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Essays in Macroeconomics

A dissertation submitted in partial satisfaction of the requirements for the degree
Doctor of Philosophy

in

Economics

by

Myung Kyu Shim

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2014

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Chair

University of California, San Diego

2014

DEDICATION

To Bomie, Songjoo, and my parents.

TABLE OF CONTENTS

Dedication	iv
Table of Contents	v
List of Figures	vii
List of Tables	viii
Acknowledgements	ix
Vita	x
Abstract of the Dissertation	xi
Chapter 1. Interindustry Wage Differentials, Technology Adoption, and Job Polarization: Empirical Analysis	1
1.1. Introduction	2
1.2. Link between Job Polarization and Interindustry Wage Differentials	5
1.2.1. Interindustry Wage Differentials	5
1.2.2. Job Polarization	7
1.2.3. Job Polarization and Interindustry Wage Differentials: Link	10
1.3. Data	10
1.4. Empirical Analysis	11
1.4.1. Job Polarization: Link to initial wage premium?	12
1.4.2. Has ICT capital been substituted for workers?	20
1.4.3. Job Polarization and Interindustry Wage Differentials before 1980	24
1.5. Conclusion	27
1.6. Appendix: Additional Tables and Figures	27
Chapter 2. Interindustry Wage Differentials, Technology Adoption, and Job Polarization: Theory	34
2.1. Introduction	35
2.2. Related Literature	37
2.3. Model	39
2.3.1. Setup	40
2.3.2. Predictions of the Model: Steady-State Analysis	45
2.3.3. Tests of Predictions	47
2.4. Conclusion	48
2.5. Appendix	48
2.5.1. Unions: Microfoundation to Interindustry Wage Differentials	48
2.5.2. Equilibrium Conditions	51
2.5.3. Appendix: Proof of Proposition 1	53

Chapter 3. Precision of Market-Generated Information in Economies with Coordination Motives	56
3.1. Introduction	57
3.2. Coordination Economies	61
3.3. Asset Market	64
3.3.1. Demand, Supply and Equilibrium	64
3.3.2. Exogenous Dividend	64
3.3.3. Endogenous Dividend	65
3.3.4. Exogenous Private Precision and Price Precision	68
3.3.5. Exogenous Public Precision and Price Precision	69
3.4. Application: Endogenous Information Acquisition	70
3.4.1. Private Information Acquisition and Market Generated Information	71
3.4.2. Private Information Acquisition and Exogenous Precision of Public Information	77
3.5. Conclusion	80
3.6. Appendix: Proofs	81
3.6.1. Proof of Proposition 2	81
3.6.2. Proof of Proposition 3	81
3.6.3. Proof of Proposition 4	82
3.6.4. Proof of Proposition 5	83
3.6.5. Proof of Lemma 1	83
3.6.6. General Payoff Function	85
References	86

LIST OF FIGURES

Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009	3
Figure 1.2: Job Polarization and Interindustry Wage Differentials	3
Figure 1.3: Persistency of Interindustry Wage Differentials: 1980 vs. 2009	6
Figure 1.4: Job Polarization	8
Figure 1.5: Growth Rate of Investment-Specific Technological Changes	9
Figure 1.6: Dynamic Responses of Firms to Interindustry Wage Differentials - Cognitive Occupations	13
Figure 1.7: Dynamic Responses of Firms to Interindustry Wage Differentials - Routine Occupations	14
Figure 1.8: Dynamic Responses of Firms to Interindustry Wage Differentials - Manual Occupations	14
Figure 1.9: Occupation-Specific Industry Wage Premium	18
Figure 1.10: ICT Capital per Worker to Initial Industry Wage Premium (1980- 2007)	21
Figure 1.11: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980- 2007)	22
Figure 1.12: Changes in Employment Share by Occupation across Industries be- tween 1960 and 1980	25
Figure 1.13: Job Polarization: Education	29
 Figure 2.1: Connection between Job Polarization and Interindustry Wage Differ- entials	 35
 Figure 3.1: Stability of Equilibria	 68

LIST OF TABLES

Table 1.1: Estimates of Employment Growth by Occupation Groups (1980-2009)	15
Table 1.2: Differences between Coefficients (1980-2009)	16
Table 1.3: Estimates of Employment Growth by Occupation Groups (1980-2007)	17
Table 1.4: Estimates of Employment Share by Occupation Groups (1980-2009)	20
Table 1.5: Estimates of Capital, Productivity, and Employment Growth (1980-2007)	22
Table 1.6: Estimates of Employment Growth by Occupation Groups (1960-1980 and 1980-2009)	25
Table 1.7: Census Industry Classification	30
Table 1.8: Census Industry Classification Continued.	31
Table 1.9: EU KLEMS Industry Classification	31
Table 1.10: OLS Estimates of the Wage Regression in 1980	32
Table 1.11: Source of Wage Variation (R-Squared)	32
Table 1.12: Estimates of Employment Growth by Occupation Groups (1980-2006)	32
Table 1.13: Occupation-Specific Industry Wage Premia in 1980	33

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ABSTRACT OF THE DISSERTATION

Essays in Macroeconomics

by

Myung Kyu Shim

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Professor Valerie A. Ramey, Chair

This dissertation consists of two papers in the field of Macro Labor and one paper in the field of global games. In particular, the first two chapters focus on studying why the progress of job polarization has been different across industries between 1980 and 2010 and the last chapter analyzes the interaction between the precision of exogenous and market-generated information in coordination economies.

The first chapter empirically explores the relationship between job polarization and interindustry wage differentials. By using the U.S. Census and EU KLEMS data, we find that the progress of job polarization between 1980 and 2009 was more evident in industries that initially paid a high wage premium to workers than in industries that did not. We argue that this phenomenon can be explained as a dynamic response of firms to interindustry wage differentials: firms with a high wage premium seek alternative ways to cut production costs by replacing workers who perform routine tasks with Information, Communication, and Technology (ICT) capital. The replacement of routine workers with ICT capital has become more pronounced as the price of ICT capital has fallen over the past 30 years. As a result, firms that are constrained to pay a relatively high wage premium have experienced slower growth of employment of routine workers than firms in low-wage industries, which led to heterogeneity in job polarization across

industries.

Then the second chapter proposes a theory that unveils the mechanism underlying the close relationship between job polarization and interindustry wage differentials, which is studied empirically in the first chapter. In particular, we develop a two-sector neoclassical growth model with three key features. First, industries differ in the wage rates they pay to workers. Second, routine workers are relative substitutes for capital while non-routine workers are relative complement to capital. Last, there is an exogenous investment-specific technology change. Main predictions of the model are that (1) job polarization is more evident and (2) capital-routine worker ratio increases more in the industry that pays higher wages to workers when there is an investment-specific technology change, which are consistent with the empirical findings in the first chapter.

In the last chapter, we study the interaction between the precision of exogenous and market-generated information in a class of economies where firms display coordination motives in presence of dispersed information and where the outcome of the coordination is traded in a competitive asset market á-la Grossman and Stiglitz (1980). We show that when more private information is injected in the coordination economy the equilibrium asset price becomes less informative. To showcase the relevance of our result we present an application to a problem of endogenous information choice where the “Knowing What Others Know” property of information acquisition derived by Hellwig and Veldkamp (2009) breaks down in presence of market-generated information.

Chapter 1

Interindustry Wage Differentials, Technology Adoption, and Job Polarization: Empirical Analysis

Abstract. This paper empirically explores the relationship between job polarization and interindustry wage differentials. Using the U.S. Census and EU KLEMS data, we find that the progress of job polarization between 1980 and 2009 was more evident in industries that initially paid a high wage premium to workers than in industries that did not. We argue that this phenomenon can be explained as a dynamic response of firms to interindustry wage differentials: firms with a high wage premium seek alternative ways to cut production costs by replacing workers who perform routine tasks with Information, Communication, and Technology (ICT) capital. The replacement of routine workers with ICT capital has become more pronounced as the price of ICT capital has fallen over the past 30 years. As a result, firms that are constrained to pay a relatively high wage premium have experienced slower growth of employment of routine workers than firms in low-wage industries, which led to heterogeneity in job polarization across industries.

1.1 Introduction

The structure of the labor market in the U.S. has changed dramatically over the past 30 years. One of the most prevalent aspects of the change is job polarization: employment has become increasingly concentrated at the tails of the skill distribution, while there has been a decrease in employment in the middle of the distribution. This hollowing out of the middle has been linked to the disappearance of jobs that are focused on routine tasks that can be easily replaced by machines.¹ In the U.S., routine occupations accounted for around 60 percent of total employment in 1981, while this share fell to 44 percent in 2010.²

While many previous studies have examined job polarization at the ‘aggregate’ level (see Goos et al. (2009), Acemoglu and Autor (2011), Cortes (2014), and Jaimovich and Siu (2013)), the extent of job polarization differs across industries (see Autor et al. (2003), Goos et al. (2013), and Michaels et al. (2013)). Figure 1.1 shows changes in employment share by industry between 1980 and 2009. In the figure, which we use the U.S. Census data, the horizontal axis denotes three occupational groups (each occupational group includes 16 industries and one aggregate variable) and the vertical axis denotes the change in employment share of a specific occupational group in each industry between 1980 and 2009. This figure demonstrates that job polarization is more pronounced in some industries than others. For instance, the decrease in the employment share of routine occupations is large in manufacturing, communication, and business related services, while the decrease is much smaller in transportation and retail trade.

This paper, contrary to other studies that focus on heterogeneity in production functions across industries (Autor et al. (2003), for instance), provides a new perspective to understand heterogeneity in job polarization. We argue that ‘interindustry wage differentials’, the phenomenon that observationally equivalent workers earn differently when employed in different industries, are a key source of heterogeneous job polarization across industries. Figure 1.2, using the U.S. Census data and American Community Survey (ACS), shows the relationship between job polarization and industry wage premium; high-wage industries in 1980 experienced large declines in the share of routine

¹As emphasized by Autor (2010), Goos et al. (2009), and Michaels et al. (2013), job polarization is not restricted to the U.S.; several European countries have experienced job polarization as well.

²Numbers are calculated from the March Current Population Survey.

workers between 1980 and 2009. i.e. job polarization was more evident in the high-wage industries.³

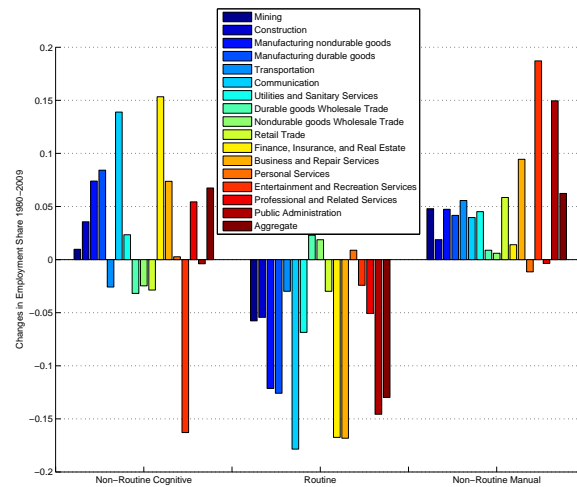


Figure 1.1: Changes in Employment Share by Industry between 1980 and 2009



Figure 1.2: Job Polarization and Interindustry Wage Differentials

We hypothesize a story to understand the relationship between job polarization and interindustry wage differentials as follows. Notice that interindustry wage differ-

³In the following figures with a circle, the size of a circle denotes the employment level of each industry in 1980.

entials imply that labor cost, product of employment (hours worked) and wage, is high for some industries to produce same amount of goods. As a result, high-wage firms have incentives to cut production cost. However, as is emphasized by Borjas and Ramey (2000), inter-industry wage structure is very persistent. Hence, as firms cannot adjust wages relative to those paid by other firms as they would wish to do, they try to change their demand for labor instead of changing wage structure by dynamically substitute labor with other production factors (eg. capital). This dynamic effort of the firm, however, affects workers in a disproportionate way because some occupations are more easy to replace by other production factors. In particular, routine occupations will decrease more intensively because they can be replaced easily by Information, Communication, Technology (henceforth, ICT) capital, which results in heterogenous job polarization across industries.⁴

We then formally test our hypothesis using U.S. Census and EU KLEMS⁵ data. Several findings emerge from the empirical analysis. Firstly, we find that the average growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 was higher by 10 percent, which is strictly greater than the estimates for non-routine occupations in absolute terms. In other words, job polarization was more apparent in the high-wage industries. We also find that ICT capital per worker grew more rapidly in high-wage industries; as the initial industry wage premium increased by 10 percent, the annualized growth rate of ICT capital per worker between 1980 and 2007 increased by 0.35 percent. We further find that the estimate for non-ICT capital per worker is much lower than the estimate for ICT capital per worker. This is consistent with non-ICT capital being a complement to all types of workers.

This study contributes to the existing literature on job polarization by aiding understanding of heterogeneity in job polarization across industries and its mechanism. In particular, this paper provides the first empirical evidence that polarized employment is connected with interindustry wage differentials.

The paper is organized as follows. Section 1.2 introduces two key concepts,

⁴This hypothesis is formalized with a two-sector neoclassical growth model in the companion paper, Shim (2014).

⁵KLEMS stands for capital (K), labor (L), energy (E), materials (M), and service inputs (S).

interindustry wage differentials and job polarization, and then explains the link between them, with reviews of related papers. Section 1.3 describes the data, while Section 1.4 presents empirical tests of the model's predictions. Section 3.5 concludes.

1.2 Link between Job Polarization and Interindustry Wage Differentials

In this section, we introduce interindustry wage differentials and job polarization in detail, with reviews of related studies, and explain the link between them.

1.2.1 Interindustry Wage Differentials

Persistent dispersion in wages across industries, which is referred to as 'interindustry wage differentials' or 'industry wage premia' interchangeably, has been one of the most challenging subjects in (competitive) labor economics. In order to understand why it is so puzzling from the perspective of competitive labor market equilibrium theory, it is useful to consider two workers with the same observable socio-economic characteristics (including education, age, race, occupation, region, and sex), but who work in different industries. Then, wages should be (at least in the long run) the same between the two workers in equilibrium. If wages differ, a worker in a low-wage industry will attempt to find a job in a high-wage industry; in equilibrium, this increases (resp. decreases) labor supply to high- (resp. low-) wage industries, and hence wages will be equalized in a competitive labor market. This notion, however, of a competitive labor market is not supported by the data; for instance, a worker employed in the petroleum-refining industry earned about 40 percent more than a worker employed in the leather-tanning and finishing industry in 1984 after controlling for all observables (Krueger and Summers (1988)). On top of that, the wage dispersion is not a transitory perturbation from the competitive equilibrium. To demonstrate this, we compute the industry wage premia in 1980 and 2009 separately with a typical wage equation, which regresses log wage over various socio-economic characteristics and industry fixed effects, and draw a scatter plot of the two sets of industry fixed effects in Figure 1.3. It then becomes apparent that industries that paid relatively high wages in 1980 also paid

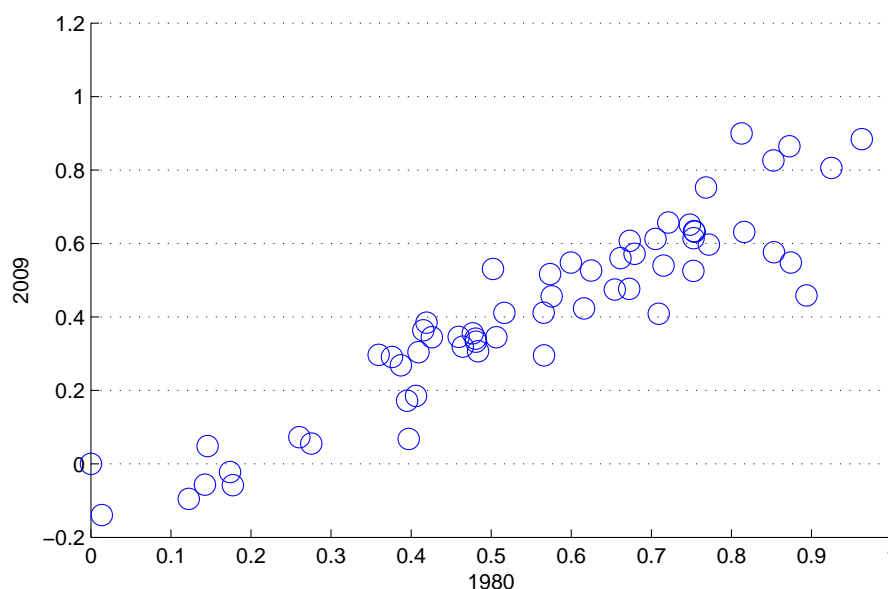


Figure 1.3: Persistency of Interindustry Wage Differentials: 1980 vs. 2009

Source: The U.S. Census and American Community Survey (ACS).

high wages in 2009, which implies that the structure of interindustry wage differentials is highly persistent. We also find, as Dickens and Katz (1987) show, that an industry variable has been a consistently important factor in explaining wage differentials.⁶

Since the focus of our paper is to study the ‘consequences’ of interindustry wage differentials, we simply point out that both our model and empirical results are based on non-competitive labor market theories of industry wage premia, not on the competitive labor market theory.⁷ While there have been many studies focusing on the causes of

⁶We run the wage regression (1.1) for different periods (1980, 1990, 2000, and 2009) and compute the explanatory power of the wage equation with and without industry dummies, following Dickens and Katz (1987). Results are reported in Table 1.11. In particular, 4 percent to 16 percent of the wage variation is explained by industry. The sum of the explanatory power reported in the second and third row is not equal to the value reported in the first row since industries and covariates are not exactly orthogonal (Dickens and Katz (1987)). Interestingly, the explanatory power attributable to the industry is very stable and substantial over time, which implies that industry should be considered as an important factor in explaining wages.

⁷For example, ‘unobserved ability of workers’ (Murphy and Topel (1987)) is consistent with the competitive equilibrium theory. Krueger and Summers (1988), Borjas and Ramey (2000), and Blackburn and Neumark (1992), however, find evidence against this theory; for instance, Blackburn and Neumark (1992) show that their measure of unobserved ability (test scores) can account for only about one-tenth of the variation in interindustry wage differentials. Given that the competitive model cannot explain the industry wage premia well, we focus on non-competitive models. These theories include the rent-sharing model (Nickell and Wadhvani (1990), Borjas and Ramey (2000) and Montgomery (1991)) and the efficiency wage model (Walsh (1999) and Alexopoulos (2006)).

interindustry wage differentials, to our knowledge, there exists only one paper, Borjas and Ramey (2000), which studies their consequences. Borjas and Ramey (2000) find that industries that paid relatively high wages to workers in 1960 experienced (1) lower employment growth, and (2) a higher capital-labor ratio growth and higher labor productivity growth between 1960 and 1990. Our findings on the heterogeneous effects of firms' dynamic responses to interindustry wage differentials distinguish our paper from that of Borjas and Ramey (2000); while they focus on the 'average' effect of interindustry wage differentials on workers, our findings emphasize the importance of considering heterogeneity across different workers (occupations) in studies of the labor market.

1.2.2 Job Polarization

To be consistent with the job polarization literature, including Autor (2010), Acemoglu and Autor (2011), and Cortes (2014), we classify occupations into three groups as follows:

- Non-routine cognitive occupations: Managers, Professionals, and Technicians.
- Routine occupations: Sales, 'Office and administration', 'Production, crafts, and repair' and 'Operators, fabricators, and laborers'.
- Non-routine manual occupations: Protective services, 'Food preparation, building and grounds cleaning', and 'Personal care and personal services'.

Using the March Current Population Study (CPS) between 1971 and 2010,⁸⁹ we plot Figure 1.4 to show job polarization graphically¹⁰: while the employment share of non-routine cognitive (henceforth cognitive) and non-routine manual (henceforth manual) occupations have grown over time, that of routine occupations has decreased.

One intuitive reason behind job polarization, which is also important to understand our findings, is that the skill (task) content of each occupation is different. Among the three groups, routine occupations are the easiest to replace by ICT capital, as demonstrated by Autor et al. (2003); the tasks that workers with routine occupations perform

⁸Data were extracted from the IPUMS website: <http://cps.ipums.org/cps> (see King et al. (2010)).

⁹We apply the method of 'conversion factors' to obtain consistent aggregate employment series. See Shim and Yang (2013) for detailed discussion on the method of conversion factors.

¹⁰The shaded regions are the official NBER recession dates.

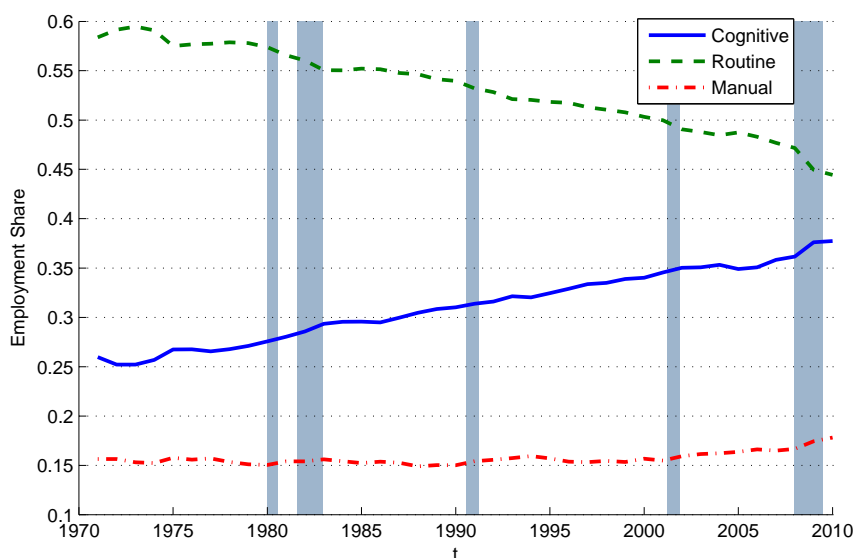


Figure 1.4: Job Polarization

Source: The March CPS.

are easier to codify than other tasks because the tasks have routine procedures. Meanwhile, cognitive and manual occupations are not easily replaced by ICT capital. For instance, business decisions of managers (cognitive occupations) cannot be replaced by technology; introduction of technology, such as advanced software, does not substitute for these managers, rather it is a complement to their tasks. In addition, people involved in cooking, or cleaning buildings (manual occupations) cannot be directly replaced by machines; these jobs require humans to do non-routine manual tasks. Instead, a great portion of the tasks that a bank clerk performs, which are included in routine occupations, are easily replaced by an ATM; deposits and withdrawals are routine tasks, and machines can perform these tasks more efficiently than humans. Hence, these jobs disappear over time as the economy experiences rapid technological progress in ICT-type capital.¹¹ Consistent with this story, Figure 1.5 shows that investment-specific technological changes have mainly occurred for ICT capital rather than for other types of

¹¹As we mentioned earlier, ‘offshorability’ is also higher for routine occupations than for cognitive and manual occupations. Most of the service jobs (manual occupations) are not tradable and occupations that require non-routine cognitive tasks are not easily offshored while factories can be relatively easily relocated to foreign countries.

capital so that the relative price of ICT capital has declined more rapidly since 1970.¹²

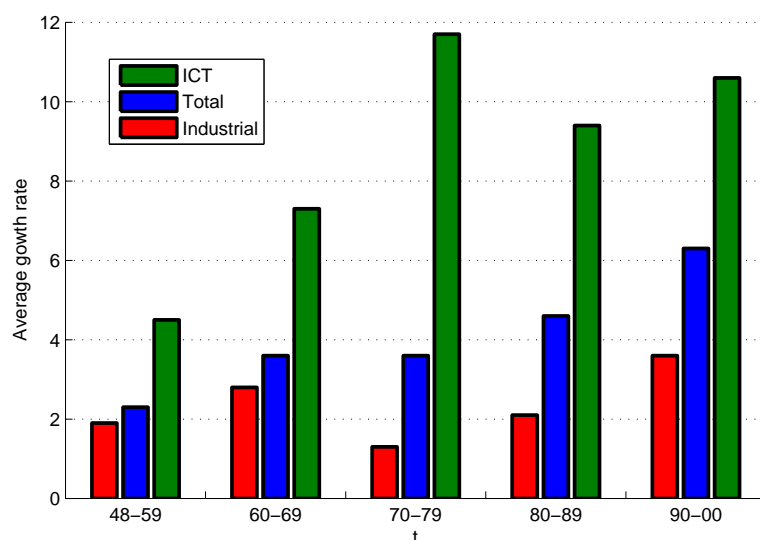


Figure 1.5: Growth Rate of Investment-Specific Technological Changes

Source: Data from Cummins and Violante (2002).

