, and the consequent effects on the local non-tradeable sector. In particular, the model features three mechanisms that affect county labor market outcomes as a result of large establishment entry; crowding out of local non-tradeable employment as a result of higher county wages, agglomeration of local non-tradeable firms due to higher market demand for non-tradeable consumption, as well as agglomeration of firms from the same industry to exploit productivity benefits from colocation.

We model entry of large establishments into counties in discrete time. Large establishments differ by industries, which experience heterogeneous industry agglomeration effects. Counties are heterogeneous in non-tradeable labor demand and labor supply response to large establishment entry, and in unobserved profits for large establishments upon entry.

Each county, indexed by i, has an output market for non-tradeable goods, a labor market, and a housing market. Each county has a pool of (for now homogeneous) potential workers, indexed by n, each of whom may supply 1 unit of labor if they choose to locate in i.[8] Each worker n has the following utility function:

[8]We can extend our model to include more than one type of labor.

$$\begin{aligned} U_{int} &= u(\alpha_i, W_{it} - R_{it}, \epsilon_{in}) \\ &= \theta(\alpha_i, W_{it} - R_{it}) + \epsilon_{in} \end{aligned} \tag{3.5}$$

In the above, α_i is a vector of time-constant county specific variables, which we will call amenities. W_{it} and R_{it} are county i wages and housing rent in period t, and ϵ_{in} is a scalar representing worker n's idiosyncratic preferences for working in county i. To make the analysis tractable, we specify that idiosyncratic preferences ϵ_{in} are linearly additive in workers' utility function, and that $\theta(\cdot, \cdot)$ is increasing in both arguments. We additionally assume that α_i and $W_{it} - R_{it}$ are q-complements in the function $\theta(\cdot, \cdot)$. That is, higher amenities increases the marginal utility of non-rent wage income, and vice versa.

Similar to Moretti (10), we assume that ϵ_{in} follows a uniform distribution, $Unif(-s^w, s^w)$, where $s^w > 0$ represents a worker mobility parameter.

Worker n will locate in i if $U_{int} > \bar{\theta}_t$, where $\bar{\theta}_t$ is θ averaged across all counties in period t. Labor supply in it can then be described by:

$$\begin{aligned} L_{it}^S &= P(\epsilon_{it} > \bar{\theta}_t - \theta_{it}) \\ &= \frac{s^w - \bar{\theta}_t + \theta_{it}}{2s^w} \end{aligned} \tag{3.6}$$

We denote by θ_x the partial derivative of the function θ with respect to the $x-$th argument. θ_1 is then the partial derivative of θ with respect to α_i, and so on. Since we have assumed that $\theta_2 > 0$, conditional on R_{it}, the labor supply curve is upward sloping in W_{it}.[9]

[9]We will show that this is true in our model whether we treat R_{it} as an endogenous or exogenous object.

Further, θ_2, the slope of the labor supply curve, depends on the parameters α_i and s^w. Specifically, since α_i and $W_{it} - R_{it}$ are q-complements, the slope of the labor supply curve is increasing in α_i. We interpret s^w as an exogenous labor mobility parameter, where small values of s^w imply that many workers are wiling to move due to small changes in θ_{it}.

Establishments located in i may either be in the non-tradeable or tradeable sector. Non-tradeable establishments, indexed by m, are assumed to be atomistic, and they employ one unit of labor to produce non-tradeable output that can only be consumed by workers located in i. Tradeable establishments produce output in some industry $j \in \mathcal{J}$, to service external demand.[10] Non-tradeable establishment m operates in county i if there are positive profits to be made. Profits made by non-tradeable sector firms are denoted by Π^{ν}_{imt}, where ν denotes non-tradeable output. The profit function for small establishment m:

$$\Pi^{\nu}_{imt} = Y^{\nu}_{it} - W_{it} + u_{im} \tag{3.7}$$

Y^{ν}_{it} is the average revenue for all non-tradeable establishments in it, while u_{im} is a mean 0, iid random variable that represents a firm-specific profit factor. We assume that u_{im} follows a uniform distribution $Unif(-s^f, s^f)$, we have the following labor demand function for the non-tradeable sector:

$$L^{\nu}_{it} = \frac{s^f + Y^{\nu}_{it} - W_{it}}{2s^f} \tag{3.8}$$

Conditional on Y^{ν}_{it}, this equation gives us a downward sloping demand for labor in the non-tradeable sector.

Y^{ν}_{it}, the average revenue of non-tradeable establishments, is an endogenous variable in our model. We assume that a fraction of non-rent wage income by workers in i goes towards

[10] We can relax the assumption that tradeable establishments do not service local demand.

consuming non-tradeable output. Assuming that workers are homogeneous consumers, consumption of non-tradeable output per worker in i is $c(W_{it} - R_{it})$, where we assume that $c_1 > 0$. Applying market clearing in the non-tradeable goods market in i so that aggregate production equals aggregate consumption, we have that $f(L^{\nu}_{it}) = c(W_{it} - R_{it})L_{it}$. We can then express the productivity (equivalently, revenue) of each non-tradeable firm as:

$$Y^{\nu}_{it} = c(W_{it} - R_{it})\frac{L_{it}}{L^{\nu}_{it}} \tag{3.9}$$

Equation 3.9 shows that profits for non-tradeable establishments in i depend on non-rent income of workers in the county, as well as the share of non-tradeable employment in total employment. This implies productivity in the non-tradeable sector rises as market demand for non-tradeable consumption rises, which rises in average age incomes and the fraction of employment in the tradeable sector. This is the basis for the first channel of agglomeration economies in our model - agglomeration in the non-tradeable sector.

Let N_{ijt} be the number of large establishments from industry j in county i in period t, where j specifies a specific tradeable output produced by industry j. Labor demand for tradeable sector in i, using superscript τ, can be described as

$$L^{\tau}_{it} = \sum_{j=1}^{J} N_{ijt}\bar{L}_j \tag{3.10}$$

$\bar{L}_j$ is the exogenously determined constant labor required by a large establishment in industry j to operate. Total labor demand in it is the sum of labor demand from the tradeable and non-tradeable sectors.

$$L^{D}_{it} = L^{\nu}_{it} + L^{\tau}_{it} \tag{3.11}$$

3.3.1 Large Establishment Entry

In each period t, the economy experiences the opening of a new industry j large establishment with positive probability. This is an unexpected shock in our model. Conditional on new opening, the large establishment optimally decides on a county to locate in. The profit function for industry j that enters county i is:

$$\Pi_{ijt} = Y_{ijt} - W_{it}\bar{L}_j + \mu_{ij} \tag{3.12}$$

In the above, Y_{ijt} is period t revenue for industry j in i. μ_{ij} is the time-constant county i specific profit factor for j. Conditional on establishment opening, industry j chooses to enter the county that maximizes its profit function.

The productivity of a j large establishment in i, Y_{ijt}, depends on N_{ijt}, the number of j large establishments in i. This can be represented by the following function for the productivity of a industry j large establishment in i.

$$\begin{aligned} Y_{ijt} &= y_j(N_{ijt}) \\ &= \bar{Y}_j + \gamma_j(N_{ijt}) \end{aligned} \tag{3.13}$$

We assume that $\forall j$, $\gamma_j(N_{ijt}) = 0$ for $N_{ijt} = 0$, $\gamma_j' \geq 0$, and crucially, that $\gamma_j'' \geq 0$. The third assumption, that the second derivative of $\gamma_j(\cdot)$ is weakly positive reflects the network effects of having similar plants colocating in the same county.[11] Intuitively, the revenue function $y_j(N_{ijt})$ is increasing in N_{ijt}, the number of same industry establishments in county i. This assumption represents productivity spillovers that derive from co-locating in a county with

[11] This simply reflects that plant productivity experiences increasing returns to scale in N_{ijt}, which is a standard assumption for network effects.

similar firms. [12] That is to say, large establishments can benefit from productivity spillovers from the presence of other large establishments in the same sector. This is the basis of same-industry agglomeration effects in out model.

Formally, the indicator variable $D_{i'jt}$ for large establishment entry into some county i' is:

$$D_{i'jt} = \begin{cases} 1 & \text{if } i' \in \arg\max i\Pi_{ijt} \text{ and if } \Pi_{i'jt} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.14}$$

At the end of each period, existing large establishments decide whether to stay in their county or relocate to a new county, in order to maximize their profits, as expressed in Equation 3.12.

3.3.2 Housing Market

Denoting the units of housing in it by H_{it}, we assume that housing supply is determined by:

$$R_{it} = k_i^H H_{it} \tag{3.15}$$

The rent elasticity of housing supply is simply determined by the exogenous parameter k_i^H, which varies across counties.

Following Moretti (10), we assume that one unit of housing serves one unit of labor. Housing demand in this model is thus characterized by manipulating the labor supply equation, 3.6, and imposing $H_{it} = L_{it}$. We can easily show that conditional on W_{it}, the housing demand curve is downward sloping.

[12] The assumption here is that entering large establishments only receive productivity spillovers from other large establishments from the same industry.

3.4 Equilibrium

County labor markets operate in a "small open economy" setting in this model. That is, changes in labor employment in one county do not affect average labor market outcomes in the national economy. This is similar to spatial equilibrium models in Edward L. Glaeser and Saiz [2001] and Notowidigdo [2011].[13] This assumption is reasonable as we are largely studying counties with small populations relative to the national economy. This allows us to study the effects of a county labor demand shock in isolation from the rest of the economy.

The part of our model that truly involves general equilibrium movements is the reallocation of large establishments across counties. If there is a large establishment entry shock in one county, existing large establishments from other counties may move to colocate with establishments of the same industry.

Our structural model can be written as a set of simultaneous equations in reduced form:

$$
\begin{aligned}
L_{it}^{D} &= l^{d}\left(W_{it}, R_{it}, L_{it}^{\tau} \; ; \; \mathbf{N}_{it}, s^{f}\right) \\
L_{it}^{S} &= l^{s}\left(\alpha_{i}, W_{it}, R_{it} \; ; \; u_{it}, s^{w}\right) \\
N_{ijt} &= n(\{N_{ijt}\}_{i\in\mathcal{I}}, \{W_{it}\}_{i\in\mathcal{I}} \; ; \; \{D_{ijt}\}, \{\mu_{ij}\}) \\
R_{it} &= r(L_{it} \; ; \; k_{i}^{H})
\end{aligned}
$$

In the above, $\mathbf{N}_{it} = \{N_{i1t}, ..., N_{iJt}\}$, the vector of N_{ijt} across j within i. Each county i is subject to labor demand shocks in the form of changes to $\mathbf{N}_{it}$ and labor supply shocks u_{it}. Although counties take N_{ijt} as exogenous, large establishments from each j endogenously allocate themselves across counties. In each period, equilibrium in this economy is defined

[13] In this class of models, the marginal worker in i has to be indifferent between staying in i and moving to another city.

as:

$$(\mathbf{W}_t, \mathbf{R}_t, \mathbf{L}_t, \mathbf{N}_{it})$$

Such that for all it, labor markets clear - $L_{it}^S = L_{it}^D = L_{it}$ and housing markets clear $H_{it} = L_{it}$. Across all counties, $\{N_{ijt}\}_{i \in \mathcal{I}}$ is a Nash Equilibrium for each j. We now characterize equilibrium $\mathbf{N}_{it}$ across the economy.

When hit by a labor demand shock D_{ijt} or labor supply shock u_{it}, evolution to a new equilibrium depends on standard supply and demand, and also agglomeration effects. Our model contains two types of agglomeration effects. First, non-tradeable establishments gain productivity benefits from rising aggregate non-rental wage incomes of local workers. We call these *non-tradeable agglomeration effects*. Secondly, establishments industry j derive productivity spillovers from entering counties with existing large establishments of the same industry. We call these *industry agglomeration effects*. We examine the equilibrium effects of each in turn.

3.4.1 Non-Tradeable Agglomeration

We analyze the equilibrium response in county i to a labor demand shock in the form of $D_{ijt} = 1$, in the non-tradeable sector. The immediate impact of $D_{ijt} = 1$ is to increase N_{ijt} by one.

We can express the total derivative of non-tradeable labor employment with respect to large establishment entry as:

$$\frac{dL_{it}^{\nu}}{dN_{ijt}} = \underbrace{\frac{\partial L_{it}^{\nu}}{\partial L_{it}^{\tau}} \frac{dL_{it}^{\tau}}{dN_{ijt}}}_{\text{Non-Tradeable Agglom.}} + \underbrace{\frac{\partial L_{it}^{\nu}}{\partial W_{it}} \frac{dW_{it}}{dN_{ijt}}}_{\text{Crowding Out}} \tag{3.16}$$

Equation 3.16 shows the key conceptual decomposition of the effects of large establishment entry in out model.

We have labeled $\frac{\partial L_{it}^{\nu}}{\partial L_{it}^{\tau}} \frac{dL_{it}^{\tau}}{dN_{ijt}}$ as the non-tradeable agglomeration effect. Referring to Equations 3.8 and 3.9, we see that $\frac{\partial L_{it}^{\nu}}{\partial L_{it}^{\tau}}$ captures the effect of rising employment of labor in the tradeable sector on Y_{it}^{ν}, the productivity of non-tradeable firms. This channel works through the rise in market demand for non-tradeable consumption. From Equation 3.9, since Y_{it}^{ν} rises inL_{it}^{τ}, entry by industry j large establishment raises L_{it}^{τ} by $\bar{L}_j$, which shifts the non-tradeable labor demand curve up.

The second term on the RHS of Equation 3.16 is labeled the Crowding Out Effect. The first object in this term, $\frac{\partial L_{it}^{\nu}}{\partial W_{it}}$, is straightforward to interpret as the price effect on non-tradeable labor demand, which gives us our downward sloping L_{it}^{ν} curve in W_{it}. The second object, $\frac{dW_{it}}{dN_{ijt}}$ is more complicated. This represents the *equilibrium* response of wages to large establishment entry from industry j. Formally, the wage response function can be expressed as:

$$\frac{dW_{it}}{dN_{ijt}} = \left[\frac{\partial L_{it}^{S}}{\partial W_{it}} - \frac{\partial L_{it}^{\nu}}{\partial W_{it}}\right]^{-1} \left[\bar{L}_j + \frac{\partial Y_{it}^{\nu}}{\partial L_{it}^{\tau}} \frac{dL_{it}^{\tau}}{dN_{ijt}}\right] \tag{3.17}$$

Equation 3.17 is derived from the equilibrium conditions in the labor market, from Equations 3.6, 3.8, 3.11, and imposing market clearing $L_{it}^{S} = L_{it}^{D}$. The standard elements of Equation 3.17 are that the wage response to a labor demand shock depend on the size of the shock, $\bar{L}_j$, and the responsiveness of labor supply and nontradeable labor demand to wage changes, $\frac{\partial L_{it}^{S}}{\partial W_{it}}$ and $\frac{\partial L_{it}^{\nu}}{\partial W_{it}}$ respectively.

The novel part of our wage response function is that the wage response also takes into account non-tradeable agglomeration, represented by the additional term $\frac{\partial Y_{it}^{\nu}}{\partial L_{it}^{\tau}} \frac{dL_{it}^{\tau}}{dN_{ijt}}$. As explained above, this term is positive. Therefore, the non-tradeable agglomeration effect am-

plifies the wage response of large establishment entry. From Equation 3.16, we can get some intuition on how county characteristics affect the size of crowding out effects. First, crowding out effects are larger in counties with large $|\frac{\partial L^{\nu}_{it}}{\partial W_{it}}|$ and/or large$\frac{dW_{it}}{dN_{ijt}}$. We supply a following result that summarizes how crowding out effects vary with amenities α_i, housing market tightness k_i^h, and initial employment L_{it}.

Proposition 7. *Crowding out effects from large establishment entry are higher for counties where:*

1. α_i *is low*
2. k_i^H *is high*
3. L_{it} *is low*

Proof. See Appendix. □

The intuitions behind Proposition 7 is simple. Wage responses from large establishment entry are large in counties that have a steep labor supply curve and a steep non-tradeable labor demand curve. Counties with low amenities α_i have steep labor supply curves as wages have to change a large amount to attract inward migration. High k_i^h counties have steep labor supply curves as wages have to rise by a large amount to compensate for the large rent increases caused by inward migration of workers.

Further, wage responses are large in counties that have large non-tradeable agglomeration effects. Counties with low initial employment L_{it} have high non-tradeable agglomeration effects as an influx of tradeable sector labor causes a large increase in demand relative to supply of non-tradeable output in i, which leads to large non-tradeable agglomeration effects.

We illustrate the impact of a single large establishment entry in a numerical example, depicted in Figure 3.4.