A few papers have studied the possibility of heterogeneous job polarization across industries.¹³ Acemoglu and Autor (2011) argue that changes in industrial composition do not play an important role in job polarization. Jaimovich and Siu (2013) and Foote and Ryan (2012) note that job polarization may be more pronounced in the construction and manufacturing industries. While Autor et al. (2003) and Goos et al. (2013) also consider possible differences in job polarization across industries, they do not consider wage differentials as the source of heterogeneity. Rather, they assume different production functions across industries. Michaels et al. (2013) is also relevant to our study: they show that industries with a high growth rate of ICT capital exhibit more pronounced job polarization in terms of the shifting of wage bills from middle-educated workers to highly-educated workers. Our paper, however, differs from that of Michaels et al. (2013) in two ways. Firstly, they consider different education groups while we instead consider different occupation groups. This distinction makes a difference in the subse-

¹²The timing that the growth rate of investment-specific technological changes increases does not perfectly match the occurrence of job polarization, which is usually said to be after 1980. Consistently with this timing problem, we show in Section 1.4.3 that job polarization also occurred, while the magnitude was small, before 1980.

¹³Some recent papers, including Mazzolari and Ragusa (2013), Autor et al. (2013a) and Autor et al. (2013b), analyze job polarization at the local labor market level.

quent analysis since ‘employment’ polarization is not observed when we use educational attainment to classify workers.¹⁴ Secondly, while Michaels et al. (2013) found a positive relationship between the growth rate of ICT capital and the degree of job polarization, they do not link them to interindustry wage differentials.

1.2.3 Job Polarization and Interindustry Wage Differentials: Link

Our key contribution is to understand the role of interindustry wage differentials and the different ‘task content’ of occupations. Cost of labor is the product of wage and employment, and it is not possible for high-wage firms to reduce the wage gap with low-wage firms because of the rigid wage structure by which they are constrained. As a consequence, the only way to respond to a high labor cost is to adjust employment over time and this can be achieved by hiring alternative production factors, as Borjas and Ramey (2000) found.

In particular, as technology improves, the price of ICT capital becomes lower, and firms with incentives to adjust employment will decrease relative demand for routine workers by replacing them with ICT capital. As a result, firms in a high-wage industry will experience more evident job polarization as the demand for routine workers declines more in these firms. In addition, the ICT capital-labor ratio rises by a greater amount than in a low-wage industry since more ICT capital is introduced to substitute for routine workers.

In summary, our hypothesis on the different degrees of job polarization across industries is as follows. Since firms cannot adjust wages relative to those paid by other firms as they would wish to do, they dynamically substitute labor with capital. In particular, routine occupations will decrease more intensively because they can be replaced easily by ICT capital, which results in heterogenous job polarization across industries.

¹⁴In Figure 1.13, we plot the employment series by each educational group, following Michaels et al. (2013).

1.3 Data

There are two main sources of data for this paper: (1) the decennial Census and American Community Survey (henceforth, ACS) data,¹⁵ and (2) the EU KLEMS data. Following Borjas and Ramey (2000) and Acemoglu and Autor (2011), we use the 1960, 1970, 1980, 1990, and 2000 Census and the 2006, 2007, and 2009 ACS. As Acemoglu and Autor (2011) note, the relatively large sample size of the Census data makes fine-grained analysis within detailed demographic groups possible.¹⁶ We drop farmers (and related industries) and the armed forces. Age is restricted to 16 - 64 and we only consider persons employed in wage-and-salary sectors. Table 1.7 in Appendix 1.6 describes the industry classification used in the analysis.

The second data set, EU KLEMS, has information on value added, labor, and capital for various industries in many developed countries, including the U.S.. The EU KLEMS is useful since it provides detailed information on capital: in the data, capital is divided into two parts, ICT capital and non-ICT capital, so we can analyze the roles of different types of capital in a firm's behavior. In particular, we use U.S. data between 1980 and 2007, where industries are defined according to the North American Industry Classification System of the United States (henceforth, NAICS). Since the industry classification is different from the Census data, we reclassify industries to be consistent between the Census and the EU KLEMS data. Table 1.9 in Appendix 1.6 describes the industry classification for the EU KLEMS data used in the analysis.

In order to overcome the inconsistency problem of occupation codes due to the frequent changes in occupation coding in the CPS and to construct a consistent occupation series,¹⁷ we use the 'occ1990dd classification system', following Dorn (2009).

1.4 Empirical Analysis

In order to formally test the our hypothesis, we first estimate industry wage premia as follows.

¹⁵Data were extracted from the Integrated Public Use Microdata Series (henceforth, IPUMS) website: <https://usa.ipums.org/usa> (Ruggles et al. (2010)).

¹⁶In determining the size of the sample, we follow Acemoglu and Autor (2011): 1 percent of the U.S. population in 1960 and 1970 and 5 percent of the population in 1980, 1990, and 2000.

¹⁷For detailed discussion on the inconsistency issue, see Dorn (2009) and Shim and Yang (2013).

$$\log w_{hit} = X_{hit}\beta_t + \omega_{it} + \varepsilon_{hit} \quad (1.1)$$

where w_{hit} is the wage rate of worker h in industry i in Census year t ; X_{hit} , a vector of socio-economic characteristics, includes the worker's age (there are five age groups: 16-24, 25-34, 35-44, 45-54, or 55-64), educational attainment (there are five educational groups: less than nine years, nine to 11 years, 12 years, 13 to 15 years, or at least 16 years of schooling), race (indicating if the worker is African-American¹⁸), sex, and region of residence (indicating in which of the nine Census regions the worker lives). We also control for three occupation dummies (cognitive, routine, and manual occupation groups). ω_{it} , an industry fixed effect, measures the industry wage premia.

The result of equation (1.1) in 1980 is reported in Table 1.10 and the coefficients are estimated to be consistent with the usual intuition: 1. African-Americans earn less, 2. wages are strictly increasing in education, and 3. wages also rise in ages until workers reach prime age, and then decrease slightly. After we obtain the estimated coefficients for 60 industry fixed effects from equation (1.1), $\hat{\omega}_{it}$, we estimate the second-stage regression as follows:

$$\Delta y_{ijt} = \theta_j \hat{\omega}_{it} + \eta_{ijt} \quad (1.2)$$

where y_{ijt} is the variable of interest such as employment of occupation group j in industry i .¹⁹ Δy_{ijt} is the annualized (average) growth rate of y_{ijt} between period t and $t + k$, and $j \in \{cognitive, routine, manual\}$. The average growth rate is $\Delta y_{ijt} = (\log(y_{ij,t+k}) - \log(y_{ijt})) / k$. We estimate equation (1.2) separately for cognitive, routine, and manual occupations.

Note that we use the estimated value, $\hat{\omega}_{it}$, as a regressor in the second-stage regression, which raises a concern about the generated regressor problem. In particular, it is possible that the error term in equation (1.2) is heteroscedastic. In order to address this issue, we weigh the regression by the initial (i.e., 1980) employment of each industry. In addition, the large sample size of the Census data weakens the generated regressor problem - there are at least 1,000 observations in each cell of occupation j in indus-

¹⁸Further classification is not possible in our data.

¹⁹In this case, $y_{ijt} = k_{it}/N_{it}$, since capital is not occupation-specific.

try i in Census year t .²⁰ Furthermore, in order to address the potential endogeneity of the wage premium and to account for the generated regressor problem, we also use the previous decade's estimated industry wage premium as an instrumental variable (IV).

1.4.1 Job Polarization: Link to initial wage premium?

In this section, we analyze if firms' dynamic responses to interindustry wage differentials have caused different degrees of job polarization across industries. Suppose that, contrary to our argument, there is no link between interindustry wage differentials and job polarization. Then, the coefficients on $\hat{\omega}_{it}$ estimated by equation (1.2) would not differ from each other, i.e., the subsequent employment growth of each occupational group does not react differently to interindustry wage differentials. If our hypothesis is right, however, we should observe $|\theta_r| > |\theta_c|, |\theta_m|$ and $\theta_r < 0$, where r are routine, c are cognitive, and m are manual occupations, respectively.

Figures 1.6 to 1.8 show graphically how initial industry wage premia are related to the subsequent employment growth of each occupational group. The horizontal axis is the 1980 industry wage premium, which is estimated using equation (1.1). The vertical axis denotes the average employment growth rate of each occupational group by industry between 1980 and 2009. We can observe that the slope of the fitted line is the steepest in Figure 1.7, which supports the hypothesis that firms with high wages changes their demand for labor more dramatically and it mostly affects routine workers. Interestingly, Figure 1.8 shows that there is no relationship between initial industry wage premia and subsequent employment growth in manual occupations. We will return to this issue later.

Table 1.1: Estimates of Employment Growth by Occupation Groups (1980-2009)

Occupation Groups	OLS		IV	
	Coefficient	R-Squared	Coefficient	R-Squared
Total	-0.0381*** (0.0073)	0.24	-0.0331*** (0.0069)	0.24
Cognitive Occupations	-0.0252*** (0.0071)	0.14	-0.0197*** (0.0066)	0.13
Routine Occupations	-0.0421*** (0.0090)	0.21	-0.0412*** (0.0086)	0.21
Manual Occupation	0.0117(0.0137)	0.03	0.0206* (0.0114)	0.13

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

²⁰For more detailed discussion on the generated regressor problem, see Wooldridge (2001).

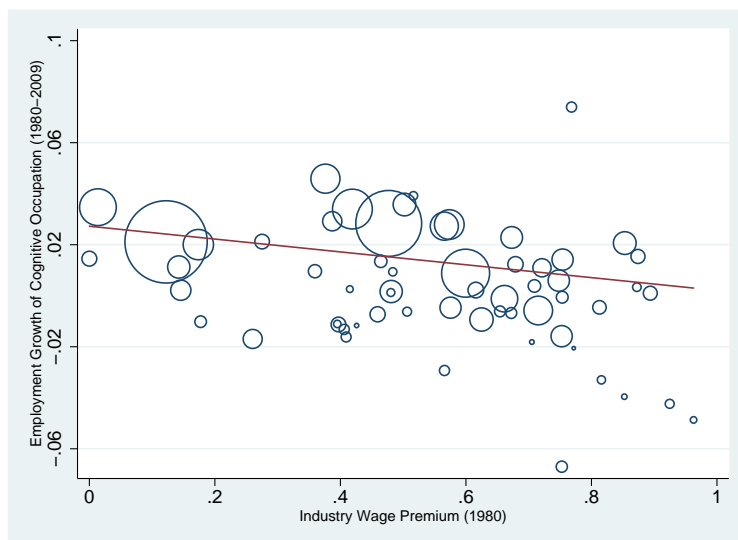


Figure 1.6: Dynamic Responses of Firms to Interindustry Wage Differentials - Cognitive Occupations

Source: The U.S. Census and American Community Survey (ACS).

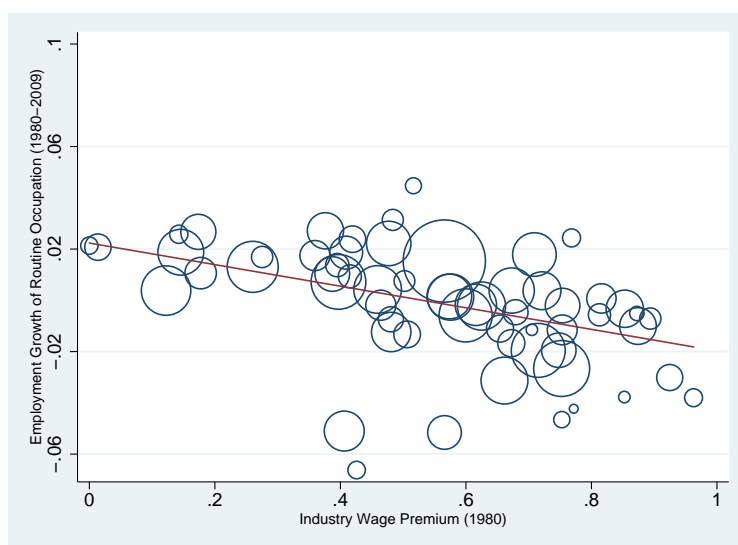


Figure 1.7: Dynamic Responses of Firms to Interindustry Wage Differentials - Routine Occupations

Source: The U.S. Census and American Community Survey (ACS).

The main empirical finding with 60 industries based on equation (1.2) is reported in Table 1.1. The first row reproduces Borjas and Ramey (2000) for a different period, 1980-2009, where the dependent variable is the average (annualized) growth rate of

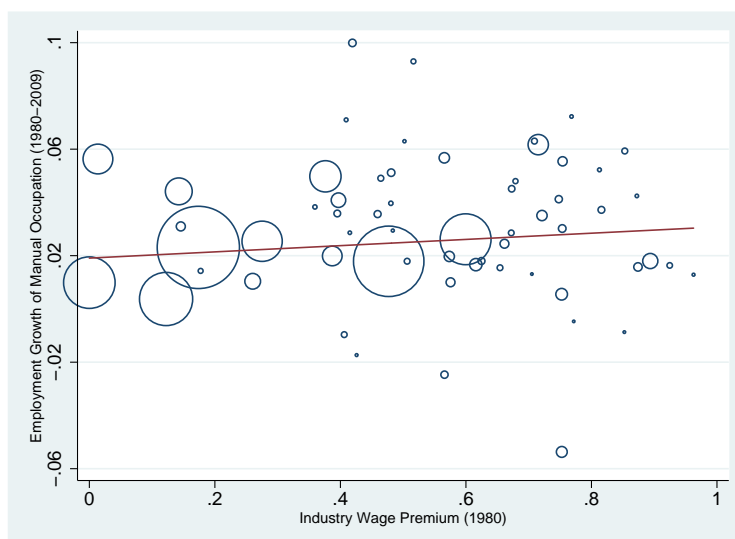


Figure 1.8: Dynamic Responses of Firms to Interindustry Wage Differentials - Manual Occupations

Source: The U.S. Census and American Community Survey (ACS).

aggregate employment for industry i . In the second, third, and fourth rows, we report the estimation of equation (1.2), where the dependent variable is the average growth rate of employment for occupation j in industry i between 1980 and 2009.

When estimating equation (1.2) for each occupation, the initial industry wage premium does not vary by occupations: i.e., in this case the industry wage premium ($\hat{\omega}_{i,1980}$) does not depend on occupations. In this sense, the regression results reported in Table 1.1 reveal how ‘average’ industry wage premia affect different occupational groups in a distinct manner.

The IV estimates are also reported in Table 1.1. Both the ordinary least squares (henceforth, OLS) and IV regressions yield similar coefficients, which implies that measurement errors in the estimated $\hat{\omega}_{it}$ and the generated regressor problem are not severe. The estimate reported in the first row confirms the robustness of the main finding of Borjas and Ramey (2000) in the sense that their finding is also observed in a different period.²¹ Firms with high initial industry wage premia see larger reductions in demand for labor over time, which is in sharp contradiction to the competitive equilibrium theory. The annualized growth rate of total employment between 1980 and 2009 decreased

²¹Borjas and Ramey (2000) use Census data between 1960 and 1990.

by 0.38 percent when the initial industry wage premium in 1980 increased by 10 percent. For the competitive equilibrium theory to be supported by data, the estimated coefficients should be positive, but the results in Table 1.1 show the opposite sign.

The estimated coefficients reported in the second to fourth rows in Table 1.1 are consistent with Figures 1.6 to 1.8. The average growth rate of routine employment between 1980 and 2009 decreased by 0.42 percent when the initial industry wage premium in 1980 increased by 10 percent, while the average growth rate of cognitive employment decreased by 0.25 percent. That is, the coefficient for the routine occupation group is negative and the highest in absolute value. The coefficient for the cognitive occupation group is also negative, and is still statistically significant, while it is much smaller than the coefficient for the routine occupation group. Furthermore, the OLS estimate confirms that the initial industry wage premium does not have any significant impact on the subsequent employment growth rate of the manual occupation group, as we observe from Figure 1.8.

We test if these coefficients are significantly different from each other. The test statistics reported in Table 1.2 confirm our hypothesis²²; at the 5 percent significance level, θ_r is not equal to either θ_c or θ_m ²³, and hence the firm's response to the initial industry wage premium is not uniform across different occupations. In summary, routine occupations are more affected by the firm's decreasing labor demand than are the cognitive and manual occupation groups. Our findings re-emphasize the importance of recognizing the heterogeneity of workers (occupations) in studies of the labor market.

Table 1.2: Differences between Coefficients (1980-2009)

	p-value (OLS)	p-value (IV)
Null: $\theta_c = \theta_r$	0.042	0.008
Null: $\theta_m = \theta_c$	0.007	0.000

One might raise concerns that the results might be exaggerated by the great re-

²²To test whether the coefficients in Table 1.1 are significantly different from each other, we pool cognitive, routine, and manual occupational data and estimate the coefficients for the interaction terms of routine occupation x industry wage premium and manual occupation x industry wage premium (omitting the interaction terms of cognitive occupation x industry wage premium) in one regression (where standard errors are clustered by industry) instead of running a regression separately for cognitive, routine, and manual occupations.

²³ θ_r is greater than θ_c in absolute terms and hence, θ_r is different from θ_m from the second row of the table.

cession that occurred at the end of 2007, which disproportionately affected employment of routine occupations (Jaimovich and Siu (2013)). In order to address this issue, we estimate the same regression with a sample period between 1980 and 2007, which is reported in Table 1.3. The results are almost identical to those reported in Table 1.1: the subsequent employment growth of routine occupations between 1980 and 2007 is still decreasing in the initial industry wage premium and its coefficient is the greatest in absolute terms. In Table 1.12, we also conduct the same exercise with a sample period between 1980 and 2006 and the results are largely unaffected by this change.

Table 1.3: Estimates of Employment Growth by Occupation Groups (1980-2007)

Occupation Groups	OLS		IV	
	Coefficient	R-Squared	Coefficient	R-Squared
Total	-0.0431*** (0.01)	0.23	-0.0369*** (0.0093)	0.22
Cognitive Occupations	-0.0259*** (0.0083)	0.12	-0.0195*** (0.0076)	0.11
Routine Occupations	-0.0412*** (0.0097)	0.18	-0.0387*** (0.0095)	0.18
Manual Occupations	-0.0005 (0.0154)	0.00	0.0105 (0.0136)	0.00

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In addition, as a robustness check for using the same industry wage premium for different occupation groups, we also consider an occupation-specific industry wage premia, denoted as ω_{ijt} , which is the wage premium of occupation j in industry i . Suppose that routine occupations are paid more highly than cognitive and manual occupations in the high-wage industry. Then, it becomes natural for firms in this industry to reduce their demand for routine occupations simply because they are paid more than other occupations; we call this narrative the ‘relative price’ explanation. The ‘task-based’ explanation may not be appropriate if the relative price explanation is true (while the property of tasks required by routine occupations may enhance the firm’s dynamic responses to interindustry wage differentials, it may not be of the first order). In order to address these issues, we estimate the following alternative wage equation:

$$\log w_{hit} = X_{hit}\beta_t + \underbrace{\omega_{it} \times \psi_{jt}}_{=\omega_{ijt}} + \varepsilon_{hit} \quad (1.3)$$

where ω_{it} is the industry fixed effect and ψ_{jt} is the occupation fixed effect. Thus, $\omega_{it} \times \psi_{jt}$ is the interaction of each industry premium and each occupation dummy. We call this the

‘occupation-specific industry wage premium’. In this alternative wage equation, we do not include the own fixed effect terms - ω_{it} and ψ_{jt} . By regressing the above equation, we obtain information about the extent to which an occupation group in a specific industry earns more than the same occupation group employed in other industries, and this also allows for within-industry comparisons of the wage premia.

Figure 1.9 depicts occupation-specific industry wage premia by industry. The horizontal axis denotes industries in order of size of the average industry wage premium. In order to see how the average industry wage premium (ω_{it}) and the occupation-specific industry wage premium (ω_{ijt}) are related, we sort industries by the initial industry wage premium in ascending order. To the left, there are low-wage industries, such as hotels and lodging places, and to the right, there are high-wage industries, such as mining or investment. All values are estimated in 1980, which is the reference year of our study.

Figure 1.9, which we use the U.S. Census and American Community Survey (ACS), shows that the occupation-specific industry wage premium rises almost monotonically in the average industry wage premia for cognitive and routine occupation groups, while there is much variation in the manual occupation-specific industry wage premium. This is one of the reasons that the effect of the average industry wage premium on the manual occupations is almost negligible; even when firms face relatively higher industry wage premia, firms may not pay high wages to workers who perform manual tasks; i.e., even in the high-wage industries, people employed in manual occupations are not paid much relative to those employed in low-wage industries. For example, the ‘security, commodity brokerage, and investment companies industry’ (on the right in Figure 1.9) paid manual occupation workers less than quite a few other industries. As a result, the wage pressure from the manual occupation group is not large for firms compared to that for other occupation groups. Therefore, firms have less incentive to decrease their labor demand for manual occupations when facing high wages, which is represented by the insignificant coefficient reported in Table 1.1.