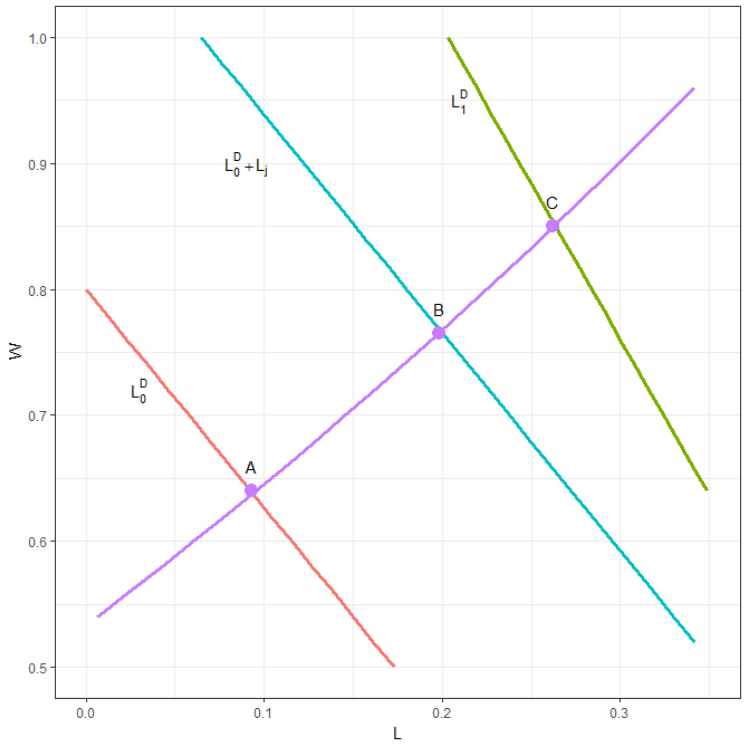


Figure 3.4: Non-Tradeable Agglomeration

At time 0, assume that $N_{ijt} = 0$ in county i. Let L_0^D represent the labor demand curve in this initial period. Assume that $D_{ij1} = 1$. The total effect of this is to move labor market equilibrium from point A to point C in Figure 3.4. This movement can be decomposed into a direct effect of the labor demand shock, which results in the demand curve shifting to $L_0^D + \bar{L}_j$, and a non-tradeable demand agglomeration effect, which moves county labor demand from $L_0^D + \bar{L}_j$ to L_1^D. The direct effect of the labor demand shock moves equilibrium form point A to point B, while the non-tradeable agglomeration effect moves equilibrium from point B to point C.

3.4.2 Industry Agglomeration

In general equilibrium, the entry of a large establishment of industry j into some county i may lead to further entry of industry j establishments. Why might this happen? Equation 3.13 implies that there are productivity benefits to colocating with firms from the same industry, as each firm's productivity rises in the number of industry j establishments N_{ijt}. We characterize industry agglomeration in our model by imposing a Nash Equilibrium assumption.

We assume that at the end of period $t-1$, $\{N_{ij(t-1)}\}_{i\in\mathcal{I}}$ is a pure strategy Nash Equilibrium for each j. That is, no j large establishment can increase profits by unilaterally relocating to some other county. In addition, we assume that all existing establishments are earning positive profits.

In period t, assume $D_{ijt} = 1$ for some i', determined by Equation 3.14.This represents an exogenous shock to the economy, which may disrupt last period's Nash Equilibrium. In particular, if after the realization of the shock, $\Pi_{i'jt}(N_{ijt}+1) > \Pi_{ijt}(N_{ij(t-1)})$, the best response for a j firm in $i' \neq i$ is to relocate to i, and the economy will move into a new Nash Equilibrium. In particular, a new Nash Equilibrium is reached when having one more j firm move from i to i' results in a reduction in its profits. (In this case, the marginal firm can unilaterally increase profits by choosing not to move.) We do not impose restrictions on how to choose among Nash Equilibria.

County Capacity for Large Establishments

Our model implies that there is a maximum number of large establishments from j in time t, $N_{ijt}^{max} \in \mathbb{N}$, such that in equilibrium, $N_{ijst} \leq N_{ijt}^{max}$. N_{ijt}^{max} is the solution to the problem

$$\arg\max NN$$

$$\text{such that } \Pi_{ijt}(N) \geq 0$$

That is, the capacity for large establishments in county i is the maximum number of establishments such that each establishment earns positive profits. We provide a numerical example of this problem in Figure 3.5.

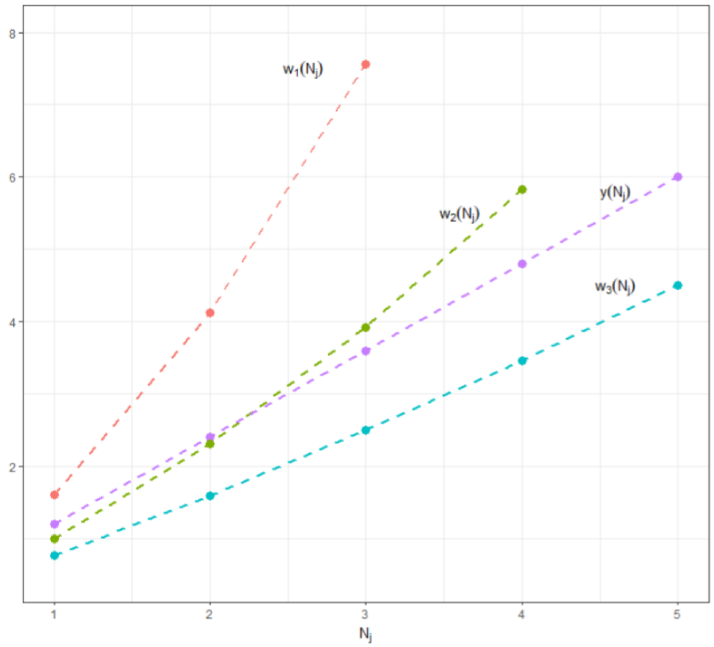


Figure 3.5: Industry Agglomeration

In Figure 3.5, we assume without loss of generality that $\mu_{ij} = 0$ for county i and industry j. Network effects for j large establishments are reflected by rising $y_j(N_{ijt})$ in N_{ijt}. The function $y_j(N_{ijt})$ is identical across counties.

$w\left(\{N_{ijt}\}\ ;\ \frac{\partial L_{it}^S}{\partial W_{it}} - \frac{\partial L_{it}^\nu}{\partial W_{it}}, L_i^0, u_{it}\right)$ is the equilibrium wage function that depends on en-

dogenous variables - notably $\{N_{ijt}\}$ the equilibrium number of large establishments, and exogenous county-specific characteristic - $\frac{\partial L_{it}^S}{\partial W_{it}}$, the wage responsiveness of labor supply, $\frac{\partial L_{it}^\nu}{\partial W_{it}}$, the wage responsiveness of non-tradeable labor demand, L_i^0, defined as equilibrium labor employment when $N_{ijt} = 0$ for all j, and labor supply shocks u_{it}. Figure 3.5 shows three parametrizations of $w\left(\{N_{ijt}\}\ ;\ \frac{\partial L_{it}^S}{\partial W_{it}} - \frac{\partial L_{it}^\nu}{\partial W_{it}}, L_i^0, u_{it}\right)$ by varying only two parameters, $\frac{\partial L_{it}^S}{\partial W_{it}} - \frac{\partial L_{it}^\nu}{\partial W_{it}}$ and L_i^0. These demonstrate three special cases of county capacities.

Case 1 demonstrates the wage function for a county with low $\frac{\partial L_{it}^S}{\partial W_{it}}$ and low L_i^0. In Figure 3.5 shows, this is depicted by the function $w_1(\cdot)$. Clearly, N_{ijt}^{max} for this county is zero, as large establishments will never be profitable. Case 2 demonstrates the wage function for a county with low $\frac{\partial L_{it}^S}{\partial W_{it}}$ and high L_i^0, depicted by the function $w_2(\cdot)$. In this case, where $N_{ijt}^{max} = 2$. Further large establishment entry beyond $N_{ijt}^{max} = 2$ is unprofitable. Case 3 demonstrates the case of high $\frac{\partial L_{it}^S}{\partial W_{it}}$ and high L_i^0, depicted in the function $w_3(\cdot)$. Here, N_{ijt}^{max} is much larger than in Case 2, and the county can accommodate many large establishments.

The Formation and Persistence of one-firm towns

An entering establishment creates a one-firm town if for some county i, profits from being the first establishment in the county are greater than the profits from entering all other multi-firm towns.

$$\Pi_{ijt}(1) > \Pi_{i'jt}(N_{i'jt} + 1) \tag{3.18}$$

for all counties $i' \neq i$.

Following the entry of a j establishment into i in period t, existing establishments move into i if there relocating to i will reap higher profits. This describes industry in i, precipitated by the entry of a single large establishment. If this happens, county i ceases to be a one-firm

town. On the other hand, nothing in our model prevents counties from persisting as one-firm towns. Our model offers a sharp characterization of counties that persist as one-firm towns.

Proposition 8. *Assume that a j large establishment enters i in period t, so that $N_{ijt} = 1$. Then no relocation of existing j establishments to i will occur if:*

$$\frac{\Delta W_{it}}{\Delta N_{ijt}}_{|D_{ijt}=1} > \frac{\Delta y_j(N_{ijt})}{\Delta N_{ijt}}_{|D_{ijt}=1}$$

Proof. Assume the stated condition. Then, for all j,

$$\Pi_{ijt}(N_{ijt} + 1) < \Pi_{ijt}(N_{ijt})$$

For j', the industry of establishment entry, this means that

$$\Pi_{ij't}(2) < \Pi_{ij't}(1)$$

At the end of period $t-1$, since $\mathbf{N}_{ij(t-1)}$ is a Nash equilibrium, we must have that for all i' such that $\{N_{i'jt}\} \neq \mathbf{0}$,

$$\Pi_{ijt}(1) < \Pi_{i'jt}(N_{i'jt}) \ \ \forall j$$

Thus, $\Pi_{ij't}(2) < \Pi_{i'j't}(N_{i'jt})$, implying that $N_{ij't} = 2$ cannot be part of a Nash Equilibrium and agglomeration of j' firms in i will not occur through relocation of existing firms

For other industries $j \neq j'$, since $\Pi_{ijt}(1) < \Pi_{ij(t-1)}(1)$, no relocation will occur. □

Proposition 8 says that a sufficient condition for counties to persist as one-firm towns is that the change in wages from further increases in N_{ijt} exceeds the rise in network effects for j. Intuitively, even if county i has the capacity for more large establishments, that is, $N_{ijt}^{max} > 1$, the wage structure in i can prevent agglomeration from occurring.

Combining the insights from Proposition 8 and 7, we can further conclude that low α_i, high k_i^H, and low L_{it} counties that experience entry of a large establishment are likely to persist as one-firm towns, and not see much industry agglomeration.

3.5 Identification

We use our model to identify and estimate the ATT of large establishment entry on wages and employment. In contrast with the empirical literature that uses reduced form DID and IV methods to estimate the ATT, we are able to break down the ATT into components that reflect underlying mechanisms driving labor market changes after large establishment entry.[14] We first give an intuitive sketch of our identification strategy.

To identify non-tradeable agglomeration effects, we estimate the responsiveness of employment in the non-tradeable sector to county wages and employment, controlling for county fixed effects. This enables us to construct a counterfactual non-tradeable agglomeration effect, which boosts labor demand on top of that provided by large establishment entry.

To identify crowding out effects, we estimate county-specific wage responsiveness to labor demand or labor supply shocks. In our framework, the magnitude of the equilibrium wage response is equal whether the county is hit with a labor demand or a labor supply shocks.[15] Knowing this, we assume that there is no pure labor demand shock in the five year interval before labor establishment entry, which is equivalent to assuming that wage and employment changes in this period are due to labor supply shocks, and the accompanying non-tradeable agglomeration effects. We thus identify county-specific wage response functions in the pre-

[14]For an exposition on why DID and IV methods are difficult to implement in our context, see Appendix C.1.

[15]To see this, note that the wage response to a labor supply shock is the negative of the RHS of Equation 3.17.

entry five year interval. Since the magnitude of wage responses are the same for labor demand and labor supply shocks, we can then construct a counterfactual for wage response to the labor demand shock of large establishment entry. The crowding out effect is then the negative impact on non-tradeable employment from the wage increase caused by large establishment entry.

To identify industry agglomeration effects, we use our result from Proposition 8, which says that industry agglomeration can occur only if the increase in wages from additional large establishment entry is smaller than the productivity increases from further entry by establishments of the same industry. Constructing counterfactual wage responses from large establishment entry, we can simulate industry agglomeration for various parameters of same-industry agglomeration effects.

We now give a detailed description of the specific features of the data we will use for identifying our model's functions.

3.5.1 Data

We use our sample of counties where large establishment entry is observed in some year $t^* \in (1990 - 2005)$. For these counties, we observe average wages (W_{it}), total employment (L_{it}), non-tradeable sector employment (L^{ν}_{it}), for all years t in the interval $t \in [t^* - 5, t^* + 10]$, from the CBP dataset. For other county-specific characteristics, we observe amenities scores from the Department of Agriculture's Natural Amenities Scale (NAS) index, and rural scores from the Department of Agriculture's 1993 Rural-Urban Continuum (RUC93) index. We also observe county rents as the median county housing rent (R_{it}). from the Census and American Community Survey.

We also observe D_{ijt} from the CBP, which refers to the county, industry and year of large

establishment entry, as well as the number of large establishments from each industry at the annual frequency, N_{ijt}.

3.5.2 Static Model

In the static model we have presented so far, a local labor demand shock moves our economy to equilibrium in the same period. On the other hand, our county-level data is at the annual frequency. In reality, the non-tradeable and industry agglomeration effects do not happen instantaneously, as there are adjustment costs for opening and relocation of establishments. It would probably take several years for a county to move to the new static equilibrium after the shock of a large establishment entry. To harmonize our model's predictions with our data, we take the five year growth path after large establishment entry as one period in our static model, and abstract from making additional assumptions about the dynamics of agglomeration.

For all counties in our sample, we observe the growth path in the five year pre-entry period, and the five-year post entry period for county wages, employment, and industry mix of establishments.

We define the pre-entry five year interval as period 0, the first post-entry five year interval as period 1, and the second post-entry five year interval as period 2.

3.5.3 Identifying Non-Tradeable Agglomeration Effects

We use Equations 3.8 and 3.9 to express local non-tradeable sector labor demand as determined by the function:

$$L_{it}^{\nu} = l^{\nu}(s^{f}, L_{it}, W_{it}, k_{i}^{H}) \text{ for } t \in \{0, 1, 2\} \tag{3.19}$$

The above equation implies that L_{it}^{ν} is a function of total employment, the average wage, and time-constant county characteristics. The l^{ν} function takes observables L_{it} and W_{it} as arguments, in addition to k_i^H and s^f. s^f is the parameter that represents a non-tradeable firm barriers to entry parameter that is assumed to be common across all counties. Dependence on s^f is thus identified as variation in L_{it}^{ν} common across counties. Recall that k_i^H is the responsiveness of housing supply to rent. Using OLS in a within-county regression across time of average rent on total employment, k_i^H is identified as the coefficient on total employment.

Equations 3.8 and 3.9 implies non-linear dependence on the three observed arguments L_{it}, W_{it} and k_i^H. For example, the effect of W_{it} on L_{it}^{ν} comprises of the price effect of higher wages on firms, in addition to the income effect of higher county wages on L_{it}^{ν}. To non-parametrically identify the function l^{ν}, we assume that the price effect dominates the income effect, and so l^{ν} is monotonically decreasing in W_{it}. We can show that the function is monotonic in other arguments, and so l^{ν} is non-parametrically identified. If the function l^{ν} is identified, we can then identify the partial derivative $\frac{\partial L_{it}^{\nu}}{\partial L_{it}}$ for every point in the domain.

$\frac{\partial L_{it}^{\nu}}{\partial L_{it}}$ represents the non-tradeable agglomeration effect in our model. Conditional on observables, this object represents the share of additional employment that is accounted for by a rise in labor demand from the non-tradeable sector.

3.5.4 Identifying Wage Responsiveness

We wish to identify the wage response function to a labor demand or labor supply shock. To do this, we exploit wage variation in each county in the pre-entry period 0. To estimate our wage response functions using pre-entry data, we first assume that shocks in the pre-entry period are due to labor supply shocks and the accompanying non-tradeable agglomeration shocks.

Using Equation 3.17, we can show that the wage response to a labor supply shock in county i in period 0 can be expressed as the following. decompose the total wage response to dL_{it} in each period into two components: the wage responsiveness and the size of the change in total employment. In the pre-entry period 0, where $N_{ij0} = 0 \forall j$, the wage response function is:

$$\frac{dW_{i0}}{du_{i0}} = \rho\left(\alpha_i, k_i^H, s_i^f, s_i^w, L_{i0}, W_{i0}, \frac{L_{i0}}{L_{i0}^\nu}\right)\left[-1 + \frac{dL_{i0}^\nu}{du_{i0}}\right] \tag{3.20}$$

Note that the expression in Equation 3.20 response is analogous to Equation 3.17, the expression for the wage response to a labor demand shock. As such, the function

$$\rho\left(\alpha_i, k_i^H, s_i^f, s_i^w, L_{i0}, W_{i0}, \frac{L_{i0}}{L_{i0}^\nu}\right) = \left[\frac{\partial L_{i0}^S}{\partial W_{i0}} - \frac{\partial L_{i0}^\nu}{\partial W_{i0}}\right]^{-1}$$

, and represents the wage responsiveness of county i in period 0. On the other hand, $du_{i0}\left[-1 + \frac{dL_{i0}^\nu}{u_{i0}}\right]$ is the sum of the labor supply shock u_{i0} and the accompanying non-tradeable agglomeration effect $\frac{\partial L_{i0}^\nu}{\partial W_{i0}}$. We wish to identify the function ρ, in order to estimate the wage response to a labor demand shock after large establishment entry.