Note again that the findings in Table 1.1 offer two explanations. The first is the ‘task content’ explanation: as routine jobs can be easily replaced by other production factors, demand for routine occupations is more sensitive to the initial industry wage premium. The second argument is the ‘relative price’ explanation: if the routine oc-

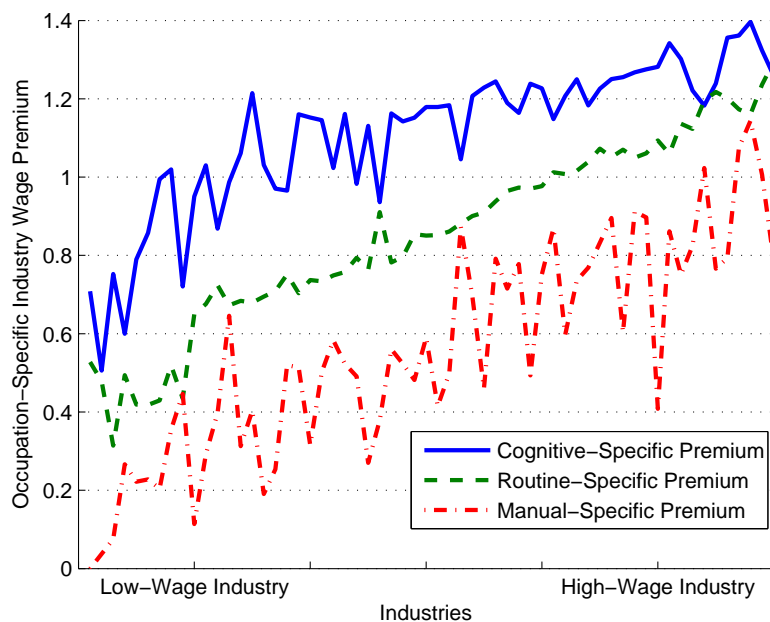


Figure 1.9: Occupation-Specific Industry Wage Premium

Note: We order industry by the industry wage premium obtained by equation (1.1).

cupations are paid more than other groups after we control for industry, firms would decrease their demand for the routine occupation group since this group is actually the most expensive production factor. The latter explanation weakens our preferred story that links job polarization and interindustry wage differentials. Figure 1.9, however, shows that the ‘relative price’ explanation is not supported by the data: in any industry, we observe that $\omega_{ict} > \omega_{irt} > \omega_{imt}$, which means that the cognitive occupations are paid the most, followed by the routine and manual occupations. Hence, we can exclude the possibility that the subsequent employment growth of routine occupations is lower than other occupation groups because they were paid relatively more than other groups.²⁴

As a robustness check, we estimate the same second-stage regression with a different dependent variable, the changes in employment share of occupation groups. As

²⁴One interesting finding is that the slope of the line in Figure 1.9 is steeper for routine occupations than for cognitive occupations. In the end, the gap between the cognitive occupation-specific industry wage premium and routine occupation-specific industry premium becomes almost zero. This fact implies that while cognitive occupations are paid more than routine occupations, there is a tendency for high-wage industries to actually pay relatively more for the routine occupations than low-wage industries. This feature may have a ‘price’ effect on our estimates, but given that the level of the cognitive occupation-specific industry wage premium is highest for any industry, we do not analyze this further, since its effect may be limited.

shown in Table 1.1, the employment growth of routine occupations has been lower than that of cognitive and manual occupations for the last 30 years. As a result, the employment share of routine occupations has declined while the share of at least one of either the cognitive or manual occupations has increased. Thus, we should observe that (1) the change in employment share of routine occupations is negatively related to the initial industry wage premium and, (2) the change in employment share of cognitive or manual occupations is (weakly) positively related to the initial industry wage premium. In estimating equation (1.2), we set $\Delta y_{ijt} = es_{ij,t+k} - es_{ijt}$, where es_{ijt} is the employment share of occupation j in industry i at t , where the number of industries is 60 and $t = 1980$. Table 1.4 summarizes the results of the alternative estimation. IV estimates are also reported in Table 1.4. The overall result is, not surprisingly, quite similar.

Table 1.4: Estimates of Employment Share by Occupation Groups (1980-2009)

Occupation Groups	OLS		IV	
	Coefficient	R-Squared	Coefficient	R-Squared
Cognitive Occupations	0.0076(0.0802)	0.00	0.0119(0.0808)	0.00
Routine Occupations	-0.1833*** (0.0572)	0.19	-0.2421*** (0.0599)	0.16
Manual Occupations	0.1306(0.0960)	0.13	0.1813** (0.0797)	0.11

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Firstly, the employment share of routine occupations decreases more in industries with a high initial wage premium, which is consistent with the fact that the subsequent employment growth of the routine occupation group decreases in the initial industry wage premium during 1980-2009. Secondly, the coefficient for manual occupations is now much greater than zero in both the OLS and IV regressions, while the coefficient for cognitive occupations is estimated to be almost zero. This is because (1) the negative responsiveness of the employment growth of cognitive occupations to the initial industry wage premium was not large compared to that of routine occupations, and (2) there was basically no correlation between the subsequent employment growth of manual occupations and the initial industry wage premium. Similarly to Table 1.2, we find that the coefficient for routine occupations is statistically different to that for cognitive occupations.

1.4.2 Has ICT capital been substituted for workers?

We now test another dimension of our hypothesis: ICT capital per worker grows more in high-wage industries than in the low-wage industries. This is because (1) routine workers are substituted by ICT capital and (2) overall demand for labor declines more in the high-wage industries. In addition, we also test if the growth rate of ICT capital per worker is different from that of non-ICT capital per worker. If non-ICT capital is general-purpose capital when compared to ICT capital, which substitutes for routine workers, the coefficients from the regression would be lower for non-ICT capital per worker than for ICT capital per worker.

Notice that the growth rate of the capital level may not be negatively related to the initial industry wage premium. If the size of an industry shrinks as labor demand decreases, capital demand itself might also decrease. If the rate at which the demand for capital decreases is lower than the rate at which the demand for labor decreases, the resulting capital-labor ratio grows in the industry wage premium.

For the analysis, we use the EU KLEMS database. We restrict our attention to U.S. data between 1980 and 2007. Since it provides information on 29 industries, we recompute the initial industry wage premium in 1980 by reclassifying the Census 60 industries into 29 industries.²⁵ Details on the classification can be found in Table 1.9. Each capital series (capital, ICT capital, and non-ICT capital) is real fixed capital stock based on 1995 prices. In order to obtain capital per worker series, we divide capital by employment for each industry where employment variable is also provided by EU KLEMS. We first show graphical evidence and then formally test the prediction of the model.

Our figures confirm our hypothesis. Firstly, Figure 1.10 shows a positive relationship between the initial industry wage premium in 1980 and the subsequent annualized growth rate of ICT capital per worker between 1980 and 2007. It supports our hypothesis that firms increase demand for ICT capital in order to substitute (certain types of) workers because of the wage burden. Figure 1.11, however, suggests that changes in non-ICT capital per worker between 1980 and 2007 may not be precisely related to

²⁵EU KLEMS also provides data with more detailed industry classifications, with more than 50 industries (using the SIC Industry classification) between 1977 and 2005. We, however, do not use this classification, since we need to classify industries in a discretionary manner.



Figure 1.10: ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

Source: The EU KLEMS and The U.S. Census.



Figure 1.11: Non-ICT Capital per Worker to Initial Industry Wage Premium (1980-2007)

Source: The EU KLEMS and The U.S. Census.

interindustry wage differentials.

For the complete analysis, we estimate equation (1.4) with 29 industries following EU KLEMS classification.

$$\Delta y_{it} = \theta \hat{\omega}_{it} + \eta_{it} \quad (1.4)$$

where y_{it} is capital per worker or capital level or employment in industry i at time t .

Table 1.5: Estimates of Capital, Productivity, and Employment Growth (1980-2007)

Dependent	OLS		IV	
	Coefficient	R-Squared	Coefficient	R-Squared
Capital/Worker	0.0145(0.0134)	0.05	0.0138(0.0139)	0.05
ICT Capital/Worker	0.0350*(0.0190)	0.09	0.0400*** (0.0171)	0.09
Non-ICT Capital/Worker	0.0037(0.0136)	0.00	0.0030(0.0144)	0.004
Capital	-0.0201*(0.0110)	0.10	-0.0181(0.0114)	0.10
ICT Capital	0.0004(0.0217)	0.00	0.0081(0.0204)	0.000
Non-ICT Capital	-0.0308*** (0.0107)	0.25	-0.0289*** (0.0115)	0.25
Output	-0.0055(0.0089)	0.01	-0.0044(0.0087)	0.01
Labor Productivity	0.0290*** (0.0089)	0.22	0.0275*** (0.0091)	0.22
Employment	-0.0345*** (0.0076)	0.27	-0.0319*** (0.0072)	0.27

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We first note that labor productivity is obtained by dividing output by employment. The OLS and IV results are reported in Table 1.5, which are quite similar. Before we discuss the main result, we first focus on the last row, in which the dependent variable is the average employment growth rate. The estimate using the EU KLEMS data is similar to the coefficient obtained from the Census data (See Table 1.1), which confirms the robustness of our findings.

The relevant coefficients for different types of capital are presented in the first three rows. As the initial industry wage premium increased by 10 percent, the annualized growth rates of aggregate ICT capital per worker, ICT capital per worker, and non-ICT capital per worker between 1980 and 2007 increased by 0.14 percent, 0.35 percent, and 0.03 percent, respectively. As expected, we confirm the relationship among the coefficients as follows: $\theta_{ICT} > \theta_{Aggregate} > \theta_{non-ICT}$. Furthermore, only θ_{ICT} is statistically significant. Hence, we conclude that firms respond dynamically to wage pressure by increasing demand for ICT capital, but not all types of capital, because only ICT capital can be replaced with routine workers. This finding is consistent with Michaels et al. (2013). They show that job polarization is more evident in industries that experience higher ICT capital growth; in so doing, they treat ICT capital growth as an exogenous change given to each industry without providing an answer as to why some industries

have experienced rapid ICT capital growth while others have not. Hence, our finding makes a unique contribution to this literature by showing that the asymmetric rises in ICT capital (per worker) across industries over the last 30 years may be the result of the endogenous responses of firms to interindustry wage differentials. Some industries exhibit more apparent job polarization since firms in these industries have higher incentives to hire more ICT capital in production than firms in other industries, and the incentives increase in the initial industry wage premium that the industry encountered.

In this sense, our finding provides evidence of ‘directed technology changes’ suggested by Acemoglu (2002): some firms have increased demand for ICT capital because the business environment pushes these firms to use ICT capital more extensively. Acemoglu and Autor (2011) also point out the possibility that directed technology changes may have contributed to job polarization during the past 30 years. Our findings suggest that an environment of interindustry wage differentials has generated the different degrees of job polarization across industries.

The fourth to the sixth rows in Table 1.5 confirm our earlier discussions and they are also consistent with other estimation results. Firstly, both capital and non-ICT capital decrease in the initial industry wage premium; firms with a relatively high initial wage premium demand less capital because they want to reduce the firm’s size. Together with the fact that these industries also decrease demand for labor, capital per worker and non-ICT capital per worker seem not to respond to interindustry wage differentials. ICT capital, however, is not affected by the initial industry wage premium because it plays an important role in a firm’s subsequent behavioral changes; as a result, ICT capital per worker rises more in industries with a high initial industry wage premium.

Furthermore, we find that the growth rate of labor productivity increases in the initial wage premium, which is consistent with Borjas and Ramey (2000). This is evidence supporting the claim that firms have dynamically substituted workers with more efficient technologies when they faced relatively high wages.

1.4.3 Job Polarization and Interindustry Wage Differentials before 1980

Interindustry wage differentials have been observed to have been occurring even prior to 1980; for instance, the benchmark estimation of Borjas and Ramey (2000) is based on the industry wage premium in 1960. Then, the natural question is whether or not the job polarization is also observed for the period prior to 1980; our theory explaining the heterogeneous aspects of job polarization across industries is based on firms' dynamic responses to interindustry wage differentials, and hence the occurrence of heterogeneous job polarization should be observed whenever an industry wage premium exists and alternative technology to replace (routine) workers is available. To address this issue, Figure 1.12 shows the changes in employment share of each occupation group across industries, between 1960 and 1980. Here, the horizontal axis denotes three occupation groups (each occupation group includes 16 industries and one aggregate variable) and the vertical axis denotes the change in employment share of a specific occupation group in each industry between 1960 and 1980. We still observe that the employment share of routine occupations decreased in most industries, which suggests the possibility of the existence of job polarization during 1960-1980, although its extent is smaller: overall, the employment share of the routine occupation group decreased by about 5 percent between 1960 and 1980, while it decreased by more than 10 percent between 1980 and 2009.

Again, we estimate equation (1.2) for the period between 1960 and 1980. We first estimate the wage equation (1.1) with the 1960 Census data to obtain the industry wage premium in 1960. In Table 1.6, we compare the OLS estimates for the two different periods.²⁶ The estimated coefficients for the earlier period (1960-1980) are reported in the first two columns and those for the latter period (1980-2009) are reported in the last two columns, which are repeated from Table 1.1 for comparison.

While the coefficient for the total employment growth rate between 1960 and 1980 is not significantly different from zero, the coefficient for the routine occupation group is negative and still significantly different from zero. This indicates that firms with a high initial industry wage premium in 1960 responded to this situation by de-

²⁶The IV regressions show the same results, and hence we omit them here.

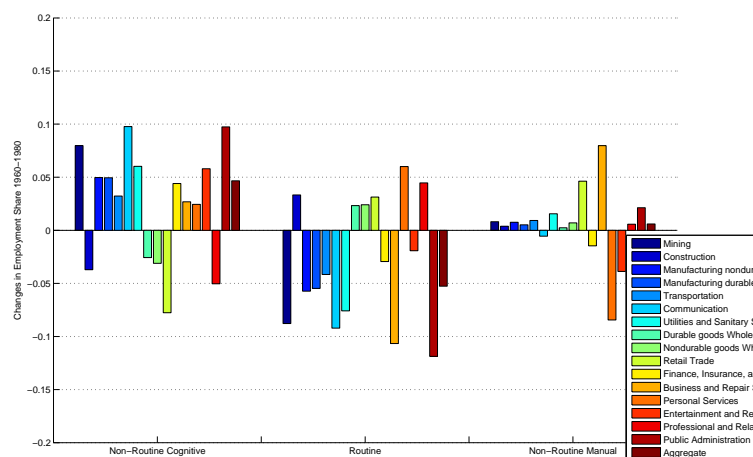


Figure 1.12: Changes in Employment Share by Occupation across Industries between 1960 and 1980

Source: The U.S. Census.

creasing demand for routine occupations relative to other occupations. The magnitude of the responsiveness (θ_r) is, however, much lower than that of the latter period and the explanatory power drops by half, indicating that the dynamic responses of firms with a high initial industry wage premium in 1980 are much stronger than those in 1960. This suggests that the heterogeneous aspect of job polarization across industries became more pronounced after 1980.

Why have the industrial differences in job polarization become larger after 1980? There are two possibilities: (1) routine-replacing technological changes, and (2) increased offshoring opportunities since the 1980s. Among the three occupation categories, only the routine occupations are replaced easily either by (ICT) capital or by offshoring (Goos et al. (2013)). Thus, for firms to adjust their labor demand dynamically, they need to change their demand for routine occupations. Consider an extreme case in which neither of the two options are available to firms. If firms could not access technologies that perform routine tasks, these firms would not change the demand for labor. Hence, changes in labor demand would not differ across different industries if firms could not replace workers. Suppose now, instead, that firms can either buy ICT capital because its price has become lower, or they can offshore some tasks to foreign countries. Then, labor demand for routine occupations will decline more (or its growth

Table 1.6: Estimates of Employment Growth by Occupation Groups (1960-1980 and 1980-2009)

Occupation Groups	1960-1980		1980-2009	
	Coefficient	R-Squared	Coefficient	R-Squared
Total	-0.0178(0.0284)	0.03	-0.0381*** (0.0073)	0.24
Cognitive Occupations	0.0053(0.0151)	0.00	-0.0252*** (0.0071)	0.14
Routine Occupations	-0.0303** (0.0122)	0.10	-0.0421*** (0.0090)	0.21
Manual Occupations	0.0595*** (0.0077)	0.03	0.0117(0.0137)	0.03

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

rate will be lower) for firms with high industry wage premia. Hence, both of these changes, which are usually argued to have become available or accessible to firms since the 1980s (Acemoglu and Autor (2011) and Jaimovich and Siu (2013)), made it easier for firms to decrease their demand for routine occupations. As a result, the heterogenous aspect of job polarization across industries becomes more evident in the latter period.

1.5 Conclusion

Over the past decades, employment has become polarized in the U.S., with composition of the labor force shifting away from routine occupations towards both cognitive and manual occupations. In this paper, we show that the degree of job polarization is different across industries and identify the factor that causes this phenomenon by demonstrating that the job polarization is connected with wide dispersion in wages across industries. In particular, our findings can be explained as dynamic responses of firms to interindustry wage differentials; firms that paid high industry wage premia responded to wage pressures by replacing routine workers with ICT capital. Therefore, the heterogenous aspect of job polarization across industries was the result of optimal responses of industries to existing interindustry wage differentials. In the companion paper, Shim (2014) provide a theory to formalize the hypothesis suggested in this paper with a two-sector neoclassical growth model and show that predictions of the models are consistent with the empirical findings we present in this paper.

This paper aids understanding of heterogeneity in job polarization across indus-

tries, presenting the underlying mechanism and empirical regularities that reveal the relationship between job polarization and the wage structure of industries, which have not been studied before. In addition, similarly to Borjas and Ramey (2000), our paper raises a question about the validity of the competitive labor market theory where flows of workers across industries provide an equilibrating mechanism for wages. Instead, our findings indicate that firms respond endogenously to the rigid wage structure by replacing routine workers with capital, and hence the mechanism for the competitive labor market may not work.

Acknowledgement

Chapter 1 is coauthored with Hee-Seung Yang. Together with Chapter 2, chapter 1 is in preparation for submission.

1.6 Appendix: Additional Tables and Figures

We first present notes for several figures.

Note for Figure 1.7:

First of all, numbers 6-15 are ‘nondurable manufacturing goods’, 16-25 are ‘durable manufacturing goods’, 26-32 are ‘transportation’, 35-36 are ‘wholesale trade’, 37-44 are ‘retail trade’, 45-49 are ‘finance, insurance, and real estate’, 49-51 are ‘business and repair services’, and 55-59 are ‘professional and related services’ industries. General merchandiser includes hardware stores, retail nurseries and garden stores, mobile home dealers, and department stores. Lastly, Miscellaneous services include child care, social services, labor unions, and religious organizations.

Note for Figure 1.10:

The Census data are used for the estimation. Region1 to Region9 correspond to New England Division, Middle Atlantic Division, East North Central Division, West North Central Division, South Atlantic Division, East South Central Division, West South Central Division, Mountain Division, and Pacific Division, respectively. Age1 to Age5 correspond to 18-24, 25-34, 35-44, 45-54, and 55-64, respectively. Edu1 to

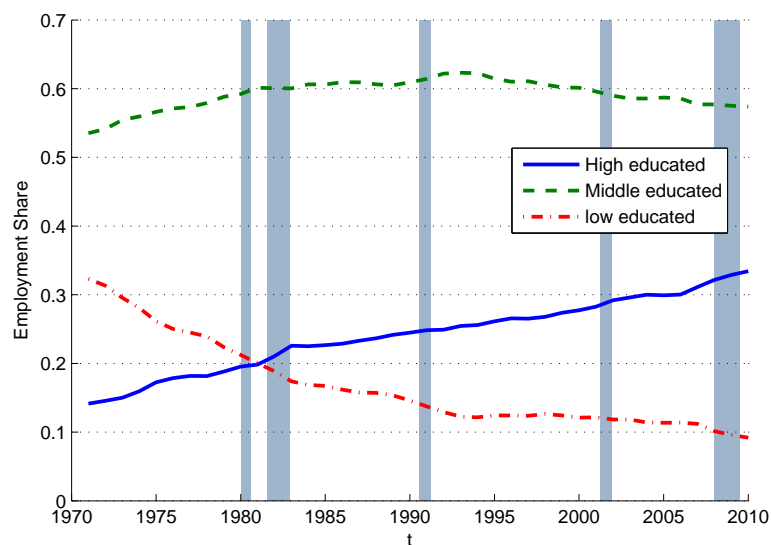


Figure 1.13: Job Polarization: Education

Edu5 correspond to worker has fewer than nine years, nine to 11 years, 12 years, 13 to 15 years, and at least 16 years of schooling, respectively.

Note for Figure 1.11:

1980, 1990, and 2000 data are from the Census and 2009 data are from the ACS. Then The first row is the explanatory power (R^2) of the wage regression when individual characteristics (including ages, education, etc. (see Section 1.4 for detail)) and 60 industries are all controlled for. The second row is the explanatory power of the wage equation when industry dummies are the only independent variables and the third row is that of the wage equation when only covariates are considered as independent variables.

Note for Figure 1.13:

Notice that industry numbers follow 1.7. Here, average is the industry wage premium estimated from equation (1.1) and cognitive, routine, and manual are the occupation-specific industry wage premia estimated from equation (1.3). We normalize the industry wage premium.

Table 1.7: Census Industry Classification

Number	Industry	IND1990 Code
1	Metal mining	40
2	Coal mining	41
3	Oil and gas extraction	42
4	Nonmetallic mining and quarrying, except fuels	50
5	Construction	60
6	Food and kindred products	100 – 122
7	Tobacco manufactures	130
8	Textile mill products	132 – 150
9	Apparel and other finished textile products	151 – 152
10	Paper and allied products	160 – 162
11	Printing, publishing, and allied industries	171 – 172
12	Chemicals and allied products	180 – 192
13	Petroleum and coal products	200 – 201
14	Rubber and miscellaneous plastics products	210 – 212
15	Leather and leather products	220 – 222
16	Lumber and woods products, except furniture	230 – 241
17	Furniture and fixtures	242
18	Stone, clay, glass, and concrete products	250 – 262
19	Metal industries	270 – 301
20	Machinery and computing equipments	310 – 332
21	Electrical machinery, equipment, and supplies	340 – 350
22	Motor vehicles and motor vehicle equipment	351
23	Other transportation equipment	352 – 370
24	Professional and photographic equipment and watches	371 – 381
25	Miscellaneous manufacturing industries / Toys, amusement, and sporting goods	390 – 392
26	Railroads	400
27	Bus service and urban transit / Taxicab service	401 – 402
28	Trucking service / Warehousing and storage	410 – 411
29	U.S. postal service	412
30	Water transportation	420
31	Air transportation	421
32	Pipe lines, except natural gas / Services incidental to transportation	422 – 432
33	Communications	440 – 442
34	Utilities and sanitary services	450 – 472
35	Durable goods	500 – 532
36	Nondurable goods	540 – 571
37	Lumber and building material retailing	580
38	General merchandiser (Note 2)	581 – 600
39	Food retail	601 – 611
40	Motor vehicle and gas retail	612 – 622

Table 1.8: Census Industry Classification Continued.

Number	Industry	IND1990 Code
41	Apparel and shoe	623 – 630
42	Furniture and appliance	631 – 640
43	Eating and drinking	641 – 650
44	Miscellaneous retail	651 – 691
45	Banking and credit	700 – 702
46	Security, commodity brokerage, and investment companies	710
47	Insurance	711
48	Real estate, including real estate-insurance offices	712
49	Business services	721 – 741
50	Automotive services	742 – 751
51	Miscellaneous repair services	752 – 760
52	Hotels and lodging places	761 – 770
53	Personal services	771 – 791
54	Entertainment and recreation services	800 – 810
55	Health care	812 – 840
56	Legal services	841
57	Education services	842 – 861
58	Miscellaneous services (Note 3)	862 – 881
59	Professional services	882 – 893
60	Public administration	900 – 932

Table 1.9: EU KLEMS Industry Classification

Number	Industry	IND1990 Code
1	Mining and quarrying	40 – 50
2	Total manufacturing	
2 – 1	Food, beverages, and tobacco	100 – 130
2 – 2	Textiles, textile, leather, and footwear	132 – 152, 220 – 222
2 – 3	Wood and of wood and cork	230 – 242
2 – 4	Pulp, paper, printing, and publishing	160 – 172
2 – 5	Chemical, rubber, plastics, and fuel	
2 – 5 – 1	Coke, refined petroleum, and nuclear fuel	200 – 201
2 – 5 – 2	Chemicals and chemical products	180 – 192
2 – 5 – 3	Rubber and plastics	210 – 212
2 – 6	Other non-metallic mineral	262
2 – 7	Basic metals and fabricated metal	270 – 301
2 – 8	Machinery, NEC	310 – 332
2 – 9	Electrical and optical equipment	340 – 350
2 – 10	Transport equipment	351 – 370
2 – 11	Manufacturing NEC; Recycling	371 – 392
3	Electricity, gas, and water supply	450 – 472
4	Construction	60
5	Wholesale and retail trade	
5 – 1	Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel	500, 612 – 622, 672, 751
5 – 2	Wholesale trade and commission trade, except of motor vehicles and motorcycles	501 – 571
5 – 3	Retail trade, except of motor vehicles and motorcycles; Repair of household goods	580 – 611, 623 – 671, 681 – 691
6	Hotels and restaurants	762 – 770
7	Transport and storage and communication	
7 – 1	Transport and storage	400 – 432
7 – 2	Post and telecommunications	440 – 442
8	Finance, insurance, real estate, and business services	
8 – 1	Financial intermediation	700 – 711
8 – 2	Real estate, renting, and business activities	712 – 760
9	Community, social, and personal services	761 – 810
10	Public administration and defence; Compulsory social security	900 – 932
11	Education	842 – 861
12	Health and social work	812 – 840, 841
13	Other community, social, and personal services	862 – 893

Table 1.10: OLS Estimates of the Wage Regression in 1980

Variable	Coefficient	Variable	Coefficient
Female	-0.5413(0.0009)	Cognitive Occupation	0.4892(0.0030)
Age1	1.0227(0.0035)	Routine Occupation	0.2267(0.0029)
Age2	1.5225(0.0035)	Manual Occupation	0.0081(0.0031)
Age3	1.7141(0.0035)	Region1	-0.0355(0.0024)
Age4	1.7916(0.0035)	Region2	0.0329(0.0020)
Age5	1.7775(0.0036)	Region3	0.0684(0.0020)
Edu1	-0.5575(0.0020)	Region4	-0.0188(0.0023)
Edu2	-0.4799(0.0017)	Region5	-0.0045(0.0020)
Edu3	-0.2689(0.0013)	Region6	-0.0612(0.0024)
Edu4	-0.2418(0.0014)	Region7	-0.0011(0.0022)
Edu5	0 (Omitted)	Region8	0 (Omitted)
African-American	-0.0842(0.0014)	Region9	0.0665(0.0021)
R-Squared	.4045	Observations	4, 307, 598

Table 1.11: Source of Wage Variation (R-Squared)

	1980	1990	2000	2009
Total	0.40	0.42	0.42	0.43
Industry Only	0.14	0.14	0.13	0.16
Covariates Only	0.36	0.37	0.38	0.38
Observations	4, 307, 598	4, 940, 215	5, 530, 409	1, 202, 671

Table 1.12: Estimates of Employment Growth by Occupation Groups (1980-2006)

OLS		
Occupation Groups	Coefficient	R-Squared
Total	-0.0432***(0.0103)	0.22
Cognitive Occupations	-0.0257***(0.0083)	0.12
Routine Occupations	-0.0417***(0.0099)	0.18
Manual Occupations	-0.0017(0.0159)	0.000

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.13: Occupation-Specific Industry Wage Premia in 1980

Industry	Average	Cognitive	Routine	Manual	Industry	Average	Cognitive	Routine	Manual
1	0.8524(.0097)	1.1828(.0181)	1.1954(.0111)	1.0234(.0660)	31	0.8938(.0060)	1.3965(.0104)	1.1606(.0071)	1.1442(.0131)
2	0.9627(.0073)	1.2585(.0173)	1.2947(.0079)	0.7852(.0838)	32	0.5164(.0090)	1.1424(.0159)	0.7964(.0105)	0.5229(.0478)
3	0.8128(.0063)	1.3019(.0094)	1.1361(.0075)	0.7512(.0539)	33	0.8531(.0049)	1.2388(.0069)	1.2174(.0056)	0.7661(.0343)
4	0.7051(.0101)	1.1480(.0250)	1.0123(.0112)	0.8694(.0600)	34	0.7212(.0049)	1.1831(.0069)	1.0390(.0056)	0.7687(.0170)
5	0.5656(.0045)	1.1518(.0065)	0.8544(.0052)	0.4819(.0194)	35	0.6248(.0048)	1.2285(.0067)	0.9098(.0055)	0.4597(.0304)
6	0.6158(.0050)	1.2072(.0080)	0.9004(.0057)	0.6949(.0155)	36	0.5755(.0049)	1.1837(.0073)	0.8610(.0056)	0.4987(.0237)
7	0.7718(.0121)	1.3420(.0231)	1.0594(.0137)	0.8614(.0673)	37	0.4835(.0071)	1.1310(.0135)	0.7634(.0080)	0.2699(.0810)
8	0.5659(.0053)	1.1789(.0108)	0.8505(.0059)	0.5900(.0231)	38	0.2603(.0048)	1.0194(.0077)	0.5185(.0056)	0.3553(.0129)
9	0.4061(.0052)	1.2145(.0127)	0.6792(.0058)	0.4035(.0305)	39	0.3969(.0050)	1.0609(.0098)	0.6838(.0056)	0.3128(.0157)
10	0.7534(.0055)	1.2674(.0098)	1.0496(.0063)	0.9124(.0270)	40	0.4593(.0050)	1.1522(.0093)	0.7371(.0057)	0.3153(.0291)
11	0.4809(.0053)	0.9827(.0079)	0.7939(.0061)	0.4910(.0312)	41	0.1773(.0062)	0.9946(.0122)	0.4295(.0070)	0.2041(.0419)
12	0.7540(.0049)	1.2752(.0065)	1.0607(.0058)	0.8968(.0180)	42	0.3595(.0063)	0.9503(.0120)	0.6492(.0071)	0.1138(.0522)
13	0.8724(.0074)	1.3563(.0116)	1.2011(.0088)	0.7933(.0530)	43	0.1737(.0045)	0.8572(.0068)	0.4181(.0067)	0.2277(.0054)
14	0.6543(.0057)	1.2446(.0097)	0.9382(.0065)	0.7914(.0289)	44	0.1457(.0055)	0.7895(.0092)	0.4188(.0063)	0.2218(.0246)
15	0.4259(.0079)	1.1603(.0254)	0.7035(.0085)	0.5134(.0522)	45	0.5735(.0046)	1.1792(.0057)	0.8521(.0055)	0.4151(.0188)
16	0.5063(.0062)	1.1625(.0143)	0.7820(.0070)	0.5604(.0337)	46	0.7683(.0079)	1.2815(.0138)	1.0938(.0092)	0.4082(.0575)
17	0.4804(.0063)	1.1613(.0142)	0.7575(.0070)	0.5229(.0458)	47	0.6730(.0048)	1.2383(.0066)	0.9704(.0055)	0.4936(.0294)
18	0.6722(.0057)	1.1642(.0109)	0.9782(.0064)	0.7780(.0346)	48	0.3871(.0058)	1.8683(.0095)	0.7241(.0072)	0.3979(.0107)
19	0.7525(.0046)	1.2502(.0065)	1.0509(.0052)	0.8954(.0150)	49	0.3762(.0051)	1.0299(.0068)	0.6757(.0066)	0.2917(.0085)
20	0.7152(.0045)	1.2500(.0059)	1.0159(.0053)	0.7358(.0184)	50	0.4092(.0063)	1.0308(.0142)	0.6946(.0069)	0.1908(.0574)
21	0.6614(.0046)	1.1896(.0060)	0.9648(.0054)	0.7154(.0199)	51	0.4151(.0083)	0.9705(.0219)	0.7090(.0090)	0.2536(.0820)
22	0.8742(.0050)	1.3618(.0079)	1.1730(.0057)	1.0748(.0178)	52	0.00(Omitted)	0.7086(.0120)	0.5276(.0102)	0.00(Omitted)
23	0.7480(.0048)	1.2259(.0061)	1.0781(.0057)	0.8322(.0241)	53	0.2753(.0061)	0.7207(.0132)	0.4343(.0093)	0.4462(.0078)
24	0.6790(.0056)	1.2268(.0075)	0.9771(.0067)	0.7521(.0330)	54	0.1425(.0063)	0.5998(.0098)	0.4938(.0104)	0.2662(.0091)
25	0.4644(.0061)	1.1455(.0109)	0.7338(.0069)	0.5019(.0339)	55	0.4770(.0043)	1.0231(.0052)	0.7489(.0056)	0.5829(.0054)
26	0.9247(.0055)	1.3237(.0100)	1.2363(.0061)	1.0065(.0281)	56	0.5021(.0069)	0.9358(.0106)	0.9103(.0080)	0.3791(.0700)
27	0.3950(.0072)	0.9870(.0161)	0.6723(.0080)	0.6458(.0297)	57	0.1223(.0044)	0.7527(.0052)	0.3141(.0058)	0.0750(.0062)
28	0.7092(.0051)	1.2070(.0107)	1.0078(.0057)	0.5972(.0350)	58	0.0137(.0053)	0.5056(.0066)	0.4788(.0078)	0.0374(.0092)
29	0.8159(.0054)	1.2214(.0120)	1.1231(.0060)	0.8248(.0256)	59	0.4192(.0052)	0.9655(.0062)	0.7514(.0076)	0.5198(.0276)
30	0.7528(.0094)	1.2554(.0170)	1.0699(.0108)	0.6032(.0541)	60	0.5995(.0043)	1.0453(.0054)	0.8814(.0054)	0.8729(.0057)

Chapter 2

Interindustry Wage Differentials, Technology Adoption, and Job Polarization: Theory

Abstract. This paper proposes a theory that unveils the mechanism underlying the close relationship between job polarization and interindustry wage differentials, which is empirically studied in the companion paper, Shim and Yang (2014). In particular, we develop a two-sector neoclassical growth model that incorporates the following three key features. First, industries differ in the wage rates they pay to workers. Second, routine workers are relative substitutes for capital while non-routine workers are relative complement to capital. Last, there is an exogenous investment-specific technology change. Main predictions of the model are that (1) job polarization is more evident and (2) capital-routine worker ratio increases more in the industry that pays higher wages to workers when there is an investment-specific technology change, which are consistent with the empirical findings in Shim and Yang (2014).

2.1 Introduction

This paper develops a theory to understand an empirical finding that the progress of job polarization differs across industries, which is empirically analyzed in the companion paper, Shim and Yang (2014). In that paper, we show that ‘interindustry wage differentials’, the phenomenon that observationally equivalent workers earn differently when employed in different industries, can be a possible explanation for why the degree of job polarization differs across industries. In particular, Shim and Yang (2014) find that industries with a higher wage premium in 1980 experienced large declines in the share of routine workers between 1980 and 2009. i.e. the progress of job polarization was more evident in the high-wage industries. Figure 2.1 shows this phenomenon clearly.

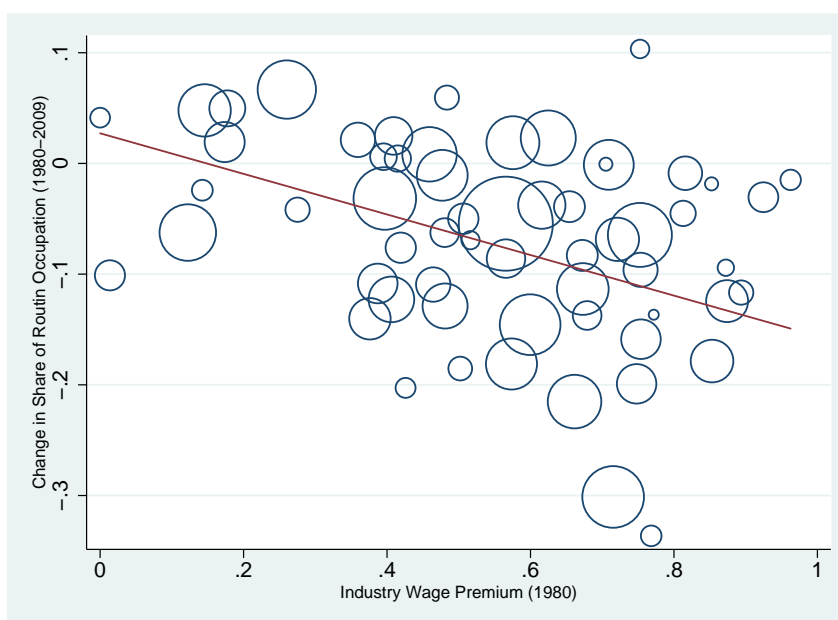


Figure 2.1: Connection between Job Polarization and Interindustry Wage Differentials

Source: Reproduced from Shim and Yang (2014).

In Shim and Yang (2014), they hypothesize that the different degrees of job polarization across industries can be explained as firms’ dynamic responses to interindustry wage differentials. As firms cannot adjust wages relative to those paid by other firms because of the ‘rigid’ inter-industry wage structure, they dynamically substitute labor with other production factors such as capital. Particularly, demand for routine workers

will decrease more intensively because they can be replaced easily by ICT capital while demand for non-routine workers decreases less since their tasks are not easily replaced by other production factors. As a result, the degree of job polarization becomes different across industries.

In order to formalize the above hypothesis, we develop a two-sector neoclassical growth model in this paper and then solve the model analytically. As usually assumed in the job polarization literature, firms can use Information, Communication, and Technology (ICT, henceforth) capital, which is assumed to be a relative substitute for workers who perform routine tasks (routine workers) and a relative complement to workers who perform non-routine tasks (non-routine workers). The main predictions from our model are as follows. Firstly, job polarization is more evident in the high-wage industries. In our model, the relative wage structure across industries is assumed to be ‘rigid’ because of some industry specific factors.¹ Hence, some firms pay higher wages than other firms for (observationally) identical workers. As a result, firms with a high wage premium seek alternative methods to cut production cost instead of changing wages: they replace labor with other production factors, such as capital. When a firm changes its labor demand, however, the effect is not even across different workers: tasks performed by routine workers are more easily codifiable or computerized, and hence they are more affected by a firm’s dynamic decision to replace labor with capital.² As the price of capital becomes lower due to investment-specific technological changes, high-wage firms rent more capital than low-wage firms because they are more willing to cut high production costs. As a consequence, high-wage firms reduce relative demand for routine workers more, resulting in different degrees of job polarization across industries. Second prediction of our model, which is consistent with the first prediction, is that the growth rate of capital per routine worker is higher in the high-wage industries, since firms in such industries have more incentives to replace routine workers with capital. Importantly, these two predictions are consistent with the empirical findings in Shim and Yang (2014).

With the companion paper, Shim and Yang (2014), this paper contributes to the existing literature on job polarization by theoretically revealing the mechanism how the

¹In the appendix, we derive the rigid interindustry wage structure as an equilibrium outcome, which does not change the predictions of the model.

²Offshoring is another possibility, as Goos et al. (2013) and Oldenski (2012) show.

progress of job polarization can be related to the wage structure that is exogenously given to firms.

The paper is organized as follows. Section 2.2 reviews related literature. We then propose a two-sector neoclassical growth model and provides its predictions in Section 2.3. Section 3.5 concludes.

2.2 Related Literature

Since we focus more on the ‘consequences’ of interindustry wage differentials in this paper, we briefly review literature that suggests possible theories to explain ‘causes’ of it. One theory that justifies the existence of interindustry wage differentials is ‘unobserved ability of workers’ (Murphy and Topel (1987)). This theory is consistent with competitive equilibrium theory; estimated persistent interindustry wage differentials is the reflection of the unobservable variables hence the phenomenon is not surprising. However, Krueger and Summers (1988), Borjas and Ramey (2000), and Blackburn and Neumark (1992) find evidence against this theory. For instance, Blackburn and Neumark (1992) show that their measure of unobserved ability (test scores) can account for only about one tenth of the variation in interindustry wage differentials. Given that the competitive model cannot explain the industry wage premia well, remaining theories should be non-competitive ones. The rent-sharing model, discussed by Nickell and Wadhvani (1990), Borjas and Ramey (2000) and Montgomery (1991)³, is one possible non-competitive model: if a firm can share its profit with a worker (insider) by negotiation and if it can sustain a worker’s productivity level with the wage level relatively higher than the competitive one, firms are willing to pay higher wages than competitive ones. Another possibility is to use efficiency wage model (Walsh (1999) and Alexopoulos (2006)). Suppose that workers can choose either to work or shirk and firms in different industries have different detection rates of shirking workers. Then wage compensations for not shirking are different across industries, which generates wage dispersions across industries. Since our interest is in the consequences of interindustry wage differentials, we choose to take the reduced way of capturing wage differentials in

³Montgomery (1991) uses a version of search and matching model, but we include it in the rent-sharing model since the model also incorporates the rent-sharing feature in it.

Section 2.3.

Notice that predictions of the theories and other empirical researches such as Murphy and Topel (1987), Alexopoulos (2006), and Krueger and Summers (1988) are basically static in the sense that their model cannot predict the dynamic behaviors of firms facing interindustry wage differentials. Suppose that the dispersion in wages across industries exists for any reason. While previous studies could explain the occurrence of interindustry wage differentials and the associated ‘static’ equilibrium properties, these studies do not explain how firms react to this phenomenon. For instance, if one believes the unobserved ability hypothesis following Murphy and Topel (1987), there should be no changes in equilibrium unless any structural transformation occurs since it is already in a competitive equilibrium where workers are sorted by their abilities. In contrast, Borjas and Ramey (2000) find that there are ‘dynamic’ responses of firms to the persistent interindustry wage differentials. To get an idea, consider a firm in an industry that pays relatively higher wages to a worker than firms in other industries at year t_0 , the initial period (of data we have). Notice that labor cost is the product of wage and employment and it is hard for firms to adjust wages (relative to that of other industries) as supported by data (see Borjas and Ramey (2000)). Then the only way to respond to the higher labor cost is to adjust employment over time. i.e. subsequent employment growth of the industries with high initial industry wage premia will be lower than those of the industries with low initial wage premia. And this prediction is a sharp contradiction to the competitive equilibrium theory; employment of an industry with high (resp. low) initial wage premium should increase (resp. decrease) over time since t_0 in a competitive equilibrium environment in which labor mobility is not restricted as workers will migrate from the low wage industries to the high wage industries. Our paper is different from Borjas and Ramey (2000) in two directions. First, they do not propose a particular theory to support their empirical findings. Second, we consider the possible heterogeneous effects of a firm’s dynamic response on different workers.

In the sense that different market environments make firms behave differently across industries, our paper is close to Alder et al. (2013). Contrary to our paper, however, Alder et al. (2013) do not consider initial wage differentials as the source of the differences. Rather, the difference they take into account is a lack of competition in la-

bor and output markets. Furthermore, they do not examine possible heterogeneous effects of labor market changes due to firms' dynamic decisions on different types of workers. Acemoglu and Shimer (2000) is also relevant to our paper; they show with a searching model how *ex-ante* equivalent firms optimally choose different technologies and wages. While the underlying idea is similar, they also do not consider that the strategy of the firm can affect different workers disproportionately.

2.3 Model

In this section, we present a two-sector neoclassical growth model and analyze properties of the steady-state equilibrium. While our model is highly stylized, it provides clear predictions that are testable with data.

We first sketch the structure of the economy. In order to capture features of job polarization, we assume that there are two types of tasks, where the first type is the 'non-routine' task (workers who perform non-routine tasks will be called non-routine workers) and the second type is the 'routine' task (routine workers).⁴ As is usually assumed in the job polarization literature,⁵ capital is a relative substitute for workers who perform routine tasks, while it is a relative complement to workers who perform non-routine tasks. In this sense, capital considered in our model can be interpreted as ICT capital. In order to generate interindustry wage differentials, we assume that industry 1 pays higher wages, by some exogenous factors, than industry 2.⁶ This assumption, which is the key in our model, is innocuous for our purpose as long as the rigid wage structure across industries originates from non-competitive theories.⁷

⁴One might further decompose non-routine workers into cognitive and manual workers; given, however, that these workers have similar roles in the production function (both workers are relative complements to capital) and their behavior is almost the same (the wage and employment relative to routine-workers increase for both workers over time), we choose to use only two types of workers in the model for simplicity of discussion. This is also the same strategy used by Beaudry et al. (2013) and Jaimovich and Siu (2013).

⁵See Autor et al. (2003), Autor and Dorn (2013), and Cortes (2014), for instance.

⁶For instance, in Appendix 2.5.1, we consider labor unions as the source of interindustry wage differentials.

⁷For example, one might argue that the 'initial' interindustry wage differentials arise from high capital-labor ratio in some industries due to industrial characteristics, which is in line with competitive theories. However, this theory does not coincide with data as is documented in Shim and Yang (2014) and Borjas and Ramey (2000); over the last several decades, the capital-labor ratio has risen more in high-wage industries. This implies that wage differentials should have been widened, which is not supported by data.

We then provide comparative statics of the steady-state equilibrium by changing the parameter that governs the relative price of capital. We show that while both industries experience job polarization, the share of non-routine over routine workers, which measures the degree of job polarization in our model, increases more in the high-wage industry when the relative price of capital declines. We also show that the heterogeneity in the degree of job polarization across industries increases in the industry wage premium. In addition, the capital-routine worker ratio rises more in the high-wage industry when the relative price of capital decreases.

2.3.1 Setup

Household

We consider an environment in which a representative household consists of identical workers, whose total hours supplied to the labor market are denoted by n_t .⁸

There is an infinitely lived representative household in the economy that solves the following deterministic maximization problem:

$$\max_{\{c_t, k_{t+1}, x_t, n_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t [\log c_t + \theta(\bar{n} - n_t)] \quad (2.1)$$

subject to

$$(1) \quad c_t + x_t = w_t n_t + r_t k_t + \pi_t$$

$$(2) \quad k_{t+1} = (1 - \delta)k_t + q_t x_t$$

where $\theta > 0$ is a constant, $k_0 > 0$ is given, $\bar{n} > 0$ is total hours with which a household is endowed, and π_t is a lump-sum transfer from the labor broker that is described below.

The period t income can be used to purchase consumption goods, c_t , or used to generate investment goods, x_t , with the technology q_t . Hence, higher q_t means that the technology to generate investment goods improves; more investment goods can be generated with the same income and consumption. We sometimes refer to $1/q_t$ as the relative price of capital. We normalize the price of the final good to 1. In addition, r_t and $\delta \in [0, 1]$ are the rental cost and the depreciation rate of capital, respectively. In

⁸The assumption on the representative household is made in order to avoid the distributional issue that arises from different wage rates across industries and types of workers.

addition, equation (2) is the law of motion for capital that a household owns and rents to firms. The household supplies labor at wage rate w_t . Detailed discussions on wage rates are provided in the next section.⁹

The key optimality condition for the household problem is given as follows:¹⁰

$$\frac{c_{t+1}}{c_t} = \beta \left[q_t r_{t+1} + (1 - \delta) \frac{q_t}{q_{t+1}} \right] \quad (2.2)$$

We focus on comparative statics in the steady state, and therefore we set $c_t = c_{t+1}$ and $q_t = q_{t+1}$ and obtain a relationship between r and q as follows.