The main challenge in identifying the function ρ is identifying the size of the pure labor supply shock du_{i0}. The result of the following Proposition shows that we can identify the size of the labor supply shock using the change in non-tradeable sector employment in period 0, combined with our estimates of the function l^ν, which we proved identification for in the above section.

Proposition 9. *We define* $\Delta l_{i0}^\nu = l^\nu\left(s^f, L_{i0}, W_{i-1}, k_i^H\right) - l^\nu\left(s^f, L_{i-1}, W_{i-1}, k_i^H\right)$. *Then, we have the following expression for the combined labor supply shock and non-tradeable agglom-*

eration effect in period 0.

$$-du_{i0} + dL^{\nu}_{i0} = \Delta l^{\nu}_{i0}\left(2 - 1/\frac{\partial L^{\nu}_{i0}}{\partial L_{i0}}\right) \tag{3.21}$$

The above Proposition implies that the growth in employment in period 0, along with $\frac{\partial L^{\nu}_{i0}}{\partial L_{i0}}$, identified from the function l^{ν}, allows us to identify the labor supply shock and accompanying non-tradeable agglomeration shock in period 0. Intuitively, a labor supply shock changes employment in i, which leads to non-tradeable agglomeration effects and a shift in the non-tradeable labor demand curve. Overall, the labor supply shock is accompanied in equilibrium by a positive shock to non-tradeable labor demand, due to higher employment caused by the labor supply shock, which is the non-tradeable demand agglomeration effect in our model, as seen in Figure 3.4. The size of the positive non-tradeable agglomeration shock (rightward shift of non-tradeable labor demand curve) is identified as Δl^{ν}_{i0} - since L_{i0} is a shifter of the non-tradeable labor demand curve, we find the size of the shock by keeping wages constant at W_{i-1} and shifting employment from L_{i-1} to L_{i0}. Since the non-tradeable labor demand agglomeration shock is a fraction $\frac{\partial L^{\nu}_{i0}}{\partial L_{i0}}$ of the combined labor supply and the non-tradeable agglomeration shock $du_{i0} + dL^{\nu}_{i0}$, we can derive the size of the labor supply shock, having estimated $\frac{\partial L^{\nu}_{i0}}{\partial L_{i0}}$. This argument lies behind Proposition 9.

An implication of Proposition 9 is that a positive labor supply shock can lead to positive growth in both wages and employment, once we take non-tradeable agglomeration effects into account. Intuitively, the positive effects on local labor demand brought about by a positive exogenous labor supply shock can lead to positive wage growth.

Using Proposition 9 and estimates for the function l^{ν}, we identify $du_{i0}\left[-1 + \frac{dL^{\nu}_{i0}}{du_{i0}}\right]$. Since we also observe dW_{i0}, wage growth in i in period 0, we have shown that the function ρ is identified by using Equation 3.20.

3.5.5 Non-tradeable Agglomeration versus Crowding Out Effects

We rely on Equation 3.16 to decompose the effect of large establishment entry into county i in period 1 on non-tradeable sector employment into non-tradeable agglomeration versus crowding out effects.

$$\frac{dL^{\nu}_{it}}{dN_{ijt}} = \underbrace{\frac{\partial l^{\nu}_{it}}{\partial L^{\tau}_{it}} \frac{dL^{\tau}_{it}}{dN_{ijt}}}_{\text{Non-Tradeable Agglom.}} + \underbrace{\frac{\partial l^{\nu}_{it}}{\partial W_{it}} \frac{dW_{it}}{dN_{ijt\,|D_{ij1}=1}}}_{\text{Crowding Out}}$$

Using Equation 3.17 and the function ρ, which we have identified, we can identify $\frac{dW_{it}}{dN_{ijt}|D_{ij1}=1}$. We have also identified the function l^{ν}. We also know that $\frac{dL^{\tau}_{it}}{dN_{ijt}} = \bar{L}_j$, where we observe $\bar{L}_j$. Thus, all the terms in the above decomposition are identified.

Intuitively, the size of the non-tradeable agglomeration effect corresponds to the positive shock to non-tradeable labor demand, due to the rise in labor demand in industry j. On the other hand, the size of the crowding out effect is the effect on non-tradeable labor demand of a rise in wages.

3.5.6 Identifying Industry Agglomeration

Following the same argument set out above, we can identify the wage response to additional entry from large establishments, and thereby recursively construct the function $w\left(\{N_{ijt}\}\ ;\ \frac{\partial L^{S}_{it}}{\partial W_{it}}, L^{0}_{i}, u_{it}\right)$. We use Proposition 8 to help us identify the industry agglomeration.

3.6 First Stage Estimation

Our estimation strategy relies on estimating general functions for non-tradeable labor demand and wage responsiveness, that each depend on county characteristics (amenities and housing supply elasticity), initial labor market conditions (initial employment, composition of industries), and industry of entering establishment. Estimating these functions then allows to construct counterfactual non-tradeable agglomeration, crowding out, and industry agglomeration effects. These effects underlie each county's total wage and employment responses to large establishment entry. In this, way, we are able to estimate the ATT of large establishment entry, and attribute our estimates to the differing strengths of agglomeration versus crowding out effects at the county and industry levels.

3.6.1 Estimating k_i^H

For each county i in our sample, we estimate housing supply responsiveness k_i^H as the OLS coefficient of the regression on the time series for average housing rent in i, R_{it} on the time series for total employment in i, L_{it}, as implied by Equation 3.15. For data on rent, we use the 1990 Census, 2000 census, and the 5 year American Community Survey databases, which provides annual median housing rent at the county level. We control for rent inflation by using the housing rental index published by the BEA which measures average housing rents across the US.[16] County employment data is from the CBP as usual.

In Figure 3.6, we plot a histogram of k_i^H estimates. The mean is 0.0303, and the standard deviation is 0.614, with the distribution being slightly right-skewed. Our sample of counties thus tends to have a higher than national average rent responsiveness to employment, in addition to having lower than average natural amenities scores, and tending to be rural.

[16]We average the quarterly data to obtain an annual measure.

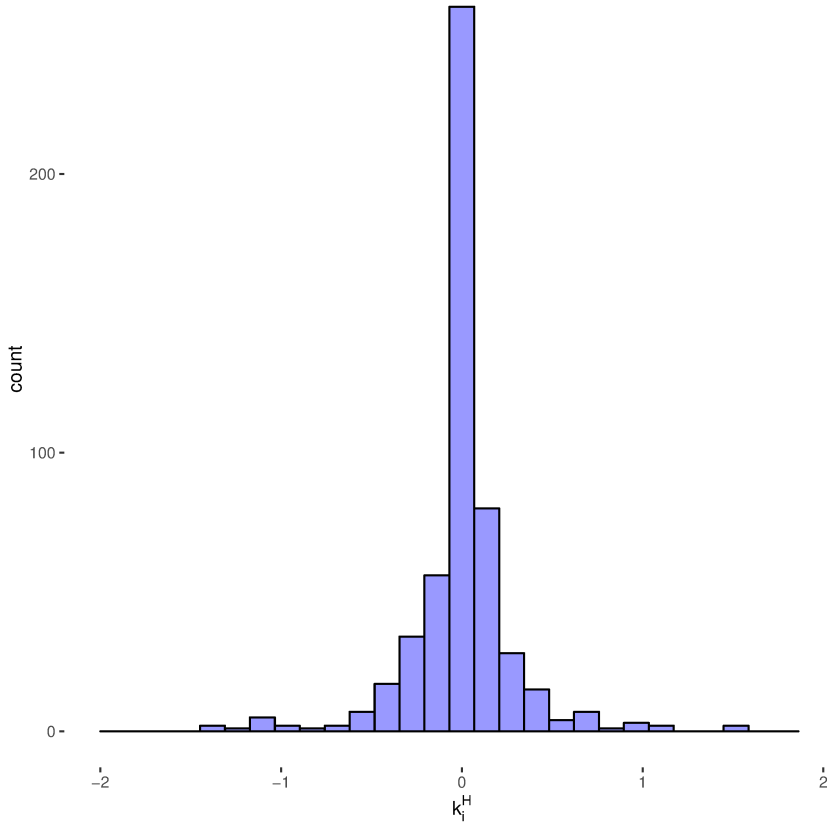


Figure 3.6: Histogram of estimates for k_i^H, rent responsiveness to county employment

3.6.2 Estimating $l^\nu(s^f, L_{it}, W_{it}, k_i^H)$

We use the sample of all counties to estimate the functional form for non-tradeable labor employment. **For our preliminary estimation**, we assume additivity in our expression for $l^\nu(s^f, L_{it}, W_{it}, k_i^H)$, and estimate coefficients using an equation of the form:

$$\begin{aligned} L_{it}^\nu =& \beta_0 + \beta_i + \beta_L L_{it} + \beta_W W_{it} + \beta_k k_i^H \\ &+ \beta_{LW} L_{it} W_{it} + \beta_{Lk} L_{it} k_i^H + \beta_{Wk} W_{it} k_i^H + \epsilon_{it}^{L^\nu} \end{aligned} \tag{3.22}$$

Guided by Equations 3.8 and 3.9, which imply that L_{it}^{ν} depends non-linearly on L_{it}, W_{it}, and k_i^H, we introduce interaction terms in all three regressors. We also include a county fixed effect β_i. The error term $\epsilon_{it}^{L^{\nu}}$ represents classical measurement error.

Column 2 of Table 3.3 displays results for our estimates of Equation 3.22 - plus quadratic terms W_{it}^2 and L_{it}^2. We also report two variants of the model in Equation 3.22 as robustness checks. Equation 3.22 is our preferred specification as the inclusion of county fixed effects exploits our panel data to control for any time-invariant county characteristics that we may have omitted in our model. The inclusion of quadratic terms allows for more nonlinearity, which firstly coheres better with our structural model, and secondly give us significant estimates, as we shall see.

Looking at Column 2 estimates, we first note that the effects of k_i^H on L_{it}^{ν} are completely soaked up by the introduction of county fixed effects in our econometric model, as we have assumed that k_i^H is time invariant.

The coefficient on both W_{it} and W_{it}^2 are both negative and significant but small. This accords with our structural model, which posits that the effect of higher wages should be to reduce the demand for labor in the non-tradeable sector. The negative coefficient on W_{it}^2 implies that high wage counties should experience larger declines in non-tradeable labor demand as wages increase. These results show that crowding out of non-tradeable labor demand should happen as initial wages increase.

The coefficients of greatest interest are those on L_{it} and L_{it}^2, and both estimates are significant. The coefficient on L_{it} is positive, while that on L_{it}^2 is negative, and smaller than that on L_{it}. This points to positive effects on higher total employment on non-tradeable employment, which decline as employment grows. Further, the coefficient on $W_{it} * L_{it}$ is also positive and significant, implying that non-tradeable labor demand increases in aggregate county income, which accords with the assumptions of our structural model. These results

Table 3.3: Estimates for Equation 3.22

	Dependent variable:		
		L_{it}^{ν}	
	(1)	(2)	(3)
	FE+Linear	**FE+Quadratic**	Controls+Quadratic
RUC93			-55.535^{***}
			(3.092)
NAS			38.616^{***}
			(2.776)
k_i^H			4.236
			(12.161)
W_{it}	-0.01^{***}	-0.002^{***}	-0.004^{***}
	(0.0005)	(0.001)	(0.001)
L_{it}	0.254^{***}	0.389^{***}	0.470^{***}
	(0.005)	(0.009)	(0.007)
W_{it}^2		$-6.34e^{-8***}$	$1.60e^{-8*}$
		(0.00)	(0.00)
L_{it}^2		$-1.22e^{-5***}$	$8.14e^{-7}$
		(0.00)	(0.00)
$W_{it} * L_{it}$	$4.22e^{-7***}$	$2.23e^{-6***}$	$3.28e^{-7**}$
	(0.00)	(0.00)	(0.00)
$W_{it} * k_i^H$	-0.002	0.009	0.015
	(0.005)	(0.005)	(0.008)
$L_{it} * k_i^H$	0.306^{***}	0.164^{***}	-0.088^{*}
	(0.054)	(0.053)	(0.049)
Obs.	20,046	20,046	19,608
R^2	0.943	0.944	0.848
Adjusted R^2	0.941	0.943	0.848
Resid. Std. Error	483.556	477.104	783.128
F Statistic	705.942^{***}	723.163^{***}	$10{,}959.100^{***}$

*p<0.1; **p<0.05; ***p<0.01

show the presence of significant non-tradeable agglomeration effects. In particular, non-tradeable agglomeration effects from a shock to L_{it} are higher in low employment, high wage counties.

Finally, we note that the coefficient on $L_{it} * k_i^H$ is also significant and positive. This implies that non-tradeable labor demand is more responsive to changes in overall employment/population in counties with tight housing markets. How can we explain this? Referring to Equation 3.9 in our structural model, this result suggests that the MPC to consume out of non-rent income is higher in counties with tight housing markets, perhaps because of higher unmeasured quality of non-tradeable output in counties with tight housing markets (such as those close to cities).

3.6.3 Pre-Entry Wage Response Estimation

We use period 0 (pre-entry five year interval) data to estimate the function ρ in Equation 3.20. Specifically, we assume a log-linear functional form for ρ in Equation 3.20.This gives the following econometric model for our estimation:

$$d\log W_{i0} = \left[\gamma_0 + \gamma_L L_{it} + \gamma_W W_{it} + \gamma_k k_i^H + \gamma_\alpha \alpha_i + \gamma_{L/L^\nu} \frac{L_{i0}}{L_{i0}^\nu}\right] d\log\left[\frac{\widehat{\partial L_{i0}^\nu}}{\partial L_{i0}} - \frac{\widehat{\Delta l_{i0}^\nu}}{\frac{\partial L_{i0}^\nu}{\partial L_{i0}}}\right] + \epsilon_{it}^\rho \tag{3.23}$$

As outlined in our section on identification, we use Proposition 9 to identify the size of the combined supply shock in period 0 and the accompanying labor demand agglomeration effect - we also form estimates $\widehat{\frac{\Delta l_{i0}^\nu}{\frac{\partial L_{i0}^\nu}{\partial L_{i0}}}}$. Using observed change in log wages in period 0, $d\log W_{i0}$, we then estimate our wage response function ρ.

Guided by our structural model, we allow ρ to be a function of county-specific characteristics $RUC93$, NAS, k_i^H and initial labor market conditions W_{i0} and L_{i0}. Equation 3.17 shows that the function ρ is the sum of the partial derivative of the labor supply and non-tradeable demand curves with respect to wages, the expressions for which are given by Equation 3.6 and 3.8 respectively. The labor supply curve is affected by county amenities α_i. We use RUC93 as our measure of urban amenities, and NAS as a measure of natural amenities. Both labor supply and non-tradeable labor demand cures are affected by k_i^H and initial labor market conditions W_{i0} and L_{i0}.

Assuming a log-linear functional form for ρ, we can interpret the γ coefficients in Equation 3.23 as measuring the relationship between observables and the magnitude of the county's wage response to a labor demand or labor supply shock.ϵ_{it}^{ρ} is a log-linear classical measurement error term.

We use our sample of counties with large establishment entry to estimate Equation 3.23, and report our estimates in Table 3.4.

We report our OLS estimates for γ coefficients in Table 3.4. Except for k_i^H, the covariates implied by our model are all significant. More rural counties (with higher RUC93 scores) and counties with better natural amenities (with higher NAS scores) have larger wage responses to shocks. Rural counties have steeper labor supply curves. The magnitude of the coefficient, at 0.072, can be interpreted as implying that a one point increase in the RUC93 score correlates with a 7.2% greater wage response to a given labor shock.

Counties with higher initial wages have high wage responses to labor shocks. The coefficient estimate of 0.00003 implies that comparing two counties with a $1000 difference in average annual wages, the high wage county sees a 3% larger change in wages in response to a labor shock. Similarly, the 0.00004 coefficient on $L_{i0} * d\log \widehat{L_{i0}^*}$ implies that a rise in employment by 1000 is correlated with a 4% higher wage response to a labor shock. Overall,

Table 3.4: Estimates for Equation 3.23

	Dependent variable:		
	$d\log W_{i0}$		
	(1)	**(2)**	(3)
RUC93$*d\log\widehat{L^*_{i0}}$	0.091***	0.072***	0.053***
	(0.009)	(0.009)	(0.009)
NAS$*d\log\widehat{L^*_{i0}}$	0.042***	0.050***	0.041***
	(0.015)	(0.016)	(0.014)
$k_i^H * d\log\widehat{L^*_{i0}}$	0.007	−0.363***	−0.026
	(0.043)	(0.045)	(0.040)
$W_{i0} * d\log\widehat{L^*_{i0}}$	0.00002***	0.00003***	0.00003***
	(0.00001)	(0.00001)	(0.00001)
$L_{i0} * d\log\widehat{L^*_{i0}}$	0.00003***	0.00004***	0.00001
	(0.00001)	(0.00001)	(0.00001)
$\frac{L_{i0}}{L^{\nu}_{i0}} * d\log\widehat{L^*_{i0}}$	0.009	0.026	0.003
	(0.026)	(0.026)	(0.024)
Constant	0.036***	0.036***	0.034***
	(0.002)	(0.002)	(0.002)
Observations	481	478	479
R^2	0.877	0.882	0.843
Adjusted R^2	0.875	0.881	0.841
Residual Std. Error	0.052	0.046	0.045
F Statistic	561.407***	587.629***	423.398***

*p<0.1; **p<0.05; ***p<0.01

Notes: Column numbers follow the specification in Table 3.3, in estimating Equation 3.3. Estimates from each column in Table 3.3 are used to construct respective values of $\widehat{L^*_{i0}}$. For example, column (2) uses the Fixed Effects + Quadratic estimates in column (2) of Table 3.3 to construct $\widehat{L^*_{i0}}$ for estimation here. Estimates from column (2) are our preferred specification as they correspond to our preferred specification in Table 3.3.

our results imply that counties with low natural amenities scores but high urban amenities scores, low wages and low employment, have low wage responses to labor demand shocks.

3.6.4 Goodness of Fit

We simulate the impact of large establishment entry on wages and employment, using Equation 3.17. We estimate the wage response to large establishment entry as:

$$\widehat{\frac{\Delta W_{i0}}{\Delta N_{ij0}}} = \hat{\rho}\left(\alpha_i, k_i^H, s_i^f, s_i^w, L_{i0}, W_{i0}, \frac{L_{i0}}{L_{i0}^\nu}\right)\left[\bar{L}_j + \frac{L_{i0} + \widehat{\Delta L_{it}^\nu} + \bar{L}_j}{L_{i0}^\nu + \widehat{\Delta L_{it}^\nu}}\right] \tag{3.24}$$

We use our estimates for $\hat{\gamma}$ from the pre-entry period estimation, and county-specific variables at the end of the pre-entry period to form our county estimates for $\hat{\rho}$, as well as observed values of $\bar{L}_j$ in the above equation. We use estimates of $l^\nu(s^f, L_{it}, W_{it}, k_i^H)$ to construct $\widehat{\Delta L_{it}^\nu}$. We can thus simulate wage responses to large establishment entry.

We present summary statistics from our wage response simulations below in Table 3.5. The first row shows statistics for observed log changes in wages in the first 5 year interval after large establishment entry, while the second shows statistics for our model's simulated wage changes after large establishment entry. Our model generates higher wage changes than are observed on average, and higher dispersion of wage changes overall.

Table 3.5: Goodness of Fit Simulations

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$\log \frac{W_{i1}}{W_{i0}\,\vert D_{ij1}=1}$	543	0.222	0.190	−0.374	0.130	0.302	1.366
$\log \widehat{\frac{W_{i1}}{W_{i0}}\,\vert D_{ij1}=1}$	522	0.392	0.283	−0.708	0.247	0.473	2.473

Note:

Notes: We compare wage responses from large establishment entry using estimates from Table 3.4 with wage responses in the data.

In Figure 3.7, we plot a comparison of simulations and observed changes in log wages.

In the left panel, we plot simulations vs observations along the initial log wage ($\log W_{i0}$) continuum, and in the right panel, along the initial log employment (L_{i0}) continuum. We notice that for both dimensions, the model does a relatively good job of matching the data at low wages and employment. At high wages and employment, however, our model overpredicts the wage rise caused by large establishment entry. This could point to the need for higher order regressors in our estimation.

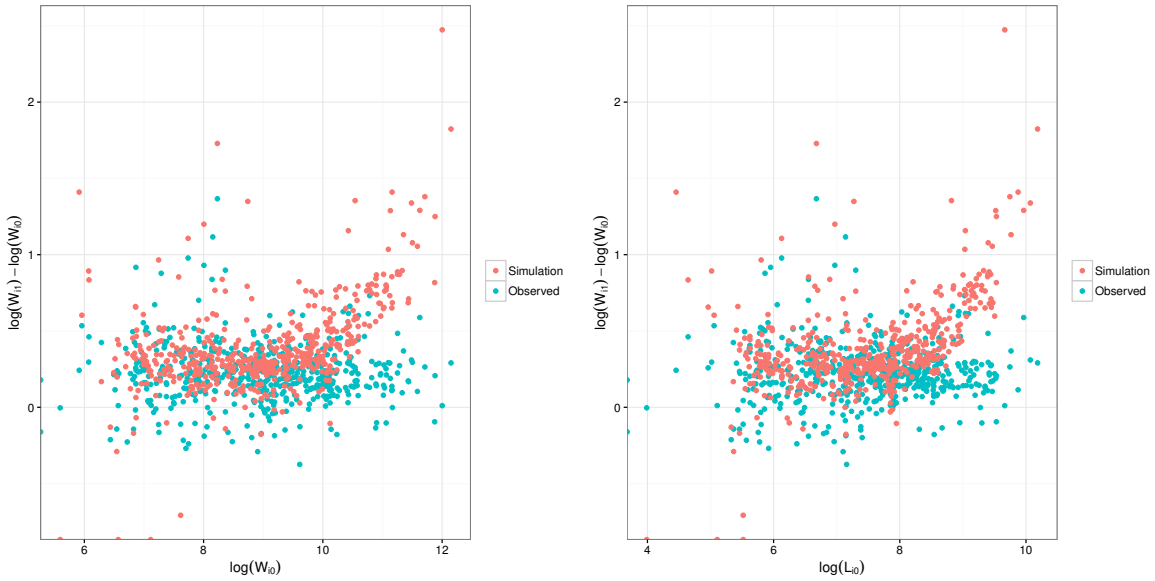


Figure 3.7: Goodness of Fit: Simulated Wage Responss to Large Establishment Entry

3.7 Second Stage Estimation and Results

3.7.1 Non-tradeable Agglomeration vs. Crowding Out

We estimate our non-tradeable agglomeration effects as the boost to non-tradeable sector labor demand due to the positive labor demand shock of large establishment entry. We obtain this as the shift to non-tradeable labor demand as a result of large establishment

entry. Crowding out in our model, on the other hand, happens due to the exit of non-tradeable sector firms in our model from increased wages after large establishment entry. We obtain this as the movement along the non-tradeable labor demand curve as a result of wage increases from large establishment entry.

Formally, we estimate:

$$\text{Crowding Out} : \widehat{l^{\nu}}(s^f, \widehat{L_{i1}}, \widehat{W_{i1}}, \widehat{k_i^H}) - \widehat{l^{\nu}}(s^f, \widehat{L_{i1}}, W_{i0}, \widehat{k_i^H}) \tag{3.25}$$

$$\text{Non-Tradeable Agglom.} : \widehat{l^{\nu}}(s^f, \widehat{L_{i1}}, W_{i0}, \widehat{k_i^H}) - \widehat{l^{\nu}}(s^f, L_{i0}, W_{i0}, \widehat{k_i^H}) \tag{3.26}$$

In the above, $\widehat{L_{i1}} = L_{i0} + \bar{L}_j$, and $\widehat{W_{i1}} = W_{i0} + \widehat{\frac{\Delta W_{i0}}{\Delta N_{ij0}}}$, where $\widehat{\frac{\Delta W_{i0}}{\Delta N_{ij0}}}$ is obtained as described in the last section and reported in Table 3.3.

We now report our estimates for crowding out and non-tradeable agglomeration effects in our sample of counties with large establishment entry. In Table 3.6, we show that on average, the crowding out effects are almost exactly cancel out non-tradeable agglomeration effects, so that the effect of large establishment entry on non-tradeable sector employment in the county is close to zero. On average, non-tradeable agglomeration from the entry of the county's first large establishment increases non-tradeable employment by 35.2% (412 in levels), while crowding out effects reduce non-tradeable employment by 34.8% (398 in levels). The net effect on non-tradeable employment is almost zero.

Our estimates from Tables 3.3 and 3.4 provide some explanations for our results. First, our estimates from Table 3.3 show that non-tradeable agglomeration effects are higher in low employment counties, and high wage counties.[17] In our sample, non-tradeable agglomeration effects of large establishment entry tend to be small due to low initial wages.

[17] Our estimate of the coefficient on L_{it}^2 is negative, and that on $W_{it} * L_{it}$ is positive.

Table 3.6: Non-Tradeable Agglomeration versus Crowding Out

	Effects on Non-Tradeable Employment (%)		
	Agglomeration	Crowding Out	Net
All	35.2	34.8	0.4
	(8.3)	(7.8)	
Manufacturing	40.3	34.6	5.7
	(6.7)	(5.6)	
Agriculture	33.4	36.2	−2.8
	(2.8)	(1.9)	
Mining	32.7	37.9	−5.2
	(3.3)	(2.9)	
Construction	33.1	38.2	−5.1
	(3.6)	(2.6)	
Transport/Utilities	35.6	35.9	0.3
	(3.7)	(4.6)	
Wholesale Trade	31.1	33.8	−2.7
	(2.1)	(2.4)	
Retail Trade	30.9	38.4	−7.5
	(1.9)	(0.9)	
Services	43.2	33.3	9.9
	(5.7)	(5.5)	

Notes: Estimates for Non-Tradeable Agglomeration are derived from Table 3.3 using Equation 3.25. Estimates for Crowding out are derived from Tables 3.3 and 3.4, using Equation 3.25.

Second, our estimates from Table 3.3 show that wage increase from a labor demand shock are low in low wage, low employment counties with low natural amenities, but high in rural counties.[18] Large wage increases lead to large crowding effects in the non-tradeable sector. In our sample, less rural counties tend to have smaller wage increases from large establishment entry, and thus smaller crowding out effects, while the majority of rural counties experience large wage increases and large crowding out effects.

In sum, since a large portion of our sample are counties situated far from urban centers, and have low pre-entry wages, crowding out effects are relatively large while non-tradeable agglomeration effects are relatively small compared to the national average county. Within our sample, counties that have high wages pre-entry and are located close to urban centers experience large non-tradeable agglomeration effects. Even though they also see large wage increases and crowding out effects, the non-tradeable agglomeration effects tend to outweigh crowding out effects for these counties.

Breaking down our results by the industry of entering establishment, we find that manufacturing and services counties experience larger non-tradeable demand agglomeration effects than crowding out effects. In Table 3.6, we show that entry of a manufacturing establishment has a large non-tradeable agglomeration effect, increasing non-tradeable employment by 40.3% (690 in levels). Crowding out effects are close to the industry average, at 34.6% (553 in levels), giving a net 5.7% increase in non-tradeable employment from first manufacturing establishment entry. Services establishment entry generates a 43.2% increase in non-tradeable employment from non-tradeable agglomeration effects, and a 33.3% decrease from crowding out effects, producing 9.9% net increase in non-tradeable employment.

Our estimates suggest that manufacturing and services counties experience larger non-

[18] Our estimate on the coefficient on W_{i0} and L_{i0} are positive, and that of the coefficient on RUC93 and NAS are positive.

tradeable agglomeration effects due to higher pre-entry wages in the counties they enter. At the same time, they also experience smaller crowding out effects because they tend to have lower RUC93 scores, and be situated closer to urban centers. This is especially true for services establishments, which tend to be in counties close to metro areas and have higher pre-entry wages.

In contrast, for retail, wholesale, agriculture, mining and construction industries, crowding out effects exceed non-tradeable agglomeration effects. This implies that non-tradeable employment tends to decline as a result of large establishment entry.

By definition, crowding out effects are generated by the rise in wages from large establishment entry. Our results imply that in our sample, large establishment entry does produce wage and employment growth, but mainly from the direct impact of the large establishment.

3.7.2 Industry Agglomeration

We simulate the extent of industry agglomeration after the entry of the first large establishment by exploiting our result in Proposition 8. For each observation of large establishment entry in our sample, we simulate county wage growth with the further entry of establishments from the same industry. Using Equation 3.24, we estimate wage growth recursively for $N_{ij1} > 1$. We also observe the number of establishments in the industry of initial large establishment annually for ten years after initial entry. From this, we use the maximum number of establishments observed, to approximate the largest extent of industry agglomeration after initial entry.

In Table 3.7, we report estimates for the expected wage growth for counties should one more j large establishment enter the county, conditional on the county being at their maximum number of establishments observed. Formally, Table 3.7 reports estimates of

$\mathbb{E}\left[\frac{\Delta W_{i1}}{\Delta N_{ij1}|N_{ij1}=\bar{N}_{ij1}}\right]$, where $\bar{N}_{ij1}$ is the maximum number of j large establishments found in county i in the ten year interval after initial entry.

Proposition 8 implies that industry agglomeration will stop once productivity benefits from agglomeration fail to exceed wage growth from further entry. The estimates from Table 3.7 thus represent the upper bound for productivity benefits from industry agglomeration for each N_{ijt}, and for each j. If industry agglomeration is uncommon, we wish to know whether the cause is high expected wage growth, or low productivity benefits from agglomeration. High estimates from Table 3.7 would tell us that high expected wage growth is preventing industry agglomeration. On the other hand, low estimates for expected wage growth would indicate that productivity benefits from industry agglomeration are low.

Our estimates from the first row of Table 3.7 show that across all industries, the rate of further entry of large establishments after initial establishment entry is low, with no further entry ($\bar{N}_{ij1} = 1$) observed in 79% of our sample. Entry of one more large firm of the same industry ($\bar{N}_{ij1} = 2$)is observed in 15% of counties, with $\bar{N}_{ij1} > 2$ occurring in just 6% of counties. Expected wage growth if a second large establishment enters the county, averaged across industries, is reported in row 2 of column 2. The estimate of \$1412 implies that expected annual wage growth due to the entry of a second large establishment is \$1412, averaged across counties in our sample. This is comparable to the estimate of \$1383, which is the estimated wage growth from entry of the first establishment. For $\bar{N}_{ij1} > 2$, however, there are large increases in expected wage growth - with estimates of \$2594 and \$3147 respectively. These results suggest that high expected wage growth after the second large establishment prevents industry agglomeration in our sample.

On an industry level, we notice that the manufacturing industry has higher rates of industry agglomeration than average, with 21% of counties having $\bar{N}_{ij1} = 2$, 10% of counties

Table 3.7: Industry Agglomeration

		$\bar{N}_{ij1}$			
		1	2	3	4
All	Share (%)	79	15	4	2
	$\mathbb{E}\left[\frac{\Delta W_{i1}}{\Delta N_{ij1}} \mid N_{ij1}=\bar{N}_{ij1}\right]$ ($)	1383	1412	2594	3147
Manufacturing		67	21	10	2
		1255	1384	2385	3028
Agriculture		100	0	0	0
		1480	1897	2623	3064
Mining		93	5	1	0
		1553	1943	2883	3498
Construction		100	0	0	0
		1579	1967	2921	3591
Transport/Utilities		85	5	10	0
		1342	1480	2212	2934
Wholesale Trade		85	14	0	0
		978	1100	1623	2055
Retail Trade		87	12	0	0
		999	1249	1763	2015
Services		64	24	8	1
		1580	1893	2136	2466

Notes: Share (%) rows show decomposition of counties by maximum number of large firms of industry j in the ten year interval after initial entry by industry j establishment. Estimates rounded to nearest percentage point. $\mathbb{E}\left[\frac{\Delta W_{i1}}{\Delta N_{ij1}} \mid N_{ij1}=\bar{N}_{ij1}\right]$ ($) rows show estimates from recursively using Equation 3.24 for $\bar{N}_{ij1} \in \{1,2,3,4\}$. Estimates are expressed in dollar terms as average county nominal annual wage growth, rounded to the nearest dollar.

having $\bar{N}_{ij1} = 3$, and 3% of counties having $\bar{N}_{ij1} > 3$. The expected wage growth estimates for manufacturing counties are slightly lower than average, but follow largely the average pattern of wage growth as $\bar{N}_{ij1}$ rises, with expected wage growth rising for the third and fourth large establishments ($2385 and $ 3028 respectively) This suggests that the productivity benefits from industry agglomeration are higher than the average industry.

The services industry also displays higher than average rates of industry agglomeration, with 24% of counties experiencing entry of a second large establishment in the ten years after initial entry. Our estimates suggest that expected wage growth from entry seems to rise more linearly for services industries, with higher than average wage growth from the first establishment entry ($1580), but lower than average wage growth from the third and fourth large establishments entering the county($2136 and $2466) respectively.

Agriculture, mining, and construction counties provide high expected wage growth from the entry of the first establishment ($1553), and high expected wage growth from subsequent establishment entry ($1943, $2883, and $3498 for the second, third, and fourth establishments respectively for mining counties). At the same time, the rate of industry agglomeration is very low for all three industries - with over 90% of counties having no industry agglomeration after first establishment entry. Retail and wholesale counties see similarly low rates of industry agglomeration. Unlike agriculture, mining and construction counties, however, retail and wholesale counties experience significantly lower than average expected wage growth from larger establishment entry. This suggests that productivity benefits from industry agglomeration are low for retail and wholesale trade industries, as industry agglomeration does not happen despite low expected wage growth from further large establishment entry.