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \quad (2.3)$$

The rental cost of capital (r) is strictly decreasing in q ; that is, the steady state level of capital can be sustained with less investment when the technology, q , is more efficient. Hence, less demand for capital lowers the rental rate of capital.

Labor Market

The labor market is assumed to be intermediated by a labor broker that receives hours worked from the household and allocates them across industries 1 and 2 and routine and non-routine occupations.¹¹ Let h_{it} (resp. \tilde{h}_{it}) be the hours of non-routine (resp. routine) workers supplied to industry i . We further define w_{it} (resp. \tilde{w}_{it}) to be the wage rate of non-routine (resp. routine) workers employed industry i .

To capture the industry wage differentials observed in the data, we assume that the wage in industry 1 is higher than that of industry 2 by a factor $\lambda > 0$ ¹² so that

⁹We assume that the utility is linear in hours worked in order to make clear predictions and to avoid the problem that the labor market may not clear when labor supply is inelastic under the existence of the industry wage premium.

¹⁰There is another optimality condition for labor supply, $w_t = \theta c_t$, which we abstract from here since it is not relevant for our analysis.

¹¹Or equivalently, one can assume rationing in the labor market so that only some fractions of workers can be employed in the high-wage industry. Households then collect total labor income as a sum of labor income from all workers, as discussed in Alder et al. (2013). All of these features are to obtain equilibrium in which all firms employ positive hours.

¹²Since we are more interested in the consequences of the industry wage premium, in this paper, we do not analyze the source of these differentials. Instead, our model postulates that firms in some sectors face a higher ‘wage markup’ by some exogenous factors. We take the stance that the source of interindustry wage differentials does not come from unobserved heterogeneity across workers; we assume *ex-ante* identical workers. There are several ways to introduce the industry wage premia. For instance, one might consider the efficiency wage model as in Alexopoulos (2006), by assuming that the detection rate of shirking is

$$w_{1t} = (1 + \lambda)w_{2t} \text{ and } \tilde{w}_{1t} = (1 + \lambda)\tilde{w}_{2t} \quad (2.4)$$

As non-routine occupations¹³ require more complex skills of a worker, the broker sets the following wage rule to compensate the skill differences across occupations:¹⁴

$$w_{it} = \chi \tilde{w}_{it} \quad (2.5)$$

where $\chi > 1$ measures the compensation to the occupations that require relatively complex skills.

The broker compensates the hours supplied by the household at the lowest wage in the market that corresponds to the wage of a routine worker in industry 2.¹⁵ It then allocates the hours according to the demand of firms in the two industries given the assumed wage differentials and wage rule. The additional wage income received by the broker on the hours supplied to industry 1 is rebated to the household as a lump-sum transfer:

$$\pi_t = \tilde{w}_{2t}(\lambda \chi h_{1t} + \chi h_{2t} + \lambda \tilde{h}_{1t}) \quad (2.6)$$

Final Goods-Producing Firms

The final good, which can be either consumed or used to purchase investment at the price $1/q_t$, is assumed to be produced by a firm that utilizes two intermediate goods. The problem of this firm, which operates in a perfectly competitive market, is given by:

$$\max_{y_{1t}, y_{2t}} y_t - p_{1t}y_{1t} - p_{2t}y_{2t} \quad (2.7)$$

heterogenous across industries; the value of matching is different across industries, as in Montgomery (1991). Instead, we can also assume that there is a labor union in industry 1 but not in industry 2, which is discussed in Appendix 2.5.1. In the appendix, we assume that there is a labor union in each industry and a firm in the particular industry can hire workers only through the labor union of the industry where the monopoly power of labor unions are heterogenous across industries. Then, the above equation (2.4) can be derived as an equilibrium condition.

Therefore, we can interpret the labor market environment used in our model as a parsimonious way to generate wage differentials across industries and λ captures the heterogeneity across industries.

¹³Here, we focus on cognitive occupations.

¹⁴Or equivalently, we can assume that there are two types of workers that constitute a household and leisure is linear in both types of workers, which yields identical results.

¹⁵One can set a different wage rule without changing equilibrium properties; for example, $w_t = w_{1t}$ is also possible but then the household should pay back the remaining labor income to the broker.

subject to the CES aggregator

$$y_t = [y_{1t}^{1-\nu} + y_{2t}^{1-\nu}]^{\frac{1}{1-\nu}}$$

where $\nu \in [0, 1)$. Hence, the elasticity of demand for each intermediate good is $\frac{1}{\nu}$.

The demand for intermediate goods in industries 1 and 2 is then given by

$$p_{it} = \left(\frac{y_t}{y_{it}} \right)^\nu \quad (2.8)$$

which is the usual form of the inverse demand function for each intermediate good.¹⁶

Intermediate Goods-Producing Firms

We assume that the intermediate goods market is perfectly competitive so that a firm's profit will be zero in equilibrium. Each firm produces an output by utilizing two types of workers and capital. A firm in industry i solves the following static profit maximization problem:

$$\max_{\{k_{it}, h_{it}, \tilde{h}_{it}\}} p_{it} y_{it} - w_{it} h_{it} - \tilde{w}_{it} \tilde{h}_{it} - r_t k_{it} \quad (2.9)$$

subject to

$$y_{it} = h_{it}^\alpha \left(\tilde{h}_{it}^\mu + k_{it}^\mu \right)^{\frac{1-\alpha}{\mu}}$$

where $\mu \in (0, 1)$, $\alpha \in (0, 1)$.

Following Autor et al. (2003), Autor et al. (2006), and Autor and Dorn (2013), we assume a CES production function. Notice that the elasticity of substitution between non-routine workers and total routine task input is 1, while the elasticity of substitution between a routine worker and capital is $\frac{1}{1-\mu} > 1$, since $\mu > 0$. Thus, as Autor and Dorn (2013) point out, capital is a *relative substitute* for workers who perform routine tasks and is a *relative complement* to workers who perform non-routine tasks. Hence, capital in our model is ICT capital. Notice that if $\mu = 1$, each input that performs a routine task is a perfect substitute for each other. Once the output, y_{it} , is produced, it is sold to the final goods-producing firm at p_{it} .

¹⁶One can show easily that the zero-profit condition holds under the above first-order condition (2.8).

Optimality conditions for the firm's optimization problem are given as follows:

$$\frac{w_{it}}{p_{it}} = \alpha \frac{y_{it}}{h_{it}} \quad (2.10)$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1 - \alpha) \frac{\tilde{h}_{it}^{\mu} y_{it}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu} \tilde{h}_{it}} \quad (2.11)$$

$$\frac{r_t}{p_{it}} = (1 - \alpha) \frac{k_{it}^{\mu} y_{it}}{\tilde{h}_{it}^{\mu} + k_{it}^{\mu} k_{it}} \quad (2.12)$$

Each equation shows that the remuneration of factors takes the form of shares, which is the property from the CRS production function. In particular, the first (resp. second) equation means that the real wage that a worker performing non-routine (resp. routine) tasks receives should be equal to the marginal product of the worker. The last equation, similarly, means that the real rental cost of capital should be equal to the marginal product of capital. As usual, demand for each input is a decreasing function of the factor price. In order to understand the role of changes in the price of capital, we divide equation (2.11) by (2.12):

$$\frac{\tilde{w}_{it}}{r_t} = \left(\frac{k_{it}}{\tilde{h}_{it}} \right)^{1-\mu} \quad (2.13)$$

This equation implies that capital per routine worker increases as the rental cost decreases because capital is a relative substitute for routine workers, and firms will replace routine workers with capital as the relative cost of utilizing capital becomes lower. In order to gain an intuition into how q is related to this property, we use the steady-state property that r and q are inversely related, as discussed earlier. An increase in q means that less investment is enough to maintain the steady-state capital level, so that demand for capital would be lower, which results in a lower rental cost of capital.

One can further check that capital per routine worker is always higher in a high-wage industry, which arises from the fact that high-wage firms can lower production costs by employing more capital than low-wage firms. Notice that this equilibrium property is consistent with empirical facts reported by Dickens and Katz (1987) and theoretical predictions provided by Alexopoulos (2006) and Acemoglu and Shimer (2000).

Equilibrium

An equilibrium of this economy consists of quantities and prices for such that, given prices, (1) a household chooses an optimal allocation plan $\{c_t, k_{t+1}, n_t\}_{t=0}^{\infty}$ that solves the utility maximization problem (2.1), (2) an intermediate firm optimally chooses a factor demand schedule $\{k_{it}, h_{it}, \tilde{h}_{it}\}_{t=0}^{\infty}$ that maximizes the firm's profit (2.9), (3) a final goods-producing firm chooses optimal demand for each intermediate good to satisfy equation (2.8), and (4) all markets clear:

$$k_{t+1} = q_t(y_t - c_t) + (1 - \delta)k_t \quad (2.14)$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \quad (2.15)$$

$$k_{1t} + k_{2t} = k_t \quad (2.16)$$

We list the whole equilibrium conditions in Appendix 2.5.2.

2.3.2 Predictions of the Model: Steady-State Analysis

In this section, we provide predictions of the model by studying the comparative statics of steady state equilibrium in which $q_t = q_{t+1}$ over time. In order to obtain analytical tractability that provides clear predictions of the model, we assume $\nu = 0$; i.e., intermediate goods are perfect substitutes, and hence $p_{1t} = p_{2t} = 1$. In Appendix 2.5.2, we provide equilibrium conditions for the steady state when values of parameters are not specified.

Since we are interested in how the changes in the price of capital due to investment-specific technological changes affect the two industries differently, we conduct the comparative statics exercise by analyzing the behavior of the steady-state economy when there is a change in q . While we only consider two industries, the analysis can be extended easily to $n > 2$ industries.

The next proposition is the collection of predictions of the model when q rises. This is introduced to capture the fact that the relative price of (ICT) capital has declined over time; one can think of the steady-state economy as the U.S economy in the beginning of 1980, and then there was a rise in q so that the new steady state is the U.S. economy in 2010. We first define s_i as follows.

$$s_i = \frac{h_i}{\bar{h}_i} \quad (2.17)$$

This term measures the usage of non-routine workers relative to routine workers. Then, job polarization in our model indicates the situation in which s_i increases. Next, we define κ_i as follows:

$$\kappa_i = \frac{k_i}{\bar{h}_i} \quad (2.18)$$

Hence, κ is the capital-routine worker ratio.

Proposition 1 (Job Polarization: Connection to Interindustry Wage Differentials). *The following results hold in the steady state:*

1. *The capital-routine worker ratio increases in both industries when the price of capital declines, while it rises more in the high-wage industry. In addition, the difference between industries increases in the wage premium (λ) and substitutability between capital and routine workers (μ). Formally,*

$$\frac{d\kappa_1}{dq} = (1 + \lambda)^{\frac{1}{1-\mu}} \frac{d\kappa_2}{dq} > 0 \quad (2.19)$$

2. *Job polarization happens in both industries when the price of capital declines. Formally,*

$$\frac{ds_i}{dq} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^\mu}{dq} > 0 \quad (2.20)$$

3. *The change in the employment share of non-routine over routine workers in industry 1 is greater than that in industry 2 when the price of capital declines; i.e., job polarization is more evident in the high-wage industry. In addition, the difference in the degree of job polarization across industries increases in the wage premium (λ) and substitutability between capital and routine workers (μ). Formally,*

$$\frac{ds_1}{dq} = (1 + \lambda)^{\frac{\mu}{1-\mu}} \frac{ds_2}{dq} \quad (2.21)$$

Proof. See Appendix 2.5.3. □

First of all, it is a natural consequence of the model that firms try to use capital more than routine workers when the price of capital declines, because capital and routine workers are substitutes. One can show that capital per routine worker rises more as the substitutability, μ , rises. In addition, the first part of the proposition shows that firms that are constrained to pay a higher wage markup use capital more intensively in production, and hence the capital-routine worker ratio grows more in those firms. The difference across industries increases in λ ; as the firm should pay more to workers, its incentive to utilize capital increases, which results in more rapid growth in the capital-routine worker ratio than in firms that can pay less to workers.

The second part of Proposition 1 shows that, consistent with previous models on job polarization, including Autor and Dorn (2013), Autor et al. (2003), and Cortes (2014), a decline in the price of capital is one of the critical factors in job polarization. The last part of the proposition is another key prediction of our model: the non-routine share of hours (employment) grows more in the high-wage industry since new technology (utilizing capital) is adopted more aggressively by the firms that face high labor costs, as discussed in the first part of the proposition. Furthermore, the difference in the degree of job polarization across industries increases in λ , the parameter that governs the industry wage premium, which shows the importance of the industry wage premium in explaining heterogeneous aspects of job polarization across industries.

We finally note that the first and the last part of the proposition together provide a theoretical background to the findings by Michaels et al. (2013). They find that the degree of job polarization is positively correlated with the growth rate of ICT capital, but they do not provide a clear explanation as to why this relationship holds in the data. Our model shows that it is interindustry wage differentials that systematically affect their finding; the high-wage industry substitutes routine workers with ICT capital more aggressively to cut production costs, and hence the progress of job polarization is more evident in this industry.

2.3.3 Tests of Predictions

In the empirical analysis conducted in Shim and Yang (2014), in order to test the prediction that κ_i (capital-routine worker ratio) grows more in the high-wage industry when the price of capital declines, we instead consider ICT capital per worker because the EU KLEMS data do not include information about occupations of workers. This provides, however, the same information as the proposition in the following sense; the capital-(total) labor ratio is $k_i/(h_i + \tilde{h}_i)$ and this can be decomposed into two parts as $\kappa_i \cdot \frac{1}{s_i+1}$. In the model, the first term increases more but the second term decreases more in the high-wage industry when q increases. Hence, if we can observe a positive relationship between the growth of ICT capital per worker and the initial industry wage premium, it implies that κ_i grows more in the high-wage industry, which is consistent with the prediction of the model.

Furthermore, in the empirical analysis, we compute the growth rate of employment for each occupational group, and compare the coefficients of the regression over the initial wage premium when evaluating the main prediction of the model (the last part of Proposition 1), which basically conveys the same information as the proposition; if the growth rate is lower in routine occupations than in non-routine occupations, which is an alternative way of defining job polarization, s_i will increase as the price of ICT capital decreases.

2.4 Conclusion

In this paper, we propose a theory to explain the link between the degree of job polarization and interindustry wage differentials. In particular, we analyze how the market responds to the interindustry wage structure with a two-sector neoclassical growth model; the model predicts that a high-wage industry would increase the capital-routine worker ratio more than a low-wage industry when the rental cost of capital declines and hence job polarization is more evident in this industry. Most importantly, the predictions of our model are consistent with empirical facts that are studied in Shim and Yang (2014).

Acknowledgement

Together with Chapter 1, chapter 2 is in preparation for submission.

2.5 Appendix

2.5.1 Unions: Microfoundation to Interindustry Wage Differentials

In this appendix, we develop a labor market environment in which the wage structure given in equation (2.4) is derived endogenously.

In particular, we adopt the labor market environment usually used in the New Keynesian literature, as in Smets and Wouters (2007) and Erceg et al. (2000). We assume that a firm can buy labor only through a labor union. Notice that the existence of a labor union is assumed only for convenience of the model; the key here is that the wage of a particular industry can be different from the wages of other industries. One might have a concern, in addition, that unionization in the U.S. is too small to be considered; according to recent estimates, only about 8 percent of U.S. private-sector workers are covered by a union agreement (Taschereau-Dumouchel (2012)). As Taschereau-Dumouchel (2012) shows in his paper, however, the ‘threat’ of forming a labor union can still have an impact on a firm’s decisions in equilibrium, and hence it is not problematic to assume the existence of a union and its effect on wages. In addition, as we pointed out earlier, a union itself is not an essential feature of our model; one can adopt alternative labor market structures so long as they can generate wages different from the ones determined in the competitive labor market. For instance, one might consider an efficiency wage model, as in Alexopoulos (2006), by assuming that the detection rate of shirking is heterogenous across industries. Instead, one might assume that the value of matching is different across industries, as in Montgomery (1991). Under the setup of our model, λ^i captures the differences across industries. Therefore, we can interpret the labor market environment used in our model as a reduced-form way to generate wage differentials across industries.

To showcase the importance of different levels of market power of labor unions, we assume for now that both industries have labor unions and a firm in industry $i \in$

$\{1, 2\}$ buys labor only from the labor union of the same industry. In addition, we allow possible differences in wage rates across non-routine and routine workers employed in the same industries, which does not change the main results. Later in this section, we assume that the labor union of industry 2 does not have market power, so that it is equivalent to the competitive labor market environment. The labor market is organized as follows. Firstly, the labor market (broker) supplies workers to the labor union of each industry at w_{ijt} , where $i \in \{1, 2\}$ and $j \in \{NR, R\}$. The labor union unpacks the labor into different varieties, $H_{it}^j(l)$, $l \in [0, 1]$, and sells them at wage rate $w_{it}^j(l)$. In so doing, the union acts as a monopolist for each single variety. The different labor varieties are purchased by perfectly competitive intermediaries, called labor packers. They produce aggregate labor for each task j according to the CES (Dixit-Stiglitz) production function:

$$H_{it}^j = \left[\int_0^1 (H_{it}^j(l))^{\frac{1}{1+\lambda^i}} dl \right]^{1+\lambda^i}$$

where λ^i , the wage markup in industry i , measures the market power of the union. We assume that the wage markup is the same across different occupations (tasks). Notice that if $\lambda^i = 0$, the labor union does not have any market power, so that wages will be determined by the competitive labor market.

The labor bundle H_{it}^j is then sold to the firm at a given price w_{it}^j . The cost minimization of labor packers yields the following labor demand equation:

$$H_{it}^j(l) = \left(\frac{w_{it}^j(l)}{w_{it}^j} \right)^{-\frac{1+\lambda^i}{\lambda^i}} H_{it}^j \quad (2.22)$$

and the wage aggregator $w_{it}^j = \left[\int_0^1 (w_{it}^j(l))^{-\frac{1}{\lambda^i}} dl \right]^{-\lambda^i}$. Furthermore, the zero profit condition of the labor packers yields $w_{it}^j H_{it}^j = \int_0^1 w_{it}^j(l) H_{it}^j(l) dl$.

Now we consider the labor union's problem:

$$\max_{w_{it}^j(l)} d_{it}^j(l) = (w_{it}^j(l) - w_{ijt}) H_{it}^j$$

subject to the labor demand equation (2.22). Substituting the constraint into the objective function reduces labor union's problem to $(w_{it}^j(l) - w_{ijt}) \left(\frac{w_{it}^j(l)}{w_{it}^j} \right)^{-\frac{1+\lambda^i}{\lambda^i}} H_{it}^j$. Differentiating with respect to $w_{it}^j(l)$ yields:

$$\begin{aligned}
H_{it}^j(l) - \frac{1 + \lambda^i}{\lambda_w^i} (w_{it}^j(l) - w_{ijt}) \frac{H_{it}^j(l)}{w_{it}^j(l)} &= 0 \\
\Leftrightarrow \lambda^i w_{it}^j(l) &= (1 + \lambda^i) (w_{it}^j(l) - w_{ijt})
\end{aligned} \tag{2.23}$$

Hence,

$$w_{it}^j(l) = (1 + \lambda^i) w_{ijt}$$

Note that in a symmetric equilibrium, $w_{it}^j(l) = w_{it}^j$, and hence,

$$w_{it}^j = (1 + \lambda^i) w_{ijt} \tag{2.24}$$

Therefore, with $\lambda > 0$, a labor union collects more labor income from firms and resulting profits (dividends) will be given back to households as a lump-sum transfer.

From now on, we will assume $\lambda^1 > \lambda^2 = 0$, and hence the labor union in industry 2 does not have any market power. This implies $w_{2t}^j = w_{2jt}$ and the indifference condition for positive employment for both industries yields:

$$w_{1t}^j = (1 + \lambda^1) w_{2t}^j \tag{2.25}$$

These are interindustry wage differentials in our economy: while workers are identical, a worker employed in industry 1 earns more than the other worker hired in industry 2.

2.5.2 Equilibrium Conditions

Non-Steady State

In this section, we present the set of equilibrium conditions that characterize the definition of the equilibrium:

$$\frac{c_{t+1}}{c_t} = \beta \left[q_t r_{t+1} + (1 - \delta) \frac{q_t}{q_{t+1}} \right] \tag{2.26}$$

$$w_t = \theta c_t = w_{2t} \tag{2.27}$$

$$w_{it} = \chi \tilde{w}_{it} \quad (2.28)$$

$$p_{it} = \left(\frac{y_t}{y_{it}} \right)^\nu \quad (2.29)$$

$$y_t = \left[\sum_{i=1}^2 y_{it}^{1-\nu} \right]^{\frac{1}{1-\nu}} \quad (2.30)$$

$$\lim_{T \rightarrow \infty} \beta^T \frac{k_{T+1}}{c_T} = 0 \quad (2.31)$$

$$w_{1t} = (1 + \lambda) w_{2t} \quad (2.32)$$

$$y_{it} = h_{it}^\alpha \left(\tilde{h}_{it}^\mu + k_{it}^\mu \right)^{\frac{1-\alpha}{\mu}} \quad (2.33)$$

$$\frac{w_{it}}{p_{it}} = \alpha \frac{y_{it}}{h_{it}} \quad (2.34)$$

$$\frac{\tilde{w}_{it}}{p_{it}} = (1 - \alpha) \frac{\tilde{h}_{it}^\mu}{\tilde{h}_{it}^\mu + k_{it}^\mu} \frac{y_{it}}{\tilde{h}_{it}} \quad (2.35)$$

$$\frac{r_t}{p_{it}} = (1 - \alpha) \frac{k_{it}^\mu}{\tilde{h}_{it}^\mu + k_{it}^\mu} \frac{y_{it}}{k_{it}} \quad (2.36)$$

$$k_{t+1} = q_t (y_t - c_t) + (1 - \delta) k_t \quad (2.37)$$

$$h_{1t} + h_{2t} + \tilde{h}_{1t} + \tilde{h}_{2t} = n_t \quad (2.38)$$

$$k_{1t} + k_{2t} = k_t \quad (2.39)$$

where $i = 1, 2$.

Steady State

In this section, we present the set of equilibrium conditions of the steady-state equilibria when $q_t = q$ for all t :

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{q} \quad (2.40)$$

$$w = \theta c = w_2 \quad (2.41)$$

$$p_i = \left(\frac{y}{y_i} \right)^\nu \quad (2.42)$$

$$y = \left[\sum_{i=1}^2 y_i^{1-\nu} \right]^{\frac{1}{1-\nu}} \quad (2.43)$$

$$w_i = \chi \tilde{w}_i \quad (2.44)$$

$$w_1 = (1 + \lambda)w_2 \quad (2.45)$$

$$y_i = h_i^\alpha \left(\tilde{h}_i^\mu + k_i^\mu \right)^{\frac{1-\alpha}{\mu}} \quad (2.46)$$

$$\frac{w_i}{p_i} = \alpha \frac{y_i}{h_i} \quad (2.47)$$

$$\frac{\tilde{w}_i}{p_i} = (1 - \alpha) \frac{\tilde{h}_i^\mu}{\tilde{h}_i^\mu + k_i^\mu} \frac{y_i}{\tilde{h}_i} \quad (2.48)$$

$$\frac{r}{p_i} = (1 - \alpha) \frac{k_i^\mu}{\tilde{h}_i^\mu + k_i^\mu} \frac{y_i}{k_i} \quad (2.49)$$

$$c + \frac{\delta}{q}k = y \quad (2.50)$$

$$h_1 + h_2 + \tilde{h}_1 + \tilde{h}_2 = n \quad (2.51)$$

$$k_1 + k_2 = k \quad (2.52)$$

where $i = 1, 2$.