3.8 Conclusions

In this paper, we estimate the overall effect of large establishment entry on non-tradeable employment as the product of two separate effects - non-tradeable agglomeration and crowding out. Non-tradeable agglomeration is the rise in non-tradeable labor employment due to higher market demand for non-tradeable consumption, generated by large establishment entry. Crowding out is the negative effect of higher overall county wages caused by large establishment entry on non-tradeable labor demand.

We estimate that on average, the positive effects of non-tradeable agglomeration on non-tradeable employment are almost exactly canceled out by crowding out effects. Our results suggest that there is a type of Catch-22 for low wage counties wishing to generate sustained employment and wage growth through large establishment entry. The labor demand shock caused by large establishment entry leads to large crowding out effects that outweigh non-tradeable labor agglomeration effects in the non-tradeable sector, which in turn limits overall employment growth. This effect is even more pronounced for rural counties. Sustained growth in employment through non-tradeable agglomeration seems out of reach for these counties.

On the contrary, exogenous positive shocks to labor supply should be an effective way to generate sustained employment growth. In our model, positive labor supply shocks produce non-tradeable agglomeration effects and no crowding out effects, which leads to net positive employment growth.

To have non-tradeable agglomeration effects outweigh crowding out effects, our model implies that both non-tradeable labor demand and labor supply needs to be relatively elastic to wages. This ensures that wage responses to large establishment entry are relatively small, which limits crowding out effects. Non-tradeable agglomeration effects then dominate,

leading to rightward shifts in the non-tradeable labor demand curve. This leads to further wage and employment growth.

Our model also suggests that counties with large crowding out effects will be unlikely to generate industry agglomeration, which is the further entry of establishments in the same industry as the initial entering firm for productivity advantages from co-location. This is because counties with large crowding out effects are exactly those that will experience large wage increases from further large establishment entry. High expected wage growth discourages more large establishments from entering the county, outweighing the productivity advantages from same industry colocation. In counties with low wage responses to large establishment entry, industry agglomeration itself generates further non-tradeable agglomeration, and even higher employment growth.

Our estimates indeed show that on average, entry of a second large establishment into our sample of counties generates high expected wage growth. This explains our observation that in the vast majority of counties, no industry agglomeration is observed.

These mechanisms explain a large part of the industry heterogeneity in the effects of large establishment entry observed in the data. Manufacturing and services establishments tend to have non-tradeable agglomeration effects that outweigh crowding out effects, generating positive growth in non-tradeable employment from large establishment entry. Relatively small crowding out effects also encourage industry agglomeration, which further increases employment and wages. In contrast, agriculture, mining, and construction establishments tend to enter counties with large crowding out effects in our sample, limiting employment growth either through the non-tradeable sector or through further industry agglomeration.

Appendix A

Appendix to Chapter 1

A.1 Sample Construction

The SIPP is a survey tracking individuals over a number of "waves", representing interviews that ask questions covering the previous 4 months. The number of waves (and so the length of the panel) varies across panels, as do the questions, but questions concerning worker employment status, reasons for unemployment, wages, sector, occupation and unemployment benefits are asked on a monthly basis for all panels we consider. Within a panel, interviewees are separated into 4 "rotations", and individuals from different rotations are interviewed in different months. For example, in the 1984 panel, the interview for wave 1 of rotation 1 was conducted in Jan 1985, covering the time period Oct 1984-Jan 1985. The interviews for wave 1, rotation 2 were conducted a month later, in Feb 1985, covering the months Nov 1984-Feb 1985. Rotations 3 and 4 work in the same way, and the cycle repeats in May 1985, for wave 2 of rotation 1. Data on rotations and waves for each individual are available for all panels, making it possible to order data for the panel in calendar time.

A.1.1 Labor Force Transitions in the SIPP

The SIPP underwent a significant redesign in 1996. Importantly, the questionnaire was modified so that labor force status definitions (E, U and O) could be harmonized with definitions in the Current Population Survey (CPS). Pre-1996, the classifications of labor force status could not be made consistent between the CPS and the SIPP because of differences in survey design and methods of recoding into labor force states.

Several changes in the methodology behind labor force status coding across SIPP panels may present the additional problems that problems comparing labor force transition statistics between SIPP panels becomes inconsistent. We delineate three such changes and their consequences for our analysis. First, only from the 1996 panel onwards are CPS questions about 'layoff' added to the SIPP survey. Workers were asked if they were given a date to return to their employer and if they expected to return to their original jobs in six months. As observed in Fujita and Moscarini [2017], this may have resulted in disparities in the stock of workers on 'Temporary Layoff' pre-1996 and post-1996. Fujita and Moscarini [2017] suggest that the absence of the CPS layoff questions may have resulted in workers on layoff being misclassified as out of the labor force.

Secondly, the 1984-1988 panels of the SIPP used different questions for weekly labor force activity, which lead to a different method of labor force status coding into E, U and O. Details are explicated in Ryscavage and Feldman-Harkins [1988] and Fujita, Nekarda, and Ramey [2007], but the differences in survey design may lead to inconsistencies in aggregate trends on labor force status transitions from pre-1988 to post-1988 SIPP panels. Comparing the 1984 SIPP panel to contemporaneous CPS data, Ryscavage and Feldman-Harkins [1988] find that trends in labor force transitions move in the same direction and with similar magnitudes. This should provide some reassurance that comparing labor force transition

data across panels should not bias cross-panel estimates significantly.

Thirdly, the SIPP redesign in 1996 also shifted from personally conducted interviews (called paper-and-pencil personal interviewing, or PAPI) to computer assisted interviews (called computer-assisted personal interviewing, or CAPI). While PAPI relies on asking interviewees to fill out employment status information by calendar week, CAPI relies on asking employer-specific questions, from which weekly employment status information is derived. Comparing results from using PAPI and CAPI on the same group of interviewees, Lamas, Palumbo, and Eargle [1996] find that CAPI produces slightly lower labor force participation rates, and lower unemployment rates compared to PAPI. This may introduce further bias to our comparisons of aggregate labor force transition trends pre-1996 and post-1996.

As a whole, while combining SIPP panels to derive aggregate trends from 1984 to post 1996 has been done, notably in Fujita et al. [2007] and Fujita and Moscarini [2017], caution must be taken in comparing pre-1996 and post-1996 trends. In the pre-1996 period, there are inconsistencies in labor force status coding that may give rise to biases in comparing the 1984-1988 panels with the 1990-1993 panels.

A.1.2 Censoring of Unemployment Spells

Unemployment duration is a key variable in our paper, but the variability in panel length across panels presents problems for how we compare unemployment durations across panels. For example, the 1984 panel is 32 months long, while the 2004 panel is 45 months long. Unemployment spells in the 2004 panel thus have a longer time to develop than those in the 1984, leading to an upward bias in unemployment durations in the 2004 panel, compared to those in the 1984 panel. Furthermore, since unemployment spells in the 2004 panel have more

time to develop, we may see a higher rate of employed outcomes than continued unemployed outcomes. To ensure comparability of unemployment duration and outcomes across panels, we restrict all unemployment spells to a maximum of 12 months. This means that even if we can tell from the full panel that an unemployment spell has a duration of 20 months and outcome of employed, in our dataset, this unemployment spell is recorded as having a duration of 12 months and an outcome of continued unemployment.

The second problem is that the data as it is does not allow us to compare our unemployment spells within panels. For example, an unemployment spell from the 2004 panel that starts in September 2007 only has 1 month to develop before the end of the panel in October 2007. Comparatively, an unemployment spell that starts in 2005 has 12 months to develop. Thus, unemployment spells that start in the last 11 months of the panel have biased durations and outcomes. To solve this problem, we filter out all unemployment spells that start in the final 11 months of each panel.

While these trimming steps result in a failure to use all the information within each sample, we make the tradeoff in sample size to ensure comparability of unemployment durations and outcomes within and across SIPP panels.

A.1.3 Task-Based Occupation Groups

The 1990-2001 SIPP panels use the 1990 Census occupation classification schemes, while the 2004 and 2008 panels use the 2000 Census occupation classification schemes. To create a consistent classification of fine occupations, we used the crosswalk between 1990 and 2000 Census occupation codes found on the Census bureau website.

For each consistent occupation code, we replicated the three aggregate task measures based on DOT data used in Autor and Dorn [2013]. The manual task measure is from the

DOT variable "eye-hand-foot coordination". The routine task measure is the mean of the DOT variables , "set limits, tolerances, and standards," and "finger dexterity". The abstract task measure is the mean of DOT variables, "direction control and planning," measuring managerial and "GED Math". Occupations are then classified as A, R, and M by their highest score among the three measures.

Each unemployment spell contains information on the individual worker's demographic characteristics (including state of residency, age, education), the industry, occupation, and wages from the previous job, the duration of the unemployment spell in months, and the outcome of the unemployment spell - employment (along with the industry, occupation, and wage of the new job), labor force exit, or continued unemployment.

A.2 Model Dynamics

A.2.1 Technology, Trade, and Demand Shocks

SBTC Simple Skill-Biased Technological Change (SBTC) is modeled as a positive shock to $y_{j\mathbf{x}}$, productivity in j that is common to type $\mathbf{x}$ workers. For workers in j of some type $\mathbf{x}'$ $neq\mathbf{x}$, the effect of an increase in $y_{j\mathbf{x}}$ is identical to that of an RRTC shock. By increasing the efficient units of factor inputs, a labor-saving motive is introduced through a decline in F_j^1, and $\alpha^*_{j\mathbf{x}'}$ rises for all $\mathbf{x}'$ $neq\mathbf{x}$ in partial equilibrium. For $\mathbf{x}$ workers, the immediate effect on $\alpha^*_{j\mathbf{x}'}$ depends on the size of the decline in F_j^1 relative to the rise in $y_{j\mathbf{x}}$.

Trade, Demand Shocks Trade and demand shocks in j work through the same channel in our model. The output price in j, p_j can be expressed as

$$p_j = z_j \Phi_j,$$

where z_j is an index of local demand for j output, which can be interpreted as a standard productivity shock in DMP models (such as that in Shimer [2005]). Φ_j a price index of sector j output prices of foreign competitors. [1] A trade shock is modeled as a negative shock to Φ_j, resulting from a reduction in a foreign competitor's output j price. A local recession is modeled in the standard way, as a negative shock to z_j. Both result in a decline in p_j. Using the same assumptions underlying Proposition 1, lower ability workers become unprofitable for firm j to employ, resulting in a rise in $\alpha^*_{j\mathbf{x}}$ in partial equilibrium via an analogous argument to that in Proposition 1.

A.2.2 Dynamic Worker Flows

We state laws of motion for all labor force states in our model.

For unemployed workers of type $\mathbf{x}$ searching in sector-occupation j, the law of motion is:

$$u'_{j\mathbf{x}} = (1 - f_j)u_{j\mathbf{x}} + P(\phi_{i\mathbf{x}} = j)\left(EU_{\mathbf{x}} + OU_{\mathbf{x}}\right) + \sum_{k \neq j} P(\psi_{i\mathbf{x}} = j) f_k G(\alpha^*_{k\mathbf{x}}) u_{k\mathbf{x}} \tag{A.1}$$

For employment in j, we have:

$$E'_j = E_j + \sum_{\mathbf{x}' \in \mathbf{X}} \left((1 - G_{j\mathbf{x}'}(\alpha^*_{j\mathbf{x}'}))f_j u_{j\mathbf{x}}\right) - EU_{\mathbf{x}} \tag{A.2}$$

The law of motion for employed workers states that gross inflows to employment are unemployed workers searching in j who are not technologically mismatched $\alpha_{ij} > \alpha^*_{j\mathbf{x}}$, summed across worker types $\mathbf{x}$, while gross outflows are the sum of exogenous and endogenous job destruction. Finally, we have the following law of motion for OLF workers of type $\mathbf{x}$.

[1] We show in an appendix using a simple trade framework based on Autor, Dorn, Hanson, and Song [2014], that we can express output price as $p_j = z_j \Phi_j$.

$$d'_{\mathbf{x}} = d_{\mathbf{x}} + \sum_{j \in \mathcal{J}} \left(P(\psi_{i\mathbf{x}} = 0) f_j G_{j\mathbf{x}}(\alpha^*_{j\mathbf{x}}) u_{j\mathbf{x}} \right) - OU_{\mathbf{x}} \tag{A.3}$$

The law of motion for OLF workers states that in the next period, gross inflows to OLF are mismatched workers who exit the labor force, while gross outflows are simply OU flows.

A simple calculation shows that that the summing equations 1.14, A.3 and A.2 across j yields:

$$\sum_{j \in \mathcal{J}} \left(\sum_{\mathbf{x} \in \mathbf{X}} u'_{jx} + E'_j \right) + \sum_{\mathbf{x} \in \mathbf{X}} d_{j\mathbf{x}} = \sum_{j \in \mathcal{J}} \left(\sum_{\mathbf{x} \in \mathbf{X}} u_{jx} + E_j \right) + \sum_{\mathbf{x} \in \mathbf{X}} d_{jx}$$

This confirms that we have a closed system, where no new workers enter and no existing workers exit the economy. Thus, the measure of workers of each type $\mathbf{x}$ in the economy is constant across time. Each worker of type $\mathbf{x}$ takes on a labor force status and sector-occupation each period.

To impart some intuition about the dynamic response of our model to shocks, we now describe some of our model's dynamic and steady state properties. We show how our model can be solved in steady state in the appendix, and in our main exposition we highlight a few key equations.[2] First, in the steady state of our model, EU flows in k must be equal to UE flows in k. To ensure this, we need the number of newly unemployed workers who choose to stay in k to be equal to the number of successful matches by stayers each period. This can be expressed as:

$$(1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})) f_k u_{k\mathbf{x}} = P(\phi_{i\mathbf{x}} = k) \lambda E_k \tag{A.4}$$

[2]Our model differs from a standard DMP model in several dimensions, and solving for steady state is substantially more complex. The biggest difference is that unemployed worker flow across segmented labor markets is endogenous. Secondly, there is both endogenous and exogenous job destruction, and endogenous job destruction in the model only occurs out of steady state. Thirdly, vacancy creation in the model takes the probability of mismatch into account.

The LHS of Equation A.4 is the measure of unemployed stayers in k who meet a vacancy *and* are not mismatched, and thus make EU transitions. The RHS is the measure of EU workers who self-select into k, their previous sector-occupation. We note that in the steady state, $\alpha^*_{k\mathbf{x}}$ is constant across periods and there is no endogenous job destruction. As such, EU transitions k are simply a constant fraction λ of employment E_k

Next, in the steady state, UO flows must be equal to OU flows. Prior to this, we have not specified any assumptions on OU flows. We do so now, assuming that a constant fraction λ of type $\mathbf{x}$ OLF workers flow into unemployment each quarter,[3] and are partitioned across sector-occupations according to the distribution $\phi_{i\mathbf{x}}$ to reflect Roy selection across $\mathcal{J}$.

$$G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})P(\psi_{i\mathbf{x}}=0)f_k u_{k\mathbf{x}} = P(\phi_{i\mathbf{x}}=k)\lambda d_{\mathbf{x}} \tag{A.5}$$

Equation A.5 says that the measure of type $\mathbf{x}$ unemployed stayers in k who meet a vacancy, are mismatched, and decide to exit the labor force (UO transitions) must be equal to the measure of type $\mathbf{x}$ OLF workers who re-enter unemployment (OU transitions).

Finally, in the steady state, net flows of unemployed workers across sector-occupations must be 0. So, for any j,k pair such that $(j,k)\in\mathcal{J}^2$, we have:

$$\begin{aligned} &P(\phi_{i\mathbf{x}}=k)\tilde{u}_{\mathbf{x}'} + P(\phi_{i\mathbf{x}'}=j)G_{j\mathbf{x}'}(\alpha^*_{j\mathbf{x}'})P(\psi_{i\mathbf{x}'}=k)u_{j\mathbf{x}'} \\ =&P(\phi_{i\mathbf{x}}=j)\tilde{u}_{\mathbf{x}} + P(\phi_{i\mathbf{x}}=k)G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})P(\psi_{i\mathbf{x}}=j)u_{k\mathbf{x}} \end{aligned} \tag{A.6}$$

On each side of Equation A.6 is the sum of self-selected switchers and mismatched switch-

[3]We assume the rate of exit from OLF is the same as the rate of exogenous job destruction, but assuming any other exogenous rate does not affect our theoretical results. We also do not rely on this assumption in our identification and estimation.

ers.

Assuming that we are in an initial steady state, we now examine the model's steady state responses to an RRTC shock. The implications for other types of shocks are analyzed in an appendix.

A.2.3 RRTC Shock

We start off with an RRTC shock. Recall that from Equation 1.5, an RRTC shock in k is simply a linearly additive shock to the amount of efficient factor inputs to k. Proposition 1 shows that under our wage assumptions, a positive RRTC shock raises $\alpha^*_{k\mathbf{x}}$ $\forall \mathbf{x}$ in k. We can prove the following steady state corollary to Proposition 1:

Corollary 4. *Let there be an RRTC shock in k. Then, ceteris paribus, if $P(\phi_{i\mathbf{x}} = k)$ stays constant, the ratio of employed workers to unemployed stayers $\frac{E_k}{u_{k\mathbf{x}}}$ must fall.*

Proof. From Equation A.4, we have:

$$P(\phi_{i\mathbf{x}} = k)\lambda\frac{E_k}{u_{k\mathbf{x}}} = (1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}}))f_k$$

An RRTC shock causes $\alpha^*_{k\mathbf{x}}$ to rise. We show that this unambiguously causes a decline in the LHS in the above equation.

First, it is trivial that $G_{j\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ rises. Second, from Equation 1.8, an increase in $G_{j\mathbf{x}}(\alpha^*_{k\mathbf{x}})$ results in a rise in q_k in equilibrium, which implies a fall in θ_k, and a fall in f_k, since we have assumed that the matching function exhibits constant returns to scale. Since both terms on the RHS of the above equation decline, in steady state, if $P(\phi_{i\mathbf{x}} = k)$ remains constant, the ratio $\frac{E_k}{u_{k\mathbf{x}}}$ must decline.

□

Corollary 4 implies that a positive RRTC shock results in a decline in the employment-unemployment ratio for all stayers, if the rate of self-selection into staying in k remains constant. Intuitively, an RRTC shock results in a decline in successful matches by stayers in the steady state, due to a higher probability of mismatch $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$. With EU flows exceeding UE flows for stayers in k, there is a net inflow to unemployment. Unless EU flows from k self-select into $j \neq k$ at higher rates, the sector-occupation k will settle into a new steady state with higher unemployment for stayers.

We now state a steady state result for the labor force participation rate for stayers after a RRTC shock.

Corollary 5. *Let there be an RRTC shock in k. Then, ceteris paribus, if $P(\psi_{i\mathbf{x}} = 0)$ stays constant, the ratio of employed workers to OLF workers from k $\frac{E_k}{d_{\mathbf{x}}}$ must fall.*

Proof. Dividing Equation A.4 by Equation A.5, we get the following equation:

$$P(\psi_{i\mathbf{x}} = 0)\frac{E_k}{d_{\mathbf{x}}} = \frac{1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}{G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}$$

Since a positive RRTC shock results in a rise in $G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})$, if $P(\psi_{i\mathbf{x}} = 0)$ remains constant, then $\frac{E_k}{d_{\mathbf{x}}}$ must fall. □

A falling $\frac{E_k}{d_{\mathbf{x}}}$ implies either lower employment in k or higher labor force exit for unemployed stayers in k. Intuitively, Corollary 5 says that a positive RRTC shock results in higher rates of mismatch for stayers in k, and as long as $P(\psi_{i\mathbf{x}} = 0)$ remains constant, this implies higher UO flows in k. UO flows can decline in steady state, as a result of lower employment in the sector and thus lower exogenous job destruction, or OU flows can rise in the steady state, due to a rise in the stock of OLF workers.

An implication of Corollaries 4 and 5 is that in a 1 sector-occupation model where $\mathcal{J} = k$,

where $P(\phi_{i\mathbf{x}} = k) = 1$ (constant) and $P(\psi_{i\mathbf{x}} = 0)$ is constant, an RRTC shock will lead to a steady state of higher non-employment for current or previously employed k workers, since both $d_{\mathbf{x}}$ and $u_{k\mathbf{x}}$ increase relative to E_k.

Interestingly, even in a many sector-occupation version of our model, where unemployed workers flow endogenously across sector-occupations, an RRTC shock in k may not result in gross outflows from k to other sector-occupations. Intuitively, the effects of lower vacancy creation on worker flows that result from a positive RRTC shock can be counteracted by maintaining a higher stock of unemployed workers searching in the affected sector-occupation. We state this formally in the next Corollary.

Corollary 6. *Let there be a positive RRTC shock in k. Holding $P(\phi_{i\mathbf{x}} = j)$ and $P(\psi_{i\mathbf{x}} = j)$ constant $\forall j \in \mathcal{J}$, the size of gross outflows from k is ambiguous in the new steady state, and can decline if employment E_k rises in the new steady state.*

Proof. In steady state, from Equation A.4, $f_k u_{k\mathbf{x}} = \frac{P(\phi_{i\mathbf{x}}=k)\lambda E_k}{1-G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}$. Substituting this into the LHS of Equation A.6, we get that

$$\text{Gross outflows from } k \text{ to } j = P(\phi_{i\mathbf{x}} = k)\lambda E_k \left[\frac{G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}{1 - G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}\right] + P(\phi_{i\mathbf{x}} = j)\lambda E_k$$

A positive RRTC shock produces a rise in $\frac{G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}{1-G_{k\mathbf{x}}(\alpha^*_{k\mathbf{x}})}$, but the effects on E_k are ambiguous. Since E_k changes in proportion to the number of matches in k in steady state, high unemployment can sustain higher matches in k in the new steady state. □

A.3 Kernel Regression Results

A.3.1 Kernel Regression Details

To conduct our estimation, we rely on functions from the 'np' package in R by Hayfield and Racine [2008]. We use five regressors in our kernel regressions, $gender, educ, age, year, j$. Since the variables $educ, age, year$ admit a natural order, we use the kernel function in Li and Racine [2008]) for ordered categorical variables for each of them. One the other hand, $gender$ and j do not admit natural ordering, and so we use the kernel function suggested in Aitchison and Aitken [1976] for unordered categorical variables. We use a second-order Gaussian kernel with a local-linear estimator for our kernel regression.[4]

For bandwidth selection, we use the Least Squares Cross-Validation for bandwidth selection. To reduce the computational burdens of the estimation, we estimate a fixed as opposed to adaptive bandwidth, meaning that the bandwidth for each of our five regressors remains constant as they vary across the $\mathbf{X}$-space. Least Squares Cross-Validation minimizes an objective function based on the Integrated Mean Square Error (IMSE) of the estimate with regards to the bandwidth. [5] Loader [1999] notes that Least Squares Cross Validation can be prone to under-smoothing and high variability in final estimates, as compared with other bandwidth selection methods such as Silverman's Rule of Thumb and plug-in methods such as that of Sheather and Chris Jones [1991]. [6] We report the results of our bandwidth selection exercises in columns 4-7 of Table A.1.

We also run significance tests of our independent variables - the components of $\mathbf{X}$, and

[4]We use a second order kernel to avoid negative density estimates which presents problems when we conduct bootstrap procedures. Our results are not sensitive to the selection of a Gaussian kernel, we conduct robustness checks with rectangular and triangular kernels instead.

[5]Recall that the IMSE of the kernel regression can be decomposed into a bias term and a variability term, and increasing the bandwidth increases bias but lowers the variance.

[6]As robustness checks, we can repeat the analysis using other bandwidth selection methods - Likelihood Cross-Validation, Silverman's Rule of Thumb.

report them in columns 7-10 of Table A.1, and find that our results are significant. Substantively, for each component $X \in \mathbf{X}$, and denoting $\mathbf{X}' = \mathbf{X} \setminus X$, we test for the rejection of the null hypothesis:

$$H_0 : \quad \mathbb{E}[y|\mathbf{X}', X] = \mathbb{E}[y|\mathbf{X}'] \ \ \forall X \in \mathbf{X}$$

We use the Bootstrap I test suggested in Racine et al (06), which constructs the P-value out of bootstrapped test statistics. [7]

	regtype	N	bw				Pval			
			educ	age	year	jn	educ	age	year	jn
$p^m(\mathbf{x}$	LL	9618	0.698	0.227	0.781	0.510	0.005	0.000	0.000	0.000
$o^{st}(\mathbf{x})$	LL	50718	0.161	0.360	0.577	0.099	0.000	0.000	0.000	0.000
$o^{ex}(\mathbf{x})$	LL	50718	0.132	1.000	0.375	0.432	0.000	0.987	0.000	0.321

Table A.1

A.3.2 Detailed Regression Estimates

In Figure A.1, we report the evolution of $p^m(\mathbf{x})$ for workers of different origin sector-occupations, gender, age groups, and education groups. Each point on each curve is $\mathbb{E}_x[p^m(x)|year = y, X^* = x^*]$, where X^* is the component of X that the dependent variable is being conditioned on. For example, the first point on the red line in Figure A.1a represents the weighted average of estimated $p^m(x)$ in 1985 for $Prod.R$ workers across gender, age and education groups. The weights used are the sample share of type x workers in 1985, at the beginning of the sample.[8] We use 1985 sample weights to attain a *composition-adjusted* evolution of $p^m(x)$, intended to prevent changes in X-composition in time from driving changes in $p^m(x)$. We

[7] We provide a brief exposition for the reader unfamiliar with these methods in an Appendix.

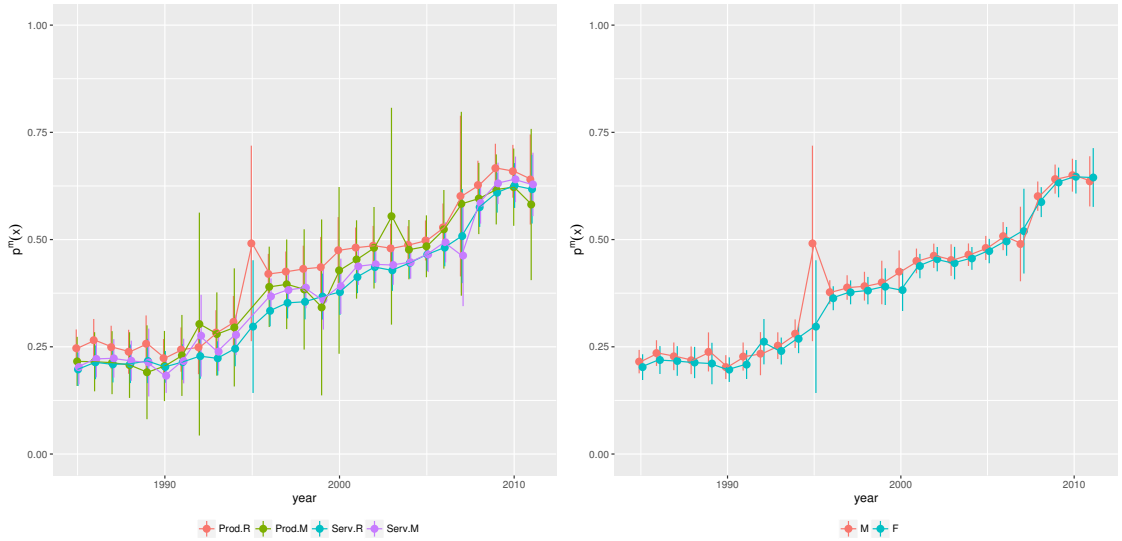
[8] We calculate $\mathbb{E}_x[p^m(x)|year = y, X^* = x^*] = \sum_{x \in X \setminus (year, X^*)} \widehat{p^m(x)} s(x)$, where $s(x)$ is the sample share of type x workers conditional on $year = 1985 \cup X^* = x^*$.

depict asymptotic standard errors for each estimate as error bars surrounding each point.

There is some evidence of a convergence by 2005. Males display a slightly higher probability of mismatch throughout the time period. Younger workers aged 16-30 also display consistently lower $p^m(x)$, with the gap between them and the two older age groups widening somewhat from 1995 onwards. Notably, while the oldest workers aged 46-64 display higher probabilities of mismatch among switchers until around 1995, thereafter prime age workers aged 30-45 catch up, essentially showing equal $p^m(x)$ by the even of the Great Recession. Finally, comparing workers with high school or less ($\leq HS$) with workers with some college (SC), while in the 1980's, $\leq HS$ switchers are substantially more likely to be mismatched, this gap closes almost entirely by the eve of the Great Recession. Higher education seems to matter less and less in the probability of mismatch among switchers. Workers with at least a bachelor's ($\geq BA$) seem to track SC workers somewhat, even outstripping $\leq HS$ workers in the Great Recession. However, estimates for $\geq BA$ workers have larger error bounds due to smaller sample representation, which we must take into account.

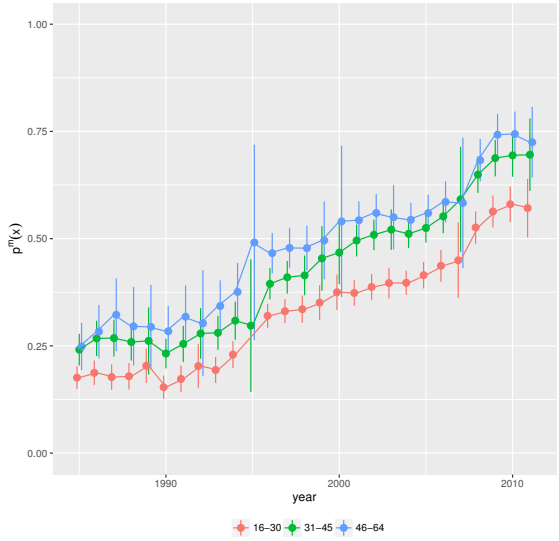
Overall, the 1990's are notable for the prominent rise in $p^m(x)$ for production sector routine workers (over service sector routine workers), and sustained higher $p^m(x)$ for lower educated workers. In the 2000's, however, significant convergence happens - between production and service sector workers, routine and manual workers, medium and low educated workers.

From all four panels of Figure A.2, the economy wide trend was that $o^{st}(\mathbf{x})$ rose from 1984 to the early 1990's, and declines broadly thereafter. Figure A.2a shows that production sector routine workers consistently display higher $o^{st}(\mathbf{x})$, but the gap between them and the other three sector-occupation groups narrowed in the 1990's. After 2000, $Prod.R$ workers experienced a substantial bump in $o^{st}(\mathbf{x})$, with $Prod.M$ workers registering a small increase as well, although these gains are canceled out by the Great Recession. Males displayed

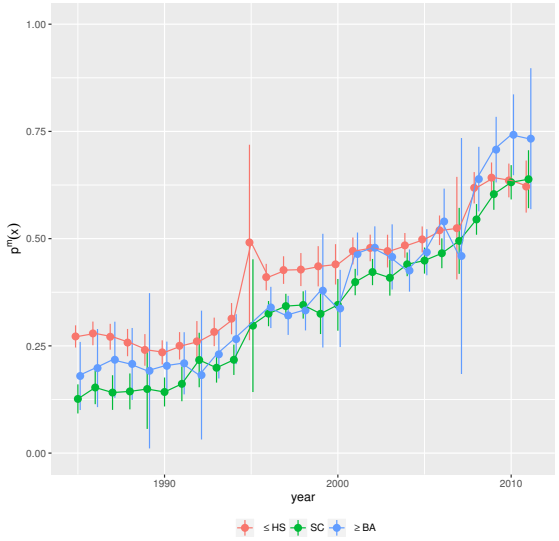


(a) Origin Sector-Occupation

(b) Gender

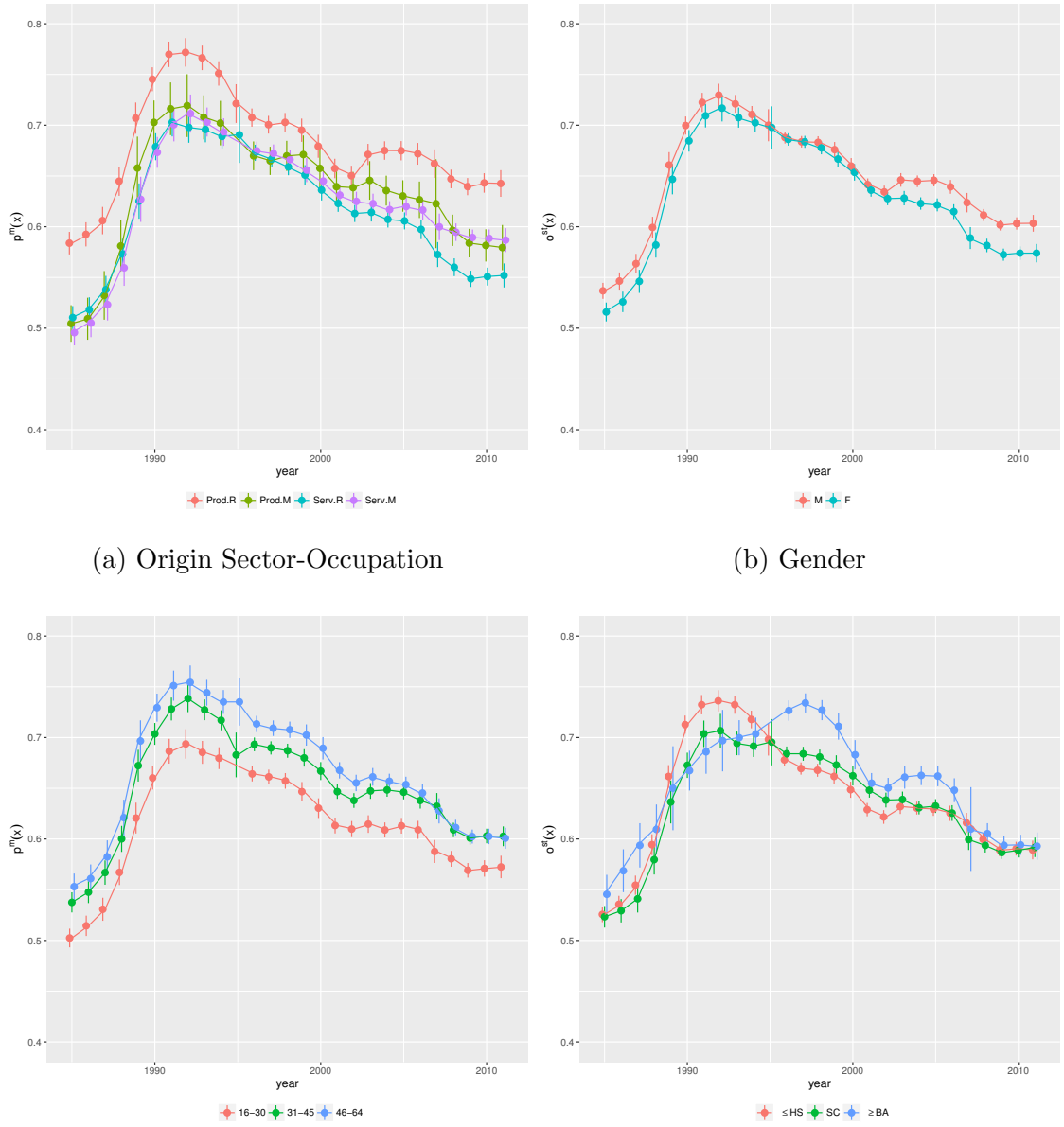


(c) Age



(d) Education

Figure A.1: Estimates for $p^m(\mathbf{x})$ - probability of mismatch unemployment for sector-occupation switchers, conditional on worker characteristics, derived from kernel regression using unemployment spells from 1984-2012.