Equilibrium conditions (2.40) and (2.41) are from the household's problem, equilibrium conditions (2.42) and (2.43) are from the final goods-producing firms' problem, (2.46) to (2.49) are from the firm's problem, (2.44) and (2.45) are wage rules, and (2.50) through (2.52) are market-clearing conditions. One can show easily that the household budget constraint is redundant (Walras' law).

2.5.3 Appendix: Proof of Proposition 1

We first obtain the following equations by dividing equation (2.47) (equations (2.48) and (2.49)) for industry 1 by equation (2.47) (equations (2.48) and (2.49)) for industry 2 and apply the wage structure given in equation (2.45):

$$1 + \lambda = \frac{y_1 h_2}{y_2 h_1} \quad (2.53)$$

$$1 + \lambda = \frac{y_1 \tilde{h}_2^{1-\mu} \tilde{h}_2^\mu + k_2^\mu}{y_2 \tilde{h}_1^{1-\mu} \tilde{h}_1^\mu + k_1^\mu} \quad (2.54)$$

$$\frac{y_1}{y_2} = \frac{k_1^{1-\mu} \tilde{h}_1^\mu + k_1^\mu}{k_2^{1-\mu} \tilde{h}_2^\mu + k_2^\mu} \quad (2.55)$$

Combining equations (2.54) and (2.55), we obtain the following relationship:

$$\frac{k_1}{\tilde{h}_1} = \phi \frac{k_2}{\tilde{h}_2} \quad (2.56)$$

where $\phi = (1 + \lambda)^{\frac{1}{1-\mu}} > 1$. For simplicity of notation, we let $\kappa_i = \frac{k_i}{h_i}$ in what follows. Hence, the above equation is now $\kappa_1 = \phi \kappa_2$.

We then combine equations (2.48) and (2.49) to obtain the following equation:

$$\tilde{w}_i = r \kappa_i^{1-\mu} \quad (2.57)$$

Recall that q and r are inversely related (see equation (2.40)) and hence a higher q implies a lower r . Accordingly, in what follows, we conduct comparative statics with

respect to r for convenience, while we report the comparative statics with respect to q in the main text. We first differentiate equation (2.57) with respect to r :

$$\frac{d\tilde{w}_i}{dr} = \kappa_i^{1-\mu} + r(1-\mu)\kappa_i^{-\mu} \frac{d\kappa_i}{dr} \quad (2.58)$$

Note that $\frac{d\tilde{w}_1}{dr} = (1+\lambda)\frac{d\tilde{w}_2}{dr}$ and $\frac{d\kappa_1}{dr} = \phi\frac{d\kappa_2}{dr}$ from the wage structure and equation (2.56). Then, we can solve for $\frac{d\kappa_2}{dr}$, whose expression is given as follows:

$$\frac{d\kappa_2}{dr} = -\frac{\kappa_2}{r(1-\mu)} < 0 \quad (2.59)$$

As a result, as one can expect from the substitutability between routine workers and capital, a lower rental cost of capital accelerates capital deepening (in terms of the capital-routine worker ratio). In addition, $\frac{d\kappa_1}{dr} = \phi\frac{d\kappa_2}{dr} < \frac{d\kappa_2}{dr} < 0$ implies that capital deepens more in the high-wage industry; the high-wage industry tries to find a way to reduce labor cost, and the reduction of the price of capital provides the incentive for the high-wage industry to rent more capital in order to replace routine workers more than the low-wage industry.

We define $s_i = \frac{h_i}{\tilde{h}_i}$. This measures, as discussed in the main text, the share of non-routine workers over routine workers. If s_i is increasing, it means that more non-routine workers are employed for given numbers (hours) of routine workers and hence it can be interpreted as job polarization. In order to study the effect of changes in r (and hence q) on job polarization, we combine equations (2.47) and (2.48):

$$\frac{1}{\chi} = \frac{1-\alpha}{\alpha} \frac{s_i}{1+\kappa_i^\mu} \quad (2.60)$$

Notice that the left-hand side of the above equation is constant at $1/\chi$ while κ_i increases as r decreases. As a result, it should be the case that $\frac{ds_i}{dr} < 0$. Formally,

$$\frac{ds_i}{dr} = \frac{\alpha}{\chi(1-\alpha)} \mu \kappa_i^{\mu-1} \frac{d\kappa_i}{dr} = \frac{\alpha}{\chi(1-\alpha)} \frac{d\kappa_i^\mu}{dr} < 0 \quad (2.61)$$

Hence, as the price of capital decreases, job polarization occurs in both industries.

Now, we compare the degree of job polarization across industries. Notice that the degree of job polarization is apparent in the high-wage industry if $|\frac{ds_1}{dr}| > |\frac{ds_2}{dr}|$. We use equation (2.61) and the relationship $\kappa_1 = \phi\kappa_2$:

$$\begin{aligned}
\frac{ds_1}{dr} &= \frac{\alpha}{\chi(1-\alpha)} \mu \kappa_1^{\mu-1} \frac{d\kappa_1}{dr} \\
&= \frac{\alpha}{\chi(1-\alpha)} \mu \phi^{\mu-1} \kappa_2^{\mu-1} \phi \frac{d\kappa_2}{dr} = \phi^\mu \frac{ds_2}{dr}
\end{aligned} \tag{2.62}$$

Hence, $|\frac{ds_1}{dr}| > |\frac{ds_2}{dr}|$ since $\phi > 1$ and $\mu > 0$.

The above equation shows clearly that the degree of job polarization becomes greater in the high-wage industry when r decreases. Suppose instead that $\lambda = 0$, so that there is no industry wage premium. Then, it is clear that $\frac{ds_1}{dr} = \frac{ds_2}{dr}$, and hence job polarization is of the same magnitude across industries. As a result, the heterogeneity in the progress of job polarization across industries increases in λ , which is consistent with our intuition.

Chapter 3

Precision of Market-Generated Information in Economies with Coordination Motives

Abstract. We study the interaction between the precision of exogenous and market-generated information in a class of economies where firms display coordination motives in presence of dispersed information and where the outcome of the coordination is traded in a competitive asset market á-la Grossman and Stiglitz (1980). We show that when more private information is injected in the coordination economy the equilibrium asset price becomes less informative. To showcase the relevance of our result we present an application to a problem of endogenous information choice where the “Knowing What Others Know” property of information acquisition derived by Hellwig and Veldkamp (2009) breaks down in presence of market-generated information.

3.1 Introduction

We study the interaction between private information and market-generated public information in the context of economies in which agents value, either positively or negatively, what other agents are doing in the aggregate. In our economy, firms play a coordination game of incomplete information (e.g. individual investment productivity function of aggregate investment) and use private and public signals to set optimally their actions. Simultaneously, an asset market is operating where risk averse traders exchange claims to dividends that are function of the outcome of the game for claims on a risk free asset. We let the equilibrium price be the main source of public information for the firms and we study how the information aggregating properties of the asset market are affected by the game played by firms.

Our main result reveals that when the private information held by firms in the incomplete information game is made more precise, the equilibrium asset price becomes less informative. Stating it differently: more precise private information leads to less precise public information.

The intuition behind this result goes as follows. In the coordination game the individual optimal strategies take the form of a linear combination of the private and public information. In the aggregate the noise in private information washes out and the game outcome is a function of the fundamentals and the public information. When private information is more precise, its relative weight in the individual optimal strategy is adjusted accordingly, which results in the outcome of the game being more sensitive to the unobserved fundamentals relative to the public information. Now consider the optimal strategies of risk averse traders in the asset market. Anything that makes the outcome of the game more predictable reduces the risk perceived by the traders and lead them to take more aggressive positions on the asset, i.e. positions that are more sensitive to the traders' private information. With more aggressive individual positions the asset market aggregates traders' private information more efficiently into the equilibrium price. When the private information of firms in the coordination game is increased the traders perceive that the dividend of the asset is riskier as it relies more on fundamentals, which are harder to predict. Traders react by taking less aggressive positions, thus using their private information less intensively, which finally results in the equilibrium

price aggregating information less efficiently, and becoming less precise.

An additional result that we derive concerns the role of the exogenous precision of public information. In our setting this precision corresponds to volatility of the part of the net supply of the risky asset that is unpredictable. We show that when the asset market is trading over claims on the outcome of the game, as opposed to trading directly on some underlying fundamental, any increase in the exogenous precision of public information results in a more than proportional increase in the precision of the market generated information. Once again, the mechanism that lies behind this magnification effect has to do with the way traders in the market react to the changes in the coordination game. Everything else equal, if public information become more precise firms rely more on it, which makes the game outcome more predictable for traders, which would now take more aggressive positions. The final result is a more efficient aggregation of information by the asset market, which magnifies the initial change in the exogenous precision.

To showcase the relevance of our results we present an information acquisition problem in presence of market-generated information. Information acquisition in our setting takes the form of a privately observed signal with a precision that is increasing in the costly effort spent on information; in this sense private information can be “produced” at the individual agent level by investing real resources. Hellwig and Veldkamp (2009) show that, in general, in economies with coordination motives, the coordination incentive is exactly transferred into the information acquisition incentives: the more agents invest in resources to produce precise private information in the aggregate, the more any individual agent has an incentive to increase (resp. decrease) her investment in private information when agents’ actions are complements (resp. substitutes). In the words of Hellwig and Veldkamp, agents want to “know what others know”.

We show that the exact transfer of incentives from the coordination game to the information acquisition breaks down when market generated information is introduced. More precisely, we show that in presence of complementarity the “knowing what others know” result is strengthened by market prices, while in presence of substitutability it is weakened, and for low enough substitutability it can be overturned.

We outline here the intuition for the result. As already mentioned, in a coordina-

tion game with incomplete information the optimal action of a firm takes the form of a linear combination of private and public signals with non-negative weights. Compared to the complete information case, in presence of strategic complementarity the agent optimally distorts the weights by reducing the relevance of private information in favor of the public signal which is a better predictor of coordination in actions, a valued characteristic of the game outcome independently of the true fundamentals. Under strategic substitutability the opposite is true, the weight on private information is optimally distorted upward, and the weight on public information downward.

Consider now the effect of increasing the aggregate information acquisition effort of the firms on the incentive to acquire information of the individual firm in presence of either complementarity or substitutability in the underlying game. When aggregate private information is more precise all firms adjust their weighting towards private information and away from public information. Under complementarity in actions, the individual firm anticipates that public information has become a worse predictor of the coordinated outcome and thus assigns more value to its own private information, which means higher effort in private information acquisition. Under substitutability, on the other hand, as public information is a worst predictor of the coordinated outcome, the individual firm assigns a higher weight to the public signal, in the attempt to distance itself from the actions of others. The final result is less effort in private information acquisition.

Suppose now that public information is obtained from the equilibrium asset price. From our main result we know that an increase in the precision of firms' private information *reduces* the information contained in the asset price. A less informative asset price has two effects on the optimal information choice of the individual firm. On the one hand, if all firms rely less on a less precise public signal, such signal becomes a worse predictor of the game outcome and firms will reduce its relevance when actions are complements, while increase its relevance if actions are substitute. We call this the "coordination" effect of price precision, as the direction of the effect depends on the type of coordination motives in the economy. Since the precision of the asset price declines when firms allocate more effort towards increasing private information precision, the coordination effect is increasing the value of private information under complementar-

ity and decreasing it under substitutability. The coordination effect in the low precision equilibrium reinforces the “knowing what others know” mechanism. On the other hand, it is always true that a less precise public signal increases the value of a more precise private signal, which means that the incentive to invest in private information increases, no matter the type of coordination incentives. We call this effect the “individual” effect of price precision. If the individual effect dominates the coordination effects, the value of the effort in improving private information increases with the increase in the aggregate effort even when the coordination game displays strategic substitutability.

RELATED LITERATURE. Several recent papers have studied, as we do here, the interaction between endogenous public signals and coordination games of incomplete information. Angeletos and Werning (2006) study the effects of introducing an endogenous public signal in games of regime change in terms of the multiplicity of equilibria. Our modeling of the market that generates public information is similar to that of Angeletos and Werning (2006), but differently from them, we focus on economies with weak coordination motives and unique equilibria and we model players in the coordination game and traders in the market as different subjects. Vives (2012) studies the welfare effects of introducing an endogenous public signal in a game with coordination motives that is similar to ours. The endogeneity of the public signal is modeled by assuming that agents can observe a linear noisy statistics of the aggregate action. Differently from Vives we explicitly model an asset market that produces the public information as a market clearing price, and, most importantly, we consider traders that are risk averse, which makes the perceived uncertainty surrounding the coordination game outcome relevant for the equilibrium outcome. Our paper is also related to Amador and Weill (2012) who study the welfare implications of releasing exogenous public information in an environment in which agents learn from endogenous public information, such as market prices, and from endogenous private information, such as local interactions.

Our application relates to a recent strand of literature on endogenous information acquisition and coordination motives. Several papers have reviewed, as we do, the generality of Hellwig and Veldkamp (2009)’s “Knowing What Others Know” result by considering different settings. Myatt and Wallace (2012) consider the setting of Hellwig and Veldkamp (2009) but endogenize the choice of information along two

dimensions: signal choice and attention to be paid to a signal. Their analysis focuses on the effects of information choice to the emergence of a unique equilibrium in situations where Hellwig and Veldkamp (2009) obtain multiple equilibria with respect to information choice. Colombo et al. (2014) consider the endogenous information choice for economies with a flexible quadratic-Gaussian structure with the objective of studying the welfare implications of different public information policies. The information coming from public signals in their setting is set by a public authority rather than being the outcome of a competitive market, and therefore it does not react to changes in the private information of agents through market interactions as it is the case in our setting. Szkup and Trevino (2013) is closest to the results that we obtain as they also show conditions where the “knowing what others know” property can break down. In particular, in their setting information acquisition can exhibit substitutability even when the underlying game exhibits strategic complementarity. Two features distinguish our model from their model. First, they consider coordination games with ‘strong’ complementarity, sometimes known as “regime-attack” games, while the model we consider exhibits ‘weak’ coordination motive as Hellwig and Veldkamp (2009) do. Second, the key mechanisms driving the results are different. In our model, the key effect is the decline of the informativeness of the public signal due to an increase in the precision of private signal of the players in the coordination game. In Szkup and Trevino (2013), instead, other players’ better information sometimes decreases the cost of incurring in a prediction error for the individual players. As a consequence, a player, everything else equal, has an incentive to choose less precise information.

The rest of the paper is organized as follows. Section 3.2 models and studies the coordination economy. Section 3.3 characterizes the information properties of the equilibrium asset price and contains our main result. Section 3.4 presents an application of our result to a problem of endogenous information acquisition. Section 3.5 concludes. Proofs can be found in Appendix A if not reported in the main text.

3.2 Coordination Economies

We focus on a class of coordination economies as modeled by Angeletos and Pavan (2007). In the economy there are a continuum of agents $i \in [0, 1]$, the individual action of agent i is denoted by a_i . Let $\Psi(a)$ denote the cumulative distribution function for individual actions across the population; the average action is $A \equiv \int a d\Psi(a)$. Let $\theta \in \mathbb{R}$ represent an exogenous payoff relevant state of the world, which we will refer to as “the fundamentals”. We assume that player’s i payoff function is

$$U(a, A, \theta) = -\frac{1}{2} \left(a - (1-r)\theta - rA \right)^2. \quad (3.1)$$

where $r \in (-1, 1)$. Under (3.1) the payoff of the agent is higher the smaller is the distance between her action a and a linear combination of the aggregate action and the fundamentals. The parameter r measures the degree of desired coordination between the individual and the aggregate action: when $r > 0$ agents actions are complements, when $r < 0$ they are substitutes. Note that U is concave at the individual level, which ensures that the optimal best response is bounded, and the slope of the best response with respect to the aggregate action A is smaller than 1, implying a unique symmetric equilibrium.¹

In what follows we will refer to the agents choosing action a under (3.1) as *firms*, in order to distinguish them from the *traders* that participate in the asset market (see Section 3.3). Firms do not observe the fundamentals θ , nor the average action A . It is assumed that each firm forms expectations using two signals, a private signal $x_i = \theta + (\alpha_{x,i})^{-\frac{1}{2}}\varepsilon_i$ with $\varepsilon_i \sim \mathcal{N}(0, 1)$, and a public signal $p = \theta + (\alpha_p)^{-\frac{1}{2}}\varepsilon$ with $\varepsilon \sim \mathcal{N}(0, 1)$. For expositional purposes it is useful to allow the signal of an arbitrary firm i to have a precision that can in principle be different from the precision of the private signals received by the other firms. In line with the existing literature we will restrict our focus on symmetric linear equilibria. As a consequence, here we proceed by solving for firm i equilibrium action assuming that all the remaining players have a private signal with a common precision α_x . Since the noise in private information is assumed to be i.i.d. across agents, in any symmetric equilibrium, the aggregate action

¹The specific form of the payoff function is assumed for analytical convenience and it is without loss of generality for the results derived below. In the Appendix we discuss a general form of the payoff function whose key features are all captured by (3.1)

A will be a function of (θ, p) only. Following Angeletos and Pavan (2007) we define the equilibrium of the economy as follows.

Definition. A linear equilibrium is a strategy $a : \mathbb{R}^2 \rightarrow \mathbb{R}$ linear in x and p such that, for all (x, p)

$$a(x, p) = \arg \max_{a'} \mathbb{E} \left[U(a', A(\theta, p), \theta) | x, p \right], \quad (3.2)$$

where $A(\theta, p) = \int_x a(x, p) d\bar{\Psi}(x|\theta, p)$ and $\bar{\Psi}(x|\theta, p)$ denotes the conditional distribution of x given (θ, p) .

Under complete information the equilibrium action is given by $a^* = \theta$. Angeletos and Pavan (2007) show that under incomplete information an individual strategy $a : \mathbb{R}^2 \rightarrow \mathbb{R}$ is an equilibrium if, and only if, for all (x, p) it satisfies

$$a(x, p) = \mathbb{E}[(1 - r) \cdot \theta + r \cdot A(\theta, p) | x, p], \quad (3.3)$$

where $A(\theta, p) = \mathbb{E}[a(x, p) | \theta, p]$ for all (θ, p) . The following proposition then immediately follows.

Proposition 2. Suppose that the precision of the private signal of firm i is given by $\alpha_{x,i}$, while the precision of the private signal for all the other firms is α_x . For any given value of (θ, p) a linear equilibrium exists and is unique. The equilibrium action of firm i is given by

$$a_i(x_i, p) = \psi_i \Lambda x_i + (1 - \psi_i \Lambda) p \quad (3.4)$$

with

$$\psi_i = \frac{\alpha_{x,i}}{\alpha_{x,i} + \alpha_p} \quad \text{and} \quad \Lambda = \frac{\alpha_x + \alpha_p}{\alpha_x + \frac{\alpha_p}{1-r}}. \quad (3.5)$$

In the linear equilibrium the aggregate action across firms is

$$A(\theta, p) = \lambda \theta + (1 - \lambda) p \quad (3.6)$$

where

$$\lambda = \frac{\alpha_x}{\alpha_x + \frac{\alpha_p}{1-r}}. \quad (3.7)$$

Compared to the complete information case, the equilibrium action (3.4) substitutes θ with a linear combination of the information available (x, p) . The weights that

a standard signal extraction exercise would suggest, ψ_i , are distorted by the term Λ . In presence of strategic substitutability, i.e. for $r < 0$, $\Lambda > 1$ and private information x_i receives a disproportionately higher weight than public information p . In presence of strategic complementarity, i.e. for $r > 0$, $\Lambda < 1$ and the opposite is true, public information p receives a disproportionately higher weight than private information x_i . The distortion is common across firms and it carries over to the aggregate so that the average action places more importance on the public signal rather than on the true fundamentals θ as shown by equations (3.6) and (3.7).

3.3 Asset Market

3.3.1 Demand, Supply and Equilibrium

We model the asset market using the CARA-Gaussian framework of Grossman and Stiglitz (1980).² The market is made of a large number of traders that have initial wealth w_0 and decide how to allocate it into a risky asset with price p and dividend $f(\theta)$ and a riskless asset with return equal to 1. The utility of the trader i is $V(w_i) = -e^{-\gamma w_i}$ with $w_i = w_0 + fk - pk$, where k is the demand for the risky asset. Traders base their prediction of the dividend on the information conveyed by the equilibrium price p and by a private signal $y = \theta + (\alpha_y)^{-\frac{1}{2}}\varepsilon_y$, where α_y is the precision of the signal and $\varepsilon_y \sim \mathcal{N}(0, 1)$. Traders individual demands take the standard “mean-variance” form

$$k^d(y, p) = \frac{\mathbb{E}(f|y, p) - p}{\gamma \mathbb{V}(f|y, p)} \quad (3.8)$$

The supply in the asset market is assumed to be stochastic and equal to $\mathbb{K}^s(\varepsilon) = (\alpha_\varepsilon)^{-\frac{1}{2}}\varepsilon$. Traders do not observe ε directly, but they try to infer it from the information that they have available. The presence of a stochastic supply in the asset market prevents the equilibrium price to reveal perfectly the fundamental θ : the lower is α_ε the lower the information about θ in p , everything else equal. In what follows we refer to α_ε as the “exogenous” precision of the public information p . The equilibrium market price ensures that the following market clearing condition holds,

²In modeling the asset market we follow closely Angeletos and Werning (2006).

$$\int_{-\infty}^{\infty} k^d(y, p) \phi(y) dy \equiv \mathbb{K}^d = \mathbb{K}^s(\varepsilon), \quad (3.9)$$

where $\phi(y)$ represents the pdf of a Normal distribution.

3.3.2 Exogenous Dividend

We consider first the case of an exogenous dividend, which corresponds to the function f being exogenously specified rather than being the outcome of some endogenous process. To maintain normality of the distributions we set $f = \theta$. We conjecture a price that is linear in θ and ε of the form $p = \theta - (\alpha_p)^{-\frac{1}{2}}\varepsilon$. The posterior of θ conditional on y and p is normally distributed with mean $\delta y + (1 - \delta)p$ and variance $(\alpha_y + \alpha_p)^{-1}$. The individual demand for the asset is therefore given by

$$k^d(y, p) = \frac{\alpha_y}{\gamma}(y - p). \quad (3.10)$$

The aggregate asset demand is obtained by aggregating over individual traders' demands, which gives $\mathbb{K}^d(\theta, p) = \frac{\alpha_y}{\gamma}(\theta - p)$. Imposing market clearing one obtains $p = \theta - \frac{\gamma}{\alpha_y}(\alpha_\varepsilon)^{-\frac{1}{2}}\varepsilon$ which results in the equilibrium precision of the asset price being

$$\alpha_p = \alpha_\varepsilon \left(\frac{\alpha_y}{\gamma} \right)^2 \quad (3.11)$$

In equilibrium α_p depends on the precision of the private information of traders and on their degree of risk aversion. In particular, the higher the precision of the private signal of the traders α_y , the higher the precision of the price. This follows from the form of the individual demand (3.10): a more precise private signal makes the demand more sensitive to the difference between y and p , which means that the aggregate demand is more sensitive to θ and thus more information is carried by the equilibrium price. A similar intuition applies for the risk aversion parameter γ : as traders become more risk averse, their demand is less sensitive to private information and so aggregate demand is less sensitive to θ , and a less informative price results. Finally, we note that the equilibrium precision of the market generated public information depends linearly on the exogenous precision of public information α_ε . As the exogenous precision is increased, the equilibrium precision is proportionally increased as well. Interestingly, for a given realization of p , α_ε does not affect the asset demand, which suggests that the exogenous

precision factors into the price precision only through the supply side of the market clearing condition.

3.3.3 Endogenous Dividend

Consider now the case of a dividend that is equal to the aggregate action in the coordination game, namely $f = A(\theta, p)$. The endogeneity of the dividend to the outcome of the coordination game is a simplified way to capture a potentially deeper interconnection between a competitive speculative market and an economic environment with coordination incentives.³ Using (3.6) the conditional average and variance of the aggregate action can be written as

$$\mathbb{E}[A(\theta, p)|y, p] = \lambda \frac{\alpha_y}{\alpha_y + \alpha_p} (y - p) + p \quad \text{and} \quad \mathbb{V}[A(\theta, p)|y, p] = \frac{\lambda^2}{\alpha_y + \alpha_p} \quad (3.12)$$

The individual asset demand is then given by

$$k^d(y, p) = \frac{\alpha_y}{\gamma \lambda} (y - p) \quad (3.13)$$

The expression differs from the exogenous dividend case for the presence of λ . Recall that λ measures how reactive is the individual (and average) action in the coordination game to changes in θ . When λ is high the dividend is very reactive to the underlying fundamentals. As a consequence, risk averse traders perceive the asset as riskier, and assume less aggressive positions. A less sensitive individual asset demand to the difference between the private signal and the price results in an aggregate demand that is less sensitive to θ . Aggregating demands one obtains $\mathbb{K}^d(\theta, p) = \frac{\alpha_y}{\gamma \lambda} (\theta - p)$. Imposing market clearing for the asset the equilibrium price is $p = \theta - \lambda \frac{2\sigma_\varepsilon}{\alpha_y} \varepsilon$ and the precision of the asset price becomes

$$\alpha_p = \alpha_\varepsilon \left(\frac{\alpha_y}{\lambda \gamma} \right)^2 \quad (3.14)$$

Note that α_p is decreasing in λ . Everything else equal, the more firms aggregate action A responds to fundamentals, the smaller the traders positions on the asset market, which results in less information being encoded into the equilibrium asset price.

³One possible micro-foundation of this feature can be obtained by considering a “market monitoring” contractual agreement as in Tirole (2006), where a principal-agent (or more appropriately “agents” in our case) problem is addressed by allowing speculative traders to trade on claims on the outcome of the project. We abstain from modeling the equilibrium resolution of the incentives problem explicitly here, but we focus on the informational consequences of allowing a market populated by agents that are different from those involved in the game whose outcome the market is pricing.

Substituting the expression for λ from Proposition 2 the fixed point condition for α_p takes the quadratic form

$$\alpha_p = \alpha_\varepsilon \left(\frac{\alpha_y}{\gamma} \right)^2 \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right)^2 \quad (3.15)$$

It can be showed that equation (3.15) has always two positive real solutions, a high precision one and a low precision one, provided that $2\frac{\alpha_y}{\gamma}\sqrt{\alpha_\varepsilon} < \sqrt{(1-r)\alpha_x}$. When the latter condition is not satisfied, an equilibrium for the asset market does not exist. Multiplicity in the asset market is generated by traders trying to predict a dividend that is itself the outcome of a signal extraction problem which depends on the asset price, and thus on traders dividend predictions.⁴ To outline an intuition for multiplicity, let us abstract from strategic incentive for a moment and consider the case of $r = 0$, so that $\lambda = \frac{\alpha_x}{\alpha_x + \alpha_p}$. When the precision of the asset price is low, firms allocate a low weight to the public signal and a high weight to their own private signal. This corresponds to a high λ , which makes the dividend very reactive to the fundamental θ . Risk averse traders, everything else equal, will respond by taking more cautious positions on the asset and this, in turn, will lead to a less reactive asset demand and a less informative price, which reinforces the initial low precision. When the precision of the asset is high, exactly the opposite argument holds: firms will rely more on the price, which will make the dividend more predictable, which will make traders take larger positions and thus make the price more informative.⁵

While both levels of price precisions are legitimate equilibria, they turn out to have different properties around the equilibrium point. To be clear, if one considers the stability of the equilibria with respect to variations in the asset price, both equilibria are stable in the sense that the asset demand is always downward sloping at the equilibrium point in both cases (see figure 3.1b). On these grounds, both prices could be considered as acceptable from a theoretical point of view. This is for instance the notion of stability that is advocated by Ganguli and Yang (2009). We instead follow Manzano and Vives (2011) and argue that a different notion of stability needs to be applied for fixed point

⁴The multiplicity in the precision of the asset price is similar to the multiplicity obtained in Ganguli and Yang (2009).

⁵It is possible to show that as the precision of private information for the firms is made arbitrarily large, the high precision equilibrium would disappear and the low precision equilibrium would coincide with the case of the exogenous dividend.

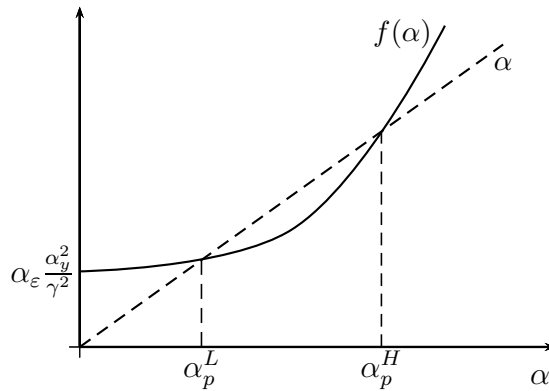


Figure 3.1a : Precision Stability

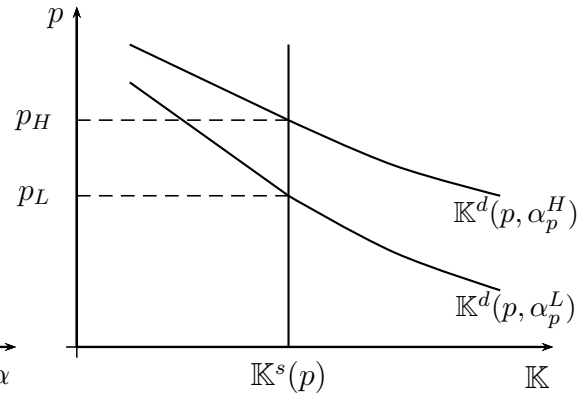


Figure 3.1b : Price Stability

Figure 3.1: Stability of Equilibria

conditions such as (3.15). Manzano and Vives (2011) propose that, if the equilibrium fixed point condition can be written as $\alpha \equiv f(\alpha)$, stability should be defined as

Definition. A fixed point α is stable if $|f'(\alpha)| < 1$.

In our case $f(\alpha) \equiv \alpha_\varepsilon \left(\frac{\alpha_y}{\gamma} \right)^2 \left(\frac{\alpha}{(1-r)\alpha_x} + 1 \right)^2$, which leads to the following result.

Proposition 3. The high precision solution to (3.15) is unstable; the low precision solution is stable.

Figure 3.1a shows the graphical representation of the fixed point in (3.15). At the low precision equilibrium the mapping f has slope less than 1, while at the high precision equilibrium the slope is greater than 1. According to our definition of stability, α_L is stable, while α_H is unstable.

Following the result of our stability analysis, from now on we restrict our attention to the low precision equilibrium. It should be noted, however, that our results would be reversed if we were to consider the case of the unstable high precision equilibria.

3.3.4 Exogenous Private Precision and Price Precision

We are now in a position to analyze the relationship between the precision of private information at the coordination game stage and the precision of the asset market generated information. The following proposition states our main result.

Proposition 4. *The precision of the equilibrium asset price is decreasing in the precision of the private information of firms. Formally*

$$\frac{\partial \alpha_p}{\partial \alpha_x} < 0. \quad (3.16)$$

The intuition for this result can be gained by recalling our discussion about the effect of λ on the perceived riskiness of the asset dividend. When more precise private information is available to firms, i.e. when $d\alpha_x > 0$, they rely more on their private signals, which makes the aggregate action in the coordination economy more responsive to the actual economic fundamentals as opposed to the signal p ; this, in turn, makes the dividend riskier from the perspective of the traders and therefore reduces the sensitivity of aggregate asset demand to the fundamental θ , which eventually results in a noisier price. The negative relationship between the information available to firms and the information contained in the asset price emerges in the context of a coordination game of incomplete information and it is, to the best of our knowledge, novel to the literature.⁶

3.3.5 Exogenous Public Precision and Price Precision

The interaction between the coordination economy and the asset market also affects the ways in which the exogenous precision of public information α_ε translates into the market generated precision of the asset price. To see this recall that in the case of an exogenous dividend the precision of the asset price is a linear function of α_ε , so that the derivative of the asset price precision with respect to the exogenous public precision is constant and equal to $\left(\frac{\alpha_y}{\gamma}\right)^2$. The following proposition shows that the presence of the coordination economy enhances the increase in public information precision.

⁶In Rondina and Shim (2013) we show that a similar result holds when the dividend of the asset is a function of the outcome of a regime change game, such as a currency attack game or a bank run game. We use the result to show that when information precision of players in the game is made arbitrarily precise, the introduction of an endogenous public signal does not necessarily imply multiplicity of equilibria, a result that qualifies the criticism of Angeletos and Werning (2006) to the uniqueness result of Morris and Shin (1998).

Proposition 5. *The precision of the equilibrium asset price is increasing in the exogenous precision of public information according to the expression*

$$\frac{\partial \alpha_p}{\partial \alpha_\varepsilon} = v \left(\frac{\alpha_y}{\gamma} \right)^2 > 0 \quad (3.17)$$

where

$$v \equiv \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right)^2 \frac{1}{1 - f'(\alpha_p)} > 1. \quad (3.18)$$

Once again, the intuition for this result lies in the role of λ in determining the perceived riskiness of the asset. When more precise public information is available firms reduce the weight they assign to their own private information, which makes their actions less sensitive to the true fundamentals. This makes traders' positions more sensitive on their private information and thus enhances the precision of the equilibrium price. Note that while in the exogenous dividend case α_ε operates only through the supply side of the market, in the endogenous dividend case the behavior of firms in response to a change in α_ε is inducing traders to use their own private information more intensively, thereby changing the demand side of the market as well. The more-than-proportional enhancement of public information precision is thus demand-driven in the endogenous dividend case.

3.4 Application: Endogenous Information Acquisition

To showcase the relevance of the results just presented we study a problem of endogenous information acquisition. In particular we allow firms to choose the precision of the private signal they receive, α_x , in exchange for exerting a costly effort. We are interested in understanding whether in presence of market-generated information the information acquisition effort choice of an individual firm is complement or substitute with respect to the information choice of other firms and with respect to the exogenous precision of public information. We think of time as made of three stages. In stage 1 firms choose how much precision to acquire and nature draws the vector of stochastic shocks. In stage 2 traders observe their private signal y and set their demand strategies and the asset market clears at the competitive equilibrium price. In stage 3, firms observe their private signal x , the equilibrium price and, conditional on both, set

their optimal strategies in the coordination economy. We focus on symmetric perfect Bayesian equilibria of the three-stage extensive form game⁷ and use backward induction to characterize the equilibrium strategies. We begin by solving the coordination game at stage 3, given a pre-specified symmetric informational choice across agents and an arbitrary asset price. Then, given the outcome of the coordination game we solve for the equilibrium asset price of stage 2, and finally, we study the information choice at stage 1 under the equilibrium restrictions that we obtained in stages 2 and 3.

3.4.1 Private Information Acquisition and Market Generated Information

We assume that the information precision of a firm i depends on the amount of effort $n_i \geq 0$ that is exerted in stage 1. We capture this relationship by denoting the private precision with $\alpha_x(n_i)$ where the function $\alpha_x(\cdot)$ is assumed to be non-negative, non-decreasing, weakly concave and differentiable. Introducing the relationship between precision and effort is not strictly necessary for our analysis, but it allows us to distinguish more easily what signal precisions are controlled by the individual firms and what are taken as given but still endogenous in equilibrium. The private signal received by a firm i can be then written as

$$x(n) = \theta + \alpha_x(n)^{-\frac{1}{2}} \varepsilon_x \quad (3.19)$$

Firms choose n taking into account the effect that the private information precision has on the utility they expect from playing the coordination game once the signals are received. The expected utility at the information choice stage is $\mathbb{E}_0[U^*(a, A, \theta)]$. Here U^* denotes the fact that, given any information choice n , the payoff function is specified using the function describing the optimal strategy at stage 3, while \mathbb{E}_0 denotes that expectations are taken with respect to the common prior before signals are realized.

For simplicity we consider symmetric equilibria in information choice at the aggregate level and so we let \mathbf{n} represent the information acquisition effort across firms, or aggregate information acquisition effort. The individual firm i chooses effort taking the

⁷Because each individual agent is infinitesimal beliefs off-equilibrium path need not be specified as any deviation from a single player cannot possibly be detected.

aggregate effort \mathbf{n} as given. The infinitesimal dimension of each individual firm is such that the individual deviation from the aggregate information choice has no detectable effect. On the other hand, the aggregate information effort \mathbf{n} affects the precision of the asset price and thus the asset price itself. We embed this into our notation by denoting the asset price by $p(\mathbf{n})$ and its precision by $\alpha_p(\mathbf{n})$. Using Proposition 2 the optimal strategy for an individual firm i is given by

$$a(x_i(n), p(\mathbf{n})) = \lambda(n, \mathbf{n})x_i(n) + (1 - \lambda(n, \mathbf{n}))p(\mathbf{n}) \quad (3.20)$$

where

$$\lambda(n, \mathbf{n}) = \Lambda(\mathbf{n})\psi(n, \mathbf{n}); \quad \psi(n, \mathbf{n}) = \frac{\alpha_x(n)}{\alpha_x(n) + \alpha_p(\mathbf{n})}; \quad \Lambda(\mathbf{n}) = \frac{\alpha_x(\mathbf{n}) + \alpha_p(\mathbf{n})}{\alpha_x(\mathbf{n}) + \frac{\alpha_p(\mathbf{n})}{1-r}}. \quad (3.21)$$

Defining $\lambda(\mathbf{n}, \mathbf{n}) \equiv \lambda(\mathbf{n})$ from the above relationships it follows that the aggregate action of firms is

$$A(\theta, p(\mathbf{n})) = \lambda(\mathbf{n})\theta + (1 - \lambda(\mathbf{n}))p(\mathbf{n}) \quad \text{where} \quad \lambda(\mathbf{n}) = \frac{\alpha_x(\mathbf{n})}{\alpha_x(\mathbf{n}) + \frac{\alpha_p(\mathbf{n})}{1-r}}. \quad (3.22)$$

At stage 1 firms anticipate that the equilibrium of the coordination satisfies (3.22) together with market clearing in the asset market. Information sets at stage 1 are the same across all agents and consist of the structure of the game and the common degenerate prior over θ . Because the utility of firms is quadratic, the expected utility at stage 1 depends only on unconditional second moments. Using the equilibrium relationships above it is possible to show the following Lemma.

Lemma 1. *Suppose that at stage 1 in the economy the aggregate information acquisition effort is \mathbf{n} . The expected utility for an individual firm with information acquisition effort n is given by*

$$\begin{aligned} \mathbb{E}_0[U^*(a, A, \theta)] \equiv u(n, \mathbf{n}) &= \frac{1}{2}\lambda(n, \mathbf{n}) \left[\frac{1 + r(1 - \lambda(\mathbf{n}))}{\alpha_p(\mathbf{n})} \right] \\ &\quad + r(1 - \lambda(n, \mathbf{n})) \left[\frac{1 - \lambda(\mathbf{n})}{\alpha_p(\mathbf{n})} \right] + \bar{u}(\mathbf{n}) \end{aligned} \quad (3.23)$$

where $\bar{u}(\mathbf{n})$ is a constant term that does not depend on the choice variable n .

To understand the terms on the right hand side of (3.23) note that the effort choice n at the individual level affects only the individual action a by redistributing the weight

$\lambda(n, \mathbf{n})$ between the private signal x and the public signal p . Since U is quadratic, it follows that the choice of n can affect only the terms in the payoff function that depend on a ; these are the variance of the individual action, $\mathbb{E}_0[a^2]$, and the covariance of the individual action with the aggregate action, $\mathbb{E}_0[aA]$, and with the state, $\mathbb{E}_0[a\theta]$. Using (3.20) and $p = \theta - \alpha_p^{-1/2}\varepsilon$ one can obtain expressions for these three terms. First, the covariance between the individual action and the state $\mathbb{E}_0[a\theta]$ is just a function of the common prior over the variance of θ , which is unaffected by the information choice and it is therefore included in $\bar{u}(\mathbf{n})$. Second, the variance of the individual action is given by the common prior over the variance of the state θ , plus a linear combination of the variance of the noise in the public and private signal, which can be expressed as the first term on the right hand side of (3.23). Finally, the covariance between the individual action and the aggregate action equals the unconditional variance of the state θ plus a covariance term that emerges because both the individual and the aggregate action rely on the noisy public signal. This is the second term on the right hand side.

The form of (3.23) is very useful in isolating the effects of investing in private information precision on the payoff of the players. There are two opposite effects at play when private information is changed. On the one hand, as n is increased the effect on $\lambda(n, \mathbf{n})$ is always positive: as private information is more precise the individual player will rely more on it and thus incur in a smaller prediction error, which always reduces the ex-ante variance of the individual action choice a . This effect is captured in the first term on the right hand side of (3.23).

Note that for $r \in (-1, 1)$, the term is always positive, which means that, no matter the strategic interactions in the coordination economy, higher effort in private information precision acquisition always increases expected utility by reducing the variance of the individual action. On the other hand, as n is increased the player will rely less on public information and thus reduce the covariance of her individual action with the aggregate action. This is captured in the second term at the right hand side of (3.23). Whether the reduction in covariance is desirable or not depends on the type of strategic interactions in the coordination economy. If actions are complement ($r > 0$) a reduction in covariance will reduce the ex-ante payoff; while the opposite is true if actions are substitutes ($r < 0$).

Complementarity or substitutability in information acquisition for firms can be evaluated by studying the sign of the cross-partial derivative

$$u_{n\mathbf{n}} \equiv \frac{\partial^2 u}{\partial n \partial \mathbf{n}}. \quad (3.24)$$

When the sign of the cross-partial is positive, the value of additional information at the individual firm level is increasing in the precision of firms' private information at the aggregate level. In such case we say that the coordination economy displays complementarity in information acquisition with respect to other firms. When the sign is negative, the value of additional information at the individual level is decreasing with the precision of information at the aggregate level. In this case we say that the economy displays substitutability in information acquisition.

We develop our analysis in two steps. First we consider the case of an exogenous dividend for the asset price. For the first term in (3.28) this corresponds the case considered by Hellwig and Veldkamp (2009); we show that their result holds our setting. Next, we allow the market price to have an endogenous precision through the equilibrium interaction. We show that the result of Hellwig and Veldkamp (2009) is modified in a very specific direction.

KNOWING WHAT OTHERS KNOW. The following proposition corresponds to a version of Hellwig and Veldkamp (2009) main proposition for environments where information acquisition is continuous.

Proposition 6. *Assume that the precision of the asset market price does not depend on the precision of the private information of firms as in Section 3.3.2.*

1. *If actions are complementary in the coordination economy ($r > 0$), the value of additional effort in private information acquisition at the individual firm level n is increasing in the aggregate effort across firms \mathbf{n} .*
2. *If actions are substitutes in the coordination economy ($r < 0$), the value of additional effort in private information acquisition at the individual firm level n is decreasing in the aggregate effort across firms \mathbf{n} .*
3. *If actions are independent of each other in the coordination economy ($r = 0$), the value of additional effort in private information acquisition at the individual firm level n is independent of the aggregate effort across firms \mathbf{n} .*

Proof. The proof of 1-3 consists in showing that $\text{sign}(u_{nn}) = \text{sign}(r)$. Holding α_p constant the cross partial derivative of (3.23) is $u_{nn} \propto 2\Lambda(\mathbf{n}) \frac{\partial \Lambda(\mathbf{n})}{\partial \mathbf{n}} \frac{\alpha'_x(n)}{(\alpha_x(n) + \alpha_p)^2}$, where $\alpha'_x(n) = \frac{\partial \alpha_x(n)}{\partial n}$. The sign of this expression depends entirely on the sign of $\frac{\partial \Lambda(\mathbf{n})}{\partial \mathbf{n}}$ as both $\alpha'_x(n)$ and $\Lambda(\mathbf{n})$ are always positive. Since α_p is constant it can be showed that

$$\frac{\partial \Lambda(\mathbf{n})}{\partial \mathbf{n}} = r \frac{(1-r)\alpha'_x(\mathbf{n})\alpha_p}{(\alpha_p + (1-r)\alpha_x(\mathbf{n}))^2}. \quad (3.25)$$

The sign of the expression on the right hand side depends only the sign on r , which completes the proof. \square

Recall that the term $\Lambda(\mathbf{n})$ represents the adjustment that individual firms apply to their actions to take into account that other firms under-react or over-react to the common noise that is present in the public signal. In presence of complementarity the adjustment is downward, so that $\Lambda(\mathbf{n}) < 1$, while in presence of substitutability the adjustment is upward, $\Lambda(\mathbf{n}) > 1$. When aggregate private information acquisition across firms \mathbf{n} is increased, all firms devote more importance to their private signals and less to their public signal. In presence of strategic complementarity individual firms recognize this and adjust $\Lambda(\mathbf{n}) < 1$ upwards in order to take into account the reduced correlation across actions from the common noise of the public signal. In presence of strategic substitutability individual firms act exactly in the opposite way and adjust $\Lambda(\mathbf{n}) > 1$ downward. As a consequence, when \mathbf{n} is increased, the value of private information is enhanced for the individual firm in the economy with complementarities, and this creates an incentive in increasing the investment in private information. On the contrary, the value of private information is reduced for the individual player in the economy with substitutability, and so the incentive is now to reduce the effort in private information. The strategic motives in the coordination economy carry over to the information acquisition stage.

MARKET-GENERATED INFORMATION. We now allow for the precision of the public information to vary with the aggregate informational choice \mathbf{n} by introducing the asset market of Section 3.3.3. Differently from the exogenous precision case, as \mathbf{n} is changed, the precision $\alpha_p(\mathbf{n})$ is changed as well. We know from Proposition 4 that the change in precision of the asset price is inversely related to the precision of private information for firms. Introducing the endogeneity of information precision, a corollary immediately

follows.