(a) Origin Sector-Occupation

(b) Gender

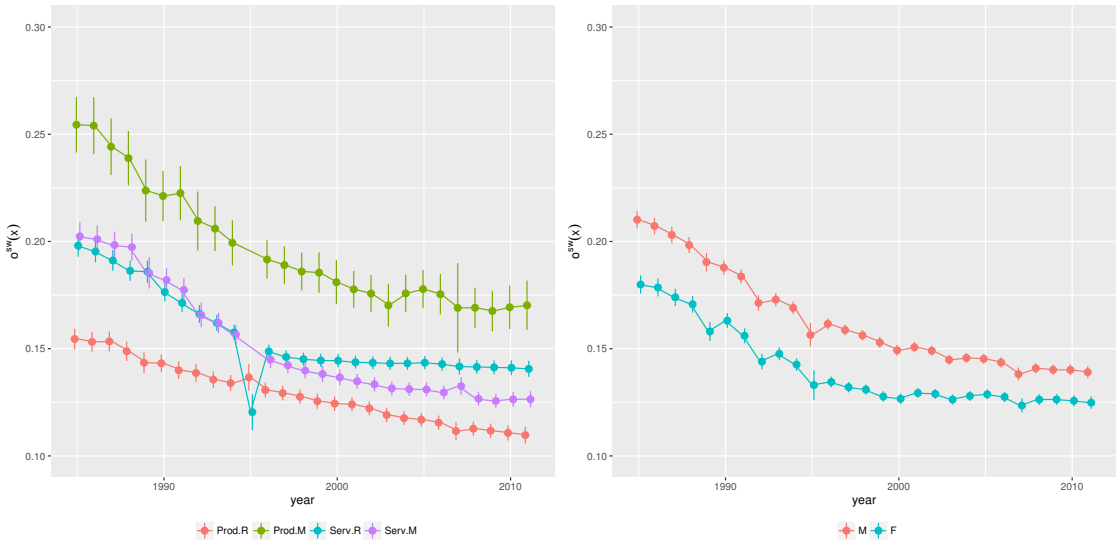
(c) Age

(d) Education

Figure A.2: Estimates for $o^{st}(\mathbf{x})$ - probability of unemployed finding employment in same sector-occupation, conditional on worker characteristics, derived from kernel regression using unemployment spells from 1984-2012.

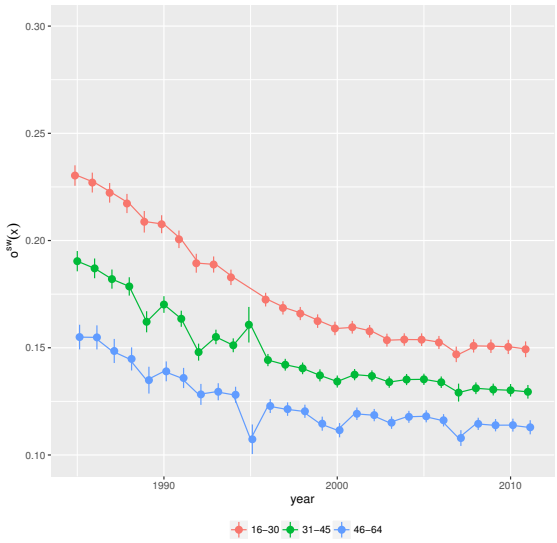
a similar bump in the early 2000's, not observed for females. Younger workers aged 16-30 are consistently less likely to find re-employment in the same sector-occupation than older workers. Older workers aged 46-64 have significantly higher $o^{st}(\mathbf{x})$ than prime age workers aged 31-45, but this feature disappears in the 2000's. The $o^{st}(\mathbf{x})$ decline for lower educated($\leq HS$) workers is steeper than that of SC workers in the 1990's, but experience a similar bump to that faced by $Prod.R$ workers in the early 2000's. High educated $\geq BA$ workers experienced sustained rises in $o^{st}(\mathbf{x})$ until the late 1990's, and displayed a similar bump in the early 1990's to that experienced by $Prod.R$ workers.

In sum, while both $Prod.R$ and $\leq BA$ workers experienced steep $o^{st}(\mathbf{x})$ declines in the 1990's, both groups displayed a substantial early 2000's bump. This feature is observed also observed in men (but not women), and high educated $\geq BA$ unemployed workers. Further, $\geq BA$ workers also experienced substantially higher $o^{st}(\mathbf{x})$ than other groups in the mid 1990's, a period where the probability of finding re-employment in the same sector-occupation was declining for other groups.

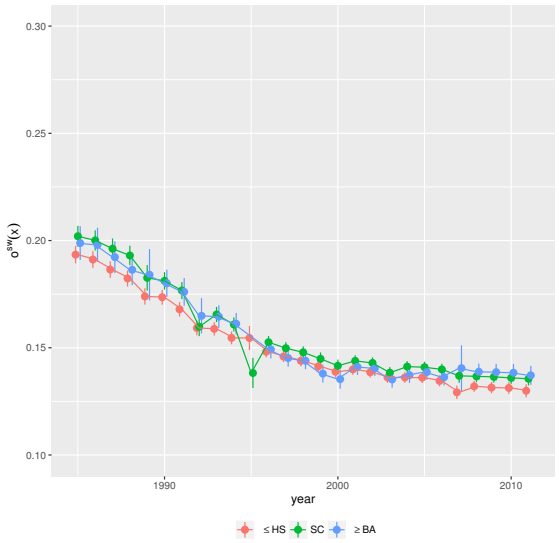


(a) Origin Sector-Occupation

(b) Gender



(c) Age



(d) Education

Figure A.3: Estimates for $o^{sw}(\mathbf{x})$ - probability of unemployed finding finding employment in another sector-occupation, conditional on worker characteristics, derived from kernel regression using unemployment spells from 1984-2012.
Males have a higher probability of switching than females, and younger workers are significantly more likely to switch than older workers. However, there is very little difference in probability of switching among education groups.

Appendix B

Appendix to Chapter 2

B.1 Markups for Superstar Firms

We plot mean market shares and markups for superstar firms across 6 major sectors of the economy (excluding Finance Sector firms due to unreliable sales data for financial firms). For all sectors, superstar firms saw increasing average (sales) market share from 1990-2014. For most sectors, the growth in market share was postive in the 1990's, accelerated in the late 1990's and continued at a rapid rate into the 2000's. The exception is in Retail, where average market share rose consistently even in the 1990's. These observations are mirrored in the declining market share across sectors of non-superstar firms, observed in the fight panel of B.1. There is some sector heterogeneity in the evolution of markups for superstar firms, with Others and Services seeing rising superstar markups from around 2000 onwards. Note that the "Others" sector comprises informations, communications, and professional industries, and contains many industries that could be considered high skil and hi-tech industries. In contrast, superstar markups have remained somewhat stagnant in other sectors. For non-superstar firms, the Manufacturing, Services, and Other sectors have seen rising markups,

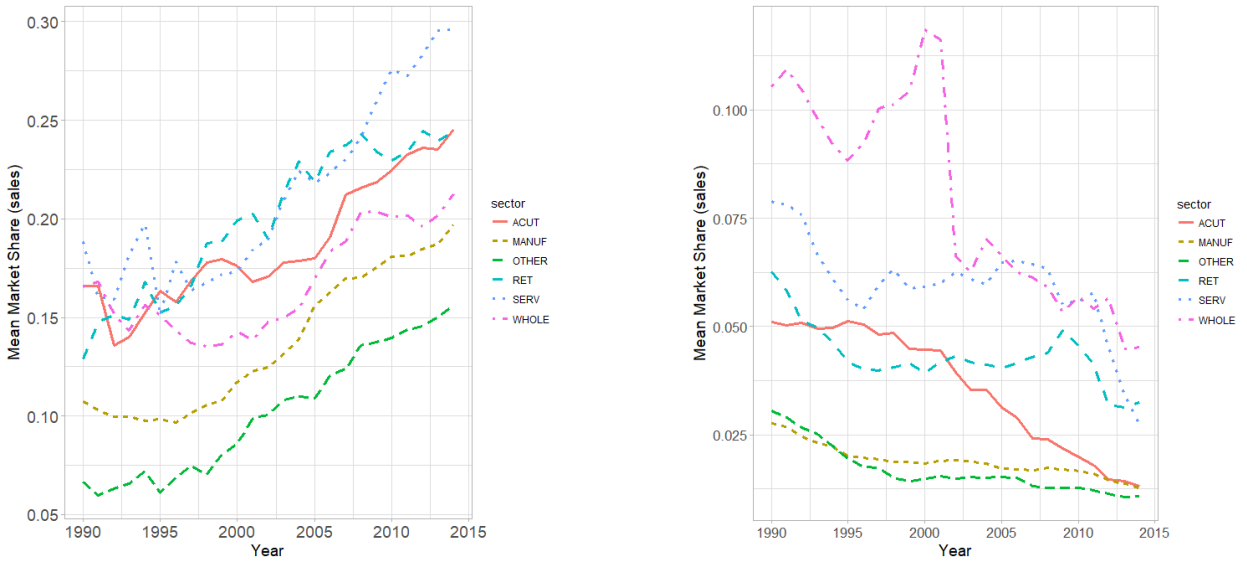


Figure B.1: Market share by total sales within 4 digit NAICS industries, averaged across major sector. Left Panel: Top 4 firms by market share growth from 1990-2014. Right Panel: All other firms.

with the rise being gradual and steady for Manufacturing and Services.

To gain some insight into markup and market share dynamics for firms most likely to adopt variable cost saving technologies, we conduct a similar exercise for the collection of 6-digit NAICS industries identified by the BLS as hi-tech industries. These include some hi-tech manufacturing industries (under 2 digit NAICS code 33), including semiconductor and computer manufacturing, information industries (under 2 digit NAICS code 51), including software and internet publishing, and professional/technical services industries (2 digit NAICS code 54), including engineering services and R&D. Figure B.3 shows that while the gradient of the rise of market share for superstar firms is similar in hi-tech and non hi-tech industries, hi-tech inustries remain significantly less concentrated than non hi-tech firms. At the same time, superstar firms in hi-tech industries have not seen a rise in firm markups from 1990-2008, with markups only rising since 2008. In contrast, superstar firms in non hi-tech industries (excluding finance) have seen steady rise in markups from 1990-2014. Compared

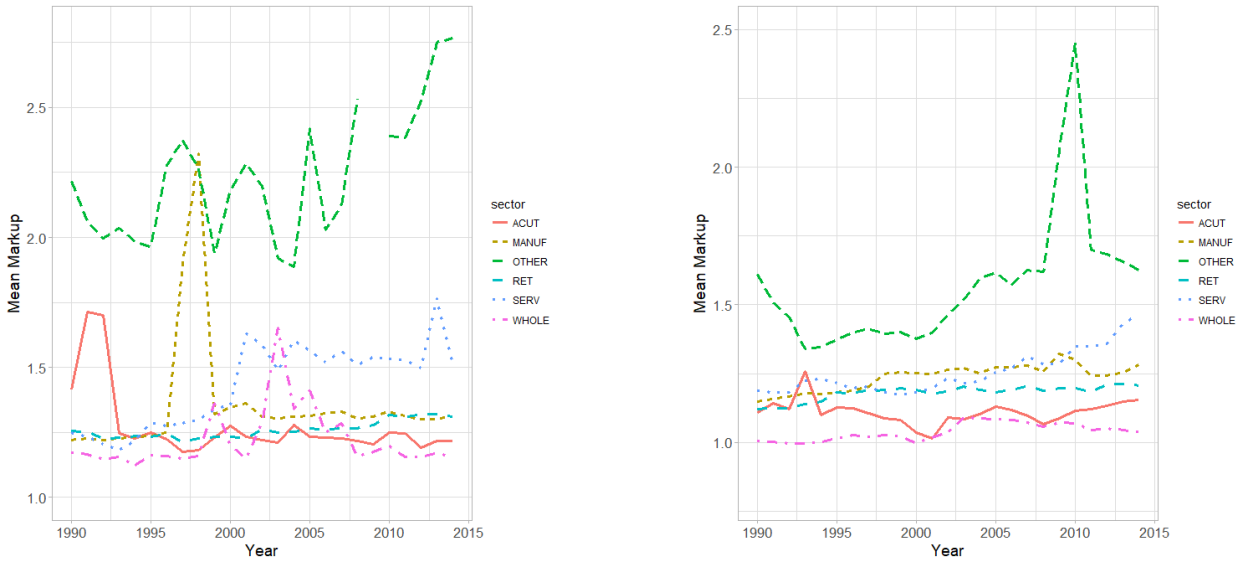


Figure B.2: Mean Markup by major sector. Left Panel: Top 4 firms by market share growth from 1990-2014. Right Panel: All other firms.

to non-superstar firms, hi-tech superstar firms indeed did have higher inital markups. However, non-superstar hi-tech firms have seen rising markups since the late 1990's, and have superceded superstar hi-tech firms since around 2000. For non hi-tech industries, however, superstar firms have consistently maintained higher markups than non-superstar firms.

Although superstar firms in hi-tech industries have been gaining market share, they have not been responsible for the rise in average markups across hi-tech firms in the 2000's. In fact, the rapid rise in size of superstar firms has actually depressed the rise of markups in the hi-tech sector as a whole, as markups for non-superstar hi-tech firms have been rising rapidly beyond superstar markups. On the other hand, superstar firms in the non hi-tech sector have not only maintained, but increased their markups relative to non-superstar firms. As such, while the rapid rise in market share for superstar firms in the 2000's may indeed be the primary force behind the rise in average markups in the non hi-tech sector, the "within-firm" rise in markups for superstar firms has been substantial as well.

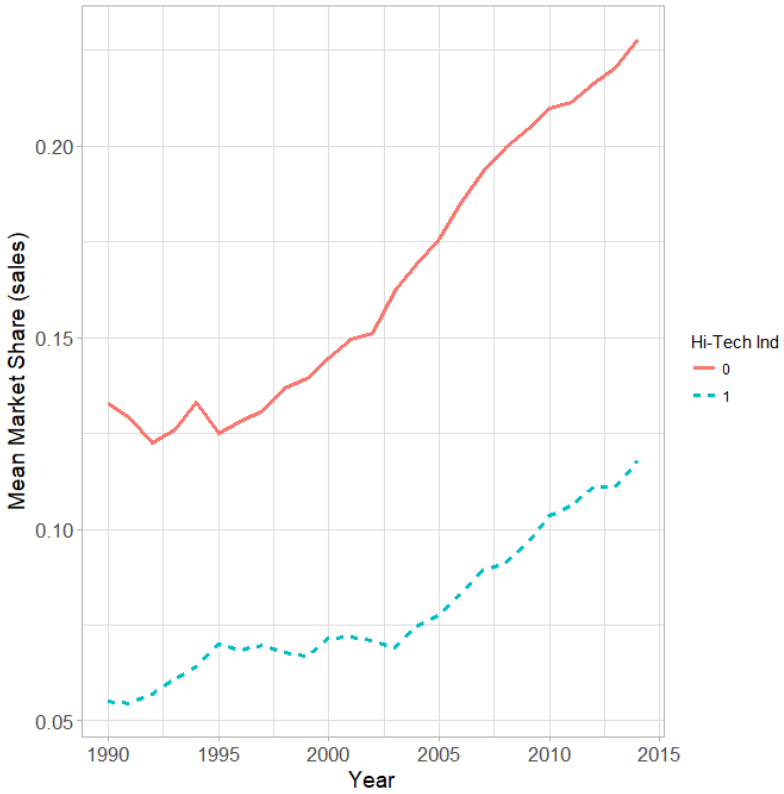


Figure B.3: Market share for superstar firms in hi-tech and non hi-tech superstar industries. Hi-tech industries are defined according to 6 digit NAICS codes identified by the US Census.