Corollary 1. *The precision of the equilibrium asset price is decreasing in the aggregate information acquisition effort of firms, formally*

$$\alpha_p^{\mathbf{n}} \equiv \frac{\partial \alpha_p(\mathbf{n})}{\partial \mathbf{n}} < 0. \quad (3.26)$$

Proof. Follows immediately from Proposition 4 and $\alpha'_x(n) > 0$. \square

Using (3.23) the cross-partial u_{nn} can be written as

$$u_{nn} \propto \Lambda_r \alpha'_x(\mathbf{n}) + (-\Lambda_r + \lambda_\alpha) \alpha_p^{\mathbf{n}} \quad (3.27)$$

where

$$\Lambda_r \equiv r \frac{(1-r)\alpha_p(\mathbf{n})}{(\alpha_p(\mathbf{n}) + (1-r)\alpha_x(\mathbf{n}))^2} \quad \text{and} \quad \lambda_\alpha \equiv -\frac{\Lambda(\mathbf{n})}{\alpha_x(n) + \alpha_p(\mathbf{n})}$$

We refer to Λ_r as the ‘‘coordination effect’’ term, as its sign and magnitude depend on r , and to λ_α as the ‘‘individual effect’’ of the market-generated information.

The expression for u_{nn} shows how the coordination effect operates across public versus private signals. If all firms increase the precision of their private signals, the value of allocating effort to private information is higher for the individual firm under complementarity. If the increase in precision concerns the *public* signal, then there is less value in allocating effort to private information, hence the minus sign in front of Λ_r . In addition to these two contrasting effects, there is a third effect measured by λ_α capturing the substitutability across different signals typical of any signal extraction problem: the relative value of a signal is reduced when another signal becomes more precise. Note that the magnitude of λ_α depends on the individual precision of the private signal, $\alpha_x(n)$, and its sign is independent of the strategic interaction motives. Since the sign of λ_α is always negative, its contribution to the information acquisition incentive depends on the direction of the change in market price precision. When $\alpha_p(\mathbf{n})$ increases, the value of private information is always reduced as better public information is available, while the opposite is true when $\alpha_p(\mathbf{n})$ decreases. In addition, the relevance of the individual substitution effect λ_α depends on the distortionary term $\Lambda(\mathbf{n})$. More precisely, the individual effect matters more in presence of substitutability, when $\Lambda(\mathbf{n}) > 1$, than

in presence of complementarity, when $\Lambda(\mathbf{n}) < 1$. The reason being that the change in precision concerns a public signal, which, while desirable in presence of positive coordination motives, it remains undesirable under substitutability.

The following proposition summarizes how the interaction of the coordination and individual effect with the asset price precision shapes the value of firms' effort in private information acquisition.

Proposition 7. *Assume that the precision of the public signal p is market-generated as in Section 3.3.3.*

1. *If actions are complementary in the coordination economy ($r > 0$), the value of additional effort in private information acquisition at the individual firm level n is always increasing in the aggregate effort across firms \mathbf{n} .*
2. *If actions are weakly substitutes in the coordination economy ($r \leq 0$), the value of additional effort in private information acquisition at the individual firm level n is increasing in the aggregate effort across firms \mathbf{n} if the individual effect is stronger than the coordination effect, i.e. $\lambda_\alpha \alpha_p^n > -\Lambda_r \alpha'_x(\mathbf{n}) + \Lambda_r \alpha_p^n > 0$*

Proof. Follows immediately from (3.27), the definitions for Λ_r and λ_α and Corollary 1. □

Under strategic complementarity $\Lambda_r > 0$ and $\lambda_\alpha < 0$, but the precision of the market price is decreasing in the aggregate effort on information acquisition of firms, which implies that both the coordination and individual effect reinforce the “knowing what others know” motive. Compared to the exogenous information case of Proposition 6, the complementarity in information acquisition effort is magnified through the decrease in precision of the public signal, which turns the coordination effect on public information in the direction of “knowing what others know”. Under strategic substitutability the coordination effects reverse their signs. However, the individual effect remains overall positive and it is larger since $\Lambda(\mathbf{n}) > 1$. It follows that information acquisition effort can display complementarity even in presence of substitutability in the coordination economy. Essentially, if the deterioration in the precision of the public signal is large enough (which is a consequence of more private aggregate information

precision), the individual firm finds it valuable to increase its private information acquisition effort in order to contrast the deterioration in its overall information precision due to a less precise market price. If this happens, the “knowing what others know” property does not hold anymore.

3.4.2 Private Information Acquisition and Exogenous Precision of Public Information

In the study of information acquisition it is important to understand how exogenous changes in the precision of public information, possibly obtained as the result of a public information policy, affect the incentive to acquire information at the individual agent level. In the present application one can think of α_ε as the information parameter on which a public policy can intervene. The consequences on the information acquisition incentives can thus be studied by looking at the behavior of the cross-partial

$$u_{n\alpha_\varepsilon} \equiv \frac{\partial^2 u}{\partial n \partial \alpha_\varepsilon}. \quad (3.28)$$

When the sign $u_{n\alpha_\varepsilon}$ is positive, the value of additional information at the individual firm level is increasing in the exogenous precision of public information. In such case we say that the coordination economy displays complementarity in information acquisition with respect to public information. When the sign is negative, the value of additional information at the individual level is decreasing with the exogenous precision of public information. In this case we say that the economy displays substitutability in information acquisition with respect to public information. Following our previous analysis it is immediate to see that the cross partial can be written as

$$u_{n\alpha_\varepsilon} \propto (-\Lambda_r + \lambda_\alpha) \frac{\partial \alpha_p}{\partial \alpha_\varepsilon} \quad (3.29)$$

The following result immediately follows.

Proposition 8. *Assume that the precision of the public signal p is market-generated as in Section 3.3.3.*

1. *If actions are complementary in the coordination economy ($r > 0$), the value of additional effort in private information acquisition at the individual firm level n is always decreasing in the exogenous precision of public information α_ε .*

2. *If actions are weakly substitutes in the coordination economy ($r \leq 0$), the value of additional effort in private information acquisition at the individual firm level n is decreasing in the exogenous precision of public information α_ε if the individual effect is weaker than the coordination effect, i.e. $|\lambda_\alpha| < |\Lambda_r|$.*
3. *Everything else equal, the change in the value of additional effort in private information acquisition at the firm level is always larger when the dividend of the asset price is endogenous to the outcome of the coordination economy.*

Proof. Follows immediately from (3.29), the definitions for Λ_r and λ_α , Corollary 1 and Proposition 5. □

To gain intuition for points 1-2 of the result, recall that λ_α is always negative, while the sign of Λ_r depends on r . When $r > 0$ both the individual and coordination effects agree and point towards a lower value for private information. For the case of $r < 0$, it is possible that the individual effect is so small that the coordination effect dominates. In a symmetric equilibrium in the information choice one has $n = \mathbf{n}$ which makes the latter condition not possible, so that the individual effect always dominates the coordination effects. In other words, the incentive to choose information so to receive signals that would ensure the maximum distance from the aggregate action is always weaker than the effect of having better information available, independently of the source. It follows that, even in the presence of substitutability, an increase in the precision of public information reduces the value of allocating effort to the acquisition of public information.

The second part of the result is a direct consequence of Proposition 5. When the dividend of the asset is endogenous there is a demand-driven information precision enhancement that reduces (or increases) the value of acquiring private information even further.

We conclude this section with a comment on the relevance of the results of our application for information policy problems. Generally speaking, a policymaker is always faced with the choice of spending resources to provide incentives to private information acquisition at the individual agent level or using resources to increase the precision of public information. Propositions 5, 7 and 8 provide reasons for caution

when designing an optimal policy in presence of market-generated information. On the one hand, Proposition 5 says that increasing private information acquisition deteriorates the precision of the asset price. To the extent that the asset price precision is of relevance to the policymaker in its own right, the proposition warns the policymaker that providing private information acquisition incentives might backfire through the endogenous public information. At the same time, Proposition 7 informs that for a given amount of resources spent in providing incentives for private information acquisition, the final outcome is magnified in presence of market-generated information, irrespectively of the sign of coordination incentives in the economy. On the other hand, Proposition 8 warns that if resources are spent on increasing the precision of public information, this may come at the cost of reducing the acquisition of private information at the firms level. In particular, when the precision of public information affects a market-generated public signal, it matters how the market forces take into account the outcome of the underlying coordination economy. If such an interaction is overlooked, the chosen release of public information might “overshoot” the optimal level by not taking into account the ensuing excessive reduction in private information acquisition.

3.5 Conclusion

There is little doubt that market prices are the primary source of publicly available information in the economy. A common presumption is that when more private information is injected in the economy, market prices reflect the increase in information and become a better source of public information. In this paper we have presented a setting in which this presumption is proven incorrect: if more private information is available to firms in the economy, the economic outcome is perceived as more uncertain to risk averse asset traders, which leads to a reduction in traders’ use of private information in the asset market. The final result is a less informative market price. Our application to a simple information choice problem highlights the importance of our result for a policymaker that needs to allocate resources to design the proper informational incentives to maximize welfare, as in Colombo et al. (2014). Disregarding the interaction between private and public information through market forces is likely to let the

policymaker choose an allocation that is sub-optimal. We leave such welfare analysis to future work.

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Chapter 3 is coauthored with Giacomo Rondina, and in full, has been submitted for publication of material.

3.6 Appendix: Proofs

3.6.1 Proof of Proposition 2

The individual optimal action is $a(x, p) = (1 - r)\mathbb{E}[\theta | x, p] + r\mathbb{E}[A(\theta, p) | x, p]$. We guess the individual and aggregate solutions $a(x, p) = \lambda_x^i x_i + \lambda_p^i p$ and $A(\theta, p) = \lambda_x \theta + \lambda_p p$. Since $\mathbb{E}[\theta | x, p] = \psi_i x_i + (1 - \psi_i)p$, where $\psi_i = \alpha_{x,i}/(\alpha_{x,i} + \alpha_p)$, it follows that

$$\mathbb{E}[A(\theta, p) | x, p] = \lambda_x(\psi_i x_i + (1 - \psi_i)p) + \lambda_p p. \quad (3.30)$$

The individual action becomes

$$a_i(x_i, p) = \underbrace{[(1 - r)\psi_i + r\lambda_x\psi_i]}_{\equiv \lambda_x^i} x_i + \underbrace{[(1 - r)(1 - \psi_i) + r\lambda_x(1 - \psi_i) + r\lambda_p]}_{\equiv \lambda_p^i} p.$$

The fixed point conditions are

$$\lambda_x^i = [(1 - r) + r\lambda_x]\psi_i \quad \text{and} \quad \lambda_p^i = (1 - r)(1 - \psi_i) + r\lambda_x(1 - \psi_i) + r\lambda_p \quad (3.31)$$

In the symmetric equilibrium $\lambda_x^i = \lambda_x$, $\psi_i = \psi$ and $\lambda_p^i = \lambda_p$ so from (3.31) one obtains

$$\lambda_x = \frac{(1 - r)\alpha_x}{(1 - r)\alpha_x + \alpha_p} \quad \text{and} \quad \lambda_p = \frac{\alpha_p}{(1 - r)\alpha_x + \alpha_p}. \quad (3.32)$$

The solution for the aggregate action $A(\theta, p)$ is

$$A(\theta, p) = [\lambda\theta + (1 - \lambda)p] \quad (3.33)$$

with $\lambda = \frac{\alpha_x}{\alpha_x + \frac{\alpha_p}{1-r}}$. It follows that $\lambda_x^i = \psi_i \Lambda$ where $\Lambda = \frac{\alpha_x + \alpha_p}{\alpha_x + \frac{\alpha_p}{1-r}}$ and λ_p^i is given by

$$\begin{aligned} \lambda_p^i &= (1 - \psi_i) \underbrace{[(1 - r) + r\lambda_x]}_{=\Lambda} + r\lambda_p \\ &= \frac{1}{(1 - r)\alpha_x + \alpha_p} [(1 - r)\alpha_x + \alpha_p - \psi_i(1 - r)(\alpha_x + \alpha_p)] \end{aligned}$$

which results in $\lambda_p^i = [1 - \psi_i \Lambda]$.

3.6.2 Proof of Proposition 3

Let $\delta = \sqrt{\alpha_\varepsilon} \alpha_y / \gamma$. The derivative $f'(\alpha_p)$ is

$$f'(\alpha_p) = 2 \left(\frac{\delta}{(1-r)\alpha_x} \right)^2 \cdot \alpha_p + \frac{2\delta^2}{(1-r)\alpha_x} \quad (3.34)$$

The solutions satisfying (3.15) are

$$\alpha_p = \frac{\left(1 - \frac{2\delta^2}{(1-r)\alpha_x}\right) \pm \sqrt{1 - 4\delta^2 \frac{1}{(1-r)\alpha_x}}}{2 \left(\frac{\delta}{(1-r)\alpha_x}\right)^2} \quad (3.35)$$

Substituting (3.35) into (3.34) yields

$$f'(\alpha_p) = 1 \pm \sqrt{1 - 4\delta^2 \frac{1}{(1-r)\alpha_x}} \quad (3.36)$$

Existence of the equilibria requires $1 - 4\delta^2 \frac{1}{(1-r)\alpha_x} > 0$ from which the result immediately follows.

3.6.3 Proof of Proposition 4

Given our definition of δ the fixed point condition for α_p is given by

$$\alpha_p = \delta^2 \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right)^2 \quad (3.37)$$

and rearranging equation (3.35) the solution for the fixed point condition can be written as

$$2 \left(\frac{\delta}{(1-r)\alpha_x} \right)^2 \alpha_p - \left(1 - \frac{2\delta^2}{(1-r)\alpha_x} \right) = \pm \sqrt{1 - 4\delta^2 \frac{1}{(1-r)\alpha_x}}. \quad (3.38)$$

The expression for $\partial\alpha_p/\partial\alpha_x$ is obtained by differentiating equation (3.37) with respect to α_x to get

$$\frac{\partial\alpha_p}{\partial\alpha_x} = - \frac{2 \frac{\delta^2}{(1-r)} \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right) \frac{\alpha_p}{\alpha_x^2}}{\left(1 - \frac{2\delta^2}{(1-r)\alpha_x} \right) - 2 \left(\frac{\delta}{(1-r)\alpha_x} \right)^2 \alpha_p} \quad (3.39)$$

Substituting equation (3.38) into (3.39) yields

$$\frac{\partial \alpha_p}{\partial \alpha_x} = \begin{cases} \frac{\frac{\delta^2}{(1-r)} \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right) \frac{\alpha_p}{\alpha_x^2}}{\sqrt{1-4\delta^2 \frac{1}{(1-r)\alpha_x}}} \text{ for High Precision Equilibrium} \\ -\frac{\frac{\delta^2}{(1-r)} \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right) \frac{\alpha_p}{\alpha_x^2}}{\sqrt{1-4\delta^2 \frac{1}{(1-r)\alpha_x}}} \text{ for Low Precision Equilibrium} \end{cases} \quad (3.40)$$

Therefore, $\frac{\partial \alpha_p}{\partial \alpha_x} < 0$ (resp. $\frac{\partial \alpha_p}{\partial \alpha_x} > 0$) for the low (resp. high) precision equilibrium.

3.6.4 Proof of Proposition 5

Totally differentiating the fixed point condition (3.15) on gets

$$d\alpha_p = \left(\frac{\alpha_y}{\gamma} \right)^2 d\alpha_\varepsilon \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right)^2 + 2 \left(\frac{\alpha_y}{\gamma} \right)^2 \alpha_\varepsilon \left(\frac{\alpha_p}{(1-r)\alpha_x} + 1 \right) \frac{1}{(1-r)\alpha_x} d\alpha_p. \quad (3.41)$$

Rearranging terms and using (3.34) one obtains the expression in the proposition. The inequality follows by noticing that along a stable solution it is always the case that $0 < f'(\alpha_p) < 1$.

3.6.5 Proof of Lemma 1

Let $U^* = U(a^*, A^*, \theta)$, be the utility function of individual firms when a_i and A are specified in the equilibrium functional forms of the second stage game. Let the generic form of the quadratic utility function U be specified as

$$U(a, A, \sigma_a, \theta) = \begin{pmatrix} a & A & \theta \end{pmatrix} \begin{pmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{pmatrix} \begin{pmatrix} a \\ A \\ \theta \end{pmatrix} \quad (3.42)$$

The equilibrium strategy for the second stage game is

$$a_i(x(n), p(\mathbf{n})) = \lambda(n, \mathbf{n})x_i + (1 - \lambda(n, \mathbf{n}))p(\mathbf{n}) \quad (3.43)$$

$$A(\theta, p(\mathbf{n})) = \lambda(\mathbf{n})\theta + (1 - \lambda(\mathbf{n}))p(\mathbf{n}) \quad (3.44)$$

Now

$$a(x(n), p(\mathbf{n})) = \lambda(n, \mathbf{n})(\theta + \alpha_x(n)^{-1/2}\varepsilon_i) + (1 - \lambda(n, \mathbf{n}))(\theta - \alpha_p(\mathbf{n})^{-1/2}\varepsilon)$$

thus

$$a(x(n), p(\mathbf{n})) = \theta + \lambda(n, \mathbf{n})\alpha_x(n)^{-1/2}\varepsilon_i - (1 - \lambda(n, \mathbf{n}))\alpha_p(\mathbf{n})^{-1/2}\varepsilon \quad (3.45)$$

Similarly,

$$A(\theta, p(\mathbf{n})) = \theta - (1 - \lambda(\mathbf{n}))\alpha_p(\mathbf{n})^{-1/2}\varepsilon \quad (3.46)$$

Then

$$a^2 = \theta^2 + \lambda(n, \mathbf{n})^2\alpha_x(n)^{-1}\varepsilon_i^2 + (1 - \lambda(n, \mathbf{n}))^2\alpha_p(\mathbf{n})^{-1}\varepsilon^2 + \mathcal{C}(\theta, \varepsilon_i, \varepsilon) \quad (3.47)$$

where $\mathcal{C}(\theta, \varepsilon_i, \varepsilon)$ summarizes all the relevant covariance terms which become zero once we take expectations,

$$A^2 = \theta^2 + (1 - \lambda(\mathbf{n}))^2\alpha_p(\mathbf{n})^{-1}\varepsilon^2 + cov(\theta, \varepsilon), \quad (3.48)$$

$$aA = \theta^2 + (1 - \lambda(n, \mathbf{n}))(1 - \lambda(\mathbf{n}))\alpha_p(\mathbf{n})^{-1}\varepsilon^2 + \mathcal{C}(\theta, \varepsilon_i, \varepsilon), \quad (3.49)$$

$$a\theta = \theta^2 + \mathcal{C}(\theta, \varepsilon_i, \varepsilon) \quad \text{and} \quad A\theta = \theta^2 - cov(\theta, \varepsilon) \quad (3.50)$$

Substituting into expected utility and rearranging

$$\begin{aligned} \mathbb{E}U^* &= \left[\frac{\lambda(n, \mathbf{n})^2}{\alpha_x(n)} + \frac{(1 - \lambda(n, \mathbf{n}))^2}{\alpha_p(\mathbf{n})} \right] M_{11} + (1 - \lambda(n, \mathbf{n})) \frac{1 - \lambda(\mathbf{n})}{\alpha_p(\mathbf{n})} (M_{21} + M_{12}) \\ &+ \mathbb{E} \left[\theta^2 [M_{11} + M_{22} + M_{33} + (M_{21} + M_{12}) + (M_{31} + M_{13}) + (M_{32} + M_{23})] \right. \\ &\left. + \frac{(1 - \lambda(\mathbf{n}))^2}{\alpha_p(\mathbf{n})} M_{22} \right]. \end{aligned} \quad (3.51)$$

From the above function, one can see that all the terms in the expectations are not relevant to the optimization since all the terms are out of control from the perspective of each individual. For the specific utility function we have chosen $M_{11} = -\frac{1}{2}$, $M_{21} + M_{12} = r$, therefore

$$\mathbb{E}U^* = -\frac{1}{2} \left[\left(\frac{\lambda(n, \mathbf{n})^2}{\alpha_x(n)} + \frac{(1 - \lambda(n, \mathbf{n}))^2}{\alpha_p(\mathbf{n})} \right) - 2r(1 - \lambda(n, \mathbf{n})) \frac{1 - \lambda(\mathbf{n})}{\alpha_p(\mathbf{n})} \right] + \bar{u}(\mathbf{n}) \quad (3.52)$$

where $\bar{u}(\mathbf{n})$ is a constant term that does not depend on the choice variable n . Recall that $\lambda(n, \mathbf{n}) = \Lambda(\mathbf{n})\psi(n, \mathbf{n})$, then

$$\frac{\lambda(n, \mathbf{n})^2}{\alpha_x(n)} + \frac{(1 - \lambda(n, \mathbf{n}))^2}{\alpha_p(\mathbf{n})} = \frac{1}{\alpha_p(\mathbf{n})} [\Lambda(\mathbf{n})\psi(n, \mathbf{n})(\Lambda(\mathbf{n}) - 2) + 1]$$

Using the definition of $\Lambda(\mathbf{n})$,

$$\frac{1}{\alpha_p(\mathbf{n})} [\Lambda(\mathbf{n})\psi(n, \mathbf{n})(\lambda(\mathbf{n}) - 2) + 1] = -\frac{\lambda(n, \mathbf{n})}{a_p(\mathbf{n})} (1 + r(1 - \lambda(\mathbf{n}))) + \frac{1}{\alpha_p(\mathbf{n})}$$

Hence,

$$\mathbb{E}U^* = \frac{1}{2} \frac{\lambda(n, \mathbf{n})}{a_p(\mathbf{n})} [1 + r(1 - \lambda(\mathbf{n}))] + r(1 - \lambda(n, \mathbf{n})) \frac{1 - \lambda(\mathbf{n})}{\alpha_p(\mathbf{n})} + \bar{u}(\mathbf{n}). \quad (3.53)$$

3.6.6 General Payoff Function

Consider the general payoff function $U(a, A, \sigma_a, \theta)$ where U is quadratic with cross-partial derivatives $U_{a\sigma_a} = U_{A\sigma_a} = U_{\theta\sigma_a} = 0$ and $U_\sigma(a, A, 0, \theta) = 0$ for any (a, A, θ) , so that dispersion has only second order, non-strategic effects. The quadratic form is made for analytical convenience as it allows closed form solutions once incomplete information is considered. The payoff function U can be usefully considered as a second order approximation to more general concave economies. To ensure that an equilibrium under complete information is unique and bounded it is sufficient to assumed that $U_{aa} < 0$, so that the payoff function is concave at the individual level and thus the optimal response bounded, and $-U_{aA}/U_{aa} < 1$, so that the slope of the best response with respect to the aggregate action is less than one. The two assumptions together also imply concavity at the aggregate level, which makes the efficient aggregate action well defined. In addition, for the fundamentals to matter for the individual action it must be that $U_{a\theta} \neq 0$. These restrictions on the payoff function are very mild. In fact, the payoff function U can exhibit either strategic complementarity, when $U_{aA} > 0$, or strategic substitutability, when $U_{aA} < 0$. To map the general payoff function with the properties just described into (3.1) it is sufficient to set $U_{aa} = -1$, $U_{aA} = r$, $U_{a\theta} = (1 - r) > 0$ and $U_{\sigma_a} = 0$.

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