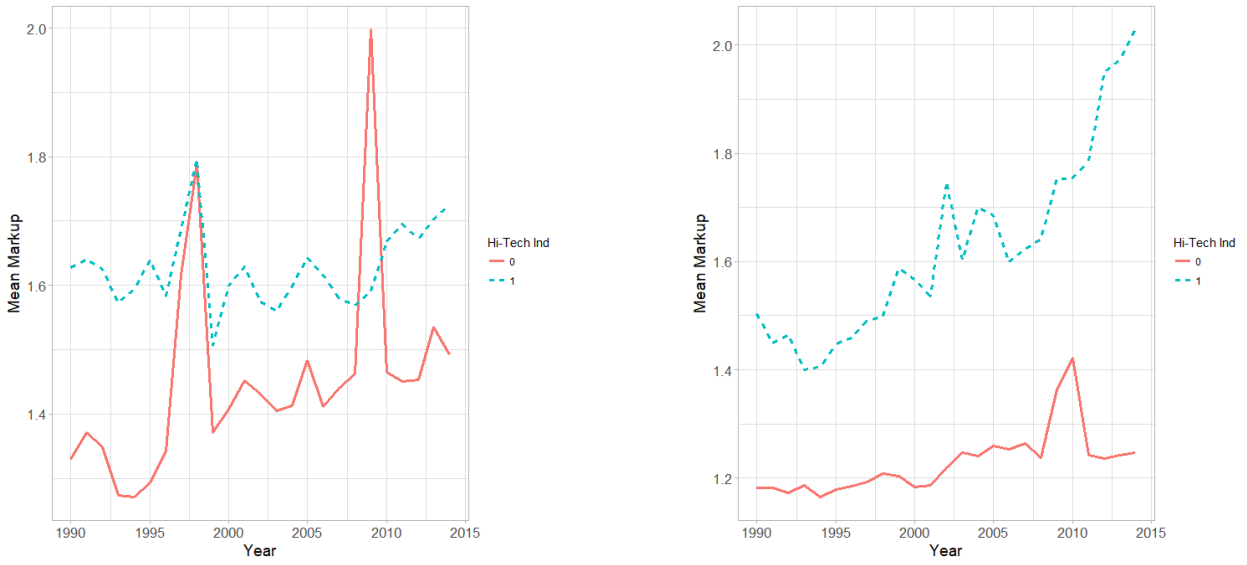


Figure B.4: Mean Markup by major sector. Left Panel: Top 4 firms by market share growth from 1990-2014. Right Panel: All other firms.

Figure B.5 displays the same trends for six major sectors. There is some heterogeneity across sectors – there is a steep and steady decline in Finance, and modest declines in Services and Agriculture+Construction+Utilites+Transportation, as well as the Services sector – but only the Retail and Wholesale sectors have seen basically constant revenue share for variable inputs from 1980-2015.

In Figure 2.3, we observe that the rise in concentration of intangible assets has been observed across almost all major sectors from the mid-1990s to 2015, with the exception of the Wholesale sector. The Finance sector has also seen a significant dip since the Great Recession.



Figure B.5: Same as Figure 2.1 - disaggregated to the sector level. We plot series for 6 major sectors (row-wise from left)- Agriculture+Construction+Utilites+Transportion, Finance, Manufacturing, Retail, Services, Wholesale.

B.2 Proofs

B.2.1 Proof for Corollary 2

Proof. For $\epsilon\gamma_i < 1$, suppose that the optimal factor quantities satisfy $K_i^* = \left(\left(1-\gamma_i\right) K_{i,t}\right)^{\frac{1}{1-\gamma_i}}$, and $L_i^* = \left(\left(1-\gamma_i\right) L_{i,t}\right)^{\frac{1}{1-\gamma_i}}$, where $K_{i,T}$ and $L_{i,T}$ represent optimal factor inputs under traditional competitive firms. To prove the proposition, we must show that $K_i^*$and L_i^*represent the optimal factor demands of a superstar profit maximizing firm facing $\tilde{Y}_i = \tilde{F}_i\left(K, L, S\right)$

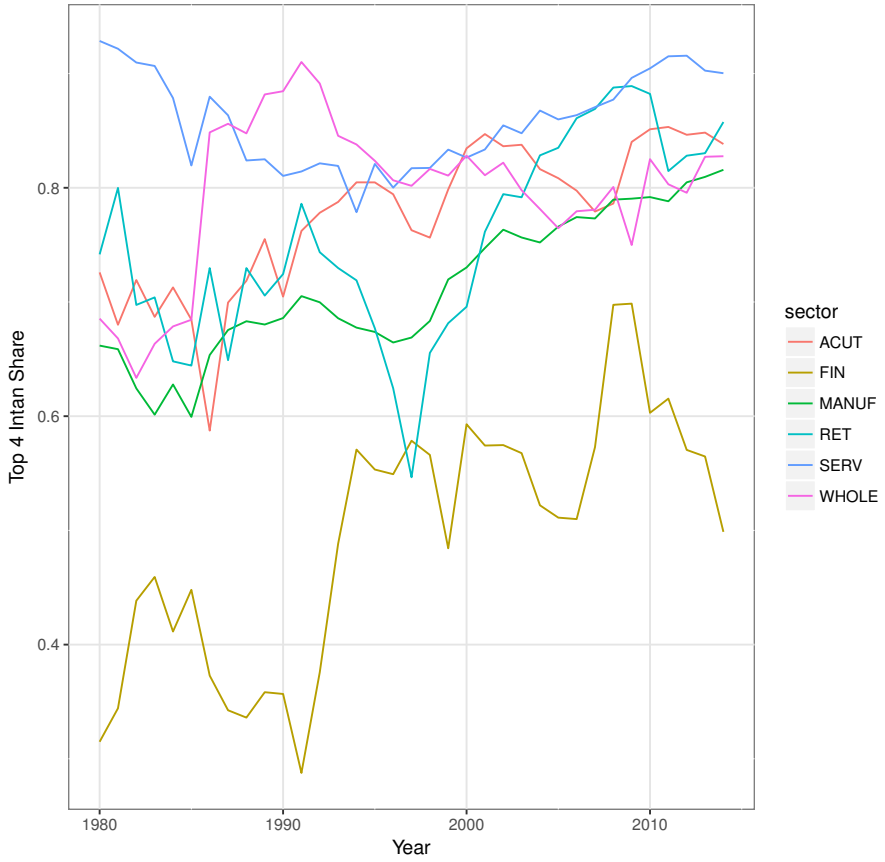


Figure B.6: Combined share of intangible assets excluding goodwill by top 4 firms within 4 digit NAICS industry codes, by sales share in industry. (Left) Average across all 4 digit industries by sector.

and factor prices R and w, such that these lead to the same factor allocation, output, and factor income shares as in our baseline model. Firstly, we see with some manipulation that $\tilde{Y}_i = \tilde{F}_i\left(K_i^*, L_i^*, S\right) = K_{i,T}^{\alpha} L_{i,T}^{(1-\alpha)} = Y_{i,T}$, the traditional competitive firm's output. This is identical to our baseline model's reult on output. Next, we show that see this, note that K_i^* and L_i^* represent optimal factor allocations. A profit-maximizing superstar firm's first order

conditions under $\tilde{Y}_i$ are:

$$FOC(K): \tilde{F}_{i,K} = P_i (1-\gamma_i)^{\gamma_i} \alpha \left(K_i^{\alpha} L_i^{(1-\alpha)}\right)^{-\gamma_i} K_i^{\alpha-1} L_i^{(1-\alpha)} = P_i \alpha (1-\gamma_i) \tilde{Y}_i K_i^{-(1-\gamma_i)} = R$$

$$FOC(L) \tilde{F}_{i,L} = P (1-\gamma_i)_i^{\gamma_i} (1-\alpha) \left(K_i^{\alpha} L_i^{(1-\alpha)}\right) K_i^{\alpha} L_i^{-\alpha} = P_i (1-\alpha)(1-\gamma_i) \tilde{Y}_i L_i^{-(1-\gamma_i)} = w$$

With some manipulation, we can show that at K_i^* and L_i^*, the optimality conditions satisfy $\tilde{F}_{i,K} = P_i \alpha K_{i,T}^{\alpha} L_{i,T}^{(1-\alpha)} K_{i,T}^{-1}$, and $FOC(L)$ reduces to $\tilde{F}_{i,L} = P_i (1-\alpha) K_{i,T}^{\alpha} L_{i,T}^{(1-\alpha)} L_{i,T}^{-1}$, the system of equations that exactly characterizes traditional firms' optimal factor demands. This shows that for given R and w, both the superstar (would-be) monopolist and traditionally competitive firms are choosing optimal capital and labor allocations to produce $\tilde{Y}_i = K_{i,t}^{\alpha} L_{i,t}^{(1-\alpha)} = Y_{i,t}$. Furthermore, from the first order conditions, we see that the income share of labor and capital satisfies$\frac{\alpha}{1-\alpha} = \frac{RK_i}{wL_i}$, which is exactly the same as in the baseline case. Finally, note that

$$RK_i + wL_i = \tilde{F}_{i,K} K_i + \tilde{F}_{i,L} L_i = (1-\gamma_i) \tilde{Y}_i$$

This implies that the superstar income share is $\gamma \tilde{Y}_i$, which again gives the identical outcome to the baseline model.

When $\epsilon \gamma_i \geq 1$, and the firm faces $\tilde{F}_i (K, L, S) = \left(\frac{1}{1-\gamma_i} K_i^{\alpha} L_i^{(1-\alpha)}\right)^{\frac{\epsilon-1}{\epsilon}} S^{\frac{1}{\epsilon}}$. Again, we first show that the superstar monopolist chooses labor and capital allocations that mirror our baseline model. The first order conditions are:

$$FOC(K): P_i \frac{\epsilon - 1}{\epsilon} \alpha \tilde{Y}_i^* = RK_i^*$$

$$FOC(L): P_i \frac{\epsilon - 1}{\epsilon} (1-\alpha) \tilde{Y}_i^* = wL_i^*$$

which gives $P_i \frac{\epsilon-1}{\epsilon} = \frac{wL_i^* + rK_i^*}{\tilde{Y}_i^*} = UC_i^S$. We know from analysis of our baseline model that for $\epsilon\gamma_i \geq 1$, $P_i^m \left[\frac{\epsilon-1}{\epsilon}\right] = (1-\gamma_i)UC_i^T$. Since by definition, $UC_i^S = (1-\gamma_i)UC_i^T$, we then have $P_i = P_i^m$, and so $Y_i = Y_i^m$, which means that output is identical to our baseline model. Next, dividing the first order conditions again shows that $\frac{\alpha}{1-\alpha} = \frac{RK_i}{wL_i}$, which again fits the relative income share of capital and labor in our baseline model. Finally, we see that

$$RK_i + wL_i = \frac{\epsilon - 1}{\epsilon} P_i \tilde{Y}_i$$

which implies that the superstar's income share is $\frac{1}{\epsilon} P_i \tilde{Y}_i$, which is the result of our baseline model. We have thus proved that a profit maximizing superstar firm that faces production function $\tilde{Y}_i$ chooses optimal factor inputs, outputs, and factor shares of income that are identical to our baseline model.

□

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Appendix C

Appendix to Chapter 3

C.1 Why does DID (or IV) not work?

For wages, this is $\mathbb{E}[\Delta W_{it}|\Delta D_{ijt} = 1] - \mathbb{E}[\Delta W_{it}|\Delta D_{ijt} = 0]$, for each j. As described previously, estimating a model like that in Equation 3.2 by DID or OLS with ΔD_{ijt} as a regressor produces inconsistent results. Specifically, $\mathbb{E}[\epsilon^W_{i(t+s)}|\Delta D_{ijt}] \neq 0$, for all $s \in \mathbb{N}$. That is, the error term for wages is not mean independent of all past and current values of ΔD_{ijt}, and weak exogeneity does not hold.

Our model offers several mechanisms that drive the correlation between large establishment entry ΔD_{ijt} and future wage and employment growth in county i, $\epsilon^W_{i(t+s)}$ and $\epsilon^L_{i(t+s)}$. First, the result from Proposition 8 shows that under certain conditions, $\Delta D_{ijt} = 1$ will lead to industry agglomeration. That is:

$$\mathbb{E}[N_{ij(t+s)}|\Delta D_{ijt} = 1] \neq \mathbb{E}[N_{ij(t+s)}|\Delta D_{ijt} = 0] \;\; \forall s \in \mathbb{N}$$

Furthermore, there is county and industry heterogeneity in industry agglomeration ef-

fects, even conditional on $\Delta D_{ijt} = 1$. Proposition 8 shows that

$$\mathbb{E}\left[N_{ij(t+s)} \mid \Delta D_{ijt} = 1, \frac{\partial L_{it}^S}{\partial W_{it}}, \frac{\partial L_{it}^\nu}{\partial W_{it}}, \frac{\Delta L_{it}}{L_{it}^\nu}\right] \neq \mathbb{E}\left[N_{ij(t+s)} \mid \Delta D_{ijt} = 1\right]$$

County and industry factors interacted with ΔD_{ijt} are correlated with future industry agglomeration, which affect future wage and employment growth.

Secondly, our model also implies local agglomeration effects of large establishment entry. That is, local non-tradeable labor demand rises as a result of large establishment entry.

$$\mathbb{E}[L_{ij(t+s)}^\nu | \Delta D_{ijt} = 1] \neq \mathbb{E}[L_{ij(t+s)}^\nu | \Delta D_{ijt} = 0]$$

Similar to our industry agglomeration effect, county and industry factors are correlated with future local agglomeration, which affect future wage and employment growth.

(In this way, it becomes very difficult for IV to work either. Instrument correlated with past entry is also correlated with error term.)

C.2 Proofs

C.2.1 Proof for Proposition 7

Proof. From Equation 3.6, we have:

$$\frac{\partial L_{it}^S}{\partial W_{it}} = \frac{\theta_2}{2s^w + \theta_2 k_i^H}$$

From the above, since θ_2 is increasing in α_i, we can conclude that $\frac{\partial L_{it}^S}{\partial W_{it}}$ is also increasing in α_i. Counties with higher amenities have higher labor supply response to changes in wages. Further, $\frac{\partial L_{it}^S}{\partial W_{it}}$ is decreasing in k_i^H.

$$\frac{\partial L_{it}^{\nu}}{\partial W_{it}} = \frac{y_1^{\nu} - 1}{2s^f + y_1^{\nu} k_i^H}$$

Since $1 > y_1^{\nu} > 0$, the numerator in the above is negative, while the denominator is positive. $\frac{\partial L_{it}^{\nu}}{\partial W_{it}}$ is also decreasing in k_i^H.

Substituting these expressions into Equation 3.17, we note that wage responses to large establishment entry are high in counties with low α_i, as these counties have a steep labor supply curve. Secondly, wage responses are high in counties with high k_i^H, as these counties have a steep labor supply curve and a steep nontradeable labor demand curve.

The size of the non-tradeable agglomeration effect on labor demand following large establishment entry in county i can be expressed as the following:

$$\frac{\Delta L_{it}/L_{it}^{\nu}}{\Delta N_{ijt}}_{|N_{ijt}=0} = \frac{L_i^0 + \Delta L_{it}^{\nu} + \bar{L}_j}{L_i^0 + \Delta L_{it}^{\nu}} \tag{C.1}$$

In the above, L_i^0 is equilibrium labor employed conditional on $\{N_{ijt}\} = 0$. We note that the size of the local agglomeration effect is declining in L_i^0. □

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Biography

Ding Xuan Ng was born in 1988, in Singapore.

Ding Xuan did his undergraduate work at the University of Chicago, and graduated with degrees in Mathematics and Economics in 2013. While an undergradaute, he was a Research Assistant for Hugo Sonnenschein and Harald Uhlig. His honors thesis at the undergraduate level was on the effect of migration from East to West Germany on regional and aggregate unemployment, under Rob Shimer.

After graduating, Ding Xuan started his PhD in Economics at Johns Hopkins University in 2013. He worked on his dissertation under the supervision of Anton Korinek and Robert Moffitt. He wrote a paper on calibrating a search-and-matching model to Singapore's labor market while a research intern at the Economics Policy Group of the Monetary Authority of Singapore. He was a Research Assistant for Anton Korinek as part of a working group on the economic costs of antimicrobial resistance, under a Johns Hopkins Discovery Award. He attended the 2016 Trento Summer School on 'Macroeconomic Coordination and Externalities'. He participated in Joseph Stiglitz's Institute for New Economic Thinking Workshop at the 2017 International Economics Association Congress in Mexico City, where he also presented work from Chapter 2 of this dissertation.

In the course of his graduate work, he was a Teaching Assistant for Robert Barbera's Elements of Macroeconomics course, Bruce Hamilton's Elements of Microeconomics course,

Anton Korinek's Theory of Macroeconomics course, Jonathan Wright's Investments course, and Muhammad Hussain's Labor Economics course. He was also the instructor for a course on International Monetary Economics in the Summer of 2018.